Agent-based approaches for representing anthropogenic fire in dynamic global vegetation models

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Abstract

Fire is an integral ecosystem process and a central driver of global vegetation dynamics. Yet at the same time, humans use fire for an extremely large range of purposes, spanning disposal of agricultural residues to religious ceremonies. Anthropogenic fire management strategies are similarly diverse, ranging from preventative strategies such as indigenous patch burning to fire exclusion through industrial fire extinguishing.

Given the diversity of human-fire interactions, it is perhaps not surprising that the first Fire Model Intercomparison Project (FIREMIP) found simplistic representations of humans are a substantial shortcoming in current global fire models. Underpinning this inadequacy in global fire modelling are two key research challenges. The first is the lack of a systematic empirical basis from which to derive improved representations of people in global models. The second challenge is the current lack of appropriate modelling frameworks through which to capture and project anthropogenic fire impacts in a way which allows ready integration with global-scale biophysical models.

This thesis addresses both these key challenges in order to progress knowledge of how humans shape global fire regimes. It presents the construction of DAFI – the Database of Anthropogenic Fire Impacts – and the use of DAFI to construct WHAM! – the Wildfire Human Agency Model. DAFI is the product of a global meta-analysis of academic and grey literature capturing human-fire interactions. WHAM! is a novel, global, and spatial model that captures the socio-ecological drivers of anthropogenic fire use and management. An offline coupling of WHAM! with the JULES-INFERNO fire-enabled dynamic global vegetation model, and future runs of WHAM! for the Shared Socioeconomic Pathways are both presented.

Therefore, through development of WHAM! this thesis presents the first global projection of managed anthropogenic fire. Furthermore, through integration of WHAM! and JULES-INFERNO, this thesis describes the first time that representation of managed anthropogenic fire has been integrated into a global process-based model of fire on Earth. This innovation allows substantial new insights into the spatial heterogeneity of human influences on fire regimes and how divergent such influences could be under contrasting future scenarios. Intermediate steps towards this achievement included: identification of seven central modes of anthropogenic fire use as the basis for global-scale modelling, development of a novel means of projecting global regimes of human fire use, and new projections of socio-economic indicators for the Shared Socioeconomic Pathways. Overall, this thesis represents a meaningful advance in global fire science and, more broadly, modelling of human-Earth system interactions across large spatial extents.

Acknowledgements

I suspect many PhD candidates feel this way, but this PhD research has coincided with a significant personal journey. The start of this thesis coincided not just with COVID-19 but also a period of personal acute mental health challenges - for unrelated reasons. These were difficult days. However, this period is now firmly in the rear-view mirror, and I am so happy to be able to look forward positively to the future.

So, I want to pay a special tribute to my primary supervisor Dr James Millington. I have grown a huge amount as a researcher under your guidance, but (perhaps more importantly?) you were also a fantastic support in those early days. Thank you. My secondary supervisor, Professor Tamsin Edwards, has been a wonderful support, mentor and role-model through this process.

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This thesis is dedicated to my son, Theodore Harriman.

Table of Common Acronyms

Acronym	Meaning
ABM	Agent-based model
AFR	Anthropogenic fire regime
CMIP	Coupled Model Intercomparison Project
DAFI	Database of Anthropogenic Fire Impacts
DGVM	Dynamic global vegetation model
ESM	Earth system model
FIREMIP	Fire Model Intercomparison Project
GFED	Global Fire Emissions Database
HANPP	Human appropriation of net primary production
HDI	Human development index
LFS	Land-fire system
MODIS	Moderate Resolution Imaging Spectrometer
NPP	Net primary production
SES	Socio-ecological system
SSP	Shared Socioeconomic Pathway
WHAM!	Wildfire Human Agency Model
WUI	Wildland-urban interface

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Chapter 1

Introduction

1.1 Thesis aims and objectives

The research conducted in this thesis was inspired by findings from the first Fire Model Intercomparison Project (FIREMIP; Hantson et al., 2016). The FIREMIP found that simplistic representations of humans were a substantial shortcoming in the fire modules of dynamic global vegetation models (DGVMs) - with little agreement between models on the direction or magnitude of human influence on burned area (Teckentrup et al., 2019). Moreover, discussion of FIREMIP outcomes argued addressing such shortcomings represented a substantial research challenge. Commenting on the work required to develop a process-based representation of human-fire interactions in global-scale models, Teckentrup et al., (2019) suggest this "will likely remain a long-term challenge and requires the synthesis of knowledge from various research fields" (p3898). Similarly, Forkel et al., (2019) argue an underlying challenge is the lack of "a solid and large-scale empirical basis that would allow researchers to derive alternative formulations on human–fire interactions for fire-enabled DGVMs" (p70).

Addressing these issues is therefore the central overarching rationale of the research presented in this thesis. To deliver on this ambition, three aims were identified, which in turn inform three key deliverable objectives. By delivering against these objectives, the research described in this thesis aims to make a significant contribution to understanding of global fire regimes, and the wider development of global-scale behavioural models of socio-environmental systems (SES). The three aims and accompanying objectives of this thesis are:

Aims

1) Synthesise available knowledge of human-fire interactions globally, assess the state of understanding and identify knowledge gaps;
2) Explore how behavioural modelling may provide the basis for improved representations of anthropogenic fire impacts in global-scale process-based models;
3) Quantify the influence of human behaviours on global wildfire regimes and explore how such behaviours may evolve under future environmental and socio-economic change.

Objectives

1) Conduct a global meta-analysis of studies of anthropogenic impacts on wildfire, spanning the breadth of the academic disciplines and grey literature;
2) Drawing on this evidence base, develop the first global behavioural model of anthropogenic fire impacts and integrate this with a dynamic global vegetation model;
3) Use this coupled model to explore the socio-ecological drivers of present-day fire regimes, and run the behavioural model under contrasting future scenarios of socio-economic development and environmental change.

1.2 Thesis structure

This thesis is structured as a literature review, four chapters of original research, and a final discussion chapter. Table 1.1 provides a brief summary of each chapter's contents and associated peer-reviewed publications (see Section 1.2). Broadly, chapter three delivers against aim and objective 1, chapters four and five deliver aim and objective 2, and chapter six delivers aim and objective 3.

Chapter two, a literature review, describes the current state of knowledge surrounding human-fire interactions. This begins with a review of findings from the first Fire Model Intercomparison Project (FIREMIP) and 'top-down' Earth observation based empirical work. It then describes advances in understanding of human-fire interactions from local and landscape-scale field studies. Chapter two concludes by describing how and why agent-based modelling may provide methods to improve representation of anthropogenic fire in global-scale models.

Chapter three presents DAFI – the database of anthropogenic fire impacts. DAFI is the product of a literature meta-analysis spanning 514 academic papers, government and NGO reports. DAFI was developed in response to the need identified in FIREMIP for a global-scale dataset to inform improved representation of human impacts on fire regimes in dynamic global vegetation models (DGVMs).

Chapter four is the first of two chapters presenting WHAM! – the Wildfire Human Agency Model. This chapter presents the land use module of WHAM!, specifically the distribution of land-fire systems (LFS). These LFS are closely related to WHAM!'s distribution of agent functional types (AFTs) and so are fundamental to overall model function. The LFS distribution is evaluated with the Human Appropriation of Net Primary Production – an independent measure of land use intensity.

Table 1.1: Summary of thesis chapters, their relationship to research aims & associated peer-reviewed publications

Chapter	Research aim(s)	Content (Section 1.1)	Associated publications (Section 1.2)
2	All	Literature review	Ford et al., 2021
3	1	DAFI: a global database of anthropogenic fire impacts	Millington et al., 2022; Smith et al., 2022
4	2	WHAM! land use engine: the global distribution of land-fire systems	Perkins et al., 2022
5	2	WHAM! fire module: parameterisation & evaluation	Perkins et al., (in submission)
6	3	WHAM! applications: offline coupling with INFERNO & 2100 model runs for SSPs 1, 3 & 5.	N/A
7	All	Discussion	N/A

Chapter five presents the fire module of WHAM!. This begins with the use of the underlying LFS distribution to determine a set of agent functional types (AFTs) and their parameterisation for managed fire use. Building on this, a set of landscape level meta-processes are described. These span fire control measures, fire extinguishing ('suppression') intensity and fire use as a weapon (i.e. arson). WHAM! outputs for crop residue burning are evaluated independently against the GFED5 cropland fires product (Hall et al., 2023), whilst other WHAM! managed fire outputs are evaluated against unseen case-study data.

Chapter six presents two applications of WHAM!. The first of these is an offline coupling of WHAM! with INFERNO, the fire module of the JULES DGVM. This model ensemble is used to explore the socio-ecological dynamics of fire regimes of the recent past. Then, WHAM! is run for the Shared Socioeconomic Pathways (SSPs 1, 3 & 5). This allows possible futures of human fire use and management to be explored under contrasting socio-economic and environmental conditions.

Chapter seven, a discussion, summarises findings and lessons learned from the work presented in chapters three to six. It does this first for global understanding and modelling of human-fire interactions, before considering wider implications for modelling of global socio-environmental systems (SES).

1.3 A note on associated publications

This thesis contains peer-reviewed publications, the detail of which is set out by chapter below. The content of Chapter 4 comes directly from a published journal article. Chapters 2 & 3 contain text, figures and tables previously published in related publications. All such content was the original contribution of the candidate. Where text, figures or tables have been previously published, this is marked in footnotes. Finally, a manuscript presenting content from Chapter 5 will shortly be submitted and is likely to be available as a pre-print at the time of oral examination.

Chapter 2

- Some of the content in the literature review became the candidate's original contribution to the wider review of the modelling of human-fire interactions conducted by Ford et al., (2021; including Perkins). This content is marked as appropriate in footnotes.
- Some portions of the literature review describe the need for a consistent dataset for global-scale modelling of human-fire interactions. Such a dataset was delivered during this PhD thesis, and is presented in Millington et al., (2022; including Perkins). Data from this paper were used in the analysis of Smith et al., (2022; including Perkins).

Chapter 3

- The database and analysis presented in this chapter formed the basis of Millington et al., (2022). Owing to multiple deadlines on concurrent journal articles (i.e. Perkins et al., 2022 – Chapter 4), the PhD supervisor lead on delivery of the published manuscript. The content in this thesis chapter is all the candidate's original work, having originally been composed for the candidate's MPhil to PhD upgrade report in 2021. Content presented that also appears in Millington et al., (2022) is marked in footnotes.
- As noted above, data from the database presented in this chapter also contributed to the study of Smith et al., (2022).

Chapter 4

- This chapter was previously published as Perkins et al., (2022).

Chapter 5

- A version of this chapter will shortly be submitted to *Geoscientific Model Development* as Perkins et al., (in submission); this related manuscript is likely to be available as a pre-print at the time of oral examination.

1.4 References of associated publications

Ford, A., Harrison, S., Kountouris, Y., Millington, J., Mistry, J., **Perkins, O.**, Rabin, S., Rein, G., Shreckenberg, K., Smith, C., Smith, T., & Yadav, K. (2021). Modelling Human-Fire Interactions: Combining Alternative Perspectives and Approaches, *Frontiers in Environmental Science*, 9. doi: 10.3389/fenvs.2021.649835

Millington, J.D.A., **Perkins, O.**, & Smith, C. (2022). Human fire use and management: A global database of anthropogenic fire impacts for modelling, *Fire*, 5(4), 87. doi: 10.3390/fire5040087

Perkins, O., Matej, S., Erb, K-H., & Millington, J.D.A. (2022). Towards a global behavioural model of anthropogenic fire: The spatio-temporal distribution of land-fire systems, *Socio-environmental Systems Modelling*, 4. doi: 10.18174/sesmo.18130

Perkins, O., Kasoar, M., Voulgarakis, A., Smith, C., Mistry, J., & Millington, J.D.A. (In submission). A global behavioural model of human fire use and management. *Geoscientific Model Development*.

Smith, C., **Perkins, O.**, & Mistry, J. (2022). Global decline in subsistence-oriented and smallholder fire use, *Nature Sustainability*, 5, 542-551. doi: 10.1038/s41893-022-00867-y

Chapter 2

Literature review

2.1 Introduction

Fire is a fundamental earth-system process and a key driver of global vegetation dynamics (Bowman 2005; Pausas and Keeley 2009; Keeley et al., 2011). At the same time, human fire use is extraordinarily diverse, with anthropogenic fire providing a simple fertiliser in shifting cultivation (Pingali et al., 1987; Carmenta et al., 2013), a means to clear agricultural and forestry residues (Korontzi et al., 2006), and to deter pests and regenerate forage in livestock farming (Kull 2003; Cano-Crespo et al., 2015). However, fire also poses significant hazard to humans, causing property damage and loss of life both directly, and indirectly through harmful aerosol emissions (Johnston et al., 2012; Molina-Terrén et al., 2019).

As a result of human activity, global fire regimes are changing profoundly (Rogers et al., 2020). Climate change is causing fires to become widespread in boreal ecosystems that were previously largely fire-independent (Feurdean et al., 2020). A combination of climate change and the unintended consequences of industrial fire suppression (Silva et al., 2010) have given rise to the era of the 'mega-fire', leading to catastrophic damage in areas including North-eastern China (Fan et al., 2017), California (Keeley and Syphard 2019) and Southern Australia (Adams et al., 2020). Yet at the same time, remote sensing data from the Moderate Resolution Imaging Spectrometer (MODIS) suggest annual global burned area is decreasing (Andela et al., 2017), with plausible explanations including anthropogenic land use change (Rabin et al., 2015), changes in rainfall patterns (Zubkova et al., 2019), and the CO_2 fertilisation effect on vegetation (Forkel et al., 2019). However, the underlying coarse (1km^2) spatial resolution of MODIS' data itself may mean that rather than reducing burned area, anthropogenic influence is merely fragmenting fire regimes into smaller fires that are undetectable in satellite-derived global burned area observations (Fornacca et al., 2017; Zhang et al., 2018; Zubkova et al., 2023).

This complex picture highlights the multifaceted nature of anthropogenic impacts on fire regimes. Not only are humans an important source of fires and intentional fire suppression, they also alter fire regimes by fragmenting landscapes (Archibald et al., 2011) and altering fuel loads through grazing and logging (Cochrane 2009a; Archibald 2016). For these reasons, Anthropocene wildfire regimes are best understood as a coupled socio-ecological system (Pausas and Keeley, 2019; Kelley et al., 2019), in which people are the largest driver of changes to the frequency, intensity and extent of fire (Rogers et al., 2020).

However, at the global scale, fire is most frequently modelled as a component of dynamic global vegetation models (DGVMs) – which are process-based biophysical models that form the terrestrial biosphere component of general circulation models (GCMs). As such, DGVMs' emphasis has historically been on representing biophysical processes, with anthropogenic influences considered primarily as external forcings (Foley et al., 2000; Quillet et al., 2010). As a result, the recent Fire Model Inter-comparison Project (FireMIP; Hantson et al., 2016) revealed substantial limitations in, and disagreements between, the current generation of Dynamic Global Vegetation Models (DGVMs) regarding the anthropogenic influence on fire regimes (Teckentrup et al., 2019). The lack of an holistic approach is symptomatic of a broader need for interdisciplinary approaches to advance understanding of fire ecology (Coughlan and Petty 2012).

Therefore, this review provides an overview of how human systems are represented in the fire modules of DGVMs, before exploring the wider state of understanding of human-fire interactions. Two principal limitations in current representations of anthropogenic fire in DGVMs are highlighted: a lack of representation of the underlying processes that drive human fire impacts, and an inability to capture interactions between human and biophysical drivers of global fire regimes. Methods from agent-based modelling (ABM) provide opportunities to address these limitations. Therefore, in the next section, agent-based methods are assessed as a means of addressing these key shortcomings in the representation of human systems within global fire models.

2.2 Current approaches to modelling and understanding global fire regimes

2.2.1 Representations of anthropogenic fire impacts in DGVMs

The recently concluded FIREMIP made wide-ranging recommendations for the improvement of the representation of fire in DGVMs (Hantson et al., 2020), including improvements to representations of fuel load based on fire return intervals and the need for higher-resolution calibration data (Forkel et al., 2019). However, a resounding and consistent conclusion was that representations of anthropogenic influences on fire are currently insufficient (Teckentrup et al., 2019). Representations of people were both the greatest source of disagreement between models, but also between models and satellite observations (Teckentrup et al., 2019; Forkel et al., 2019). Furthermore, when assessed on their ability to reproduce observed burned area patterns from global remote sensing fire product, those models which had more detailed representation of anthropogenic influences performed best (Hantson et al., 2020).

The FIREMIP highlighted fundamental issues in DGVMs' representation of humans' direct and indirect influences on fire regimes. Issues in humans' direct influences on fire regimes relate firstly to human fire ignitions, and secondly to human impacts on fire spread. Firstly, current DGVM representations of anthropogenic ignitions are based on the concept that each human globally will create an average number of ignitions per year (Venevsky et al., 2002; Rabin et al., 2017). As such, ignitions are projected based on globally-homogenous functions of coarse-resolution proxy variables such as population density or GDP (Figure 2.1). These anthropogenic ignition functions are produced by top-down model calibration to observations, and so do not represent the diverse modes of human fire use or their underlying rationales (Forkel et al., 2019; Teckentrup et al., 2019). The consequences of this are evident in the FIREMIP results themselves. For example, five out of seven DGVMs simply exclude fires from croplands (Table 2.1). By contrast, the Community Land Model (CLM) contains a separate ignition function for cropland fires (Li et al., 2012), and so was the only model able to capture the fire belt in the Indo-Gangetic plain (Hantson et al., 2020), which is strongly associated with agricultural residue burning (Gupta 2012; Liu et al 2019; Sembhi et al., 2020).

Secondly, current DGVMs do not represent direct anthropogenic influences on fire spread outside of population-density derived representations of fire suppression (extinguishing of active fires; Table 2.1). As such, reflecting on the state of fire science, Shuman et al., (2022) argue that integrating representation of *managed* anthropogenic fires into fire models is one of five key research challenges facing the field. This is reflective of a growing recognition of a distinction between damaging uncontrolled 'wildfires' and controlled, potentially beneficial 'landscape' fires (Berlinck and Batista, 2020; UNEP, 2022). However, whilst acknowledging that representation of human-fire interactions is the most serious deficiency in current global fire models, Jones et al., (2022) question the feasibility of capturing the heterogeneity of managed human fire uses globally.

A further set of anthropogenic influences on fire regimes not captured by current DGVMs relate to humans' *indirect* impact on fire regimes, particularly through fragmentation of vegetation (Harrison et al., 2022). Fragmentation processes include road building and conversion of natural vegetation to croplands, which together lead to reduced fire size and burned area, particularly in fire-adapted savannas (Andela et al., 2017 Haas et al., 2021). Conversely, logging of fire-prone tropical forests can lead to increased vegetation flammability and burned area (Cochrane 2009a). There is also an inter-relation between managed fire use and fragmentation, as humans often use fire to prevent large wildfires by deliberately fragmenting flammable fuel (Laris 2002; Section 2.2.3). Representation of fragmentation processes in current DGVMs is limited to adjustments to burned area on croplands and simple changes to the vegetation characteristics of pastures in some models (Table 2.1).

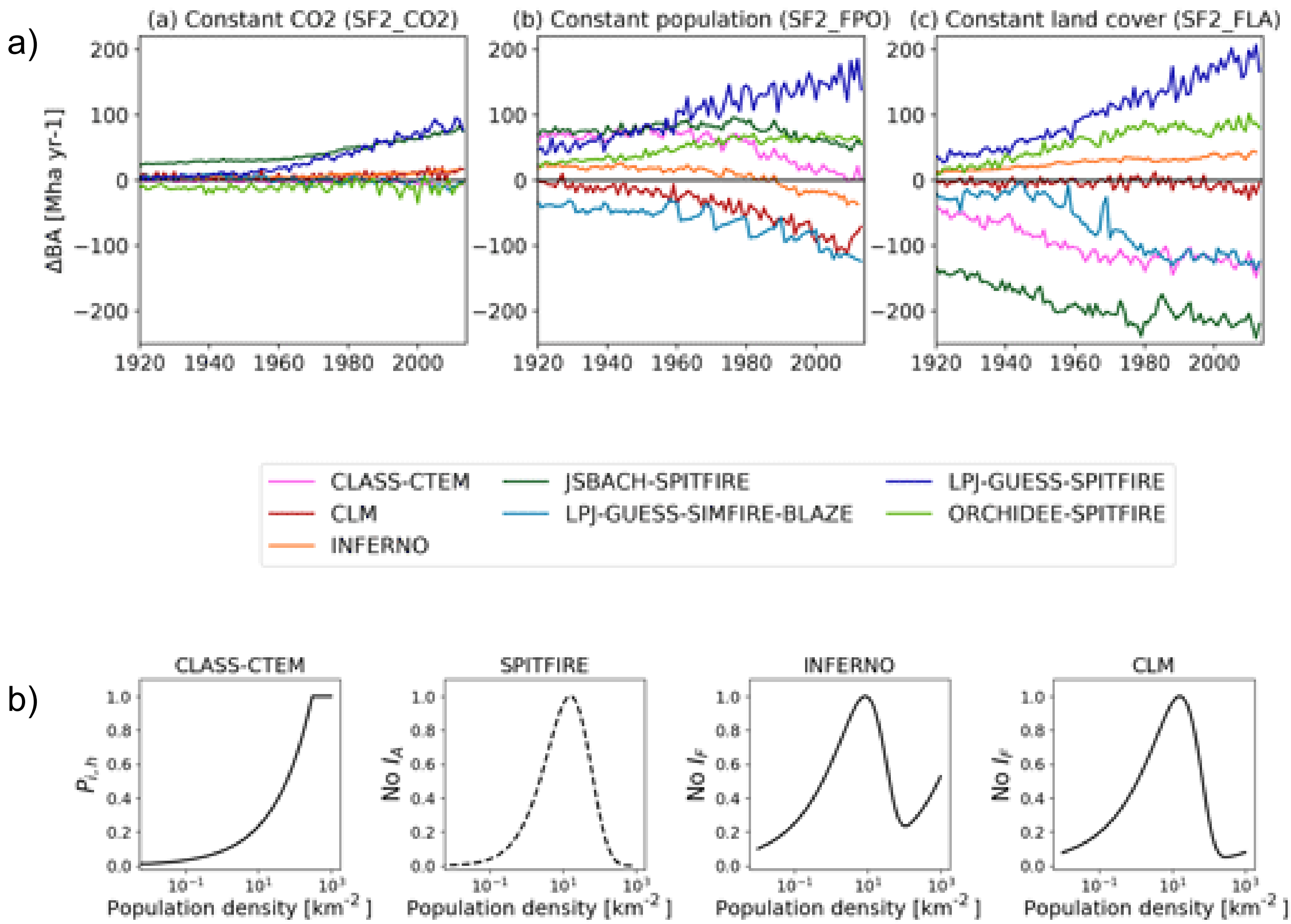


Figure 2.1: From Teckentrup et al., 2019. Results of a sensitivity analysis conducted during the FIREMIP: a) percentage change in burned area of the model ensemble against a baseline run when CO_2 (SF2_CO2), population (SF2_FPO) and land cover (SF2_FLA) were held constant at 1700 levels; b) underlying functions to represent anthropogenic ignitions in four of the five fire models used (three model ensembles comprised the SPITFIRE fire module coupled to differing DGVMs). Whilst two model combinations capture a net negative contribution of anthropogenic CO_2 emissions on burned area, and others do not, there is little to no agreement between models about the net impact of human population growth and land use change since 1900 – less still the magnitude of such effects. This can be linked to the simple empirical functions used to represent anthropogenic impacts. See Table 2.1 for references.

Table 2.1: An overview of approaches to representing anthropogenic influences in models included within the FIREMIP (from Teckentrup et al. 2019, with additions from Rabin et al. 2017). In models with an explicit representation of anthropogenic ignitions, these are calculated as a function of population density, which may be globally uniform or vary spatially. Where anthropogenic suppression is 'implicit' it is calculated within the initial ignitions' calculation, whilst in models where it is represented explicitly this forms a separate calculation (Rabin et al., 2017).

Model	Cropland fire	Pasture fire	Deforestation fire	Anthropogenic ignitions	Anthropogenic suppression
CLASS-CTEM	None	No pasture	None	Population density, fixed	None
CLM	Yes	Same as grasslands	Yes	Population and GDP, spatially-varying	Explicit
INFERNO	Same as grasslands	Same as grasslands	None	Population density, fixed	Explicit
JSBACH-SPITFIRE	None	Higher fuel bulk density than grasslands	None	Population density, spatially-varying	Implicit
LPJ-Guess-SIMFIRE-BLAZE	None	Harvest of biomass	None	NA	NA
LPJ-GUESS-SPITFIRE	None	Same as grasslands	None	Population density, spatially-varying	Implicit
ORCHIDEE-SPITFIRE	None	Same as grasslands	None	Population density, fixed	Implicit

References: CLASS-CTEM (Melton and Arora 2016); CLM (Li et al., 2012, 2013); INFERNO (Mangeon et al., 2016); JSBACH-SPITFIRE (Lasslop et al., 2014, Hantson et al., 2015), LPJ-Guess-SIMFIRE-BLAZE (Smith et al., 2013; Lindeskog et al., 2014), LPJ-GUESS-SPITFIRE (Lehsten et al., 2009; 2016), ORCHIDEE-SPITFIRE (Yue et al., 2014, 2015).

The results of DGVMs' limited representation of human impacts on fire regimes include weak agreement between models on whether anthropogenic influence has increased or decreased global burned area since 1700 (Teckentrup et al., 2019; Figure 2.1), and only moderate model capacity to reproduce observed global burned area (Forkel et al., 2019). One major cause of the limited representation of humans' impact on fire regimes in DGVMs is the lack of a globally applicable evidence base from which to develop alternative parameterisations (Jones et al., 2022). Therefore, the following section assesses the current state of knowledge of human-fire interactions. It argues that, as with global-scale modelling, global-level attempts to characterise anthropogenic fire impacts empirically have focused on their observed outcomes in fire regimes, but less so on the underlying systems and processes that drive them.

Conversely, much progress has been made on understanding the drivers of anthropogenic fire impacts at more local scales. There is therefore a major opportunity to draw together knowledge from multiple disciplines to bridge the gap between local-scale studies that engage with the drivers of anthropogenic fire regimes and coarser-scale studies focused on diagnosing the quantitative signatures of anthropogenic impacts. Combining knowledge from across different spatial scales will be an important first step in developing global-scale models that are able to capture the interactions of socio-economic and biophysical drivers of fire regimes.

2.2.2 Global human-fire interactions

Globally, the key biophysical drivers of wildfire patterns are ecosystem net primary production (NPP) and vegetation moisture content (Krawchuk et al., 2009). In a Savannah ecosystem with plentiful and dry fuel, burned area is maximised, whilst fire is rare in either low NPP environments such as deserts and tundras or very moist vegetation types such as undisturbed tropical forest (Krawchuk and Moritz 2011). Attempts to characterise human-fire interactions at the global scale have tended to adopt a 'top-down' approach - working backwards from observations to try and detect and determine the anthropogenic signal. Such approaches have often conceptualised anthropogenic impacts as deviations along the same core axis as the key drivers of natural variation in fire regimes.

For example, drawing on the 'dual constraint' hypothesis of Krawchuk et al., (2009), McWethey et al. (2013), argue humans' impact is to increase the amount of fire in moisture-constrained high NPP ecosystems, whilst decreasing the amount and extent of grassland and savanna fires due to suppression and fuel fragmentation (Figure 2.2). As such, the broad anthropogenic impact on fire regimes could be considered to be homogenisation – reducing fire in the world's most flammable regions, whilst increasing fire elsewhere. This hypothesis was bolstered by Archibald et al., (2013) who used unsupervised learning to identify a globally-occurring 'pyrome' (a set of fire regimes with common characteristics) typified by regular, low intensity ignitions as the signature of anthropogenic fire regimes.

By contrast, Pereira et al., (2022) use quantitative characteristics of fire regimes (including burned area, interannual variability, fire season length) derived from remote sensing to define three classes of regime along an access of natural to anthropogenic: 'Wild', 'Tamed' and 'Domesticated'. However, such a classification does not engage with the drivers of human fire use, and so regards large-scale cropland burning as indicative of a 'Tamed' fire regime. Yet identified drivers of cropland burning reflect the logic of anthropogenic land use: crop type, yield gains due to fertiliser use, and mechanised harvesting (Kaur et al., 2022; Lin and Begho, 2022). Cropland burning cannot therefore be meaningfully considered a derivation of an underlying biophysical fire regime and should perhaps be instead understood as 'Introduced'.

A top-down approach is also presented by Bowman et al., (2011) who, in addition to factors identified by McWethey et al., (2013), highlight the importance of industrial suppression in creating crown fires in temperate forests, and the introduction of invasive grasses leading to fires in mid-latitude deserts. Furthermore, in exploring the interrelationships between biophysical factors and anthropogenic influences, Kelley et al., (2019) found anthropogenic suppression to be critical in determining the degree of fire in cropland-dominated landscapes. This finding concurs with Bistinas et al., (2014), who found that cropland area was significantly negatively associated with burned area. However, Bistinas et al., (2014) also find that the influence of grazing lands was to increase burned area in grasslands, perhaps contradicting the findings of Archibald et al., (2011), that deliberate anthropogenic ignitions were a weaker influence on Savanna and grassland fire regimes than reduced fuel load from grazing (Figure 2.2). Finally, Benali et al., (2017) argue that the predominant signal of anthropogenic fire regimes is a seasonal bimodality – with fire peaks driven by the rationale of anthropogenic land use rather than the naturally 'optimal' conditions for fire.

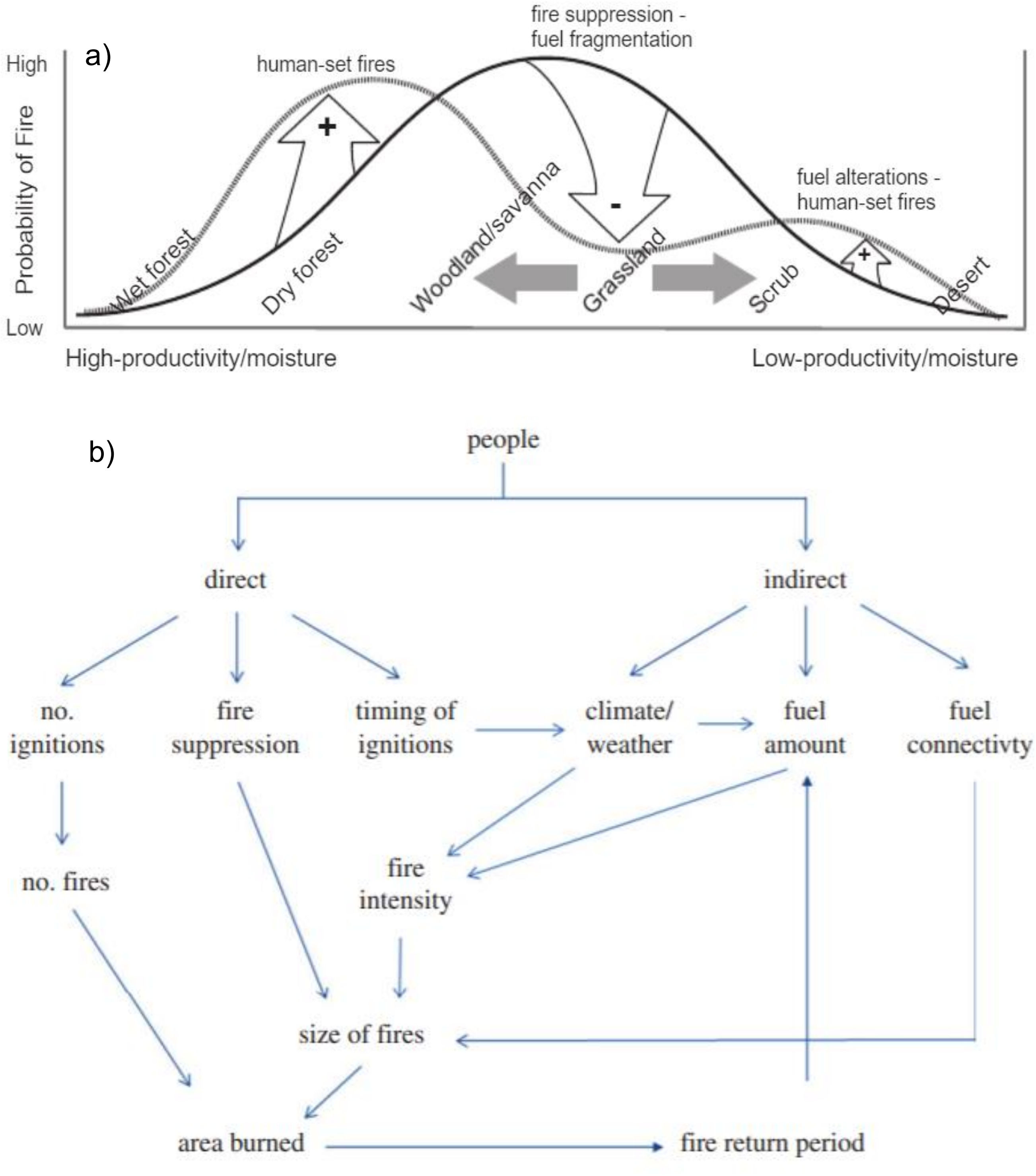


Figure 2.2: Conceptualising anthropogenic impacts on wildfire regimes. a) a 'top-down' approach from McWethey et al., (2013) - human impacts (dotted line) to wildfire placed along an axis representing the 'dual constraint hypothesis' of natural variation (black line) in wildfire regimes; b) a more granular approach from Archibald (2016) - a conceptual model of the multi-faceted anthropogenic impacts on fire regimes in an African savanna ecosystem. Whilst in the framework presented in a), reductions to fuel connectivity (fragmentation) are assumed to dominate the impact of increased ignition numbers, at the global scale, others, including Bistinas et al., (2014) have found the opposite in grasslands and pastures.

Therefore, existing attempts to characterise anthropogenic fire impacts as deviations from the prevailing biophysical drivers of fire regimes have not found an overall coherent structure to describe human influences. Rather, the interactions between anthropogenic land use systems and the biophysical drivers of fire regimes serve to create a diverse web of feedbacks that require more granular exploration (Table 2.2).

Table 2.2[1]: Literature examples of socio-ecological feedbacks driving global fire regimes.

Anthropogenic fire influence	Fire regime	Vegetation
Anthropogenic ignitions	Extent of anthropogenic ignitions is a fundamental driver of global pyromes (Archibald et al., 2013); widespread fire use in agricultural communities can be self-reinforcing, as capital investment is discouraged due to the high risk of fire damage (Cammelli et al., 2020)	NPP of grassland ecosystems influences livestock farmers' decisions about how frequently to burn to regenerate forage (Taylor 2003); communities based in highly flammable vegetation types have developed complex 'patch-mosaic' burning to fragment fuel loads (Laris 2002)
Fire suppression	Shocks in the fire regime tend to drive shifts in suppression policy, for example towards more preventative fuel load management (Ruiz-Mizaro et al., 2011) and prescribed burning (Fernandes et al., 2016; Ansell et al., 2020) or simply through more stringent fire regulations (Watts et al., 2019)	Fire suppression can lead to the so-called "fire paradox" (Mahmoud and Chulahwat 2019) - fuel build-ups due to blanket suppression policies lead to larger fires, and possibly then also to changes in suppression policies (Eloy et al., 2018)
Fragmentation and fuel load	Logging of tropical forests increases their flammability (Cochrane 2009a); conversely, grazing reduces the fire proneness of savannah and grassland ecosystems (Archibald 2016)	Agricultural expansion and abandonment drive fundamental shifts in vegetation composition and therefore fuel load (Dara et al., 2019); grazing removes grassy biomass from the landscape and can contribute to an increase of woody shrubs (Asner et al., 2004)

[1] This table is taken from the author's original contribution to Ford et al., (2021)

Moreover, all such 'top-down' approaches to discerning anthropogenic influences on fire are reliant on satellite observations to quantify fire regimes globally. The Global Fire Emissions Database is the perhaps the most prominent global remote-sensing product for fire emissions and burned area (van der Werf et al., 2017), and was used throughout FIREMIP for model evaluation (Hantson et al., 2016). Up until the 4th version of GFED (GFED4; Giglio et al., 2013), products have been derived from a combination of the Moderate Resolution Imaging Spectrometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS).

However, these sensors are known to perform poorly in landscapes dominated by anthropogenic fires (Zhang et al., 2018). This is because the majority of anthropogenic fires are smaller than the minimum fire size (21ha) that can be reliably captured by MODIS (Andela et al., 2019), whilst in a global analysis VIIRS detected an average of only 24% of fires <25ha in size (Oliva and Schroeder 2015). Indeed, most crop residue fires in rice producing regions are less than 1 ha in size (Haider et al., 2013; Lasko et al., 2017; Zhang et al., 2018). In comparison with higher resolution ($30m^2$) data from Landsat, it was found that MODIS data underestimated the fire count and burned area by a factor of 10 in a dense agricultural landscape in Western Russia (McCarty et al., 2016).

Such shortcomings have led to the integration of fine-scale remote sensing observations (i.e. Landsat at $30m^2$ and Sentinel-2 at $20m^2$) into coarser-resolution global-scale burned area products. Notably, the 5th Global Fire and Emissions Database (GFED5), which is currently under review (Chen et al., 2023), integrates a global sample of ground-truthed observations from these fine-scale products with MODIS observations to scale the MODIS record to reflect real-world burned area more closely. Furthermore, GFED5 includes a new crop fires algorithm (Hall et al. 2023), developed in a similar way with ground-truthed scaling factors, which suggests as much as 81Mha yr^{-1} of burned area is due to cropland fires. Consequently, global burned area in GFED5 between 2001-2020 is 774Mha yr^{-1}, *a 124% increase* from GFED4 (345Mha), which did not incorporate finer-scale remote sensing products (Giglio et al., 2013). Therefore, previous top-down attempts to classify anthropogenic fire impacts will need to be re-evaluated in the light of a much-revised observational record.

An alternative to discerning anthropogenic fire impacts from their observed outcomes in fire regimes is to classify the processes and anthropogenic systems that shape how people use fire. One example of this is presented by Lauk and Erb (2016). Lauk and Erb identify five anthropogenic regimes in current use: fires by hunter-gatherers and pastoralists; shifting cultivation fires; fire as a weapon; fire for vegetation clearance; and 'combatting and preventing vegetation fires', which describes industrial fire suppression. However, a weakness in this classification is that it is not exhaustive, for example it excludes crop residue fires, and moreover it does not capture the underlying socio-ecological drivers that lead to the emergence of such patterns of fire use.

By contrast, the historical approach of Pyne (2001) identifies three underlying sets of conditions that shape human attitudes towards fire use and management. These are termed 'first', 'second' and 'third' fire. 'First fire' broadly describes pre-human, lightning ignited fire regimes. Pyne's second fire describes regimes shaped by human use of fire as a land management tool. Finally, 'third fire' describes the transfer of fire from landscapes to industrial centres: landscapes are shaped by industrial fire suppression and exclusion. However, a weakness of qualitative accounts of anthropogenic fire regimes - such as those of both Pyne (2001) & Lauk and Erb (2016) - is that they are unable to bridge the gap from their process-oriented typology to their outcomes in observed fire regimes. This highlights the fundamental absence of quantitative data that link anthropogenic fire use and management in different contexts to observations of the resulting fire regime (Forkel et al., 2019).

Current attempts to understand anthropogenic impacts on wildfires at the global scale, therefore, are hampered by the lack of a comprehensive dataset that analyses the socioeconomic drivers of human fire use, quantifies how humans use fire in different contexts and then links this to fire regime observations from satellites and other secondary data sources. This absence is also a central reason why the more detailed attempt of Rabin et al., (2015; 2018) to integrate anthropogenic fire use into a DGVM has been restricted to reproducing patterns from the past: without a basis on which to model the underlying factors that drive human decision-making regarding fire, it is not possible robustly to project how these may change in future.

2.2.3 Human fire interactions beneath the global scale

Whilst detecting, quantifying and understanding human fire impacts systematically at the global scale remains a major challenge, much progress has been made in understanding human fire use in specific land use systems and at more granular spatial scales. For example, a large body of literature documents the integral role of fire in shifting cultivation (see Mertz et al., 2009; Van Vliet et al., 2013 for reviews). However, whilst this system is widely studied, no recent review of the role of fire within it could be identified. Rather, data around fire use in shifting cultivation is most frequently captured incidentally in studies focused on wider humanitarian, agronomic, ecological or biodiversity conservation issues (see Chapter 3). For this reason, studies such as Archibald (2016) that evaluate the impact of specific human behaviours on fire regimes by linking them with observations of fire regimes remain comparatively rare beyond the local scale (Figure 2.2).

An area in which fire use has been explicitly studied is in the place of fire knowledge within the broader traditional ecological knowledge of pastoral and hunter gatherer societies (Huffman 2013). Laris (2002) seems to be the first study to recognise the practice of 'patch mosaic' burning of Savanna vegetation types. This practice, first described in Mali, is conducted early in the dry season by indigenous peoples to prevent damaging late dry-season fires, and has since been documented in Ethiopian grasslands (Johansson et al., 2019), the Miombo Woodlands of Zambia (Eriksen et al., 2007), the Brazilian Cerrado (Eloy et al., 2018), the savannas of Guyana and Venezuela (Bilbao et al. 2019), and across Northern and Central Australia (Bird et al., 2005; McKemey et al., 2019). Such a system has been shown to be effective at controlling a fire regime: where Aboriginal burning ceased in the Arnhem lands of Northern Australia, lightning ignited megafires replaced previously controlled small-scale burning leading to an increase in burned area (Burrows et al., 2006).

Within indigenous communities, fire knowledge may be encoded in communal fire governance and a community fire calendar (Shaffer 2010; Welch 2014). Further, when under pressure from external economic forces, such communal governance has been observed to fracture (Gil-Romera 2011; Bilbao et al., 2019), leading to less targeted and nuanced fire use, and greater potential for accidental catastrophic wildfires (Hoffman et al., 2008; Butz 2009; Rodríguez et al., 2018). The existence of fire knowledge as a form of social capital was also observed in Spanish chestnut growers (Seijo et al., 2015), and is increasingly recognised amongst state institutions: for example, in Australia, federal and state government agencies now commonly work alongside Aboriginal peoples to manage the fire regimes of protected areas and national parks (Petty et al., 2015; Neale et al., 2019; Ansell et al., 2020). Fire use may also be self-reinforcing in agricultural communities either due to imitation between farmers (Lopes et al., 2020), or because risk of damage from escaped fire prohibits investment in more capital-intensive fire-free alternatives (Cammelli et al., 2020).

Conversely, where fire use is not commonly practiced in a community (often as the legacy of legal prohibitions), it has proved challenging to encourage land mangers to recommence fire use for conservation or fuel load management reasons (Kreuter et al., 2008; Harr et al., 2014; Bendel et al., 2020; Weir et al., 2020). A lack of fire culture can cause challenges at the wildland urban interface, where urban residents may lack understanding of how to manage and live with fire (Curt and Frejaville 2017; Xanthopoulos 2018). Together, these cases provide growing and compelling evidence that fire knowledge and practice is transmitted through communities as a form of social and cultural capital. However, a majority of studies of traditional fire knowledge are conducted from an anthropological perspective, and so quantification of the anthropogenic fire regimes created in such conditions remains comparatively sparse (see Chapter 3).

A third area in which there is growing understanding of anthropogenic fire use is in the case of deforestation. Cochrane (2009b) provides a robust overview of how the interplay between different land use actors drives deforestation fires in the Tropics. For example, in the Amazon and in Southeast Asian peat swamp forests, logging has played a crucial role in increasing both the susceptibility of forests to fire and their accessibility to local farmers through the creation of roads and waterways (Page et al., 2009; Cochrane 2009a).

Furthermore, growing concern about the role of uncontrolled wildfire in tropical forests as a driver of climate change (Van der Werf et al., 2017; Withey et al., 2018) has led to more detailed analysis of how and why local people use fire in such contexts (e.g. Van Vliet et al., 2012; Carmenta et al., 2013, 2019), and a growing recognition that political disagreements over land tenure and access to forest resources play a central role (Chokkalingam et al., 2007; Kull and Laris 2008; Carmenta et al., 2017). This assessment of the importance of the political dimensions of fire builds on previous findings that fire governance across much of the global South has been inextricably bound up with colonialism (Pyne 2001; Kull et al., 2003; Dendi et al., 2004; Hoffmann et al., 2008).

In contrast to the cases of shifting cultivation and traditional fire knowledge, there has been much quantitative analysis of the extent of fire use in deforestation (Aragao and Simabukuro 2010; van Marle et al., 2017; Verhegghen et al, 2016; Morgan et al., 2019). However, there is currently a disconnect between such regional-scale quantitative approaches, typically based upon satellite data, and the comparatively local-scale, often qualitative approaches seeking to understand the underlying socio-economic drivers of deforestation fires.

Advances in understanding are not limited to the drivers and consequences of human fire use, but also to fire suppression (extinguishing of active fires). The so-called ‘fire paradox’ occurs where industrial fire suppression leads to fuel-build ups on the landscape that ultimately cause mega-fires when suppression measures fail (Silva et al., 2010; Williams 2013). This situation can be exacerbated by rural abandonment (Miguel-Ayanz et al., 2013), particularly where former timber plantations become large, unmanaged fire-prone fuel loads on the landscape (Gomez-Gonzalez et al., 2018).

Solutions proposed include reintroducing traditional burning practices (Kolden 2019), increased fuel load management through ‘prescribed grazing’ (Lovreglio et al., 2013), as well as mechanical fuel treatments (Cochrane et al., 2012). Moreover, academic work has analysed the extent of implementation of such methods, as well as the institutional processes and barriers that influence their adoption (North et al., 2015; Spencer et al., 2015; Smith 2019). This is one of many examples demonstrating the integral role of feedbacks between direct and indirect anthropogenic influences and the biophysical processes of wildfire (Table 2.2). As in the previous cases described, however, no global system for classifying or assessing anthropogenic fire suppression measures has been developed.

Therefore, across human fire use, management and suppression, there is an opportunity to draw together substantial advances in local-scale understanding of human-fire interactions into a systematic framework that enables analysis of anthropogenic fire impacts at the global scale. Constructing such a dataset would entail drawing on insights from diverse disciplines: anthropology, geography, ecology, conservation biology, agronomy, development and behavioural economics and political science. Critically, synthesising insights from across subject areas into a common format would provide the empirical basis for modellers to explore how fire regimes may change under different scenarios of future global warming and socio-economic development.

One such synthesis of human impacts on fire regimes is presented in Chapter 3. Furthermore, the data that were collected through this work also contributed to the Livelihood Fire Database (LIFE) of Smith et al., (including Perkins; 2022). Comprising some 587 case studies, LIFE focuses on indigenous and small-holder farmers and seeks to capture the heterogeneity in fire uses and fire governance in such communities (Smith et al., 2022). By contrast, the dataset presented in Chapter 3 seeks to cover all types of land user and to identify broad quantitative patterns of fire use and management for global-scale modelling. Finally, LIFE contains a qualitative assessment of the temporal trend in fire use (decreasing, increasing, no change), which is used to evaluate the managed fire outputs of the global model presented in Chapters 4 & 5.

2.3 New methods for modelling anthropogenic fire impacts at the global scale

Alongside developing a robust empirical basis, improved global modelling of anthropogenic fire impacts will require new methods to represent human systems and decision making. Present approaches are not only limited in scope, but also do not seek to model the underlying drivers of human fire impacts, and hence their explanatory and predictive potential is limited (Rabin et al., 2018). Agent-based modelling (ABM) has been proposed as a method for improving understanding of complex socio-ecological systems (SES; Murray-Rust et al., 2011; Rounsevell et al., 2012).

However, whilst use of ABM to understand land use change has become comparatively widespread (see Schulze et al., 2017 for a review), the use of ABM to study anthropogenic fire regimes and wildfire impacts remains more limited (Table 2.3). Furthermore, implementation of ABM for study of SES at the global-scale remains a major technical challenge (Verburg et al., 2019; Dressler et al., 2022). Here, a brief introduction to the strengths of ABM for modelling SES is given, followed by an overview of some key modelling choices related to use of ABM to model human-fire interactions, including the trade-offs involved with different model coupling frameworks for capturing socio-ecological feedbacks.

2.3.1 What is agent-based modelling?

The central defining characteristic of ABM is that it is driven by explicit representation of micro-scale anthropogenic decision-making (Bonabeau 2002). Agents in an ABM can be individuals, households, communities, or government agencies, depending on the scale of the study system in question and the underlying research questions the model is intended to address (Robinson et al., 2006; Crooks and Heppenstall 2012). This bottom-up approach to simulation of systems means ABM is particularly adept at exploring how complex social phenomena can emerge as the aggregate result of comparatively simple small-scale decisions (Epstein 1999). Perhaps the most famous example of this is the Schelling model of community segregation (Schelling 1971).

As agents in an ABM can be parameterised to perceive their environment, and to make decisions based on their beliefs about it, ABM can be highly effective at modelling the impact of environmental change on human behaviour (Meyfroidt et al., 2012). However, whilst these evident strengths make ABM a strong candidate for modelling of SES, they also point to ABM's potential drawbacks: such nuanced parameterisation of a model is inevitably data hungry, making model validation a consistent challenge (Filatova et al., 2013; Brown et al., 2023). Furthermore, a danger of ABM is that granular representation of the detailed processes by which heterogenous agents arrive at decisions can risk producing highly complex models whose outputs are at best challenging to understand and are therefore potentially of limited explanatory power (O'Sullivan et al., 2012).

2.3.2 Overview of ABMs of human-fire interactions

An overview of existing ABMs exploring human-fire interactions is given in Table 2.3. Seven out of nine identified studies are focused on developed world contexts. Perhaps as a consequence, studies are focused more towards anthropogenic influences on vegetation or fire suppression rather than managed anthropogenic fire use. In such studies, fire therefore emerges incidentally as a function of anthropogenic land use decisions (e.g. Ribeiro et al., 2023; Scheller et al., 2019). Indeed, only one identified study explores a managed anthropogenic fire use system: Ngo et al., (2012) study fire use amongst shifting cultivation farmers in Nghe An province, Vietnam.

An important modelling choice in ABM is the specification of agent objective functions (Muller et al., 2013; Huber et al., 2018). Agent objective functions define how agents decide on a course of action to achieve a given outcome; they are analogous to 'utility' functions as widely-used in neoclassical economics and are a primary means through which ABM can represent human decision making (Railsback and Grimm 2011). As such, they should be rooted in a credible representation of human psychology (Groeneveld et al., 2017). However, choices between different objective function specification involve trade-offs between computational cost, data requirements and implications for the interpretability of model outputs, and the degree of nuance with which a model represents a study system (Balke and Gilbert 2014; Sun et al., 2016). These concerns will be particularly important in ABM at the global scale as the size of data sets and range of processes needing to be represented grows.

The simplest way to represent agent decisions is to directly code them into the model as an empirical statistical function. For example, Spies et al., (2017) determined fuel treatment targets (as a percentage of the land area they manage) for each land user type from social surveys and secondary data. Such a specification mitigates the need for explicit representation of the decision-making process of, e.g., complex federal agencies or large commercial forestry ventures. A further comparatively simple objective function design is the expected utility maximisation (EUM) framework from neo-classical economics. Even though the limitations of EUM for representing human behaviour have in part driven the uptake of ABM, EUM functions remain common in ABM (Groeneveld et al., 2017). For example, Millington et al., (2008) use expected utility calculations to model behaviour of commercial farmers.

Table 2.3: An overview of objective functions in agent-based models of human-fire interactions; it is notable that, given the comparatively small study areas (and corresponding fine spatial resolution), that most models either rely on neo-classical economics or empirically defined deterministic functions to represent human decision making.

Source	Location	Study area (km^2)	Study system(s)	Primary agent types	Objective function (s)	Comments
Hu & Sun 2007	Theoretical space	NA	Fire suppression (industrial)	Firefighter, fire breaks	Firefighters' objective is to extinguish a fire, actioned based on their beliefs about the future spread of the fire, and effectiveness of suppression measures	Operational firefighting model
Millington et al., 2008	Central Spain	830	Land use change (principally agricultural land use) & associated wildfire risk	Commercial land user; traditional land user	Commercial agents maximise utility using economic calculations; Traditional agents' decisions satisfice economic and cultural objectives	Influence of cultural factors on traditional agents calculated from their relative spatial density at a given location
Etienne et al., 2008	Nimes, Southern France	57.27	Fire suppression at the wildland urban interface	Farmers; urban developer; mayor & urban planners	Farmers abandon fields based on an economic utility function, including representation of the CAP; Urban developers, the mayoralty and urban policymakers act in an empirically defined way to propose / agree urban developments	Model structure and urban development process determined through a participatory framework; implications of model for wildfire dynamics emerges from land use choices
Ngo et al., 2012	Nghe An province, Vietnam	7.4	Shifting cultivation; fire use is intrinsic to the system	Farming household	Field locations chosen for cultivation based on utility maximisation; number of fields chosen per household based on satisfying subsistence food requirement Policy, comprising both economic incentives and restrictions on farming acts as a weight on this utility calculation	Household succession, migration and partitioning all represented explicitly based on extensive social survey data

Source	Location	Study area (km^2)	Study system(s)	Primary agent types	Objective function (s)	Comments
Spies et al., 2017*	Oregon, USA	12529	Wildfire & forest management using coupled socio-ecological approach	Major landowner; family forest owner	Agents have empirically defined targets for fuel treatment (as a % of land area managed) and ecosystem service provision, modified by previous year burned area and fuel density	Ecosystem service and fuel treatment targets defined from social survey (Spies et al., 2014)
Minelli and Tonini 2018	Canton Ticino, Switzerland	*Pilot study area* (local)	Wildfires; wildland urban interface	Individual (urban resident); firefighters	Full model development was in progress; fire ignitions are generated statistically, with locations based on movement of individual agents around a road network	Principally an operational firefighting model, combined with a spatial representation of the WUI
Scheller et al., 2019	Lake Tahoe Basin	c. 500	Wildfires; fire spread modelled physically, whilst anthropogenic behaviours are modelled using empirically-defined statistical functions	Firefighters; park ranger; other	Number of anthropogenic ignitions is an empirically defined Poisson distribution modified by the Fire Weather Index for a given day; accidental and deliberate ignitions calculated separately. Suppression is a represented using a 0-3 ordinal scale (none, minimal, moderate, maximal), this becomes a constant that restricts the fire spread algorithm	Deliberate anthropogenic ignitions represent prescribed fuel load reduction fires Suppression scale designed 'in collaboration with fire mangers & approximates the decisions made whether to suppress and the overall suppression effort'

Source	Location	Study area (km^2)	Study system(s)	Primary agent types	Objective function (s)	Comments
Widyastuti et al., 2020	South Sumatra, Indonesia	441	Anthropogenic peat fires	Farming households	Farming households create peat fires based on a search radius around their home location; this is prescribed and independent of any representation of underlying land-use systems	Model is primarily of peatland fire spread, with comparatively detailed parameterisation of peatland hydrology compared to agent behaviours
Ribeiro et al., 2023	Centro region, Portugal	4518	Wildfire risk mitigation; land owner vegetation management choices	Land owners	Landowners maximise their utility by choosing between agriculture, forest and shrubland land covers However, 'forest inertia' – a status quo bias for forest land covers – is used to constraint utility maximisation calculations	Resulting fire regime, after landowner decisions, is based on a logistic regression

*Model developed by Spies et al., (2017) also applied in Ager et al., (2018) and Johnson et al., (2023a).

Perhaps the simplest means of implementing psychological or behaviour economical theory in an ABM is to set agents to 'satisfice' (a combination of suffice and satisfy) a range of criteria, typically combining economic, cultural and other objectives (Groeneveld et al., 2017). 'Satisficing' was first proposed by Simon (1955) as a means of describing the 'bounded' or 'procedural' rationality of human decision making (Barros 2010). Satisficing implies people may choose suboptimal solutions out of habit, loss aversion or because of the information effort involved with researching alternatives (Corr and Plagnol 2019). Boundedly rationale representations of decision-making are adopted by Millington et al., (2008) and Ribeiro et al., (2023). For example, in Ribeiro et al., (2023) 'forest-inertia' – a status quo bias amongst forest owners – is implemented as a simple constraint on the rate of land cover change.

Further behaviourally-grounded accounts of human decision-making include 'prospect theory' (Kahneman and Tversky 1979) and 'regret theory' (Loomes and Sugden 1982). However, such nuanced representations of have not yet been implemented in ABMs of human-fire interactions. As behavioural science gains traction as a means of understanding community fire use (e.g. Cammelli et al., 2019a; 2019b; 2020), there may be increasing opportunities for researchers to implement such behavioural approaches in ABM to advance understanding of anthropogenic fire.

Therefore, most existing ABMs of human-fire interactions, whilst local to regional in scale, employ comparatively simple agent objective functions – typically empirical statistical functions or an economic utility calculation. The degree of simplification also increases with study area. Possible reasons for this include the substantial technical challenge of firstly developing an ABM and then coupling it with a physically-based fire spread model (Voinov and Shugart 2013), or more simply a lack of available data and understanding concerning anthropogenic fire use (Forkel et al., 2019). Perhaps the most significant current gap in ABMs of human fire use is the lack of a full account of fire knowledge and use as a capital or stock within a given community (Huffman 2013). This reflects a broader technical challenge of representing social influence networks within ABMs of SES (Brown et al., 2018); one simple example of how this may be accomplished is provided by Millington et al., (2008), who allow the density of their 'traditional' land user type to influence their determination to continue their (economically sub-optimal) land use practice for social and cultural reasons.

2.3.3 Towards global ABM of SES

A further issue in the integration of anthropogenic fire impacts into DGVMs using ABM, is the challenge of developing behavioural models at the global scale (Rounsevell et al., 2012). Major outstanding questions include how to capture the diversity of human decision making relevant to a given SES at the global scale, as well as how to represent the diversity of local, national and global actors who can influence a system in a given location (Rounsevell et al., 2014). The major current proposal for how to represent human decision-making in global behavioural models for integration with DGVMs is the Agent Functional Type (AFT; Arneth et al., 2014). AFTs provide a set of categories that capture the core functional diversity of human behaviours relevant to a given system.

AFTs are the ABM equivalent of plant functional types (PFTs) that are commonly used to represent the key aspects of vegetation functional diversity in DGVMs (Harrison et al., 2010). For example, JULES, the DGVM that contains the INFERNO fire module, can be run with either five or nine PFTs to represent key global vegetation traits (Harper et al., 2016; 2018). Whilst PFT distributions are driven primarily by the ecological niches of differing plants, AFT distributions can be driven by the availability of different capitals – economic, social, natural etc. (Arneth et al., 2014).

Although there is similarity in the conceptualisation and degree of aggregation between AFTs and PFTs, there are also important differences. Most importantly, whilst a PFT may have all of its attributes encoded in deterministic mathematical functions, to be rooted in a robust representation of human psychology, AFTs should be able to evaluate the outcomes of their actions and adapt, as well as interacting with the behaviour of spatially proximate AFTs (Briegel et al., 2012; Arneth et al., 2014). However - aside from WHAM! (Chapters 4 & 5) - at time of writing no global land use ABM has yet been developed. CRAFTY (Competition for Resources between Agent Functional Types; Murray-Rust et al., 2014) is the closest current attempt, and has been deployed up to the continental scale (Brown et al., 2020). This highlights the enduring research and technical challenges with developing global-scale ABM in the land use sciences (Dressler et al., 2022).

A further major challenge in the application of ABM to global SES is representation of the policy development process (Brown et al., 2019). For example, whilst ABM analysis of policy outcomes and their (un-)intended consequences is comparatively widespread, few models have included explicit representation of the policymaking process itself (Castro et al., 2020). At the regional to the global scale, policy has so far been represented simply as a weight towards a given outcome or ecosystem service provision within land user calculations (e.g. Holzhauer et al., 2018).

This poses several questions for the case of wildfire. Firstly, as noted in Section 2.1.3, in many contexts, human fire use is inherently political, bound up in questions of land ownership and the rights of different actors to access resources and produce commodities. A further important shortcoming of a representation of policy only as an input weight parameter on ABM decision making is an inability to account for abrupt policy changes in response to shocks in a fire regime (see Table 2.2). However, even when representing policy simply through input parameters, combining consideration of local, national, and global policy influences with land user preferences may lead to highly complex emergent phenomena such as oscillations and ultimately to chaotic behaviour in a model, with substantial complications for model interpretation and utility (Caillaut et al., 2013).[2]

Consequently, there are likely trade-offs between running ABMs globally, and therefore at the same scale as DGVMs, versus capturing local diversity and complexity in human-fire interactions. This same tension is common to several land-system sustainability questions, and hence the meso-scale – spanning scales between the global and local – is a current area of focus for coupled socio-ecological modelling (Johnson et al., 2023b). For vegetation fire, this challenge is perhaps most pertinent in landscapes where human influences on fire emerge from the complex interplay of both direct and indirect impacts. For example, capturing how human fire use, grazing intensity and cropland conversion interact in the savannas of sub-Sahara Africa, as described by Archibald (2016; Figure 2.2), may be best explored at meso-scale. Similarly, capturing the impact of policy change on selective logging, deforestation and pasture management fire in the Amazon basin would require detailed representation of governance that would be challenging to implement globally (Lapola et al., 2023).

[2] This paragraph is taken from the author's original contribution to Ford et al., (2021)

2.3.4 Capturing socio-ecological feedbacks: model coupling

Capturing the dynamics of SES in modelling studies often requires coupling of different models – typically at least a model representing social and economic processes and a separate model of biophysical processes (Antle et al., 2001; Filatova et al., 2013; Robinson et al., 2018). In the case of wildfire, the difficulty of integrating social science insights into ABMs in a way that allows ready integration with biophysical models remains a central challenge, particularly where anthropogenic management decisions may be too small-scale for the spatial resolution of a given biophysical model (Kline et al., 2017). Furthermore, models in which agent behaviours are determined through constant empirically-derived targets or functions – rather than through dynamic agent appraisal of their environment – may not adequately capture anthropogenic responses to changing fire regimes during coupled model runs (Ager et al., 2018).

Antle et al., (2001) first proposed the ideas of 'loose' and 'close' model coupling to determine the degree of integration between models in studies of SES. In 'loose' coupling, one model provides inputs that drive another model, so for example an ABM may provide anthropogenic ignition numbers to a DGVM; in 'close' or 'tight' model coupling, there is a two-way flow of information, such that states in both models are dependent on outputs of the other (Antle et al., 2001). Building on this framework, Robinson et al., (2018) propose a four-stage continuum from loosest to tightest, which in addition to the level of information passed between models also considers the frequency of information exchange between the models and the degree to which forcing data sets are shared.

An illustration of the implementations of broadly defined 'loose' and 'tight' coupling options in the case of wildfire are presented in Figure 2.3. Capturing feedbacks such as the 'fire paradox' or policy and management responses to shocks in a fire regime requires tight model coupling. However, given the limited nature of existing approaches, a loose model coupling still has potential to provide a significant improvement in the representation of anthropogenic impacts on wildfire regimes in DGVMs.

A further consideration for model-coupling is the degree to which the technical complexity of the resulting ensemble, and the complexity of its outputs may be prohibitive to potential users (Larsen et al., 2016). Here, a loose coupling may have the benefit of facilitating prototyping of alternate parameterisations of human-fire interactions that can later be incorporated into computationally-expensive coupled Earth system models (ESMs). Indeed, after the recent FIREMIP there has been a renewed focus on such reduced complexity approaches to identify possible parameterisations of human-fire interactions in DGVMs and ESMs (Haas et al., 2021; Mukunga et al., 2023; Teixeira et al., 2023).

However, the drawback of loose (or offline) coupling is that it would not enable full consideration of interactions between socio-economic and environmental change (Robinson et al., 2018). The limitations of this approach for understanding fire are well-illustrated by current research challenges stemming from biophysical and socio-economic modelling occurring in isolation. For example, the fire modules of DGVMs have struggled to attribute changes in global fire regimes to climate change due to the confounding role of wider human impacts on fire (Burton et al., 2023). Similarly, integrated assessment model scenarios routinely assume the possibility of carbon dioxide removals through reforestation without accounting for fire risk (Jäger et al., 2024). The principal downside of a tight coupling would be to restrict potential users to those with access to high performance computing, likely excluding practitioner communities on whose knowledge socio-ecological modelling of fire regimes will ultimately depend (Copes-Gerbitz et al., 2024).

2.4 Conclusion

This chapter has presented existing approaches to modelling and empirical analysis of anthropogenic impacts on fire regimes. At the global scale, it has highlighted the inadequacy of existing modelling approaches and the limitations of 'top-down' empirical approaches as a means of understanding anthropogenic fire impacts. Conversely, huge research progress has been made in understanding human-fire interactions in diverse contexts at the local and landscape scale. This therefore provides a major opportunity to compile this more granular-scale research into the first globally-applicable synthesis of anthropogenic fire impacts. Chapter 3 describes and analyses such a synthesis.

Beyond this undertaking, substantial technical challenges remain in developing modelling frameworks that allow effective representation of anthropogenic fire impacts within DGVMs. In the context of ABM, key challenges remain defining AFTs that adequately capture the diversity of human-fire interactions globally, the credible representation of wildfire policies that captures the possibility of sharp responses to destructive wildfires, and the coupling of such a model with a DGVM. Whilst key challenges remain, the shortcomings of existing model approaches demand new approaches and suggest that incremental improvements to current methods are unlikely to capture the complexity of socio-ecological feedbacks that increasingly drive Anthropocene wildfire regimes.

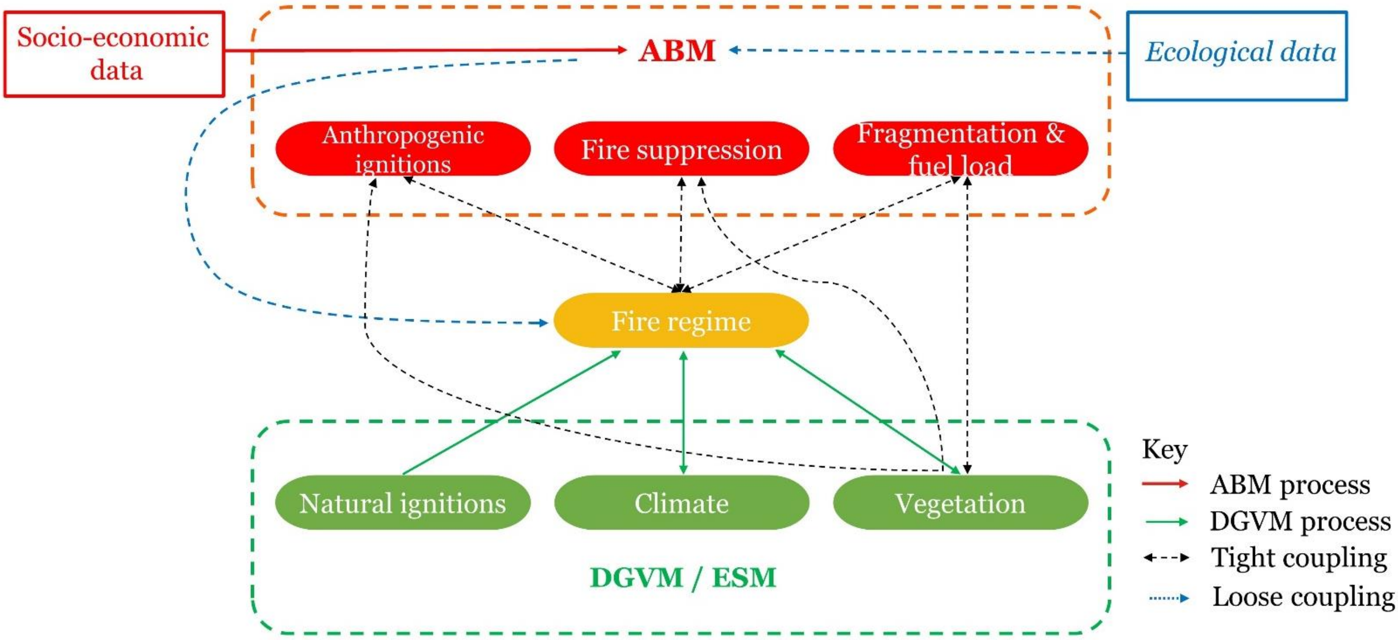


Figure 2.3[3]: Options for integrating an ABM of human-fire interactions into a DGVM or earth system model (ESM). Under a loose model coupling, the ABM would provide static inputs to the DGVM, for example by replacing anthropogenic ignitions from population density with an ABM output. Under a tighter-coupling, the ABM would be run alongside the DGVM, potentially allowing cross-system feedbacks to be captured, but at the expense of significant additional model complexity. In a loose coupling, the ABM's ecological inputs such as land cover and NPP would come from secondary data. Examples of socio-ecological feedbacks that could be captured by tight model coupling are given in Table 2.2.

[3] This figure is taken from the author's original contribution to Ford et al., (2021); it was developed in partnership with collaborators in the INFERNO model development team.

Chapter 3

A global database of anthropogenic fire impacts

A version of the text presented here was originally drafted in 2021. Subsequently, the database described in this Chapter was published in Millington et al., (2022). The content of that paper drew on the content in this Chapter. Material in Millington et al., (2022) sourced directly from that presented here is flagged to the reader in footnotes.

3.1 Introduction

As described in Chapter 2, providing an empirical basis for global modelling of anthropogenic fire impacts has been a major research challenge. Data are needed that draw together advances in understanding of anthropogenic fire use and management with quantification of their impacts on fire regimes. Lack of data that bridge this divide is an underlying cause of limitations in existing modelling approaches (Chapter 2). Therefore, this chapter presents a new global Database of Anthropogenic Fire Impacts (DAFI), developed to meet this challenge. DAFI is the product of a meta-analysis of literature concerning human-fire interactions.

This chapter provides an overview of how DAFI was constructed, as well as analysis of the newly compiled data set. DAFI was conceived both with the general aim of advancing understanding of human-fire interactions, but also with the specific goal of providing the basis for a global ABM of anthropogenic fire impacts. Therefore, data in DAFI may have multiple applications beyond the particular purpose of defining and parameterising an ABM. However, to focus discussion on DAFI's contribution to this thesis, results presented here are centred around three issues pertinent to global-scale ABM:

1. What are the key modes of anthropogenic fire use that should be captured in a global ABM of anthropogenic fire impacts?
2. How do anthropogenic fire suppression and fire policies combine with these fire uses to produce observed fire regimes?
3. What is the most effective framework to capture modes of anthropogenic fire use and the resulting anthropogenic fire regimes at the global scale?

3.2 Methods

Methods are structured as follows. Firstly, Section 3.2.1 describes the framework used to structure the literature search. Secondly, Section 3.2.2 describes the data collected in DAFI, the rationale for collecting it, and the recording methods used for differing data (quantitative, qualitive, etc,). Section 3.2.3 describes testing of the database format during construction, and subsequent revisions to ensure robustness and consistency across records. Fourthly, Section 3.2.4 describes analysis techniques adopted in light of the breadth, structure and recording method of the data collected described in the first three sections.

3.2.1 Structure of literature review

The study of SES is inherently interdisciplinary, and so frequently involves synthesising not only literature evidence from multiple disciplines, but diverse data types spanning a range of qualitative and quantitative data (Magliocca et al., 2015a; Van Vliet et al., 2016). As such, Magliocca et al., (2018) developed a cohesive framework for conducting such complex reviews in the multidisciplinary land use sciences in general, whilst the particular use of meta-analyses to define agent types for agent-based modelling is also widespread (Magliocca et al., 2015b).

The preliminary literature review suggested that not only were human-fire interactions at the global scale highly varied, but knowledge about them was highly diffuse (Chapter 2). Therefore, adopting the methodology proposed by Magliocca et al., (2018), the first stage in developing DAFI was to define a theoretical framework to structure the literature search. Two candidate frameworks were identified: that of Pyne (2001) derived from a qualitative historical narrative and that of Lauk and Erb (2016). There are strong similarities between the two frameworks, with both broadly reflecting a key distinction between pre-industrial and industrial fire regimes (Seijo and Gray 2012). The framework of Pyne provides an overall, process-based narrative description of how and why anthropogenic fire use has changed over time, whilst the Lauk and Erb framework is based at the fire *regime* level. Given the need to represent human decision-making regarding fire use and management in an ABM, the framework of Pyne was deemed more appropriate to guide development of DAFI, but results from DAFI were later compared against the typology of anthropogenic fire regimes proposed by Lauk and Erb.

The framework outlined in Pyne (2001) implicitly conceptualises human fire use as a function of wider land use objectives, although it does not give an exhaustive account of how this plays out globally and in a contemporary context. Therefore, having selected Pyne as an overarching theoretical framework, meta-analyses from the land use literature were identified which could ground each of Pyne's anthropogenic fire regimes[4] in more granular land user types. Quantitative meta-analyses were identified where possible, but qualitative studies were used where no quantitative, globally-applicable meta-analysis was available. The result of this cross-referencing of Pyne with land use meta-analyses was a modified version of Pyne's framework, that spanned four anthropogenic fire regimes:

- *Pre-industrial* - analogous to Pyne's 2nd fire, pre-industrial fire regimes are typified by active use of fire and limited mechanisation in land management;
- *Transition* - adopting elements of both pre-industrial and industrial regimes;
- *Industrial* - analogous to Pyne's 3rd fire, fire use for land management is replaced by mechanisation and chemical fertilisers;
- *Post-industrial* - deliberate or unintentional re-introduction of fire to a landscape as an ecological process.

As the goal of the database was to capture anthropogenic activities, the adapted version of Pyne's fire regimes were split across three land use systems:

- *Cropland*, which included secondary vegetation in a shifting cultivation mosaic;
- *Pasture*, which included both planted pastures and semi-natural rangelands; and
- *Forests*, including all natural, plantation and degraded forests.

