Supplement to *A global behavioural model of anthropogenic fire use and management: WHAM! v1.0*

Contents

Supplement A: WHAM Earth-Observation

1. Introduction

This supplement to Perkins et al., (in submission) describes the parameterisation of WHAM! using Earth Observation data sets rather than outputs from JULES (hereafter: WHAM Earth Observation or WHAM-EO). This was done firstly to WHAM! more readily transferrable to other DGVM fire modules, but also to assess to what extent errors in WHAM! are inherited from JULES underlying representations of ecosystem dynamics. It first describes changes in model structure, before giving a brief overview of headline results.

2. Methods

Table S1 gives the variables that were taken from JULES in WHAM!, and hence were replaced with Earth observation data in WHAM-EO. In order to integrate these data fully into the structure of WHAM-EO, all AFT distribution, fire use and management sub-models were reparameterised using these new data as inputs.

Table S1: Overview of changes to input data in WHAM-EO

JULES input	**WHAM-EO replacement**	**Citation**
Potential evapotranspiration	GLEAM potential evapotranspiration	Martens et al., 2017
Net primary production	MUSES NPP	Wang et al., 2021
Bare soil	MODIS NDVI	Didan et al., 2021

In addition, the vegetation constraint, which is parameterised using JULES bare-soil fraction in WHAM!, was reparameterised using MODIS-derived normalised difference vegetation index as follows. The vegetation constraint and its impact on burned area were calculated as:

$$V = \frac{(NDVI_t - v_1)}{v_2 - v_1} \qquad \text{(S1)}$$

$$VC_t = \begin{Bmatrix} 1 \; if \; V \geq v_3 \\ V \; otherwise \end{Bmatrix} \qquad \text{(S2)}$$

$$BA_t = \widehat{BA}_t * VC_t \qquad \text{(S3)}$$

where V is a static threshold based on the NDVI of a given grid cell and two free parameters, v_1 and v_2; VC_t is the vegetation constraint at time = t, dependent on a free parameter threshold v_3; and $\widehat{BA}_t$ and BA_t are raw burned area from bottom-up AFT calculations, and burned area adjusted for the vegetation constraint.

3. Results: headline differences

Presentation of results here focuses on differences with results presented in the main text. Globally, the central differences between WHAM_EO and WHAM! using JULES inputs (WHAM_JULES) are that WHAM_EO shows a steeper decline in pasture fires, and a more stable use of vegetation fire (Figure S1). Cropland fires are very similar, pointing the dominance of economic drivers of this fire use type. Spatially, the central difference is in sub-Saharan Africa; in WHAM_EO managed fire is more evenly distributed across the Guinean savanna fire belt and Madagascar than in WHAM_JULES, which shows a patchier distribution (Figure S2).