These three land cover types broadly cohered with the framework of Lauk and Erb (2016), who distinguished, e.g., between shifting cultivation and pastoral fires, as well as forest fire management and suppression. Therefore, the combination of the modified version of Pyne's framework and three land cover types provided a structure to guide the literature search, and in effect became a preliminary set of AFTs (Table 3.1).

[4] Pyne's '1st fire' describes a pre-anthropogenic, lightning-ignited fire regime

Table 3.1: Framework used to structure the development of DAFI. The fire regimes of Pyne (2001) provided the overall theoretical framework, with more detailed meta-analyses providing specific land use / fire development stage AFT types to be defined through data gathering. The transitional and post-industrial fire stages are not part of Pyne's original framework but were present in the global meta-analyses used to define preliminary AFTs for both cropland and pasture land use types, and so were included here. Preliminary AFT categories marked '*' were not defined prior to database construction but emerged from literature reviewed during the gathering of data itself.

	Land use (land cover) type		
Fire regime (Pyne 2001)	**Forest & plantation forests**	**Pasture & grassland**	**Cropland & secondary vegetation**
Pre-industrial ('2nd fire')	Hunter gatherer[3]	Migratory pastoralist[4]	Shifting cultivation farmer[1]
Transition	Small-scale forester*	Extensive rancher[4]	Small-holder (survival-oriented)[1]
	Agroforester*	Mixed crop-livestock small-holder[4]	Small-holder (market-oriented)[1]
Industrial ('3rd fire')	Industrial forester[2];	Intensive rancher[4]	Industrial / commercial farmer[1]
	Conservationist[2]	Landless livestock farmer[4]	
Post-industrial fire	Tourist / tourist manager[2]	Abandoned farmland*	Agro-ecologist[1]
	Urban resident / planner*		Abandoned farmland*

Sources: 1) Quantitative analysis of Malek et al., (2019); 2) Quantitative analysis of Blanco et al., (2015); 3) Mixed-method analysis of Coughlan et al., 2018; 4) Qualitative typology of de Haan et al., (2010); * Category emerged during data gathering

Whilst several papers have attempted to categorise the signatures of anthropogenic fire regimes from their quantitative signal in remote sensing and other secondary data (Chapter 2), no study has yet compiled a global synthesis of understanding across all types of anthropogenic fire use. Although Huffman (2013) and Coughlan et al., (2018) have conducted global syntheses, these were restricted to traditional fire use, principally in a hunter-gatherer or pastoralist context. Similarly, Smith et al., (2022; including Perkins) focus on indigenous and small-holder fire users. Furthermore, despite the crucial role of fire in the land system, a review of meta-analyses in the land use sciences conducted by Van Vliet et al., (2016), did not identify any such studies focused explicitly on fire use. As such, no framework from which to define formal literature search terms could be identified.

Additionally, attempts to conduct formal meta-analyses with specific search terms have tended to report limited numbers of papers identified for human fire use compared to the wider fire management and ecological literature (Nikolakis and Roberts 2020). Finally, during database scoping, it became clear there was vastly diverging terminology used across differing subject disciplines, even when reporting on similar aspects of human fire use. Terms used to describe crop residue burning are provided as an example in Table 3.2. This diverse terminology is symptomatic of fire being studied primarily as incidental to, or as a function of, a separate study system. For example, deforestation fires being studied in the context of wider discourse about biodiversity loss (e.g. Mangora 2005; Meyfroidt et al., 2012; Cano-Crespo et al., 2015), or shifting cultivation fire being studied in the context of political ecology or sustainable development discourses (e.g. Pingali 1987; Dawoe et al., 2012; Norgrove and Hauser 2015).

Therefore, given the fragmented literature and associated terminology across multiple sub-disciplines, within each preliminary AFT category a snowball search method was adopted to ensure the multiple 'hidden' literature populations could be identified (Johnson 2014). The implications of snowball sampling for the analysis techniques used on the resulting data are discussed in Section 3.2.4.

Table 3.2: Overview of diverging terminology in literature containing data on burning of agricultural residues. In the case of 'crop' residue burning, the crop would frequently be commodity specific – (e.g. rice, wheat, etc). The diversity of terminology reflects the fragmented nature of academic literature on anthropogenic fire use and served to confound a wholly systematic meta-analysis methodology.

Primary focus of study	Terminology	Example(s)
Agronomy, agricultural economics	"straw use"	Sun et al., 2019
	"straw management"	Allen et al., 2019
	"(crop) residue management"	Dubinin et al., 2011; Lopes et al., 2020
Remote sensing, environmental monitoring	"agricultural fires"	McCarty et al., (2016)
	"(agricultural) residue burning"	Ahmed et al., (2015)
	"stubble burning"	Singh and Kumar 2020
	"crop residue burning"	Yang et al, 2008
Air quality, public health	"Air quality AND burning"	Mittal et al., 2009; Bray et al., 2019
	"Air pollution AND burning"	Kaushal 2020
	"Haze AND burning"	Zhao et al., 2017
	"Respiratory health AND burning"	Uriarte et al., 2009
Regional and / or commodity-specific case study	"veld fires"	Dube 2015
	"sugar cane AND fire"	Rudorff et al., 2010

The literature search was conducted in a number of stages for each preliminary AFT category:

1. The first step was to locate existing reviews or foundational papers within each preliminary AFT category that could provide the basis to identify potential sources of data; a complete list is provided as Appendix 3A. Where possible, these were specifically focused on fire use and management, but were chosen from the land use literature where none could be identified.
2. Using the citations within these meta-analyses and subsequent papers citing them as a starting point, a body of papers was developed with the snowball approach. This was complemented with targeted searching of particular terms where a substantial population was identified. A list of search terms identified is provided in Appendix 3B. This could provide the basis for reproducing DAFI, and / or building upon data gathered to date with further systematic searching.
3. The literature identified relevant to a particular preliminary AFT was then checked for geographic representativeness by additional searches for papers with keywords from those identified with the addition of country names from underrepresented geographic regions. For example, 'Russia AND crop residue burning'.

As a central goal of DAFI was to underpin development of a global ABM and the main aim of that model will be to help understand future wildfire patterns under varying socio-ecological conditions, the focus of the review period was set as 1990-2020. However, earlier data were included if they were reported alongside data post 1990, or in the case of shifting cultivation, where including papers from the late 1980s facilitated stronger spatial coverage in available data and allowed the system to be observed without disruption from external economic and social forces. This was done to facilitate parameterisation of a 'baseline' state for this system in the ABM.

3.2.2 Data collection

The strategy for data collection was to record information in quantitative format where possible, but to encode qualitative data in the database where this was not possible. The literature review (Chapter 2) indicated the key areas of data to be collected to improve DGVMs were:

- Anthropogenic fire use;
- Fire suppression; and
- Fire policies adopted by both government and non-governmental institutional actors.

Papers were considered for inclusion in the database if they reported at least one human fire behaviour from at least one of these three categories. The following sub-sections provide detail of data captured in each of these three areas, as well as data collection and decisions made on database structure that were informed by the planned use of the database to develop an ABM. An overview of data captured by DAFI and formats is provided in Table 3.3, whilst database metadata are in Appendix 3C.

Table 3.3: Summary of data recorded and format in DAFI; although anthropogenic fire use was recorded as quantitative information, this was recorded as binned ranges where these numbers were estimated from proxy variables.

Information type	Principal data format	Recording method	Notes
Anthropogenic fire use	Quantitative	Quantitative	Values recorded for both intended and actual fire use
Fire suppression	Mixed	Ordinal scale	Scale values - 0: none, 1: limited or ad-hoc, 2: moderate or traditional; 3: intensive or industrial
Fire policy	Qualitative	Boolean	Boolean values for fire bans, restrictions short of a ban and economic incentives offered by government and non-governmental institutional actors
Land use type, intensity & land cover	Mixed	Quantitative & categorical	Quantitative values for land cover and land use intensity; qualitative categories for land use and land tenure type

3.2.2.1 Capturing human intentions

The framework of Pyne (2001; Table 3.1) and the ABM presented in Chapters 4 & 5 conceptualise human fire use and management in the context of underlying land use intentions and objectives. This central organising assumption informed a range of choices in the structure of DAFI. Firstly, the principal data type included in DAFI was primary field data, as this had the best chance of linking together specific human behaviours with observed fire regimes. However, it was found during database construction that such data were weighted towards pre-industrial fire uses, and so remote sensing and secondary data from government and institutional records were also included where these reported human fire behaviours. Remote sensing was also valuable in capturing data from regions which are challenging for fieldwork, such as the Congo basin. As noted in Chapter 2, MODIS and VIIRS data do not perform well in studies of anthropogenic fire regimes. As such these were not included, and only local to landscape remote sensing data at spatial resolution of Landsat ($30m^2$) or finer were used; this included studies based on visual interpretation of high-resolution satellite imagery and landscape photographs (e.g. Araki 2007).

Similarly, because of the importance of underlying land use rationale of anthropogenic fire use to the planned ABM, a set of initial fire intentions were devised to classify fire uses. Drawing on the frameworks of Pyne (2001) and Lauk and Erb (2016) and wider initial review, these were set as: field preparation in the context of shifting cultivation; pasture renewal; deforestation; arson; and accidental. As new categories emerged during data collection these were added, leading to a final list of 21 fire uses (appendix 3D).

Data in DAFI were reported in units where the underlying land use regime was constant. For example, a study reporting data from two locations would be reported as at least two case studies, but this might be split further if there was a pronounced change in land use at these sites during the study period, e.g. before and after the collapse of the Soviet Union (Dara et al., 2019). Recording of case studies in this way allowed data about the land use context of human fire behaviours to be recorded. Land use data selected for inclusion were those with an impact on the fire regime and those criteria that helped to define the land use typology of Malek et al., (2019). Therefore, the presence and rate of biomass removal through extractive logging, and the stocking rate of livestock were recorded, as they directly impact fuel loads and subsequently influence fire regimes. Average farm size, mean crop yield, and land tenure regime were recorded as they were factors driving the typology of Malek. Finally, to facilitate modelling of the spatial distribution of AFTs, the land cover percentage was recorded under the categories given in Table 3.1. Land cover categories were kept deliberately broad to allow ready integration of the planned ABM with DGVMs (Chapter 4). Categories for land tenure types were based on Payne (2004).

3.2.2.2 Anthropogenic fire use data[5]

In anthropological literature describing pre-industrial fire practices, the entire distribution of fire sizes within a study area was rarely reported, with authors instead reporting summary statistics such as a mean or minimum and maximum value. Therefore, data were gathered for minimum, median, mean and maximum fire size and were recorded separately under these distinct categories. Furthermore, fire use data were collected on both *intended* and *actual* fire sizes and burned area. This was to ensure the resulting ABM could be used to explore how anthropogenic land use systems, and their accompanying fire use rationales, lead to observed fire regimes.

Intended fire use can be determined from reported preferences in field interviews (e.g. Thaler and Anandi 2017) or institutional management plans (e.g. van Wilgen et al., 2013). Alternatively, intentions can be inferred from crop field size (e.g. Liu et al., 2019; Ahmed et al., 2015), or from median patch size in a pastoral or patch mosaic burning system (e.g. Wesche et al., 2000a, 2000b). The median is taken to account for fires becoming out of control, as was the case during a particularly dry year in the study period of Wesche et al., (2000b). Where inferences about intended fire sizes were made from proxy variables such as field size, the resulting uncertainty was reflected by recording data in binned ranges (Section 3.2.3). By contrast, actual fire sizes were reported from observations of a fire regime, such as the landscape-scale remote sensing study of pasture fires in the Brazilian Amazon of Jakimow et al., (2018), or the field data gathered by Kull (2003). Similarly, anthropogenic fires were recorded in DAFI as either deliberate, accidental or escaped (fires started deliberately that grew beyond their original purpose and intended size).

As noted in Chapter 2, humans' influence on fire regimes is not restricted to direct, or intentional, impacts. For example, landscape fragmentation through building of roads or reducing fuel loads through grazing of livestock may indirectly have a greater impact on fire regimes in African savannas than direct fire impacts such as anthropogenic burning (Archibald et al., 2011). For this reason, in the initial database structure both direct and indirect impacts of fire use, suppression and policy were recorded. However, records of indirect impacts were reduced substantially during database testing (see Section 3.2.3).

Finally, recognising the importance of changes in seasonality are in important anthropogenic impact on global fire regimes (Benali et al., 2017; Le Page et al., 2010), the first and last month in which a given fire practice was used was recorded where available.

[5] The first two paragraphs in this section form the basis of section 2.2.1 in Millington et al., (2022)

3.2.2.3 Anthropogenic fire suppression data[6]

The literature review indicated that information on human fire suppression is presented in both quantitative (e.g. percentage of the land where fuel treatments were prescribed, Barret et al. 2016) and qualitative formats (e.g. use of improvised fire beaters, Carmenta et al., 2019). Furthermore, no existing framework could be found at the global scale to structure the recording of such information. Therefore, as in Stein et al., (2017) who co-developed a scale alongside fire suppression experts for use in the forests of Oregon, a four point (0-3) ordinal scale was adopted. Zero represented a reported absence, 1 indicating a minimal or ad-hoc approach, 2 indicating the application of traditional fire knowledge or an intermediate industrialised approach, and 3 indicating an intensive industrialised approach. Finally, suppression was split into:

- fire control, for actions taken immediately prior to lighting a deliberate fire to control its behaviour;
- fire prevention, for actions taken to control the wider fire regime, particularly to prevent catastrophic wildfires; and
- fire extinguishing, for actions taken to put out active wildfires.

3.2.2.4 Fire policy data[7]

Fire policy data were overwhelmingly reported in a qualitative format, typically describing the history and rationale of a particular policy, and possibly the range of actors involved in forming it. Policies were recorded where they involved either legislative bans or restrictions on fire use short of an outright ban, as well as economic incentives that encouraged or discouraged fire use. Policy actors included in the database were National governments, state and local government, NGOs, private companies, and supranatural bodies such as the EU and UN. During database construction, three underlying rationales for fire policy measures were found to occur regularly and provide a coherent framework to capture the driving force behind policy choices. These were:

- environmental policies, which included measures made to protect biodiversity, water quality or to prevent soil erosion;
- economic policies, covering bans that aimed to eradicate fire use to encourage agricultural intensification, as well as incentives to clear primary forest for economic development;
- human health policies, principally capturing fire policies made to improve air quality, but also those that aimed to protect people from death directly due to wildfire.

[6] This section forms the basis of Section 2.2.2 in Millington et al., (2022)
[7] Text in this section is found in Millington et al., (2022), section 2.2.3

3.2.3 Database testing and construction

To ensure the planned database structure was both clear and robust, a process of iterative improvement was conducted. Under this process, sets of three papers were entered into the database by three different researchers (the author, supervisor and a research volunteer), allowing inputs to be compared and checked for consistency. After the first set of three papers, it was found that indirect anthropogenic impacts on fire regimes are currently too poorly understood and constrained to allow consistent recording at a global scale. Therefore, these were removed from the database. However, given that Teckentrup et al., (2019) highlighted representation of fuel loads as an important area in which global fire models could be improved, quantitative data on biomass extraction from the landscape through grazing and extractive forestry continued to be recorded.

The inputs from the second set of trial papers were in closer alignment. The major change made at this stage was to split quantitative information on anthropogenic fire use into 'reported' and 'estimated'. This was done because, as noted in Section 3.2.2, much fire data available in papers was incidental to the core focus of the study, and therefore a degree of calculation was required to convert or interpolate this data into a consistent format for recording.

For example, in some cases, mean intended fire size could be estimated for crop residue fires from the mean field size because where residues are burned in situ the two are very closely linked (Liu et al., 2019). However, where residues are gathered and pile burned, only around $1/9^{th}$ of the field area is burned (Hong van et al., 204; Liu et al., 2019). The assumptions made in these calculations were recorded in the notes of each relevant database record for information and scrutiny by future users. Estimated fire use data, where such interpolation was required, was recorded in binned ranges, whilst reported data remained reported as simple numbers. Ranges of values for the bins were taken from existing literature approaches.

3.2.4 Data analysis

Given the necessity to use snowball sampling, a formal meta-analysis framework for the review - involving significance testing of distinct hypotheses - was not appropriate (Magliocca et al., 2015a). For example, the assumptions of many statistical tests include the independence of observations to calculate degrees of freedom, which was likely violated given the data collection process required. Therefore, rather than a strict meta-analysis, the review took the form of a 'site comparison' (Magliocca et al., 2015a). As a result, analysis of the database drew on multiple techniques.

Firstly, case analysis, in which the proportion of database records matching certain Boolean or categorical criteria were calculated, was used to assess broad patterns of anthropogenic fire behaviour. However, where possible, spatio-temporal variation in quantitative database variables was assessed under a multiple working hypotheses framework (Millington and Perry 2011; Magliocca et al., 2015a). Such an approach enables contrasting hypotheses to be encoded as alternate models of the data, and their relative merits evaluated without the strict experimental design requirements of null-hypothesis significance testing (Millington and Perry 2011). The Akaike Information Criterion (AIC) was used as a metric to evaluate alternative models of the data (Akaike 1973). AIC is commonly used as a statistical measure of model performance in multi-model inference. It is derived from the Kullback-Leibler divergence (Kullback and Leibler 1951), which can be conceptualised as describing the information lost by describing the true distribution of a data set with a given model (Lambert 2018).

An additional challenge was presented by the 83 database records (271 case studies) which presented an overall quantification of a fire regime, and noted the underlying anthropogenic behaviours that created it, but did not quantify the relative impact of each behaviour directly. These 'regime and behaviour' records were typically derived from secondary data (185 cases), such as government statistics, or remote sensing (38 cases), where quantitative assessment of the overall fire regime was complemented with a qualitative account of anthropogenic behaviours. A further 36 cases were based on primary data, typically ecological surveys with only incidental description of human impacts. Given the difficulty of discerning the degree to which each recorded behaviour impacted the overall regime, regime and behaviour records were held back from initial analysis so they could be used for calibration of the planned ABM.

An exception to this approach was taken for records at the wildland urban interface (WUI). This was because records at the WUI were dominated by the regime and behaviour type, and so quantifying human influences on these regimes required extrapolation from these records: just five quantifications of fire use by urban residents were directly reported, whilst 73 were obtainable through use of regime and behaviour records. To extrapolate from the overall regime to specific anthropogenic behaviours, the overall regime reported from secondary data or remote sensing was simply divided evenly between the underlying behaviours – e.g. if the overall burned area was 20% and four fire uses were reported, these would be assigned 5% burned area each. In all cases where this extrapolation took place, the resulting information was recorded as an estimate in the appropriate binned range.

3.2.5 Database availability

The data presented here are made freely available online (Perkins and Millington 2021), as well as analysis code (Perkins and Millington 2020).

3.3 Results[8]

DAFI comprises data from 514 papers containing 1841 case studies. Data were overwhelmingly taken from the academic literature (94% of case studies), but were also sourced from grey literature produced by governments and NGOs (5%). A plurality of data were sourced from primary field sources (47%), but remote sensing (19%) and secondary data sources (31%) including both government statistics (25%) and literature reviews (6%), were also important. Data included from literature reviews were principally fire policy information for a given location or region. Other smaller data sources were expert elicitation (2.6% of cases, n = 48), but also included media reports (n = 4), a report on a practitioner prescribed burning workshop (n = 3), archival research (n = 2), and a personal communication from a study author (n = 1). The geographic distribution of papers compiled by data source is given in Figure 3.1.

Reflecting the fragmented nature of the fire literature, data across all DAFI fields are sparse, with only an average of three quantitative fire metrics per case study, meaning 92% of the quantitative variables for each fire use record were missing. No single case study contained data for all variables in the database. The implications of this are addressed in the discussion (Section 3.4).

[8] This introductory results section (Section 3.3) appears in Millington et al., (2022) as section 2.3

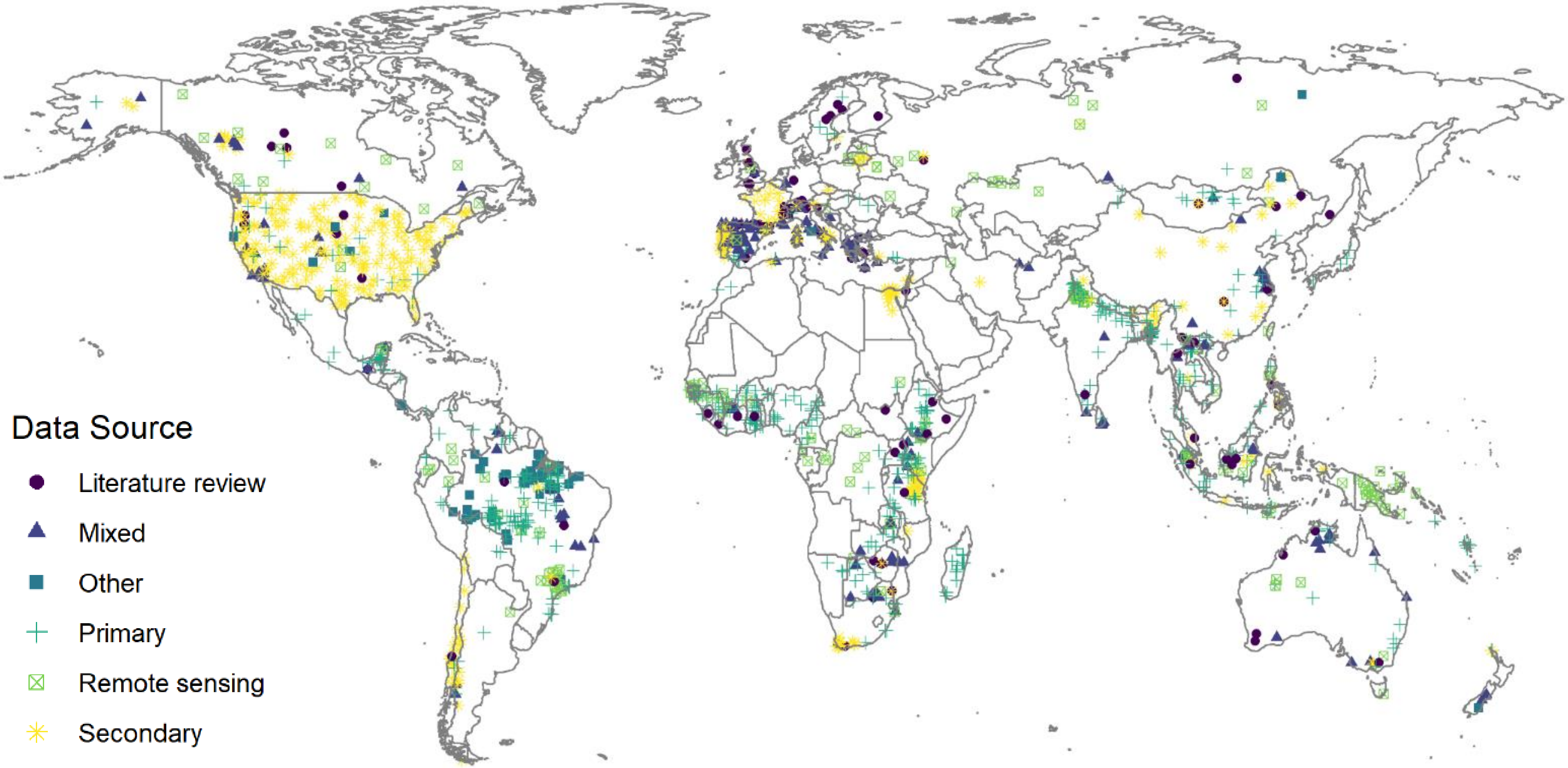


Figure 3.1: Spatial distribution of records compiled in DAFI, grouped by data source. Secondary data from government and institutional records were widely available across the Continental USA, as well as in Mediterranean Europe and fire-prone areas of China and South America. Primary field data were overwhelmingly focused towards studies of behaviours that were also of anthropological, agronomic or development economics interest such as shifting cultivation and the presence and practice of traditional fire knowledge. Remote sensing was effective for studying larger study areas (e.g. Boreal Canada, Central Australia, Siberia), but was also an important source of data for less accessible locations such as the Congo Basin and the rainforests of Papua New Guinea.

3.3.1 Characteristics of an anthropogenic fire regime

Perhaps the most striking aspect of the data collated in DAFI is the very high density of fires that typify anthropogenic fire regimes (Figure 3.2). Whilst MODIS-derived fire data suggest a median value of <0.01 fires km^{-2} $year^{-1}$ (Andela et al., 2019), DAFI data show that deliberate anthropogenic fires occur (where present) at a median and mean rate of 0.06 and 1.6 km^{-2} $year^{-1}$ respectively. Highly dense anthropogenic fires are found in very fertile agricultural areas such as the Mekong River Delta, where around 96 fires km^{-2} $Year^{-1}$ are reported, whilst at the sparser end of the scale pasture fires are reported at 0.11 fires km^{-2} $Year^{-1}$. Similarly, fire return intervals were typically short, with median of 3 and mean of 5.5 years.

Conversely, whilst anthropogenic regimes are typified by large numbers of fires, they are also defined by small fire sizes. The median anthropogenic fire size is just 1 ha, with interquartile range of 0.4-13.5 ha. However, the mean fire size was 1357.2 ha and the overall distribution of fire sizes most closely followed an exponential distribution – but only when the logarithm of the observed sizes was taken (AIC: log exponential 1626.11, log normal 3143.71). A Weibull distribution - which may partially account for overdispersion - provided the best fit to the untransformed data (AIC 8122.39; exponential 15979.34). This may suggest that previous studies of fire sizes that have found the un-transformed distribution to be itself exponential may undercount the number of very small (<1 ha) fires in anthropogenic fire regimes, which serve to create such a skewed distribution.

In both the spatial density of fires and fire size there is a pronounced difference between fires in cropland systems and those lit or 'broadcast' onto the wider landscape (Figure 5). Median anthropogenic cropland fire size was 0.5 ha, whilst pasture and other broadcast fires had a median size of 6.2ha. This pattern was mirrored in a substantial difference in sizes of escaped fires: whilst the overall mean fire size for cropland fires remained small (1.6ha), the mean broadcast fire size was 59.2ha. Cropland fire sizes are closer to a log exponential distribution (AIC 492.81) log Weibull (AIC 502.63). Broadcast fire sizes are closer to a log Weibull (AIC = 1680.40) than log exponential (1693.51). Taken together, this represents reasonable evidence that fires broadcast onto (semi-) natural landscapes are best considered as a separate process to cropland fires.

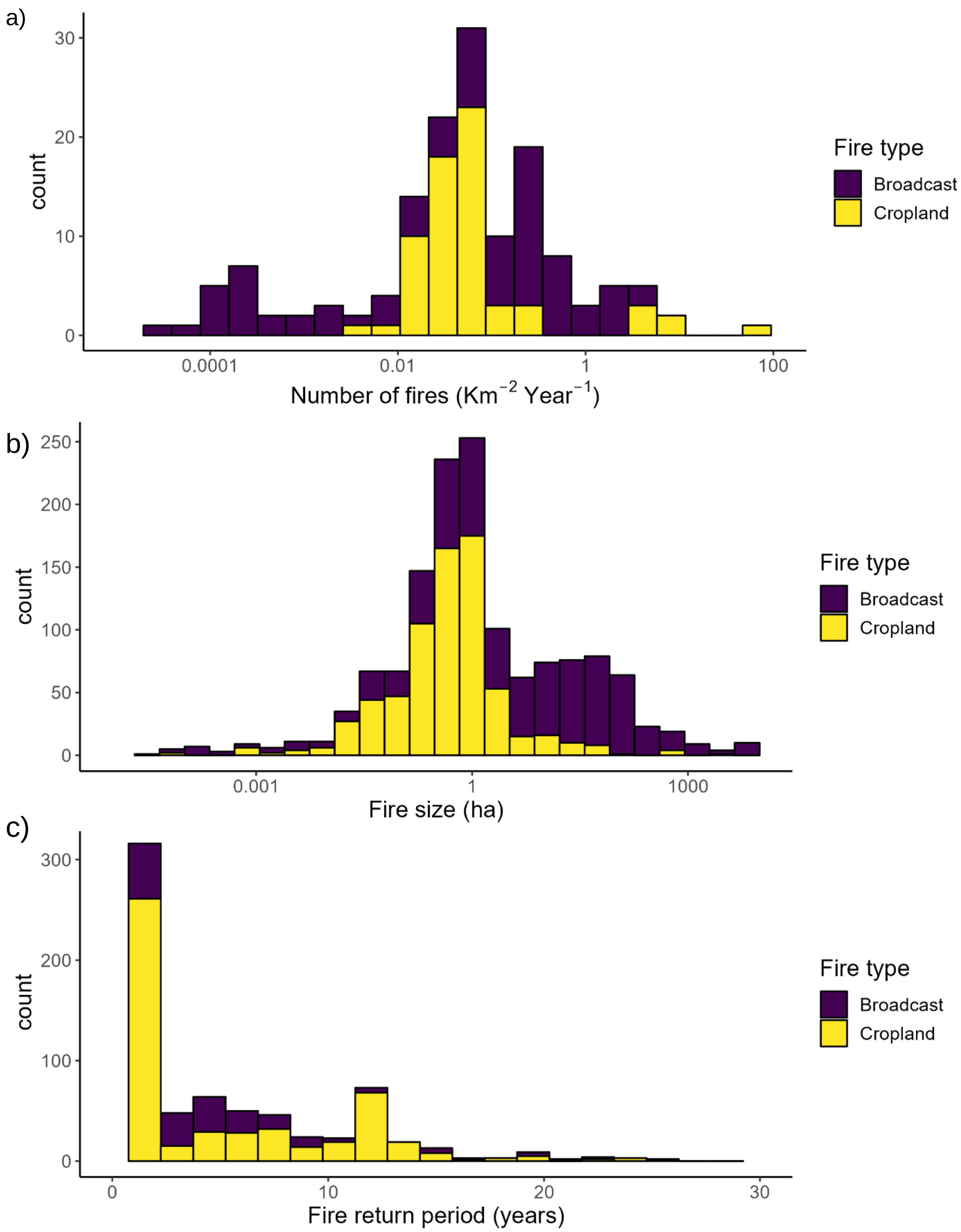


Figure 3.2: Distribution of metrics for anthropogenic fires - a) number of fires; b) fire sizes and c) fire return period. Fire density data are heavily positively skewed, but both the median and mean are four times higher than suggested by MODIS fire products. The distinction between cropland and wider landscape fires is particularly pronounced for fire sizes, where even on a logarithmic scale, so-called ‘broadcast’ landscape fires remain over-dispersed. Fire return period follows an exponential distribution, with a second peak at 12 years driven by one large study of shifting cultivation (Araki 2007).

3.3.2 Assessment of preliminary AFT framework

Overall, 21 anthropogenic fire uses were identified during database construction (appendix 3D). However, several of these were substantially similar, for example: pasture renewal and rangeland management; or prescribed fire for biodiversity conservation and prescribed burns for wildfire mitigation. Therefore, after such similar types were combined, seven fire uses emerged that had more than 100 instances in the database (or more than 2% of recorded instances of anthropogenic fire use). Together these seven types accounted for 93% of human fire use records. These seven were: arson, crop field preparation in shifting cultivation, crop residue burning, vegetation clearance fires (deforestation), pasture management fires, hunting and gathering, and fires lit to manage the wider pyrome.

The seven identified fire use types closely correspond to the anthropogenic fire regimes in the typology of Lauk and Erb (2016), but with the addition of residue burning and with pastoralism and hunting and gathering split into two categories. Further, data coverage is mostly strong across the seven fire use types, with all quantitative fire metrics captured for six of the seven key types (Figure 3.3). This comes with two important caveats. Firstly, as an inherently illicit practice, arson, for obvious pragmatic reasons, is not well quantified. Secondly, although use of fire for hunting and gathering is well represented in the numbers of instances (n = 213), the studies of this fire type were principally anthropological and therefore primarily reported qualitative results, particularly for fire suppression behaviours (n = 110). This leads to fewer than five quantitative data points being captured for fire use in hunting and gathering in the two fire density variables in the database. However, overall, agreement with existing research and good data availability make these seven fire use types a strong starting point for defining the fire use aspects of AFTs in the planned ABM.

Similarly, the preliminary AFT framework defined from previous quantitative analysis and theory (Table 3.1), proved effective at capturing the broad global patterns of anthropogenic fire uses. The preliminary AFTs showed strong coherence with particular fire uses (Figure 3.4) and fire suppression behaviours (Section 3.3.4). Whilst a formal statistical test would be unwarranted, owing to uncertainty about the independence of data in database records, this coherence between key fire uses identified through database construction and preliminary AFTs provides assurance that they are robust starting point to capture the core modes of human fire use globally.

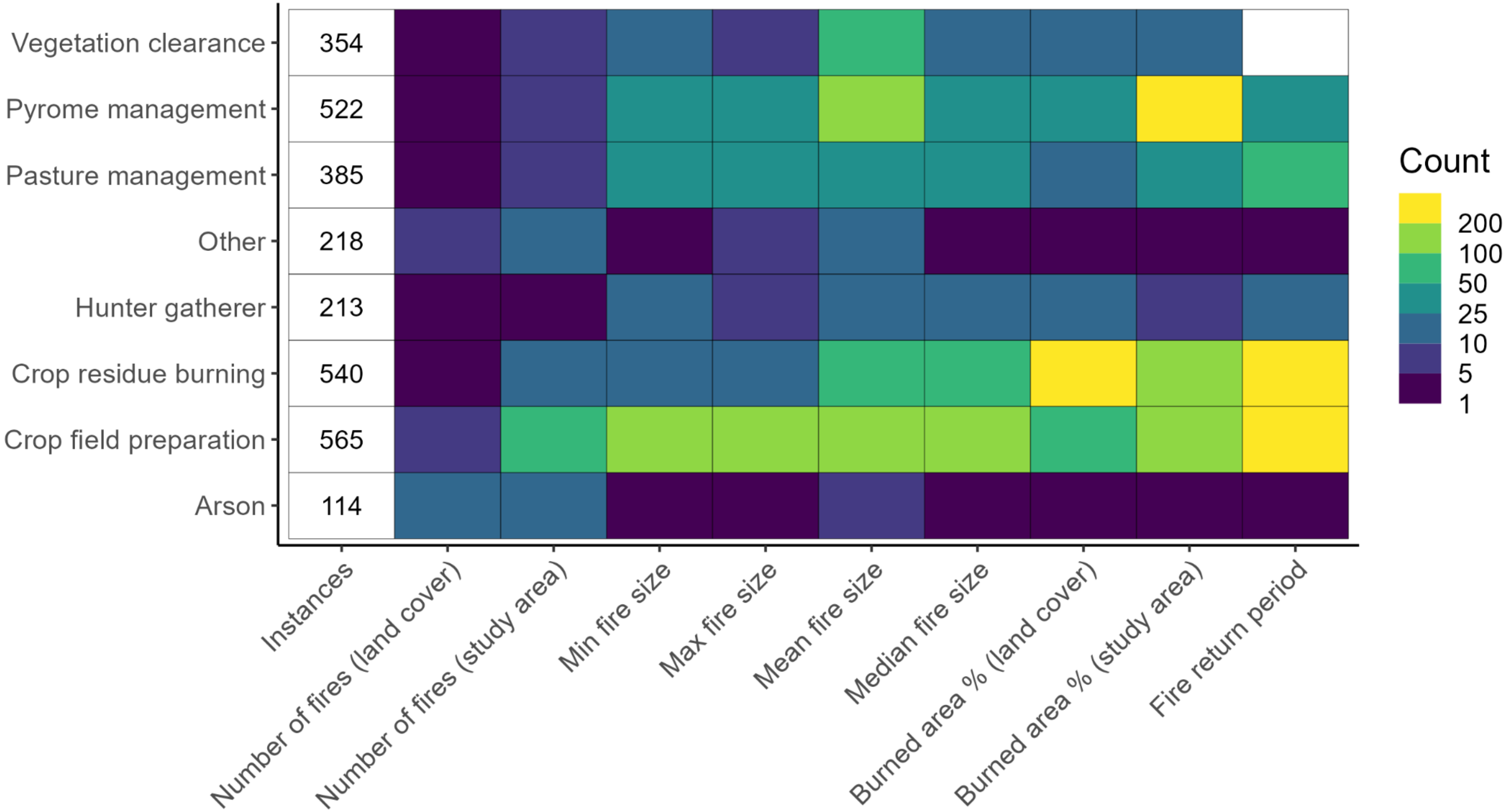


Figure 3.3: Number of DAFI instances and corresponding counts of quantitative metrics for each major fire use type. Data for intended and actual fire sizes and burned area percentage are grouped together. Primary vegetation clearance fires were treated as one-off, rather than cyclical events, so no fire return period is recorded.

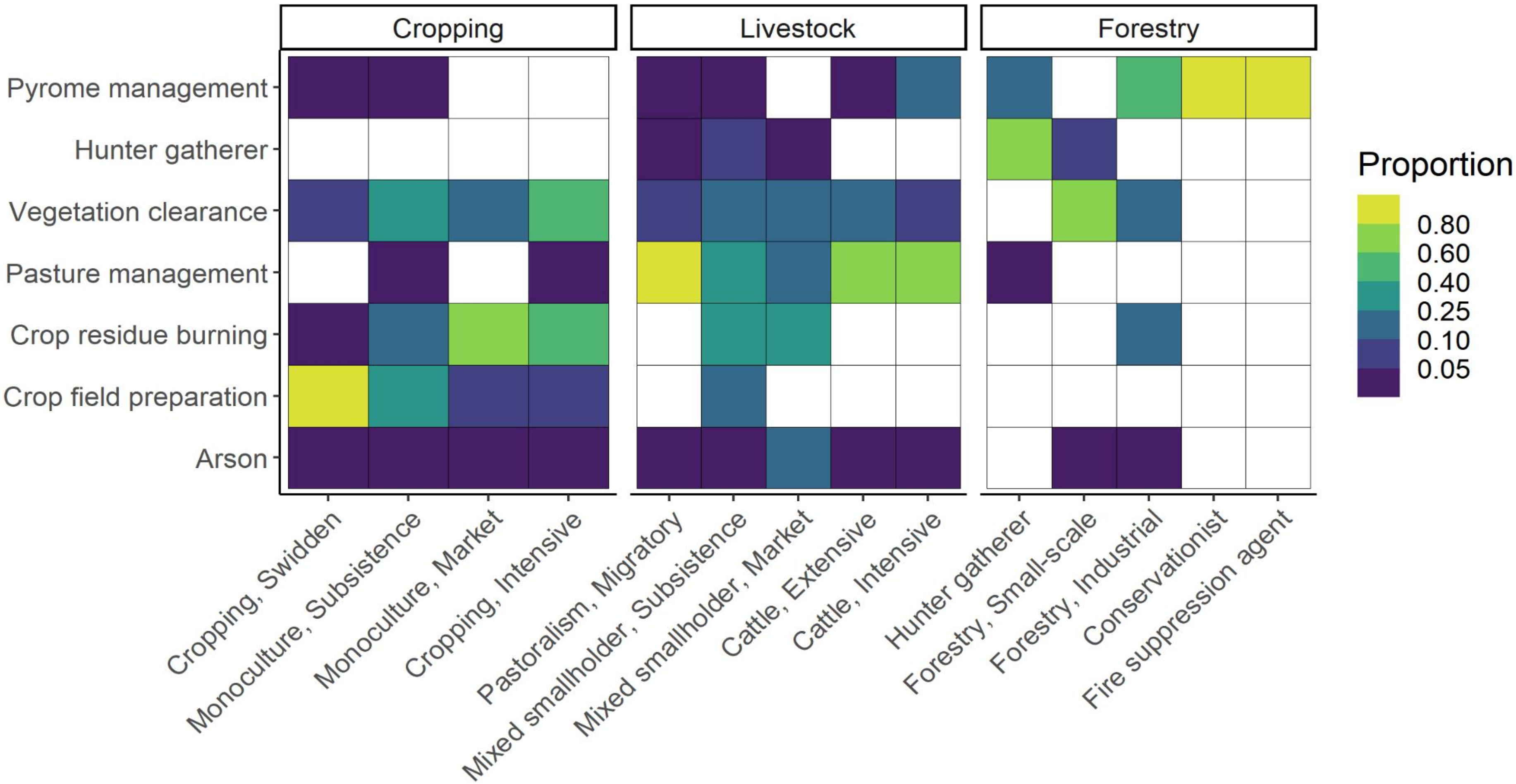


Figure 3.4: Intersection of key fire types with preliminary AFTs in DAFI; key fire types were defined as those with more than 100 instances. Colour scale gives the proportion of database instances of fire use for each AFT that belong to each key fire type. Burning of forestry residues is grouped under 'crop residue burning'. AFTs are organised from pre-industrial to post-industrial (left to right) within each land use system.

3.3.3 Analysis of fire use types[9]

This section provides a quantitative overview of the seven key anthropogenic fire uses captured in DAFI, as well as the underlying land use rationale that drives the observed spatial distribution and quantitative patterns observed in the database. A map of these fire use types is given in Figure 3.5, whilst a summary of their quantitative signatures is given in Table 3.4.

3.3.3.1 Shifting cultivation fires

Fires to facilitate shifting cultivation ('slash and burn') are overwhelmingly clustered in the tropics (Figure 3.5). At the latitudinal boundaries of shifting cultivation practice, where it is conducted in savanna woodlands or shrubby grasslands rather than dense tropical forests, fire use is sometimes replaced with labour-intensive 'mulching' practices (Dawoe et al., 2012). This points to net primary production (NPP) playing a restrictive role on fire use in shifting cultivation, as in lower NPP ecosystems biomass is insufficient to fertilise fields with the ash resulting from small fires. An intermediate stage, where biomass is collected from a wide area and then burned on a small plot, is observed, for example in the Miombo woodlands (Araki 2007).

As with cropland fires overall, shifting cultivation fires are typically 1ha or less in size, reflecting the size of plots cleared by farmers. Much research has focused on fallow periods as an indicator of the sustainability of shifting cultivation systems, which vary substantially with population density and land availability (Van Vliet et al., 2013). Data in DAFI point to a mean fire return period, which is closely linked to fallow length, of 9.8 years. Finally, although shifting cultivation may be densely practiced within a mosaic of agricultural plots, secondary vegetation and fallows, the overall system is sparsely distributed. Whilst shifting cultivation systems burn an average of 14.2% of the secondary vegetation mosaic, they only burned an average of 2.8% of the entire reported study area. This may reflect accessibility as a significant driver of the density of shifting cultivation, as whilst farmers may prefer the higher yields produced by clearing longer fallow lengths, often these are further from a settlement and more labour intensive to clear (Jakovac et al., 2017).

[9] This section (3.3.3) is provided in full as Supplementary Information A in Millington et al., (2022)

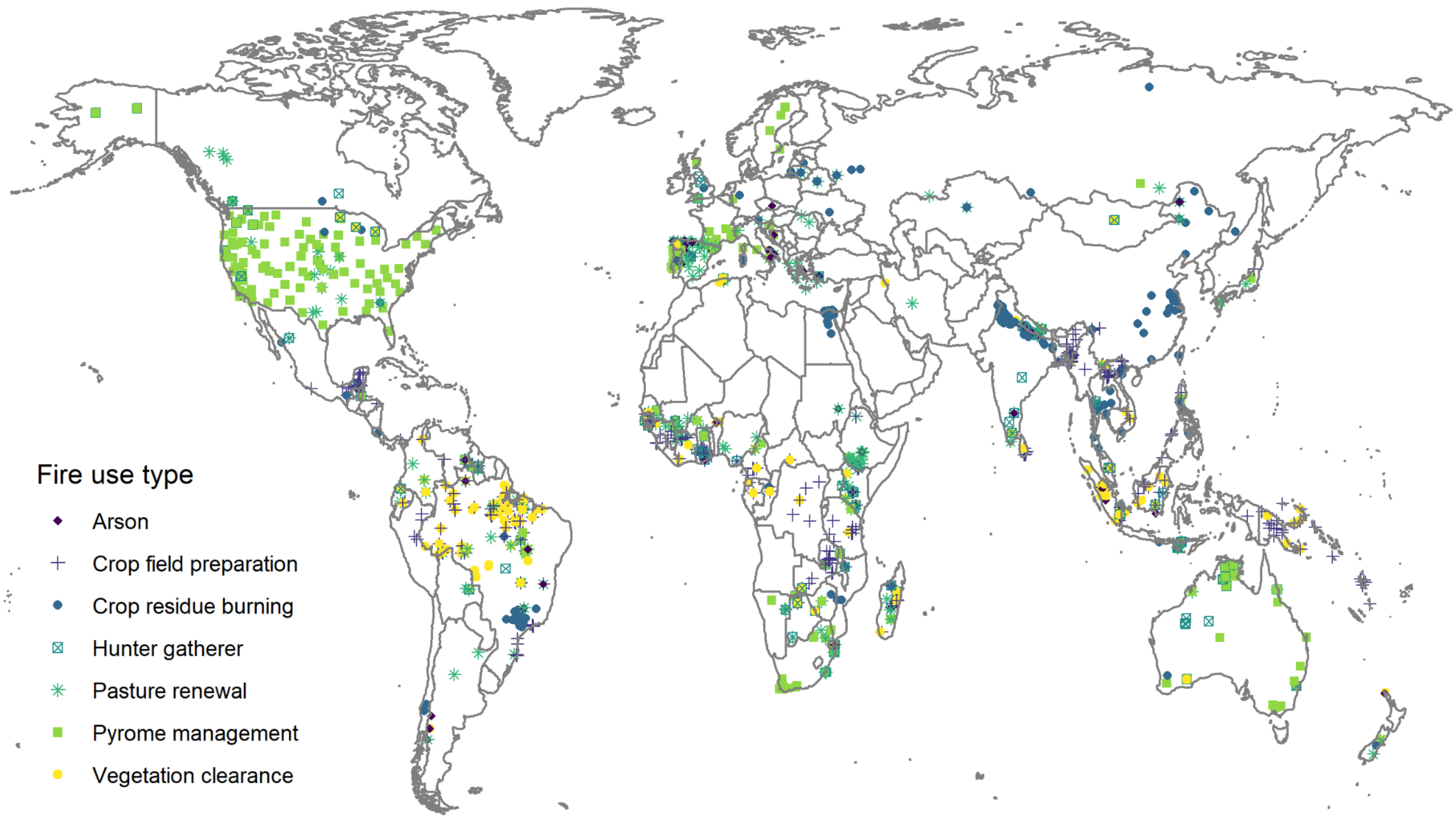


Figure 3.5: Spatial distribution of key fire use types identified in DAFI. The seven fire use types listed here accounted for 93% of all anthropogenic fire use instances in the data.

Table 3.4: Overview of quantitative characteristics of the seven central modes of anthropogenic fire use identified in DAFI. Primary vegetation clearance was assumed to be a one-off event and hence has no fire return period.

Fire use	**Mean fire size (ha)**	**Mean burned area (% Land cover yr^{-1})**	**Mean burned area (% Study area yr^{-1})**	**Mean fire return period (years)**	**Escape rate (% fires)**
Crop field preparation	0.7	14.2	2.83	9.8	0.09
Crop residue burning	3.2	37.3	13.2	1.5	0.03
Pasture management	18.7	32.1	17.1	3.2	6.47
Hunting and gathering	1.7	14.3	16.7	4.3	2.70
Primary vegetation clearance	7.5	6.6	1.2	N/A	0.95
Pyrome management	207.1	8.9	1.2	5.7	0.08
Arson	N/A	N/A	N/A	N/A	N/A

3.3.3.2 Crop residue burning

As agriculture intensifies and becomes sedentary, yields increase and crop residue disposal comes to be a significant activity for farmers. Burning of surplus residues typically peaks in the latter stages of transition to an industrial fire regime, particularly as use of machinery becomes more widespread (Kumar et al., 2015). Machinery use frequently leads to increased rates of residue burning, because when residues are hand harvested it is less burdensome to gather them for use either as domestic fuel or fodder for cattle (Hong van 2014; Lasko et al., 2017), and because machinery is associated with larger farm sizes where residue availability exceeds amounts that can be practically used (Ahmed et al., 2015). Therefore, in mixed arable-pastoral subsistence small-holders, burning may be absent because residues present an important source of livestock feed (Keck and Hung 2019).

Furthermore, where burning is conducted on hand-harvested residues, these may be pile burned (Lasko et al., 2017), leading to approximately 1/9th of the area of a field being burned (Liu et al., 2019). Whilst where machine harvested residues are broadcast burned in situ, the intended fire size is typically approximate to the field size (Mendoza et al., 2015; Liu et al., 2019). The main restriction on residue burning in an industrial or post-industrial fire regime is air quality legislation (Jajtic et al., 2019; Sun et al., 2019; Boossabong and Chamchong 2020). For this reason, the practice is largely absent in intensive agricultural regions in Northern America and Northern Europe (Smil 1999), as well as Australia and Brazil (Mendoza 2015). Similar concerns are now driving policy in areas of Northern India and China (Peng et al., 2016; Sembhi et al., 2020).

Whilst the mean fire size for residue fires is similar to that of crop field preparation fires in shifting cultivation systems (Table 3.4), anthropogenic fire regimes dominated by residue fires typically produce a much higher burned area percentage, with a mean value of 37.3%. This is largely because residue fires are predominantly lit annually, or even more frequently under double-cropping or triple-cropping systems (Hong van 2014; Kumar et al., 2015). However, this increased burned area compared to shifting cultivation may also occur because permanent fields are situated in a tighter mosaic, as accessibility concerns are less relevant. Finally, the amount of residue burning varies with commodities: for example, in Suqian province of China, potatoes, legumes and corn were more frequently used as fuel or mulched back into the soil, whilst burning of rice and wheat straw was endemic (Yang et al., 2008). Similarly, sugarcane produces lots of residue removal fires, as these must be cleared to allow efficient harvest (Rudorff et al., 2010).

3.3.3.3 Pasture management fires

Burning of both planted pastures and native grasslands used for livestock grazing is a widespread practice, serving to rejuvenate the nutrient quality of forage for livestock (Laris 2002; Jakimow et al., 2018; Johansson et al. ,2019) and prevent the encroachment of woody shrubs (Twidwell et al., 2013; Vehrs 2016). As with shifting cultivation, NPP is a principal driver of whether livestock farmers use fire, and how frequently. For example, whilst pasture renewal fires are widespread across much of Sub-Saharan Africa and Amazonia, the practice is not used by pastoralists on the Mongolian steppe (Saladyga et al., 2013) or in mountainous areas of Patagonia (Easdale and Aguiar 2018). Simply put, if all available forage in an ecosystem is required to feed a livestock herd, a farmer will not burn it to improve its nutrient quality; this trade-off has been observed not only in pre-industrial, but also in comparatively intensive farming in the USA (Taylor 2003).

However, fire use among livestock farmers is driven by a range of factors in addition to NPP. Fire use to control the tsetse fly is common in Sub-Saharan Africa and can cause farmers to decrease fire return period to around two years (global mean of 3.2 years) to keep grass short enough to prevent tsetse fly infestations (Trollope 2011). Similarly, on communal rangelands, livestock farmers may also use fire to facilitate accessibility and ward off predators and snakes (Mbow et al., 2000). Furthermore, Kull (2003) noted that in Madagascar use of fire to combat locusts and to renew pastures were often interchangeable – and pests were often used to justify pasture fires as the latter fire use was illegal. Therefore, depending on location, such additional considerations may increase fire use, or only suggest that a single fire may be lit for multiple reasons.

Finally, the decision to use fire for livestock farmers can be heavily shaped by the existence of fire knowledge or culture in a community. For example, in rangelands used for livestock grazing in the USA, state agricultural and conservation organisations have made significant efforts to reintroduce prescribed burning to prevent woody encroachment and to conserve biodiversity, but have been met with substantial resistance by farmers (Chapter 2).

As areas used for livestock grazing are typically larger than crop fields, pasture fires are notably larger (mean = 18.7 ha) than crop residue fires (3.2ha). Furthermore, perhaps because the average intended fire size is larger than for arable fire, escaped pasture fires are more frequently noted as a cause of uncontrolled wildfires than cropland fires: 6.5% of pasture management fires were noted as escaped, compared with 1.3% overall, and less than 0.1% of cropland fires. Two factors suggested as influencing the rate of escaped pasture fires are logging of surrounding vegetation and non-native grasses (Uhl et al., 1985; Bowman et al., 2011). However, no meaningful difference in the rate of escaped fires could be found due to the presence of extractive forestry (5.5% of fires vs 6.6% of cases where extractive forest was not present or not reported in a case study). Data on presence of invasive grasses was not recorded systematically, but studies in Northern Australia (Neale and Macdonald 2019) and Amazonian Brazil (Cammelli et al., 2019b) both noted flammable exotic grasses originally introduced for their nutrient content as contributing to the occurrence of wildfires. Pasture fires lead to a mean burned area of 32.1% of the pasture in a landscape, and 17.1% of the overall study area.

3.3.3.4 Hunting and gathering

Similar to shifting cultivation, use of fire for hunting and gathering is closely linked to the properties of the underlying ecosystem. However, the range of techniques used in hunting and gathering and resultant impacts on the fire regime are more diverse than other preindustrial fire types (Table 3.5). For example, in the Western Australian Desert, Aboriginals can light hunting ‘drive’ fires – where fire is lit to push wild animals towards a certain location – over very long distances (up to 130km) (Burrows et al., 2006). Conversely, Aboriginal people hunting for turtles in a wetland environment used fires with a mean size <1ha (McGregor et al., 2010); fire use for fishing in peat swamps follows a broadly similar pattern, with multiple very small fires (<$10m^2$) lit each year on the same patch of ground. By contrast, gathering of non-timber forest products (NTFPs) consistently results in small fires. Harvesting of wild honey, for example, uses fires often no bigger than a single fire stick, but can be important to a fire regime due to escaped fires (Schmerbeck 2003; Shaffer et al., 2010). In addition to the diversity of practices involved, and as noted above, a further challenge in quantifying fire use in hunting and gathering is the limited *quantitative* data available.

Table 3.5: Overview of fire size in hectares of fire use for hunting and gathering in DAFI. Whilst the minimum, median, mean and intended maximum appear to be from a similar distribution, the actual maximum is multiple orders of magnitude greater, indicative of great heterogeneity in the practice.

	Minimum	Median	Mean	Maximum
Intended	0.63	1.17	2.13	12.2
Actual	1.38	1.31	1.31	8345.00

3.3.3.5 Primary vegetation clearance

As a frequently illicit practice, just 97/354 instances of primary vegetation clearance were based on primary field data. 'Primary' is explicitly used here to differentiate such fires from shifting cultivation, in which fire is used rotationally to burn secondary vegetation (Table 3.4). Alternative methods used include remote sensing (137/354) and expert elicitation (63/354). In many cases, such studies of primary vegetation clearance fires were focused on deforestation and biodiversity conservation concerns, and therefore reported the size and rate of clearings, but not the frequency with which fire, rather than machinery, was used (Morton et al., 2006; Cochrane 2009a). Therefore, data on deforestation fire sizes are widely available, but burned area percentages were often challenging to calculate. However, there is an apparent trend that as land use becomes more industrialised, the size of vegetation areas cleared increases (Figure 3.6). Furthermore, the proportion of fire use records attributed to primary vegetation clearance was 42% for intensive farmers, compared to only 26% for arable small-holders.

A large literature documents the processes that lead to tropical deforestation in a degree of nuance that is beyond the scope of DAFI (Eliasch 2008; Rakatama et al., 2017; Fischer et al., 2020). However, in general terms, as the size of clearances increased with economic development, and a greater proportion of fire use instances for livestock and intensive arable farmers were attributed to deforestation than for more subsistence-oriented land users. This may suggest that, rather than enabling land to be spared (Cerri et al., 2018), land use intensification increases farmers' economic incentives to deforest land (Kubitza et al., 2018) and may increase the overall quantity of fire use in land clearing.

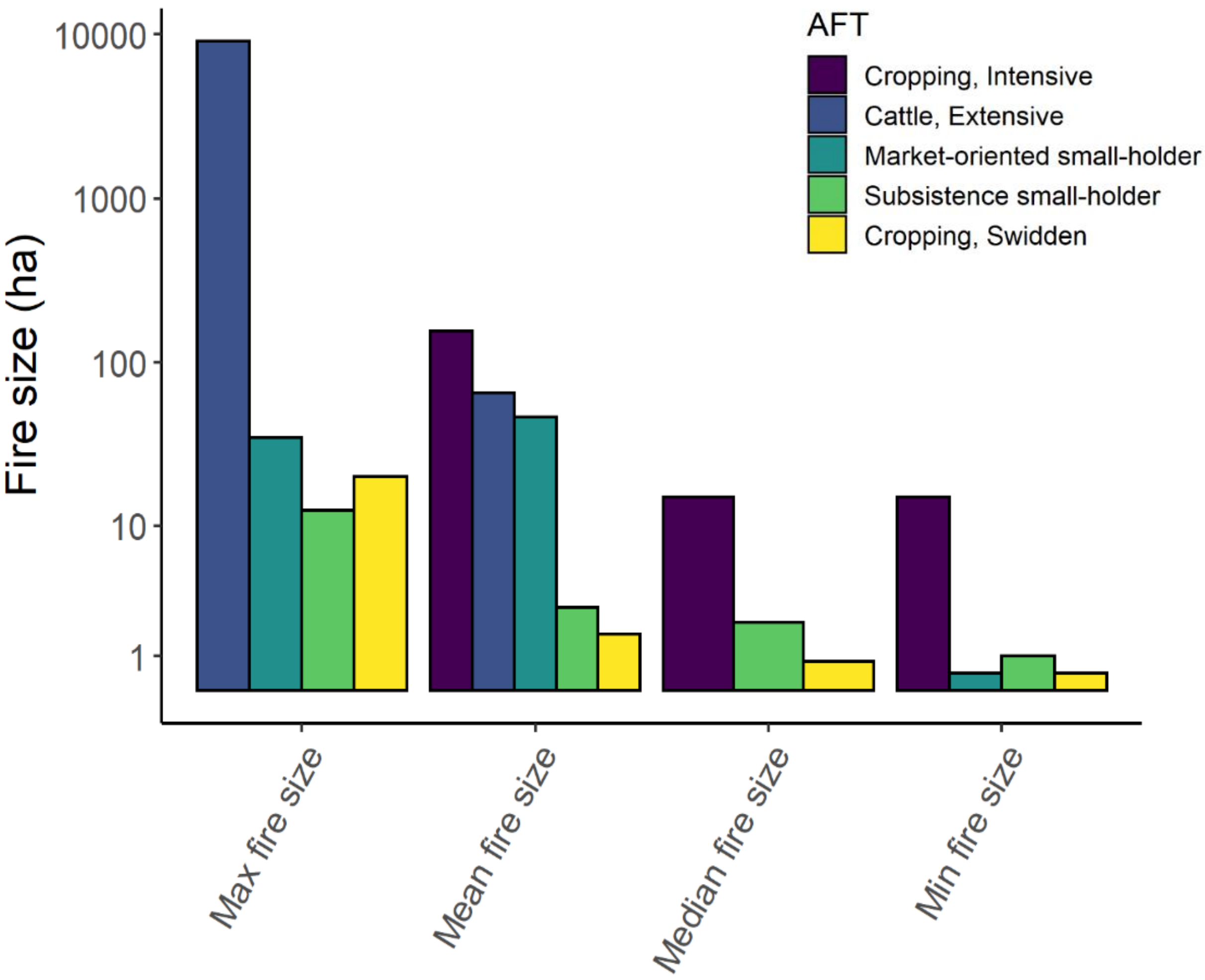


Figure 3.6: Comparison of sizes of vegetation clearance fires in DAFI for different agent functional types. There is a clear trend for clearing sizes to become larger with larger operation sizes and with availability of machinery. Compared to the arable land use types of a similar fire regime, livestock farmers tend to clear larger areas, a pattern reflected in the typical fire sizes in their respective cyclical fire uses and driven by the relative area of land required by each farming system. Where deforestation fire was present in the context of shifting cultivation (swidden), this was most commonly where, after a plot was used for agriculture temporarily, it was converted into pasture or other productive land use.

3.3.3.6 Pyrome management and pyro-diversity

Fire is widely adopted by a range of land users to manipulate the overall fire regime of a landscape. This includes burning done to reduce the risk of wildfire damage to persons and property, but also fires lit for biodiversity conservation purposes – where fire creates vegetation of differing successional stages on a landscape, and therefore encourages biodiversity (Parr and Andersen 2006; Bowman et al., 2016).

Fire regimes generated by these behaviours differ widely, based on both the environmental and socio-economic context in which prescribed burning takes place. For example, although fire fighting agencies do conduct prescribed burns, these are often met with internal resistance from fire fighters (Spencer et al., 2015; Section 3.3.4.1), resulting in smaller burned areas on average and smaller fires (Figure 3.7). However, there is also large variation in how state forestry agencies used fire depending on the climate and vegetation type managed: the US Forestry Service prescribed burn size averaged around 20ha in densely populated California, but was between 500-1000ha in the Sonoran Desert in Arizona (Barnett et al., 2016).

Conversely, where biodiversity conservationists manage large areas, such as in the Savannas and grasslands of Southern Africa, these can be rotationally burned in blocks of 60-400ha to foster pyro- and bio-diversity (Goodenough et al., 2017). The most extensive and intensive burning programmes for pyrome management were found in Northern Australia, where a combination of the traditional ecological knowledge of Aboriginal peoples, and industrial technology, has enabled a post-industrial implementation of a quasi-traditional (pre-industrial) fire regime (Petty et al., 2015; Neale et al., 2019; Ansell et al., 2020).

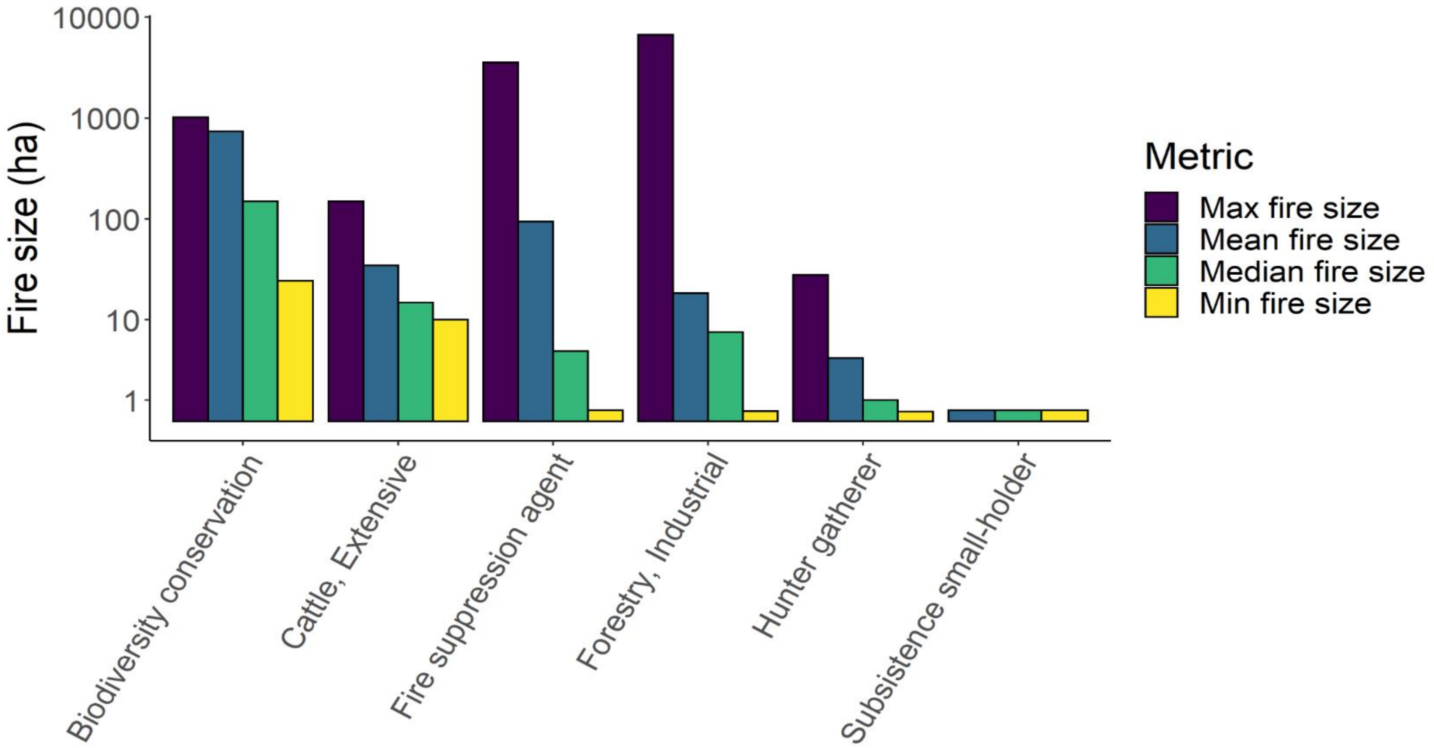


Figure 3.7: Fire size distributions for pyrome management fires. Fire sizes are closely related to the area of land management by a given land user: large fire sizes used by conservationists reflect large protected areas which may be rotationally 'block burned'. Conversely, industrial forestry and fire fighting agencies ('fire suppression agent') generally light smaller fires, often owing to policy barriers and other institutional resistance to prescribed burning; however, where prescribed burning was widely practiced, the size of managed area gave potential for very large fires. Subsistence-based farmers burned to protect their crops, often where broader agricultural fire uses were widespread. Intended and actual fire sizes are combined.

3.3.3.7 Arson

As an inherently illicit and often clandestine practice, arson was poorly quantified in the available data. Therefore, analysis here is restricted to case analysis. Arson was most frequently observed where conflicts over land use occurred: land tenure was recorded as insecure in 48 of 82 database instances where arson was present and a description of land tenure was also given in a case study. A further 15 of these 82 cases were recorded as 'mixed' land tenure. Arson as a weapon in land use and land tenure conflict was most frequent where shifting cultivation and industrial forestry were present, as local small-holders protested allocation of their former lands held under traditional land tenure to large-scale commercial plantations (e.g. Suyanto et al., 2004; Chokkalingam et al., 2007). A similar pattern was also observed where arson was present on lands allocated for biodiversity conservation: in 23/35 cases such arson was used by small-holder farmers or hunter-gatherers, primarily to protest the restrictions placed on their livelihoods by protected areas. However, in 9/10 of these cases where land tenure was noted, it was described as centrally-allocated or mixed, perhaps reflecting the perspective and focus of the underlying biodiversity conservation literature.

3.3.4 Fire suppression

Although recorded on an aggregated ordinal scale, clear patterns of fire suppression behaviours come through in the data (Figure 3.8). In general, the emphasis in pre-industrial AFTs is on fire prevention using traditional fire knowledge (66/106 cases). This pattern tends to fracture during transition, which shows the greatest proportion of uncontrolled fire (46/148 cases) or fire used with only ad-hoc control (61/148). AFTs from the industrial fire regime focus on suppressing fire through extinction, typically with industrial or intensive means (107/184 cases).

However, a more complex picture emerges in the post-industrial fire regime. On the one hand, fire prevention and control using traditional fire practices begin to re-emerge (37/201, 22/54 cases respectively), whilst simultaneously, a lack of knowledge of living with fire and agricultural abandonment lead the dominant signal to be an absence of fire prevention (117/201 cases). Two striking examples of how suppression behaviours define and shape fire regimes are at the wildland urban interface (WUI), and in the practice of traditional fire knowledge. These are discussed in more detail below.

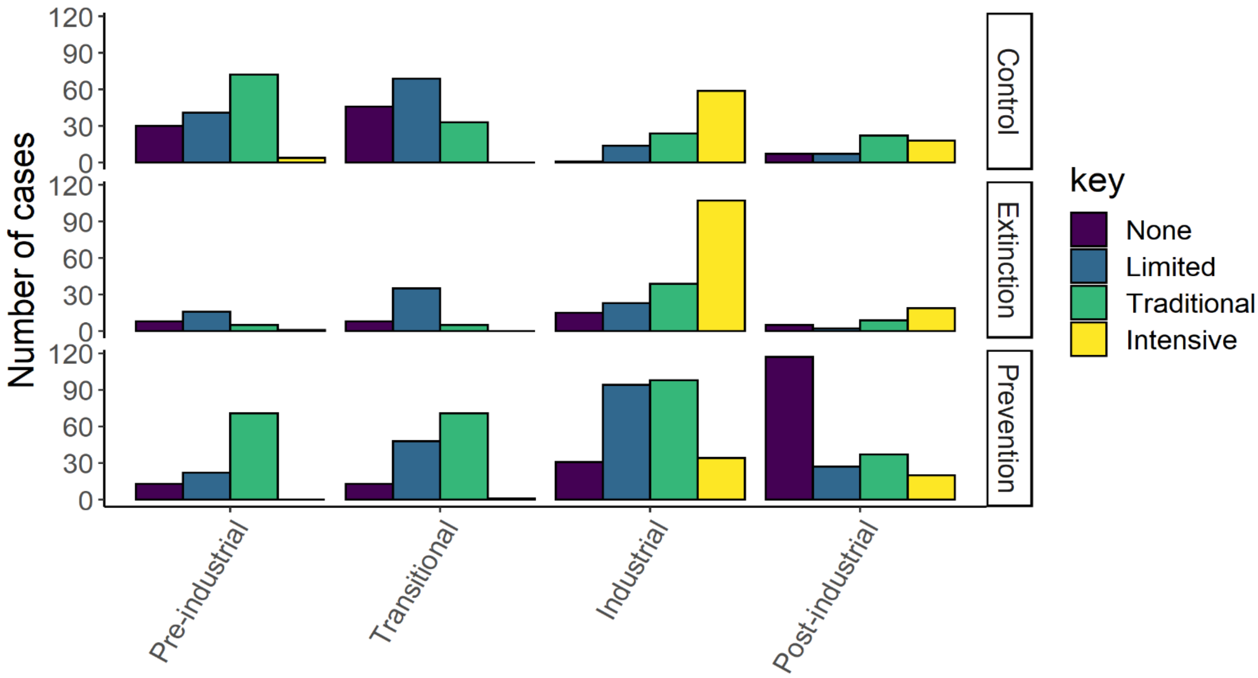


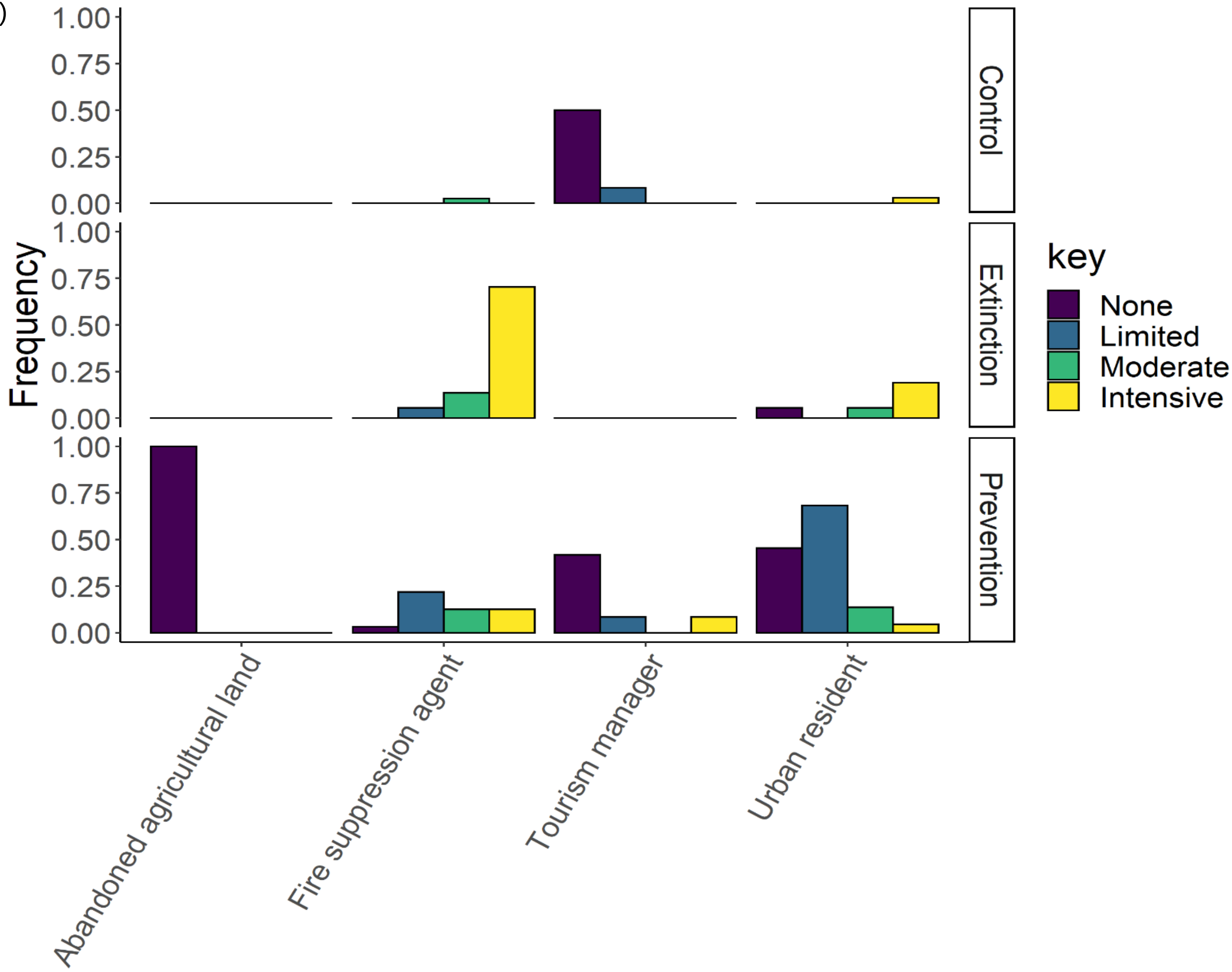
Figure 3.8: Overview of fire suppression behaviours in DAFI. AFTs were grouped according to their respective Pyne fire regime. Fire prevention and control of deliberate fire use are the dominant suppression behaviours undertaken in the pre-industrial era, whilst extinction becomes more dominant in later stages. Agricultural abandonment and the wildland urban interface together drive the lack of fire prevention activities undertaken in post-industrial fire regimes.

3.3.4.1 The Wildland Urban Interface

The WUI emerges as a distinct phenomenon in the data through the collision of multiple actions. Firstly, both tourists and urban residents are associated with high levels of accidental ignitions: 59% and 42% of fire instances associated with urban residents and tourists respectively were accidental. Accidental ignition sources include cigarette buts, car exhausts, and escaped domestic fires. The result is a fire regime which is almost never ignition limited (Figure 3.9). However, such frequent ignitions are typically combined with intensive fire extinguishing, which means virtually all fires are suppressed at less than <1ha. Furthermore, the quantitative overview of the WUI presented in Figure 3.9 may underestimate ignitions: because of the disaggregation required to define fire behaviours at the WUI, numbers only include fires started by urban AFTs. This may mean, particularly in developing world contexts, that fire used in agriculture close to urban areas is not fully captured (de Torres Curth et al., 2012).

As well as providing significant levels of accidental ignitions, urban residents also consistently resisted fuel-load management on their properties, either through a lack of awareness of fire risk (e.g. Curt and Frejaville 2017; Xanthopoulos 2018) or because dense vegetation is seen as aesthetically attractive (e.g. Gibbons et al., 2017). For this reason, and for air quality concerns with prescribed burns (Burrows and McCaw 2013), government agencies responsible for tackling wildfires typically only engaged in modest fire prevention measures at the WUI. Finally, particularly in Mediterranean landscapes, abandoned farmland and plantation forests present large, unmanaged fuel-build ups that are highly susceptible to fire (e.g. Koutsias et al., 2012; San-Miguel-Ayanz et al., 2013). The result is a fire regime characterised by abundant very small fires, with occasional megafires multiple orders of magnitude larger than the median fire size in the regime.

a)



b)

Number of fires (study area; km^{-2} yr^{-1})	Actual median fire size (ha)	Actual mean fire size (ha)	Actual max fire size (ha)	Actual Burned Area % (study area)
0.3068	0.5	0.7307	18607.3	2.34

Figure 3.9: Anthropogenic fire behaviours at the Wildland Urban Interface - a) suppression behaviours of key actors and b) resulting fire regime from fires started by urban residents. Data in a) were filtered for case studies in which urban areas were present; b) contains both deliberate and accidental fires. The burned area number only accounts for fires started by urban residents at the WUI (not including escaped agricultural fires, e.g.) and so may be an underestimate, particularly in developing world contexts. Plentiful ignitions, combined with abandoned land, intensive fire extinction and a lack of rigorous fire prevention combine to create the conditions for megafires.

3.3.4.2 Traditional fire knowledge

Traditional fire knowledge (TFK) is highly evident amongst pre-industrial AFTs, particularly in case studies where the dominant preliminary AFTs were of the pre-industrial fire regime ("first fire" *sensu* Pyne). This is demonstrated by the frequency of 'moderate or traditional' fire control and fire prevention attributes for pre-industrial AFTs where they constituted the dominant land use and fire regime: 58% of fire suppression behaviours were categorised as 'moderate or traditional' in the pre-industrial regime, compared with only 42% of cases in transition and beyond. Given that TFK frequently involved community fire control and prevention – for example a communal fire calendar or means of fire governance (Section 2.2.3) it is possible to identify the influence of such community actors on fire use in the pre-industrial fire regime. The fracturing of communities possessing and practicing TFK is evident in how a more mixed picture develops during economic development (and corresponding fire regimes). For example, fire control in pre-industrial shifting cultivation landscapes frequently applied TFK to prevent escaped wildfires (15 of 27 cases, 56%), whilst where shifting cultivation occurred alongside more intensive land uses, this dropped to only 14/35 cases (40%) with the remaining 21 cases having limited and no fire control. A similar decrease in TFK was noted amongst migratory pastoralists when alongside more intensive land uses.

However, hunter gatherer communities overwhelmingly maintained TFK in both the pre-industrial regime and beyond – in 30/49 of all cases (61%) TFK was used to control deliberate fires whilst in 37/45 (82%) of cases TFK was used in fire prevention (Figure 3.10). Furthermore, seven cases were recorded of TFK being reintroduced with active government support in a post-industrial context (four of which were in Australia), indicative of the cultural importance and longevity of fire knowledge in some indigenous communities (e.g. Hill et al., 1999; Prober et al., 2016). An outlier to this trend is found in Indonesia, where even in predominantly pre-industrial fire use contexts, fires for hunting are regularly lit without any control (11 cases). This may be caused by locals not having reason to value peat swamp forests, which are seen as a source of disease and pests (Chokkalingam et al., 2005; Tacconi et al., 2006). Furthermore, the extent of wildfires caused by uncontrolled hunting fires in this country is in part attributed to climatic variability driven by El-Nino droughts (Stockwell et al., 2016), perhaps pointing to the difficulty of adapting for subsistence land users.

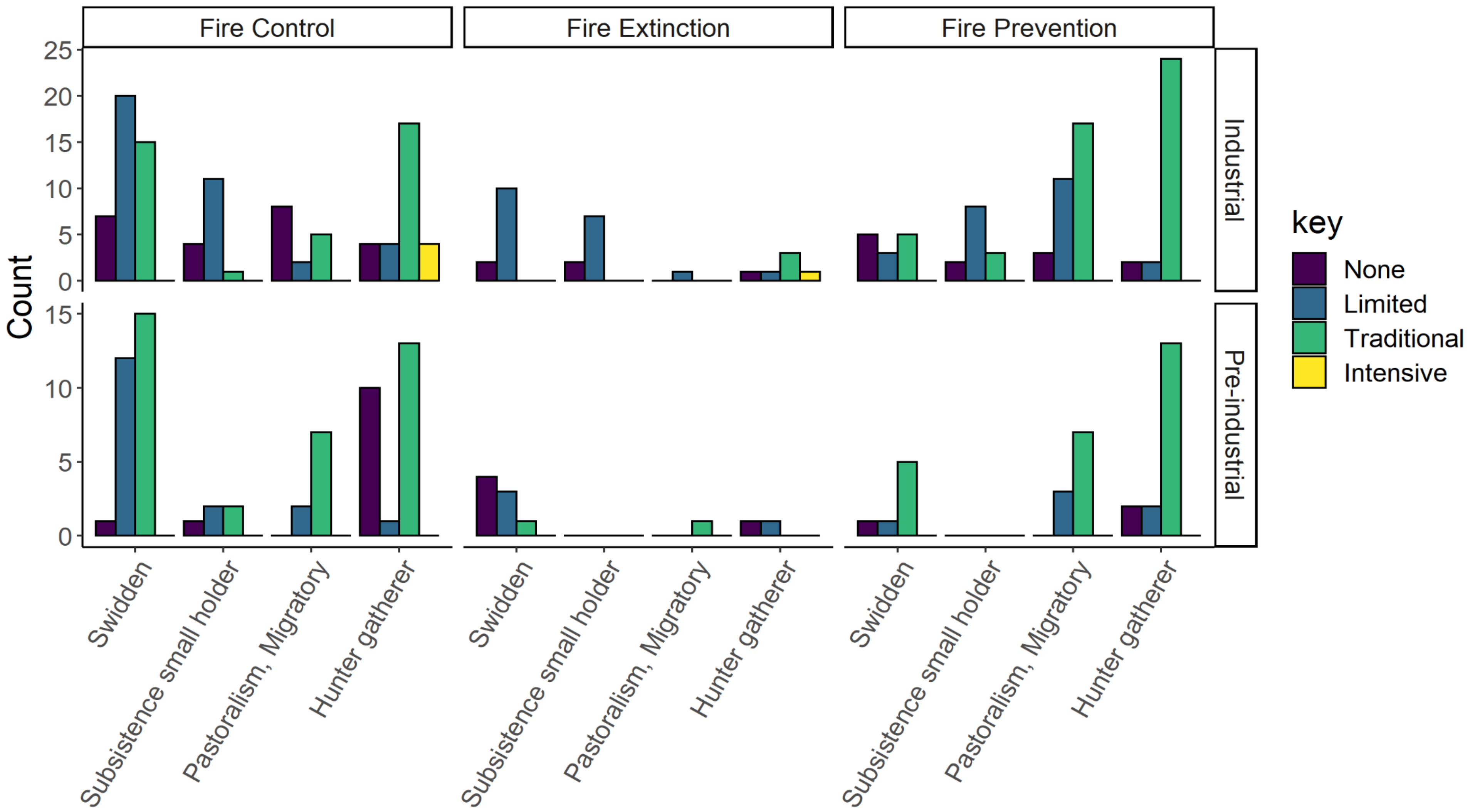


Figure 3.10: Overview of traditional fire knowledge (TFK) in DAFI for selected AFTs. TFK is present in 58% of reported fire suppression behaviours in the pre-industrial regime, but only 42% of cases otherwise. 5% of examples of TFK beyond the preindustrial phase were where traditional burning was actively reintroduced with government funding and support.

3.3.5 Fire Policy

Whilst multiple policy actors, spanning local, regional and national governments, NGOs and supra-national institutions were included in DAFI, national governments were the dominant policy actor, accounting for 91% of policy prescriptions, with NGOs and the European Union / United Nations accounting for 4%, and private companies 1%. The majority of land users targeted by fire policy were from the pre-industrial fire regime, and the dominant policy interventions recorded in the database were to ban or restrict use of fire, together accounting for 69% of fire policies (Figure 3.11).

There is some evidence that fire bans may be counter-productive, with bans leading to less-controlled or clandestine fire use and less effective fire prevention, particularly amongst non-arable, pastoral or hunting ('broadcast') fires (Figure 3.12). For example, where fire was used by livestock farmers, it was more than three times as likely to be applied with no control where fire was banned (8/20 cases; 40%) than when it was not (4/34 cases; 12%); hunter gatherers were more than twice as likely to do so. Conversely, where shifting cultivation fire was present, farmers were more likely to apply traditional fire knowledge to controlling their fires in contexts where fire was banned – perhaps indicating that many bans were not enforced. This is possibly because such practices typically took place in remote locations (Brinkmann et al., 2014) or because fire users had no alternative (e.g. Carmenta et al., 2019), or because bans were holdovers from colonial policies that were rarely enforced (Kull 2003; Eriksen 2007). However, shifting cultivation farmers were also more likely to use fire without control when banned (5/23 cases) than when not (3/47 cases).

Although the rationale for policy *change* was not encoded directly in DAFI data, where a single case study had more than one fire policy governing a similar behaviour over the study period, a review of free text notes in the relevant database records suggested in 25 of 60 cases this change was linked to concerns over damage from specific wildfire events to people or the environment. This constitutes additional evidence to that presented in Chapter 2, that much wildfire policy is made in reaction to shocks in a fire regime.

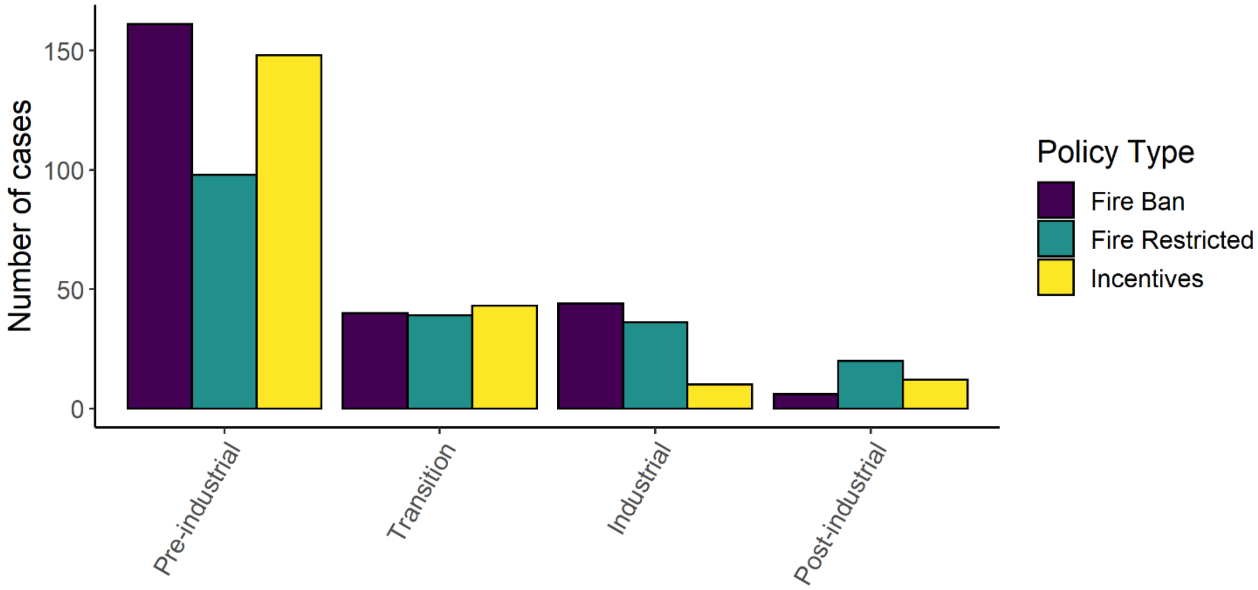


Figure 3.11: Distribution of fire policy types by fire regime, showing policy was overwhelmingly targeted towards pre-industrial fire use types.

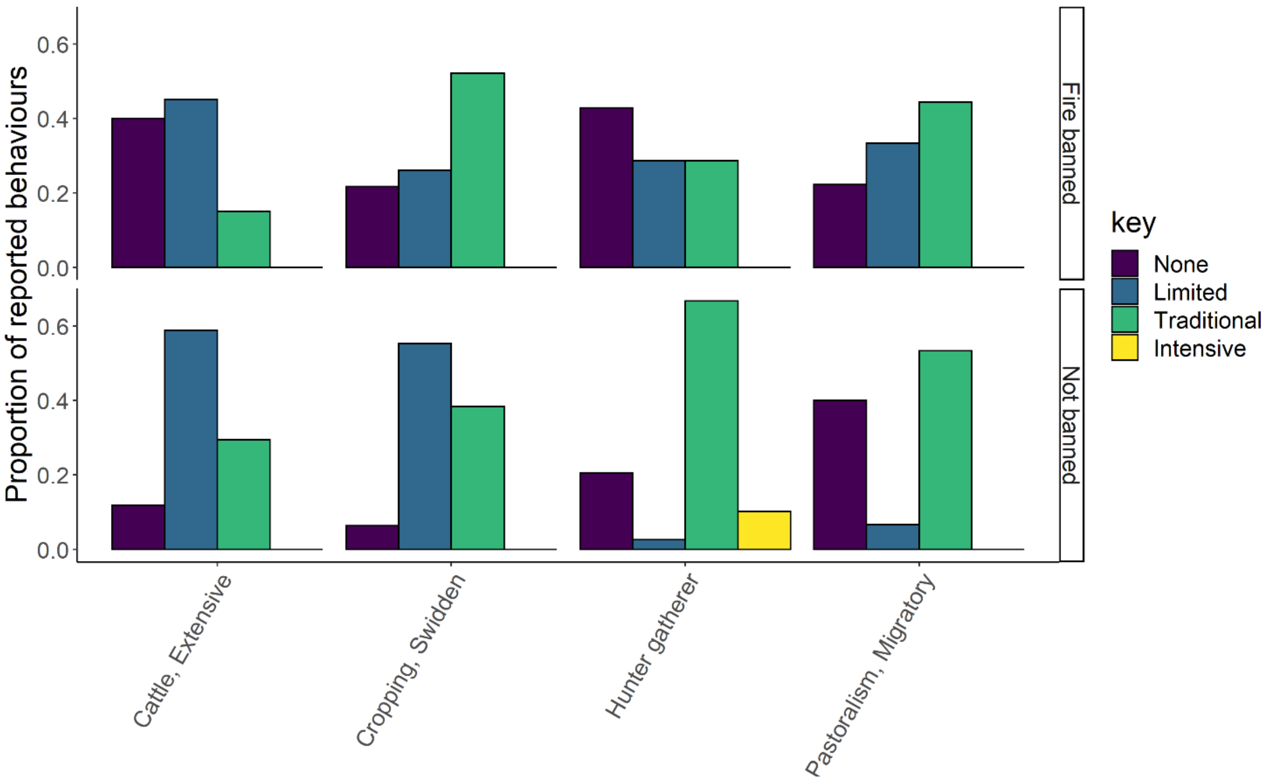


Figure 3.12: Impact of fire bans on degree of fire control amongst selected AFTs. Bans appear counter-productive when applied to hunter gatherers and extensive cattle farmers, leading to an increase in uncontrolled fire use.

3.4 Discussion

This chapter has presented DAFI, a new global database of anthropogenic fire impacts. It has sought to identify the key global modes of anthropogenic fire use, as well as the most appropriate underlying framework to capture them in a global model. Finally, it has sought to explore how fire use, suppression and policy combine to produce observed anthropogenic fire regimes. Analysis has identified seven key drivers of anthropogenic fire use, which capture 92% of recorded instances of deliberate anthropogenic fire in DAFI. The differing quantitative characteristics of these seven modes of fire demonstrates how anthropogenic land management objectives ultimately shape anthropogenic fire regimes. As such, treating all anthropogenic 'ignitions' similarly, without considering the fire users' objectives, as in current dynamic global vegetation model representations (Teckentrup et al., 2019), is unlikely to capture the drivers of global fire regimes. Furthermore, the preliminary AFT framework used to structure the literature review is effective at capturing both these core modes of fire use, as well as key patterns of diversity within them. Together, the seven identified central fire use types and the preliminary AFT framework therefore provide a strong starting point for the development of a global ABM.

However, challenges remain concerning the availability of data and the geographic representativeness of existing literature studies. Furthermore, whilst the WUI, practice and transmission of TFK and the potential for fire bans to lead to uncontrolled, illicit fire use could be clearly identified as three instances of how anthropogenic-influenced fire regimes emerge from combinations of fire use, suppression and policy, much work remains to capture these more robustly at the global scale. Therefore, discussion focuses on an assessment of data quality and availability, before discussing the overall signatures of anthropogenic fire regimes, and how these emerge from underlying human behaviours and land use systems.

3.4.1 Data quality and availability

As noted in Section 3.2.1, globally, anthropogenic fire use has been studied by a wide array of disciplines, but often only as a function or incidental consequence of another process or system. Conversely, where anthropogenic fire use has been studied explicitly, it has often been in the context of anthropological literature that primarily reports qualitative data: instances of fire use for hunting and gathering in the database averaged 0.52 quantitative metrics reported compared to 0.92 overall. There is, therefore, still a substantial need for detailed studies of industrial fire uses that link fire regime observations to land use rationale, and studies of pre-industrial fire uses such as Johansson et al., (2019) that provide detailed field-based quantification of anthropogenic fire regimes alongside an account of the rationale driving fire use in the location[10].

[10] This paragraph appears in Millington et al., (2022), section 4.1

One consequence of this fragmented literature is that quantification of data poorer fire uses, particularly hunting and gathering and arson, retains a high degree of uncertainty. From existing data, it is not possible, for example, to discern whether hunting fires > 8000 ha are a true outlier or a part of a separate population of large fire drives that should be considered and parameterised separately (Table 3.5). Furthermore, at the WUI, reliance on extrapolation of secondary data sources to construct the contribution of differing actors to this phenomenon adds significant uncertainty. This is compounded by the differing definitions of a 'fire' in government statistics according to varied cultural or operational practices. For example, in the United Kingdom, all known fires are recorded in government statistics, which implicitly assumes that few or no fires are started deliberately (Gazzard et al., 2016). Conversely, in China, data are recorded for a word that translates literally as 'fire disaster' or 'forest fire disaster', which does not include controlled 'biomass burning', leading to a much smaller count of fires (Yan et. al, 2006; Liu et al., 2010).

A further consideration common to many meta-analyses in the land use sciences is the geographical representativeness of the available literature. Here, DAFI does achieve geographic coverage in areas such as the Nile Delta, Northern India and the Congo Basin that where data on the drivers of land use change are currently sparse (Malek and Verburg 2020). An advantage available in the study of fire use as opposed to land use change is that local-scale, high resolution remote sensing is able to quantify behaviours to a degree to which it can be linked directly to a particular human behaviour.

However, data are still sparse in Russia and Kazakhstan. For example, just 32 case studies (1.7%) in DAFI are from Russia, despite it occupying some 13% of ice-free land area. This data gap is partly because some government statistics in the region need to be treated with caution (Goldammer et al., 2013), and so are not included in DAFI, and perhaps also partly because wildfires in the Northern Boreal and Arctic regions of Russia are still a relatively recent emerging environmental hazard on a large scale (Feurdean et al., 2020)[11]. However, a limitation of DAFI is that it did not include non-English language publications. Hence including Russian-language publications in a future iteration of DAFI could help fill this important knowledge gap. This is particularly pertinent given southern Russia is a region where GFED5 shows a particularly substantial increase in burned area over GFED4 (Chen et al., 2023), and because of the growing issue of peatland fires due to climate change (Blackford et al., 2023). By contrast, not including Spanish or Portuguese language publications did not substantively hinder geographic coverage in South America, which accounts for 18.6% of case studies (13.6 % of global ice-free land area).

[11] This paragraph appears in Millington et al., (2022), section 4.1

Whilst geographical coverage is perhaps less of an issue than in some land use meta-analyses, a particular problem for the study of fire use is the presence of fire free land users or AFTs. For example, whilst the abandoned farmland preliminary AFT clearly does not intentionally start agricultural fires, the fuel build-ups associated with rural abandonment contributed to damaging wildfires at the WUI. Whilst papers discussing the role of land abandonment in fire regimes met the inclusion criteria of featuring at least one anthropogenic fire behaviour, studies which did not discuss anthropogenic fire impacts, particularly where fire-free land use dominated, and where no indirect impacts on fire regimes were reported, did not meet criteria for inclusion[12].

Therefore, the extent to which DAFI is representative of fire-free farming methods such as intensive mechanised cropping or agroforestry will need to be considered during AFT distribution modelling (Chapters 4&5). Two measures were taken to mitigate against this issue: firstly, the recording of fire 'absence' records where a fire use was noted as such in a paper (15% of all fire use records) and secondly by recording all AFTs noted in a study, regardless of whether they were noted as contributing to the fire regime[13].

3.4.2 Emergence of anthropogenic fire regimes

At the global scale, the quantitative signature of anthropogenic fire regimes found in these results are closest to the 'pyromes' approach of Archibald et al., (2013), who suggest that the anthropogenic footprint is principally to push diverse natural fire regimes towards a homogenous picture of many, cool and small fires. However, exceptions to this are found in large-scale deforestation for commercial agriculture, as well as the potential for blanket fire suppression to contribute to the occurrence of megafires. This points to the underlying difficulty of categorising anthropogenic fire impacts based on their quantitative signal alone, as multiple interacting social and ecological drivers frequently collide to produce observed fire patterns in ways that are hard to discern from a purely 'top-down' approach. For example, in the case of how isolated rural communities respond to economic development, the combination of persistent fire use, diminishing fire knowledge and fracturing of communities under market forces and population growth can together lead to phases of chaotic and uncontrolled fire use.

[12] This paragraph appears in Millington et al., (2022), section 4.1
[13] This paragraph appears in Millington et al., (2022), section 4.1

However, although this phenomenon is perhaps the starkest example of the influence of fire knowledge and culture in the data, it is far from the only one. Rather, attempts to reintroduce prescribed burning in diverse post-industrial contexts highlight the pervasive influence of such social dynamics in fire use decision-making (Figure 3.7). Differing land users have tended to respond in diverse ways to the reintroduction of deliberate fire: from resistance amongst fire fighting agencies, to limited uptake amongst livestock farmers, to acceptance and advocacy amongst conservation organisations. This dynamic highlights the need identified in Chapter 2 for local-scale ABM that explores the transmission of fire knowledge through communities such that robust theories can be developed.

In spite of these complications, results paint a clear picture of the overall signature of anthropogenic fire regimes. Previous empirical and modelling studies have found fire sizes in a regime to follow a (negative) exponential or power-law distribution (Malamud et al., 2005). This study provides some support for this finding, but also adds important caveats and considerations. Firstly, when *all* fires, including very small anthropogenic fires are considered, fire sizes may be best described by an over-dispersed exponential, and secondly that cropland fire sizes are closer to a lognormal distribution (Figure 3.2).

A possible explanation for the over-dispersion of the distribution of broadcast landscape fire sizes is fire suppression. For example, at the WUI, the impact of fire suppression seemed to be to concentrate burned area into a very few mega fires, further skewing the density of the distribution into smaller fire sizes (<1ha). The original cellular automata model that projected fires should follow an exponential did not include representation of fire suppression (Malamud et al., 1998). Therefore, the role of suppression in shaping the distribution of fire sizes should be comparatively easy to reproduce theoretically with some simple additions. Conversely, in the case of landslides, Guzzetti et al., (2002) argue that the overdispersion of the observed sizes of landslides suggests large landslides (>30m) are driven by fundamentally different physical processes to those small enough to follow river channels. A similar phenomenon may be observed in DAFI, with anthropogenic cropland fires and wildfires best considered as separate populations governed by differing underlying processes.

The spatial density of fires in anthropogenic landscapes is the flip-side of their small mean and median fire sizes. Whilst several authors have noted the mediocre performance of coarse-resolution remote sensing products in arable landscapes (e.g. McCarty et al., 2016; Zhang et al., 2018), results here also point to deficiencies across a wider range of anthropogenic fire regimes. This presents a substantial technical challenge and barrier to advancing understanding of the relationship between anthropogenic behaviours and observed fire regimes. However, the disagreement remains most acute in fire regimes dominated by cropland fires. Although the upper end of the distribution of fire density of ~90 fires km^{-2} $year^{-1}$ suggested by DAFI may be surprising, we argue that this makes sense when placed in the context of the fire-generating land-use system.

For example, in the Mekong Delta, there are typically three harvests a year, on fields averaging 0.9 ha in size (Hong van 2014; Zhang et al., 2018). Applying a conservative assumption that a third of fields are burned at each harvest, suggests 111 fires per km^2 of cropland: allowing space for unfarmed spaces such as hedges, marginal lands etc. makes 90 fires km^{-2} $year^{-1}$ seem a reasonable number. Therefore, whilst previous Landsat studies had suggested that MODIS data underestimated the number of fires in similar agricultural landscapes by a factor of 10 (McCarty et al., 2016), these results suggest the underestimation to be an order of magnitude larger than this at the upper end[14].

3.4.3 Future development of DAFI and data on human fire interactions

The most substantial geographical weaknesses in DAFI are in Northern and Eastern Russia. Russian language publications were not included in the database, so these may provide a resource for improving coverage. Conversely, whilst studies of hunter gatherer fire use are numerous (n = 320), as noted in Section 3.3.2, the anthropological focus of these studies entailed that quantitative data were sparse. One option to improve coverage is for field-based human-fire researchers to conduct surveys of the local landscape during their fieldwork placement with unmanned aerial vehicles (commonly known as UAVs or drones). This could allow estimation of the number of fires km^{2-1} $year^{-1}$ in the landscape, as well as calculation of the distribution of fire sizes.

[14] This paragraph appears in Millington et al., (2022), section 4.2

This points to a wider need in remote sensing studies of human-fire interactions – not only must they be of an appropriate spatial resolution to capture anthropogenic fires (Section 3.3.1), but they must be robustly linked to specific anthropogenic behaviours. Without this precise link to anthropogenic process, the resulting research tends to be of the 'regime & behaviour' type (Section 3.2.4), which is less useful for precise quantification of systems of anthropogenic fire use and management. Similarly, there is potential for more *qualitatively*-focused research of fire use in an industrial or post-industrial context. The WUI was dominated by 'regime & behaviour' studies, and future studies could work on defining and quantifying specific anthropogenic behaviours at the WUI more precisely.

3.5 Conclusion

The lack of a globally applicable data set has presented a major hindrance to the development of improved representation of anthropogenic fire impacts in DGVMs. The database presented here should make a significant contribution to addressing that knowledge gap and help to formalise understanding of anthropogenic fire use globally, which to this point has been fragmented across multiple disciplines and addressed primarily at local and regional scales. Analysis has focused on establishing the most important anthropogenic fire uses for inclusion in a global ABM, on defining a framework to capture the central modes of anthropogenic fire use and suppression, and on how anthropogenic fire regimes emerge from the interaction of fire use, suppression and policy contexts.

Seven fire use types have been identified, which account for 92% of fire use instances in DAFI, and therefore provide a robust starting point for global modelling. Furthermore, both the variation between and within different fire use systems are captured effectively by the preliminary AFT framework presented. Two prominent cases of the emergence of anthropogenic fire regimes have been identified – the presence (or absence) of TFK and the WUI. However, further research is needed to explore emergent properties of anthropogenic fire regimes which have not previously been identified in the literature.

However, significant data gaps remain, particularly in Siberia and in the quantification of fire use by hunter gatherers. The ordinal scale required to capture suppression behaviours in DAFI could be improved by analysis of the effectiveness of fire suppression measures against fires of different size and radiative power. This would allow further and more comprehensive analysis of the emergence of anthropogenic fire regimes from combinations of fire use, suppression and policy. The next two Chapters now describe the use of DAFI to build a global agent-based model of anthropogenic fire use and management.

Chapter 4

Towards a global behavioural model of anthropogenic fire: the spatiotemporal distribution of land fire systems

The following chapter was published in Socio-Environmental Systems Modelling (Perkins et al., 2022). Therefore, here, an introduction frames the Chapter in the context of overall thesis objectives and wider analysis presented. The published paper follows below. Figures and tables in the published paper are referred to below and elsewhere in this thesis as "4.x" for clarity. Sections in the published paper are referred to as "4.2.x".

4.1 Chapter introduction

4.1.1 Published paper in the context of this thesis

The previous chapter described DAFI, the database of anthropogenic fire impacts. This new database provides the empirical basis for global-scale behavioural modelling of anthropogenic fire use and management. The next two chapters now present the Wildfire Human Agency Model (WHAM!), a new and global behavioural model of anthropogenic fire use and management. This is the first of those two chapters.

Analysis of DAFI demonstrated that differing modes of anthropogenic fire use have contrasting quantitative characteristics and are closely linked to the underlying logic of differing land use systems (Chapter 3, Section 3.3.3). Furthermore, analysis of DAFI also shows how landscape level characteristics of anthropogenic fire regimes (for example, the wildland urban interface, or the presence of community fire governance) emerge from combinations of land system type and their wider socio-ecological environment (Chapter 3, Section 3.3.4).

Therefore, the first step towards developing a global model capable of capturing these contrasting patterns of anthropogenic fire use and management was to model their underlying land system drivers so that they could be projected spatially and temporally. As such, this Chapter quantitatively defines, and then projects the global distribution of, land fire systems (LFS). These land fire systems are derived from the meta-analysis framework given in Table 3.1. Indeed, 12 of the LFS are directly analogous to categories in this initial framework. However, during DAFI analysis, it became clear that an additional category of land use system – a non-extractive land use system – was required to capture the full diversity of human fire use and management (Table 4.1 in the published paper).

The non-extractive land use system was needed was for several reasons. Firstly, the initial framework presented in Table 3.1 did not capture Pyne's 1st (pre-human) fire (Pyne 2001); this lightning ignited regime was necessary to include for those regions of the world where human influence remains limited (Jacobson et al., 2019). Secondly, many of the land users in the 'forestry' category in the initial framework occupy a diversity of natural and semi-natural landscapes in addition to forest landcovers. For example, in 75 of 92 cases of fire use by the conservationist AFT in DAFI, the landcover burned was either grassland or shrubland (mixed grass and forest). The same was true of hunter-gatherers, for whom 91 of 133 cases of fire use related to grasslands and shrublands.

Therefore, with the addition of non-extractive land uses, the resulting LFS framework had 16 categories (Table 4.1), which formed the basis of the land use distribution engine presented. These 16 categories had a very close relationship to the eventual set of agent functional types (AFTs) in WHAM! (presented in Chapter 5, Table 5.3).

4.1.2 Model evaluation: an overview

As noted above, WHAM! is presented across Chapters 4 & 5, whilst Chapter 6 presents the offline coupling of WHAM! with JULES-INFERNO. Each of these chapters contains evaluation of the respective model components they present. Here, a summary of model evaluation measures is given (Table 4A). Model evaluation protocols can provide clarity around the purpose and scope of evaluation steps conducted for complicated environmental models (Grimm et al., 2014). Brown et al., (2023) propose an evaluation protocol (named LUC-TRACE) specifically for spatial land use models, and hence their terminology is adopted here. Broadly, four categories of evaluation procedures are conducted. The first of these is 'goodness-of-fit' – assessment of how well the model fits data used in its construction. Secondly, 'output corroboration' (commonly 'validation') compares model outputs with independent data. Thirdly, model benchmarking compares performance with alternative modelling approaches. Fourthly, sensitivity analysis assesses the impact of model parameters on outputs.

Model performance metrics selected are those most commonly adopted as evaluation measures for the process in question. Hence, for goodness-of-fit assessment, r^2 is used for regression and the area under the received operated curve (AUC) is used for classification (Steyerberg et al., 2010). For overall performance, the FIREMIP used pearson's r and overall global burned area in Mha (Teckentrup et al., 2019); to allow direct comparison of results with the FIREMIP ensemble, these measures are adopted here as well.

The published paper describing the spatiotemporal distribution of LFS is now presented, followed by a brief section (4.3) placing findings from the paper in the context of the overall thesis.

Table 4A: Overview of evaluation of WHAM!. Evaluation in Chapter 4 focuses on the land fire system (LFS) distribution, Chapter 5 evaluates parameterisations of anthropogenic fire use and management, particularly for managed fire, whilst Chapter 6 evaluates all aspects of WHAM! including unmanaged fire and fire suppression.

Thesis section	WHAM! process evaluated	Data or null model used	Evaluation metrics
4.2.3.2	LFS distribution: goodness-of-fit	DAFI data	AUC
4.2.3.2	LFS distribution: benchmarking	Null model: multinomial regression	AUC
4.2.3.3	LFS distribution: output corroboration	HANPP (Haberl et al., 2014)	Distribution of HANPP by AFR
5.3.1.2	Managed fire: goodness-of-fit	DAFI data	AUC & r^2
5.3.1.3	Unmanaged fire & fire suppression: goodness-of-fit	DAFI data	AUC & r^2
5.3.3.1	Managed fire: sensitivity analysis	N/A	Burned area response to parameter perturbation (Mha)
5.3.3.2	Crop residue burning: output corroboration	GFED5 crop fires (Hall et al., 2023)	Correlation coefficient (r)
5.3.3.3	Managed fire: output corroboration	Unseen DAFI data	Correlation coefficient (r)
5.3.3.4	Managed fire: output corroboration (temporal trend)	LIFE database (Smith et al, 2022)	Binary assessment of temporal trend
6.3.1.2	Combined burned area: benchmarking	Null model: INFERNO v1.0 offline	Correlation coefficient (r); Burned area (Mha)
6.3.3.2	Combined burned area: output corroboration	GFED5 (Chen et al., 2023)	Correlation coefficient (r); Burned area (Mha)

4.2 Published paper

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Towards a global behavioural model of anthropogenic fire: The spatiotemporal distribution of land-fire systems

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Abstract
Landscape fire regimes are created through socio-ecological processes, yet in current global models the representation of anthropogenic impacts on fire regimes is restricted to simplistic functions derived from coarse measures such as GDP and population density. As a result, fire-enabled dynamic global vegetation models (DGVMs) have limited ability to reproduce observed patterns of fire, and limited prognostic value. At the heart of this challenge is a failure to represent human agency and decision-making related to fire. This paper outlines progress towards a global behavioural model that captures the categorical differences in human fire use and management that arise from diverse land use objectives under varying socio-ecological contexts. We present a modelled global spatiotemporal distribution of what we term 'land-fire systems' (LFSs), a classification that combines land use systems and anthropogenic fire regimes. Our model simulates competition between LFSs with a novel bootstrapped classification tree approach that performs favourably against reference multinomial regressions. We evaluate model outputs with the human appropriation of net primary production (HANPP) framework and find good overall agreement. We discuss limitations to our methods, as well as remaining challenges to the integration of behavioural modelling in DGVMs and associated model-intercomparison protocols.

Keywords
Fire; DGVM; behavioural model; HANPP

Code availability
Supplementary material, including model code & outputs, as well as data used to produce our results, are made freely available via Figshare under an MIT open-source licence: https://doi.org/10.6084/m9.figshare.c.5523840. Code is also shared on Github for convenience: https://github.com/OliPerkins1987/Fire_GBM.

1. Introduction

In the Anthropocene, landscape fire is best understood as a coupled socio-ecological process, driven by complex interactions between biophysical and socio-economic factors (Pausas and Keeley, 2019; Kelley et al., 2019). For example, the Amazonian fires of 2019 were caused by a combination of international trade conflict between the USA and China (Fuchs et al., 2019; Taheripour et al., 2019) and national-scale political change (Stewart et al., 2020), but also a regional drought (Dong et al., 2021). Although much debate has focused on such destructive fires, and in particular so-called 'mega-fires' (e.g., Adams et al., 2020; Pliscoff et al., 2020), humans continue to

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use fire as a management tool for diverse purposes across land systems (Smith et al., 2022; UNEP, 2022). For example, fire is used to rejuvenate pastures and deter pests in livestock systems (Kull, 2004; Jakimow et al., 2018), to prepare fields and dispose of residues in agriculture (Van Vliet et al., 2012; Liu et al., 2019), to manage fuel loads in fire prone environments (Laris, 2002), and as a weapon in land tenure disputes (Suyanto et al., 2004).

Human approaches towards fire suppression are similarly diverse – spanning industrial fire suppression and exclusion (Silva Sande et al., 2010) to traditional fire knowledge and community fire practice amongst indigenous populations (Mistry et al., 2005), to the growing 'pyro-diversity' narrative amongst conservationists (Bowman et al., 2016). Humans also have multiple indirect impacts on fire regimes – by altering fuel loads through logging and grazing (Cochrane, 2009; Archibald, 2016), by fragmenting landscapes with roads and croplands (Archibald et al., 2012), and by draining peat swamps (Page and Hooijer 2016).

In each case above, fire regimes emerge from a combination of local land use objectives, policy goals and wider economic developments playing out in the landscape. Furthermore, although climate attribution studies have found that climate change increases the likelihood of weather patterns associated with extreme wildfire events (Goss et al., 2020), multi-faceted human impacts on global fire regimes entail that the direct relationship between climate change and fire remains poorly quantified (van Oldenborgh et al., 2020; IPCC 2022).

In this context, it is perhaps unsurprising that the first Fire Model Intercomparison project (FIREMIP) found simplistic approaches to representing anthropogenic impacts on fire are a substantial shortcoming in dynamic global vegetation models (DGVMs; Teckentrup et al., 2019). Current approaches to modelling anthropogenic fire are limited to analytic functions derived from GDP and population density data (Teckentrup et al., 2019). As a result, representations of human activity were found to be both the largest single cause of disagreement between burned area outputs of different DGVMs, and between model outputs and remote sensing observations (Forkel et al., 2019). Not only do current DGVMs have limited ability to reproduce observed patterns of fire use, but they also have little predictive power, as they do not represent the underlying processes that drive human-fire interactions (Rabin et al., 2015, 2018).

This paper contributes to improving this situation by presenting progress on behavioural modelling of anthropogenic impacts on wildfire regimes at the global scale. Importantly, this work incorporates the underlying land-system processes that drive human-fire interactions (Pyne 2001; Lauk and Erb 2016) by characterising the categorically different anthropogenic fire use and suppression systems that emerge under differing land use systems and socio-ecological contexts. Specifically, we present a novel approach to modelling the global spatiotemporal distribution of what we term 'land-fire systems' (LFSs) from 1990 to 2014. Our LFSs are derived by combining classes of land use systems and anthropogenic fire regimes (AFRs), each of which are discussed and defined below (Section 2.1).

With LFSs defined, we take a novel approach to model their spatial and temporal distribution by combining a suite of classification trees and a simple simulation of competition. As anthropogenic fire is closely linked to land use (Archibald 2016; Andela et al., 2017), we evaluate our approach with indicators from the human appropriation of net primary production (HANPP) framework. HANPP, which is derived from data independent to our model, provides a multi-dimensional, spatially explicit and functional view of human-ecosystem interactions (Haberl et al., 2014; Gingrich et al., 2015).

Our spatiotemporal modelling of LFSs is an important step towards defining and spatially allocating agent functional types (Arneth et al., 2014) in a global model of anthropogenic fire impacts. We anticipate a close, though not exact, relationship between our LFSs and agent functional types. Our ultimate intention is for this model of anthropogenic fire impacts to be coupled with the JULES-INFERNO fire-enabled DGVM (Best et al., 2011; Mangeon et al., 2016). This eventual goal informs several choices regarding model development, from spatial resolution to our choice of forcing data sets. These restrictions and their implications for future modelling are addressed in the discussion.

2. Methods

Modelling the spatiotemporal distribution of land-fire systems (LFSs) involved several steps (Figure 1). First, we drew on the global Database of Anthropogenic Fire Impacts (DAFI; Perkins et al., 2021; Perkins and Millington et al., 2021a) to define each LFS through a combination of theory and empirical data (sections 2.1, 2.2). Second, we sourced appropriate secondary data sets as independent variables to drive the model (section 2.2). Third, we assessed the representativeness of data in DAFI (section 2.3.1) and weighted these data to address sampling biases. Fourth, using this weighted data, we developed a single classification tree for each LFS (section 2.3.2, 2.3.3). Fifth, the output probabilities of these trees were used to drive a simple representation of competition for land (section 2.3.4). Finally, model outputs were evaluated against land use efficiency data from the HANPP framework (section 2.4).

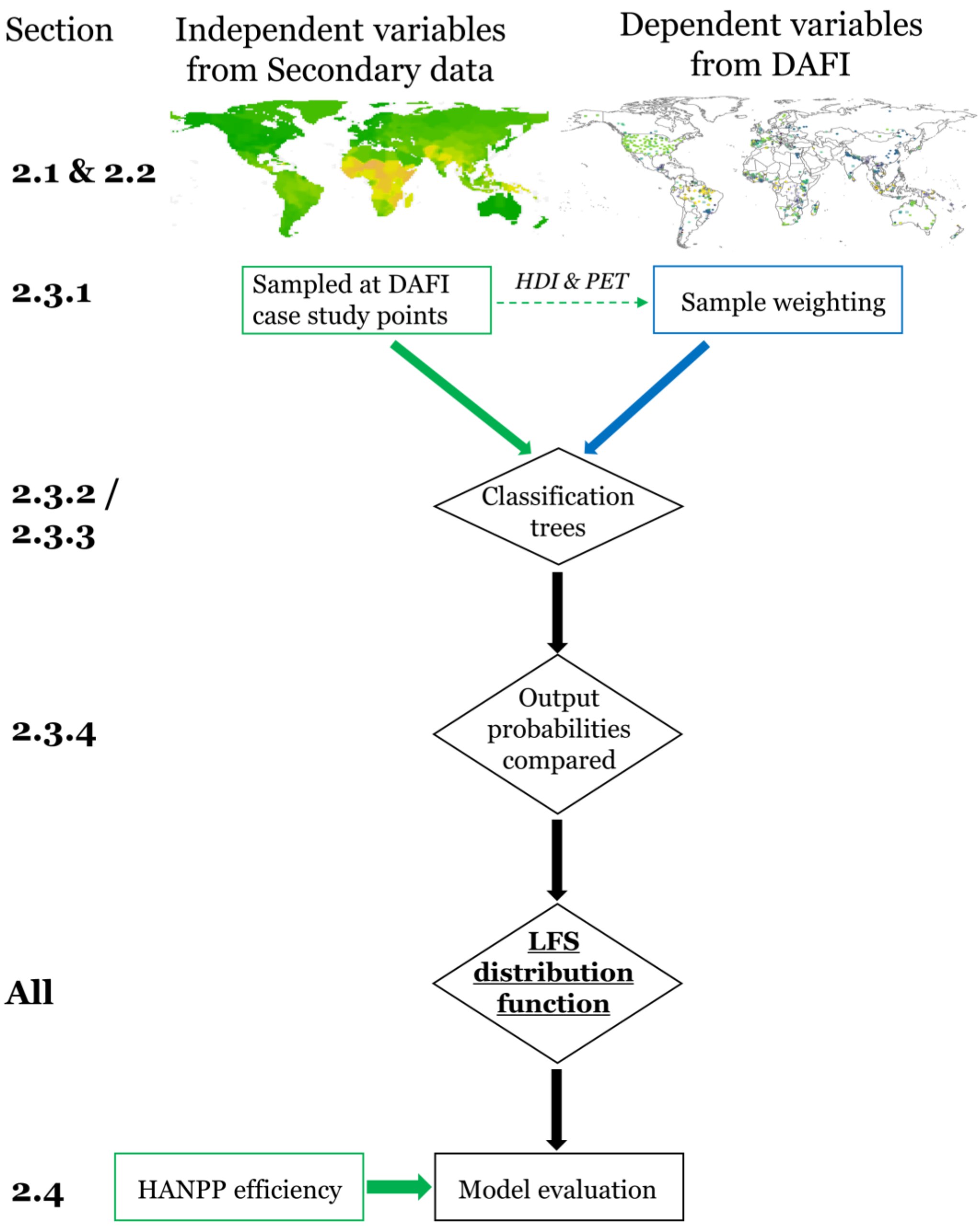


Figure 1: Overview of methods used in this paper to define and evaluate a global land-fire system distribution function. DAFI is the Database of Anthropogenic Fire Impacts, HDI is the Human Development Index, PET is potential evapotranspiration, HANPP is the Human Appropriation of Net Primary Production.

2.1 Definition of land-fire systems

Land use systems are defined based on land use intensity and land management practices (Foley et al., 2005; Václavík et al., 2013). For example, Dou et al. (2021) classified 24 land systems across Europe distinguishing high-, medium- and low-intensity use of forests, arable lands and grasslands (among others). We extend this concept and define land-fire systems (LFSs) as the fire use and management practices that emerge from a combination of local land user objectives and wider socio-cultural attitudes towards fire. Specifically, we use a conceptual framework that cross-references land use systems with 'anthropogenic fire regimes' (AFRs) to define and categorise global LFSs (Table 1).

We consider three primary land uses that dominate land systems globally – forestry, livestock and crops – in addition to a combined 'non-extractive' (recreational, residential or conservationist) land use system. Our AFRs are classified based on previous work that identifies differences in fire practices dependent on industrialisation and attitudes towards fire (e.g., Pyne, 2001; Seijo & Gray, 2012; Lauk & Erb 2016). These AFRs are:

- *Pre-Industrial* – active use of fire and limited mechanisation in land management;
- *Transition* – adopting elements of both pre-industrial and industrial regimes;
- *Industrial* – fire use replaced by mechanisation and chemical fertilisers;
- *Post-Industrial* – deliberate or unintentional re-introduction of fire to a landscape as an ecological process.

By cross-referencing AFRs with land use systems, the LFSs produced are categories of distinct fire- and land-management strategies that represent human behaviour and can be applied globally.

Table 1: Land-fire systems (LFSs) conceptualised as a combination of four land use systems (LUSs) and four anthropogenic fire regimes (AFRs). Italics give exemplar papers describing the activities and fire regimes of each LFS.

	LUS			
AFR	**Non-Extractive**	**Forestry**	**Livestock**	**Crops**
Pre-Industrial	Unoccupied N/A	Hunter-Gatherer *Fowler & Welch, 2018*	Pastoralism *Solomon et al., 2007; Johansson et al., 2019*	Swidden *Araki, 2007; Jakovac et al., 2017*
Transition	Limited or Contested Management *Sletto 2008; de Torres Curth et al., 2012*	Logging *Nepstad et al., 1999; Dennis et al., 2001*	Extensive Ranching *Eloy et al., 2017; Jakimow et al., 2018;*	Small-Holdings *Kumar et al., 2015; Liu et al., 2019*
Industrial	Pyro-Exclusion *Pavleichik & Chibilev 2018; Suhs et al., 2020*	Managed Forests *Kalies et al., 2016; Steen-Adams et al., 2017*	Intensive Ranching *Taylor, 2003; Bendel et al., 2020*	Intensive Farming *McCarty et al., 2009; Hall et al., 2016*
Post-Industrial	Pyro-Diversity *Govender et al., 2006; Fernandes et al., 2016*	Abandoned *Gomez-Gonzalez et al., 2018*	Abandoned or Subsidised *Hadjigeorgiou et al., 2011; Varela et al., 2018*	Abandoned *MacDonald et al., 2000; Dara et al., 2019*

2.2 Materials used

Our method for modelling the global spatiotemporal distribution of LFSs is empirical, using data from a recently completed and first global database of anthropogenic fire impacts (DAFI; Perkins et al., 2021; Perkins and Millington 2021a). Currently, DAFI comprises 1809 case studies from 504 academic papers, government and NGO reports. As previous work has emphasised the central role of land use in anthropogenic impacts on fire (Andela et al., 2017), DAFI presents data on anthropogenic fire use, suppression, and policy within its underlying land use context. Data on the distribution of LFSs in DAFI therefore provided the dependent variables for our modelling. DAFI is freely available online (Perkins & Millington, 2021a).

DAFI data were combined with secondary data sets, which were used as independent variables in subsequent models (Table 2). Our initial choices for independent variables began with data found to be valuable in modelling global patterns of land use by Malek and Verburg (2020). We augmented these initial choices with factors likely to be important for determining fire use. Additional variables were primarily those that could capture the 'dual-constraint' hypothesis of the biophysical drivers of fire (Krawchuk et al., 2009). Specifically, we used net primary production to capture cases where a lack of vegetation leads to a lack of fuel for fires to burn - 'the fuel constraint' - and potential evapotranspiration to capture cases where fuel is too wet to burn - 'the moisture constraint'. Data for both of these variables were drawn from the JULES DGVM (Best et al., 2011) to facilitate later integration of our model outputs.

Additionally, given the importance of politics to fire use and management (Carmenta et al., 2017, 2019), we also experimented with the 'Human Freedom Index' (Cato Institute, 2020). This was identified as a possible candidate to capture the relative importance placed on individuals' subsistence livelihoods or societal economic development within policy frameworks. Finally, as DAFI revealed that biodiversity conservation is a substantial driver of anthropogenic fire use (Perkins et al., 2021), data on the location of protected areas (UNEP-WCMC, 2020) and species' richness (IUCN, 2015) were included as possible predictors of the distribution of AFRs in non-extractive land use systems. A detailed overview of the pre-processing of secondary data sets that was conducted is given in Supplementary Material A; the resulting processed data sets are made available as Supplementary Material B.

Table 2: Overview of secondary data sets used as predictor variables in this study. Only variables used in the final model are shown. All data were resampled to the resolution of JULES-INFERNO (1.875º x 1.25º).

Variable type	Variable name	Spatial resolution	Temporal range	Source
Socio economic	Population density	0.04º	2000-2020	CIESIN, 2017
	Gross Domestic Product	0.08º	1990-2015	Kummu et al., 2018
	Human Development Index	0.08º	1990-2015	Kummu et al., 2018
	Market access+	0.08º	2000 (1990-2015)	Verburg et al., 2011)
	Human impact mask	$1km^2$	2016	Jacobson et al., 2019
Land cover & Land use	Fractional land cover (anthropogenic)	0.25º	1990-2020	Hurtt et al., 2020
	Land cover composition (natural)	1.875º x 1.25º	1990-2020	Clark et al., 2011
Biophysical	Potential evapotranspiration	1.875º x 1.25º	1990-2014	Best et al., 2011
	Ecosystem net primary production	1.875º x 1.25º	1990-2014	Clark et al., 2011
	Topography	30m	N/A	Van Zyl et al., 2001

Key: + single year of data extrapolated to other years from other secondary data (see Supplementary Material A). All data sets have an annual temporal resolution.

2.3 Global distribution of land-fire systems

Before using DAFI as the basis of our model, we first assessed the global representativeness of these data. Weights were then applied to address any sampling biases in DAFI (section 2.3.1). Using these weighted data, the determination of the distribution of each LFS was done in two parts (Figure 2). The first part in the fractional allocation of cells to each LFS was to divide each grid cell (1.875º x 1.25º; section 2.3.1) of a global raster map into the fractional coverage of each land use system. This was done using a combination of prescribed inputs and classification tree models (section 2.3.2). The second part was to allocate the fractional coverage of each AFR within each land system present in the cell. This was done using classification trees trained with predictor variables from secondary data sets sampled at the locations of DAFI case studies, and the LFS recorded in DAFI as the target variable (section 2.3.3).

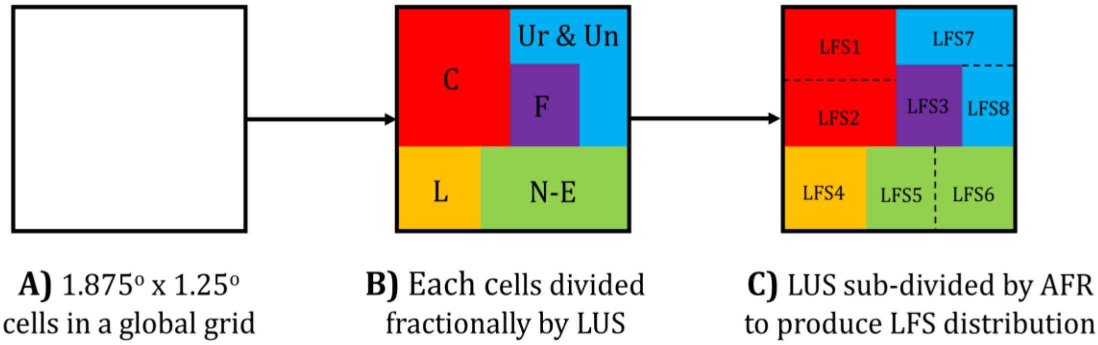


Figure 2: Process of allocating a grid cell proportionally by land-fire system (LFS) through the combination of land use systems (LUSs) and anthropogenic fire regimes (AFRs). All AFRs were distributed using the classification tree method set out in the main text, whilst the fractional coverage of LUS was determined through a combination of external forcing and inter-system competition. The fractions of a grid cell occupied by crops (C) and livestock farming (L) were determined from forcing data (Hurtt et al., 2020). Forestry (F) and non-extractive (N-E) LUSs were determined through a combination of JULES-INFERNO plant functional type outputs and statistical functions (see sections 2.3.2 & 2.3.4). The unoccupied fraction (Un) was determined by a classification tree, as with the AFRs, whilst the urban fraction (Ur) was also driven by CMIP6 forcing data. All fractional coverage was non-spatial within a cell.

2.3.1 Data representativeness check and weighting

The first potential source of bias in DAFI was the imbalance of the database towards few studies that reported results relating to the same LFS from multiple sites in close proximity. This imbalance is reflected in the large difference between the median and maximum number of locations reported in a single source (1 and 84 respectively). For example, Araki (2007) reported fire use in shifting cultivation across 51 different villages in the Muchinga region of Zambia. Although this information is valuable for understanding variability in anthropogenic fire use, concentrations of case studies in localised areas could skew results at the global extent. Therefore, four locations were randomly sampled when a source reported data from more locations (for the same LFS in the same country) than the overall mean number per source (3.7). Additionally, case studies that reported policy or other information at the country level were excluded as they likely lacked spatial specificity. Consequently, from an initial set of 1809 case study locations, 1170 were used for modelling.

The global representativeness of the chosen 1170 case studies from DAFI were assessed by comparing the distribution of values for the human development index (HDI) and potential evapotranspiration (PET) at locations for DAFI case studies against their respective global distributions. HDI was chosen to represent the availability of social and economic resources as it is focused on the fundamentals of human development across the broad base of a population (UN, 2020). Furthermore, HDI was chosen over GDP as fire is often conceptualised as a land management strategy used in the absence of alternative industrial tools such as machinery (Carmenta et al., 2019; Cammelli et al., 2020). PET was used as a proxy for the 'dual-constraint' hypothesis (Krawchuk et al., 2009), which describes the global biophysical variation in fire regimes.

To conduct this comparison, values of the reference variables were sampled from raster grids at the locations of DAFI case studies (Table 2). As our eventual goal is to work with the JULES-INFERNO DGVM, secondary data were first aggregated to that model's coarse resolution for global runs: 1.875° x 1.25°. The means of the distributions in DAFI were found to be substantially different from the global values (t-tests: all $p < 0.0001$; Figure 3). The source of bias is that DAFI oversamples data from fire-prone areas - where anthropogenic fire use is more likely - and from economically poorer areas - where people have tended to use fire because other land management approaches are unavailable.

Therefore, a process of 'raking' (Lovelace et al., 2015) was used to weight DAFI such that it more closely reflected the global distributions of HDI and PET. First, the 25th, 50th and 75th percentiles of the global distributions of HDI and PET were calculated. Each DAFI case study was then allocated to a quartile of the global distribution for the two reference variables. Where DAFI was found to over- or under-sample a particular quartile of the global distribution, data were down- or upweighted. For example, if 27.5% (respectively 22.5%) of DAFI case studies were in the second quartile of the global PET distribution, then those case studies would receive an PET weight of 0.909 (respectively 1.11). The weights for HDI and PET were multiplied together to produce a final case study weight. Trimming thresholds were applied at values of 0.7 and 3 to avoid excessive emphasis being placed on a single data point (Elliot, 2008).

The central tendency of the weighted data was found to approximate the global distribution of HDI (t-test: $p = 0.47$). For PET, a bias persisted as areas of very low evapotranspiration (principally the Northern Boreal Forest and Arctic Circle) remained under-sampled. These areas have very low human impacts on fire regimes, and when they were excluded, the distributions had converged acceptably (t-test; $p = 0.82$). This process was repeated for each of our four land use systems. For each land use system, the global values of HDI and PET were filtered to include only cells that contained >1% of the land use system in question, and this subset of the data was compared against DAFI case studies containing an LFS from the relevant land use system. Similar results were achieved at the land system level as for the data overall (t-tests: all $p > 0.05$). These weighted data formed the basis of subsequent modelling.

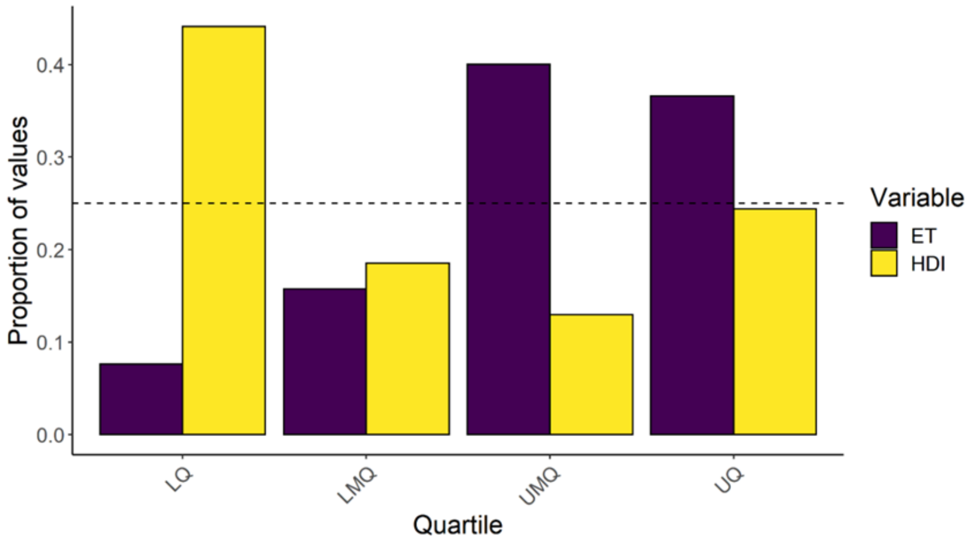


Figure 3: Distribution of data in the database of anthropogenic fire impacts (DAFI) by quartile of two reference variables, potential evapotranspiration (ET), and the human development index (HDI). DAFI oversamples low HDI (poorer) locations where anthropogenic fire is a dominant land use strategy and higher ET environments, which are more likely to be more fire prone. LQ, LMQ, UMQ, UQ refer to lower, lower middle, upper middle and upper quartiles. Dashed line represents an equal proportion of values across quartiles.

2.3.2 Modelling the spatiotemporal distribution of land use systems

To ensure our model outputs could be consistently integrated with JULES-INFERNO, we needed to consider the two ways in which land cover types are defined in the DGVM. First, the distribution of vegetation within 'natural' ecosystems is calculated based on competition between plant functional types (PFTs; Harper et al., 2016). Second, the presence of anthropogenic land systems (currently crops, livestock farming and urban) is determined through prescribed inputs. These inputs to JULES-INFERNO are currently typically the standardised land cover inputs for the CMIP6 (Coupled model intercomparison project simulations; Hurtt et al., 2020). CMIP6 was the standardised model protocol that informed climate projections for the IPCC AR6 (Eyring et al., 2016). JULES-INFERNO then only allows grass PFTs to occupy anthropogenic or 'disturbed' portions of a grid cell (Burton et al., 2019). Therefore, for the land use system component of our LFS distribution modelling, the fraction of each grid cell covered by crops, pasture, rangeland, and urban areas were taken directly from the CMIP6 forcing data. In these forcing data, Hurtt et al. (2020) divided grazing lands into planted pastures and 'rangelands' (semi-natural grasslands). We assumed that livestock land use systems dominated in both land cover types. The consequences of this division for model outputs are discussed in section 4.3.

The remaining fraction of the grid cells were then allocated between forestry, non-extractive land uses, and 'unoccupied' – the absence of any human land management. To do this, classification trees were used (Krywinski and Altman, 2017). Classification trees have been widely applied in agent-based modelling (Rounsevell et al., 2012) - their advantages include simplicity and an ability to represent categorically different behaviours. For the classification trees allocating non-extractive and forestry land use systems, the target variable was the respective land use system in DAFI. However, given that DAFI does not include case studies without at least one anthropogenic fire impact, it could not form the basis of the 'unoccupied' model. Therefore, the dependent variable for the 'unoccupied' model was the 'very low (anthropogenic) impact areas' defined by Jacobson et al. (2019). The full process used for defining the classification tree models is presented in section 2.3.3.

2.3.3 Modelling the distribution of anthropogenic fire regimes

Multinomial regression has frequently been used for statistically-derived distribution of land use/cover types (e.g. Millington et al., 2007; Lin et al., 2014). Here, we adopted an alternate approach based on a suite of classification tree models, in which a classification tree was defined for each LFS (Figure 4). The principal benefit of this approach was that it allows the socio-ecological niche of each LFS to be defined individually, and for that niche to be evaluated both quantitatively and relative to our understanding of process. For example, although soil composition and hydrology may play a role in determining the suitability of a given region for intensive agriculture (Malek and Verburg, 2020), including this as a variable across our LFSs risks making it a proxy for the trend towards lower economic development in tropical regions. Because only a sub-set of independent variables need be included in a given tree, the effect of these variables can be separated from each other, and isolated to where they are warranted from a process perspective. Our approach therefore substantially reduces multi-collinearity concerns. Furthermore, grounding the foundations of the model in both empiricism and process should make future projections robust.

Some LFS had few (< 20) instances in DAFI, meaning that several AFRs accounted for less than 10% of cases in some land use systems. This risked the classification-tree algorithm returning a null tree predicting all absence cases, which is little use for our modelling purposes. Therefore, for each LFS, a training set was developed with 50% presence and 50% absence cases of the relevant LFS. Absence cases were up-sampled to the number of presence cases in the initial training data and 20% of the resulting data were first held back as a testing set. On this training set, an initial process of variable (or 'feature') selection was conducted to identify viable predictor variables. In this process an initial tree was learned against the training set with no restrictions on the number of nodes it contained. This was then 'pruned' based on misclassification of data points, to identify a simpler model, less prone to out-of-sample prediction variance due to overfitting (Mingers et al., 1989). The pruned trees were then evaluated against the testing set, to assess trade-offs between parsimony and predictive accuracy.

As classification trees are known to be sensitive to small changes in the training data (Krywinski and Altman 2017), bootstrapping of the training data is commonly employed to improve the stability of their out-of-sample prediction. In machine learning algorithms such as the random-forest, an ensemble of differing tree structures then forms the final model (Breiman, 2001). However, given our goal is to build a global, process-based behavioural model, we wanted to avoid the lack of interpretability associated with random-forests (Haddouchi and Berrado, 2019) and thereby to ensure each of our trees were robustly grounded in process. Therefore, rather than using bootstrapping to develop an ensemble of tree structures, we used it to identify the most robust single structure across samples.

Having conduced an initial variable selection, therefore, we made 1000 bootstrap samples of the full data set used for variable selection – the training and test data with equal proportions of presence and absence cases (section 2.3.1). Using a subset of variables defined during variable selection, a classification tree structure was learned on each sample and pruned to the level identified as robust against over-fitting during variable selection. From these 1000 trees, the most frequent tree structure was identified and chosen as a final model. In some cases, two variables formed the initial model split approximately 50% of the time. In these instances, convolutions of variables were attempted to define a single variable that consistently formed the first split. For example, HDI was multiplied by the logarithm of GDP for the Small-Holdings (transitional crop) LFS and the single resulting HDI-GDP hybrid variable was subsequently found to be valuable in seven other cases.

In addition to defining a resilient tree structure, the added advantage of our approach is that it creates a numerical distribution of values for the thresholds and output probabilities of a tree, based on their values for each bootstrapped sample. This allows a degree of data and sampling uncertainty to be captured and expressed.

For this study, we took 100 random deviates for each set of tree split thresholds and their associated output probabilities and present this as a quantification of parameter uncertainty.

The process described above created a single classification tree structure per LFS, where each split in the tree was given a numerical distribution and each node an associated set of output probabilities. The outputs of each classification tree are best interpreted as the probability that a given LFS is the dominant type in the fraction of a grid cell occupied by the relevant land use system. This allows, for example, that Swidden (i.e. pre-industrial crops) and Managed Forests (i.e. industrial forestry) could be the dominant LFS in their respective land use fractions of a single model cell.

2.3.4 Simulating competition between LFS

To produce maps of the fractional coverage of each LFS in each model grid cell we take a two-step process (Figure 2). The first step of combining the outputs of individual classification trees was to assign fractional coverage of each grid cell to each of our four land use systems (Figure 2b). Crop, pasture, rangeland and urban areas were derived directly from CMIP6 land cover (Hurtt et al., 2020). The remaining vegetation area was then allocated based on outputs of classification trees for forestry, unoccupied and non-extractive areas of a cell. Forestry was calculated as:

$$Forestry_i = Treecover_i * (1 - Nonextractive_i) * (1 - Unoccupied_i) \quad (1)$$

Where $Forestry_i$ is the proportional allocation of the *i*th grid cell to forestry. The remaining area covered by grass, shrubs and trees falling outside human land use was allocated between unoccupied and non-extractive land systems. This was done by summing the output probabilities of their two respective classification trees and dividing by the total. For example, the fraction of the ith grid cell allocated to non-extractive land uses was calculated as:

$$Nonextractive_i = Vegetation_i * \frac{Nonextractive_i}{Nonextractive_i + Unoccupied_i} \quad (2)$$

where $Vegetation_i$ is the fraction of the grid cell not allocated to extractive land uses. Having allocated each grid cell fractionally between land use systems, LFS distribution within each corresponding grid-cell fraction was then calculated (Figure 2c). This was done by representing 'competition' between LFSs using output probabilities of the trees for each AFR:

$$AFR_{ij} = {p(AFR_{ij})}\Big/{\sum p(AFR_j)} \quad (3)$$

where AFR_{ij} is the fractional coverage of the *i*th AFR in the *j*th cell, and $p(AFRij)$ and $\sum p(AFRj)$ are the probability of the classification tree for the *i*th AFR and for all AFRs respectively.

Before calculating the fractional coverage by AFR using equation (3), a threshold (θ) of 0.1 was applied: output probabilities from a given classification tree less than this threshold were set to 0. The θ parameter was applied to prevent very small output probabilities for a given AFR from influencing LFS distributions inappropriately. This occurs because we used simple tree structures to avoid overfitting, and so the smallest output probability of a given tree was typically 0.05-0.1. For example, the Swidden LFS could be projected to occupy a small-fraction of cropland in the intensive USA corn belt (where such a land management strategy simply does not exist). This θ value will eventually become a free parameter when this model is coupled with JULES-INFERNO. After applying equation (3) to classification tree outputs, the relevant AFR and land use system fractions were multiplied together to produce LFS fractions within each cell.

2.4 Model Evaluation

Model outputs were evaluated in two ways. First, the classification-tree based approach set out above was compared against a reference (and more parsimonious) multinomial regression approach using the area under the ROC curve or 'AUC' – a standard measure of classification accuracy (Melo, 2013). To ensure a fair comparison, one multinomial regression was fit per land use system. A brief description of the multinomial model is available as Supplementary Material F. Second, model outputs were compared against independent data in the form of global maps of Human Appropriation of Net Primary Production (HANPP; Kastner et al., 2021).

HANPP is a measure of the intensity of land use. It quantifies the extent of human domination of an ecosystem and therefore also provides a measure of land use as a planetary boundary to socioeconomic development (Vitousek et al., 1997; Running, 2012; Haberl et al., 2014). The HANPP framework has been used to analyse long-term trajectories of land systems (Krausmann et al., 2012, 2013), disentangle processes of area change, intensification and efficiency gains (Gingrich et al., 2015), and understand impacts on biodiversity (Haberl et al., 2005) and other ecosystem services (Mayer et al., 2021). HANPP quantifies the effects of land use and land-cover conversions (HANPPluc), as well as of biomass harvest (HANPPharv) on terrestrial net primary production and is thus a multi-dimensional indicator for land-use intensity (Erb et al., 2013).

The ratio between HANPPharv and HANPP gives the fraction of appropriated biomass that can be used for human purposes related to the overall land-use pressure on ecosystem productivity. The resulting metric – HANPP efficiency (HANPPe) – provides a measure of land use efficiency. HANPPe has been shown to be useful to depict land-use transitions, in particular from the agrarian to the industrial mode of subsistence (Fetzel et al., 2014; Niedertscheider et al., 2014). While production increases in agrarian societies tend to rely on expansions of existing land-use practices, and thus result in a stable HANPPe, industrialisation-based production increases are usually associated with increases in plant productivity that result in strong, often sudden, increases in HANPPe.

Here, we use global maps of HANPP to derive HANPPe for 1990, 2000 and 2010 (Haberl et al., 2007; Kastner et al., 2021). The compilation of these maps relied on the integration of census statistics (FAOSTAT, 2021) with information on potential ecosystem net primary production derived from a model run with the LPJ-GUESS DGVM (Smith et al., 2014) assuming a hypothetical no-land-use situation. Therefore, HANPP calculations were based on separate data from those used to develop the LFS distribution, with the exception of the land-use information which were derived from related CMIP6 and Hyde data sets (Goldewijk et al., 2017; Ellis et al., 2020; Hurtt et al., 2020). Model evaluation using HANPPe focused on the crop land use system, where HANPPe dynamics are most pronounced. Therefore, cells with less than 10% cropland in the CMIP6 land cover data were excluded from evaluation. Since HANPPe should increase with industrialisation, we expected HANPPe to increase from pre-industrial, to transitional, to industrial crop LFS.

2.5 Model simulations and code

We ran our model from 1990-2014. These years represent the beginning of the time-period covered by DAFI (1990) and the end of CMIP6 historical simulation runs (2014) respectively. Analysis code to create tree structures is written in R version 4.0.1. Principal packages used were 'tree' version 1.0.4 (Ripley, 2019) for classification trees and 'tidyverse' version 1.3.0 (Wickham et al., 2019) for data manipulation and processing. Code to integrate tree models into a cohesive simulation is written in Python 3.8, using the 'Agentpy' framework version 0.0.1 (Formatti, 2021). Code is made available as Supplementary Material C and Github (Perkins and Millington, 2021b).

3. Results

3.1 Model outputs

Overall, our model suggests that in 2014, 54.15% of the Earth's land surface was in either transitional or industrial fire regimes (Figure 4). By contrast, just 9.37% of the planet was occupied by the pre-industrial AFR and 12.70% was occupied by the post-industrial AFR. The largest shift globally between 1990 and 2014 was an increase in industrial and post-industrial AFRs. The Industrial AFR grew from 22.47% of the global land surface in 1990 to 27.61% in 2014 (Figure 5). This increase was predominantly driven by an increase in the industrial crops LFS. The industrial crops LFS increased from 40.20% to 50.70% of cropland area globally (Figure 6). There was a smaller increase in the industrial livestock LFS, which increased from 31.95% to 35.00% of livestock land use systems globally. This picture of increased land use intensity is complemented by unoccupied areas of the land surface decreasing from 23.23% to 17.78% over the study period.

By contrast, the largest change in non-extractive LFSs was the increase of the post-industrial AFR ('Pyro-Diversity'), which grew by 6.69%. However, the industrial ('Pyro-Exclusion') AFR also grew by 4.48% in the non-extractive land use system. Furthermore, the distribution of AFRs within the non-extractive land use system was more static than in extractive land use systems. In 1990, the four non-extractive AFRs occupied between 20.93% and 29.54%, whilst by 2014, this range had changed only to 16.12% to 32.05%.