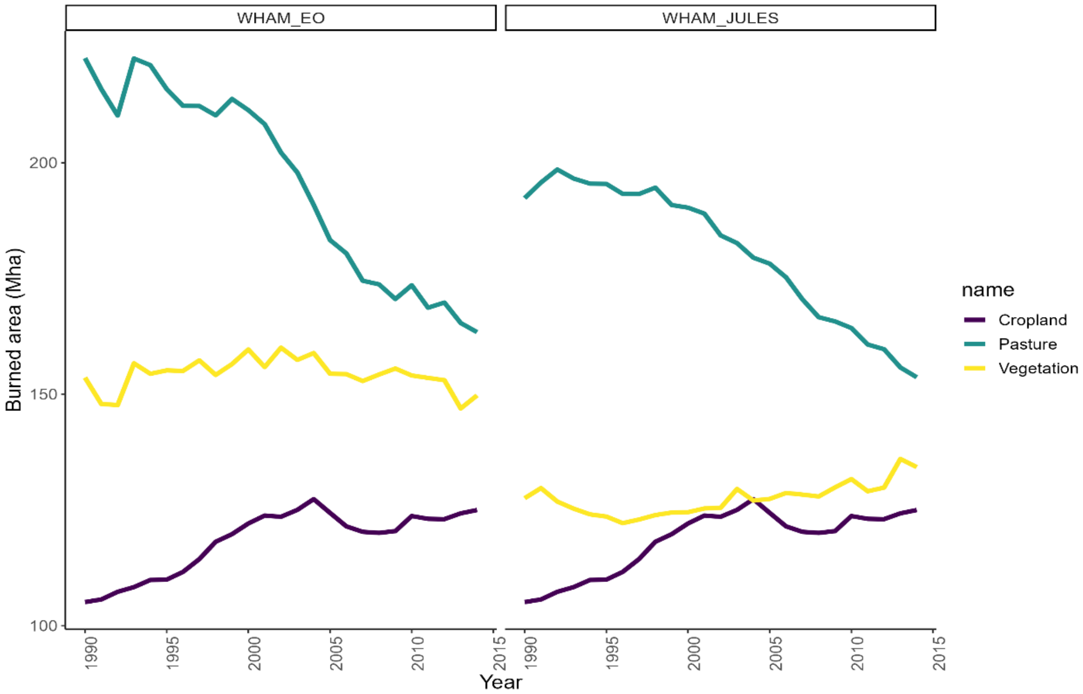

Figure S1: Global trends in managed anthropogenic fire between WHAM parameterised with Earth observation data (WHAM_EO) and WHAM parameterised with JULES biophysical inputs (WHAM_JULES).

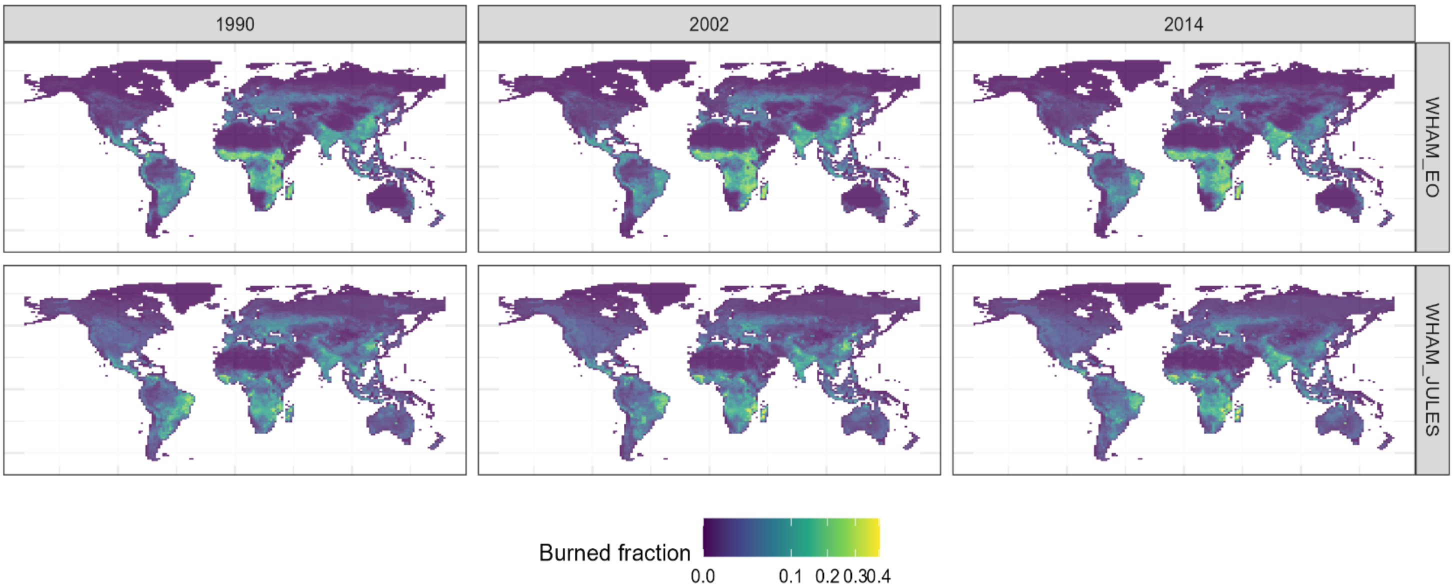

Figure S2: Spatial distribution of fire in WHAM parameterised with Earth observation data (WHAM_EO) and WHAM parameterised with JULES biophysical inputs (WHAM_JULES).