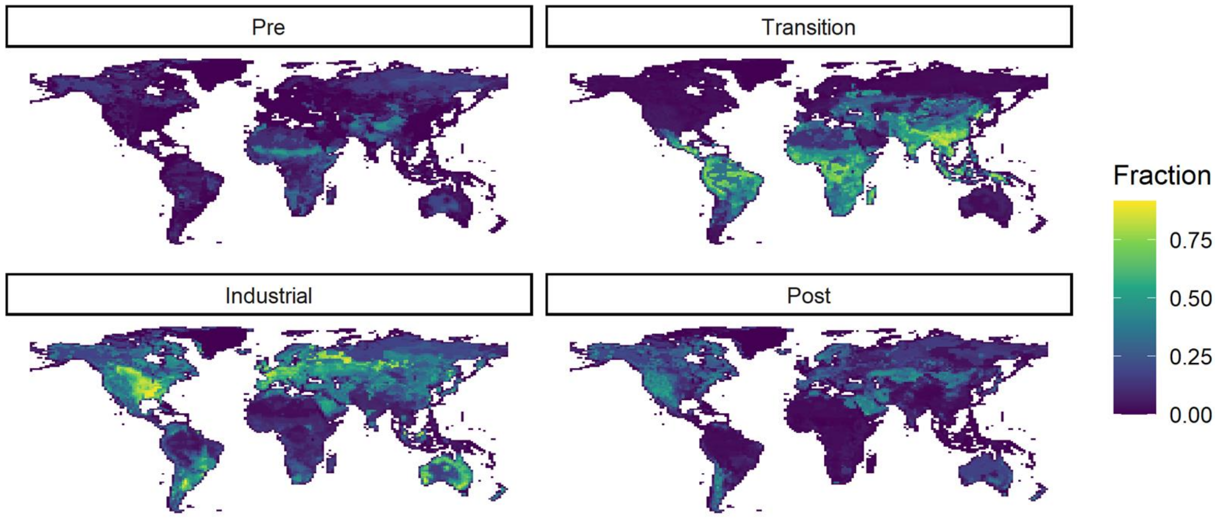


Figure 4: Fractional coverage of the global land surface by anthropogenic fire regime (AFRs) in 2014. The transition and industrial AFRs form the largest share of global land surface coverage.

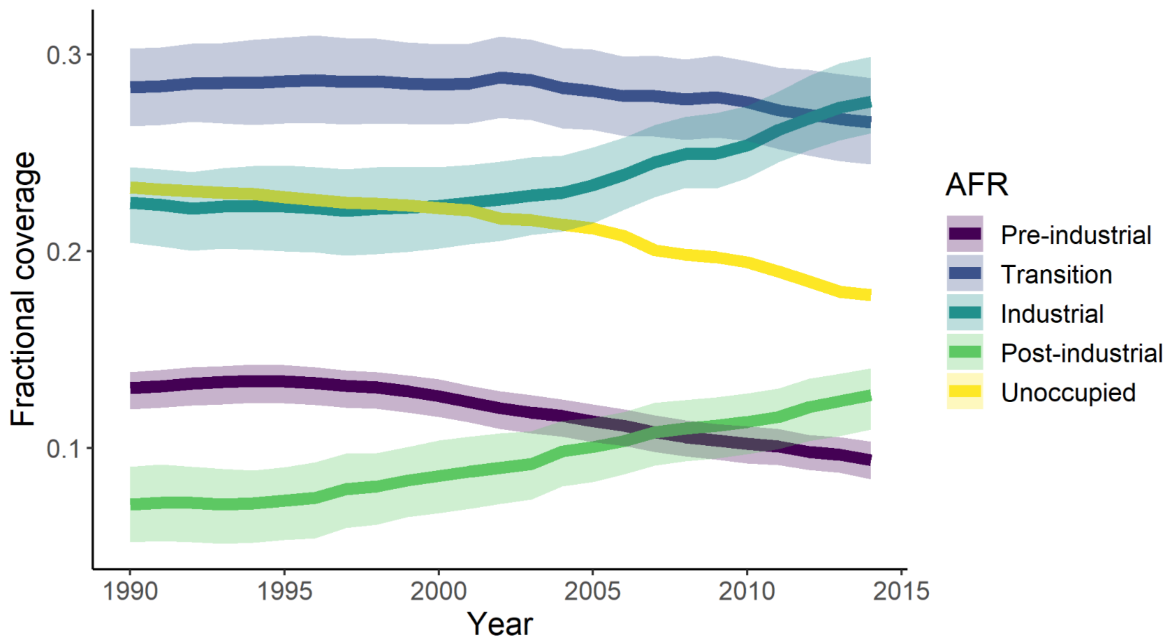
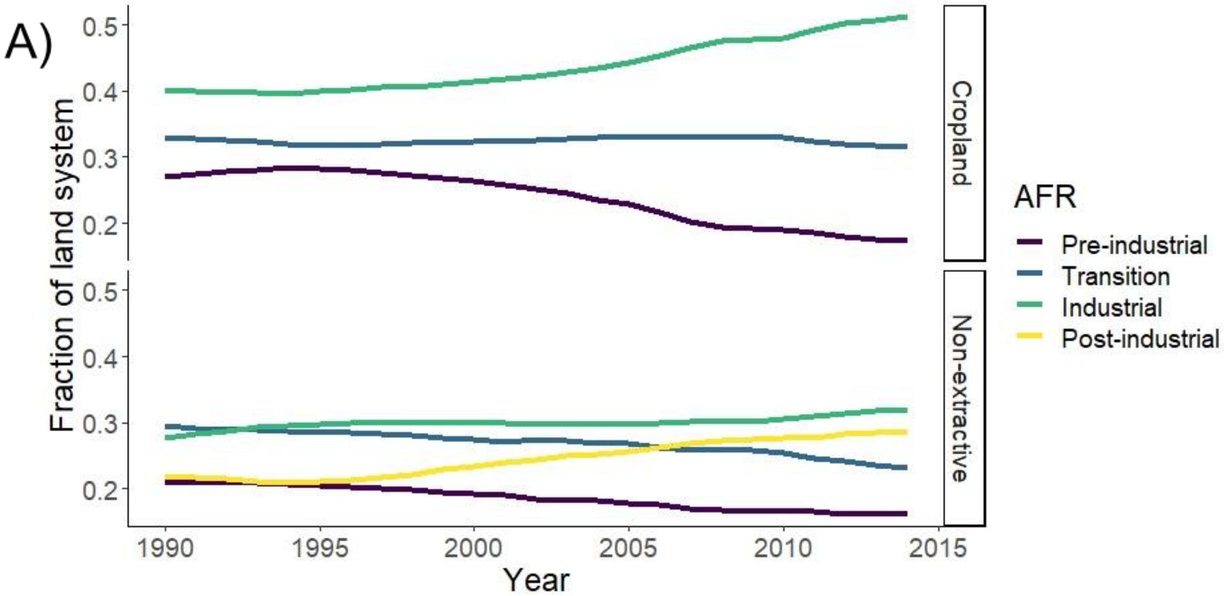


Figure 5: Fractional coverage of global land surface by anthropogenic fire regimes (AFRs) from 1990-2014. Shading represents 95% confidence interval around the mean, derived from bootstrapped numerical distribution of classification tree thresholds. The largest change in AFR distribution is an increase in the industrial AFR, accompanied by declines in the pre-industrial AFR and unoccupied areas.



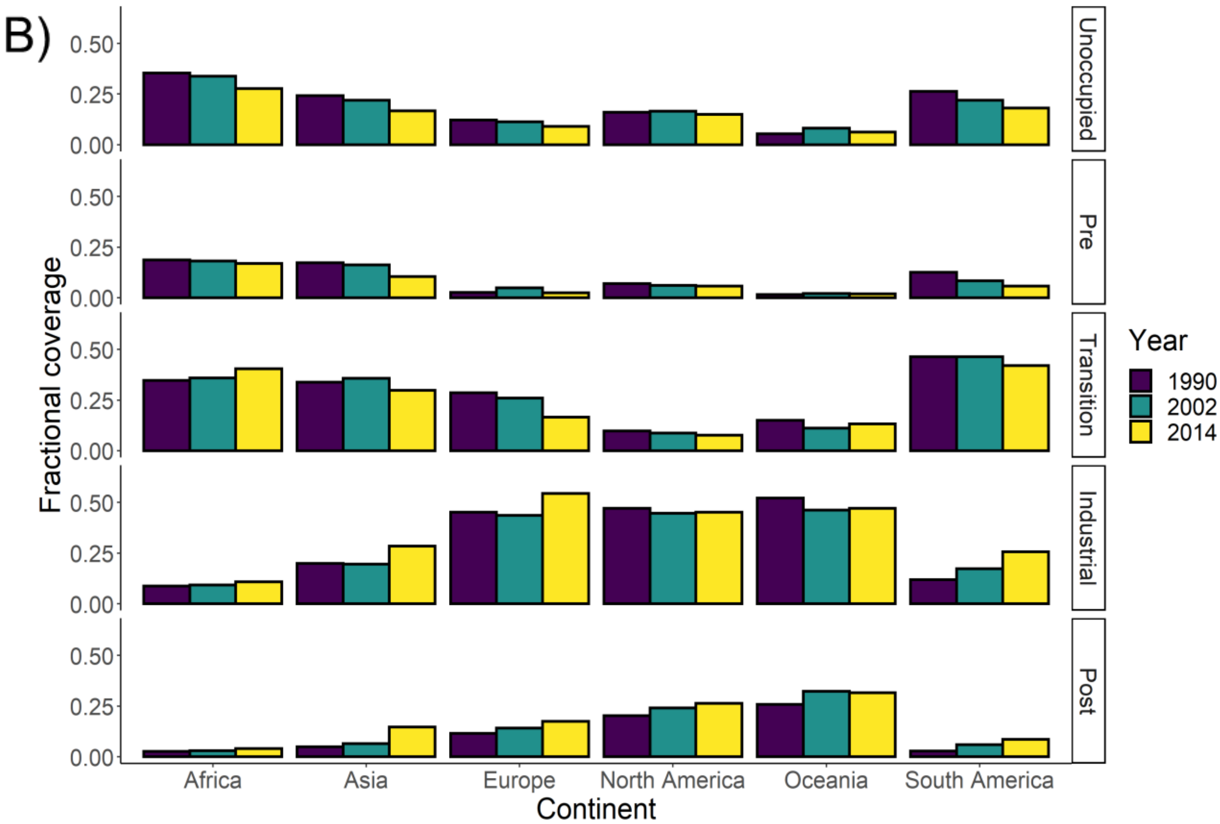


Figure 6: Change in global land-fire systems (LFSs): A) distribution of anthropogenic fire regimes (AFRs) in the cropland and non-extractive land use systems through time and B) AFR by Continent. Together, model outputs point to a substantial increase in the intensive crops LFS in Asia and South America. The accompanying decline in shifting cultivation (pre-industrial crops) is particularly acute in Asia. The increase in post-industrial regimes, particularly in Europe and North America, points to land abandonment, but also the growth of 'pyro-diverse' land management strategies (Fernandes et al., 2016).

Beneath this global picture, there is substantial regional heterogeneity. For example, at the continental level, whilst the pre-industrial AFR decreased from 17.24% to 10.50% in Asia across the study period, the pre-industrial AFR remained broadly static in Africa (18.64% to 16.95%). By contrast in Europe and North America, a prevailing trend is the growth of the post-industrial AFR, which increase from 11.48% to 17.47% in Europe and 20.21% to 26.40% in North America. The decline in unoccupied area was most sharp in South America - from 26.37% to 18.13% of the land surface - reflecting rapid deforestation of the Amazon. A complete set of model outputs, including maps for all years and LFSs, are made available as Supplementary Material E.

3.2 Overview of model performance

When compared to reference multinomial regression models, the classification tree approach demonstrates a slight improvement in quantitative performance. On average the classification trees achieve an AUC of 0.018 higher than the multinomial models (Table 3). Classification trees perform particularly well for livestock and non-extractive systems. Management practices in these systems have been found to drive substantial differences in fire regimes at both landscape and global scales (Bird et al., 2012; Rabin et al., 2015). Therefore, the classification trees' improved performance in these land use systems will support robust projections of anthropogenic fire use and suppression when coupled with JULES-INFERNO.

Table 3: Model performance of classification tree approach in comparison with reference multinomial regressions. Values are mean area under the ROC curve ('AUC'), weighted by the number of DAFI case studies in each land use system. Although the better performance of the classification tree approach is modest in a purely quantitative sense, the approach also captures a more nuanced view of process that should aid the credibility and interpretability of future forecasts.

Land use system	Multinomial	Classification trees
Crops	0.807	0.785
Livestock	0.742	0.761
Forestry	0.899	0.915
Non-extractive	0.729	0.785
Overall	0.794	0.812

Additionally, the classification tree approach captures a wider range of socio-ecological processes compared to the multinomial models (Figure 7): the most robust multinomial fits contained HDI and market access as independent variables (Table 4). By contrast, the classification trees are derived from a final set of seven independent variables, and therefore capture important inter-relationships between socio-economic and ecological factors that enable improved performance in critical areas (Figure 8). For example, the spatial distribution of the pre-industrial livestock LFS ('Pastoralism') is found to be concentrated towards higher altitude regions with less socio-economic development. As pastoralism is typically found in more marginal and sometimes harsher environments, such a parameterisation is consistent with prior knowledge of the process (Saladyga et al., 2013; Easdale and Aguiar, 2018).

Table 4: Mean regression coefficients for the reference multinomial models. The industrial anthropogenic fire regime (AFR) was taken as a reference (zero values for all coefficients). Taken together, the model is indicative of a linear progression through the four AFRs in step with economic development. HDI is the human development index.

AFR	Intercept	HDI	Market access
Pre-industrial	11.495	-18.085	-1.261
Transition	9.236	-15.254	11.486
Post-industrial	-5.524	5.149	9.307

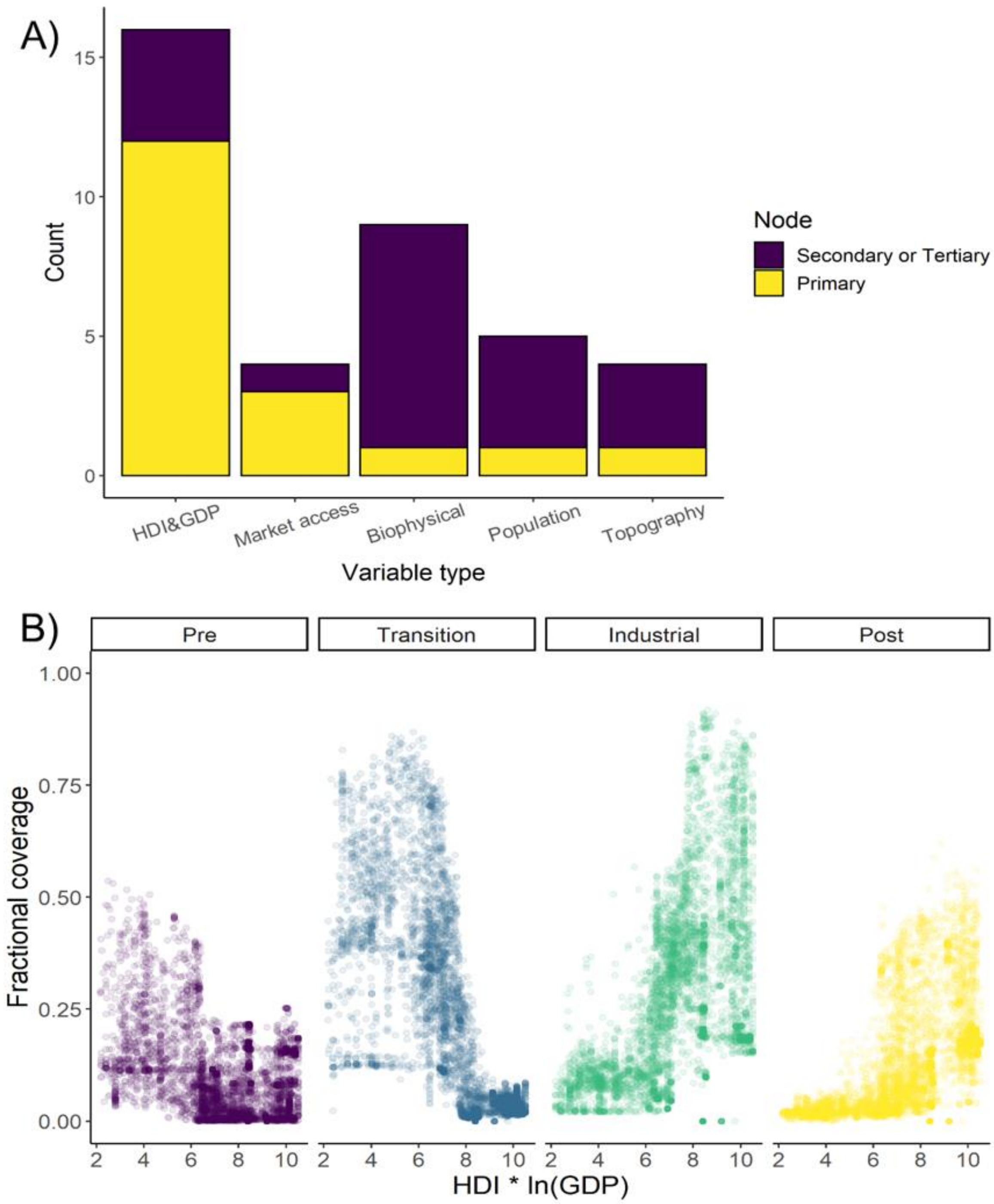
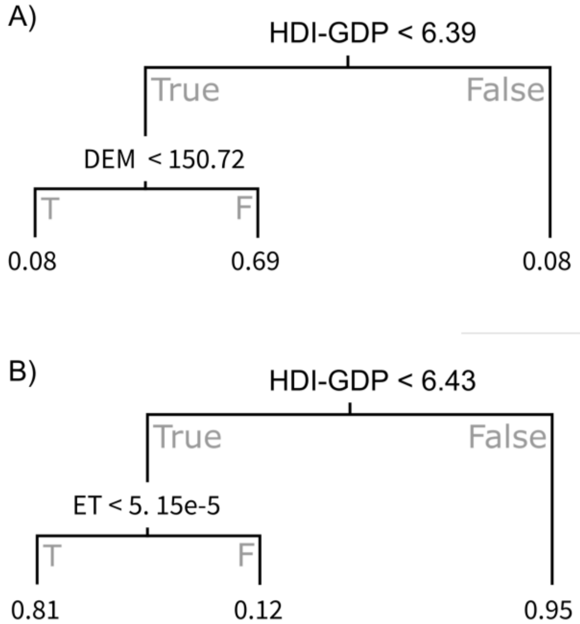
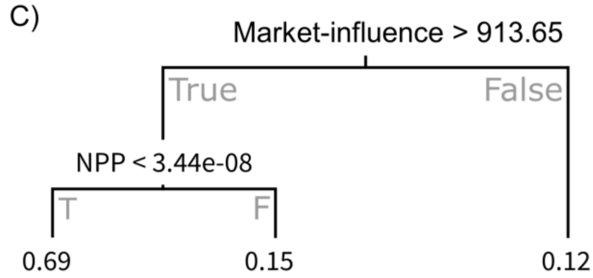


Figure 7: Relationship of model outputs to predictor variables. A) Frequency of variables as primary or subsequent splits in classification tree models, and B) relationships of global fractional land surface coverage with the HDI & GDP hybrid variable (by anthropogenic fire regime (AFR) for 2014 model output). Economic factors, represented by HDI & GDP as well as market access, dominate classification trees and play a substantial, though not exclusive, role in driving AFR distribution. Biophysical factors represented by potential evapotranspiration and ecosystem net primary productivity provide important second and third order effects, highlighting the socio-ecological dynamics at the heart of anthropogenic fire impacts.





D)

AUC	a)	b)	c)
Classification - trees	0.805	0.741	0.787
Multinomial	0.765	0.705	0.845

Figure 8: Selected land-fire system (LFS) classification trees: A), pre-industrial livestock ('Pastoralism'), B) post-industrial non-extractive ('Pyro-Diverse'), C) industrial crops (Intensive Farming). D) shows model performance for each compared to reference multinomial models. These trees illustrate how the approach enables representation of interactions between socio-economic and ecological factors in the models. In A) both economic development and the more fertile conditions associated with lower altitude (DEM) serve to constrain the system. Conversely, in B) the combination of comparatively more prosperous and populated areas and lower NPP are conducive to the system (and at very high NPP, moisture can limit the 'natural' role of fire; McWethey et al., 2013). The intensive crops LFS (C) is found in wealthier areas, and also areas in the developing world where the hydrological cycle permits appropriate conditions for intensive agriculture. In two of three cases, capturing the additional ecological process leads to improved area under the ROC curve (AUC; D).

Similarly, the presence of the post-industrial non-extractive ('Pyro-Diverse') LFS is found not only nearer to wealthier cities, but also outside of very high NPP environments – where fire does not play a substantial 'natural' role in the ecosystem and so its use in biodiversity conservation is not as widely adopted (e.g., Barnett et al., 2016). By capturing the details of these processes, the classification tree approach achieves an average AUC 0.038 greater than the multinomial models for these particular LFSs (Figure 8d).

Finally, the Intensive Farming LFS is found to be influenced not only by socio-economic development, but also by PET in the classification tree approach. Specifically, at very high PET, intensive farming becomes much less likely. This may reflect the poorer soil quality typically found in such regions (Sanchez et al., 2003), mirroring findings of Malek and Verburg (2020). However, for this LFS, the reference multinomial (with a purely socioeconomic approach) performs better (AUC 0.845 vs. 0.787). This is addressed further in the Discussion. A complete set of classification trees used to define the distribution of LFSs is presented in Supplementary Material D.

3.3 Model evaluation

Overall, there is good agreement between model outputs and HANPPe (Figure 9). For example, in 2010, the pre-industrial crops LFS (Swidden) has mean area weighted HANPP efficiency (wHANPPe) that is 41.68% lower than the industrial crops LFS and 36.67% lower than the transition crops LFS. This pattern is repeated in both 1990 and 2000. Likewise, there is a similar, but smaller proportional increase in wHANNPe from the transition to industrial cropland LFS of 33.15% in 1990. However, the relative increase from transition to industrial AFRs decreases to just 7.78% in 2010. The trend is driven by increases in wHANPPe in eastern China, a region where wHANPPe has increased rapidly, but which remains in the transitional crops LFS (Small-Holdings) in model outputs (Figure 10). This temporal trend towards convergence in wHANPPe between the transition and industrial cropland LFS is assessed further in section 4.2.

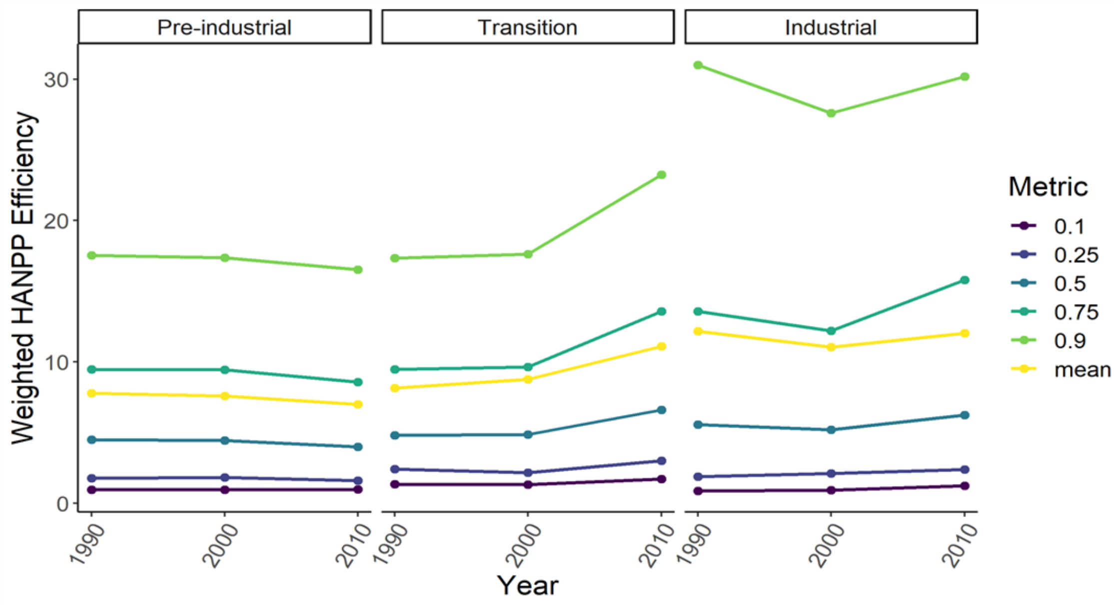


Figure 9: HANPP efficiency weighted by fractional cell coverage for the three productive crops land-fire systems. In all cases, mean HANPP efficiency increases in line with increasing land use intensity, although this trend becomes weaker between the transitional and industrial anthropogenic fire regimes through time. Metrics give mean and quantiles of the respective distributions.

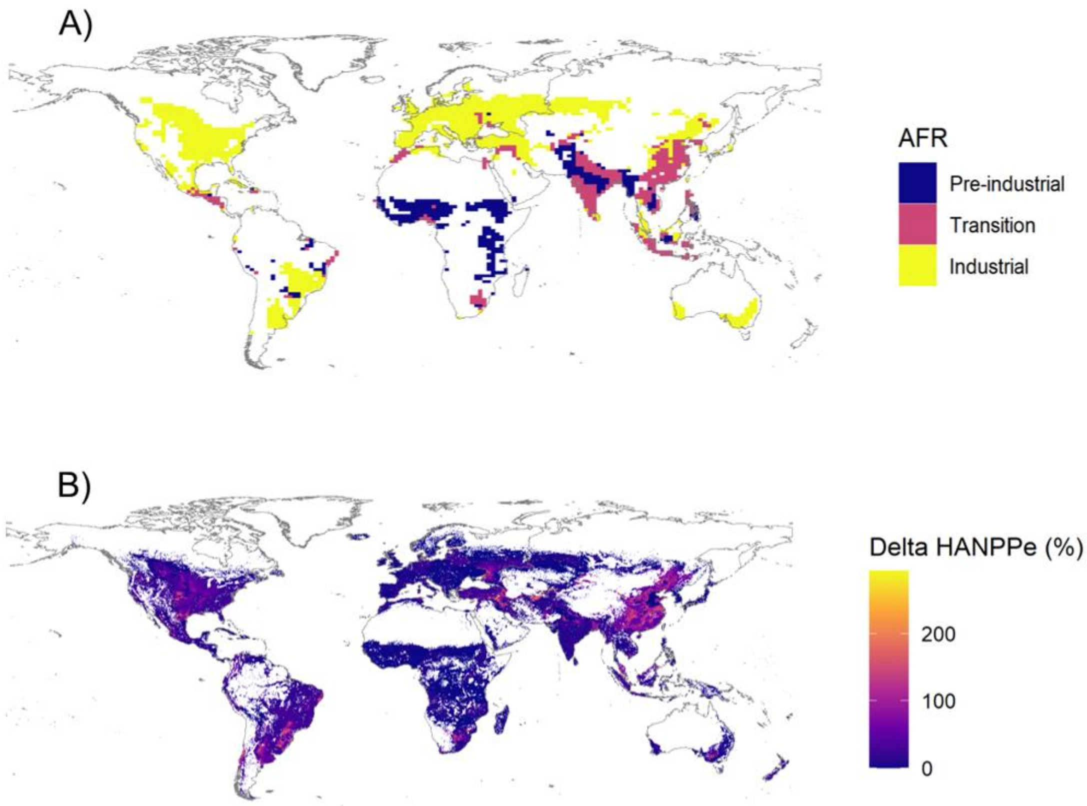


Figure 10: Drivers of converging HANPP efficiency (HANNPe) between crops land-fire systems (LFSs). A) Dominant cropland land fire-system in cells with > 10% cropland coverage & B) change in HANPPe between 1990 & 2010. Very large increases in land use intensity are reflected in increased HANPPe in China, but much of these areas remain within the transitional LFS ('Small-Holdings') in model outputs.

4. Discussion

4.1 Contribution to modelling of socio-ecological systems

Our approach using a new conceptualisation of land-fire systems (LFSs) with classification trees represents an important step forward in modelling the impacts of human behaviour on global fire regimes. The use of classification trees is (modestly) quantitatively better than multinomial regression (Table 3, Figure 8), and produces a similar degree of predictive accuracy as other models of human behaviour at a global scale (e.g. land use change; Malek and Verburg, 2020). Furthermore, using an ensemble of classification trees, our approach provides two additional key benefits in underpinning a robust process-driven model.

First, the approach enables explicit representation of socio-ecological processes, such as the relationship between net primary production and the emerging 'pyro-diversity' land management perspective. Because we have a unique tree for each of our defined LFSs, we can isolate these effects to where they are warranted from a process perspective. The specificity of the role of different independent variables in our approach should also improve the prognostic value of future predictions: we will be confident that any feedbacks diagnosed in coupled model runs are based on observed processes and not spurious collinearity effects. Conversely, the reference multinomial models suggest a linear progression through AFRs from pre-industrial to post-industrial. Specifically, the pre-industrial AFR is typified by low HDI and market access, the transition AFR by low HDI but high market access, the industrial AFR by high HDI but low market access, and the post-industrial AFR by high values for both predictor variables (Table 4). Such a linear conceptualisation has been criticised in the context of anthropogenic fire use for not capturing the nuance and diversity of how humans use and manage fire in diverse contexts (Coughlan and Petty, 2012).

Second, our results show that the classification tree approach can represent systematic change within land systems, identified as a grand challenge in socio-ecological systems' modelling (Elsawah et al., 2020). This can be seen in Figure 7 in which a clear threshold effect is seen in the industrial crops LFS at HDI-GDP ~6.5. However, our model is also able to reproduce more gradual change thanks to the bootstrapped distributions we apply to the threshold values in each tree. In the context of coupling our model with JULES-INFERNO, this represents a substantial advantage over multinomial regression, which would be more limited in projecting land systems' responses to changes in socio-ecological circumstances. An example benefit of this nuance is that our model reproduces the noted rapid decline of swidden agriculture in Asia simultaneous with swidden's persistence in much of sub-Saharan Africa (Figures 6 & 10; Van Vliet et al., 2012).

4.2 Evaluation of model outputs

The overall agreement between our model and independent data for the empirically-derived HANPPe measure (Haberl et al., 2007) establishes the credibility of the model outputs, particularly for delineating between the pre-industrial crop LFS and the industrial crop LFS (Figure 9). More fundamentally, the alignment between our LFS modelling and the HANPPe measure of land use intensity strengthens the case for a tight link between land use and anthropogenic fire. However, the apparent convergence of HANPPe in transitional and industrial AFRs from 1990-2010 warrants further exploration.

In eastern China, we observe large increases in HANPPe, but model outputs to 2014 continue to place much of this region in the transitional crops LFS (Figure 10). Case studies in this region were assigned the transitional crops LFS in our model input data (i.e., DAFI) not on the basis of yields, but because they are areas of widespread burning of crop residues in arable regions (e.g. Sun et al., 2019). Indeed, residue burning in many parts of Asia has become so widespread as to have a substantial negative impact on air quality (Peng et al., 2016; Sembhi et al., 2020). This is indicative of a lack of cohesive fire management, and hence is classified in the transition AFR. By contrast, in the industrial crops LFS, residue burning is typically absent due to concerns around public health that drive legislation to restrict or ban it (Smil, 1999). To some degree, this tension may be resolved through the assignment of agent-functional types to our LFS. For example, Malek et al. (2019), identified distinct market-oriented and subsistence-oriented small-holder land user types. We may find that such a sub-division in our Small-Holding LFS, to create a market-oriented small-holder agent class, would better represent high-yielding farming with limited associated management of fire use.

Fundamentally, however, the observed tension points to the nature of transitions in the land system – with multiple and often concurrent factors leading to varied, lagged, and non-linear responses in the system (Brown et al., 2018). More longitudinal and location-specific research is required to understand the drivers of change in fire practices and land use intensity and efficiency and the degree to which they are related.

4.3 Future modelling challenges

Two primary challenges in the modelling presented here relate to available data and the intended future coupling to existing models. Firstly, although the creation of global spatially disaggregated HDI and GDP data (Kummu et al., 2018) has been important in our ability to model the spatiotemporal distribution of LFSs, we also made multiple simplifications to our representation of human behaviour due to data constraints and concerns. Secondly, our focus on coupling with the JULES-INFERNO DGVM caused us to lose a degree of information, not only by working at JULES-INFERNO's coarse spatial resolution (1.875 x 1.25 degrees), but also by refraining from using data sets that would have conflicted with JULES-INFERNO outputs yet otherwise may have added value to the model. These two related issues are now discussed further, in turn.

Due to a lack of data, the primary simplification important for modelling global anthropogenic fire is the absence of an explicit representation of policy. This must be considered a substantial limitation as the inherently political nature of fire governance determining who can use fire, for what purpose and when, is often a proxy battle for the favoured land system and land tenure type in a given location (e.g., Kull, 2004; Trigg et al., 2012). To account for this, we initially experimented with the 'Human Freedom Index' (Cato Institute, 2020) as a measure of the degree of centralisation of a government system. However, this was dropped from the analysis, primarily because of concerns regarding the neutrality of the index (Plehwe, 2021). Furthermore, as we plan to use this model for future scenario-based projections, we were concerned that making projections about such an index for the shared socio-economic pathways (SSPs; Popp et al., 2017) would be an inherently subjective process.

Therefore, a representation of government policy will need to be defined through theory in combination with information on fire policy (such as that gathered in DAFI). However, such a top-down parameterisation of policy impacts on the land system will need to be careful not merely to mirror or double effects already captured implicitly in existing data. For example, the consequences of political efforts to eradicate swidden in Southeast Asia (Mertz et al., 2009) are already seemingly captured in our empirical modelling. This question of circularity, and the degree to which empirical and strictly behaviourally-driven model components may be combined in a coherent manner will likely only become clear once coupling with JULES-INFERNO is completed and assessed.

A further data-related simplification made during model construction was to remove variables representing species richness and the distribution of protected areas. These variables were moderately useful in defining the distribution of non-extractive AFRs but would have added substantial challenges to scenario forecasting – likely requiring complex assessments and calculations of future anthropogenic impacts on biodiversity globally. Together, these data issues reiterate the argument of Verburg et al. (2019) that a lack of future projections in land system modelling and its underlying data sets remains a major challenge.

A second set of challenges in our approach is found in our planned model coupling with the JULES-INFERNO DGVM. As we plan for our model to be used in model runs following the CMIP6 protocol, we adopted the CMIP6 land cover data as the primary driver of our land use system distribution (Figure 2). The consequences of this are perhaps most pronounced for the livestock land use system. One positive outcome was that pastoralism could be restricted to the 'rangeland' land cover class, as by definition this nomadic LFS cannot occur on managed pastures. However, a substantial resulting issue is the representation of land abandonment. For planted pastures, coherence demands the rate of abandonment must be driven by declining fractional coverage in the land cover data. Conversely, in rangelands, abandonment can occur without substantial change to land cover (Peco et al., 2006). Therefore, in this case abandonment need not be dictated from forcing data and can be represented behaviourally. Indeed, the post-industrial AFR for rangelands was among the best performing aspects of the model (AUC = 0.862).

This tension in the relationship of CMIP6 land cover data with our land use systems points to similar structural challenges for modelling of future scenarios. Although CMIP6 land cover data for the recent past are derived from observations, for future scenarios they are based on Integrated Assessment Model outputs (Hurtt et al., 2020). Therefore, future projections from our model will be somewhat reliant on the assumptions of Integrated

Assessment Models to drive the distribution of land systems, whilst the distribution of AFRs will be driven entirely by our behavioural approach. This may cause issues with the coherence of future scenarios but is a necessary issue to tackle if behavioural modelling is to be integrated into the coupled model intercomparison project and associated protocols. Furthermore, by separating concerns between land use system distribution and AFR distribution, our modelling approach should be readily adaptable for modellers interested in other discrete aspects of anthropogenic land use such as water consumption or biogeochemical cycling.

Finally, to allow seamless transmission of information between our models, we adopted JULES-INFERNO outputs as synthetic data sets for NPP and PET. However, data derived from remote sensing and field observations may have been preferable. This limitation may be at the heart of our model's modest performance in predicting the industrial crops LFS. Although Malek and Verburg (2020) used soil type to capture the biophysical constraint on such intensive or market-oriented production, including such a data set in our model would have involved substantial enhancements to the ways in which JULES-INFERNO represents changes to soil biogeochemical composition due to agriculture (Osborne et al., 2015; Burton et al., 2019). Recognising this, and to ensure our model is readily integrable with other DGVMs, we plan to create a version of the model using only remotely-sensed (empirical) inputs.

5. Conclusion

We have presented a new approach to modelling the global distribution of land use systems and their inter-relationship with anthropogenic fire regimes, through the concept of land-fire systems (LFS). Our spatiotemporal modelling of LFS distributions is an important step towards a substantial improvement in the representation of anthropogenic fire in dynamic global vegetation models. We have demonstrated how a reasonably simple empirical approach can capture complex non-linear interactions in land systems whilst being derived from just seven independent variables (with corresponding data sets). However, a major implication of this study is that effective large-scale behavioural land system modelling under the shared socio-economic pathways will require development of standardised and spatially disaggregated data sets, with associated future projections, across a range of socio-ecological indicators.

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4.3 Conclusion: published paper findings in the context of this thesis

The published paper composing the core of this Chapter has presented the land use module of a global behavioural model of anthropogenic fire use. This is based on a simple, empirical representation of land use competition between land-fire systems (LFS). As the results of the paper show, the approach used coheres well with the human appropriation of net primary production (HANPP) and performs favourably against a baseline multinomial regression.

The following Chapter will show how the spatiotemporal LFS distribution formed the basis of a global model of human fire use and management. This model is now named WHAM! – the wildfire human agency model.

In developing the LFS distribution, it became clear that drawing on a range of human indicators in addition to population density and GDP was crucial to capturing the socio-ecological niches of the differing LFS. As such, running WHAM! for the future required new spatial projections of human indicators for the Shared Socioeconomic Pathways (O'Neill et al., 2017). Projections of the Human Development Index and market access are therefore presented in Chapter 6, Section 6.2.5.

Chapter 5

A global behavioural model of anthropogenic fire use and management: parameterisation & evaluation of WHAM!

5.1 Introduction

5.1.1 Chapter outline

The previous chapter described how a global distribution of land-fire systems (LFS) was defined from a combination of DAFI and secondary data. This chapter now describes how this LFS distribution was used to drive a global behavioural model of human impacts on wildfire regimes, which we name WHAM! (Wildfire Human Agency Model). The ultimate aim of this model is to form a component of a coupled model with the JULES-INFERNO dynamic global vegetation model (DGVM; Mangeon et al., 2016). That coupling is described subsequently in Chapter 6, while this chapter describes WHAM! and its outputs as a standalone model.

This Chapter begins by noting key considerations in model construction to enable coupling with JULES-INFERNO, before describing how a distribution of agent functional types (AFTs; Arneth et al., 2014) was derived from the distribution of LFS. These AFTs are subsequently parameterised for fire use and management actions. Model evaluation is done using a combination of literature and remote sensing sources, with a focus on comparison of model outputs for crop residue burning with the new Global Fire Emissions Database v5 crop fire product (GFED; Hall et al., 2023). Discussion focuses on insights from WHAM! regarding the relationships of human fire use to their land use drivers, as well as model limitations and priorities for future development.

5.1.2 Coupling WHAM! with JULES-INFERNO: key considerations

From the perspective of model structure, the goal of coupling WHAM! with JULES-INFERNO is to replace INFERNO's simplistic functions representing human 'ignitions' and suppression of fires (Chapter 2, Section 2.2.1), with explicit representation of the modes through which people use fire and manage fire regimes (Figure 5.1; Table 5.1). In version 1.0 of INFERNO described by Mangeon et al., (2016), anthropogenic ignitions ($Ignitions_A$) are calculated as:

$$Ignitions_A = 6.8 \times PD^{-0.6} \times 0.03 \times PD \qquad (5.1)$$

where PD is population density. This equation is not derived from the underlying processes by which humans use or manage fire, rather it is a top-down function calibrated to give broadly the same distributions of fire numbers observed in GFED v4 (Pechony and Shindell, 2009).

DAFI data demonstrate not only that coarse-resolution Earth observation fire products (such as GFED v4) do not capture the majority of human fire globally, but also that anthropogenic fires have different quantitative characteristics (size, frequency, land cover burned) according to land user intentions. Therefore, WHAM!-INFERNO will replace this single anthropogenic ignitions function with a more mechanistic representation of the processes which drive human fire use globally, by projecting not only human ignitions, but three classes of human fires. These are: managed fires, unmanaged fires and escaped fires – the latter being those that begin as managed fires but grow to become unmanaged (Figure 5.1).

Similarly, INFERNO uses a further function of population density to define the fraction of these ignitions that are supressed:

$$Suppression = 7.7 \times (0.05 + 0.9 \times e^{-0.05PD}) \qquad (5.2)$$

where $Suppression$ is a 0-1 value representing the number of ignitions that are extinguished before they light a fire. The constant 7.7, as with the constant 6.8 in (1), is an empirical scaling factor used to calibrate model outputs to GFED v4. Similarly to anthropogenic ignitions, in WHAM!-INFERNO this empirical suppression function will be replaced by process-based representations of human fire extinguishing. Note that in DGVMs, anthropogenic fire 'suppression' commonly refers to extinguishing of active fires, whilst DAFI treats suppression as a group of three specific actions: fire control, fire prevention and fire extinguishing (Chapter 3, Section 3.2.2.3). Here, for ease of terminology, fire suppression is used to denote fire extinguishing, whilst control and prevention are termed as fire management actions.

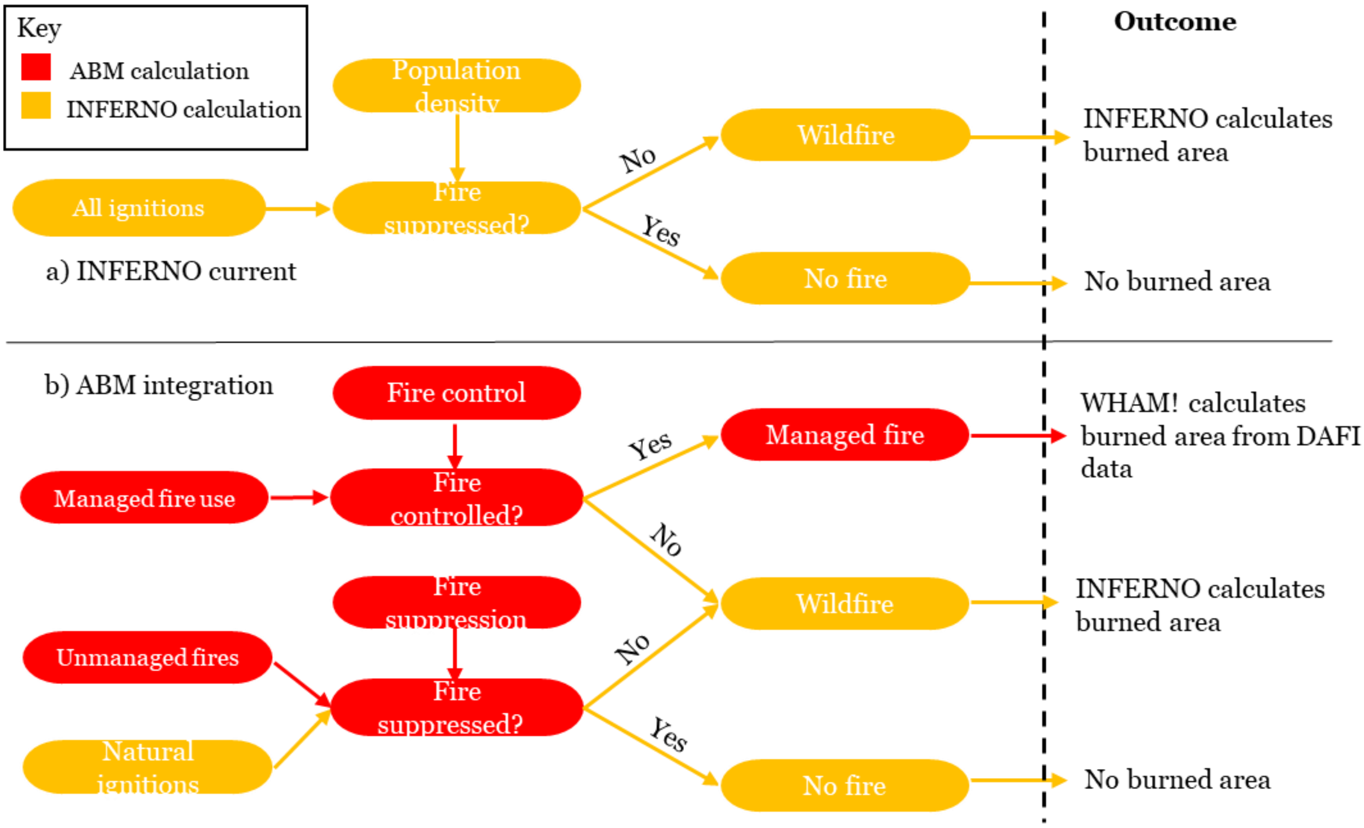


Figure 5.1: Schematic representation of the structural changes to INFERNO enabled by WHAM! integration. Rather than treating all fires as similar events, as in the original version of INFERNO, the WHAM! integration can differentiate between managed fires that and firesthat spread unmanaged according to biophysical drivers.

Table 5.1: Overview of WHAM! outputs and respective units; burned area from unmanaged anthropogenic fires will be calculated by JULES-INFERNO as a part of a coupled model ensemble. The parameterisation of fire suppression is described in the following chapter.

Variable	Chapter Section	Output units
Managed fire	5.2.2	Burned area (fraction of grid cell)
Unmanaged fire	5.2.4	Number of fires (km^{-2} year^{-1})
Fire suppression (extinguishing)	6.2.2.2	Dimensionless (0-1)

As described in Chapter 4, the distribution of LFS was an important step towards a distribution of agent functional types (AFTs), which are representative classes of human land systems (Arneth et al., 2014). In the Arneth et al., (2014) definition, AFTs are comprised of roles and behaviours. In WHAM!, the roles of the AFTs are comprised of the land use system and anthropogenic fire regime that they occupy. Their behaviours, which are described in detail in this chapter, are comprised of fire use and suppression actions. As such, the AFTs' spatiotemporal distribution determines which fire use options are considered in a model cell, whilst the AFTs' parameterised behaviours determine the degree of fire use and suppression given the cell's specific socio-ecological conditions.

As with the LFS distribution, several aspects of model design were driven by the intended coupling with JULES-INFERNO. As with the LFS distribution described in Chapter 4, WHAM! adopts the coarse spatial resolution of JULES-INFERNO (1.875^{o} x 1.25^{o}). Furthermore, JULES land cover outputs (Plant Functional Type distribution) are used – specifically tree coverage and bare soil coverage – where otherwise remote sensing data could have been used. JULES representation of anthropogenic land cover falls into cropland, pasture, and natural vegetation (grasses, trees, and shrubs) and hence this is how WHAM! fire use outputs are reported in this Chapter. Rangelands - semi-natural grassland grazing lands (Hurtt et al., 2020) - are treated by WHAM! as an anthropogenic land cover, but by JULES as a natural land cover (Sellar et al., 2020); the resolution of this discrepancy is described in Section 5.2.2.3. By contrast to this spatial alignment, the temporal resolution of WHAM! is determined by timescales of anthropogenic decision making (Arneth et al., 2014) and the availability of data in DAFI. As such, WHAM! runs at an annual timestep.

Any evaluation of WHAM! as a standalone model is necessarily incomplete as unmanaged fire outputs require coupling with JULES-INFERNO to calculate burned area. Whilst crop residue fires could be compared directly with the new GFED5 crop fires product (Hall et al., 2023) other satellite burned area products were challenging to use, as these cannot differentiate between managed and unmanaged fire types without local-scale fieldwork. Consequently, model outputs for managed anthropogenic fire are evaluated against mixed data sources, including DAFI data not used in model calibration, but also the LIFE database compiled by Smith et al., (2022). Similarly, sensitivity analysis, counterfactual experiments and discussion focus on WHAM! managed fire outputs. The complete picture of managed, unmanaged and lightning fires is then presented and analysed in Chapter 6.

WHAM! is written in Python 3.8. It was developed using the Agentpy library, version 0.2.0 (Foramitti, 2021). Code and data to run the model, along with installation guidance, are available via Zenodo (Perkins et al., 2023a).

5.2 Methods

As shown in Figure 5.1, WHAM! represents anthropogenic fire use, management and suppression. Fire use is comprised of managed fire use, and the deliberate or unintentional creation of unmanaged fires. The fire management behaviour represented is fire control (measures taken to ensure managed fires do not become unmanaged wildfires) and suppression behaviour represented is fire extinguishing (putting out of active fires).

The managed anthropogenic fires represented in WHAM! are the central modes of anthropogenic fire identified through analysis of DAFI (Chapter 3). Unmanaged fires are calculated as a combination of accidental fire, managed fires that escape to become unmanaged wildfires (hereafter 'escaped fires'), and arson – which is defined as in Chapter 3 as fire use as a deliberate weapon. Where fires are successfully managed – performing a land use purpose and then burning out or being extinguished - WHAM! calculates the burned area directly (Table 5.1). However, where fires were unmanaged (whether by design or by accident), WHAM! outputs a number of fires km^{-2} $year^{-1}$, which will be passed to JULES-INFERNO to calculate their resulting burned area.

Fire control is an internal calculation of WHAM! that influences the rate of escaped fire. Therefore, this is presented in this chapter. By contrast, the parameterisation and calculation of fire suppression ('extinguishing' in DAFI) is directly intertwined with JULES-INFERNO's calculation of burned area from unmanaged fire. Therefore, the development and calibration of this aspect of WHAM! is presented in the chapter detailing the coupled model (Section 6.2.2.2).

Model development is presented in several stages. Firstly, the finalisation and distribution of AFTs from the modelled distribution of LFS is described in Section 5.2.1. Secondly, the parameterisation of these AFTs using DAFI data for the central modes of anthropogenic managed fire identified in Chapter 3 is presented (Section 5.2.2). Thirdly, top-down constraints were placed on managed fire to account for sampling biases in DAFI (Section 5.2.3). Fourthly, unmanaged fires were modelled using a combination of 'observer' agents and landscape-level effects (Section 5.2.4). This includes calculation of fire control actions.

Having presented the model's structure and parameterisation, model evaluation, including an assessment of sensitivity is described in Section 5.2.5. Finally, a set of counterfactual experiments, which explore the drivers of managed anthropogenic fire are described in Section 5.2.6.

5.2.1 Finalisation and distribution of agent functional types

5.2.1.1 Finalisation of AFT classes

The first step in constructing the fire parameterisations in WHAM! was to finalise the preliminary AFT classes defined in Chapter 3. The preliminary AFTs were derived from the fire regimes of Pyne (2001) and land user meta-analyses such as that of Malek et al., (2019). This initial framework was refined iteratively during the database testing process described in Chapter 3 (Section 3.2.2) and the development of the land use module of WHAM! described in Chapter 4.

Before parametrising the resulting AFTs in WHAM!, the AFTs were reassessed from a top-down perspective. The criteria used were whether AFT classes contained a clear modal fire use pattern, and whether they burned similar land cover types. These two criteria were assessed on both the frequency of given fire use & land cover combinations within an AFT class, but also whether they were separable geographically or from a qualitative and process-based perspective. There were two particularly areas of focus during this reassessment.

Firstly, the identification of the non-extractive land system (Chapter 4) required revisiting of the preliminary forestry AFT classes. As a result, the 'industrial forestry' preliminary class was split into 'managed forestry', which describes the industrialised management of forests to produce timber and associated goods, and 'state land manager'. The state land manager class corresponds to bodies such as the US Bureau of Land Management, which manage large amounts of public lands, with not just forest but also grassland and other land cover types for multi-faceted purposes (Brice et al., 2020). For example, the difference between these two types is best seen in the primary land cover to which they applied fire for pyrome management: managed forestry burned exclusively forest (97.62%), whilst state land managers' modal land cover burned was shrublands (52.78%). Managed forestry also used fire for burning of residues (36.20% of fire use cases), a behaviour that was absent from the state land manager class.

Secondly, given that the LFSs were found to be a coherent framework for global modelling (Chapter 4), cases where an LFS contained more than one AFT were a focus of reanalysis. Where an AFT occupied the same LFS as another, in all cases there was found to be a difference in that AFTs modal fire use (Table 5.2). As such, after a multi-stage iterative process, a final set of AFTs was identified. In 12 of 16 cases there was a one-to-one relationship between LFS and AFT (Table 5.3). In the remaining five cases, multiple AFTs competed for the space within that LFS.

Table 5.2: Land-fire systems (LFS) which are allocated between more than one agent functional type (AFT). In all such cases the AFTs adopt a differing modal fire use, indicative of their substantively differing roles within each LFS. In the case of recreationalists, the transitional type tended to be an overseas tourist, whilst in the post-industrial case this tended to be local or national-scale activity.

LFS	AFTs	Modal fire use	Proportion of cases (%)
Cropland, transitional	Small-holder (Subsistence) Small-holder (Market)	Vegetation clearance Crop residue burning	48.70 66.81
Forestry, transitional	Agroforestry Logging	None Vegetation clearance	86.05 41.17
Non-extractive, transitional	Conservationist Recreationalist	Pyrome management Hunter-gatherer	97.62 71.43
Non-extractive, post-industrial	Conservationist Recreationalist	Pyrome management Hunter-gatherer	97.62 71.43

Table 5.3: Overview of relationships between final agent functional types (AFT) and land-fire systems (LFS). In 12 of 16 cases, there is a simple one-to-one AFT-LFS relationship. Cases where the relationship is not one-to-one (i.e., where there are multiple AFTs per LFS) are *italicised*.

AFR	***Land Use***			
	Non-extractive	**Forestry**	**Livestock**	**Cropland**
Pre-Industrial	Unoccupied	Hunter-Gatherer	Pastoralist	Shifting cultivation
Transition	*Recreationalist, Conservationist*	*Logging, Agroforestry*	Extensive Livestock Farmer	*Small-holder (Subsistence), Small-holder (Market)*
Industrial	State Land Manager	Managed Forestry	Intensive Livestock Farmer	Intensive Farmer
Post-Industrial	*Conservationist, Recreationalist*	Abandoned forest plantation	Abandoned livestock farming	Abandoned cropland

5.2.1.2 Distribution of AFTs

In the 12 out of 16 cases in which there was a one-to-one relationship between LFS and AFT, the AFT distribution could be assigned directly from the LFS distribution calculated in Chapter 4. In the four cases where more than one AFT was competing for space within a LFS, competition between AFTs was simulated using the same process (with one small simplification noted below) as that for deriving the distribution of LFS themselves.

Briefly to recap, a tree model was created which defined the fraction of the relevant LFS occupied by the competing AFTs. Training data for the tree models were the same weighted data from DAFI used in Chapter 4. To identify data for the relevant LFS, these were filtered by land system using the method in Chapter 4 but were additionally filtered for the relevant AFR using the case study assignment in DAFI. Therefore, rather than comparing the output probabilities of multiple trees in each pixel as in the competition *between* LFS, the fractional coverage of each AFT competing *within* an LFS could be assigned directly from a single tree's output probabilities (Figure 5.2).

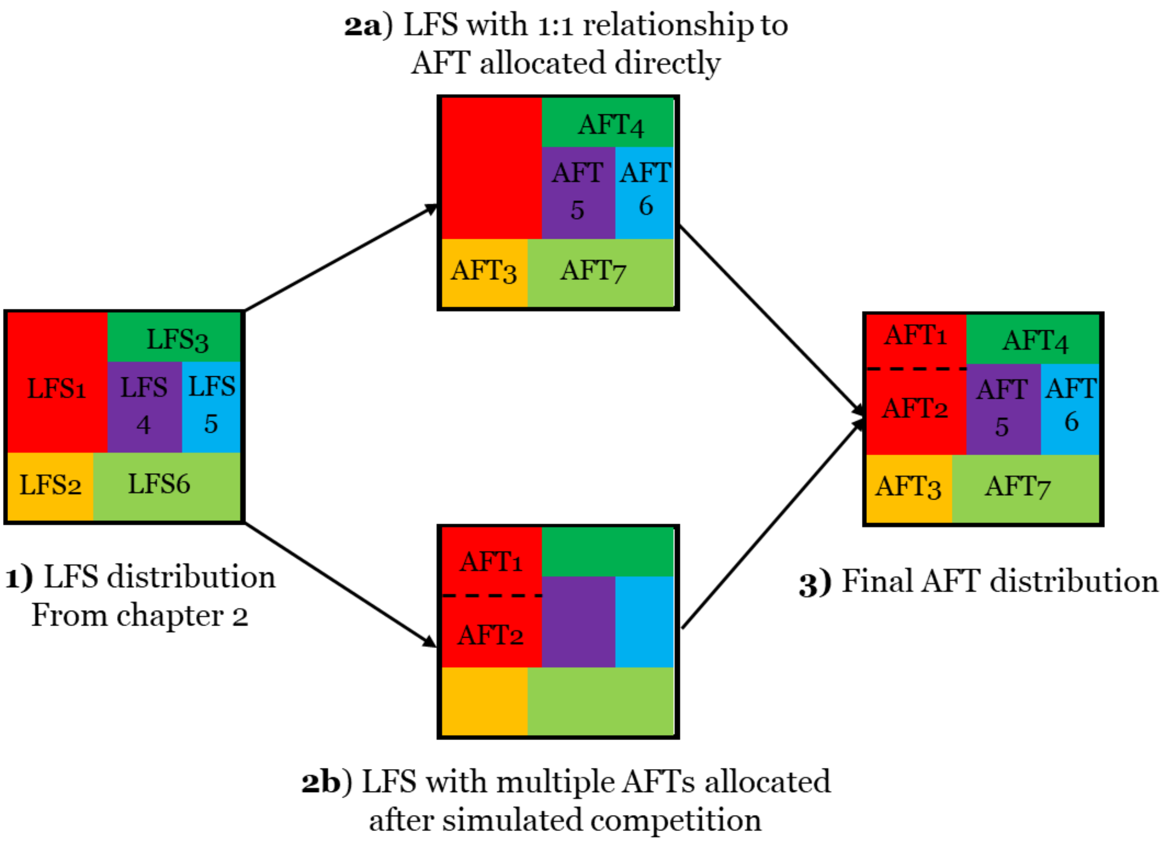


Figure 5.2: Illustration of derivation of AFT distribution from distribution of land fire systems (LFS). Box represents a single theoretical model cell. In 12:16 cases an AFT could be allocated directly to an LFS (2a), whilst in the remaining four cases, this was done by simulated competition between AFTs.

5.2.2 Parameterisation of agent functional types for managed fire use

Analysis of DAFI revealed seven central modes of global anthropogenic fire use (Chapter 3). Of these, six were treated as managed fire types (crop field preparation, crop residue burning, pasture management, hunting and gathering, pyrome management, and vegetation clearance), whilst arson was treated as unmanaged. As DAFI showed that these six managed fire use types have distinct spatial distributions and quantitative characteristics, each AFT was parameterised for their use of each type individually. The process used to parameterise AFTs for five of the managed fire types is set out in Figure 5.3 – vegetation clearance required a bespoke approach (Section 5.2.2.6). Furthermore, for some AFT / fire use combinations, deviations from the process outlined in Figure 5.3 were required due to data availability, these are described below (sections 5.2.2.1-5.2.2.5).

In the default parameterisation of AFT fire use, for each of five managed fire use types, each AFT was parameterised for their tendency to use fire for the given purpose (defined as a 0-1 probability), and where relevant the extent of their use (defined as a 0-1 burned area fraction of a model grid cell). Where no DAFI instances existed of a given AFT and a particular fire use, tendency was assigned a probability of 0. Fire use burned area fraction was calculated using case study data from DAFI. As DAFI case studies are both geographically small, and focused towards areas of active anthropogenic fire use (Chapters 3 & 4), using these alone as the basis for burned area fraction in a spatially coarse (1.875^{o} x 1.25^{o}) model would have led to overestimation of burned area. Consequently, 0-1 fire use tendency and 0-1 fractional burned area outputs were multiplied together to give a burned area fraction per cell for a given fire use (for the fraction of each cell occupied by a given AFT). This tension between fire data from comparatively granular case studies and the coarse resolution of JULES-INFERNO (and therefore WHAM!) is highlighted in model evaluation (Section 5.2.5) and explored in the discussion.

Fire use tendency and burned area fraction maps were calculated statistically using classification and regression trees, generalised linear models (glms) and stacked combinations of both. These tools were chosen for their simplicity, interpretability, and complementarity. Broadly, glms were used for linear relationships (Haas et al., 2022), and tree models to capture non-linear or threshold effects in predictor variables (Krzywinski and Altman, 2017). Whereas data were plentiful for calculating the spatiotemporal distribution of each LFS, data availability for calculating fire use by AFTs were more limited, reflecting the underlying fragmentation and inconsistency of the anthropogenic fire literature; Chapter 3). Where data were most sparse, and/or where no meaningful statistical model could be constructed, a constant value was used. These cases are highlighted in sections 5.2.2.1-5.2.2.5.

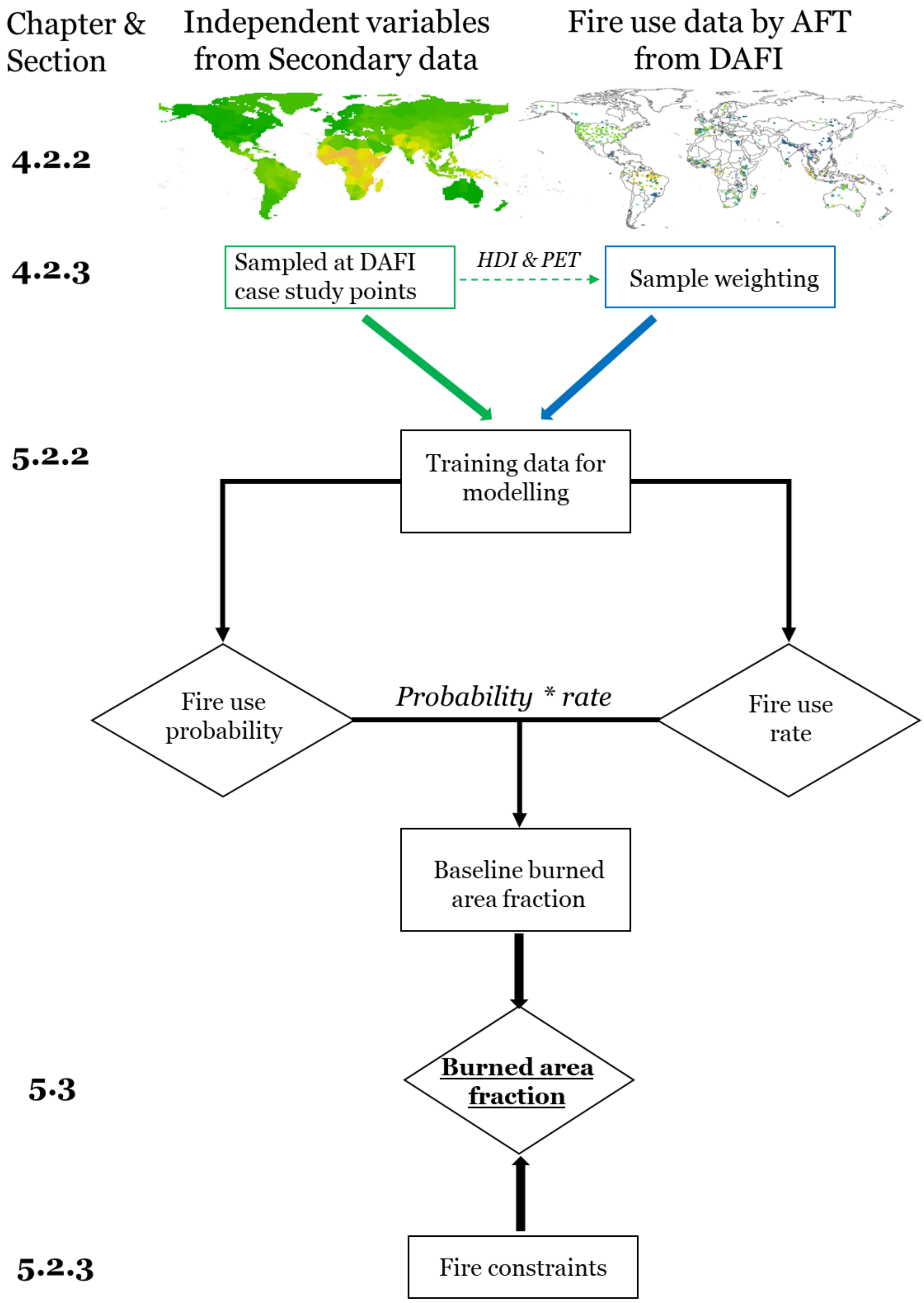


Figure 5.3: Overview of the process used to model managed anthropogenic fire in WHAM! This process was applied to each AFT for each mode of anthropogenic fire. Where an AFT had no recorded cases of a given fire use a probability of 0 was applied. Owing to data constraints, several deviations from this process were required, which are detailed in Sections 5.2.2.1-5.2.2.5.

In addition to cases in which no appropriate model could be found to capture the distribution of a given fire use / AFT, this sparsity of data led to two fundamental modelling challenges. The first related to calculation of fire use tendency, whilst the second challenge related to fire use rate.

The first challenge was to correct for sampling biases in DAFI. As DAFI provides data on active fire use and suppression behaviours, it does not systematically capture the *absence* of fire use. Data on absence cases were collected incidentally, for example where a case study documented a well-enforced policy ban (e.g. Abate and Angassa, 2016). As a result, only 13.7% of fire use records documented the absence of a particular fire use in a case study. Without appropriate adjustment, this inconsistent sampling of fire absence would have biased calculations fire use tendency. Therefore, absence data were resampled to form an equal portion of the training data for fire use tendency models. This is a standard approach in classification of 'class imbalanced' data, which has been shown to perform well in real-world applications (He and Garcia, 2009).

Furthermore, as highlighted in Chapter 4, DAFI simply does not sample from locations where anthropogenic fire use would be a biophysical impossibility due to an absence of vegetation (primarily in deserts), and also systematically under-samples more economic developed regions of the world. Such systematic biases could not be corrected by resampling of DAFI. Therefore, in addition to up-sampling of absence cases, top-down constraints were applied to account for these two identified sampling biases in DAFI. Such top-down constraints are described in Section 5.2.3. Finally, where a constraint was required to capture a specific sampling bias relevant to a particular fire use type, these were added to the calculations at the AFT level. Fire use specific constraints are described in sections 5.2.2.1 – 5.2.2.5 below.

The second modelling challenge presented by data sparsity was that the lack of standardised ways for reporting fire data in DAFI case studies. The result was burned area of managed fires could not be calculated using the same dependent variable for each fire use. For example, fire use for shifting cultivation was commonly reported as a fire return period (owing to the importance of fallow period for describing the system), whilst fire use for pyrome management was primarily reported as a burned area fraction in management plans or government reports. These issues were specific to each fire use type, and so the solution was to make best use of available quantitative fire data for each type. Burned area fraction was used as the dependent variable where data in DAFI allowed it, and where this was not possible the fire return period was used (as described below).

Therefore, given the necessary heterogeneity of the methods used to parameterise differing AFT-fire use combinations, the specific adjustments made for each fire use are described in turn below. Table 5.4 gives an overview of the adjustments to the default parameterisation approach set out above.

Table 5.4: Fire-specific amendments to parameterisations of managed fire by fire use type and agent functional type (AFT); the choice between tree models and linear models was based on their empirical performance. Where an AFT is not listed under a fire use, it was found not to use that mode of fire. The core method used for fire use parameterisation is set out in Figure 5.3.

Fire use	AFTs	Fire use tendency: method	Burned area: method	Burned area: DAFI target variable	Fire-specific constraint
Crop field preparation	Shifting cultivation	Classification tree	Regression tree	Fire return period	None
	Small-holder (Subsistence)	None	Regression tree	BA fraction	None
	Small-holder (Market)	None	Regression tree	BA fraction	None
Crop residue burning	Intensive arable farmer	Classification tree	Constant	N/A	None
Hunter gatherer	Hunter gatherer	Classification tree	Linear model	BA fraction	Section 5.2.2.5
	Pastoralist	Classification tree	Regression tree	BA fraction	Section 5.2.2.3
	Extensive livestock farmer	Classification tree	Regression tree	BA fraction	Section 5.2.2.3
Pasture management	Intensive livestock farmer	Classification tree	Constant	N/A	Section 5.2.2.3
	Conservationist	Classification tree	Linear model	BA fraction	None
	Hunter gatherer	Classification tree	Linear model	BA fraction	None
	Managed forester	Classification tree	Constant	N/A	None
Pyrome management	State land manager	Classification tree	Regression tree	BA fraction	None

5.2.2.1 Crop field preparation

For crop field preparation, fallow length and therefore fire return period (FRP), is an important measure of the state and stability of a shifting cultivation system. FRP was much widely reported in DAFI (n = 263) than burned area fraction (n = 39) for swidden systems. Therefore, the dependent variable used for burned area modelling was FRP, which assumed to approximate the inverse of the burned area fraction.

5.2.2.2 Crop residue burning

Crop residue burning is a widespread practice amongst sedentary small-holder farmers (Chapter 3). This tendency was reflected in DAFI, in which just 29 of 297 crop residue burning records (10%) for arable small-holders were documented absences. As no meaningful relationships could be found between absence cases and independent variables, these absence cases were included in the single burned area model as burned area = 0. As a consequence, the resulting tree models for both subsistence-oriented and market-oriented smallholders each contained an output node where burned area fraction was < 0.1.

Conversely, in the case of intensive farming, residue burning was a comparatively sparse practice: 15 of 75 records were absence cases (20%) and only one case study reported a burned area fraction greater than 3%. Therefore, a fire tendency (Boolean) model was combined with a constant of 2.5% used to parameterise burned area. A value of 2.5% was chosen as it was the geometric mean of the data (2.47%); the geometric mean was used as the arithmetic mean was highly skewed by one case study where 85% of the cropland was burned in a sugarcane production system (McCarty et al., 2009).

5.2.2.3 Pasture management

Two adjustments to the default fire parameterisation process were made for pasture management fires. Firstly, as with intensive arable farmers' crop residue burning, a constant value was used for burned area calculations for intensive livestock farmers due to sparse data (n = 6) and, therefore, no meaningful relationships being found with predictor variables. Secondly, fire return period was used rather than burned area fraction to generate burned area maps for other AFTs owing to data availability.

Secondly, a more fundamental challenge was presented by the 'rangeland' land use class, which was a new inclusion in the CMIP6 land use & land cover data (Hurtt et al., 2020). In describing land use classes in the Hyde database v3.2 that were subsequently adopted by Hurtt et al., (2020), Goldewijk et al., (2017) define rangelands as extensively managed grazing lands comprising *'natural grasslands, shrublands, woodlands, wetlands, and deserts (which) grow primarily native vegetation'.* So, as rangelands occupy hugely differing biophysical niches, and in particular include arid and semi-arid regions, they could have greatly divergent livestock stocking levels and use of fire.

A top-down constraint was therefore applied to livestock farmers occupying rangeland land covers to account for this potential large variation. This constraint was calculated by summing the raw competitiveness scores of the 'active' rangeland AFTs (pastoralist, extensive and intensive livestock farmers). Where these values summed to less than 1, this was interpreted as a lack of competition for land – and hence less densely stocked semi-natural rangelands. The adjusted rangeland burned area was therefore:

$$rc = \min\left(1, \sum AFT_{rangeland}\right) \qquad (5.3)$$

$$BA_{rangeland} = BA_{livestock} * rc \qquad (5.4)$$

where $\sum AFT_{rangeland}$ is the sum of the un-normalised competitiveness scores for the three 'active' rangeland livestock farming AFTs, rc is the rangeland occupancy constraint, and BA is burned area. Abandoned rangeland was not directly included in this calculation as it does not represent 'active' rangeland use.

5.2.2.4 Pyrome management

Pyrome management was perhaps the most diverse fire use, involving four different AFTs – hunter gatherer, state land manager, conservationists, and managed forestry. Two adjustments were made to the default process for fire use parametrisation. Firstly, the global mean was used as a constant (0.01) for the managed forestry burned area fraction owing to a lack of data; fire use tendency (probability of use) was calculated according to the default method. Secondly, owing to a lack of quantification of burned area fraction for the hunter gatherer AFT using pyrome management fire (n = 1), available data for hunter gatherers were combined with those for conservationists. This was done as, increasingly, conservationists and indigenous peoples are working together on fire regime management in fire prone regions (e.g. Neale et al., 2019; Ansell et al., 2020).

5.2.2.5 Hunting and gathering

Fire use for hunting and gathering occurred across larger areas in grasslands and savannas (18.0% of land cover burned on average) than forests (6.7% of land cover burned). This in part reflects a difference in strategy between open hunting and gathering of non-timber forest products. As the simple land cover types used in DAFI could not be directly transplanted into JULES PFT types, a constraint based on the amount of tree cover in JULES PFT distribution was implemented. This was calculated as:

$$BA_{HG,t} = \widehat{BA}_{HG,t} * 1 - (0.5 * Treecover_t) \qquad (5.5)$$

where $\widehat{BA}_{HG,i}$is the burned area for hunting and gathering at time = t, and $Treecover$ is the fraction of the cell covered by JULES tree PFTs.

5.2.2.6 Vegetation clearance

Parameterisation of fire for clearance of primary vegetation was complicated by the planned coupling with the JULES-INFERNO DGVM. This is because JULES takes land cover inputs of managed anthropogenic areas directly from CMIP6 land cover inputs (Sellar et al., 2020). Further, to allow WHAM! to be implemented within future model intercomparison projects it should operate within these common protocols and frameworks. Therefore, rather than seeking to model change in land cover directly – for example through AFTs demand for land, the cost of converting forest to agricultural lands or the impact of environmental legislation – we instead used the vegetation transitions specified by the CMIP6 land cover data (Ma et al., 2020). Using these pre-defined land cover changes between simulated time steps, we calculate the portion of newly cleared land occupied by each anthropogenic fire regime, and on this basis calculate the fraction of cleared (deforested) area that would have involved fire use. Due to a sparsity of data, WHAM! uses anthropogenic fire regimes, rather than AFTs.

Further, as process that is frequently clandestine, vegetation clearance fire proved highly difficult to quantify in DAFI. Remote sensing data are widely available for the size of deforestation patches, but not for the specific amount of deforestation driven by differing actors and its relationship to fire (Chapter 3, Section 3.3.3.5). We therefore parameterise the ratio of deforested area to burned area for each AFR as free parameters; given the inherent resulting uncertainty, their impact on burned area is explored in model sensitivity analysis.

Initial values for these fire to deforestation ratios were sourced separately from DAFI data, using literature values as set out in Table 5.5. These are the r^2 values from linear regression models describing the relationship between fire and deforestation under more extensively managed (transitional) and intensively managed (industrial) conditions. The ratio between fire and deforestation was assumed to be 1.0 for the pre-industrial AFR as by definition this AFR does not use machinery for land management (Chapter 3, Section 3.2.1). Furthermore, none of the AFTs for the post-industrial AFR would clear primary vegetation for extractive land use systems and associated land cover types so there is no ratio for these AFTs.

Table 5.5: Ratio of burned area to total area of vegetation cleared used to parameterise vegetation clearance fire use. A ratio of 1.00 means all 100% of vegetation was cleared by fire use.

Anthropogenic fire regime	Ratio	Source
Pre-industrial	1.00	Ontological: the pre-industrial AFR does not make use of machinery
Transitional	0.84	Aragão et al., 2008
Industrial	0.31	van Marle et al., 2017
Post-industrial	N/A	No post-industrial AFTs cleared vegetation for extractive purposes

5.2.3 Top-down fire constraints on fire use

In addition to the fire-use-specific constraints described above, two global constraints were applied to all anthropogenic fire uses – i.e. the seven modes of anthropogenic fire use described in DAFI, including arson. These were introduced to capture the impact of constraints or restrictions on fire use that were not captured fully in DAFI due to sampling bias (Chapter 4, Section 4.2.2.3.1). These two constraints were a vegetation constraint, and a dominant anthropogenic fire regime (AFR) effect. The vegetation constraint corrected for the lack of DAFI case studies in deserts and other very arid environments (Chapter 4, Section 4.2.2.3.1). This is similar to the use of the fraction of absorbed photosynthetically active radiation (FAPAR) as a vegetation constraint in the SIMFIRE model – a simple and empirical biophysical fire model (Knorr et al., 2014). The AFR constraint was needed as DAFI under-sampled places where fire use was absent in more developed contexts (Chapter 4, Section 4.2.2.3.1). From a process perspective, it aimed to capture the impact of imitation in fire management amongst land users and the impact of legal and other social barriers that prevent restrict managed fire use where fire restriction has become the dominant management paradigm (Chapter 2, Section 2.2.3).

The vegetation constraint and its impact on burned area were calculated as:

$$VC_t = \begin{Bmatrix} 1 \;\; if \; soil_t \;\; \leq T_{soil} \\ 1 - soil_t \; otherwise \end{Bmatrix} \qquad (5.6)$$

$$BA_t = \widehat{BA}_t * VC_t \qquad (5.7)$$

where $soil_t$ is the bare soil fraction from JULES outputs at time = t; T_{soil} is a free parameter determining at what fractional coverage of soil in a cell the vegetation constraint should apply; VC_t is the vegetation constraint, and $\widehat{BA}_t$ and BA_t are raw burned area from bottom-up AFT calculations, and burned area adjusted for the vegetation constraint. Similarly, the dominant AFR constraint was applied in model cells where the intensive AFR had the largest coverage of the four AFRs in that cell. It was calculated as:

$$AFRC_t = \begin{Bmatrix} 1 \;\; if \; Industrial_t \;\; \leq T_{AFR} \\ 1 - Industrial_t \; otherwise \end{Bmatrix} \qquad (5.8)$$

$$BA_t = \widehat{BA}_t * AFRC_t \qquad (5.9)$$

where $Industrial_t$ is the fractional coverage of the Industrial AFR at time = t; T_{AFR} is a free parameter determining at what fractional coverage the constraint should apply; and $AFRC_t$ is the industrial AFR constraint. As a result of this process, the model gained two free parameters: the two critical thresholds at which the bare soil and dominant AFR constraints were applied. Methods for exploring the sensitivity of WHAM! outputs to its free parameters is explored in section 5.2.5.1.

5.2.4 Unmanaged fire outputs

5.2.4.1 Escaped fires

As with managed fire use, escaped fire parameterisations were derived from data in DAFI. The starting point was the calculation of a baseline escape rate (the fraction of managed fires that become wildfires; Chapter 3, Section 3.2.2.2) for each of the six managed fire types described in Section 5.2.2 above. DAFI also contains data on the degree of control measures applied during managed fire use as a 0-3 ordinal scale. These data were used to parameterise the degree to which a given AFT would attempt to control a given fire use in each cell. This fire control parameterisation was used to adjust the baseline escape rate. Initial analysis showed there was a clear divide in outcome between no or little control (i.e. 0 or 1) and moderate or intensive fire control (ie.2 or 3; Table 5.6) So, the 0-3 ordinal scale for fire control was reduced down to a Boolean scale: 0-1 were grouped as no substantive attempt to control, 2-3 grouped as a substantive attempt to control.

The result was in effect a Bernoulli random variable reflecting a meaningful attempt to control a given fire. This 'fire controlled?' variable was used, not to calculate the rate of fire escape with or without control measures, but rather *the ratio of escaped fires with control measures to those without*. This was because of the limited number of records in DAFI (n=3) that had reported values for all of a) number of fires per km^2 for a particular fire use, b) the relevant fire control measures for that fire use, and c) the rate of escaped fires. Therefore, rather than a number of *fires*, the number of DAFI *records* of successfully managed and escaped fires for each fire use was used to calculate the impact of fire control measures. The rate of escaped fire for each fire use type and fire control present/absent was calculated as:

$$escape_{rate_i} | \, control_i = \rho_i * {(\sum fire_{escape_i} \mid control_i)} \Big/ {\left(\sum fire_{escape_i} \middle| \, !\, control_i\right)} \quad (5.10)$$

$$escape_{rate_i} | \, !\, control_i = \rho_i * {(\sum fire_{escape_i} \mid !\, control_i)} \Big/ {\left(\sum fire_{escape_i} \middle| \, control_i\right)} \quad (5.11)$$

where ρ is the global mean rate of escape for each fire type, $fire_{escape_i}$ is the number of DAFI records for fire use i which describe escaped fire, and $control_i$ is a Bernoulli random variable representing the presence or absence of fire control measures.

Table 5.6: Impact of fire control behaviours on fire escape rate by two categories of fire use. Fire control is presented according to the ordinal scale adopted in DAFI: 0 represents no fire control, 1 indicates 'limited or adhoc measures', 2 represents 'moderate or traditional (TEK)', and 3 indicates industrialised or intensive fire control measures. The ordinal scale captures the difference between fire control (2-3) and no fire control (0-1), but further distinction is not justified quantitatively. Owing to limited data, the number of DAFI *records* is used to calculate rate of escape rather than numbers of *fires*.

Fire use types	Fire control (0-3)	Escape rate	Count
Crop residue, Crop field preparation & vegetation clearance	0	0.167	32
	1	0.197	88
	2	0.091	79
	3	ND	0
Pasture management & Hunter gatherer	0	0.088	57
	1	0.381	62
	2	0.026	38
	3	0	1
Pyrome management	0	ND	0
	1	0	17
	2	0.029	35
	3	0.004	513

Having calculated rates of escaped fire for each fire use given an attempt to control, and with no control, the next step was to develop a distribution model of the 'fire controlled?' variable. Analysis of DAFI demonstrates how regimes of fire governance and associated degree of fire control measures emerge through complex patterns of socio-economic and ecological factors (Chapter 3; Section 3.3.4). Therefore, rather than modelling the degree of fire control as a function of secondary variables such as HDI or ET, the modelled distribution of anthropogenic fire regimes (AFRs) in WHAM! were used as predictor variables.

As data were limited (e.g. n = 12 for hunter gatherer fire with control >=2), control measures for pasture fire and hunter gatherer fire were grouped together, as were crop residue, field preparation, and vegetation clearance. These two categories were identified through a simple (2-node) classification tree. Pyrome management was found to be controlled in almost all instances (548 of 565) and no impact was found of control on escape rate. Therefore, as a simplifying assumption, pyrome management fires were assumed not to escape. Finally, it was originally intended to include vegetation flammability (an output of INFERNO) as a predictor of fire escape, however it was found not to be associated with the rate of escaped fire during analysis. However, INFERNO's flammability calculations will still play a substantial role in the eventual coupled modelling of escaped fire by determining the *size* of wildfires started from escaped managed fire (Figure 5.1).

5.2.4.2 Arson

Arson was defined as fire used deliberately to harm persons or damage property. Fires caused through carelessness or callousness such as through untended campfires or cigarettes dropped from car windows were categorised as background or accidental ignitions (Chapter 3; section 3.3.4). As arson is intentional, the tendency of AFTs to use fire for arson was parameterised similarly to the managed fire types described in Section 5.2.2. However, as arson fires are lit to cause damage, they are not managed and cannot be considered to have an intended burned area in the same way as a pasture or crop residue fire. Therefore, rather than using burned fraction as the dependent variable in the burned area calculation, fires km^2 $year^{-1}$ was used.

Furthermore, similar to escaped fire, arson is frequently associated with landscape-level effects, particularly conflict between land users over tenure (Chapter 3; Section 3.3.3.7). Therefore, the modelled distribution of AFRs was again used as predictor variables. The impact of very inaccessible terrain such as deserts, the arctic tundras and rainforests with associated very low populations was not fully accounted for in initial model outputs. Therefore, in addition to constraints described in Section 5.2.3, to capture this effect, arson fires were multiplied by one minus the modelled unoccupied fraction.

5.2.4.3 Background fires

In addition to fire generated by humans for a specific purpose, WHAM! also models fires generated accidentally or incidentally by anthropogenic activities. These include sparks from cigarettes, forestry machinery, fire-arms during hunting, and from faulty powerlines and other anthropogenic infrastructure (Chapter 3; Section 3.3.4.1). It also includes fires used in urban areas for waste disposal that escape to become wildfires (e.g. Langer et al., 2017), as WHAM! does not explicitly parameterise the behaviour of urban residents who do not actively manage the land. Therefore, to capture this broad range of fire types, fire density data (fires km^{-2} yr^{-1}) were selected from DAFI where the recorded fire purpose was accidental or unknown, or covered *all* fires in the study area. A simple regression tree was then developed to project these globally. As the *burned area* from accidental fires will ultimately be calculated by JULES-INFERNO, the top-down constraints described in Section 5.2.3 were not applied to the background rate calculations.

5.2.5 Model sensitivity-exploration & evaluation

5.2.5.1 Model sensitivity exploration

Given the intention to couple WHAM! with the JULES-INFERNO, sensitivity analysis at this stage was conducted to explore and understand the model's behaviour rather than assess overall model uncertainty. Therefore, a simple single parameter perturbation approach was undertaken to understand model sensitivity to its free parameters. As principally an empirical model, WHAM! has only 6 free parameters (Table 5.7). Two of these relate to the two top-down fire constraints described in section 2.3; three relate to the rate of vegetation clearance fire, and the final parameter, theta, is a land system distribution parameter described in Chapter 4.

For Theta, the fuel fire threshold and AFR fire threshold, the range over which perturbations were conducted was the full range over which the parameter was likely to meaningfully alter model outputs. For example, as very few model cells had >0.8 fractional coverage of the industrial AFR once the AFR fire threshold reached this level it was likely to have no impact on model outputs. For the vegetation clearance fire parameters, the full range of values (0-1) was examined for the transitional and industrial AFR parameters, whilst ensuring that the transitional AFR parameter value was higher than the industrial AFR value. The range of free parameters used for sensitivity analysis is given in Table 5.7.

Table 5.7: WHAM! free parameters and ranges used during sensitivity analysis.

Variable	Model domain	Section	Parameter range	Use
Theta	Land system distribution	Chapter 4; Section 4.2.3.4	0-0.2	AFT competitiveness scores < Theta are set to 0.
Vegetation clearance fractions (x3)	AFT fire use	5.2.2.6	Preindustrial: 1 Transitional 0.5-1 Industrial 0-0.5	Fraction of vegetation clearance conducted using fire for each AFR
Fuel fire threshold	Top-down fire constraint	5.2.3	0-0.4	Fraction of bare soil coverage in a cell at which the fuel constraint is applied
AFR fire threshold	Top-down fire constraint	5.2.3	0.4-0.8	Fraction of cell coverage of industrial AFR at which it reduces overall fire use

5.2.5.2 Model evaluation

The land use engine of WHAM! was evaluated in Chapter 4 by comparison with a null (multinomial regression) model and with the Human Appropriation of Net Primary Production. Calculating burned area from unmanaged fires projected by WHAM! will require coupling with JULES-INFERNO. So, evaluation of model outputs in this Chapter focuses on managed fire only. Evaluation of unmanaged fire and fire suppression (extinguishing) outputs is conducted in Chapter 6 (Table 4A).

Evaluation of model outputs for managed fire was conducted in four ways. The first three were purely empirical evaluations, whilst the third adopts a pattern-oriented approach, an approach which seeks to evaluate the realism of model structure (Grimm and Railsback, 2012). Firstly, within sample performance of individual fire use models against their respective training data was assessed with r^2 (burned area) and AUC (tendency). These two metrics are standard measures of model predictive accuracy for regression (r^2) and classification (AUC) respectively (Steyerberg et al., 2010). Within sample performance is presented alongside the sub-models in section 5.3.1, whilst results for the remaining model evaluation methods are reported in section 5.3.4.

Secondly, model outputs for crop residue burning were compared against the recently released crop fire outputs from the Global Fire Emissions Database version 5 (GFED5; Hall et al., 2023). Similar to the first FIREMIP, this was done using data for the overlapping period of WHAM! historical runs and the MODIS-era of GFED5 (2001-2014; Rabin et al., 2018). Pearson's correlation coefficient between WHAM! outputs and GFED5 was calculated using a square-root transformation to account for the skewed distribution of burned area. To account for differences in underlying cropland distributions that are inputs to the GFED5 (the MODIS-derived MCD12Q1; Hall et al., 2023) and WHAM! (LUH2; Hurtt et al., 2020), correlations were also calculated for a rate of cropland burned per pixel.

Thirdly, such that model outputs for all modes of managed fire use could be evaluated, managed fire outputs were compared against unseen DAFI data – i.e. those that were not used during AFT parameterisation. For example, if fire return period was used to parameterise a particular AFT fire use, then it could be evaluated against unseen burned area % data from other case studies. Pearson's r (correlation coefficient) was used to assess performance. As noted in Chapter 3, small case studies in WHAM! tended to focus on niche areas of widespread anthropogenic fire use, so larger case studies may be more representative at landscape scale and above. Therefore, the correlation coefficient was calculated for WHAM! outputs against the raw unseen DAFI data, and for WHAM! outputs against DAFI case studies weighted by their geographic area. Weights were calculated as a fraction of the largest case study in the evaluation set; those without a reported area were assigned the median weight.

Finally, a pattern-oriented assessment was conducted by comparing the temporal trend in WHAM! outputs against the qualitative evaluation of temporal trend in fire use in the LIFE database of Smith et al., (2022). This assessment of temporal trend was not present in the DAFI data, and was not used to develop the model. Assessment of the temporal trend in WHAM! managed fire outputs should test whether AFT parameterisations are capturing 'structurally realistic' system dynamics (Gallagher et al., 2021). Unlike DAFI (Chapter 3), the LIFE database contains qualitative assessments of whether 'subsistence'- and 'market'- oriented fire uses were increasing or decreasing at a given location.

Comparison with the LIFE database was conducted at two scales. Firstly, it was assessed whether WHAM! reproduced the global finding of Smith et al., (2022), that subsistence-oriented fire had decreased whilst market-oriented fire had increased. Secondly, data were compared at a case-study level. Crop field preparation, pasture management and hunter gatherer fire uses were considered primarily subsistence-oriented; crop residue burning and vegetation clearance were considered primarily market-oriented; pyrome management was not classifiable as either. Given the LIFE database does not quantify the magnitude of change, the evaluation metric used was the proportion of WHAM! model runs that produced the same temporal trend as LIFE.

5.2.6 Model experiments

To assess and understand the model's outputs and behaviour, WHAM! was run annually across a historical period from 1990-2014. The rationale of this timeframe was driven by data availability. DAFI focused on 1990-2020, whilst 2014 represented the end of the CMIP6 historical run period. The same 100 bootstrap parameter sets used for the tree models driving distribution of LFS presented in Chapter 4 were used.

To explore the relationship between land cover, land use and fire management, two counterfactual experiments were run, and compared with a baseline historical run:

- LC90 (land cover 90) - in which land cover was held constant at 1990 levels; and
- LU90 (land use 90) – in which socio-economic forcing data (GDP, HDI, market access & population) were held constant at 1990 levels.

5.3 Results

5.3.1 Sub-model parameterisation and performance

5.3.1.1 AFT distribution

The performance of the four AFT distribution models is broadly in line with the distribution models for the Land-fire systems themselves (Chapter 4). The mean AUC for the AFT models was 0.766, compared with 0.812 for the LFS models. Furthermore, the variables driving the distribution of AFTs within an LFS was again broadly similar to the LFS – with socio-economic factors such as HDI, GDP and market access playing the dominant role, with a secondary role for biophysical factors (Figure 5.4). In the AFT distribution models, seven of nine nodes are occupied by economic variables, with two occupied by biophysical variables.

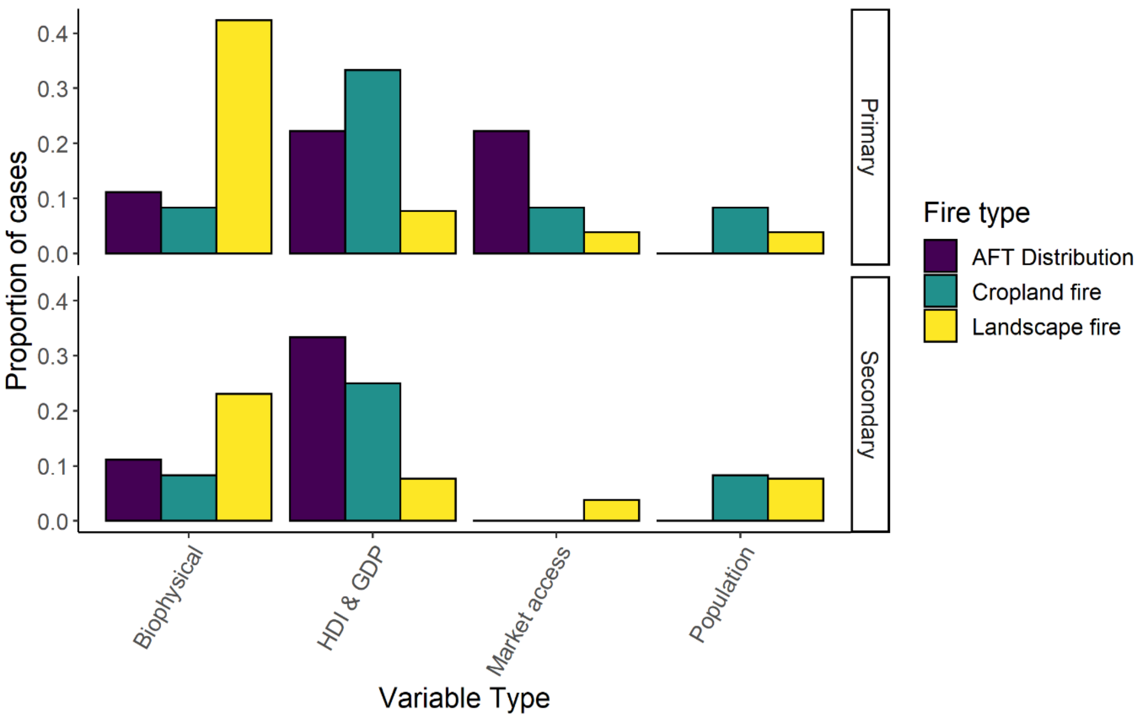


Figure 5.4: Distribution of predictor variables for AFT distribution models (n = 4), AFT parameterisations for cropland fire (n = 6) & landscape fire (n = 14). AFT parameterisations for managed fire showed a clear distinction between cropland fires, which were primarily driven by socio-economic factors, and landscape fire parameterisations, which tended towards biophysical variables.

5.3.1.2 AFT managed fire parameterisations

Sub-model performance is reasonably robust performance given prior knowledge gaps and areas of sparse data on anthropogenic fire use. The combined mean r^2 for the managed fire sub-models was 0.266, whilst the mean AUC for the tendency of an AFT to a given managed fire use was 0.772 (Table 5.8). However, within this broad picture there were clear areas where model performance was more reliable, and these corresponded closely with areas where underlying data were most robust.

Firstly, models performed better for sedentary forms of land use than for (semi-) nomadic systems such as shifting cultivation and pastoralists. The mean AUC and r^2 were 0.761 and 0.321 respectively for fire use by sedentary types against 0.623 (AUC) and 0.069 (r^2) for the nomadic types. This is largely a reflection of the underlying data used to build the models and is assessed further in the discussion. A possible outlier to this trend is hunting and gathering fire, for which a stronger model performance was observed (auc = 0.860, r^2 = 0.547). However, only 7 data points were available for developing the burned area model.

The variables used in the AFT fire use parameterisations show a distinct pattern between those for cropland fires (crop field preparation and crop residue burning) and landscape fires (pasture management, pyrome management and hunting and gathering; Figure 5.4). Cropland fire models are primarily parameterised with economic variables (8 of 12 cases), whilst landscape fires are parameterised chiefly with biophysical variables (17 of 26 cases). This pattern is in line with literature understanding of such processes. For example, crop residue burning is known to be driven by agricultural intensification (Kumar et al., 2015), whilst use of fire for hunting and gathering amongst indigenous communities is known to closely follow global biophysical gradients (Coughlan et al., 2018).

Table 5.8: Summary of performance of parameterisation of managed fire by mode of fire use and AFT. The performance of sub-models is stronger for AFTs associated with sedentary agricultural systems than for nomadic and semi-nomadic systems such as shifting cultivation, pastoralism.

Fire use	AFT	AUC	R^2
Crop field preparation	Shifting cultivation	0.602	0.064
Crop residue burning	SOSH	N/A	0.237
	MOSH	N/A	0.326
	Intensive arable farmer	0.723	N/A
Hunter gatherer	Hunter gatherer	0.860	0.547
Pasture management	Pastoralist	0.644	0.073
	Extensive livestock farmer	0.828	0.400
	Intensive livestock farmer	0.731	N/A
Pyrome management	Conservationist	0.736	0.400
	Hunter gatherer	0.788	0.304
	Managed forester	0.860	N/A
	State land manager	0.952	0.178
Overall	**All**	**0.772**	**0.266**

5.3.1.3 Unmanaged fire parameterisations

Performance of models of unmanaged fires from arson and accidental (background) sources follow a similar pattern to those of managed fire (Table 5.9). Namely, those practices that are legal (or not explicitly clandestine) perform well reasonably well (r^2 = 0.286), whilst arson (an illicit practice) is more challenging to model (r^2 = 0.042). The difference can be attributed to the challenge in gathering data on violent and clandestine fire use, whereas the background rate of accidental or unattributed fires is readily documented in government and fire service statistics. However, the presence of a strong theoretical framework for *why* fire is used as a weapon – namely as a form of resistance for those without access to other forms of redress (Scott, 1985) – enables a robust performance in predicting its presence (AUC = 0.800), but not the number of associated fires.

Finally, model performance for the distribution of fire control practices, which in turn inform the rate of escaped fire by mode of fire use, is strong, with mean AUC of 0.856. This can be considered good evidence that the AFRs are a useful means of describing anthropogenic fire regime management on a landscape.

Table 5.9: Summary of performance of parameterisation of un-managed fire by fire type (where relevant). Similarly, to managed fire, the performance of sub-models is stronger for unattributed or accidental background fires - than for the inherently illicit practice of arson. The strong performance of modelled AFR distribution in predicting the degree of fire control behaviour highlights their strength in capturing anthropogenic fire regime management.

Fire type	Escaped fire type(s)	AUC	R^2
Background fires	-	NA	0.286
Arson	-	0.800	0.042
Escaped fire (degree of fire control)	Hunter gatherer & pasture fire;	0.854	NA
	Crop residue & Crop field preparation & vegetation clearance	0.858	NA
	Pyrome management, arson	NA	NA

5.3.2 Overall model outputs

5.3.2.1 Managed fire

Over the study period of 1990-2014, the mean burned area from managed fire across the 100 bootstrapped model runs decreases from 431.9 to 419.1 Mega hectares (Mha; Figure 5.5). In percentage terms, this equates to a 3% decline. However, the size of the modelled decline is only 7.5% of the mean difference between the 5^{th} and 95^{th} percentiles of the 100 runs: the 5^{th} percentile of model runs in 1990 was 358.8 Mha, whilst the 95^{th} percentile in 2014 was 517.0 Mha. Contrastingly, treating each model run individually, managed burned area declined in 97 of 100 model runs. This indicates that whilst the overall extent of burned area is substantially impacted by data uncertainty, the trend of a slight temporal decline is not. Together these results indicate moderate confidence in a modelled decline in burned area from managed fire over the study period.

There is substantial heterogeneity in the trend amongst fire use types. The overall modelled decline in burned area is primarily due to a decrease in fire for pasture management, which declines 20.1% from 192.04 Mha to 153.7 Mha over 1990-2014 (Figure 5.6). This is complemented by declines in shifting cultivation (crop field preparation) fire (31.5 Mha to 26.9 Mha) and hunter gatherer fire (23.2 Mha to 19.4 Mha). By contrast, crop residue burning increases by 17.0% from 112.0 Mha to 131.1 Mha and pyrome management fire use increases by 15.7% from 69.5 Mha to 80.4 Mha. In absolute terms, vegetation clearance fires burn the smallest area (3.4-9.1 Mha), but in relative terms, their increase is much the largest (217%), highlighting this growing environmental challenge.

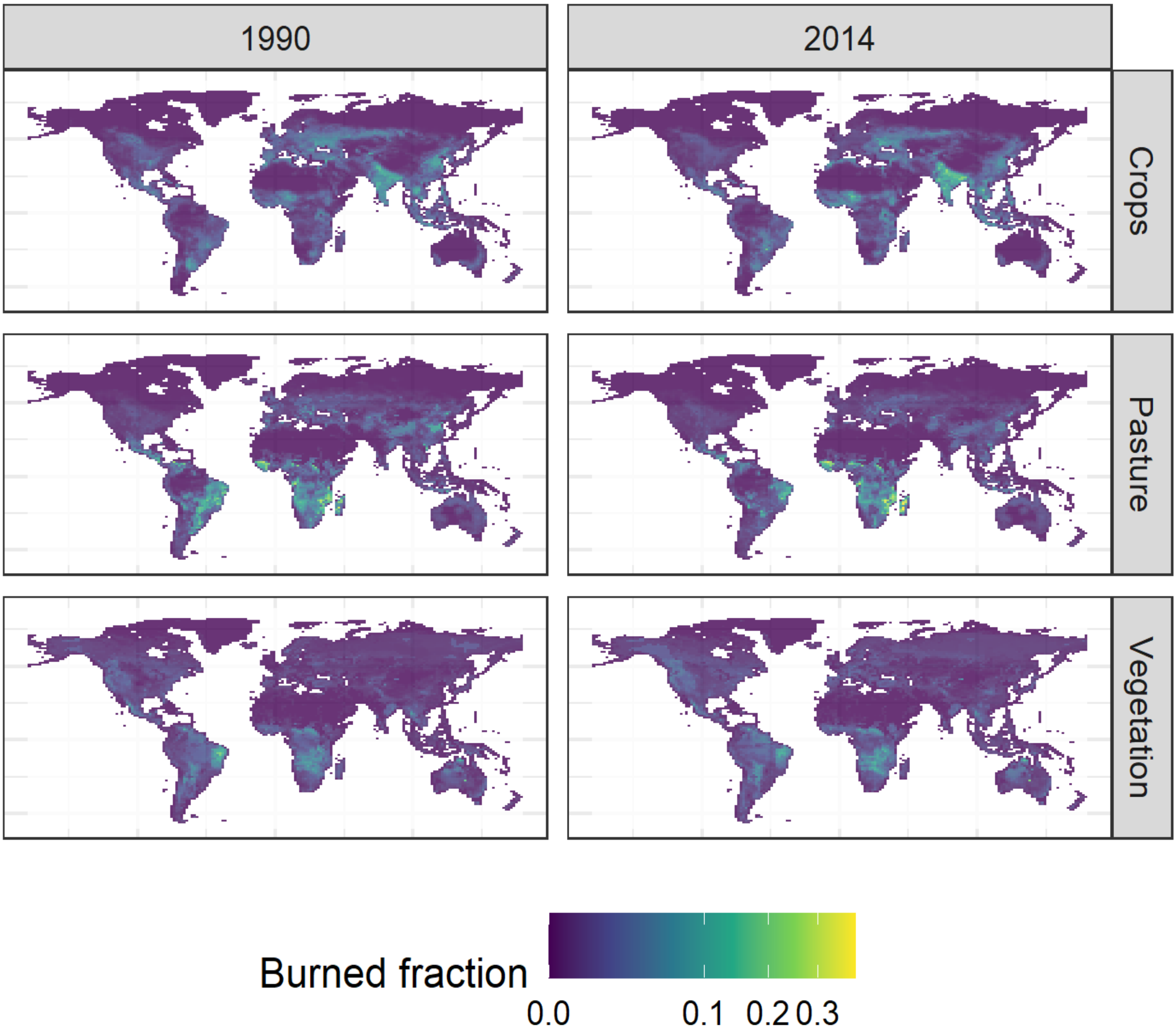


Figure 5.5: Global model outputs for managed fire in 1990 & 2014 grouped by land cover. Forestry and non-extractive fire use types are grouped together as this will be how they are interpreted by JULES-INFERNO (Section 5.1.2). Maps highlight the decline in pasture fires in South America. Conversely, pasture fire increases in Sub-Saharan Africa. Crop fires increase in Northern India, South Asia and modestly in South America, but decline elsewhere.

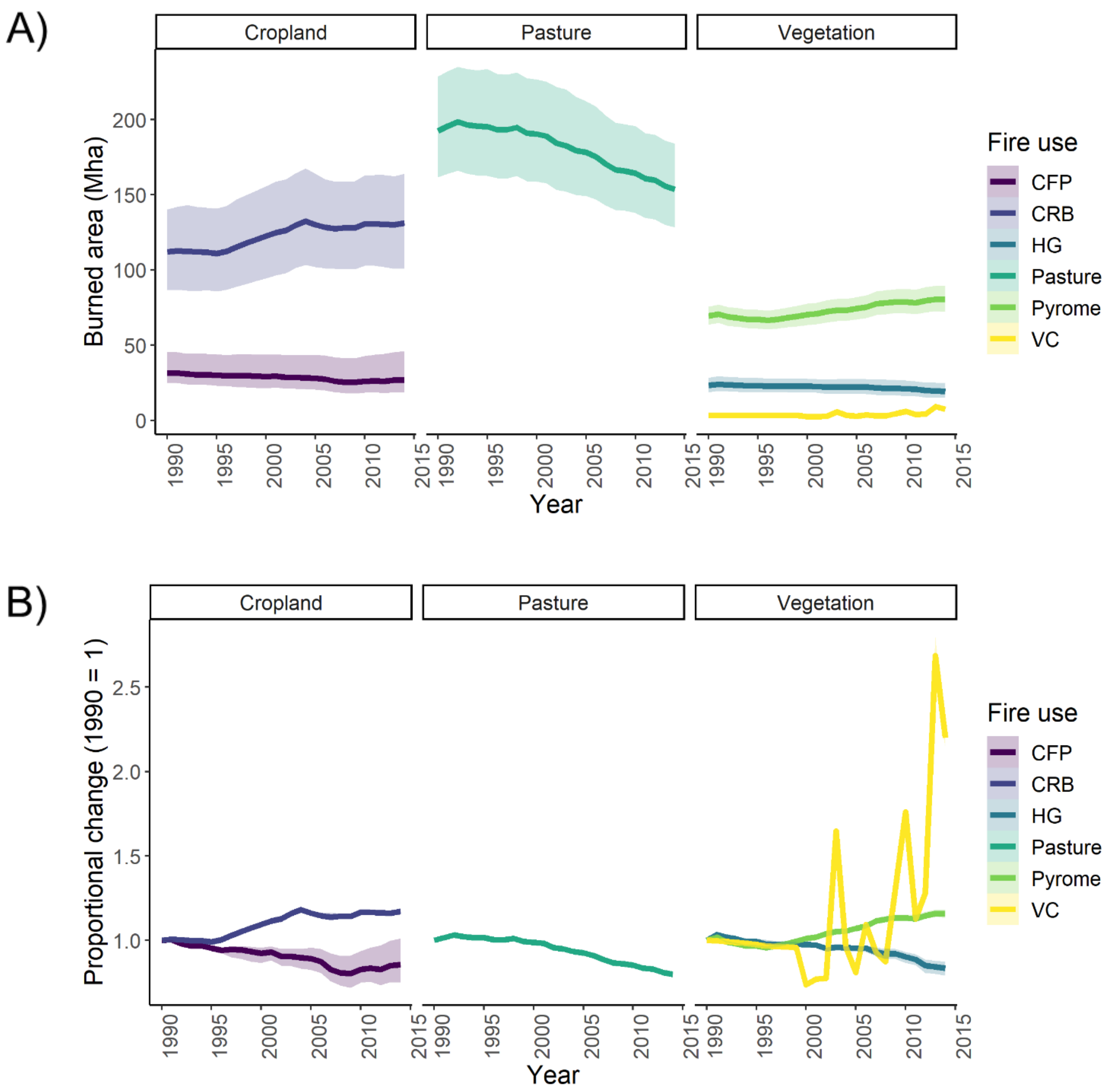


Figure 5.6: Trends in managed fire use grouped by land system. A) burned area, and B) relative change in burned area against a 1990 baseline. Shading shows the 5th and 95th percentiles of the distribution across model runs. Overall, pasture fire accounts for both the largest amount of fire and the largest absolute decline. In cropland systems, shifting cultivation fire and residue burning exhibit opposite trends. Whilst vegetation clearance fire is small in absolute terms, it shows the largest relative increase over the model period. Narrow uncertainty ranges around pasture fire and residue burning in B) are indicative of consistent proportional change in burned area, even with substantial uncertainty in absolute terms (A). Key: CFP = Crop field preparation, CRB = Crop residue burning, HG = Hunter gatherer, Pasture = Pasture management, Pyrome = Pyrome management, VC = Vegetation clearance.

Uncertainties in managed fire across the 100 model runs are greatest in absolute terms for fire types producing the largest amount of burned area (1σ, crop residue burning: 74.9 Mha, pasture management 78.2 Mha). The proportional change in burned area from these two fire use types is essentially unchanged across runs (Figure 5.6b), in spite of their variance in absolute burned area. Furthermore, in all 100 runs, pasture management and crop residue burning were found to decrease and increase respectively. As a proportion of their total burned area, uncertainty is greatest for nomadic land systems, shifting cultivation and hunter gatherer fire, reflecting the uncertainty in the underlying parametrisations (Figure 5.6b).

Beneath the global trends in managed fire, there is substantial spatial heterogeneity. At the continental scale, the decline in pasture management fire dominates in South America, declining from 55.31 Mha in 1990 to 25.15 Mha in 2014, leading to a decline in overall managed fire from 102.14 Mha to 71.12 Mha (Figure 5.7). By contrast, in Africa pasture fire *increases* by 6.51 Mha, whilst in Asia a decrease in pasture fire of 9.83 Mha is more than offset by a steep increase in crop residue burning of 18.17 Mha.

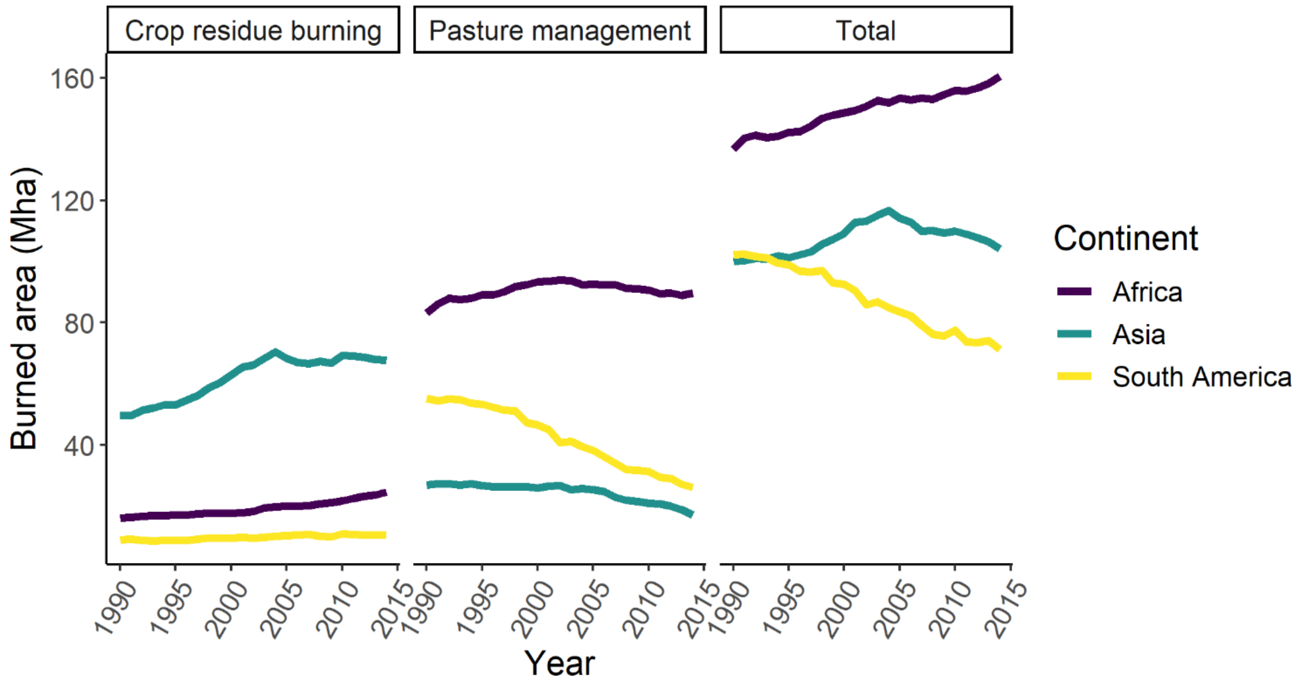


Figure 5.7: Managed fire burned area for the two dominant modes of managed fire & total managed fire for the three continents with largest burned area from managed fire. Whilst the global declining trend in pasture management fire is dominant in South America, in Africa, pasture and crop residue fires contribute to an overall slight increase. Similarly, in Asia, a decline in pasture fire is offset by a marked increase in crop residue fires.

5.3.2.2 Unmanaged fire

Whilst burned area from managed fire modestly decreases globally, the picture from unmanaged fire is mixed. Arson and accidental anthropogenic fires both increase (Figure 5.8), whilst the number of escaped fires is broadly static, even as burned area from managed fire decreases. The background rate of accidental fires increases 24.9% whilst the rate of arson increases 17.3%. However, until WHAM! is coupled with JULES-INFERNO, it will not be possible to deduce if this has led to increase in burned area from unmanaged anthropogenic fire. This consideration is particularly important given the distribution of unmanaged fires is seemingly clustered around wildland urban interface areas (Figure 5.8b), meaning that many of these ignitions will likely be extinguished through industrialised fire fighting (Chapter 3).

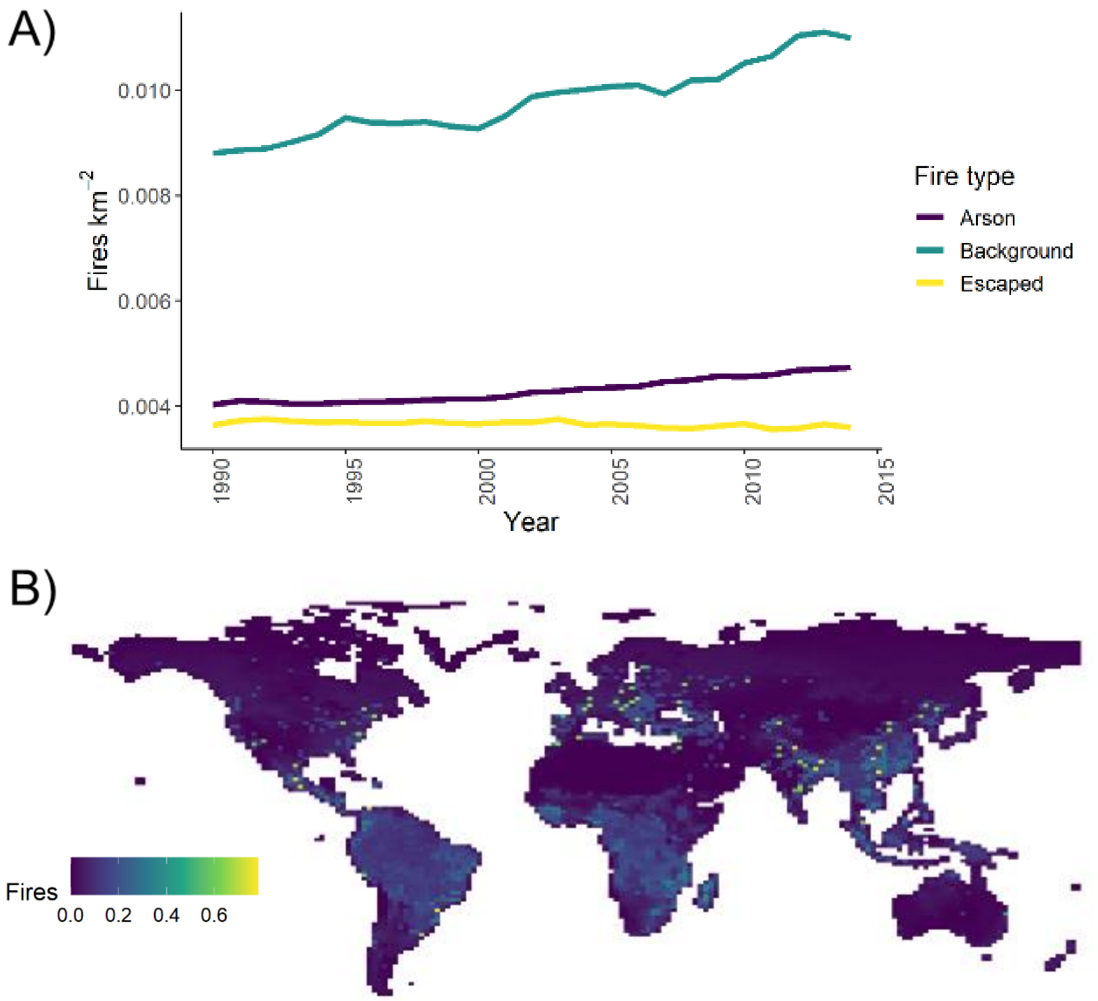


Figure 5.8: Unmanaged fire outputs as fires km^{-2}: A) temporal change and B) spatial distribution in 2014. The rate of unmanaged fires increases over the modelled period. However, this increase is clustered towards Wildland Urban Interface areas (visible as spatial anomalies in B), and the impact of this on burned area can only be assessed through coupling with JULES-INFERNO (Chapter 6).

5.3.3 Model experiments: drivers of anthropogenic fire use

Counterfactual experiments reveal divergent impacts between land cover change and changes in land use intensity. In the LC90 experiment, where land cover was held constant at 1990 levels, managed fire declines more starkly than in the baseline model run (431.94 to 388.74 Mha; Figure 5.9). By contrast, LU90 (land use intensity - and therefore AFR - constant at 1990 levels) leads to an *increase* in overall managed fire from 431.94 to 472.10 Mha.

The effects of land cover and land use intensity on human fire use have clear spatial patterns (Figure 5.9b). In LU90, the increase in fire over the baseline scenario is most evident in South America, further highlighting the importance of land use intensification in this continent as a driver for change in global fire regimes. Similar increases over the baseline are present in North-eastern China and Mexico. By contrast, in Northern India, the LU90 counterfactual leads to decreased fire against the baseline, indicating land use intensification has led to increased fire use. This finding fits previous analyses of crop residue burning in the Indo-Gangetic Plain (Kumar et al., 2015). The LC90 (constant land cover) counterfactual has more consistent global effects, with decreases in fire over the baseline observed in regions with large amounts of extensive livestock farming, Madagascar, the Guinean Savanah, and Southern Brazil.

Divergent trends between land use and land cover change on human fire use point to similarly divergent socio-economic drivers across differing modes of fire use (Figure 5.10). For example, at global scale, population density seems to be associated with increased crop residue burning ($r = 0.31$). By contrast, population density has a more ambiguous effect on pasture management fires ($r = -0.05$), the distribution of which is negatively correlated with socio-economic development (as measured by the HDI; $r = -0.47$).

Similarly, across the three continents with the highest rates of agricultural fire – Africa, Asia, and South America – increased HDI consistently leads to decreased fire use for pasture management (Figure 5.10b). However, in these three continents, increased HDI can lead to either increased *or* decreased fire use for crop residue burning: at a mean HDI of ~0.6 such fire use increases substantially in Asia, but decreases in South America. Possible process-based explanations of this trend are offered in the discussion (Section 5.4.1).

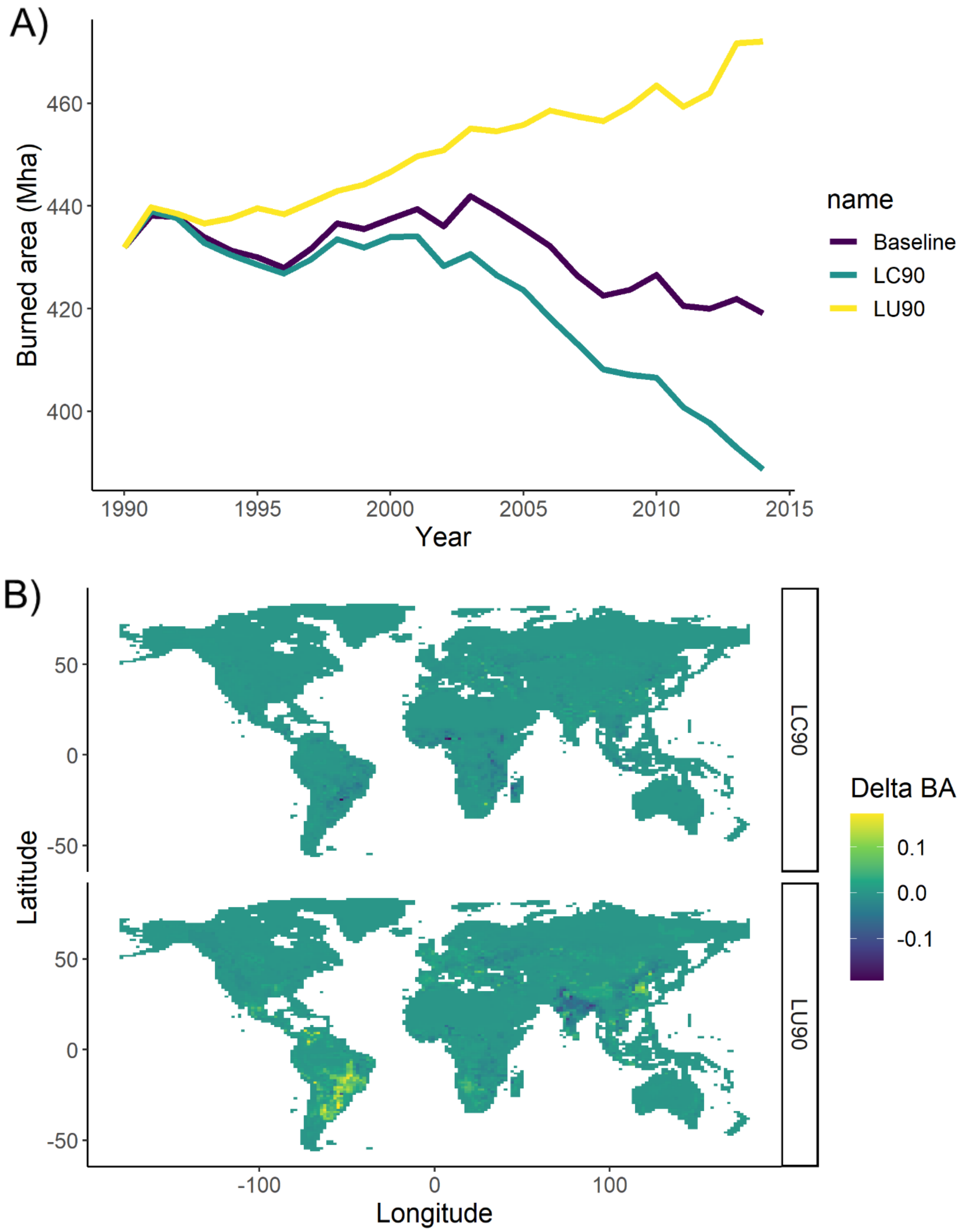


Figure 5.9: Global burned area from managed fire under counterfactual scenarios. A) global trends 1990-2014; B) change in burned area between counterfactual and baseline scenario in 2014. Key: LC90 – land cover held constant at 1990 levels; LU90 – land use intensity held constant at 1990 levels.

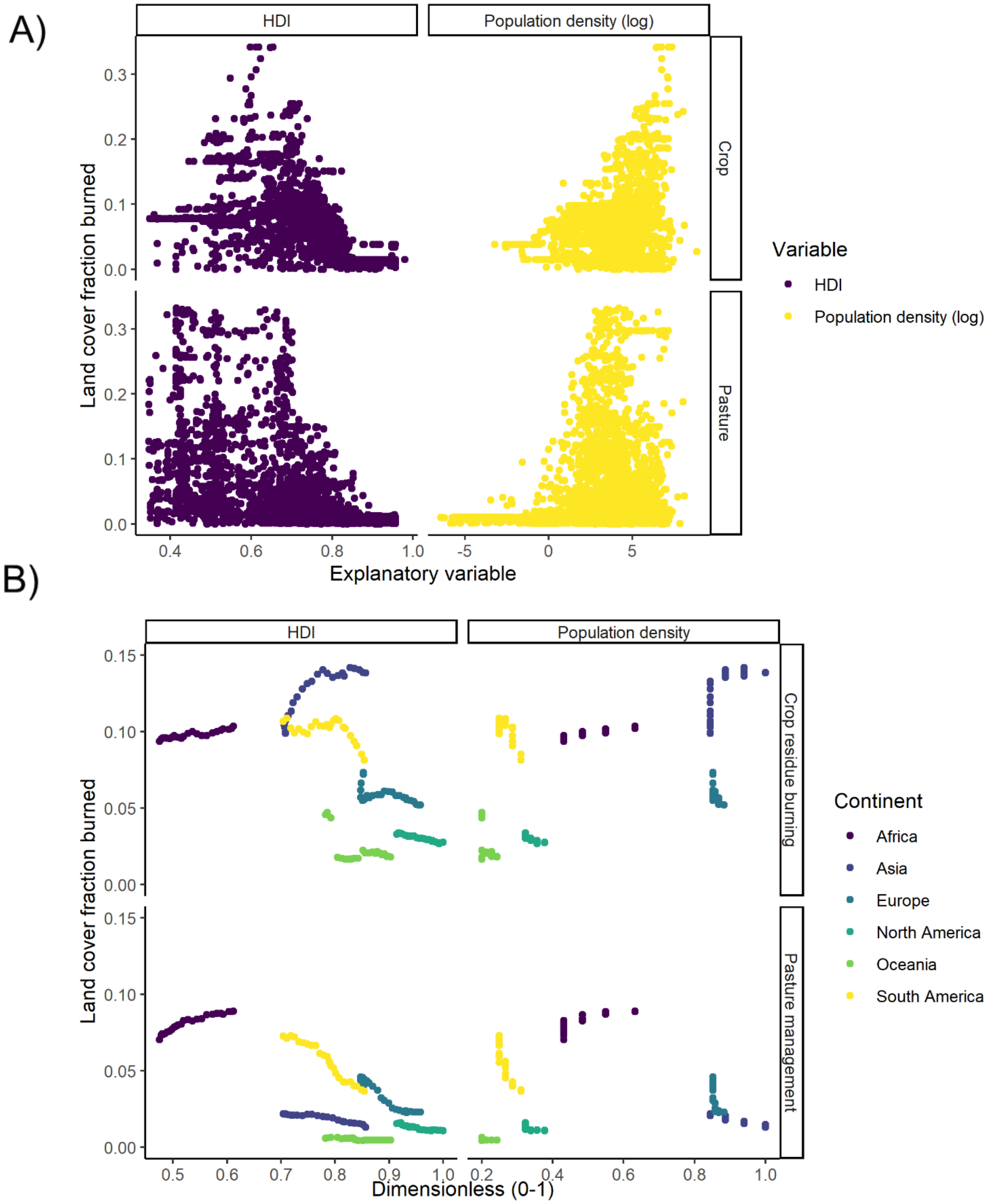


Figure 5.10: Drivers of managed burned area for the two modes of anthropogenic fire use with largest global burned area: A) by pixel, and B) by continental mean. Population density seemingly increases the rate of crop residue burning but has an unclear impact on pasture management. The human development index (HDI) has a similarly complex relationship with fire use: increased HDI consistently leads to decreased pasture fire but can lead to divergent outcomes for residue burning. Data are from baseline model runs in a) 2014 & b) 1990-2014.

5.3.3 Model sensitivity and evaluation

5.3.3.1 Model sensitivity

Parameter perturbation reveals a maximum sensitivity of global managed burned area outputs to a single parameter of ± 17.9 Mha - for the 'theta' threshold (Figure 5.11). This equates to a variation of ± 4.4% averaged over 1990-2014. Mean sensitivity across the three parameters that impact all managed fire types (the vegetation threshold, the dominant AFR threshold and the theta threshold) is ± 13.9 Mha (± 3.2%). The total range of global burned area outputs in the model sensitivity exploration is 42.9 Mha, which is just 19.5% of the data uncertainty defined by bootstrap resampling of DAFI (219.8 Mha; Section 5.3.2). Although full parameter uncertainty cannot be assessed before model coupling, it is likely that WHAM! is substantially more sensitive to uncertainties in its underlying data than to uncertainty in model free parameters.

A partial exception is found in the case of the vegetation clearance fire parameters. As a proportion of burned area from vegetation clearance alone, parameter perturbation leads to a total sensitivity of 41.7% (± 1.7 Mha). This occurs as the relationship between vegetation clearance and fire could not be defined empirically from DAFI data, and so is captured by free parameters.

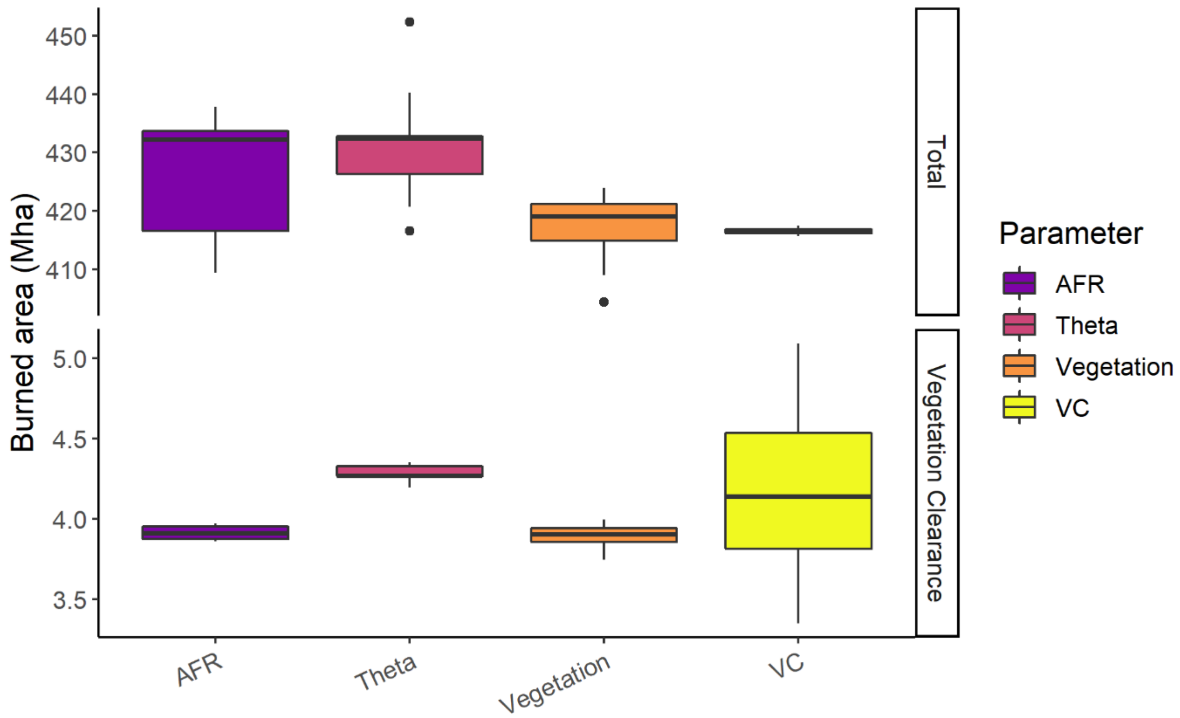


Figure 5.11: Sensitivity of model mean burned area from managed fire (1990-2014) from one parameter perturbations. The model is most sensitive overall to the Theta fire constraint, but the overall range of sensitivity is just +-4.4%. Key: AFR = Anthropogenic fire regime, Vegetation = Vegetation constraint, VC = Vegetation Clearance

5.3.3.2 Evaluation with GFED5 crop data

WHAM! outputs for crop residue burning are in broad agreement with GFED5 crop fires. Correlation (Pearson's r) is 0.673 for burned area per pixel, and 0.665 for rate of cropland burned per pixel. WHAM! crop residue outputs project more burning than GFED5, with a mean of 129.2Mha over the overlapping period (2001-2014) compared to 87.6Mha for GFED5. The main continent driving this disagreement is Asia: 67.8Mha in WHAM! compared to 31.2Mha in GFED5 (Figure 5.12; Figure 5.13).

Furthermore, WHAM! and GFED5 disagree on the trend of global crop fires, with WHAM! projecting a global increase and GFED5 suggesting a decrease (Figure 5.13). At the continental-scale, WHAM! and GFED5 agree on the trends in Europe and North America (decreasing). However, WHAM! projects gains in Asia (GFED decreasing), as well as increases in Africa (GFED decreasing). It should be noted that the trend in the GFED data shows close alignment with the trend in the overall fire regime (Figure 5.14), suggesting the crop fire signal may not be fully isolated. By contrast WHAM! exhibits contrasting trends between crop residue fires and other managed fires. For example, in South America and Asia, WHAM! residue fires and other managed fires are negatively correlated ($r = -0.91, -0.74$ respectively), whilst GFED5 outputs for crop fires and the overall regime are positively correlated in all cases.

Analysis of the difference between WHAM! and GFED rate of cropland burning demonstrates disagreement is most correlated to the transitional cropland anthropogenic fire regime ($r = 0.342$; Table 5.10). This mirrors the findings in Chapter 4, where the transitional anthropogenic fire regime was the greatest source of disagreement between WHAM! AFR outputs and HANPP efficiency (Chapter 4, Figure 4.10). Furthermore, the disagreement between temporal trend in HANPP efficiency and AFR outputs was greatest in Nothern India, South and Eastern China – which aligns with disagreements between WHAM! and GFED5 crop fires. The distribution of rice also plays a role – with errors weakly correlated to its distribution ($r = 0.087$).

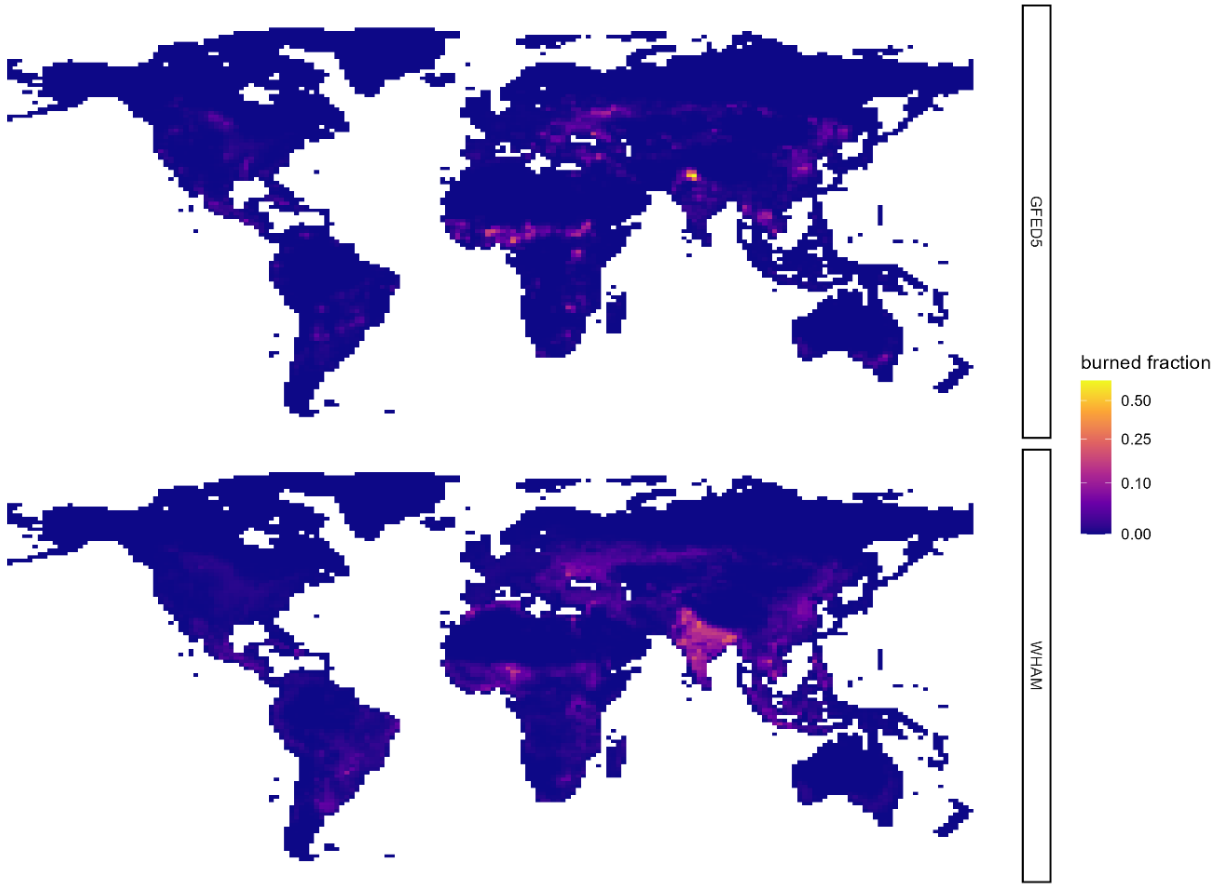


Figure 5.12: Comparison of WHAM! crop residue burning outputs and GFED5 crop fire outputs. Disagreements are evident in Northern India, mirroring the intercomparison of HANPP efficiency and WHAM! AFRs (Chapter 4, Figure 4.10).

Table 5.10: Correlation (r) of differences between WHAM! crop residue fires and GFED5 crop fires to crop types & WHAM! Anthropogenic fire regimes (pre-industrial, transition and industrial). 'Rate' gives the proportion of cropland burned per pixel, and 'Total' gives the fraction of the pixel burned from cropland fires. Only pixels with cropland present in the underlying distributions for WHAM! and MODIS were included; a square root transformation was applied.

	Cropland	Maize	Rice	Soybean	Wheat	Pre-industrial	Transition	Industrial
Rate	-0.069	-0.103	0.087	-0.096	-0.116	0.237	0.342	-0.237
Total	0.703	0.310	0.447	0.212	0.393	0.041	0.389	-0.269

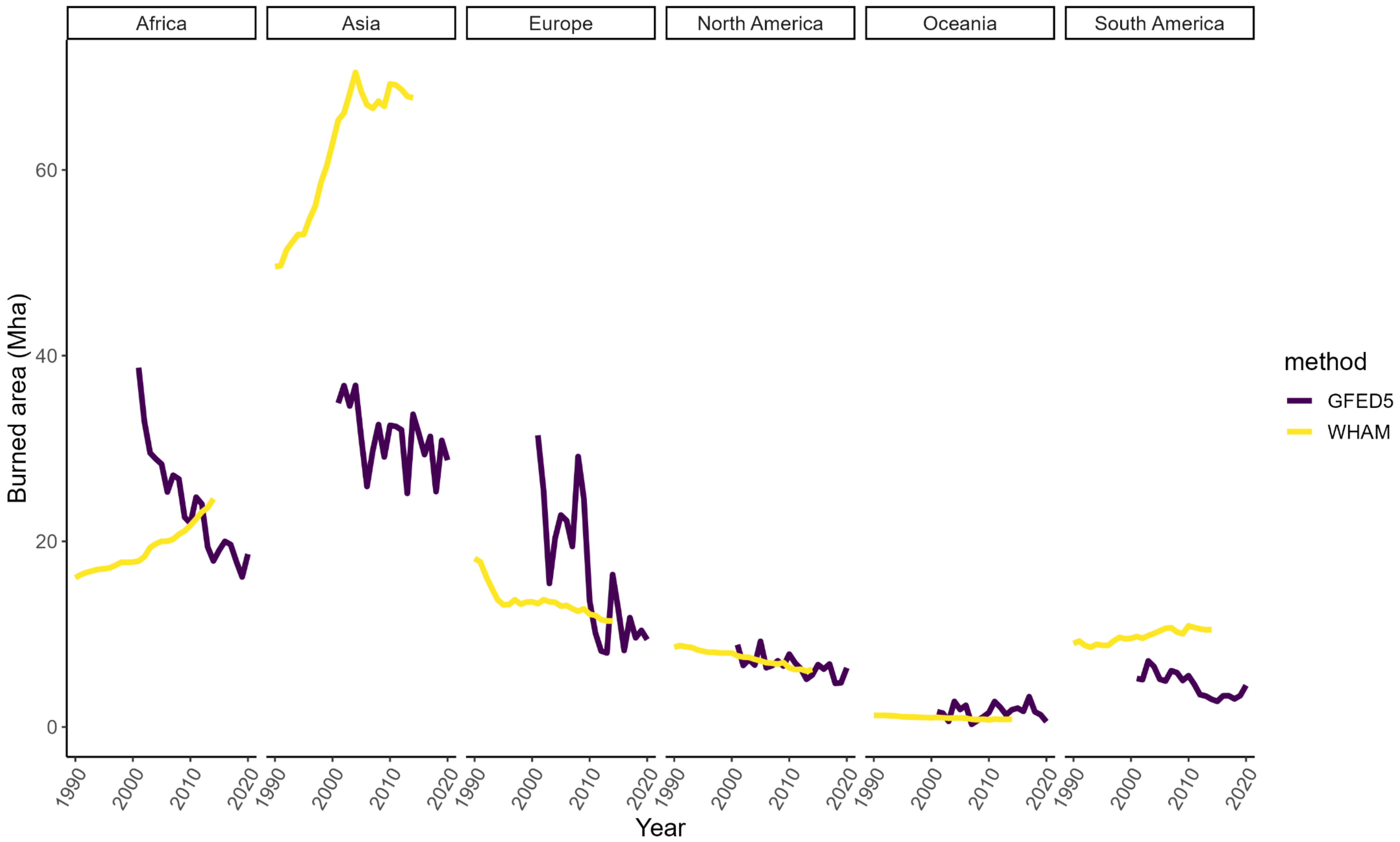


Figure 5.13: Continent-scale trends in burned area for WHAM! crop residue fires and GFED5 crop fires. As with the intercomparison with HANPP efficiency and WHAM! AFRs (Chapter 4), the biggest area of disagreement is in Asia.

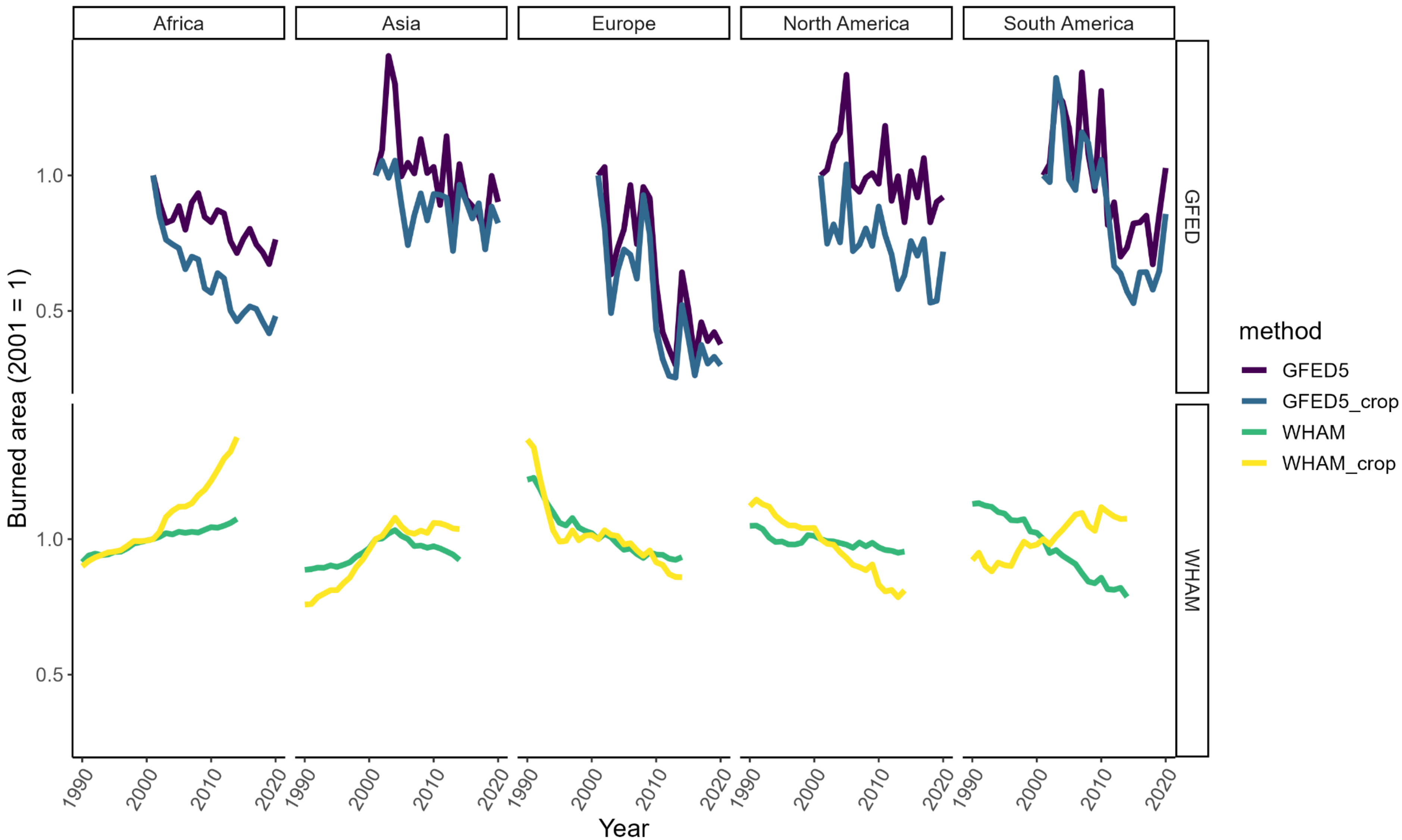


Figure 5.14: Comparison of WHAM! and GFED5 crop fires compared with the wider regime (other managed fires / all other GFED5 fires respectively). WHAM! is able to detect contrasting trends in fire uses, whilst in GFED5 the crop fire signal appears incompletely separated from the wider fire regime. Conversely, GFED5 is better able, in principle, to detect inter-annual variability.

5.3.3.3 Evaluation with unseen DAFI data

WHAM! reproduces the broad patterns of burned area in unseen DAFI data (Table 5.11). The ability of WHAM! to reproduce these data increases when they are weighted by case study area . WHAM! achieves a mean Pearson's r of 0.35 against unseen DAFI case study data. However, when case studies were weighted by their spatial extent, this rises to 0.71. Performance is best for those fire types which occupy most of the land surface: crop residue burning (r = 0.93) and pasture management fire (r = 0.81).

Further, WHAM! consistently produces lower burned area for a given case study location than is recorded in DAFI (Figure 5.15). DAFI by design comprises case studies from locations with active anthropogenic fire use, so it may well be a positive indicator that WHAM! reverts towards a lower overall mean across larger areas. This underestimation of fire by WHAM! is most acute in areas of crop residue burning, which can be very tightly packed in areas such as river deltas (e.g. Hong van 2014), in ways that cannot be captured at a coarse spatial resolution.

5.3.3.4 Evaluation with LIFE database

At global-scale, WHAM! and the LIFE database are in strong agreement (Table 5.12). All model runs for crop residue burning, pasture management and vegetation clearance agree with the global trend presented in LIFE. Agreement for crop field preparation is more modest (77/100 model runs in agreement). There is no agreement in global trends for hunting and gathering fire (11/100 model runs), this may be as data were limited for this parameterisation (Section 5.2.2.5).

By contrast, case-study level comparison yields a no-result. The mean number of model runs in agreement with the trend assessment in LIFE for individual fire types is 53 – essentially no better than a coin flip. Therefore, WHAM! and LIFE project the same trends at macro-scale, but at finer spatial resolution there is little agreement. This reiterates the finding of the comparison with unseen WHAM! data: that it is challenging to compare small-scale case studies and a coarse-scale model such as WHAM! This tension is unpacked further in the discussion.

Table 5.11: Correlation coefficient (r) of WHAM! outputs against unseen data in the DAFI database. WHAM! performance is greatly enhanced once the size of the case study was accounted for (size weighted).