Supplement B: Sub-model parameterisation

This supplement to Perkins et al., (in submission) covers the parameterisation of agent functional types (AFTs) for five of the seven modes of anthropogenic fire use identified in the database of anthropogenic fire impacts (DAFI; Millington et al., 2022). As noted in the main text, there was an underlying method for parameterisation of each of these five fire uses (Figure S3); as such the text below notes adjustments of this process for the specific data availability of each fire use. An overview of the adjustments made for each fire use type is given in Table S2.

1.1 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.

1.2 Crop residue burning

Crop residue burning is a ubiquitous practice amongst sedentary small-holder farmers (Smith et al., 2022). 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. 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).

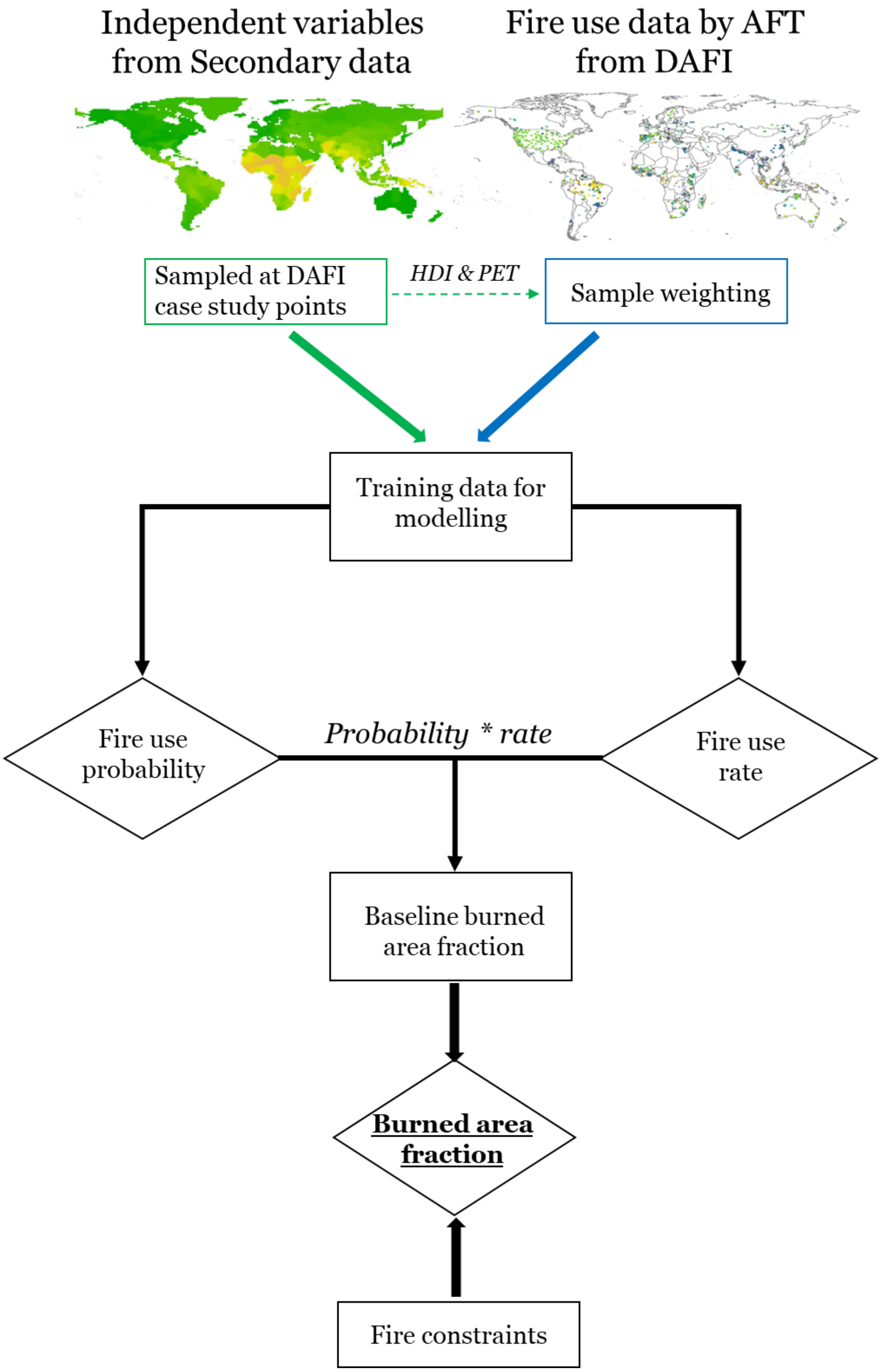

Figure S3: Core method of parameterising five of the seven fire use types in WHAM!. Burned area for each agent functional type for each fire use type was the product of fire use probability and fire use rate subject to both top-down and fire-specific constraints. Top-down constraints, which corrected underlying sampling biases in DAFI are detailed in the main text, whilst fire use specific constraints are detailed in this supplement.

Table S2: 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 the main text.

Fire use	**AFTs**	**Fire use tendency: method**	**Burned area: method**	**Burned area: 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 1.5
	Pastoralist	Classification tree	Regression tree	BA fraction	Section 1.3
	Extensive livestock farmer	Classification tree	Regression tree	BA fraction	Section 1.3
Pasture management	Intensive livestock farmer	Classification tree	Constant	N/A	Section 1.3
	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

1.3 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'.* Therefore, with rangelands occupying hugely differing biophysical niches, and in particular including arid and semi-arid regions, they could have greatly divergent livestock stocking levels, and therefore use of fire. A top-down constraint was 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 unity, 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:

$$rc = \min\left(1, \sum AFT_{rangeland}\right) \quad \text{(S4)}$$

$$BA_{rangeland} = BA_{livestock} * rc \quad \text{(S5)}$$

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.

1.4 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 (Ansell and Evans, 2019; Neale et al., 2019).

1.5 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:

$$BA_{HG,t} = \widehat{BA}_{HG,t} * 1 - (0.5 * Treecover_t) \qquad (S6)$$

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.

Supplement C: Evaluation of sub-models

This supplementary information accompanies Perkins et al., (in submission). It covers evaluation of the sub-models of fire use and management in WHAM!: the Wildfire Human Agency Model. This complements overall evaluation, which is presented in the main text. Evaluation of unmanaged fire and fire suppression outputs will only be possible once WHAM! is coupled with the JULES-INFERNO dynamic global vegetation model (Wiltshire et al., 2020). Evaluation is presented first as methods, results, and a brief discussion.

1. Evaluation methods

WHAM! sub-models were evaluated in three ways. The first two 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).

Secondly, model outputs for all modes of managed fire were compared against unseen data in the Database for Anthropogenic Fire Impacts (DAFI; Millington et al., 2022) - 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 the main text, smaller case studies in DAFI tended to focus on niche areas of widespread anthropogenic fire use, so larger case studies may be more representative at landscape scale and above. Indeed, 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 (24,684 vs 3,508 km^2). 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). 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). The LIFE database contains assessment 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.

2. Evaluation results

2.1 AFT managed fire parameterisations

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 S3). This represents reasonably robust performance given the prior knowledge gaps and lack of reliable data on anthropogenic fire use. 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.

Table S3: 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*

2.2 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 S4). 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. Together with the notable influence of fire control on rates of fire escape (main text Table 5), this can be considered good evidence that the AFRs are a useful means of describing anthropogenic fire regime management on a landscape.

Table S4: 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 utility 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

2.3 Evaluation with unseen DAFI data

WHAM! reproduces the broad patterns of burned area in unseen DAFI data (Table S5). 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 S4). 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, and particularly tightly packed rice fields (e.g. Lasko et al., 2017), in ways that cannot be captured at a coarse spatial resolution.