Fire type	Equal weights	Size weighted
Crop field preparation	0.45	0.52
Crop residue burning	0.12	0.93
Pasture management	0.39	0.81
Vegetation clearance	0.43	0.56
Overall	0.35	0.71

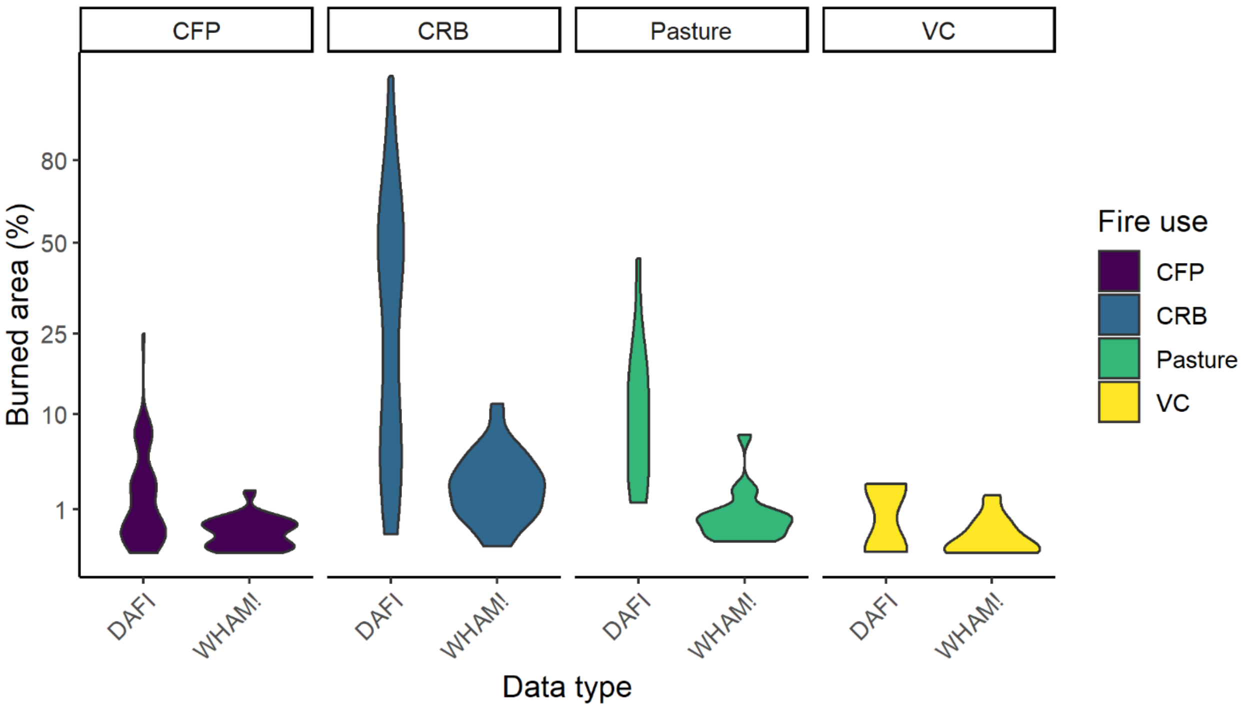


Figure 5.15: Violin plot comparing distributions of outputs from WHAM! and unseen data from the Database of Anthropogenic Fire Impacts (DAFI); WHAM! consistently projects lower burned area than DAFI, indicative of their greatly differing spatial resolution. Key: CFP = Crop field preparation, CRB = Crop residue burning, Pasture = Pasture management, VC = Vegetation clearance

Table 5.12: Change in WHAM! model runs compared to the assessment in the LIFE database of Smith et al., (2022): A) at global scale, and B) at case-study level. Numbers reflect the proportion of the 100 WHAM! runs which agree with the Smith et al., assessment. At global scale, there is robust agreement; however, at case study level less agreement is observed. Results are shown for fire types individually and for market / subsistence (Sub'ce) oriented types grouped together.

Key: CFP = Crop field preparation, CRB = Crop residue burning, HG = Hunter gatherer, Pasture = Pasture management, Pyrome = Pyrome management, VC = Vegetation clearance; (s) = primarily subsistence oriented, (m) = primarily market oriented.

A)

LIFE Database		**WHAM! outputs (proportion of model runs)**						
Orientation	**Status**	**CFP (s)**	**CRB (m)**	**HG (s)**	**Pasture (s)**	**VC (m)**	**Market (m)**	**Sub'ce (s)**
Market	Increasing	N/A	1	N/A	N/A	1	1	N/A
Subsistence	Decreasing	0.77	N/A	0.11	1	N/A	N/A	0.98

B)

LIFE Database		**WHAM! outputs (proportion of model runs)**						
Orientation	**Status**	**CFP (s)**	**CRB (m)**	**HG (s)**	**Pasture (s)**	**VC (m)**	**Market (m)**	**Sub'ce (s)**
Market	Decreasing	N/A	0.90	N/A	N/A	0.47	0.64	N/A
Market	Increasing	N/A	0.66	N/A	N/A	0.53	0.59	N/A
Subsistence	Decreasing	0.41	N/A	0.30	0.47	N/A	N/A	0.44
Subsistence	Increasing	0.61	N/A	0.41	0.48	N/A	N/A	0.43

5.4 Discussion

This chapter has presented WHAM!, the first global behavioural land system model of human-fire interactions. The ultimate intention is to couple WHAM! with the JULES-INFERNO DGVM. Here, WHAM! has been presented in standalone form. Therefore, discussion focuses on managed fire, which can be independently evaluated without input from JULES-INFERNO.

5.4.1 WHAM! outputs

WHAM! outputs suggest burned area from managed anthropogenic fire declined over the period 1990-2014, driven by a decline in fire use for pasture management, particularly in South America (Figure 5.7). By contrast, fires for crop residue disposal increase by 19.1 Mha. It is notable that cropland fires are typically the smallest anthropogenic fires (median = 0.5 ha; Chapter 3), which is far below the threshold at which MODIS can detect fires (21ha). With cropland fires excluded, WHAM! managed burned area declines by 24 Mha over the overlapping period with MODIS observations (2000-2014). The global projection of cropland fires in GFED5 is a novel Earth observation product - and *is itself a model* relying on empirical scaling factors to infer burned area per active fire detection in cropland areas (Hall et al., 2023). These scaling factors for rice burning were developed from fieldwork in Ukraine (Hall et al., 2021), in study locations where the mean field size of 40ha is much larger than the smallholder fields in Northern India (~1ha). Together, the modelled decrease in pasture fire alongside the ongoing challenge of detecting small cropland fires, supports the finding of Smith et al., (2022) that changing patterns of anthropogenic fire use may in part explain the observed decline in global burned area (Andela et al, 2017).

Counterfactual experiments and analysis of the drivers of pasture management fire in WHAM! demonstrate that the modelled decline in pasture fire is primarily due to land use intensification (as represented by HDI in Figure 5.10). This finding matches real-world observations. The rapid pace of land use intensification in South America was documented by (Silva et al., 2017), who attribute changes to the ‘telecoupled’ system of soybean production in response to increased Chinese demand for meat. Furthermore, this process of declining fire under increased land use intensity was explored in the field experiments of Cammelli et al., (2020), who find that increased capital investment discourages fire use as a management strategy: fire increasingly becomes a risk to machinery, irrigation, and other capital investments.

By contrast, the relationship between increasing societal development (represented by the Human Development Index) and cropland residue burning is more ambiguous (Figure 5.10). In Africa (HDI: 0.3-0.5), increased HDI seems to increase crop residue burning, consistent with land use intensification driving this practice. However, at intermediate (0.6-0.85) levels of HDI, increased development can have divergent impacts on residue burning. In Asia, increased HDI was associated with increased cropland burning, whereas the opposite was true in South America.

It is possible that farm size, and therefore the production system plays a role here: large soybean farmers in South America engaged in formal, legalised supply chains are somewhat likely to comply with fire use policies and wider environmental legislation (Soares-Filho et al., 2014; Villoria et al., 2022). By contrast, in Asia, and the Indo-Gangetic Plain in particular, high rural population and small average farm size entails that production is dominated by small-holder farms who frequently participate in ad-hoc or informal supply chains (Birthal et al., 2017), making environmental enforcement more challenging (Bhuvaneshwari et al., 2019; Liverpool-Tasie et al., 2020). In WHAM!, this difference is seemingly captured through the impact of population density, which features in the classification tree for the small-holder land fire system (Chapter 4).

Finally, WHAM! suggests that human fire use can either increase or decrease with increasing population, in ways that are highly specific to the rationale of the underlying land system and associated modes of fire use. At global scale, crop residue burning increases with population density, but there a weak negative relationship with pasture fire. Taken together, these complexities illustrate the shortcomings of relying on a single function of population density to capture the full spectrum of human-fire interactions globally (eq. 5.1).

5.4.2 WHAM! performance

WHAM! was developed from a meta-analysis of literature case studies and is driven by simple statistical tools (generalised linear models, classification and regression trees). Yet, WHAM! outputs, particularly for managed fire, are surprisingly complex (Figure 5.10). Relationships between predictor variables and burned area are not consistent across fire types, nor are they consistent across space. WHAM!'s capacity for capturing these complex dynamics stems from the use of AFRs: categorical variables that describe patterns of anthropogenic response to contrasting socio-ecological environments across different land use systems.

For example, the AFRs prove valuable in modelling emergent phenomena on the landscape. Both arson and fire control behaviours emerge from complex interactions between socio-ecological factors (Chapter 3). For example, in the case of fire control behaviours, these include the impact of market forces on, and the degree of capital investment in an agricultural system (Cammelli et al., 2020), cultural traditions of fire use and associated ecological knowledge (Seijo et al., 2015), political attitudes towards agricultural fire use – particularly the presence of bans (Bilbao et al., 2019), the degree of flammable vegetation surrounding agricultural regions (Cano-Crespo et al., 2015), and the value land users place on vegetation outside of the immediate parcel of land intended to be burned (Chokkalingam et al., 2005; Tacconi et al., 2006). Using the AFRs directly in models of arson and fire control behaviours results in high predictive accuracy (AUC >= 0.8) for the degree of control applied to managed fire use and for the presence of arson due to land tenure conflict (Table 5.9). This direct use of AFRs allows differing trends in escaped fire (due to a lack of control) and arson (due to land tenure conflict) to be modelled (Figure 5.8).

The effectiveness of the AFRs at capturing complex emergent processes highlights the value of working within a strong conceptual framework for empirically-based land system modelling, as it allows AFT-level and landscape-level effects to be modelled coherently. Similarly, the utility of the AFRs as a modelling tool in WHAM! highlights the limitation of modelling approaches that attempt to link socio-economic indicators directly to human fire use and management. The AFRs enable WHAM! to represent how categorical differences in land management practices can cause divergent outcomes for fire use and management given similar socio-economic forcing (Figure 5.10).

However, as with any categorisation or ontology of land system processes, the AFRs are imperfect. In particular, tying crop residue burning directly to the transitional fire regime seems to lead to overestimations in burning in comparison with the GFED5 crop fires product, particularly in Northern India. The rationale for this relationship is that fire use with limited community management and with damaging secondary consequences (in the case of residue burning primarily air quality; Lan et al., 2022) is an inherent part of the transition between community fire management (pre-industrial) and state-driven suppression (industrial). However, as indicated by the relationship of the AFR distribution and HANPP efficiency in Chapter 4, comparison of WHAM! and GFED5 indicates widespread residue burning need not be a necessary consequence of cropland intensification. Therefore, further understanding is needed to define the relationship between agricultural intensification - including double cropping, artificial fertiliser use, mechanisation - and crop residue burning. This issue is explored further in the overall thesis Discussion (Chapter 7, Section 7.3.2).

As with any empirical model, WHAM! is inherently limited by the strengths and weaknesses of its underlying data. There were three ways in which uncertainties in the underlying data came through in model outputs, which are discussed in turn below. The first of these was in the parameterisation of fire use in nomadic land use systems – particularly shifting cultivation and pastoralism. The low AUC and r^2 values for the underlying models is indicative of the difficulty of quantifying fire regimes produced by such land use systems. Shifting cultivation is challenging to study with remote sensing, not only as it is semi-nomadic, but also to the spectral signals produced (Jiang et al., 2022). This makes differentiating between fields and early-successional regrowth a substantial challenge (Heinimann et al., 2017). As a result, the fallow period was typically used from field studies as a proxy for fire return period. Yet this involved assumptions about the duration of cultivation after fallow; here assumed to be two years – yet this can vary from 1-5 years (e.g. Maharani et al., 2019).

Pastoralism is also challenging to study with remote sensing, due to the difficulty of tracking pastoralists location across the large areas over which they may migrate seasonally (Nelson et al., 2020). However, it should be noted that these fire uses represent a small amount of global burned area: burned area from shifting cultivation was just 26.9Mha, whilst migratory pastoralist fire accounted for just 18.4Mha of burned area in 2014. In the case of shifting cultivation, the use of fire is inherently limited by the need to fallow land to allow biomass to regrow sufficiently (Chapter 3, Section 3.3.3.1). Similarly, pastoralists often occupy arid, marginal environments, and fire use is limited by the availability of biomass to sustain fire (Chapter 3, Section 3.3.3.3). A further limitation to the representation of pastoralism is the use of LUH2 data for landcover, which has known issues with capturing the distribution of livestock systems in general and of rangelands in particular (Chini et al., 2021; Qiu et al., 2023). This is addressed further in Chapter 7, Section 7.3.2.

Secondly, the more structural sampling biases within DAFI (as noted in Chapter 4) led to the need for top-down constraints being applied to the bottom-up parameterisation of fire uses. These arose firstly as DAFI did not sample very arid environments (the vegetation constraint in WHAM!); and secondly, because DAFI under-sampled more developed contexts (the industrial AFR constraint in WHAM!). However, sensitivity analysis demonstrated that WHAM! is not overly sensitive to the resulting free parameters – with burned area outputs varying by a maximum of ±4.4%.

Furthermore, the most sensitive parameter was not for a top-down constraint, but the 'theta' parameter, which sets threshold at which a given AFR's competitiveness score was set to 0. This is somewhat analogous to the 'giving-up' parameter in the CRAFTY land system model, which determines when land becomes abandoned in that model (Murray-Rust et al., 2014). CRAFTY is highly sensitive to this parameter (Seo et al., 2018), which is an uncertain function of agent behaviour. This seems a strength of the empirical approach taken here, as it appears less reliant on uncertain abstraction.

A third fundamental issue arises from the coarse spatial resolution of WHAM! Specifically, the spatial resolution of WHAM! and DAFI case study data are substantially different: the median WHAM! cell is seven times larger than the median DAFI case study (24684 vs 3508 km^2). However, this is likely a large underestimate of the true discrepancy. Only 30% of case studies reporting pre-industrial AFRs quantified their study area, compared with 82% of industrial AFR case studies. The median reported study area is 36.5 times larger for industrial AFR case studies than for the pre-industrial AFR. This trend is likely even more acute for LIFE, as it focuses on 'livelihood fire' – which broadly corresponds to the pre-industrial and early transitional AFRs in WHAM! However, case study area is not recorded in LIFE. The consequence of this contrast in spatial resolution is seen in the evaluation of model outputs against unseen case study data.

In comparisons against both DAFI and LIFE, WHAM! outputs capture macro-scale trends, but struggle to capture trends at the case-study level (Table 5.12). In the case of the comparison against unseen DAFI data, this lack of case-study level agreement was partly deliberate. As a part of the managed burned area parameterisation, WHAM! multiplies together a probability of fire use (0-1), which was calculated with up-sampled absence cases, and a burned area fraction map (0-1), which was calculated against case study data (Figure 5.3). This directly leads to burned area predictions that are lower than the raw DAFI data. Justification for this decision is further seen in the comparison of crop fire outputs with GFED5 – as with additional DAFI case studies in transitioning agricultural systems without widespread residue burning WHAM! may have better constrained this relationship.

WHAM! therefore explicitly assumes that DAFI may bias locations with very active, or perhaps problematic fire use, as these may be most pertinent for study of human-fire interactions. This assumption can be justified as fire is often studied where it poses a risk to humans, whether from direct damage (e.g. Radeloff et al., 2018); air quality (e.g. Abdurrahman et al., 2020); or biodiversity loss through deforestation (e.g. Cardil et al., 2020). The extent to which this parameterisation holds true will only be fully clear after evaluation of the coupled WHAM!-INFERNO ensemble. Therefore, the very different spatial resolution of WHAM! and available evaluation data makes assessment of how far WHAM! captures the robust real-world drivers of changes in anthropogenic fire use challenging.

5.5 Conclusion

This chapter has presented WHAM!, the first global behavioural land system model of human-fire interactions. WHAM! is able to reproduce a decline in burned area from managed anthropogenic fire, driven by land use intensification and declining fire use for extensive livestock farming particularly in South America. By contrast, WHAM! projects an increase in fires for crop residue burning. Drivers of human fire use in WHAM! are divergent across differing fire use types and spatially heterogenous.

Evaluation of WHAM! is necessarily only partially possible without coupling to the JULES-INFERNO DGVM. However, WHAM! is able to reproduce broad patterns in unseen data, particularly for anthropogenic fire use within sedentary land use systems, which are easier to quantify using fine-scale remote sensing than nomadic practices. As such, WHAM! crop residue burning outputs show good coherence with the GFED5 crop fires product. Overall, the diversity of anthropogenic fire practices and their divergent spatiotemporal trends and drivers highlight a fundamental need for consideration of categorical differences in land use systems in studies and models of anthropogenic fire use and management.

Chapter 6

Applications of WHAM!: the socio-ecological dynamics of global fire regimes in the recent past and future scenarios

6.1 Introduction

The previous Chapter set out how WHAM! was parameterised to represent managed anthropogenic fires, unmanaged anthropogenic fires and fire control measures. This chapter now describes how this new model was applied to explore two aspects of global fire regimes. The first area of model application is the socio-ecological dynamics of fire regimes of the recent past, and the second is how anthropogenic fire use and management may evolve under different future scenarios of environmental and socioeconomic change.

To explore the first question, outputs from WHAM! were combined with those from the JULES-INFERNO DGVM in an offline model ensemble. Specifically, using the definitions of Robinson et al., (2018; Chapter 2, Section 2.3.4), the WHAM!-INFERNO ensemble is a 'periodic-prescribed' model coupling. This means that whilst outputs of the ensemble are dependent on interactions between models, information is transferred one-way between models (from WHAM! to INFERNO), and this does not occur at every model timestep.

This novel model combination enables several innovations in modelling of global fire regimes. For example, it allows the role of landscape fire – productive and managed vegetation fires (UNEP, 2022) – to be explored in a global and process-based simulation. Similarly, by representing the socio-economic processes that drive the starting of unmanaged anthropogenic fires, the WHAM!-INFERNO ensemble removes the need for a globally-uniform representation of human 'ignitions' (Chapter 2, Section 2.2.1). The combined WHAM!-INFERNO ensemble also allows the role of human fire management, in the form of the degree of control applied to managed fire and fire extinguishing, to be analysed alongside the biophysical drivers of uncontrolled fire spread.

Furthermore, whilst WHAM! focuses on representing anthropogenic agency, humans also have many indirect influences on fire regimes globally (Chapter 2). Multiple authors have argued that anthropogenic fragmentation of vegetation is a key process in global fire regimes (e.g. Archibald et al., 2012; Driscoll et al., 2021; Harrison et al., 2022). Fragmentation can have opposite effects across ecosystems – with logging and degradation increasing fire in otherwise fire-independent forests, and reduced fuel connectivity reducing burned area in grassland and savannah ecosystems (Rosan et al., 2022). Therefore, a simple representation of these two fragmentation processes is implemented.

A model calibration is then used to rule-out implausible parameter model values (McNeall et al., 2016) and identify a pareto-optimal model parameter space. Use of a pareto parameter space (as opposed to a single optimal parameter set) allows model performance against multiple evaluation metrics to be considered simultaneously (Dumedah et al., 2012; Koppa et al., 2019).

After calibration, pareto-optimal parameter sets are compared with a baseline version of INFERNO, to assess how far the WHAM!-INFERNO ensemble improves model capacity to reproduce observed patterns of fire globally. This baseline version of INFERNO is an offline implementation of INFERNO v1.0 as described in Mangeon et al., (2016). In contrast to the 'online' version of INFERNO, in which outputs are passed to INFERNO by JULES dynamically, the offline version uses a static set of outputs from JULES to force INFERNO's underlying equations.

An important and open question in fire science is why observed global burned area is decreasing, particularly in sub-Saharan Africa (Andela et al., 2017). Therefore, analysis of WHAM!-INFERNO outputs focuses on exploring drivers of inter-annual change at continental-scale, particularly in the overlapping period of historical model runs and the GFED5 observational record (2001-2014).

The second question that WHAM! is applied to is how anthropogenic fire use and management may evolve in the future under different scenarios of climatic and socioeconomic change. This is done through model runs for the Shared Socioeconomic Pathways (SSPs) for the period 2015 to 2100. The SSPs are common future scenarios of both environmental and socioeconomic change used in Model Intercomparison Projects, and to support IPCC assessment reports (O'Neill et al., 2017).

Methods for both model applications are described in Section 6.2, and their respective results in Section 6.3. The discussion (Section 6.4) draws out themes from both model applications to assess new insights into the socio-ecological dynamics of global fire regimes.

6.2 Methods

As noted in the Introduction, this chapter describes two applications of WHAM! The first, the development of the offline WHAM!-INFERNO model ensemble, is described in Sections 6.2.1 and 6.2.2. The structure of the model ensemble is shown in Figure 6.1. Section 6.2.3 describes calibration, evaluation and analysis of model outputs; this includes description of the offline implementation of INFERNO used for evaluation of WHAM!-INFERNO performance. Following this, the application of WHAM! for model experiments using the Shared Socioeconomic Pathways (SSPs) is described. Section 6.2.4 details the set-up of WHAM! model runs for the SSPs, including sourcing of forcing data. Section 6.2.5 then describes methods used to make new projections of variables for the SSPs, where no existing spatial projection could be located. Running the WHAM!-INFERNO ensemble for the SSPs is a medium-term ambition, and the steps required to deliver this are addressed in the discussion.

Code to run and analyse the combined WHAM!-INFERNO ensemble is written in R version 4.2.2 (R Core Team 2022), using the 'raster' library version 3.6-20 (Hijmans et al., 2023). Code and data to run and analyse outputs of the combined model are made available on Zenodo (Perkins et al., 2023b).

6.2.1 Combined model inputs

Both WHAM! and JULES-INFERNO standalone outputs were used as inputs to the combined model. WHAM! outputs used are those described in Chapter 5. Therefore, as with WHAM! standalone historical runs, historical runs of WHAM!-INFERNO span 1990 to 2014. JULES-INFERNO outputs are taken from the 6th Coupled Model Intercomparison Project (CMIP6; Wiltshire et al., 2020). Therefore, both models were run at a spatial resolution of 1.875° x 1.25°; WHAM! outputs are annual, whilst as per CMIP6, JULES-INFERNO outputs are aggregated monthly means. Therefore, the ensemble runs at a monthly timestep, and WHAM! outputs for a given year are assumed to be uniformly distributed across calendar months. Hence, the model ensemble is a '*periodic*' ensemble (*sensu* Robinson et al., 2018) – as WHAM! does not pass information at each of INFERNO's monthly timesteps. In addition to these two models, three sets of secondary data were used as inputs: lightning ground strikes, road density and anthropogenic land covers – cropland, pasture, rangeland and urban. These inputs are detailed below, and an overview is given in Table 6.1.

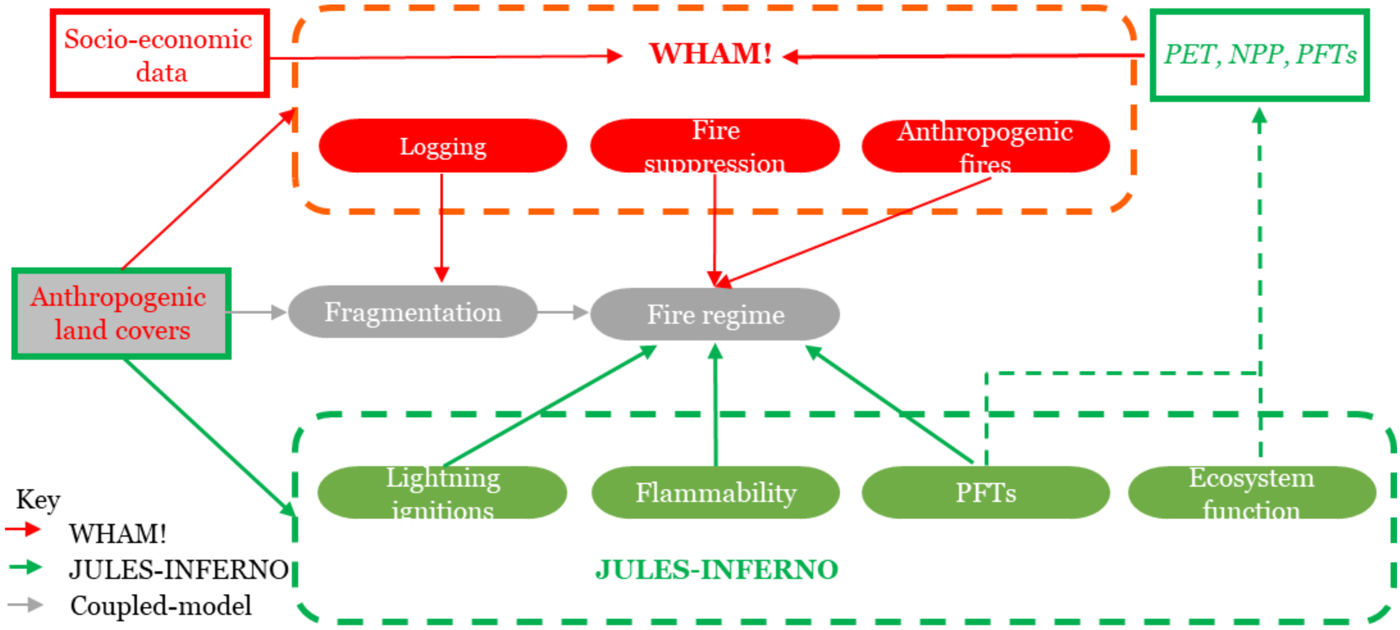


Figure 6.1: Processes represented in the WHAM!-INFERNO model ensemble. Full arrows denote dynamic model calculations, whilst dashed lines denote static exchange of information. Hence, ecological inputs to WHAM! (Potential Evapotranspiration (PET), Net Primary Production (NPP) and Plant Functional Types (PFTs) were taken from JULES-INFERNO model outputs and input to WHAM! as static variables prior to model ensemble calculations.

Table 6.1: Overview of inputs to the combined WHAM!-INFERNO ensemble model. PFT = plant functional type. Data inputs for lightning strikes, road density and anthropogenic land covers were rescaled to the resolution of WHAM!-INFERNO (1.875º x 1.25º). Differing temporal resolutions of inputs were reconciled as noted in Section 6.2.1.

Coupled model input	Source	Units	Temporal resolution
Managed burned area	WHAM!	Cell fraction (0-1)	Annual
Unmanaged anthropogenic fires	WHAM!	Number Count km^{-2}	Annual
Fire suppression	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)	Number km^{-2}	Fixed (single daily average)
Road density	Meijer et al., (2018)	m^2 km^{-2}	Annual
Anthropogenic land cover	Hurtt et al., (2020)	Cell fraction (0-1)	Annual

6.2.1.1 WHAM! inputs

WHAM! inputs to the coupled model comprised managed burned area as a fraction of each cell, unmanaged fires in km^{-2} yr^{-1} and the distribution of Anthropogenic Fire Regimes (pre-industrial, transitional, industrial and post-industrial). Anthropogenic fire regime outputs were used to calculate the intensity of fire extinguishing (or 'suppression'; 6.2.2.2 below). WHAM! inputs taken were the mean of the 100 runs described in Chapter 5.

6.2.1.2 JULES-INFERNO inputs

INFERNO calculates burned area from fires with two key components. The first is a mean global burned area per Plant Functional Type – a set of PFT-specific model free parameters. Model parameters for burned area per PFT were sourced from Burton et al., (2019); these are stated in km^{-2} $fire^{-1}$, but were converted to a fraction of the pixel burned per fire (0-1). The second component of INFERNO burned area calculations is flammability, which INFERNO calculates as a function of leaf Carbon and soil Carbon pools, vapour pressure, precipitation, and soil moisture (Mangeon et al., 2016). Flammability is therefore important in capturing the impact of both climate and spatial heterogeneity in vegetation on fire regimes. Flammability is calculated per Plant Functional Type in each grid box at each timestep. Flammability outputs, as well as the underlying distribution of plant functional types, were sourced from model runs conducted for CMIP6. Finally, as in JULES-INFERNO standalone (Mathison et al., 2023), numbers of lightning strikes were sourced from the Lightning Imaging Sensor—Optical Transient Detector (Christian et al., 2003).

6.2.2 Combining WHAM! and JULES-INFERNO

As noted in the introduction, the combined WHAM!-INFERNO model was a 'prescribed' model coupling (*sensu* Robinson et al., 2018). As such, whilst projections of global burned area depend on calculations involving outputs of both models, information transfer was one way: from WHAM! to INFERNO (as detailed in Section 6.2.2.1). This meant that, whilst socio-economic and biophysical drivers of fire regimes could be integrated on an annual timestep, inter-annual feedbacks could not be captured. For example, in a fully-coupled (or 'feedbacks' model ensemble per Robinson) ensemble, burned area would impact the distribution of plant functional types (PFTs), and hence ecosystem function such as net primary production, at the next timestep (Ford et al., 2021). However, in this model ensemble, PFT distributions were passed to WHAM! as a prescribed data input (Figure 6.1).

Therefore, for each model year, annual burned area from managed fire was taken directly from WHAM!, with $\frac{1}{12}$ assigned to each calendar month. For unmanaged fire, the number of anthropogenic fires (km^{-2} yr^{-1}) was taken from WHAM!, but their burned area was calculated by JULES-INFERNO. Therefore, description of model integration here focuses on calculating the burned area of unmanaged fires (Section 6.2.2.1), which also includes a new, empirical representation of fire extinguishing (or 'suppression'; Section 6.2.2.2). Finally, representation of landscape fragmentation is described in Section 2.2.3. A process flow, describing calculation of burned area from unmanaged fire is given in Figure 6.2.

6.2.2.1 Unmanaged fire

6.2.2.1.1 Number of fires

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

$$I_L = 7.7 \times Lightning \times (1 - Suppression) \quad (6.1)$$

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 was kept with two changes. Firstly, the suppression function was replaced with an empirically-defined representation of suppression intensity (Section 6.2.2.2); and secondly the empirically-defined linear scaling parameter (=7.7) was replaced with a free parameter (λ; Table 6.2) to allow re-calibration.

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

$$Fires_{UM} = Arson + Escaped + (1 - Suppression) * (Background + Lightning) \ (6.2)$$

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 km^{-2} yr^{-1} taken from WHAM! outputs, and $Lightning$ is the number of lightning fires calculated from mean daily ground strikes as in equation (6.1). For both arson and background fires, given limited available data for their parameterisation and the impossibility of prior evaluation of these standalone model outputs, free parameters were included to allow calibration. Escaped fires were not scaled with a free parameter for reasons of model coherence (Section 6.2.3).

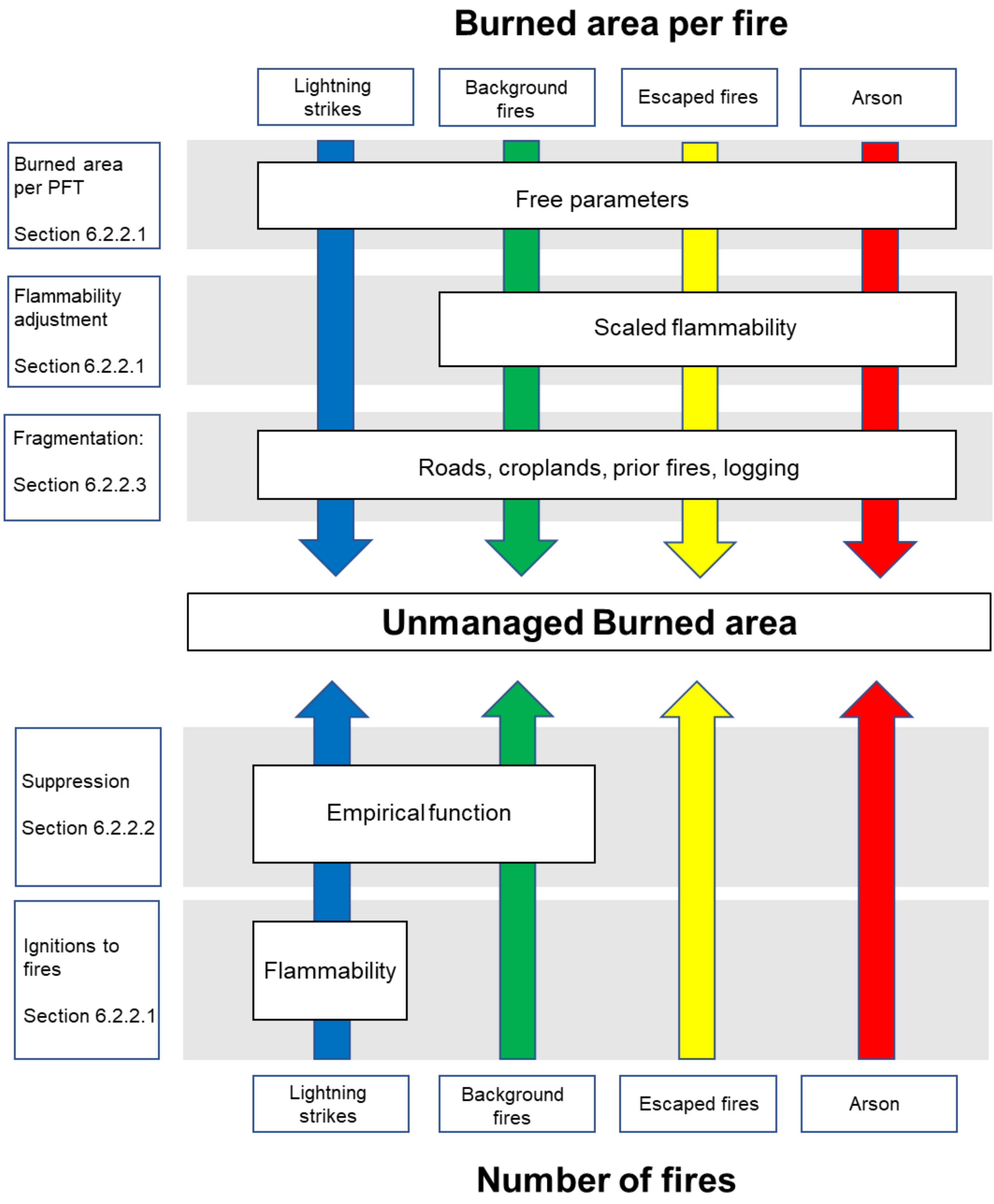


Figure 6.2: Calculation of burned area from unmanaged fires in the WHAM!-INFERNO coupled model.

The background rate of accidental and miscellaneous fires ($Background$) in (6.2) was intended to be parameterised using the empirically-derived representation in WHAM! (Chapter 5). However, this was found to agree poorly with observations. Therefore, a simple globally constant rate is 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. The poor performance of the empirical background rate function likely stemmed from the issues with collating this data in DAFI, including the skewed data sample for accidental and incidental fires, as well as differences in definitions and recording practices across countries and government agencies (Chapter 3).

Fire suppression (Section 6.2.2.2) 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, which drives WHAM!'s calculation of arson and escaped *fires*, numbers of *fires* are recorded, therefore by definition these have burned area > 0. As such, it is illogical to apply modelled suppression to them. By contrast, suppression is applied to the background rate. Firstly, where the background rate was calculated using a constant, clearly this did not account for the impact of suppression. When calculated empirically, more than 50% of accidental fires in DAFI were <1ha (mean 0.72ha; Chapter 3), often occurring in dense areas at the wildland urban interface (WUI). Therefore, suppression should be applied to capture the reality that WUI areas are typically home to intensive fire suppression (Elia et al., 2016; Mell et al., 2010).

6.2.2.1.2 Burned area per fire

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

$$Fires = Ignitions * Flammability \ (6.3)$$

In other words, both humans and lightning are conceptualised as producing ignitions, which may or may not become fires based on the flammability of the surrounding vegetation (Chapter 5, Figure 5.1). By contrast, because most human fires are started deliberately, WHAM! does not output numbers of *ignitions*, but numbers of *fires* directly (Figure 6.2). 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. This is because INFERNO calculates burned area per fire with a simple global mean value per Plant Functional Type. Therefore, simply removing flammability from the calculation and taking numbers of unmanaged fires from WHAM! was not a feasible option.

Table 6.2: Model free parameters, their initial, maximum and minimum values in WHAM!-INFERNO calibration There is no mean burned area for cropland PFTs as it was 0 in all cases, so replaced by outputs from WHAM! Given the substantial uncertainty around parameter values, values were sampled from a uniform distribution around an initial value. Grass and pasture burned area per PFT were given two values for C3 and C4 respectively.

Parameter name	**Parameter function**	**Initial value**	**Minimum value**	**Maximum value**
TreeBL_BA	Mean global BA for broadleaf trees	1.7	0.85	2.55
TreeNL_BA	Mean global BA for needleleaf trees	1.7	0.85	2.55
Grass_BA	Mean global BA for grass PFTs (C3 & C4)	3.2	1.6	4.8
Shrub_BA	Mean global BA for shrubs	3.2	1.6	4.8
Pasture_BA	Mean global BA for pasture PFTs (C3 & C4)	2.7	1.35	4.05
δ_1	Scaling managed burned area from pasture fires	1	0.5	1.5
δ_2	Scaling managed burned area from vegetation fires	1	0.5	1.5
σ_1	Scaling background ignitions	0.03	0.01	0.05
σ_2	Scaling arson fires	30	10	50
λ	Scaling parameter for lightning strikes	7.7	3.85	11.55
Φ	Harmonising model ontologies of ignitions & fires	700	350	900
Sup_PI	Rate of extinguished fires for the pre-industrial AFR	0	0	0.05
Sup_Trans	Rate of extinguished fires for the transitional AFR	0.05	0	0.1
Sup_Intense	Rate of extinguished fires for the industrial AFR	0.9	0.8	1
ρ	Scaling impact of road density on fire sizes	8.91	4.455	13.4
Λ	Impact of logging on burned area in forests	1.5	1	2.25
α	Threshold for impact of prior fires on fire size	0.2	0.1	0.4
β	Rate of decline in fire size due to prior fires	0.2	0.1	0.4

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

$$BA_{UM} = Fires_{UM} * \Phi * \sum_{PFT=1}^{PFT=n} PFT * Flammability_{PFT} * BA_{PFT} \quad (6.4)$$

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; $Flammability_{PFT}$ 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 parameters as a pixel fraction (0-1); and Φ is scaling factor reflecting the differing model ontologies of WHAM! and JULES-INFERNO.

6.2.2.2 Fire suppression

As noted above, fire suppression – here denoting the extinguishing of active fires – was included in WHAM!-INFERNO calculations to reduce numbers of background and lightning fires. Rather than being driven by individual Agent Functional Types (AFTs), the degree of suppression was treated as a meta-effect, emerging at landscape-level from interactions between AFTs and their respective fire management preferences (Cammelli and Angelsen, 2019; Cammelli et al., 2019). Therefore, similar to the level of fire-control and rate of arson, fire suppression was calculated as a function of distribution of Anthropogenic Fire Regimes (AFRs) in WHAM! outputs.

Fitting with WHAM!'s empirical design, suppression was modelled using data from DAFI (Chapter 3). AFR outputs from WHAM! were sampled at case study points with information on fire extinguishing. Fire extinguishing in WHAM! was recorded as with all aspects of suppression on a 0-3 ordinal scale: 0 = None, 1 = Limited, 2 = Moderate or Traditional, and 3 = Intensive. To convert this to a 0-1 dimensionless scaling factor as in the original INFERNO conception, numeric values on this same scale were adopted for each ordinal level (Table 6.2). This resulted in three free parameters for the levels from 1-3, whose values were determined during model calibration. The absence of fire suppression in DAFI was always treated as a suppression rate of 0. These three parameter values were then used as the dependent variable in a linear model using the modelled distribution of AFRs as independent variables.

6.2.2.3 Fragmentation

Alongside direct impacts of humans on fire regimes through starting and extinguishing fires, humans also impact fire regimes by fragmenting fuels (Jones et al., 2022). Fragmentation is particularly pertinent in flammable grassland and savannah ecosystems, in which these effects may be the dominant mode of anthropogenic influence on fire regimes by decreasing fire size (Archibald et al., 2013). Neither WHAM! nor INFERNO directly calculate the impact of landscape fragmentation on fire. However, Haas et al., (2021) demonstrate the efficacy of using global road density and cropland cover as proxies for vegetation fragmentation, and this finding was used to develop a simple parameterisation of fragmentation in the coupled model.

Fragmentation effects were applied 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. INFERNO to some degree considers the impacts of croplands on fire, by setting the global burned area for cropland PFTs to less than that of other vegetation (and in all cases <1km^2 fire^{-1}; Mangeon et al., 2016; Burton et al., 2019). As WHAM! now directly provides outputs for cropland fire, burned area per unmanaged fire in the coupled ensemble was set to 0. However, INFERNO does not account for the role of roads (and road density) in fragmenting landscapes and reducing fire size. Therefore, this was parameterised as a simple negative exponential function:

$$BA_{UM\_frag} = BA_{UM} * \left(1 - \frac{\ln(RD)}{\rho}\right) \quad (6.5)$$

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 scaling parameter, whose starting value was the maximum of the natural logarithm of road density over the historical period (Table 6.2).

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 et al., 2009). 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 became:

$$BA_{broadleaf} | \, logging = \; BA_{broadleaf} * \; \Lambda(Logging) \; (6.6)$$

where $BA_{broadleaf}$ is the fraction of a model pixel burned 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.

6.2.2.4 Combining managed and unmanaged fire

JULES-INFERNO typically runs at a timestep of between 30-60 seconds (Clark et al., 2010). This is required for the stability of model equations and has the advantage of capturing temporal fluctuations in vegetation flammability. As such, as fire burns in a landscape, INFERNO will increase the amount of bare soil in a given model pixel, which reduces fuel availability and the amount of area burned from subsequent fires until vegetation resprouts (Burton et al., 2019). However, as human decision-making regarding fire is not meaningful to represent at such fine temporal scales, managed fire is output at an annual timestep by WHAM! For these reasons, calculating the combined burned area of managed and unmanaged fires required an adjustment to account for the effect of preceding fires:

$$BA_{tot} = BA_{Managed} + BA_{UM} * \; \gamma \; (6.7)$$

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: firstly, because WHAM! has its own internal calculation for including fuel limitations in agent calculations; secondly, because WHAM! outputs are empirically grounded, derived from data that would include such limitations to a degree; and thirdly, because many anthropogenic fires are lit to deliberately reduce rates of unmanaged fire.

The γ function was calculated using a linear function after a threshold:

$$\gamma = \begin{cases} 1 \;\; if \; BA_{UM} \leq \alpha \\ \beta \quad otherwise \end{cases} \qquad (6.8)$$

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 behaviour observed by Archibald et al., (2013), who explored the impact of fragmentation on burned area in flammable ecosystems.

6.2.3 WHAM!-INFERNO Calibration

The calculations set out in Section 6.2.2 resulted in 18 free parameters, to which two additional parameters were added to account for uncertainty in WHAM! managed fire outputs, giving a final set of 20 free parameters (Table 6.2). Given that global and independent assessment of managed pasture fires and managed vegetation fires (comprising crop field preparation, hunting and gathering, pyrome management and vegetation clearance) was not possible, two additional free parameters were added reflecting the unexplored uncertainty in these WHAM! outputs. For this reason, no free parameter was added to the rate of escaped fires (Section 6.2.1): the rate of escaped fires is implicitly changed with the rate of managed burned area and altering both processes would have led to implausible rates of escaped fire in some model parameter sets.

Therefore, these 20 parameters formed the basis of a perturbed parameter ensemble. The overriding objective was to advance understanding of the socio-ecological drivers of fire regimes of the recent past. This was done in two stages, firstly by ruling out 'implausible' parameter sets, and then by identifying a set of pareto optimal parameter sets. This allowed, firstly, the evaluation of different model processes in capturing historical fire regimes, and secondly overall evaluation of the performance of the WHAM!-INFERNO ensemble.

A total of 10,000 parameter sets were sampled from the distributions given in Table 6.2 using a minimax latin hypercube sampling design (Carnell 2022). Such a sampling design allows for robust exploration of the model parameter space in a computationally efficient way (Florian, 1992). Parameter limits were defined as +-50% of the default values, except for the case of fire suppression, in which a narrower range could be defined ontologically from the ordinal scale in DAFI, and for logging, in which a flammability adjustment < 1 was not ontologically consistent.

Using the resulting parameter sets, 10,000 model runs were conducted of the WHAM!-INFERNO ensemble, each with a perturbed parameter set and compared with the recent GFED5 global burned area product (Chen et al., 2023). The comparison (Section 6.2.3.1) was calculated for each run, as well as global burned area, and correlation (r) with a square root transformation applied. These latter two metrics were those used in the FIREMIP (Teckentrup et al., 2019), and so were used to calculate the pareto optimal parameter space of the model (Section 6.2.3.2). Performance of the model in the pareto space was then compared against a baseline model – an offline version of the INFERNO DGVM (Section 6.2.3.3) – which was run using 10,000 parameter sets, sampled in a similar way.

6.2.3.1 Parameter implausibility assessment – history matching

History matching is the process of constraining the parameter space of a model using observations (Craig et al., 1997). A common method of constraining model parameter spaces is to 'rule out' implausible parameter combinations which result in model outputs that are inconsistent with observations (Williamson et al., 2013). Parameter sets that satisfy the implausibility criteria area are deemed 'not yet ruled out', whilst in the event an implausibility assessment returns a null parameter space, the model is assessed to be structurally unsuitable (Williamson et al., 2015). Model implausibility, the measure used to rule out parameter sets, is denoted as I and is calculated as:

$$I = \left| \frac{y_{mod} - y_{obs}}{\sqrt{({\sigma_{mod}}^2 + {\sigma_{obs}}^2)}} \right| \qquad (6.9)$$

where y_{mod} and y_{obs} are the model outputs and observations respectively; and σ_{mod} and σ_{obs} are the model and observational error, respectively. Applying the I calculation on a pixel-by-pixel basis requires complicated assessment of spatial and temporal autocorrelations, given the resulting non-independence of observations and model outputs (Edwards et al., 2014; Rougier and Beven, 2013). Furthermore, the goal of implausibility assessment here is not to optimise model parameter values, but rather to provide an initial filtering of parameter space. Therefore, the mean global burned area across 2001-2014 is used as the basis of the implausibility calculation.

As such, observational error can be measured directly and here has a value of 106.72 – the product of the mean annual burned area in the GFED5 product (802.5Mha) and the Dice similarity coefficient of Sentinel-2 burned area observations (0.133). The Dice similarity coefficient (also known as the F1-Score) is used as a measure of true positive detection accuracy in image processing (Lin et al., 2020). The resulting value (106.72Mha) is a conservative estimate of observational error: GFED5, against which model evaluation was conducted, does not use Sentinel-2 burned area directly, but rather scales MODIS burned area observations to Sentinel-2 and Landsat outputs using empirical relationships (Chen et al., 2023). Given this, the GFED5 product does not report observational error directly, and so the underlying Sentinel-2 error is used (Roteta et al., 2019).

Model error, also referred to as structural error, is used to define acceptable divergence from observations, and therefore must be set by the modeller in relation to the domain and research question (Ritz et al., 2015). Here, we adopt the error in the ensemble of models from the first Fire Model Intercomparison Project (FIREMIP; Teckentrup et al., 2019) – specifically the median disagreement between the mean burned area of the model ensemble and the three remote sensing products used for evaluation – 68.33Mha. The median was chosen to down-weight outlier outputs from the FIREMIP ensemble. The result was a denominator value for (6.9) of 126.72 - i.e. $\sqrt{(68.33^2 + 106.72^2)}$. Adopting a commonly-used and theoretically-robust threshold (Pukelsheim, 1994), parameter sets that produced an I value greater than 3 (equivalent to +-380.2Mha) were taken as implausible, with remaining parameter combinations taken as not ruled out yet (NROY).

6.2.3.2 Pareto optimal parameter space

From the set of parameters 'not ruled-out yet' by the implausibility assessment (hereafter NROY), the pareto optimal parameter sets were defined. Intuitively, pareto optimality refers to a trade-off space between multiple criteria in which one criteria cannot be further increased without reducing performance of another (Gupta et al., 1998). Or, more formally, a parameter space in which alternative sets are all 'non-dominated' against a set of objective functions (Lu et al., 2011). A parameter set $x_1 \in X$ is considered to dominate another parameter set $x_2 \in X$ if for a vector of objective functions $\vec{y}$ of length L:

$$\forall i \in \{1, 2 \dots L\}$$

$$y_i(x_1) \geq y_i(x_2) \quad (6.10)$$

Hence in a pareto parameter space, no parameter sets would satisfy the inequality in (6.10).

The strength of pareto-optimal parameter selection is that it enables simultaneous evaluation of performance against multiple model evaluation criteria (Koppa et al., 2019). However, the sets of parameter values returned by pareto optimisation are unlikely to be representative of the total model uncertainty - including data and structural uncertainty - that could be captured by Bayesian model calibration (Lu et al., 2017). Here, pareto optimisation is used for parameter selection rather than Bayesian calibration because of the early stage of model development; comprehensive model uncertainty quantification with Bayesian calibration may be more pertinent following future refinements to WHAM! (Chapter 7; Section 7.3).

Here, the two criteria chosen for assessing model performance were those used in the recent FIREMIP: global burned area and Pearson's r (Teckentrup et al., 2019). The global burned area metric used was simply the difference in Mha between WHAM!-INFERNO outputs and GFED5 global burned area (802.5Mha). For Pearson's r, as in Teckentrup et al., (2019), a square root transformation was applied to both GFED5 burned area and WHAM!-INFERNO outputs before calculating correlations. Therefore, model outputs for NROY parameter sets outside of the pareto parameter space contained more disagreement with observations (as measured by either global burned area or their pixel-based correlation) than those within the pareto parameter space. The parameters whose marginal distributions were significantly associated with whether a given parameter set was ruled-out, NROY or pareto optimal were then assessed using Kruskal-Wallis tests, using a Bonferroni correction on the resulting 20 p-values.

6.2.3.3 Comparison with baseline model – INFERNO v1.0 offline

To assess how far improved representation of anthropogenic influences on fire regimes increase WHAM!-INFERNO's capacity to reproduce burned area observations, outputs of the pareto parameter space were compared against a baseline model. This was an offline version of INFERNO v1.0 (Mangeon et al., 2016; hereafter 'the baseline model'), and followed that model's structure as closely as possible in an offline format. INFERNO v1.0 calculates burned area as:

$$BA_{INFERNO} = Ignitions * Suppression * Flammability * \widehat{BA}_{PFT} \quad (6.11)$$

Therefore, flammability and burned area per PFT ($\widehat{BA}_{PFT}$) were taken from the same sources as WHAM!-INFERNO (Table 6.1). Lightning ignitions were calculated using equation (6.1), whilst as in Mangeon et al., (2016), anthropogenic ignitions and suppression were calculated respectively as:

$$Ignitions_A = (6.8 * PD^{-0.6}) * (0.03 * PD) \ (6.12)$$

$$Supression = 1 - 7.7 * (0.05 + 0.9 * e^{-0.05*PD}) \ (6.13)$$

where $Ignitions_A$ are anthropogenic ignitions, and PD is population density. Two scaling factors {6.8, 7.7} in these equations were first defined by Pechony and Shindell (2009) to calibrate population density with observed fire counts in GFED v4. Therefore, these were replaced by free parameters to enable recalibration with the new GFED5 (Table 6.3).

Table 6.3: Free parameters in INFERNO v1.0 offline - a baseline model used for evaluation of performance of WHAM!-INFERNO. Parameters' initial, maximum and minimum values in model calibration are shown. The baseline model was run with and without the use of road density in constraining global fire sizes. Given the substantial uncertainty around parameter values, values were sampled from a uniform distribution around an initial value. Cropland, grass and pasture burned area per PFT were given two values for C3 and C4 respectively.

Parameter name	Parameter function	Initial value	Minimum value	Maximum value
TreeBL_BA	Mean global BA for broadleaf trees	1.7	0.85	2.55
TreeNL_BA	Mean global BA for needleleaf trees	1.7	0.85	2.55
Grass_BA	Mean global BA for grass PFTs (C3 & C4)	3.2	1.6	4.8
Shrub_BA	Mean global BA for shrubs	3.2	1.6	4.8
Pasture_BA	Mean global BA for pasture PFTs (C3 & C4)	2.7	1.35	4.05
Cropland_BA	Mean global BA for cropland PFTs (C3 & C4)	3.2	1.6	4.8
σ_1	Scaling parameter for anthropogenic ignitions	1	1.5	0.5
λ	Scaling parameter for lightning strikes	7.7	3.85	11.55
Sup	Suppression scaling parameter	1	0.5	1.5
ρ	Scaling impact of road density on fire sizes	8.91	4.455	13.4
α	Threshold for impact of prior fires on fire size	0.2	0.1	0.4
β	Rate of decline in fire size due to prior fires	0.2	0.1	0.4

Two further amendments were in the baseline model from INFERNO v1.0. Firstly, as in WHAM!-INFERNO, equations (6.7) and (6.8) were used to account for prior fires restricting the connectivity and availability of vegetation. The second change made was to run the baseline model with and without the road density adjustment (Section 6.2.2.3; equation 6.5) applied in WHAM!-INFERNO to the mean burned area per plant functional type parameters to represent fuel fragmentation. This final change was made to allow assessment of how far any improved performance in WHAM!-INFERNO was due to direct anthropogenic impacts on fire regimes (i.e. starting and extinguishing fires) vs indirect fragmentation effects. Furthermore, recent work on INFERNO has found including HDI as a representation of fire suppression improves the model's capacity to reproduce GFEDv4 (Teixeira et al., 2023) suggesting that improved representation of societal infrastructure developments might help to improve model outputs. Therefore, INFERNO v1.0 run offline *without* road density adjustment is named '*INFERNO_offline*' and INFERNO run offline with the road density adjustment is named '*INFERNO_road*'.

Outputs from the two versions of the baseline model were analysed in the same way to the WHAM!-INFERNO ensemble – firstly by ruling out implausible parameter combinations, and secondly by defining a pareto optimal parameter space. The performance of the baseline model(s) and WHAM!-INFERNO in this pareto space was then compared.

6.2.4 WHAM! future runs for the Shared Socio-economic Pathways

For WHAM! standalone model runs under the Shared Socio-economic Pathways (SSPs), WHAM! was set up as described in Chapter 5, with the addition of the suppression parameterisation, which was taken from the combined WHAM!-INFERNO model ensemble (Section 6.2.2.2). Where possible, forcing data for each of the SSPs were sourced from existing projections adopted by established model protocols (Table 6.4). These were the Coupled Model Intercomparison Project (CMIP; (Eyring et al., 2016), the Intersectoral Model Intercomparison Project (ISIMIP; (Rosenzweig et al., 2017) and the Scenario Modelling Intercomparison Project (ScenarioMIP; (O'Neill et al., 2016). Biophysical projections for the SSPs (potential evapotranspiration, net primary production) were taken from JULES outputs for CMIP6 model runs. The annual mean was taken from the monthly means provided in CMIP6 outputs. As primarily a diagnostic output, potential evapotranspiration was only available for SSP-RCP 1-2.6., 3-7.0 & 5-8.5. Therefore, these SSP-RCP combinations are those presented here.

Land cover data were taken from the LUH2 product, which was also used for CMIP6 (Hurtt et al., 2020). Population density projections were those of Jones and O'Neill, (2016) used for both ISIMIP and CMIP. Gridded GDP data were taken from the projections of Murakami et al., (2021) – these are spatially downscaled versions of the core GDP projections used for ScenarioMIP. However, no projections of the Human Development Index or Market Access for the SSPs could be located. Therefore, new projections of these were made, using the methods outlined in Section 6.2.5.

Table 6.4: Overview of forcing data used for WHAM! model runs under the Shared Socioeconomic Pathways (SSPs). Data were available at an annual timestep for all years, aside from topography, which was treated as a static variable.

Variable type	Variable name	Source
Socio economic	Population density	Jones & O'Neill 2016
	Gross Domestic Product	Murakami et al., 2021
	Human Development Index	Own projections
	Market access	Own projections
Land cover & Land use	Fractional land cover (anthropogenic)	Hurtt et al., (2020)
	Land cover composition (natural)	Wiltshire et al., (2020)
Biophysical	Potential evapotranspiration	Wiltshire et al., (2020)
	Ecosystem net primary production	Wiltshire et al., (2020)

6.2.5 New data projections

No spatial projections of the Human Development Index and Market Access for the SSPs could be located so new data projections were needed, as now described in this section. Outputs of these new projections are shared as Appendix 6A.

6.2.5.1 Human Development Index

The human development index (HDI) is comprised of three indices – 'a long and healthy life' (hereafter 'health index'), 'access to education' (hereafter 'education index'), and 'a decent standard of living' (hereafter 'economic index'; UNDP 2018). Each component index is scaled 0-1:

$$index_{i,j} = {(value_{i,j} - \min_i)}\Big/{(\max_i - \min_i)} \qquad (6.14)$$

where $index_{i,j}$ is the value for the ith index in the jth country; $value_{i,j}$ is a raw computed value of the given index, and $\max_i$ / $\min_i$ are prescribed thresholds. The overall index is then calculated as the geometric mean of the three components. The health index is based on life expectancy, with a maximum value of 85 years, and a minimum of 20. The education index is comprised of two parts: mean years of schooling (years of education participation in the adult population) the expected years of schooling (based on participation rates each year). Projections of the HDI were computed in two stages. Firstly, an annual, national-level projection was made for each country under each SSP from 2010-2100 (Section 6.2.5.1.1). Secondly, these national-level projections were downscaled to the sub-country units used by (Kummu et al., 2018) – for example USA or Brazilian States (!Section 2.5.1.2). The resulting polygon-based maps were rasterised to the resolution of JULES-INFERNO (1.875° x 1.25°; Section 6.2.5.1.3).

6.2.5.1.1 National-level projections

For the health index, national-level life expectancy data were sourced from the United Nations Department of Economic and Social Affairs (UNDESA 2022). These are presented as a baseline, 'high' and 'low' scenario. The SSP narratives of O'Neill et al. (2017) describe SSP1 & 5 as having high health investments, SSP2 as having 'medium' health investments and SSP3 & 4 as having 'low' health investments. Therefore, the UN baseline scenario was interpreted as reflecting SSP2, the 'low' scenario as reflecting SSPs 3&4, and the 'high' scenario as SSPs 1&5. These projections were then used to calculate the health index at national level using equation (6.14).

The basis of the national-level education index is the projection of education participation of KC & Lutz (2017). However, the HDI education index is based on years of schooling, whilst KC & Lutz give fractions of the adult population with primary, secondary and tertiary education. To convert these population fractions into estimated years of schooling per person, they were multiplied by the global values of mean years per stage of education presented by Potančoková et al., (2014). These are estimates that may vary substantially by country, and so were adjusted with a linear bias correction (KC & Lutz 2017). This adjustment was made using a linear model of predictions against historical data for 2019 (the most recent year with historical data available). For the education index, biases were different across global regions (ANOVA, $p < 2.2e^{-16}$), and therefore each sub-national unit's world bank region was used as a categorical predictor variable. After this bias correction, the predictions of the education index achieved $r^2 = 0.850$ for 2019 (Figure 6.3). Similarly, for the health index there were very slight differences between historical and calculations based on future projections, and after bias correction, predictions achieved $r^2 = 0.997$ for 2019.

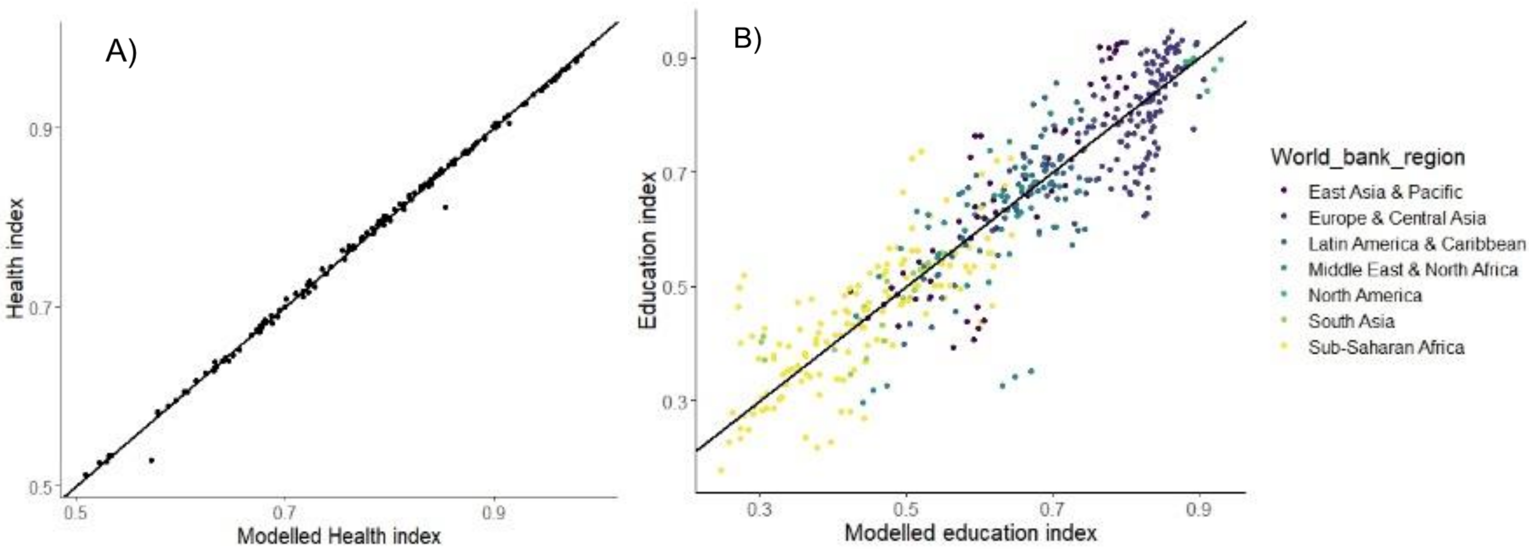


Figure 6.3: Linear bias correction of modelled HDI indices (A) health, B) education) against historical data for 2019. The health index is reproduced almost exactly ($r^2 = 0.997$). Two outliers in the health index are Syria and Yemen – sadly areas of current military conflict, leading to unreliable data. The education index has more uncertainty, though historical data is still reproduced effectively ($r^2 = 0.850$).

The third element of the HDI is the economic index, based on gross national income per person (GNI), was more challenging to model. Calculations of GNI were attempted by adjusting GDP per capita with the remittance projections of Beneviste et al., (2021). However, the education and health indices alone were better able to reproduce historical HDI data (r^2 = 0.810) than the three indices combined (r^2 = 0.516). Therefore, the economic projections were discarded and replaced with an economic weight based on the relationship of the combined health and education indices and historical data (Section 6.2.5.1.3).

6.2.5.1.2 Sub-national projections

Downscaling of projections from national to sub-national level was conducted by calculating a down-scaling factor for each sub-national unit based on historical data. The value of these downscaling factors was the ratio of the national-level index to the subnational unit in historical data. For years up to and including 2020, these values were calculated annually based on historical values. From 2021 onwards, the value at 2020 was taken as a baseline. This was then adjusted for each scenario using the SSP Gini coefficient projections of Rao et al., (2019). Therefore, for location *l*, for the *i*th index, in scenario *j* at time *t*, the downscaling factor would be:

$$DF_{l,i,j,t} = DF_{l,i,j,t-1} + \left(\left(DF_{l,i,j,t-1} - 1 \right) \times \frac{Gini_{l,j,t} - Gini_{l,j,t-1}}{Gini_{l,j,t-1}} \right) \quad (6.15)$$

were DF is the downscaling factor, and $Gini$ the national-level Gini coefficient value. In other words, a fractional decrease in the Gini inequality coefficient in a given country would lead to a proportional fractional decrease in the inequality in the sub-national distribution of a given index, and vice versa. This left 10 sets of down-scaling factors for each year (1990-2100) for each sub-national unit: one for each of the two projected indices for each of the five SSPs. These were multiplied by the national-level projection to give a sub-national scale projection of the health and education indices.

6.2.5.1.3 Combined index

The calculations described in Sections 6.2.5.1.1 and 6.2.5.1.2 resulted in spatial projections of the Health and Education indices of the HDI across the SSPs. Before combining the indices, the sub-national, polygon-based projections were rasterised to the resolution of JULES-INFERNO (1.875^o x 1.25^o), taking the mean value where multiple polygons occupied a given pixel. The resulting gridded projections were combined by taking their geometric mean. The resulting map was combined with projections of the natural logarithm of GDP per capita; these were calculated with the population projections of Jones & O'Neill (2016) and GDP projections of (Murakami et al., 2021). These two variables - health and education combined indices, and the natural logarithm of GDP - became linear predictors of the historical HDI values from 1990-2015. The resulting linear model achieved r^2 = 0.938 and was used to adjust future projections of the combined health and education indices.

6.2.5.2 Market Access

The original market access data of (Verburg et al., 2011) was constructed by calculating the travel time to the nearest city or port for each pixel on a 1km^2 grid. Replicating this calculation for the future, therefore, would not only require projections of city locations and sizes, but also of ports. Given that these have not be constructed, an alternate approach was adopted. A random forest regression was trained using the original data of Verburg et al., (2011) as a dependent variable, and secondary variables as independent variables (Table 6.5). This random forest regression achieved r^2 = 0.75, and was then used to calculate market access for the SSPs. To ensure coherence of model outputs, the projections of urban fraction, population density and GDP per capita used for the SSPs were the same as those used as direct forcing inputs to WHAM! for the SSP runs.

Table 6.5: Sources of predictor variables in the random forest model of market access.

Independent variable	Historical data source	SSP projection data source
Urban fraction	Hurtt et al., (2020)	Hurtt et al., (2020)
Population density	CIESIN (2017)	Jones & O'Neill 2016
Road density	Meijer et al., (2018)	Meijer et al., (2018)
GDP per capita	Kummu et al., (2018)	Murakami et al., (2021)

6.3 Results

Results first explore the parameter space of WHAM!-INFERNO and benchmark models. Secondly, they compare WHAM!-INFERNO's spatiotemporal projections with GFED5. In these two sections, results first present insights into the socio-ecological dynamics of global fire regimes before evaluating model performance. Thirdly, results are presented for SSP runs of WHAM! standalone.

6.3.1 Model calibration

6.3.1.1 Insights from the perturbed parameter ensemble

Of the 10,000 parameter sets examined, 1075 are ruled out by the implausibility assessment, leaving 8925 parameter sets as 'not yet ruled out' (NROY). Ruled out parameter sets overwhelmingly have too much burned area – just three ruled out runs have burned area less than the GFED5 record. The mean burned area of ruled out runs is 1305.8Mha compared to 906.1Mha for NROY runs. There are 10 parameters with significantly different means (at $p<0.0025$; i.e. 0.05 with Bonferroni correction) between the NROY and ruled out parameter sets (Table 6.6; Figure 6.4). All significantly different parameter sets serve to reduce burned area; the road density threshold parameter (ρ) and fires to ignitions (model ontology; Φ) scaling parameter have the absolute largest t-values (46.92, 38.65) respectively.

Table 6.6: Parameters with significantly different mean values between ruled out and NROY sets. Parameters whose t-test had p-values <0.0025 were included. The road density threshold parameter (ρ) has the largest t-value, where a lower value indicates an increased impact of road density on fire regimes.

Variable	Mean - NROY	Mean – ruled out	t-value
Grass_BA (C3)	3.32	3.57	-13.18
Grass_BA (C4)	3.29	3.64	-20.26
TreeBL_BA	1.63	1.69	-4.36
TreeNL_BA	1.63	1.67	-4.27
δ_2	1.03	1.09	-4.76
σ_1	0.029	0.033	-19.21
σ_2	30.43	28.56	8.33
λ	7.63	8.10	-6.36
Φ	635.11	766.01	-38.65
ρ	8.71	11.22	-46.91

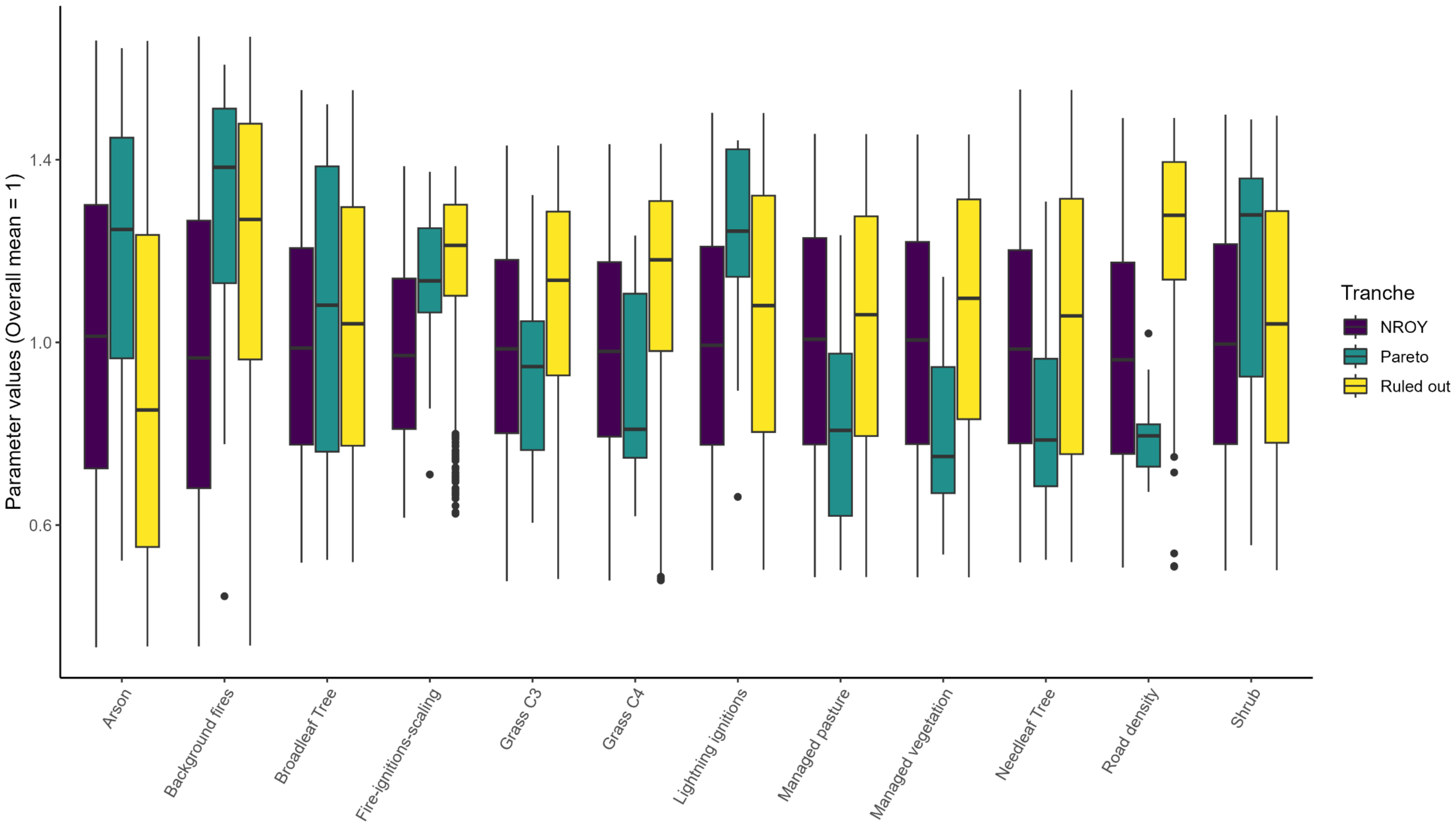


Figure 6.4: Parameters with significantly different values by tranche (Ruled out, NROY, and pareto sets). Significance was determined using Kruskal-Wallis tests with p<0.0025 (0.05 with a Bonferroni correction for the twenty parameters tested).

By contrast, only the road density threshold parameter (ρ) has significantly different mean values between the NROY and pareto parameter spaces (Figure 6.5). Parameter values in the pareto space serve further to decrease burned area in comparison with NROY parameters. Therefore, we might conclude that vegetation fragmentation issues are the key aspect of human-fire interactions in driving overall fire regimes.

However, when individual parameter correlations with overall WHAM!-GFED5 correlation are calculated and weighted by their respective impact on burned area, a more nuanced picture emerges (Figure 6.6). This calculation allowed parameters with smaller global effects on burned area, but still meaningful spatiotemporal effects to be identified. Weighted by impact on overall burned area, logging has the most impact on correlations between WHAM! and GFED5, followed by fire suppression and burned area per fire for Pasture and Shrub PFTs. By contrast, road density and the rate of unmanaged fires, which have a large impact on burned area, have correspondingly less weighted impact on correlations. Therefore, some aspects of the coupled model ensemble have a small impact on overall burned area, but nevertheless pick up meaningful aspects of the burned area record in GFED5; this is addressed further in the discussion.

6.3.1.2 WHAM!-INFERNO evaluation: comparison with baseline models

Measured by correlation with the GFED5 record, WHAM!-INFERNO performs significantly better than the baseline models (Z Tests; $p < 2.2e^{-16}$). The mean correlation of the pareto parameter space is 0.739, compared with 0.584 & 0.572 for the baseline models (Table 6.7). Global burned area projected by WHAM!-INFERNO is closest to that in GFED5; consequently WHAM!-INFERNO has the least number of parameter sets ruled out by history matching. Notably, addition of road density as a representation of fragmentation to INFERNO v1.0 (*INFERNO_road*) does not improve model performance. Further, in NROY and pareto runs, the mean parameter value of the road density threshold is 11.5 and 10.3 in pareto and NROY runs respectively compared to 8.29 in ruled out runs. Reducing the impact of road density on burned area improves the performance of *INFERNO_road*.

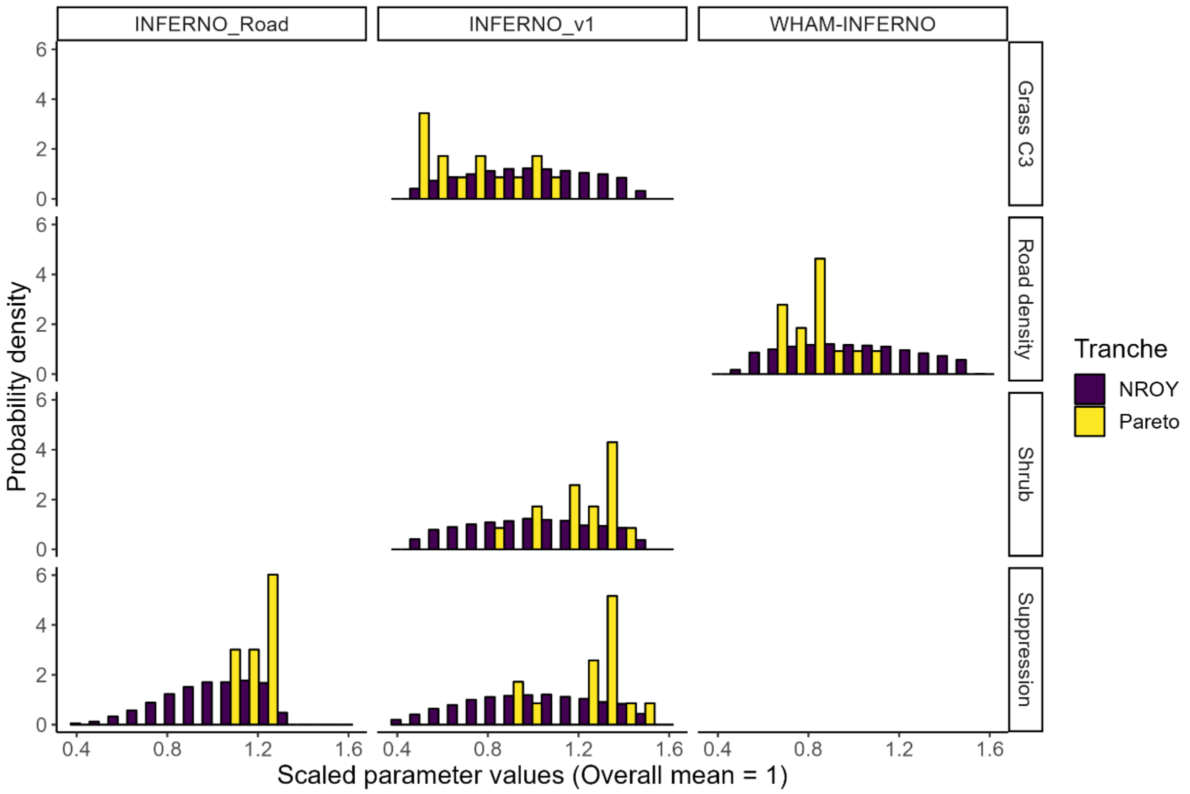


Figure 6.5: Comparison of parameter distributions across models and parameter tranches. Distributions shown are for $p<0.05$ (Bonferroni correction applied). Road density is important in constraining the distribution of fire in WHAM!-INFERNO, but INFERNO's own population-density-based suppression function plays this role in INFERNO v1.0 and *INFERNO_road*.

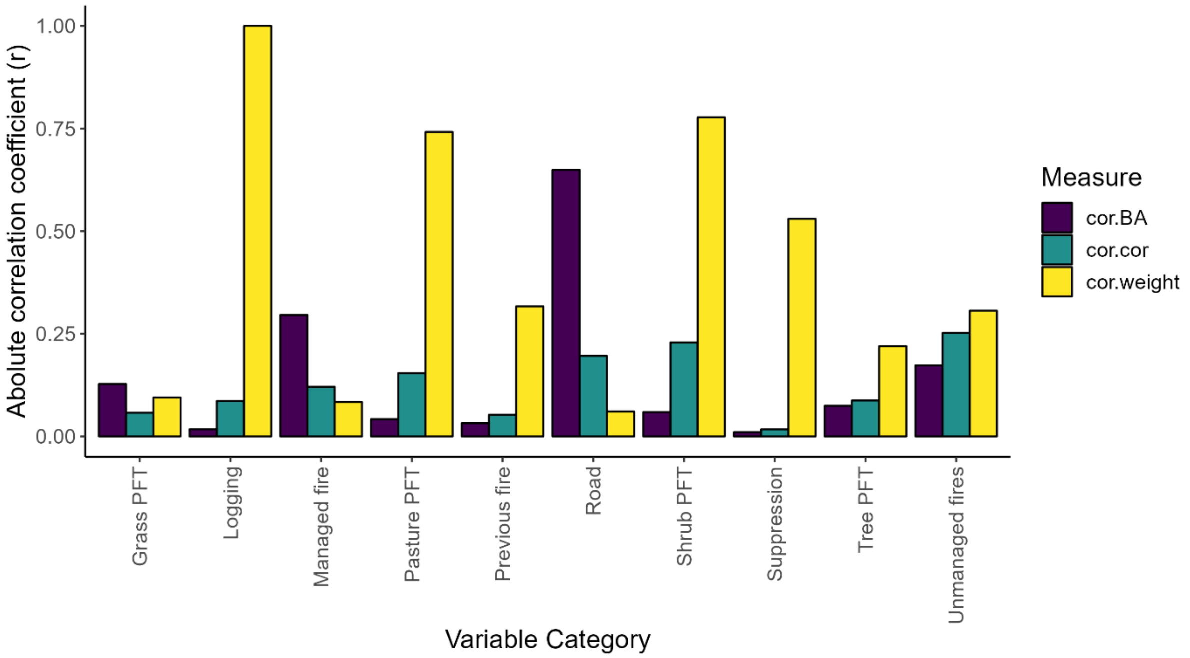


Figure 6.6: Impact of WHAM!-INFERNO model parameters on model correlation with GFED5 across NROY & pareto runs. Key: cor.BA – correlation (r) of parameter with global burned area; cor.cor – correlation of parameter values with overall model correlation; cor.weight – correlation of parameter values with overall correlation, weighted by parameter impact on burned area. The number of arson fires has little impact on global burned area – but nonetheless seems an important aspect of fire regimes.

Table 6.7: Overview of WHAM!-INFERNO performance in comparison with a re-calibrated version of Mangeon et al., (2016; INFERNO v1.0) and with the addition of road density to represent fuel-load fragmentation (*INFERNO_road*). WHAM!-INFERNO performs significantly better as measured by correlation and is closest to GFED5 burned area of 802.5Mha.

Model	Parameter Tranche	n	Correlation (r)	Burned area (Mha)
WHAM!-INFERNO	Pareto	13	0.739	812
INFERNO v1.0	Pareto	14	0.584	750
INFERNO_road	Pareto	8	0.572	775
WHAM!-INFERNO	NROY	8912	0.721	906
INFERNO v1.0	NROY	3239	0.560	686
INFERNO_road	NROY	3433	0.553	562
WHAM!-INFERNO	Ruled out	1075	0.725	1306
INFERNO v1.0	Ruled out	6747	0.554	276
INFERNO_road	Ruled out	6559	0.540	274

6.3.2 Analysis of WHAM!-INFERNO outputs

Across the pareto parameter runs, WHAM! burned area (mean 815Mha) is split approximately evenly between managed and unmanaged fires: over the historical period (1990-2014) a mean of 441.9Mha (54%) comes from unmanaged fires and 379.2 (46%) from managed fires (Figure 6.7). At the continental-scale, diverse patterns of this balance between managed and unmanaged fire emerge (Figure 6.8). Of the 402.1Mha mean burned area in Africa (1990-2014), 68% (275.0Mha) is from unmanaged fire. By contrast, fire regimes in Asia are dominated by managed anthropogenic fires, which comprise 100.0Mha (73%) out of 137.7Mha burned in total, whilst in South America the proportion is approximately equal: 75.3Mha of managed fire (52%) and 70.5Mha of unmanaged (48%).

Furthermore, across the overlapping period with GFED5 (2001-2014) WHAM! burned area declines by 52.2Mha, with 13.4Mha of this coming from a decline in managed fire and 38.8Mha of this coming from unmanaged fires. Similar to the managed and unmanaged fire balance, the overall declining trend also has substantial continent-level heterogeneity (Figure 6.8). In Africa, from 2001-2014, unmanaged fire declines by 25.0Mha, whilst managed fire *increases* 10.8Mha. Both unmanaged (-16.0Mha) and managed (-15.6Mha) fire decrease in South America; whilst in Asia there are small declines in managed (-6.6Mha) or unmanaged (-6.8Mha) fire.

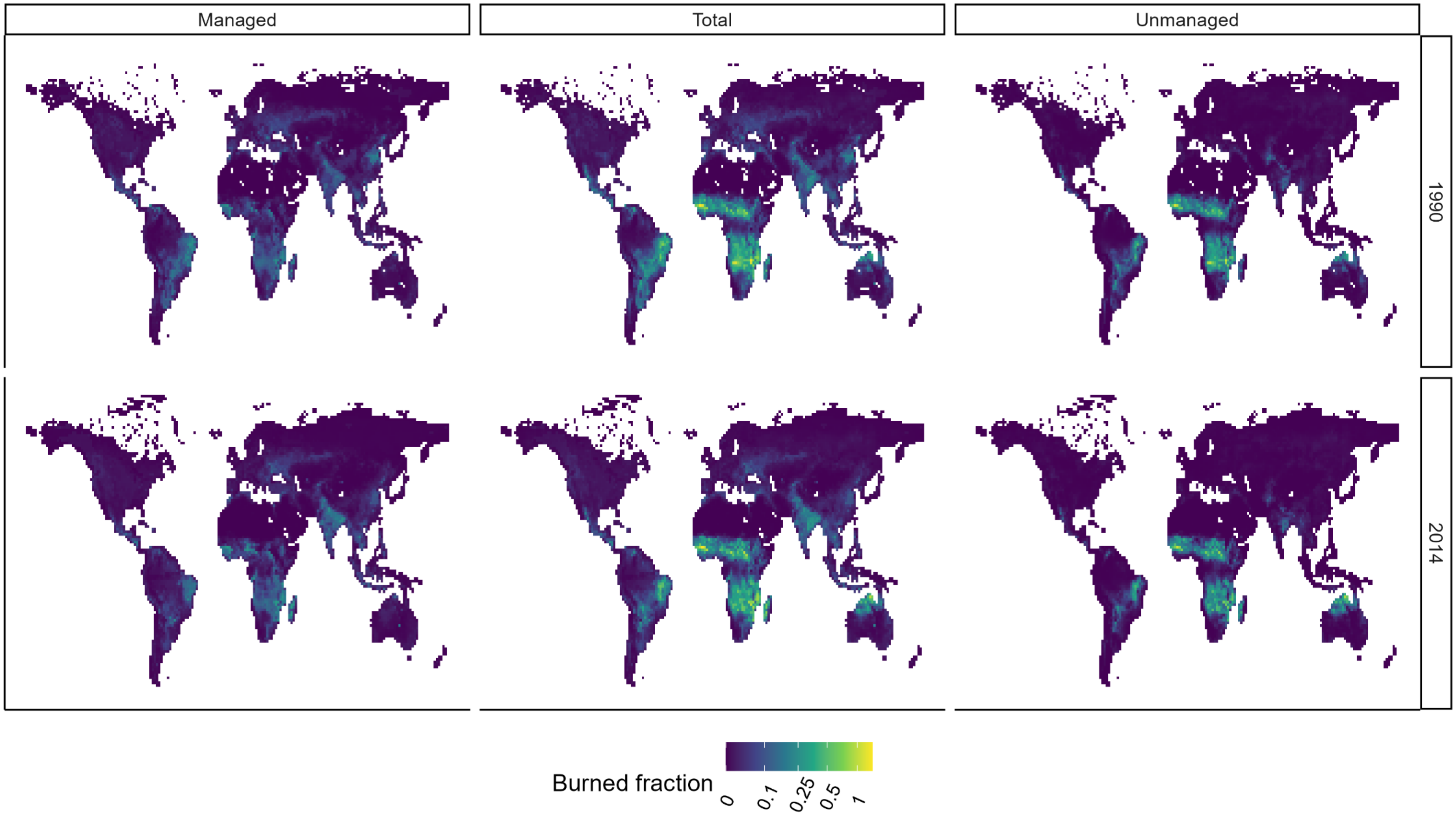


Figure 6.7: WHAM!-INFERNO outputs for 1990 & 2014. Unmanaged fires are clustered towards Sub-Saharan Africa, Northern Australia and the Caatinga region of Brazil. By contrast, managed fires are more evenly distributed, including through India, China, Eastern Europe and Russia.

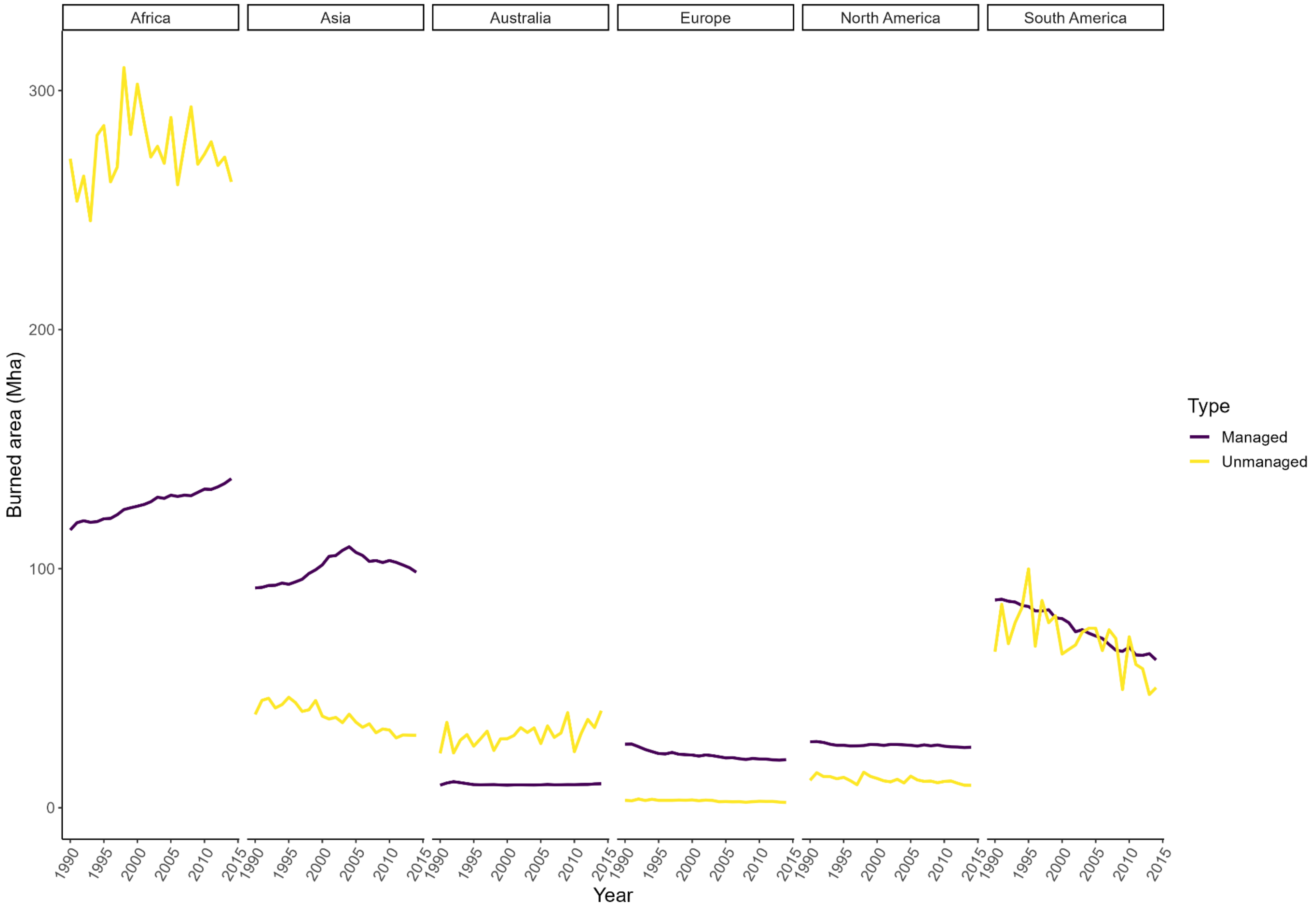


Figure 6.8: WHAM!-INFERNO burned area for managed and unmanaged fires by continent. Both the proportion of fire between managed and unmanaged sources and their respective trends differ substantially across continents.

6.3.3 WHAM!-INFERNO & GFED5 comparison

6.3.3.1 Temporal comparison

Overall, there is broad agreement between WHAM!-INFERNO and GFED5 on the decrease in global burned area from 2001-2014 (Figure 6.9). However, the decline in GFED5 (-192.9Mha) is more pronounced than WHAM!-INFERNO (-52.2Mha). Furthermore, there is broad continent-scale agreement in trends in South America, Europe and North America (declining). In Asia, primarily due to differences in cropland fires (Chapter 5), WHAM! projects a slight decline (-13.4Mha), whilst GFED5 shows a modest increase (12.1Mha). The greatest difference between WHAM!-INFERNO and GFED5, then, is in Africa, where WHAM!-INFERNO projects a modest decline (-14.2 Mha) compared to the pronounced trend in GFED5 (-111.8 Mha).

The modest decline projected by WHAM!-INFERNO in Africa can be explained primarily by the static flammability in the continent (Table 6.8; Figure 6.10). This static flammability partially constrains the impact of increased road density (fragmentation) and increased fire suppression, leading to only a modest decrease in unmanaged fire. This contrasts with South America and Asia, in which fire suppression and road density are strongly negatively correlated with changes in unmanaged burned area. Notably, the number of unmanaged fires is strongly correlated with the unmanaged burned area only in South America. This fits prior understanding of anthropogenic fire use in the region, which emphasises the role of fire use for pasture regeneration (Brunel et al., 2021; Jakimow et al., 2018), a form of fire use associated with large numbers of escaped fires (Chapter 5). The relationship between JULES-INFERNO flammability and human drivers of unmanaged fire is addressed further in the discussion.

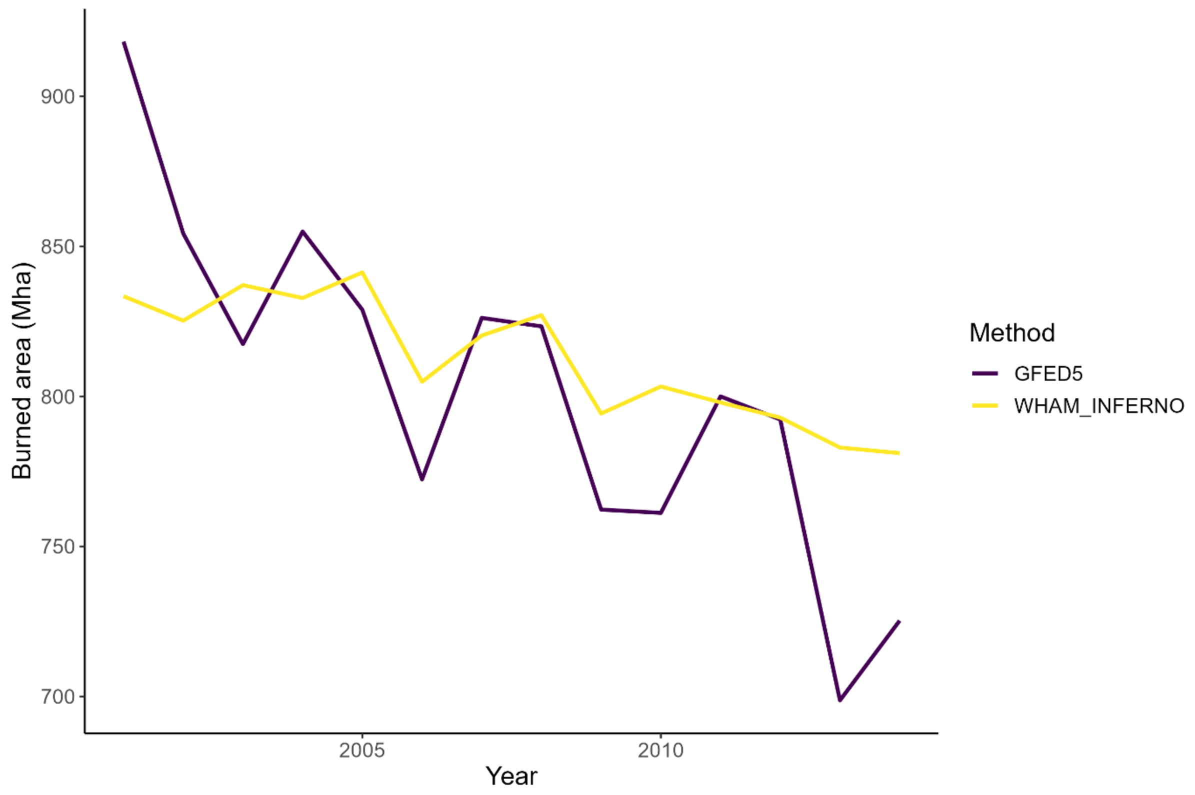


Figure 6.9: Comparison of global burned area between GFED5 and WHAM!-INFERNO over the overlapping period (2001-2014).

Table 6.8: Correlation (r) of arithmetic means of WHAM!-INFERNO unmanaged burned area and its drivers at continent-scale. Nfires is the sum of escaped and arson fires (i.e. purposefully started, yet unmanaged, fires).

Continent	**Flammability**	**Nfires**	**Road density**	**Suppression**
Africa	0.73	0.01	-0.05	-0.05
Asia	-0.21	0.13	-0.92	-0.90
South America	0.56	0.67	-0.65	-0.66

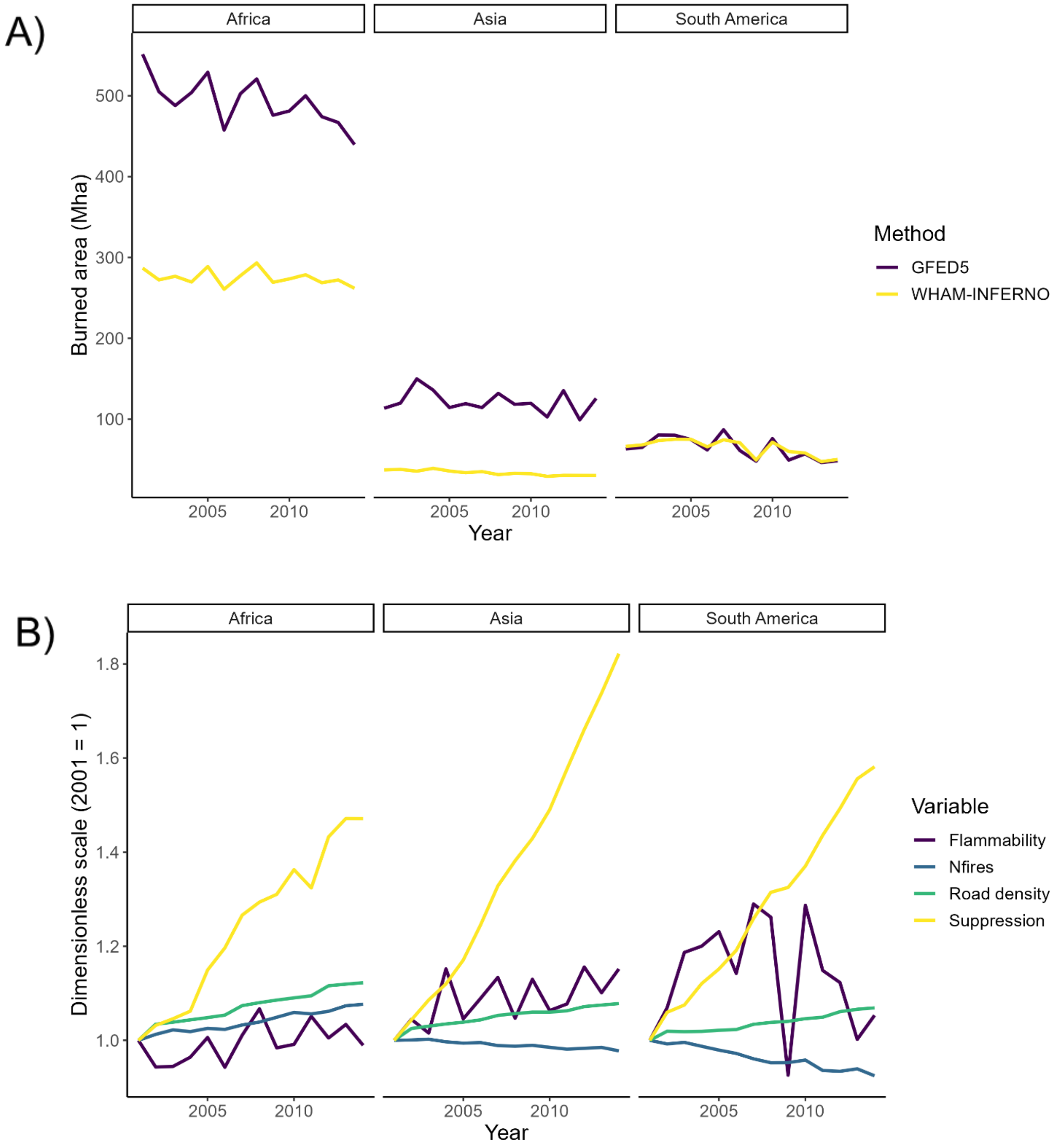


Figure 6.10: Trends in burned area for three continents with the largest burned area. A) burned area comparison between WHAM!-INFERNO unmanaged fire and GFED5; B) drivers of unmanaged fire in WHAM!-INFERNO. Variables in B) were normalised on a 0-1 scale. The combination of increased fire suppression and road density, alongside static (though volatile) flammability entails burned area in South America declines. By contrast, in sub-Saharan Africa changes in flammability dominate these fragmentation and suppression processes. As the background rate of fires was a global constant, Nfires (B) is the sum of arson and escaped fires.

6.3.3.2 Spatio-temporal comparison

Analysis of differences between WHAM!-INFERNO outputs and GFED5 shows that a range of factors explain patterns of divergence. A regression tree model, fit using bootstrap methods described in Chapter 4, shows that at their most basic level, errors seem related to lower HDI locations and cattle pastures (Figure 6.11). This particularly points to regions of Sub-Saharan Africa, and the issues highlighted above regarding drivers of unmanaged fire.

Similarly, correlations between underlying socio-ecological variables and absolute model errors suggest they are focused towards less developed (HDI: r = -0.40), more flammable landscapes (PET: r= 0.39) with livestock grazing (pasture: r = 0.35) and the transitional anthropogenic fire regime (r = 0.39).

Furthermore, weighting absolute model errors by the proportion of WHAM!-INFERNO burned area in a pixel from managed or unmanaged fire adds clarity to these relationships (Table 6.9). As suggested in Chapter 5, the transitional fire regime (r = 0.43) and cropland (r = 0.39) are most associated with errors from managed fires. By contrast, PET is most closely associated to errors for unmanaged fire, pointing the obvious importance of biophysical factors in wildfire spread. However, cropland (r = 0.00) and the transitional fire regime (0.26) are less strongly associated with errors in unmanaged fires. Pastures are correlated with errors for both managed (r= 0.33) and unmanaged fires (r= 0.28), an issue which is explored further in the discussion.

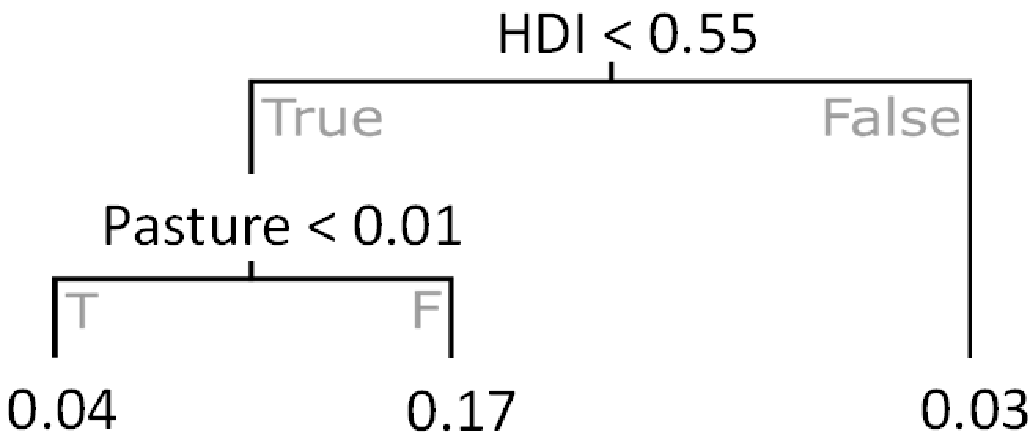


Figure 6.11: Regression tree model of absolute model errors – the difference between WHAM!-INFERNO and GFED5. The tree achieves r^2 of 0.27 with this simple parameterisation, pointing to the importance of grazing lands in the world's poorer areas to both model errors and global fire regimes.

Table 6.9: Relationships of WHAM!-INFERNO forcing variables to absolute model error with observations. Drivers differ across unmanaged and manage fire. Potential evapotranspiration and planted pastures and most strongly associated with model error for unmanaged fires; the transitional fire regime and croplands alongside potential evapotranspiration are most strongly associated with errors for managed fire.

Variable	All fires (r)	Unmanaged fires (r)	Managed fires (r)
Pre-industrial fire regime	0.18	0.18	0.10
Transitional fire regime	0.39	0.26	0.43
Industrial fire regime	-0.11	-0.12	-0.04
Post-industrial fire regime	-0.17	-0.15	-0.13
Potential evapotranspiration	0.39	0.36	0.29
Net primary production	0.14	0.08	0.17
Human Development Index	-0.40	-0.37	-0.29
GDP	-0.39	-0.33	-0.34
Population density	0.19	0.08	0.29
Cropland	0.18	0.00	0.39
Pasture	0.35	0.28	0.33
Rangeland	0.05	0.08	-0.02

Correlations between model input variables and errors can be seen in the respective global distribution of burned area, and error between WHAM!-INFERNO and GFED5 (Figures 6.12 & 6.13). For example, burned area in WHAM!-INFERNO is consistently too high in the Caatinga region of Brazil – a region where JULES is known to overestimate evapotranspiration (Mathison et al., 2023). The errors noted in Chapter 5 associated with crop residue burning in Northern India and uncertainties surrounding the transitional fire regime are also evident. Overall, no single factor dominates the distribution of model errors and the drivers of model error differ substantially between fire types. Taken together, this paints a complicated picture that is explored further in the discussion.

6.3.4 WHAM! future projections for the shared socioeconomic pathways

Two major contrasts define managed fire projections between the SSPs. Firstly, in SSPs 1&5, crop residue burning, crop field preparation and pasture fires decline rapidly (Table 6.10; Figure 6.14). By contrast, in SSP3, these are either static (crop field preparation) or increase (crop residue burning & pasture management). Secondly, in SSP1, fire for hunting and gathering and pyrome management increase to 2050 before plateauing, but increase through to 2100 in SSP3 & 5. There is, therefore, an evident difference in drivers between crop residue burning, crop field preparation and pasture management fire, whose trajectories broadly follow the socio-economic drivers of the scenario, and hunter gatherer and pyrome management fire, whose trajectory is primarily determined by the extent of future climate change.

Vegetation clearance fire remains a small component of overall burned area (Figure 6.14) and decreases in all scenarios (Table 6.10). However, perplexingly, in SSP1 there is a spike around 2080. This points to the rapid rates of land use change for delivery of bioenergy with carbon capture and storage, and the possibility of substantial ecological harm resulting from rapid implementation of this negative emissions technology (Heck et al., 2018; Henry et al., 2018).

For unmanaged fires, the number of fires for arson decreases in SSPs 1&5 but remains static in SSP3. The background rate of fires increases in all scenarios, but most rapidly in SSP5 – this is consistent with that scenarios' high rate of population growth and urbanisation (O'Neill et al., 2017; Riahi et al., 2017): pointing to growth of wildland urban interface regions as a particular adaptation challenge in this scenario. Escaped fires decrease in SSP1 in line with decreasing pasture fires and decline in SSP5 until 2060, when rates increase again with sharp increases in hunter-gatherer and pyrome management fires. Finally, in SSP3, escaped fires remain static. Fire suppression increases in all scenarios but increases most in SSP5 and least in SSP3.

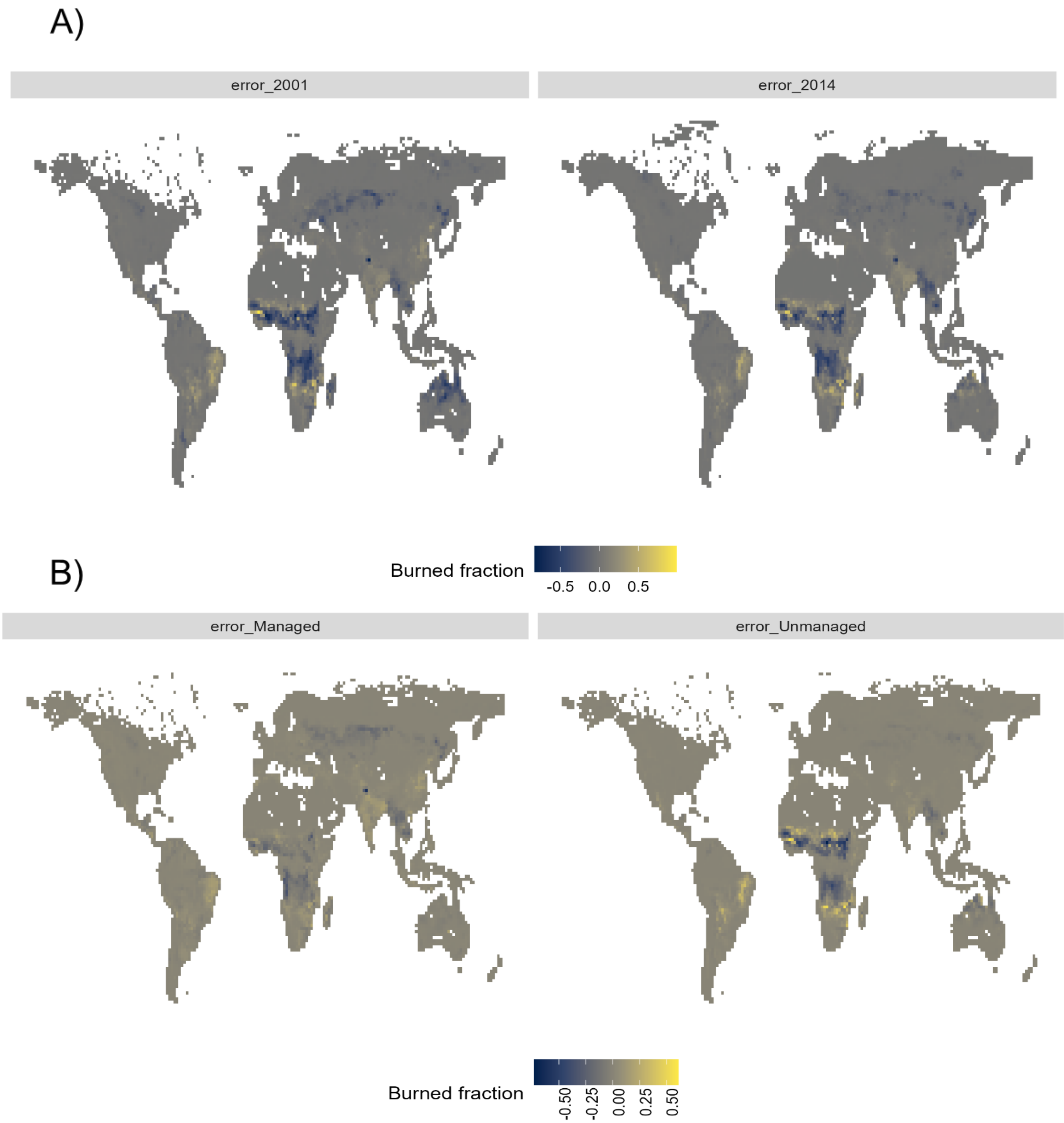


Figure 6.12: Difference between WHAM!-INFERNO and GFED5; for A) all fires in 2001 and 2014 & B) mean errors (2001-2014) weighted by the proportion of WHAM!-INFERNO outputs belonging to managed and unmanaged fires respectively. Negative (respectively positive) numbers indicate WHAM!-INFERNO outputs are too low (high).

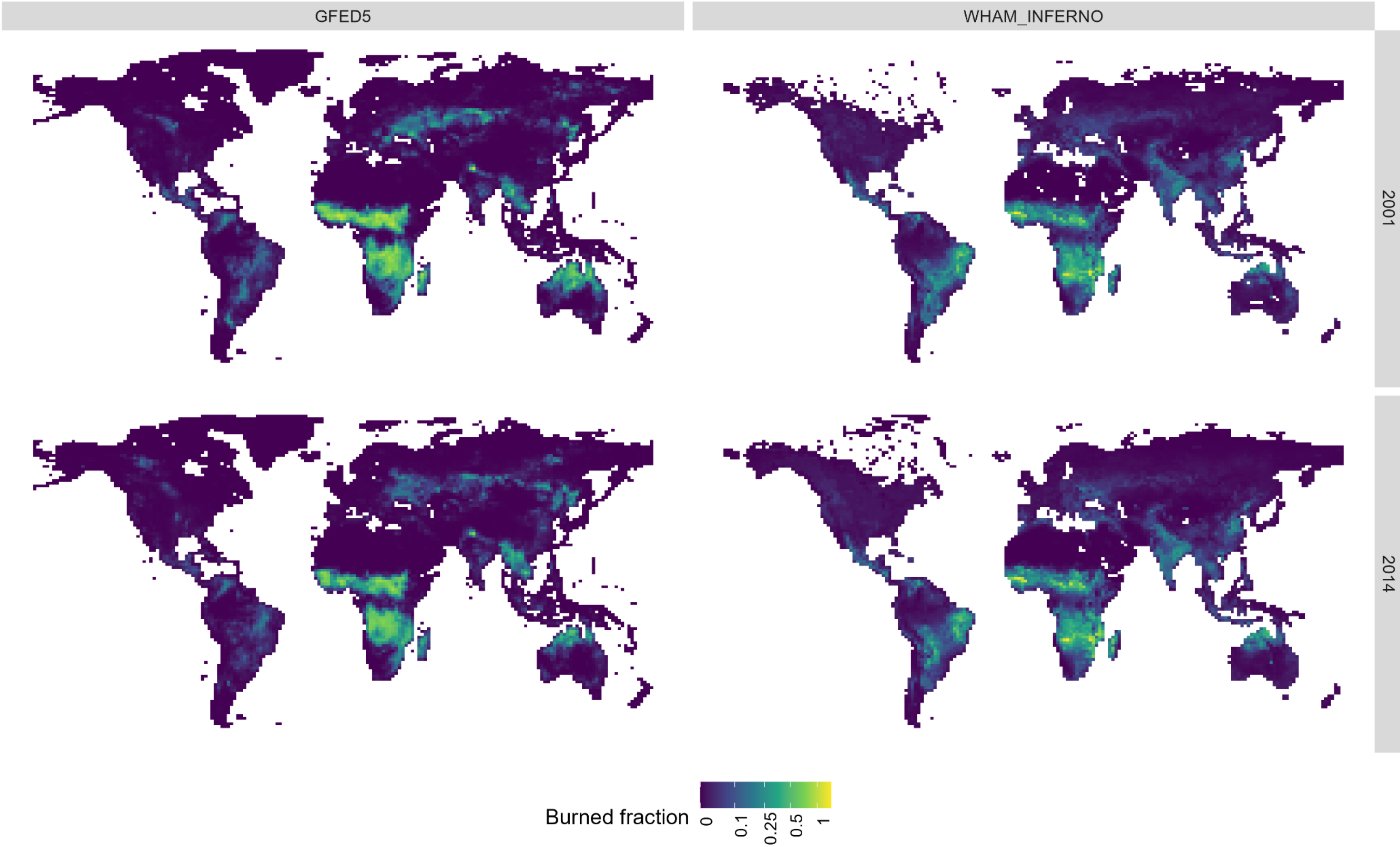
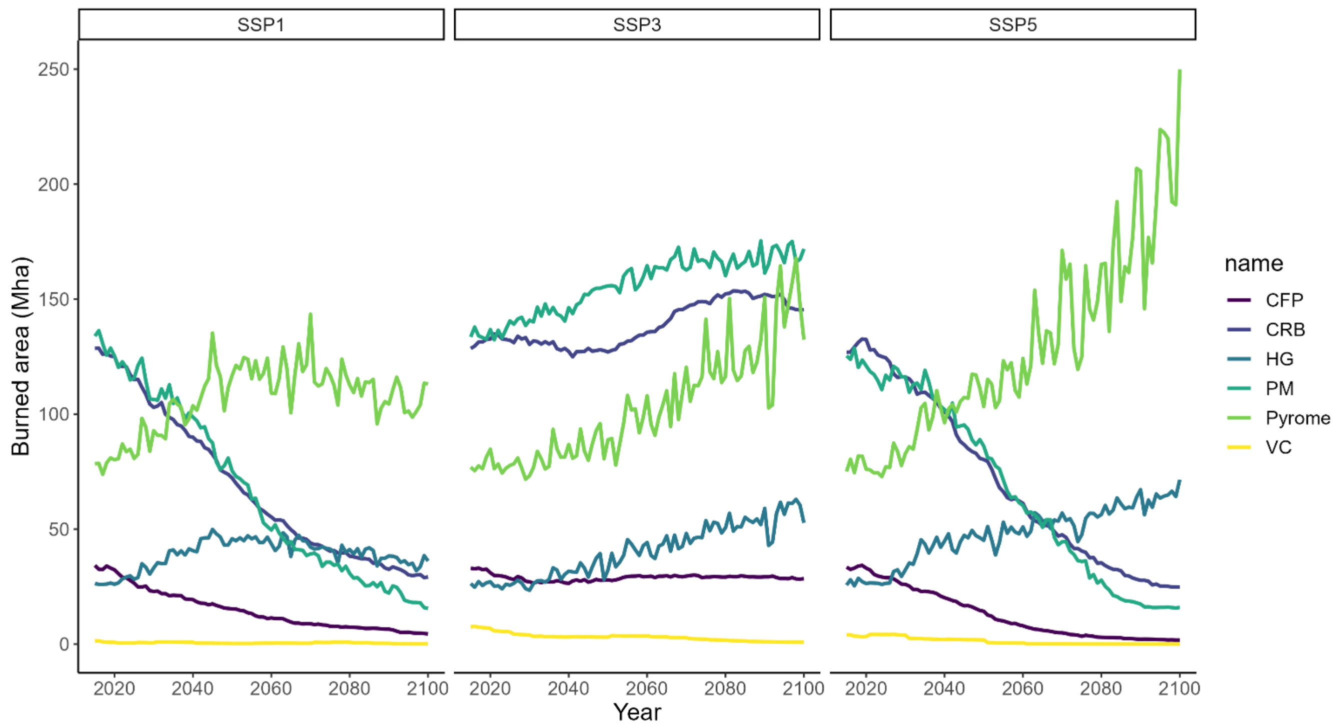


Figure 6.13: Comparison of WHAM!-INFERNO and GFED5 in 2001 & 2014. Overall good coherence is evident, with perhaps the biggest area of disagreement in Sub-Saharan Africa, where GFED5 shows comparatively homogenous burned area of ~0.4-0.8 of the land surface across the northern and southern savanna belts, whereas WHAM!-INFERNO has a more heterogenous pattern.

A)



B)

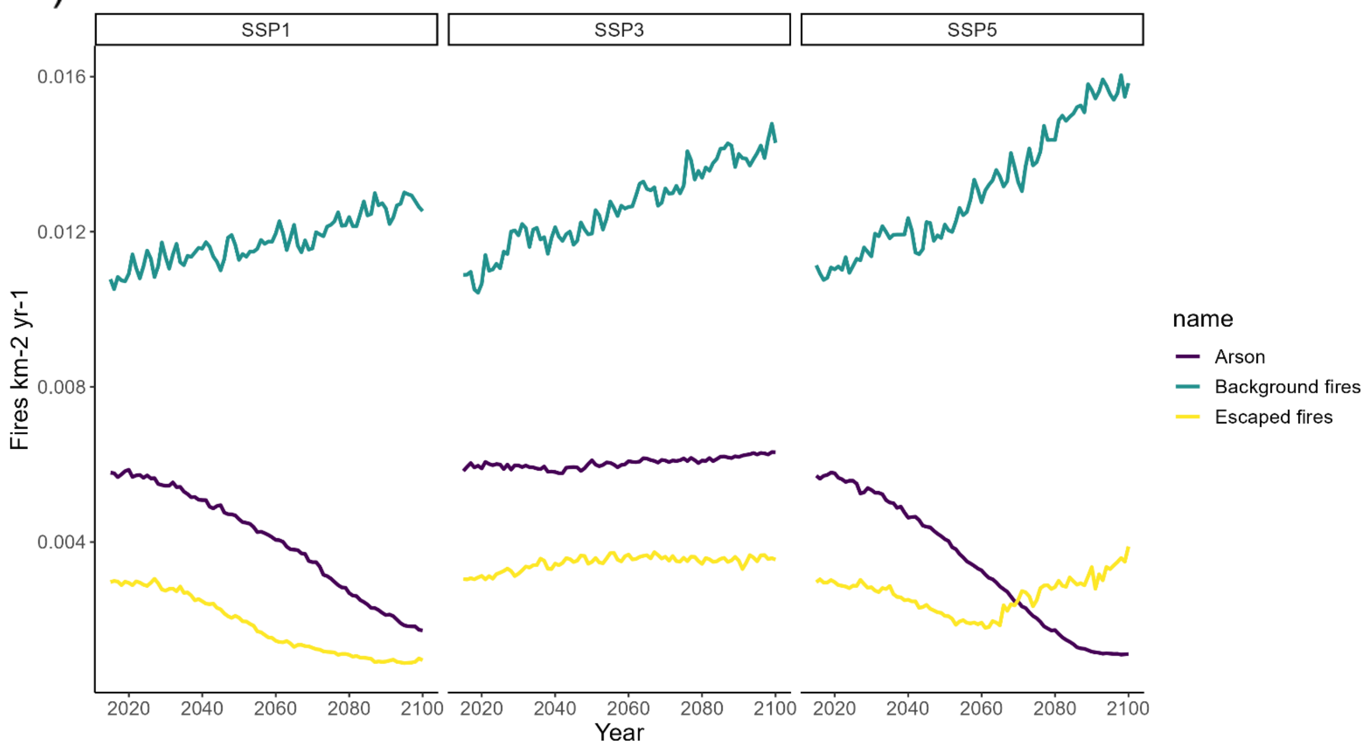


Figure 6.14: Anthropogenic fire from 2015-2100 across SSPs1, 3, & 5. A) gives burned area from managed fires, whilst B) gives the *number* of unmanaged fires.

Key: CFP = crop field preparation; CRB = crop residue burning; HG = hunter gatherer; PM = pasture management ; Pyrome = pyrome management; VC = vegetation clearance.

Table 6.10: Proportional change in WHAM! projected managed burned area, unmanaged anthropogenic fires and fire suppression under the Shared Socioeconomic Pathways; outputs are scaled to 2020 = 1.

	SSP1			SSP3			SSP5		
Anthropogenic fire impact	**2050**	**2080**	**2100**	**2050**	**2080**	**2100**	**2050**	**2080**	**2100**
Crop field preparation	0.45	0.21	0.13	0.84	0.88	0.86	0.43	0.09	0.05
Crop residue burning	0.56	0.30	0.23	0.99	1.19	1.13	0.63	0.28	0.20
Pasture management fire	0.56	0.23	0.12	1.17	1.20	1.29	0.69	0.22	0.13
Hunter gatherer fire	1.74	1.56	1.37	1.22	1.92	2.00	1.76	2.19	2.79
Pyrome management fire	1.49	1.44	1.44	1.15	1.51	1.72	1.38	2.20	3.33
Vegetation clearance fire	0.22	0.54	0.07	0.40	0.23	0.11	0.45	0.01	0.00
Arson fires	0.79	0.46	0.30	1.06	1.05	1.09	0.70	0.30	0.19
Background fire rate	1.04	1.15	1.16	1.11	1.24	1.33	1.13	1.33	1.47
Escaped fires	0.69	0.37	0.32	1.18	1.16	1.20	0.71	0.96	1.31
Fire suppression	1.38	1.60	1.65	1.29	1.38	1.42	1.47	1.70	1.72

6.4 Discussion

This Chapter has presented applications of WHAM!, a global behavioural model of human fire use and management. Discussion is structured in three sections. Firstly, insights derived from the coupling of WHAM! with INFERNO are explored. Secondly, the performance of the combined model is evaluated. Thirdly, discussion focuses on projections of WHAM! for the SSPs.

6.4.1 WHAM!-INFERNO: Insights for global-human fire interactions

The WHAM!-INFERNO model reveals both the extent and the diversity of the socio-ecological dynamics of 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 between continents. Whilst anthropogenic fire use, primarily for crop residue burning (Chapter 5), dominates the fire regime in the Asian continent, in Africa >66% of burned area is from unmanaged fires (Figure 6.8). Such differences should, at the very least, be a final demonstration of the inadequacy of model approaches seeking to represent direct anthropogenic influence on fire regimes as a global function of population density (Hantson et al., 2020).

Moreover, just as the anthropogenic and biophysical influences on fire regimes differ greatly globally, so do apparent drivers of change, with landscape fragmentation and suppression dominant in South America, and biophysical changes (vegetation flammability) dominant in Sub-Saharan Africa (Table 6.8). It should be noted, however, that the observed decline in burned area in Sub-Saharan Africa (Andela et al., 2017) is only partially reproduced by WHAM!-INFERNO, tempering the certainty of this finding (Section 6.4.2). Further, the increase in managed fire projected by WHAM!-INFERNO in Africa is primarily due to increased crop fires (Chapter 5), a trend not picked-up by GFED5, perhaps due to incomplete separation of cropland and wider vegetation fires (Hall et al., 2023). However, what is clear is how widespread and diverse humans' indirect impacts on fire regimes are. This is demonstrated not only in the drivers of change in fire regimes within WHAM!-INFERNO, but also the sensitivity of model calibration to the impact of road density, and the small but discernible impact of logging on the flammability of tropical forests (Figure 6.6).

A further, an important finding relates to the role of fuel-loads in grassland, pasture and savanna landscapes. In both Mangeon et al., (2016) and (Burton et al., 2019) burned area per for plant functional types in INFERNO were the same for grasses as planted pastures, with shrubs at a lower burned area than grasses. However, here, the pareto parameters of WHAM!-INFERNO have lower burned area per fire for grass PFTs, but higher burned area for C4 pastures than the overall parameter space (Figure 6.4). Burned area per PFT for pastures and shrubs are both also particularly effective at capturing the distribution of fire regimes globally, given their smaller impact on global burned area than other model parameters (Figure 6.6). Therefore, together this points to the importance of planted pastures in fire regimes: maintaining lands suitable for livestock in regions with substantial net primary production creates landscapes with plentiful and flammable vegetation. This therefore contrasts with natural grasslands, in which lower underlying NPP may lead to fuel-constrained fire regimes (Krawchuk et al., 2009). Conversely, increased grazing pressure has been highlighted as a possible explanation for the pronounced decline in burned area in Sub-Saharan Africa (Archibald et al., 2012; Randerson et al., 2022), further illustrating the complexity of fire-regime dynamics in such landscapes (Section 6.4.2).

6.4.2 WHAM!-INFERNO: Evaluation of model performance

WHAM!-INFERNO has substantially improved capacity to reproduce historical global annual burned area over the baseline models (Table 6.7), and indeed over the online version 1.0 of INFERNO against GFED4 (r= 0.70; Mangeon et al., 2016). This demonstrates the importance of a process-based approach to understanding anthropogenic impacts on fire regimes in global modelling. 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 (Figure 6.4). However, representation of landscape fragmentation, its interaction with different ecosystem types and other anthropogenic pressures remains incomplete.

The first means through which WHAM!-INFERNO represents fragmentation is roads' role in reducing fire size (Haas et al., 2021). Although applying a road density correction to fire sizes per PFT is impactful, a single global function is a somewhat simplistic way of capturing such effects – and hence the impact on WHAM!-INFERNO burned area outputs is substantially larger than its impact on correlation with GFED5 (Figure 6.6). Hence, we may draw an analogy between the road density parameterisation here to capture fragmentation effects and representations of anthropogenic 'ignitions' as a global function of population density: a first step with outstanding issues to be addressed. For example, one immediate improvement could be to account for the varying impacts of different classes of roads (e.g. following the GRIP classification; Meijer et al., 2018).

The shortcomings of the road density parameterisation are perhaps best seen in Sub-Saharan Africa. Here, only a weak relationship was found between road density and declining burned area (Table 6.8). Consequently, WHAM!-INFERNO does not fully capture the drivers of declining fire in the Sub-Sharan Africa. This may be purely due to the global parameterisation of the function, but may also be due to the lack of representation of grazing pressure, and also the *interaction* of roads with cropland conversion. Understanding such issues likely requires a more targeted approach on such regions, perhaps building on reduced complexity approaches (e.g. Archibald et al., 2012). An alternative approach would be to include a direct representation of grazing pressure (see Chapter 7). The importance of grazing lands in sub-Saharan Africa in determining model error is highlighted by the regression tree of model errors, Figure 6.11 and by their relationships with error in unmanaged fires (Table 6.9).

A further shortcoming in the model is the representation of previous fires on fuel load availability and connectivity. Such dynamics are known to be important in determining burned area in flammable savanna grasslands (Kuhn-Régnier et al., 2021), yet model parameterisations here do not contribution substantially to model performance (Figure 6.4). In part, this is a simple limitation of the off-line model presented here, which cannot account for such dynamics in a process-based manner. However, just as crucially, WHAM!-INFERNO does not account for *deliberate* fuel-fragmentation through pyrome management fire. This is illustrated best in Northern Australia, where re-introduction of indigenous fire has led to smaller fires, and therefore reduced annual burned area (Bliege Bird et al., 2008). However, in WHAM!-INFERNO, increased vegetation flammability results in increased burned area from unmanaged fires (Figure 6.7).

The second fragmentation process represented in WHAM!-INFERNO is the impact of logging on the flammability of fire-prone tropical forests. The impact of the logging parameterisation is the inverse of road density: it has a small overall impact on global burned area, but is effective at increasing the correlation of WHAM!-INFERNO and GFED5 burned area. 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 parameterisation.

Finally, an unavoidable limitation of the model is in errors in biophysical parameters passed from JULES-INFERNO. This can be seen clearly in the relationship of potential evapotranspiration to model errors for unmanaged fires (Table 6.9). Notably, JULES version 7 used for ecosystem and hydrological inputs to INFERNO here (Wiltshire et al., 2020) is known to overestimate evapotranspiration in the tropics, as well as having a particular issue of underestimating ecosystem primary production in the Caatinga region of Brazil (Figure 6.12; Mathison et al., 2023). Additionally, as in Mangeon et al., (2016; particularly their Figure 2), the Guinean Savanna fire belt extends too far north into the Sahel region. Fires here are overwhelmingly unmanaged – i.e. driven by biophysical factors – and so correcting this error would require mode fundamental changes to JULES-INFERNO's distribution of plant functional types and/or vegetation flammability. The role and remit of human-Earth system modelling in relation to inherited model error is reflected on further in the thesis discussion.

6.4.3 Possible futures of human-fire interactions

Projections of managed fire use reiterate how its drivers differ between more biophysically driven, and more socio-economically driven fire uses. This illustrates how complicated interactions between human and natural processes will define future fire regimes. Notably, the differences in socio-economic drivers see large differences in crop residue burning and pasture management fires between SSP1/5 and SSP3, whilst differing emissions pathways (RCP 2.6 in SSP1, & RCPs 7.0/8.5 in SSP3/5) drive different trends in pyrome management and hunter gatherer fire.

In some ways, explicit projection of fire use and management in the context of changing fire regimes highlights tensions in the SSP storylines. For example, SSP5 is defined by high challenges to climate mitigation (i.e. high greenhouse gas emissions), but low challenges to climate adaptation (O'Neill 2017). Yet it seems clear in the SSP5 scenario that pyrome management fire is close to breaking point as a useful adaptation tool – in 2100 it accounts for the equivalent of 1/3 of all present day burned area (~250 Mha vs ~750Mha in the present day). At the same time, the rapid pace of urbanisation in SSP5, leads to large increases of the background rate of fire at the wildland urban interface – an environment associated with very challenging fire regime management (Beltrán-Marcos et al., 2023). Such fire management challenges would only increase under the extreme emissions scenario of RCP8.5 (Riahi et al., 2011).

Furthermore, in SSP1, a scenario with low challenges to both climate adaptation and mitigation, WHAM! projects large increases in fire suppression in the sub-Saharan savanna fire belt. Not only would such an approach have negative impacts on biodiversity – as has been found in savannas in South America (Eloy et al., 2018) – but the risk of over-suppression and subsequent intense and damaging mega-fires is real (Cochrane and Bowman, 2021).

Additionally, the spike in vegetation clearance fires around 2080 in SSP1 (Table 6.10) is driven by land use conversion for bioenergy with carbon capture and storage (or C4 perennial cropland in the LUH2 land cover data; Hurtt et al., 2020). A negative emissions strategy that risks driving a wave of ecological damaging fires to clear primary vegetation is problematic at best (Merfort et al., 2023). However, the apparent tension between the assumptions of the C4 perennial cropland LUH2 land cover class (i.e. land conversion for carbon dioxide removal) and the reaction of WHAM! AFTs (who use fire to clear land for this purpose) may also be a function of model structure. Possible alternative land cover projections to LUH2, which may have allowed more internally consistent scenario modelling are discussed further in Section 7.3.2.

All of this highlights how understanding future climate change adaptation and mitigation challenges – particularly the delivery of land-based carbon dioxide removal – requires deeper understanding of the socio-ecological dynamics of land system processes. One way to advance this understanding would be to run the coupled WHAM!-INFERNO ensemble for future runs. This remains a medium-term ambition. At present key outputs of INFERNO are not available for the SSPs, particularly vegetation flammability. This is planned to be output by the INFERNO team for the Intersectoral Impact Model Intercomparison Project (ISIMIP); however future runs are not scheduled to be completed until autumn 2024 (Chantelle Burton, personal communication).

Nonetheless, the standalone runs of WHAM! for the SSPs demonstrate the value of socio-ecological modelling in identifying unforeseen interactions and feedbacks between socio-economic and biophysical change. Furthermore, the design of WHAM!, with a land use module and a subsequent AFT parameterisation, has the advantage of in principle being readily repurposable for additional land system processes – such as water consumption or nitrogen fertiliser application.

6.5 Conclusion

This chapter has presented application of WHAM! It has presented the coupling of WHAM! with JULES-INFERNO and projections of WHAM! for the shared-socioeconomic pathways. Overall, findings demonstrate the complexity of human-fire interactions, particularly under ongoing biophysical and socio-economic changes. By demonstrating the different spatiotemporal distributions of managed and unmanaged fires globally, we have highlighted the inadequacy of approaches assuming anthropogenic impacts on fire regimes can be conceptualised using globally uniform functions. This is reiterated in future runs of WHAM! in which a clear distinction in the drivers of cropland and pasture fires and wider vegetation fires is observed.

A key area for future work identified here is landscape fragmentation, particularly in grazing lands in sub-Saharan Africa. The first attempt to parameterise such effects with a global function of road density is only partially successful and could be greatly improved by more detailed landscape-level work. Finally, although defining the transitional fire regime appears a crucial factor for improving understanding of crop residue burning (Chapter 5), its impacts on unmanaged fires are small.

Chapter 7

Discussion and conclusions

7.1 Introduction

This PhD had three aims, which were presented in Chapter 2. Briefly to restate these aims, they were: (1) to synthesise available knowledge of human-fire interactions globally; (2) to explore how behavioural modelling may improve representations of anthropogenic fire impacts in global-scale process-based models; and (3) to quantify the influence of human behaviours on global wildfire regimes of the recent past and in possible future scenarios. Additionally, this thesis has been informed by, and contributes to, the wider development of transdisciplinary land-system modelling as a discipline, and in particular the application of such models to large spatial extents.

Therefore, the body of this discussion is structured in four sections. Section 7.2 discusses the primary insights made regarding human influences on global fire regimes, whilst Section 7.3 places the work here in the context of the development of large-scale behavioural land system models. Section 7.4 then describes some specific short and medium-term next steps for the further development and application of WHAM!-INFERNO. Section 7.5, which concludes this thesis, provides a final summary of its key findings.

7.2 Socio-ecological dynamics of global fire regimes

7.2.1 Advances to understanding

WHAM!-INFERNO represents the first time that, at global scale, observations of burned area have been dissected into managed anthropogenic fires and unmanaged fires. Capturing this distinction has been noted as one of five major challenges in fire science (Shuman et al., 2022). In so doing, we have demonstrated that the distribution of managed fires varies substantially from unmanaged fires, and that across differing regions of the world, the proportion of fire regimes that is contributed from managed and unmanaged fires is highly heterogenous. For example, from 2001-2014, WHAM!-INFERNO suggests 68% of burned area in Africa was from unmanaged fires, whilst in Asia as much as 73% of burned area was from managed anthropogenic fires – particularly crop residue burning (Chapter 6; Figure 6.8).

This finding has several implications for current representations of anthropogenic influences on fire regimes in dynamic global vegetation modules. These relate to current DGVMs two primary deficiencies in representation of human impacts on fire regimes noted in Chapter 2 (Section 2.2.1): modelling of numbers of anthropogenic fires, and anthropogenic management of fire spread.

Most fundamentally, the finding that humans' use of fire is heterogenous between contrasting socio-ecological contexts suggests the conceptualisation of humans' role as globally consistent generators of 'ignitions' (Chapter 2; Figure 2.1) should now be discarded and replaced with process-based representations of the drivers of anthropogenic fire use. The appropriate means of achieving this are perhaps domain-dependent. For example, in studies focused specifically on fire, modellers should closely consider how to incorporate representations of the anthropogenic processes identified in DAFI and captured by WHAM! (Shuman et al., 2022). However, in coupled Earth-system modelling under prescribed socio-economic and emissions scenarios, online human feedbacks may not be appropriate to the underlying research focus (Gidden et al., 2019). In such contexts, a step-wise approach to incorporation may be a pragmatic way forward, with separable, economically-driven model aspects such as crop fires perhaps the first candidate for inclusion (Chapter 5; Figure 5.4).

Just as crucial to modelling numbers of fires, are implications of WHAM!-INFERNO's results for modelling fire spread. Current DGVMs assume fires will spread according to biophysical drivers alone (Chapter 2; Table 2.1). However, WHAM!-INFERNO demonstrates the importance of representing managed fires – that not only ignite, *but also spread* according to land user objectives (Chapter 3; Table 3.4 & Chapter 6; Figure 6.8).

Furthermore, WHAM!-INFERNO corroborates empirical findings that vegetation fragmentation due to roads and logging have substantial impacts on unmanaged fire (Haas et al., 2021; Rosan et al., 2022). At global scale, road density is found to have a significant role in constraining unmanaged fire spread (Chapter 6 Figure 6.5), whilst logging is found to have a smaller impact on burned area, but is effective in reproducing burned area observations in forested areas (Chapter 6; Figure 6.6). As such, parameterising fire spread according to biophysical equations without accounting for humans' direct and indirect influences is likely to lead to a structurally biased model. Given the stark contrasts in the roles of managed fire (Chapter 6, Figure 6.8) and fragmentation (Chapter 6, Figure 6.10) across continents, a very simple first step may be to parameterise fire spread separately in each continent.

Therefore, innovations made through WHAM!-INFERNO should open up possibilities for substantial progress in global understanding of fire regimes and their possible evolution under socio-economic and environmental change. This is not least because, by extracting the anthropogenic signal from global burned area observations, we can enable improved modelling and understanding of fires' biophysical drivers. Indeed, we have begun to demonstrate this potential here by isolating the impact of INFERNO's flammability representation on temporal changes to burned area in sub-Saharan Africa (Chapter 6; Figure 6.10).

Furthermore, as a standalone model, WHAM! projections for the SSPs add specificity to differences in human-fire interactions between more positive and less desirable futures. For example, WHAM! projects the expansion of crop residue burning under SSP3, which suggests persistence and even growth of the associated negative impacts on air quality (Chapter 6; Figure 6.14; Raza et al., 2022). By contrast, in SSP1, WHAM! projects increased use of pyrome management fire across the world, pointing to a future in which humanity learns (or remembers how) better to live with fire as a natural, often beneficial, ecosystem process. Therefore, such insights can now be integrated into future modelling of fire regimes in DGVM.

In the literature review, it was also noted that capturing the presence and diffusion of traditional fire knowledge within fire using communities was a major challenge in modelling of human-fire interactions (Chapter 2; Section 2.2.3). WHAM! has a simple means of capturing this, based on the presence of the pre-industrial anthropogenic fire regime. This influences the degree to which landscape fires are controlled by the people and communities using them (Chapter 5; Table 5.6). A further use of the AFRs to capture landscape-level socio economic effects on fire regimes is the use of the industrial AFR to represent the regulatory barriers that can prevent adoption of prescribed fire in developed world contexts (Chapter 5; Section 5.2.3). However, further work could develop these empirical effects into explicit representation of policy responses to managed fires, including changes in suppression intensity resulting from extreme events (Chapter 2; Table 2.2).

Finally, development and analysis of DAFI has made several notable contributions to understanding of global human-fire interactions. These include the qualitive definition and quantitative characteristics of seven central modes of anthropogenic fire use (Chapter 3; Table 3.4), and the spatial and subject-matter distributions of the global human-fire literature (Chapter 3; Figure 3.1).

7.2.2 Remaining challenges

Work presented here demonstrates that there is sufficient data on human-fire interactions to enable process-based representations of human fire use and management to be integrated into DGVMs. However, that does not indicate data could not be improved. A particular issue identified has been in quantification of nomadic and semi-nomadic fire use practices such as shifting cultivation, pastoralist and hunter-gatherer fire (Chapter 5, Table 5.8). Studies that have linked detailed fieldwork documenting anthropogenic fire use and fire regime outcomes for such practices are few, and hence those that do exist (Johansson et al., 2017, Bird et al., 2009, Kull 2004) are invaluable for global-scale fire modelling.

In principle, there is no reason field-based researchers should not link detailed qualitative work with quantitative fire regime analysis; this could be based through transect walks or observations with unmanned autonomous vehicles (i.e. drones; Ecke et al., 2022). However, in practice, there are multiple barriers to this. For example, the goal of researchers documenting fire use and management by indigenous groups (who are the primary users of nomadic fire practices) is - rightly - not to improve global fire modelling. Rather, such research is frequently engaged with complex issues around fire management, land tenure conflict and social justice in particular landscapes and localities (Mistry et al., 2016; Christianson et al., 2022).

Researchers with relevant skills to engage in such critical questions may not be trained in the data collection or analysis skills needed to gather quantitative data on fire regimes. Therefore, the output of fieldwork exploring indigenous fire practices tends to be *qualitative* – noting types of fire use, their rationale and seasonal timing (Chapter 3). This is perhaps demonstrated in the central findings from analysis of the LIFE livelihood fire database, to which data in DAFI contributed: we may discern from field-based qualitative data that subsistence-oriented livelihood fire use is “declining” globally, but we cannot say (from the literature alone) by how much (Smith et al., incl. Perkins 2022).

Yet, quantitative analysis of the impact of systemic changes in approach to fire management on fire regimes can bolster the case for indigenous fire. For example, Bird et al., (2009) show how reintroduction of indigenous patch-burning led to a *decrease* in burned area in Northern Australia, and not only that, but a decline in large, potentially destructive fires. Here, we have shown that this form of managed fire use (i.e. ‘pyrome management’; Chapter 3) poses little risk of leading to uncontrolled wildfires – just 0.4% of intensively controlled pyrome management fires escape (Chapter 5; Table 5.6). Transdisciplinary initiatives, indeed such as the Leverhulme Centre for Wildfires, Environment and Society, could therefore provide the basis for field-based and anthropologically-trained researchers also to quantify the impact of indigenous fire use on overall fire regime outcomes. In this PhD, the focus has been on drawing insights from field-based work into quantitative analysis methods: the reverse process should also be explored.

A particular geographic challenge highlighted in this thesis relates to southern Russia. In Chapter 2, it was noted that this was a particular geographic gap in the data, owing to a combination of difficulties using secondary data in the region, and a lack of Russian-language publications in DAFI. This limitation can be traced through to the outputs of WHAM-INFERNO, which substantially underestimate GFED5 burned area in this region (Figure 6.13). This is particularly pertinent as recent modelling of peat fires suggests these currently occur to the North of the large anomaly between WHAM-INFERNO and GFED5 (Blackford et al., 2023). Indeed, the limited available English language publications on human-fire interactions in the region suggest crop residue burning may play a substantial role in the overall fire regime (Theesfield and Jelinek 2017).

At the outset of this PhD research, the proposed route to developing a global-scale ABM was to develop several meso-scale ABMs of critical landscapes for human-fire interactions (e.g., grazing lands in sub-Saharan Africa, peat fires in Indonesia, emerging megafires at the wildland-urban interface) and subsequently extrapolate these using gaussian process emulation to project outputs globally. A view was taken within the first year of the research to instead develop a single global model. The reasons for this focused on the difficulties of capturing indirect anthropogenic influences on fire regimes.

Firstly, given it was not possible to systematically capture indirect anthropogenic fire impacts in DAFI, it was unlikely that data would have been available to enable the more detailed representation appropriate for meso-scale models (Johnson et al., 2023b) – for example the impacts of peat drainage (Page and Hooijer, 2016) or invasive pasture grasses on fire regimes (Walker and Morgan, 2022). Furthermore, previous syntheses such as Cochrane et al. (2009) highlight the extreme heterogeneity of how different direct and indirect human influences on fire regimes interact in contrasting socio-ecological environments. Hence, it was judged that emulation from one type of socio-ecological fire regime to another was likely to be challenging, not least because the distribution of differing modes of socio-ecological fire regime was, and - notwithstanding insights presented here – remains, poorly understood.

The benefits of having adopted a single global model structure has been that it enables direct inter-continental comparison of fire regimes and advances in broad-scale patterns of human fire use and management. However, it has also highlighted regions in which a meso-scale approach should be a high priority focus for future work. In particular, the finding that a top-down parameterisation of fragmentation in the WHAM!-INFERNO ensemble was not able to capture declining burned area in sub-Sarahan Africa suggests understanding the impact of landscape fragmentation processes in this region's fire-dependent savannas should be a central research priority (Chapter 6; Figure 6.8). Furthermore, as vegetation flammability appears crucial to inter-annual change in burned area in Africa (Chapter 6; Table 6.8), this more focused work should include aspects of flammability not well captured by DGVMs (Harrison et al., 2022). These include vegetation fire-adaptive traits (Keeley and Pausas, 2022) and the impact of CO_2 thickening on vegetation flammability (Bond and Midgley, 2012; Manea and Leishman, 2019).

Finally, it was originally attempted to integrate WHAM! into INFERNO in a fully-coupled or 'online' structure, so that inter-temporal feedbacks could be captured and explored. However, technical difficulties entailed this was not possible. Specifically, the current vegetation engine within JULES – TRIFFID (Cox 2001) – was originally designed as an equilibrium vegetation model, to which representations of disturbance have only recently been added (Burton et al., 2019). Indeed, in Burton et al., (2019) it was found that including both land use change and fire as disturbances in JULES led to too much bare soil in the global land cover distribution. Inclusion of WHAM! would have increased levels of fire in line with improved Earth Observation data (GFED5) from levels projected by INFERNO (i.e. ~450Mha yr^{-1}) to ~800Mha yr^{-1}.

Consequently, a preliminary assessment was conducted to understand impacts of such increased rates of fire on JULES' distribution of plant functional types. This used WHAM! burned area and the relationship of NPP to vegetation resprouting in JULES (Harper et al., 2016) to assess probable impacts on model behaviour. The preliminary assessment indicated including WHAM! in an online coupling with JULES would lead to widespread desertification of the modelled world. As TRIFFID is currently being redeveloped (Chantelle Burton, personal communication), a practical decision was taken to attempt online coupling after this has been completed. However, with fine-scale remote sensing data indicating much greater global burned area than previously thought (Chen et al., 2023), re-calibration of JULES to account for this evidence of increased real-world rates of disturbance should be a research priority.

7.3 Modelling of human-Earth system interactions

7.3.1 Advances in understanding and model capacity

Advances to the development human-Earth system modelling are presented in two sections. The first section presents insights from WHAM! standalone runs for the SSPs, arguing that they demonstrate the value of modelling approaches that capture the inter-relationships of ecological and socio-economic processes. Secondly, the major technical advances in WHAM! that could have wider applications in human-Earth system modelling are summarised.

7.3.1.1 Advances in understanding

The value of adopting a transdisciplinary, socio-ecological approach to modelling of land system sustainability challenges is demonstrated in the standalone runs of WHAM! for the SSPs. WHAM! can identify emergent sustainability challenges implied by more positive future scenarios, and particularly by the economic development assumed in SSPs 1 & 5. For example, in SSP5, whose narrative definition assumes low climate adaptation challenges (O'Neill et al., 2017), rapid urbanisation leads to expansion of uncontrolled fires in wildland urban interface areas (Chapter 6; Figure 6.14b). This, combined with extreme levels of climate change points to, at best, highly challenging adaptation conditions. Furthermore, whilst the underlying SSP narrative perhaps assumes that technological progress will allow such issues to be overcome, it is unclear whether any level of intensive fire suppression would allow resulting societal harms to be addressed (Hoffman et al., 2022). Indeed, intensive fire suppression can lead to the 'fire paradox' – fuel build-up due to fire exclusion that ultimately leads to increased fire (Calkin et al., 2015; Hayes, 2021; Wunder et al., 2021) – and so may do more harm than good as an adaptation measure (Fernandes et al., 2020).