2.4 Evaluation with LIFE database

At global-scale, WHAM! and the LIFE database are in strong agreement (Table S6). 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 (Supplement B).

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 S5: 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*

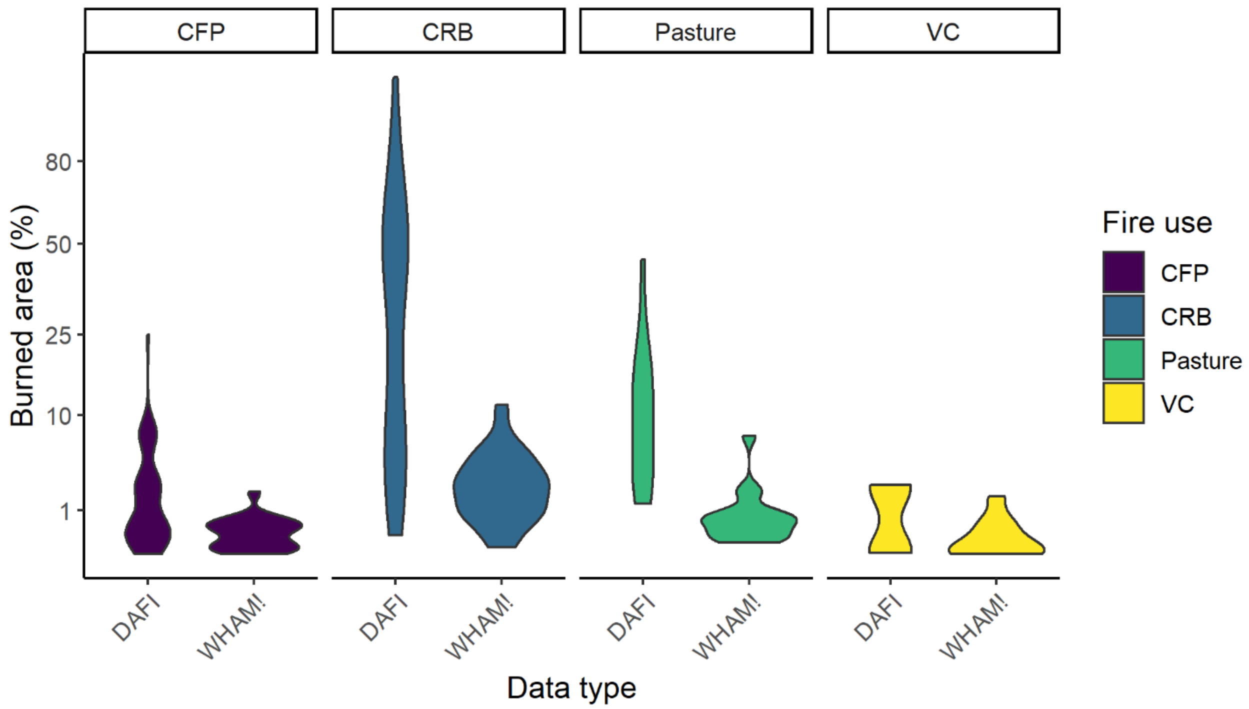

Figure S4: Violin plot comparing distributions of outputs from WHAM! and unseen data from the Database of Anthropogenic Fire Impacts (DAFI); WHAM! consistently projects lower burned area than DAFI, indicative of their greatly differing spatial resolution. Key: CFP = Crop field preparation, CRB = Crop residue burning, Pasture = Pasture management, VC = Vegetation clearance

Table S6: 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

3. Evaluation discussion

In comparisons against both DAFI and LIFE, WHAM! outputs capture macro-scale trends, but struggle to capture trends at the case-study level (Tables S5 & S6). In the case of the comparison against unseen DAFI data, this lack of case-study level agreement was partly intentional. 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 S3). 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 (See main text; Section 3.2).

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 (Abdurrahman et al., 2020); or biodiversity loss through deforestation (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. Nevertheless, WHAM! outputs demonstrate broad coherence with DAFI & LIFE case study data, which is notable given the divergent spatial-scales of WHAM! and the respective data sources.