Furthermore, even in SSP1, WHAM! identifies significant emergent climate mitigation and adaptation questions. LUH2 land cover projections for the SSPs are driven by integrated assessment model outputs (Hurtt et al., 2020); one controversial aspect of such models is their projection of large-scale bioenergy as a means of removing Carbon dioxide from the atmosphere (Low and Schäfer, 2020). As such, in the LUH2 projections for SSP1 there is significant land conversion for planting of bioenergy feedstocks ("perennial C4 cropland" in the LUH2 data). Consequently, WHAM! projects a spike in deforestation fires around 2080 as land is cleared for bioenergy crops (Chapter 6; Table 6.10). This finding highlights the potential pitfalls of considering climate change mitigation strategies in the absence of holistic understanding of socio-ecological land system processes (Heck et al., 2018).

7.3.1.2 Advances in model capacity

Scaling-up of agent-based land use models to run at large spatial extents was a major technical challenge at the start of this PhD, and remains so at its end (Dressler et al., 2022). However, the work described in this thesis has contributed towards developing such modelling capacity. Indeed, as far as I am aware, WHAM! is the first agent-based model representing anthropogenic land use decision-making to run at global-scale.

Perhaps the most fundamental advance from a technical perspective was in finding a simple empirical means of representing competition between agent functional types (AFTs). As first proposed by Arneth et al., (2014), AFTs should compete for land in a similar way to plant functional types (PFTs). The competitiveness of different AFTs is specified within capital spaces – be they social, technological, economic or environmental – just as PFTs compete based on availability of biophysical resources such as sunlight or water. This essentially theoretical proposition is mirrored in the CRAFTY model, in which AFTs compete for land based on the outcome of a Cobb-Douglas objective function based on unitless capital spaces (Murray-Rust et al., 2014).

Rather than such a theoretical approach, WHAM! uses empirically-defined tree models specifying each AFT's preferred capital niche. This not only works effectively at reproducing observed patterns of land use occupancy, but also has several benefits for model behaviours. For example, as tree outputs for a given land system need not sum to unity in a given pixel, this can be used to capture how competitive the contest for land is. This property was used in WHAM! to capture the stocking density of rangelands, and particularly for where stocking rates were projected to be low (Chapter 5; Section 5.2.2.3). Given the diversity of land cover types described by 'rangelands' - from high productivity tropical savannas to arid grasslands – such land cover types can have greatly divergent rates of grazing intensity (Goldewijk et al., 2017). Capturing this dynamic was valuable in projecting the global distribution of pasture management fires (Chapter 6; Table 6.7 & Figure 6.7). Therefore, the capacity to represent *a lack of competition for land* in WHAM!'s land use module is an example of the flexibility of the simple underlying approach.

The use of meta-analysis to inform representation of land management decisions was identified by Magliocca et al., (2015b) as an important avenue for advancing land use modelling - hence, the empirical parameterisation of WHAM! is not strictly novel in a technical sense. However, it does demonstrate proof of concept for this approach in developing global-scale ABMs. Furthermore, WHAM! combines empirical parameterisation of AFTs' fire use and management actions with the theoretically-specified anthropogenic fire regimes as the basis of landscape-level meta effects. Processes represented in this way include presence of traditional fire knowledge, suppression-oriented fire policies, and arson due to land tenure conflict.

WHAM! therefore takes an intermediate course between the theoretical approach of CRAFTY (Murray-Rust et al., 2014) and the empirical approach taken by models such as CLUE (Verburg and Overmars, 2009) by empirically parameterising a theoretical conceptualisation of 'land fire systems'. As such, by focusing on one aspect of the land system (fire), WHAM! can draw on the most appropriate modelling strategies to capture the specific dynamics of this target process. Of course, a downside to this specificity is that models such as CRAFTY and CLUE may be applied to a wide array of land system questions (e.g. Das et al., 2020; Mamanis et al., 2021; Yin et al., 2022) whereas WHAM! cannot. Yet, repurposing of WHAM! to focus on, for example, water consumption, would be readily achievable subject to sufficient field-based data being available on water management practices amongst land users to parameterise relevant AFTs (Kaiser et al., 2020). However, applying WHAM! simultaneously to several land system processes would likely require more fundamental model redesign.

7.3.2 Remaining challenges

Attempts to capture human-Earth system feedbacks through process-based biophysical and ABM coupling are in their infancy (Calvin and Bond-Lamberty, 2018). Furthermore, much of the impetus for integrating agent-based models with process-based biophysical models has come from within the interdisciplinary land use science community itself (e.g. Robinson et al., 2018). Consequently, whilst literature on possible ABM approaches to scaling-up was available at the commencement of this PhD project (e.g. Arneth et al., 2014), no such assessment had been made of the strengths and weaknesses of differing DGVM approaches for capturing human-Earth system feedbacks. Here, therefore, a brief assessment is made of lessons learned through working with JULES-INFERNO in a socio-ecological systems modelling context. Discussion focuses first on how the structure of INFERNO shaped the present research, and then secondly on the broader modelling protocols and associated common forcing datasets currently used by DGVM and ESM communities.

INFERNO is a model of intermediate complexity (Mangeon et al., 2016). Amongst models in the FIREMIP ensemble, INFERNO is a simpler, more empirical model than SPITFIRE or the Community Land Model's fire module (Rabin et al., 2017). For example, SPITFIRE explicitly represents fire spread between model timesteps using the Rothermel physical fire spread equations (Thonicke et al., 2001). However, as INFERNO empirically calculates the burned area of individual fires (using a single burned area per PFT per fire - Chapter 6; equation 6.10), it is not as simple as the purely empirical approach of SIMFIRE, which calculates burned area per pixel directly through a regression approach (Knorr et al., 2014). INFERNO's intermediate-complexity approach was what dictated the ultimate structure of WHAM!-INFERNO. For example, integrating with SIMFIRE would have resulted in WHAM! outputs becoming additional independent variables in SIMFIRE's underlying regression model. Conversely, a fully physically-based model such as SPITFIRE would have entailed running few iterations of a more complicated and computationally hungry coupled model.

As such, INFERNO's structure supported the exploration of a large parameter space - 10k runs of a perturbed parameter ensemble - with sufficient biophysical process-representation to allow interactions of anthropogenic and biophysical factors to be modelled explicitly. Importantly, INFERNO models vegetation flammability using physically-grounded equations, which incorporate the respective roles of leaf Carbon and soil Carbon pools, vapour pressure, precipitation, and soil moisture (Mangeon et al., 2016). This enables INFERNO to calculate burned area from numbers of unmanaged fires projected by WHAM!. Therefore, the ability to explore the interactions of anthropogenic and biophysical drivers of fire regimes across diverse parameter spaces was enabled by INFERNO's simple, but not simplistic, approach.

The primary limitation of using INFERNO compared to a more complex process-based model such as SPITFIRE relates to the exploration of feedbacks. As noted above, exploring the 'fire paradox' requires representation of fire suppression and vegetation fuel build-up. WHAM! provides a process-based representation of fire suppression, grounded in both theory and empiricism. However, although INFERNO's calculation of vegetation flammability incorporates soil and vegetation Carbon pools, these effects saturate at 0.2 kgC m^{-2} (Mangeon et al., 2016), which corresponds to the point at which a cell is covered by tree plant functional types (Clark et al., 2011). Hence, intensive fire suppression would have no impact on INFERNO's projection of vegetation flammability beyond this threshold. Indeed, representation of the impact of antecedent fires (or lack thereof) is an identified challenge in INFERNO, even within frequently burning grassland ecosystems (Kuhn-Régnier et al., 2021). Hence, there is a trade-off between the free exploration of parameter spaces possible in WHAM-INFERNO and capacity to capture more complex feedbacks.

A further outcome of this PhD has been to highlight the importance of understanding land use transitions for both anthropogenic fire use and human-Earth system relations more broadly. WHAM! performs best for crop residue fires in pre-industrial (e.g. swidden) or industrial (intensive monoculture) agricultural systems but less well in mixed or transitional land system states (Chapter 5; Table 5.10). This can be traced back to underlying uncertainties in the distribution of anthropogenic fire regimes in Chapter 4, where the transitional anthropogenic fire regime was the focus of disagreement between WHAM's land use engine and land use intensity measured by the Human Appropriation of Net Primary Production (HANPP; Figure 4.10).

This finding has substantial implications for parameterisations of land user behaviours in large-scale models. Notably, understanding differing land use intensification pathways and their relationship to specific land user actions is vital. For example, in spite of rapid agriculture expansion and intensification (Marin et al., 2022). South America has not experienced problems with crop residue burning on the same scale as India and China (Hall et al., 2023). In WHAM!, this pattern is captured through population density: because population density is lower in South America, croplands move more rapidly through to the industrial AFR, whilst the inverse is true in India and China. Implicitly, therefore, at a process-level WHAM! suggests that higher (lower) population density is associated with small (larger) farms. On the one hand, larger farms may be better able to mechanise production and so cease fire use (Cammelli et al., 2020), whilst at the same time smaller farms - particularly in the developing world - tend to participate in informal supply chains, which are more challenging to regulate (Birthal et al., 2017; Bhuvaneshwari et al., 2019).

However, an alternative explanation of the divergence between South America and Asia in patterns of crop residue burning could be the larger volume of residues produced by rice versus soybeans (Yang et al., 2008). Pertinently, one area where reside burning has become an environmental and air quality issue in South America centres around the sugarcane ethanol industry in the Sao Paulo region of Brazil (Pestana et al., 2017), which is therefore an outlier given the dominance of soybean production in the Brazilian agricultural heartlands (Song et al., 2021).

The first land use model intercomparison project found that current land use models struggle even to produce spatial patterns of land cover change (Alexander et al., 2017). Furthermore, the currently dominant optimisation-based approaches to land use modelling systematically over-predict rates of land use change (Turner et al., 2018). Therefore, incorporating the kind of detailed process-based understanding required to capture the heterogeneity of real-world land use transitions and their relationships to specific land user actions and management strategies remain a major research challenge (Verburg et al., 2019).

At the project outset, a pragmatic choice was made to adopt the land cover data used by DGVM and ESM communities in both FIREMIP and CMIP6 (i.e. LUH2; Chapter 4). This enabled direct comparison of model outputs with those from FIREMIP, as well as allowing ready integration with JULES outputs – which assume anthropogenic land covers occupy the pixel fractions suggested by the LUH2 (Hurtt et al., 2022; Wiltshire et al., 2020).

This thesis has noted several limitations of WHAM!'s representation of land system dynamics that resulted from the choice of land cover data. These include the handling of the 'rangeland' land cover class in LUH2, which covers grazing lands in semi-natural grasslands across a diverse climatic gradient (Klein Goldewijk et al., 2017, Section 4.2.4.3). Implementing representation of pasture management fire in rangelands required a top-down correction in WHAM! (5.2.2.3). Furthermore, representation of cropland abandonment, which can have a substantial impact on fire regimes (Chapter 3; Figure 3.9), was restricted by use of LUH2, where such effects are already implicitly represented in the data. Similarly, it was originally intended to adopt AFTs for mixed smallholders (cropping and livestock farming; de Haan et al., 2010; Table 3.1). However, LUH2 disaggregates mixed or mosaic land cover classes into fractions of cropland and pasture (Klein Goldewijk et al., 2017), and hence mixed AFT types were not used in the final model.

Capturing the complexity of land use dynamics, and particularly anthropogenic land management, in globally harmonised datasets is an active area of research, and hence several alternatives to LUH2 could have been adopted (Table 7.1). Broadly, these can be categorised into land cover data sets based on Earth observation, and those that seek to integrate such satellite-derived data with government and other land management data. In this latter category, the HILDA+ data of Winkler et al., (2021) is a recent and high-resolution data set that integrates fine-scale remote sensing (e.g. Sentinel-3 at 300m2 resolution) with FAO land use data.

HILDA+ demonstrates that global rates of land use change are around four-times greater than suggested by coarser-resolution data sets such as LUH2 (Winkler et al., 2021). Adopting HILDA+ data could have been particularly beneficial for representation of grazing lands: LUH2 suggests that the annual mean change in pasture & rangeland is just 5.7Mha, compared with 42Mha in HILDA+. This points to underlying issues in the distribution of grazing lands in LUH2, which have been identified in numerous regional studies (see Qiu et al., 2023 for a brief review), with particular issues noted in Brazil (Chini et al., 2021). Similarly, adopting the widely-used MODIS-based land cover data product (Friedl et al. 2010) would have had the benefit of the 'cropland-mosaic' land cover class, which could have constrained the distribution of shifting cultivation. LUH2 distributes shifting cultivation based on the expert elicitation and visual inspection of Heinimann et al., (2017), which results in coarse categorisation of its presence as "very-low", "low", "moderate" or "high" (Hurtt et al., 2020).

A further alternative to MODIS-based land cover or the HILDA+ reconstruction would be to use model outputs. The principal advantage of this for historical runs would be to include additional information on land use intensity (e.g. Nitrogen fertiliser application, irrigation). These data could have been used to constrain land use transitions in WHAM!, for example the drivers of crop residue burning under land use intensification (Sections 4.2.4.2 & 5.3.3.2). However, current land use models have substantial challenges in reproducing observed rates of land use change (Turner et al., 2018), with model structure (ABM, partial general equilibrium) being more predictive of modelled rates of change than differences in socio-economic scenarios (Alexander et al., 2017; Brown et al., 2020). Hence, use of modelled land use may be most suitable for future model runs, potentially mitigating observed scenario (in)coherence in WHAM! SSP runs with LUH2 (Section 6.3.4).

Table 7.1: Overview of some key possible alternatives to LUH2 data as land cover inputs to a global-scale model. LUH2 fulfils a critical need of Earth system modelling – integrating future runs with paleo-reconstructions of the Holocene – but this may be at the expense of specificity in reconstructions of the recent past.

Dataset	**Type**	**Temporal range**	**Spatial resolution**	**Notes**
LUH2	Harmonised long-term reconstruction & future projection	10,000 BCE-2100	0.25º	Current standard input for global model intercomparison protocols; known issues with distribution of grazing lands
ESA-CCI	Earth observation (land cover)	1992-2020	300m²	Includes land use mosaic classes that could support mixed smallholder types
MODIS	Earth observation (land cover)	1997-2020	500m²	Includes a cropland mosaic that could be used to capture shifting cultivation
HILDA+	Land use reconstruction	1960-2018	1km²	Detailed treatment of land use transitions delineates between deforestation and short-term disturbances (e.g. shifting cultivation)
PLUM	Land use model (future projections)	1990-2100	0.5º	Spatially-explicit land use and land cover projections; currently integrated with LPJ-GUESS model for crop yields

Citations: LUH2 (Hurt et al., 2022); ESA-CCI (Li et al., 2018); MODIS (Field et al., 2010); HILDA+ (Winkler et al., 2021); PLUM (Alexander et al., 2018); LPJ-GUESS (Lindeskog et al., 2013).

7.4 Future Work

In the previous sections of this Chapter some limitations to the work presented have been identified. These are principally: improving quantification of indigenous (nomadic and semi-nomadic) fire use; improving understanding of the drivers of crop residue burning in India and China and their relationship to land use intensification; improving understanding of the drivers of landscape fragmentation in sub-Saharan Africa and its relationship to declining burned area; and online coupling of WHAM!-INFERNO. Addressing each of these limitations will require substantive research efforts beyond the scope of this PhD. This section, therefore, focuses on opportunities for shorter-term development and application of WHAM!-INFERNO.

7.4.1 Development of WHAM!-INFERNO

7.4.1.1 Seasonality of anthropogenic fire

Data on the seasonality of anthropogenic fire use were recorded in DAFI as the first and last month a given practice was used or not used in each case study (Chapter 3; Section 3.2.2.2). Using kriging, an attempt was made to interpolate these data points to the global JULES-INFERNO model grid for each of the seven central modes of anthropogenic fire use identified through analysis of DAFI. The output of this was 12 boolean maps (one for each calendar month) for each of the seven modes of fire use, denoting whether a fire use type should be present in a given pixel. These 12 maps were summed by pixel and divided by the total, resulting in maps giving the proportion of a given fire use that should occur in each month. Where the sum of the Boolean maps was zero, a uniform distribution was assumed ($\frac{1}{12}$ in each month).

However, these maps had multiple issues (Figure 7.1). The patchiness and spatially-skewed data available led to identification of implausible patterns of seasonality. Smoothing of the original extrapolations led to more coherent maps, but did not capture some of the underlying patterns. Therefore, WHAM! was run at an annual timestep for coupled results presented here. It should be noted that removing the seasonality of anthropogenic fire use in WHAM! had only a very limited impact on outputs of WHAM!-INFERNO. As managed fire burned area was calculated at an annual timestep within WHAM! this was not impacted. Furthermore, of the three sources of unmanaged anthropogenic fires in WHAM!-INFERNO, only escaped managed fires were impacted. This was because the background rate was uniform, and as no reliable seasonality data were available for arson, a global uniform distribution was already assumed. To sense check the possible influence of seasonality of escaped fires on burned area, model outputs were re-run using the seasonality maps described above. Model performance was essentially unchanged: the correlation across the pareto parameter space of 10k model runs was 0.734.

A possible improved means of representing anthropogenic fire seasonality is detailed in Smith et al.., (including Perkins; in review) in which calendar months of burning were related to the underlying drivers of the seasonal cycle (potential evapotranspiration, precipitation and their combination). This produces more credible outputs. However, this analysis only focuses on livelihood fire by small-holder and indigenous fire uses and so does not include many fire use cases represented in WHAM! Furthermore, timing of fire use depends not only on seasonal cycle, but also multiple socio-economic factors. For example, the presence (or absence) of community fire governance can determine whether fire is set at the start of the dry season (when fire use is typically controlled) or later in the dry season (when fire use is much harder to control; Laris 2002; Butz 2009). Capturing the global seasonality of anthropogenic fire in a systematic way therefore remains a challenge in fire modelling.

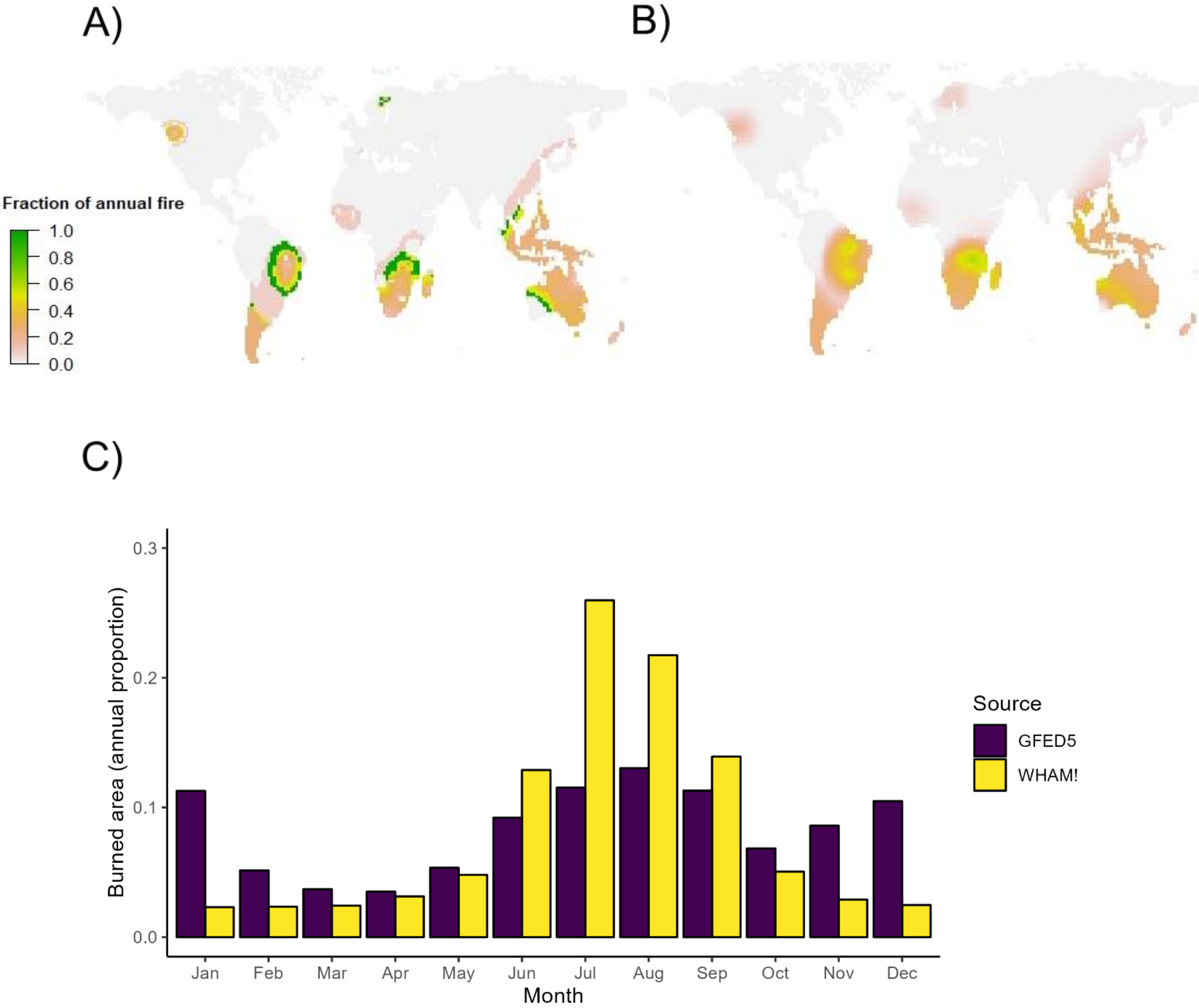


Figure 7.1: Example of the attempt to include fire seasonality in WHAM. Maps describe proportion of pyrome management fire in a pixel that occurred during the month of July, a) before a smoothing window was applied, and b) after smoothing; c) gives the seasonality of burned area from managed fire in comparison to GFED5. This approach to seasonality was discarded from WHAM! as it did not add meaningful representation of process or serve to improve model performance.

.7.4.1.2 WHAM!-EO

It is clear from outputs in Mangeon et al., (2016) and unmanaged fire in the WHAM!-INFERNO ensemble presented in Chapter 6 that INFERNO contains some structural biases. For example, fire extends too far north at the Southern edge of the Sahara Desert, and the Caatinga dry forest region of Brazil is instead a savanna and hence too flammable (Chapter 6; Figure 6.7). These two biases relate to known underlying issues in JULES' hydrological and vegetation growth parameterisations (Wiltshire et al., 2020). Hence, to understand how much these might constrain the capacity of WHAM!-INFERNO to reproduce and understand observed patterns of fire, an additional version of WHAM! could be constructed, in which inputs from JULES would be replaced with remote sensing observations. This additional parameterisation of WHAM! could also serve to facilitate coupling of WHAM! to additional DGVMs and potentially generic inputs to CMIP7 (see Section 7.4.2.1).

7.4.1.3 Grazing intensity

Attempts were made in WHAM! to capture the effects of livestock grazing intensity on unmanaged fire spread both in semi-natural grasslands ('rangelands') and planted pastures. The representation of grazing sparsity in WHAM!, for example, was trialled (Chapter 5; Section 5.2.2.3). However, this constraint was designed to limit managed fire use in low NPP rangelands, whilst the major unknown impact of livestock grazing is in dense or 'overgrazing' fragmenting fuel loads in fire-prone, higher NPP, savannas (Hempson et al., 2017; Zubkova et al., 2019). As such, use of this constraint was not fully coherent from a perspective, and also did not seem to improve model performance. Another option explored was to use the grazing intensity output of the Parsimonious Land Use Model (PLUM; (Alexander et al., 2018). This worked well in initial trials for model years 2012-2014, and this parameterisation could now be expanded to the full WHAM!-INFERNO historical period (1990-2014) pending updated historical runs of PLUM (Peter Alexander, personal communication).

7.4.2 Further applications of WHAM!-INFERNO

7.4.2.1 Crop fire emissions

Alongside burned area, the GFED5 cropland product of Hall et al., (2023), includes a new set of emissions factors for cropland fires derived from a literature metanalysis. As such, it should be possible now to use WHAM! to project cropland emissions across the SSPs. This output should then be able to form the basis of a prescribed input to Earth System Models in the next coupled model intercomparison project (CMIP7). In CMIP6, cropland burning emissions were derived from non-spatial IAMs without explicit representation of the processes driving crop fires. As such, a global WHAM! projection would represent an important improvement.

7.4.2.2 Narrative interpretation of WHAM! SSPs

The outputs of WHAM! for the SSPs paint contrasting pictures of anthropogenic fire use and management. In particular, the difference in pasture and crop residue burning between SSPs 1&5 versus SSP3 is stark (Chapter 6; Figure 6.14a) and is of a scale that needs to be considered alongside global environmental change when exploring future fire regimes. Of course, WHAM! is just one model, and its outputs contain some errors that are specific to JULES (Section 7.4.1.2). As such, one method to increase the applicability of broad findings from WHAM! future runs could be to create narrative interpretations of its outputs for the SSPs.

Narrative interpretations of ABMs have been previously suggested as ways both to increase the generalisability of ABM findings (Perry and O'Sullivan 2017), but also to sense-check model representations of human behaviours (Millington and Wainwright 2016). One way to develop SSP narratives for human-fire use and management, would be to convene a group of researchers and practitioners to interpret the broad kinds of pyro-futures described by WHAM! outputs.

7.4.2.3 SSP runs of WHAM!-INFERNO offline coupling

Running the offline WHAM!-INFERNO ensemble for the SSPs is a realistic medium-term goal. At present, this goal is constrained only by practical considerations. Firstly, flammability, which is a key input into the offline coupling is not routinely output during JULES-INFERNO runs. Hence, flammability is not available for the CMIP6 runs from which other JULES inputs to WHAM! were sourced. The INFERNO core team plan to output flammability for the SSP runs as a part of the inter-sectoral model intercomparison project (ISIMIP), but this not scheduled until autumn 2024 (Chantelle Burton, personal communication).

7.4.2.4 Towards anthropogenic pyromes

Several authors have made attempts to categorise global fire regimes, including their anthropogenic components (Chapter 2). However, as top-down approaches, these rely on categorisation quantitative measures of the fire regime (fire size, timing, burned area), rather than on the processes that drive them (Chapter 2). As WHAM!-INFERNO now provides a breakdown of burned area, but also its socio-ecological drivers, there is potential to use these outputs to define 'anthropogenic pyromes'. The primary route to achieving this would be by combining WHAM! outputs, remote sensing observations, and indicators of human land use intensity, such as the Human Appropriation of Net Primary Production (Haberl et al., 2007; Chapter 4).

7.4.2.5 Beyond GDP: human capitals under the SSPs

Running WHAM! for the SPPs required new spatial projections of the Human Development Index and the market access metric of Verburg et al., (2011). Beyond their immediate application, these projections contribute to the removal of a barrier towards global application of behavioural land use modelling – the absence of appropriate datasets from which to define AFT capital spaces (Perkins et al., 2022; Chapter 4). Hence, in partnership with other land system modelling groups working on projections of further indicators, we plan to create a suite of human indicators for spatial modelling of human-Earth system interactions.

7.5 Conclusion

Capturing the distinction between managed and unmanaged fires in fire models has been highlighted as a major challenge in fire science (Teckentrup et al., 2019; Ford et al., 2021; UNEP 2022), and perhaps even a requirement to 'repurpose fire science for the Anthropocene' (Shuman et al., 2022). This PhD thesis represents a large step towards achieving this research goal.

Analysis of DAFI, the database of anthropogenic fire impacts, identifies seven central modes of anthropogenic fire use, their respective spatial distributions and quantitative fire regime characteristics (Chapter 3). WHAM!, the wildfire human agency model, projects these seven modes of fire globally. WHAM! outputs for crop residue fires show good coherence with the GFED5 crop fires product, the first time a global spatial model of this process and a global Earth observation product of crop fires have been compared (Chapter 5). Furthermore, wider WHAM! outputs, including for managed vegetation fires, unmanaged fires and fire suppression serve significantly to improve the capacity of INFERNO to reproduce observed burned area in GDED5 (Chapter 6).

More broadly, work here demonstrates the importance of coupled socio-ecological modelling for understanding present-day environmental processes and sustainability questions. For example, errors in distribution of WHAM! crop residue fires are closely related to the challenge of modelling land use transitions (Chapter 4). Moreover, running WHAM! for the SSPs identifies emergent climate adaptation and mitigation challenges under contrasting futures (Chapter 6). For example, WHAM! runs for SSP1 point to the potential environmental damage from rapid land use conversion for biofuel crops; whilst SSP5 runs suggest extreme adaptation challenges due to rapid climate warming and growth of the wildland urban interface.

Future research priorities highlighted by this thesis (this Chapter) include improving field-based quantification of anthropogenic fire uses, particularly nomadic and indigenous fire; and the need for meso-scale modelling of the interactions between direct and indirect anthropogenic influences on fire regimes, particularly in the savannas of sub-Saharan Africa.

Overall, this thesis provides valuable advances in understanding for global fire science and modelling of human-Earth system interactions.

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Appendices

Appendix 3A: Foundational reviews & meta-analyses used to structure DAFI literature search

These papers were used to begin the snowball search for literature in each preliminary AFT category; papers were focused on fire management where possible, or otherwise search began from the land use (LULC) literature

Category	Source	Type	Focus	Comments
Shifting cultivation	Van Vliet et al., 2012; Mertz et al., 2009	Systematic review (global); Systematic review (SE Asia)	LULC; LULC	Van Vliet was global, Mert focused on South East Asia; search terms from Van Vliet used to identify more recent papers
Migratory pastoralism	Nori and Scoones 2019; Liechti & Biber 2016	Global review & research agenda Regional review (Europe)	LULC; LULC	Both studies primarily used to define search terms to identify sources; references in Liechti identified as candidates for inclusion
Hunter gatherer	Laris 2002; Fowler & Welch 2018	Foundational paper; Comprehensive global overview	Fire; Fire	Papers citing / cited by sources were beginning of snowball sample
Monoculture cropping: residue burning	Kumar et al., 2015	Primary research and comprehensive regional literature review	Fire	Used to directly identify papers and define search terms
Extensive livestock farming	Briske 2017; Asner 2004	Robust introductory text; Literature review	LULC; LULC	Both texts used to define search terms; references in Briske and papers citing Asner used to begin snowball
Small-scale forestry	Cochrane 2009a; Nepstad et al., 1999	Comprehensive pan-Tropical literature review Foundational paper	Fire; LULC	For both papers, citations and papers citing used to begin snowball

Category	Source	Type	Focus	Comments
Monoculture cropping: deforestation	Cochrane 2009a;	Comprehensive pan-Tropical literature review	Fire	Citations and papers citing used to begin snowball
Livestock farming: deforestation	Cochrane 2009a;	Comprehensive pan-Tropical literature review	Fire	Citations and papers citing used to begin snowball
Industrial forestry	Blanco et al., 2015; Kalies & Kent 2016	Systematic review; Systematic review	LULC; Fire	Citations and papers citing used to begin snowball
Agricultural abandonment	Seijo & Gray 2012	Literature review	Fire	Citations and papers citing used to begin snowball
Biodiversity conservation	Govender et al., 2006; Fernandes et al., 2016	Foundational paper; Quantitative review / field manual	Fire; Fire	Citations and papers citing used to begin snowball Data directly included; citations used for snowball
Wildland urban interface	NA	NA	NA	"Wildland urban interface AND fire" was searched directly to identify papers

Appendix 3B: Suggested systematic search terms for a meta-analysis of global anthropogenic fire use

Whilst all search terms are assigned to one land use / fire development stage category, several such as residue burning, and biodiversity conservation are applicable across divisions.

Anthropogenic fire regime	**Forests & forestry**	**Pasture & grassland**	**Cropland & secondary vegetation**
Pre-industrial	Traditional fire knowledge; traditional fire use; traditional ecological knowledge AND fire; Indigenous fire use; Aboriginal burning; Aboriginal fire use; hunting AND fire; patch mosaic burning;	Migratory pastoralism AND fire; pastoralist AND fire; transhumant herder AND fire; nomadic herder AND fire	Shifting cultivation AND fire; swidden; "slash and burn" AND fire; *Citamene* AND fire; "slash and mulch"
Transitional	Charcoal making; charcoal production; fire use timber harvesting; logging fires; fire illegal forestry; fire tropical timber extraction Fire-free agroforestry; agroforestry fire use	Rangeland burning; rangeland AND prescribed fire; pasture burning; pasture renewal fire; pasture fire; escaped pasture fire; rangeland management fire; pasture AND deforestation	Straw use AND fire; straw management AND fire; crop residue disposal AND fire; agricultural fires, field burning, agricultural burning, stubble burning; crop residue burning; haze AND agricultural fire; air quality AND agricultural fire; air pollution AND agricultural fire; veld fire; sugar cane burning; pre-harvest sugar cane burning; rice straw burning

Anthropogenic fire regime	Forests & forestry	Pasture & grassland	Cropland & secondary vegetation
Industrial	Forest management AND fire; salvage logging fire; prescribed burning AND forestry; fuel load management; fuel load management AND fire; forest fuel load management; stand thinning AND forestry	Woody encroachment AND fire; rangeland AND fire reintroduction; livestock AND fire management; patch-burning AND livestock	Deforestation AND fire; deforestation AND wildfire; land clearance AND fire; agricultural land clearance AND fire; fire use deforestation
	Wildland urban interface; wildland urban interface AND fire; wildland urban interface AND fire management; fire paradox; wildland urban interface AND fire paradox; wildland urban interface AND fire suppression; tourist AND accidental AND fire		
Post-industrial	Pyrodiversity prescribed burn; pyrodiversity management; conservation AND fire; conservation AND prescribed fire; biodiversity conservation AND prescribed fire	Grazing AND fire management; prescribed grazing; prescribed grazing AND fire management	Land abandonment AND fire; agricultural abandonment AND fire; land abandonment AND fuel load;

Appendix 3C: Variables recorded in DAFI

Fire use contexts were recorded for all fire use, suppression and policy records. Fire use data were recorded as numeric values where directly reported & binned ranges where estimated from reported proxy variables.

Data type	Field	Values
Record information	Study type	One of: Academic, NGO, Government, Other
	Data type	One or combination of: Primary, remote sensing, secondary, literature review, other
	Location	Smallest given administrative unit comprising whole study area
	Region or district	Reported geographical which contains study location(s)
	Country	Country of interest, multi-country studies should be in separate case studies
	Latitude	Latitude in decimal degrees
	Longitude	Longitude in decimal degrees
	Study area	km^2
	Study date (start)	Integer, years CE
	Study date (end)	Integer, years CE

Data type	Field	Values
Land use	Land tenure	One of: Traditional, government-allocated, private, insecure, mixed.
	Pyne fire development stage	One of: Pre-industrial, Transition, Industrial, Post-industrial
	AFTs	Up to four preliminary AFT types chosen from Pyne/Malek framework
	Stocking rate (head ha^{-1})	Numeric value
	Farm area (ha)	Numeric value: what was the mean farm area in the study?
	Yield (t ha^{-1})	Numeric value for dominant commodity grown, note commodity under notes
	Extractive forestry	Was there extractive logging taking place in not-plantation forest?
	Biomass harvesting (m^2 ha^{-1} yr^{-1} or t ha^{-1} yr^{-1})	Amount of timber harvested from primary and secondary forest
	Forestry area (%)	Numeric: refers to all forest landscapes that are actively managed for either timber, fruit or other NTFPs
	Pasture area (%)	Numeric
	Cropland area (%)	Numeric
	Secondary vegetation (%)	Numeric: refers to all vegetation that is degraded through human activity, but not actively managed. For example, a secondary forest regrowing on a previous swidden plot.
	Natural ecosystems (%)	Numeric
	Natural ecosystem conversion rate(%)	What % of the existing natural ecosystems are being converted to cropland or pasture, or being destroyed and replaced with plantation forest?

Data type	Field	Values
Fire use context (recorded for fire use, suppression and policy)	Fire type	One of: Human Deliberate, Human Accidental, Human Escaped, Lightning, Other Natural, Unknown
	Fire intention	21 options: check for existing categories before creation of a new one; can also be "ND" or "All" for all fire behaviours present in that case study
	AFT	Preliminary AFT from Pyne/Malek framework
	Intended land cover	Which land cover was the fire intended to burn? One of: Cropland, pasture, secondary vegetation, plantation forest, forest, grassland, shrubland (mixed forest and grassland).
	Actual land cover	Actual land cover the fire burned - may be different from intended, if e.g., an agricultural fire spread into the surrounding forest
	Presence / Absence	Is this record noting an instance of the presence of burning or the absence of it? One of: Presence, Absence

Data type	Field	Values
Fire use	Number of fires, land cover	# $km^{2\ -1}$: How many fires of this kind occurred per sq km within the relevant land cover?
	Number of fires, study area	# $km^{2\ -1}$: How many fires of this kind occurred per sq km of the study area?
	Intended fire size min, median, max, mean	ha: what were the min, max and mean of the intended fire size for each ignition?
	Actual fire size min, max, mean	ha: what were the actual reported min, max and mean fire size for each ignition?
	Intended burned area	ha: How much area was intended to be burned for this fire type?
	Actual burned area	(ha): How much area was reported as burned for this fire type?
	Intended burned area	%: How much of the intended land cover was intended to be burned for this fire type?
	Actual burned area	%: How much area was reported as burned for this fire type of the relevant land cover
	Intended burned area	%: How much of the land surface was intended to be burned?
	Actual burned area	%: How much of the land surface was burned?
	Fire return period	Years: How frequently was a given piece of land burned with this intention. 1 = every year
	Fire season start & end	Month of the Julian calendar
	Fire ignition pattern	One of: One-off, Consistent, Seasonal back-loaded, Seasonal front-loaded, Seasonal consistent

Data type	Field	Values
Fire suppression	Fire control (0-3)	0: None 1: Limited or adhoc 2: Moderate or traditional 3: Intensive or industrial
	Fire prevention (0-3)	Ordinal scale as control
	Fire extinction (0-3)	Ordinal scale as control
Fire policy	Institutional agent type	Usually national government; can also be regional/local government, NGO, other international organisation.
	Incentives	Did the fire policy involve economic incentives? One of: No, Yes (fire prevention) Yes (pro-fire)
	Incentive rationale	What was the purpose of the incentives? One of: Economic, Environmental, Health
	Fire Restricted	Did the fire policy involve restrictions on fire use? One of: Yes -spatial restriction, Yes - temporal restriction, , Yes - both spatial and temporal restriction, Yes (other), No.
	Restriction rationale	What was the purpose of the restriction? One of: Economic, Environmental, Health
	Restriction Enforcement (1-5)	1) none or limited, 2) partial; fine or civil action, 3) partial prison or criminal action, 4) widespread; fine or civil action, 5) widespread prison or criminal action)
	Fire banned	Did the fire policy involve outright bans on fire use? One of: Yes, No
	Ban rationale	What was the purpose of the ban? One of: Economic, Environmental, Health
	Ban Enforcement (1-5)	Scale as with restriction

Appendix 3D: Categorisation of fire use purposes in WHAM!

Long list of categories, and 7 simplified categories that captured 93% of instances of anthropogenic fire use in DAFI.

Original category (n = 21)	Simplified category (n = 7)	Description
Accessibility	Other (N/A)	Fire use to clear pathways through vegetation, typically in savannah landscapes. Used to facilitate land uses across pre-industrial land use systems
Accidental	Other (N/A)	Anthropogenic fires started unintentionally, for example from cigarettes, exhaust fumes or faulty power cables
Arson	Arson	Fire used to cause damage to persons or property; in some contexts, fire damage caused through negligence may also be considered arson
Charcoal production	Other (N/A)	Fire used to burn wood for charcoal, principally important as a source of escaped fires
Conservation	Pyrome management	Fires lit to conserve biodiversity by creating diverse stages of vegetational succession in a landscape
Crop field preparation	Crop field preparation	Fire use in the context of shifting cultivation
Crop residue burning	Crop residue burning	Fire used to remove agricultural residues, either pre or post harvest
Cultural & Spiritual	Other (N/A)	Fire used for social or religious ceremonies; other fire uses may also take on a cultural or religious significance
Domestic	Other (N/A)	Relevant for escaped fires
Fishing	Hunting and gathering	Fires to facilitate fishing
Forest clearance	Vegetation clearance	Fire used to clear forest land cover
Forest management	Other (N/A)	Typically to promote / manipulate timber growth (does not include fuel load management, which is under pyrome management)

Original category (n = 21)	Simplified category (n = 7)	Description
Harvesting of NTFP	Hunting and gathering	Fire to harvest non-timber forest products such as honey, fruit or mushrooms
Harvesting of Timber	Arson	Fire was used for burning of forests to facilitate illicit salvage logging (n = 21)
Hunting	Hunting and gathering	Fires to facilitate hunting of wild animals
Land clearance	Vegetation clearance	Fires to clear non-forest vegetation types, typically savannas
Pasture renewal	Pasture management	Fires to regenerate livestock forage, typically in managed pastures
Pest management	Pasture management / Other (NA)	Pest management fires were most often used in the context of livestock (46%) - where fires for pest control and forage restoration were sometimes interchangeable. Therefore, this category was split between pasture management and 'other' where conducted by arable and forestry fire user types.
Pyrome management	Pyrome management	Fires lit to manage the wider fire regime, for any purpose other than conservation - typically to prevent damage to persons or property from wildfires
Rangeland management	Pasture management	Fires to regenerate livestock forage, typically on open rangeland; fire may also have served purpose to remove coverage for predators or prevent livestock from tripping on hidden holes in the ground
Vegetation management	Crop residue burning / Other (NA)	Many instances were for sugar cane burning to facilitate harvest; this was grouped with crop residue burning (pre-burning)

Appendix 4A: Data processing

This appendix covers processing of secondary data undertaken to support modelling and findings presented in Chapter 4 (Perkins et al., 2022). It covers rescaling, extrapolation, sampling and smoothing of secondary data sets.

1. Data Processing

1.1 Preparation of DAFI data

Data in the Database of Anthropogenic Fire Impacts (Chapter 3) are the basis of the dependent variable in models presented. Perhaps the most substantial in data preparation was how many case study locations to allow for a single source. We chose to include a maximum of four covering the same anthropogenic fire regime from the same country. We could, for example, have only allowed one location per source.

However, given the nature of our data, many of the papers reporting multiple case studies reported locations in contrasting land system states or regions: 50% of case studies that were included from papers with more than 3 case studies contained locations in multiple countries or regions (states or districts). Alternatively, a paper might sample, e.g., an agricultural region and a nearby conservation reserve: 27% of sources with more than 3 included case studies reported cases from more than one anthropogenic fire regime. Therefore, reducing the number of case studies (and therefore locations) per source to 1 would substantially reduce the information in our data. For this reason, we think the global mean value of 4 (rounded from 3.7) is a good threshold for locations per source.

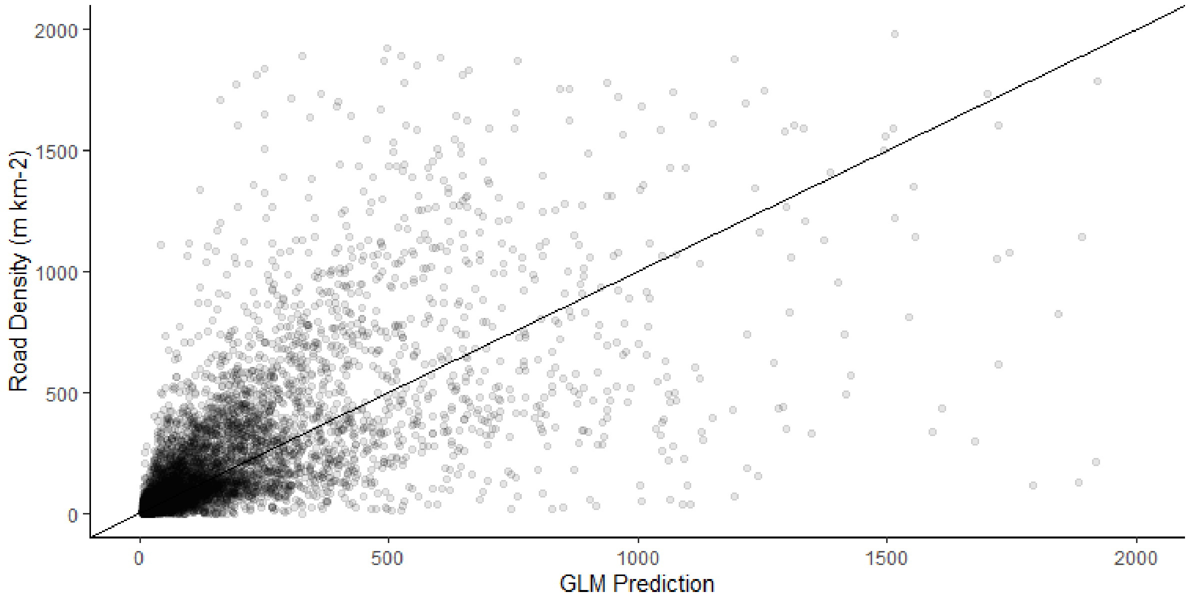
1.2 Rescaling of data

The ultimate goal of the land-fire system distribution presented in Chapter 4 is to develop a model of human fire impacts that may be coupled with the JULES-INFERNO DGVM. JULES-INFERNO runs at a resolution of 1.875° x 1.25°. Therefore, all secondary data sets employed in our model were re-scaled to this (coarse) resolution. This was done in R using the 'raster' package version 3.3.13 (Hijmans 2020) using bilinear interpolation.

1.3 Extrapolating data sets

Data sets used came with a varying level of temporal coverage over the period of model runs (1990-2015; see Chapter 4, Table 4.1 for a complete list). Missing years in data sets were handled in two ways. Data which contained direct measurements (for example population density) which did not have full coverage across the study period were extrapolated using a simple last observation carried forward or first observation carried backwards approach. By contrast, market access data were not directly measured but were themselves compiled from calculations based on secondary data. Therefore, as these were only available for one study year, they were extrapolated across years study years using a generalised linear model.

A)



B)

Variable	Coefficient
Intercept	0.7709
Log(Population)	0.1013
GDP	-1.689 e-06
HDI	0.6874

Figure 4A.1: Overview of generalised linear model used to predict global road density: A) Predictions against original data set & B) model coefficients. The model achieves good predictive accuracy (pseudo $r^2 = 0.71$), but tends to under-predict the variance in the response variable (standard deviation: 604.8, data vs 306.3, modelled). The glm used a gaussian response variable with a logarithmic link. The original data were for 2015 (Weijer et al., 2018).

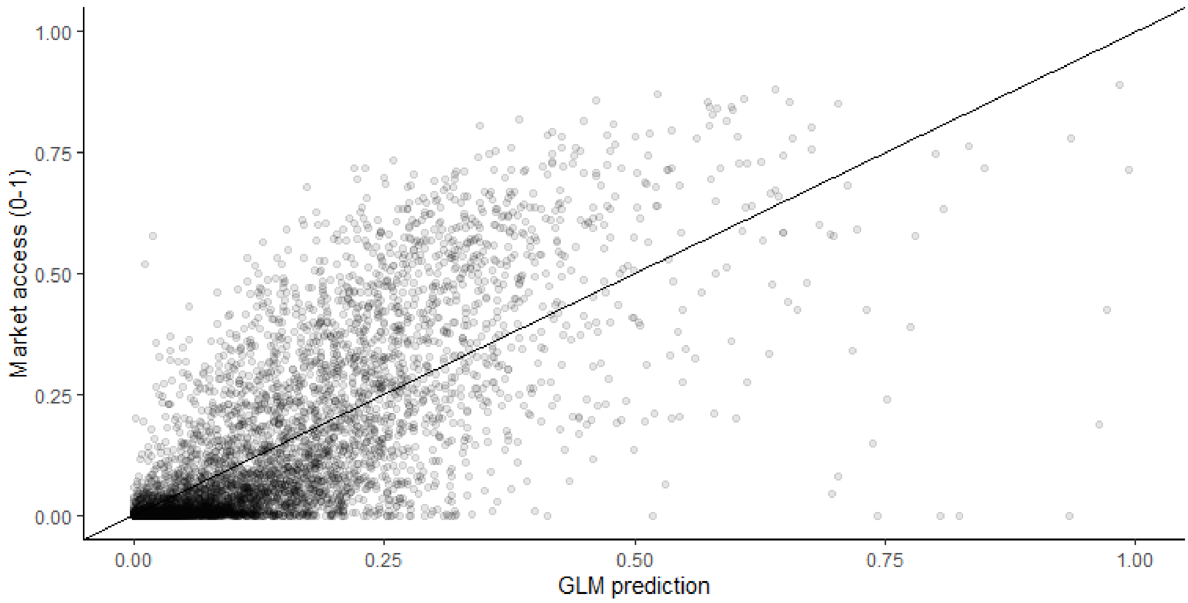
2. Extrapolation of market access data

Market access data (Verburg et al., 2011), (which describes the travel time to the nearest city or port on a 0-1 scale), were found to be valuable as a driver of the distribution of land-fire systems (LFS). However, they were only available for the year 2000. Furthermore, as the original data were themselves derived from secondary data - the location of ports and cities and road density – it should be possible to extrapolate the measure across all study years. This was done using a generalised linear model (GLM) using the following steps.

Given the importance of travel times in calculating the accessibility of the nearest city or port from a given location, the first step was to find predictor variables to capture this aspect of market access. A number of methods were tried, including use of the 'accessibility' and friction layers for 2015 developed by the Global Malaria Project (Weiss et al., 2018). This was projected across 1990-2015 by modelling the friction layer as a generalised linear model, and using this extrapolated temporal variable to calculate the least cost path from each grid cell to the nearest city or port. However, perhaps due to the complexity of this calculation, the extrapolated accessibility and friction layers were found not to be predictive of the 2000 market access data. The eventual adopted approach, therefore, was to use the global road density data set of Meijer et al., (2018) as a proxy for travel times across a given grid cell. These road density data were extrapolated across the study period using a generalised linear model, with GDP, HDI and the natural logarithm of population density as predictor variables (Figure 4A.1). The underlying model achieved an r^2 of 0.71.

Along with this extrapolated road density layer, the glm of market access also used the logarithm of population density and the un-extrapolated accessibility layer of Weiss et al., (2018). The resulting model achieved a pseudo r^2 of 0.73 (Figure 4A.2). Whilst the use of the static accessibility layer of Weiss added bias to the model, the glm still achieved good predictive accuracy. Ultimately, the use of extrapolated market access data is justified in its empirical performance: the AUC of classification trees that used the market access or related market influence variables increased by an average of 0.01 when the extrapolated data was used. Furthermore, for the planned global model of human impacts on fire to be run into the future data will need to be able to be projected forwards. Our work suggests this is feasible for market access, which underpins its utility as a predictor variable of human fire use.

A)



B)

Variable	Coefficient
Intercept	-3.396
Population	7.998e-05
Log(Road density) +1	0.3383
Accessibility	-4.809e-03

Figure 4A.2: Generalised linear model used to predict global market access: A) Predictions against original data set & B) model coefficients. The model achieves good predictive accuracy (pseudo r^2 = 0.73), but underestimates market access at low to moderate levels (particularly 0.25-0.5). The glm used a gaussian response variable with a logarithmic link. The original data were for 2000 (Verburg et al., 2011).

3. Calculation of variable convolutions and other derivatives data sets

Three derivative predictor variables were calculated based on the original secondary data sets employed in the study. These were:

- HDI*log(GDP)

During the construction of classification tree models, GDP and HDI were found consistently to be chosen as the first split in a tree structure in approximately 50% of a bootstrapped ensemble. It was found that the product of HDI and the natural logarithm of GDP was chosen preferentially in place of GDP and HDI in the majority of such instances. This may be because HDI captures information most effectively at low GDP, where economic data may be distorted by a few vary large salaries, whilst GDP is more effective at capturing information in more developed contexts.

- Terrain Roughness Index

The Terrain Roughness Index (TRI; Riley et al., 1999) is a measure of the variance in topography. It was calculated using using the spatialEco package in R version 1.3.7 (Evans 2020).

- *Wealthy flat index*

Similar to the case of GDP and HDI, some LFS classification trees were split approximately evenly between (low or flat) topography and (high) GDP as the first split measure – primarily for intensive land uses. Therefore, a combined variable was created to capture both these concerns, calculated as: GDP x 1/TRI. A high TRI represents very rugged terrain, so this index is highest in areas of high GDP and flat terrain. We term this the 'Wealthy flat index'.

4. Processing of HANPP data

Data for the human appropriation of net primary productivity (Haberl et al., 2007) were available at 5 arcminute resolution. Therefore, these were resampled to the resolution of JULES-INFERNO, as described above.

5. Use of data for modelling

5.1 Data sampling

In order to train the classification tree models that drive our LFS distribution, we sampled the secondary data sets at the locations of case studies in DAFI. This was done using the central point of a DAFI case study area as the sampling location. The year sampled was the mean of the study period, rounding upwards – so a study beginning in 2002 and ending in 2005 would be allocated the values from secondary data sets for 2004.

5.2 Data smoothing

During model runs, it was found that interannual variability in biophysical variables caused some cells on the boundary between LFS to oscillate between two states. For example, between intensive farming and small-holder cropping based on fluctuations of reference evapotranspiration. Therefore, a 10-year average was calculated from the data, comprised of the model year (t) and the previous 9 model years. This removed the oscillation issue. The impact of imposing a moving window on socio-economic variables was also explored, but not found to change model outputs significantly.

Appendix 4F: Reference multinomial model

This appendix covers the construction of a multinomial regression model. This 'null' or reference model was used as a benchmark for predictive performance of the bootstrapped classification tree approach outlined in the main text (Perkins et al., 2022).

1. Preparation of data

Data used were the same as for the classification trees. They were split by land systems and weighted in the same way. All available data points for each land system were used to train the models. Similarly to the classification trees, data were resampled such that all states of the target variable occurred an equal number of times in the training data. In other words, each AFR had equal frequency in the dependent variable for each land use system.

2. Selection of variables

Models were fit in R using the nnet package of Venables and Ripley (2002), version 7.3-17. The default log-linear link function was used throughout. Initially, all variables available were trialled, however this led to likely symptoms of collinearity – such as large negative and positive coefficients for correlated variables. Furthermore, to be a fair comparison – parsimonious multinomial models were needed. This was because a premium was placed on classification trees being simple and grounded in process – more complex trees could have achieved much higher AUC (classification accuracy), but at the expense of producing high variance when projected across global rasters.

Therefore, a simple model of HDI & market access was deployed. These two variables performed most strongly amongst all available predictors and adding a third predictor made little difference to predictive accuracy. Two variables was also the same number as in 18/19 classification trees used, ensuring a broad like-for-like comparison.

3. Code availability

Code & data to run reference multinomial models are made available online (Perkins and Millington 2022).

Appendix 6A: HDI and market access under the shared socioeconomic pathways

This appendix provides an overview of the new projections of market access and the human development index constructed to enable future runs of WHAM! for the Shared socioeconomic pathways. Global timeseries (Figure 6A.1) and maps from 2050 and 2100 are provided for each of the two indicators (Figures 6A.2-6A.5).

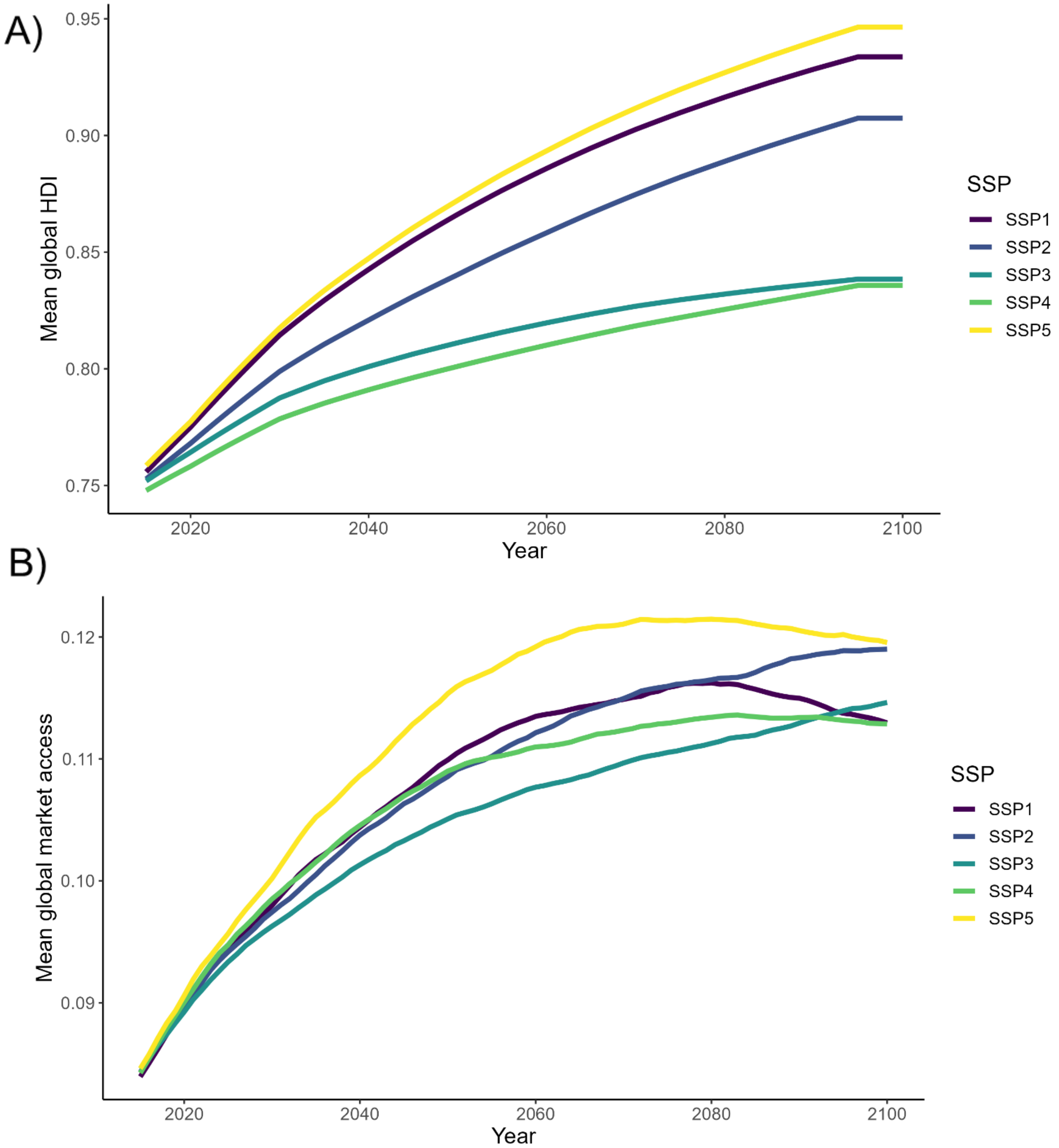


Figure 6A.1: Time series of A) Human Development Index (HDI) and B) market access under the shared socioeconomic pathways.

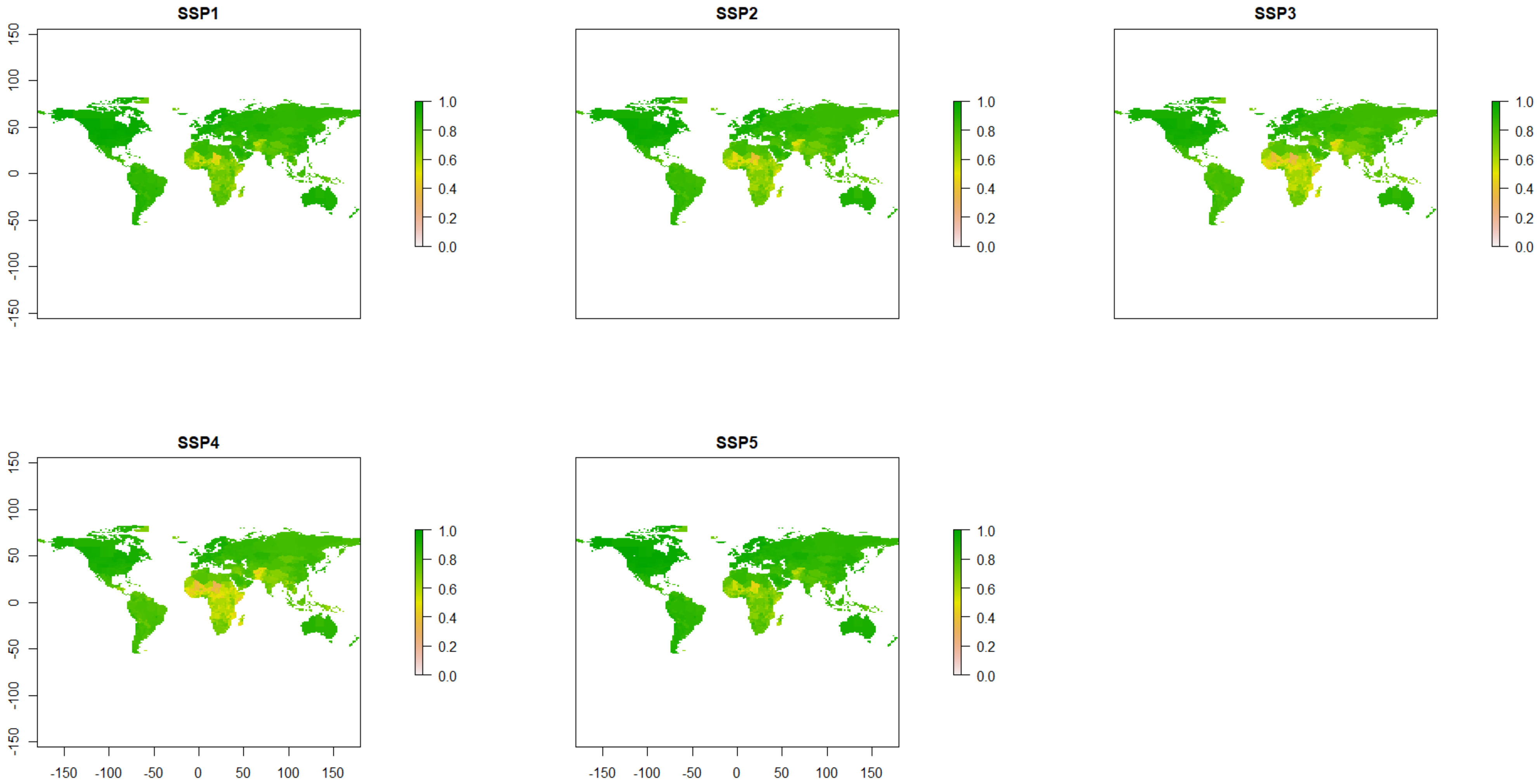


Figure 6A.2: The human development index in 2050 across the shared socioeconomic pathways.

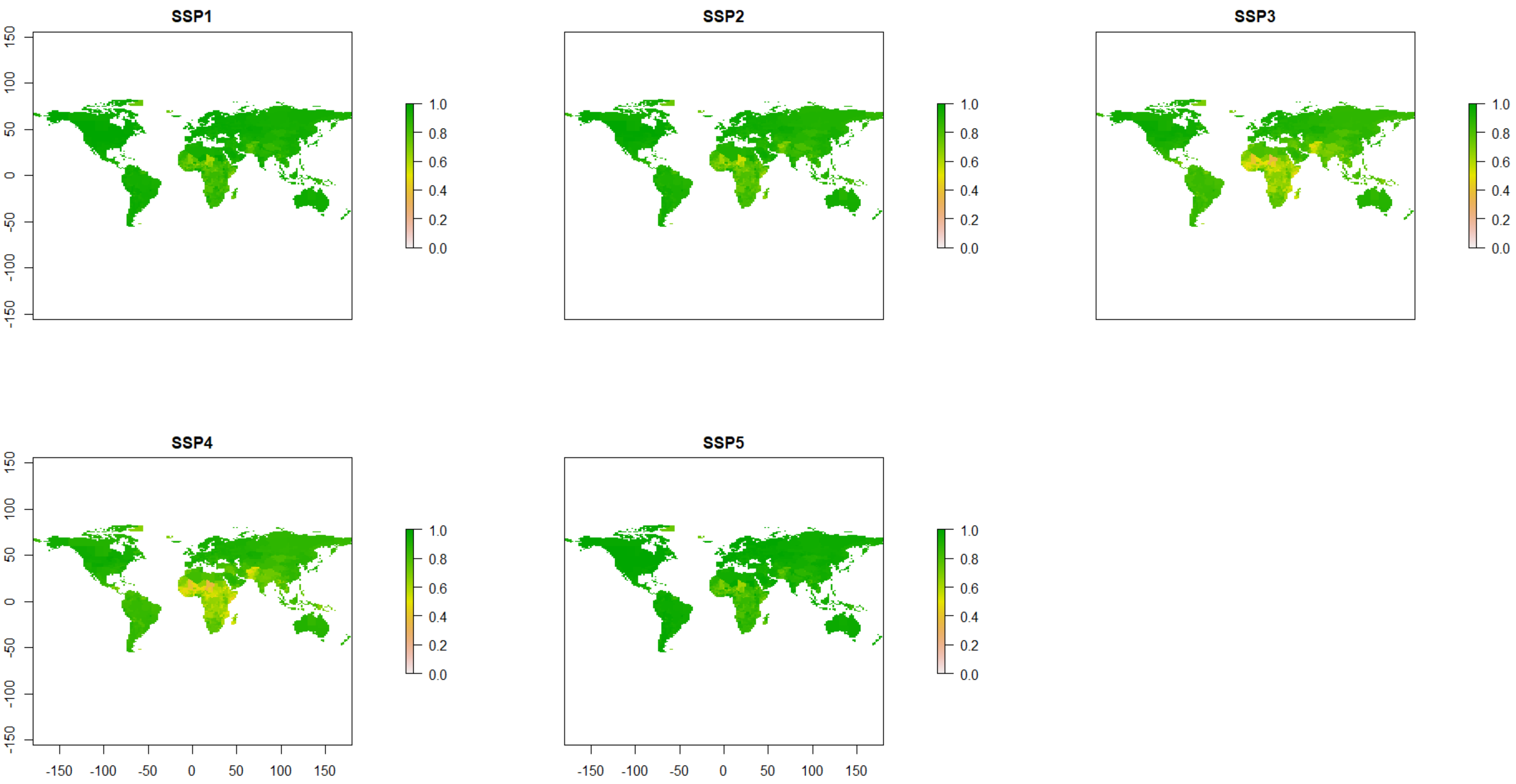


Figure 6A.3: The human development index in 2100 across the shared socioeconomic pathways.

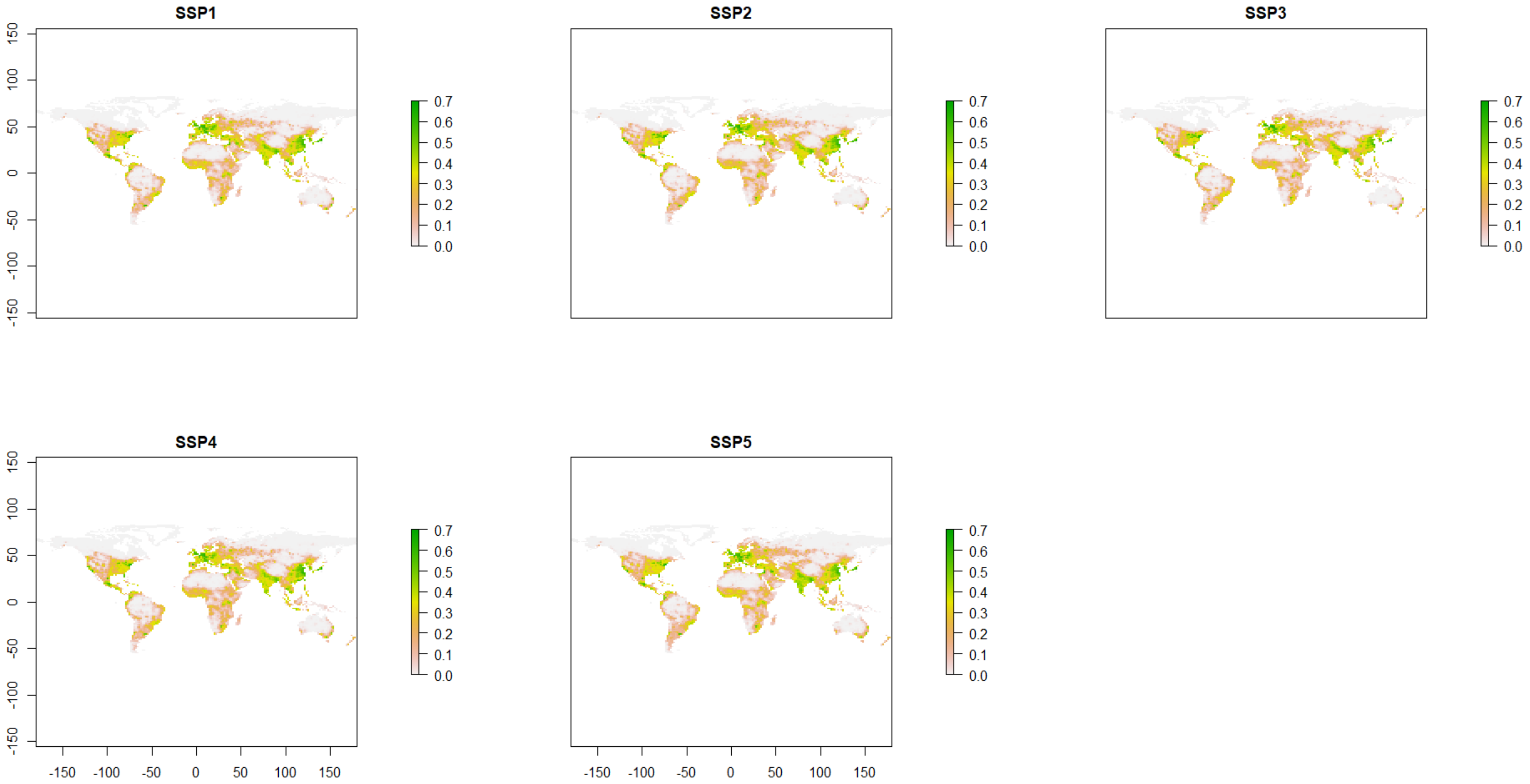


Figure 6A.4: Market access in 2050 across the shared socioeconomic pathways.

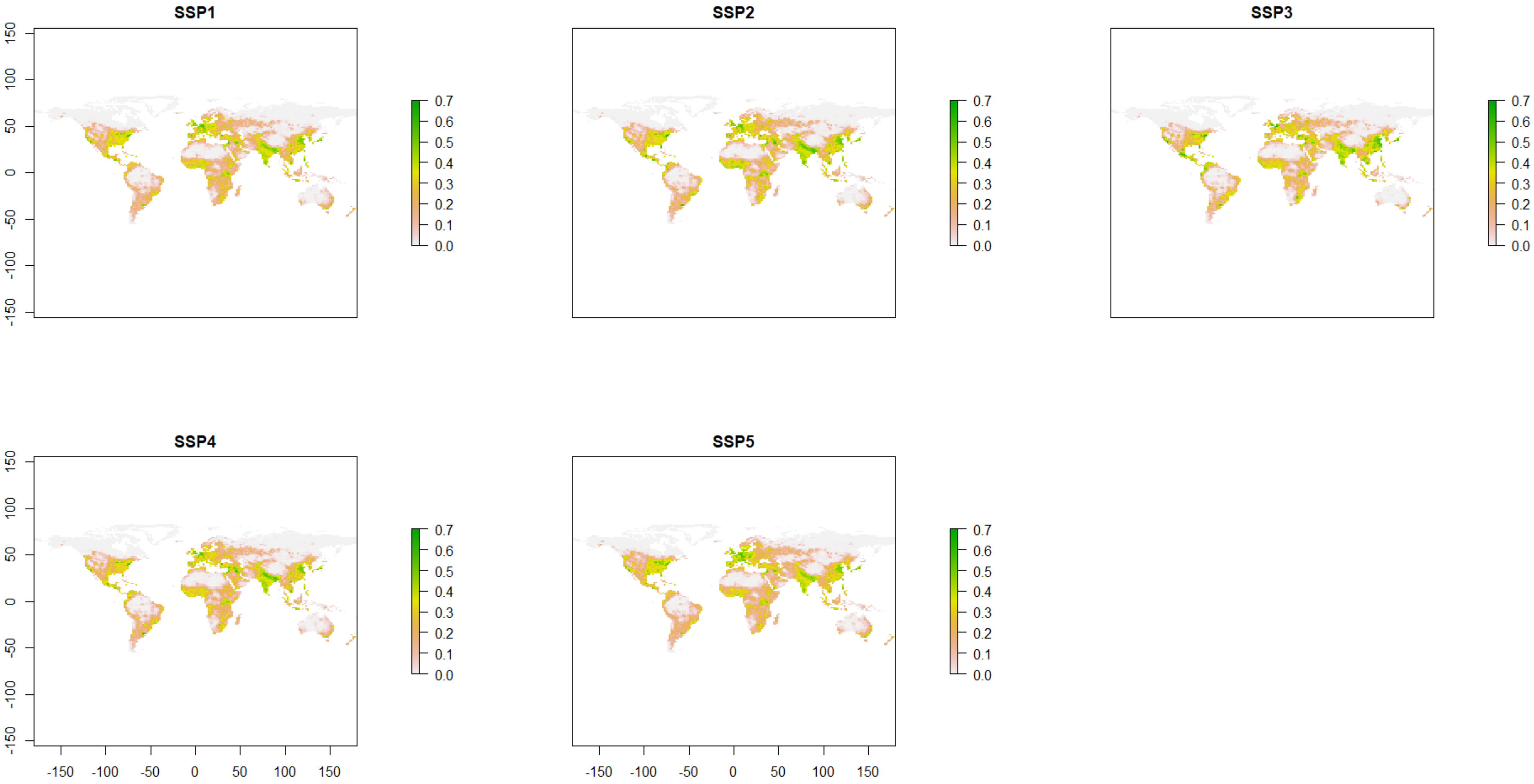


Figure 6A.5: Market access in 2100 across the shared socioeconomic pathways.