Supplement D: Model sensitivity analysis

This supplement to Perkins et al., (in submission) describes a sensitivity exploration of WHAM!: the Wildfire Human Agency Model. This is presented first as methods, then results.

1. Methods

Given that the purpose of WHAM! is to couple with the JULES-INFERNO, sensitivity analysis of WHAM! as a standalone model was conducted to explore and understand the model's behaviour rather than assess overall parameter uncertainty. Therefore, in the first instance, an exploratory 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 S7). 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 (Perkins et al., 2022)

For Theta, the fuel fire threshold and AFR fire threshold, the range over which pertubations 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.

Table S7: WHAM! free parameters and ranges used during sensitivity analysis.

Variable	**Model domain**	**Parameter range**	**Use**
Theta	Land system distribution	0-0.2	AFT competitiveness scores < Theta are set to 0.
Vegetation clearance fractions (x3)	AFT fire use	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	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	0.4-0.8	Fraction of cell coverage of industrial AFR at which it reduces overall fire use

2. Results

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 S5). 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; See main text). 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.

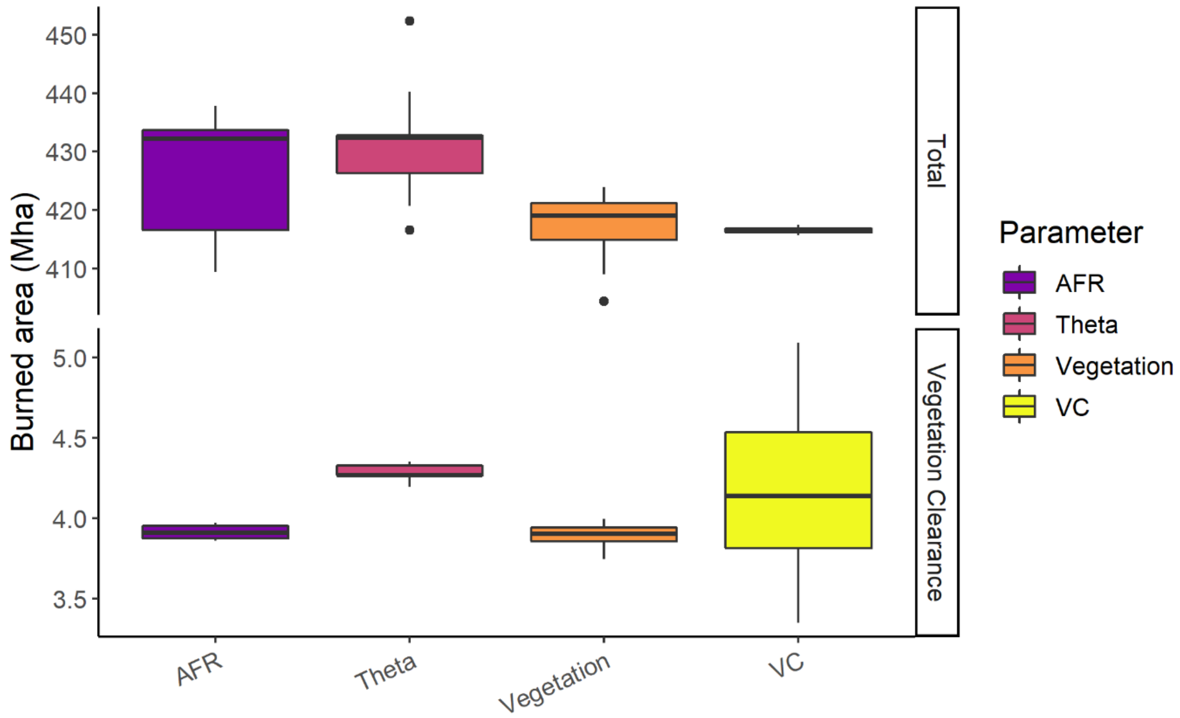

Figure S5: Sensitivity of model mean burned area from managed fire (1990-2014) from one parameter perturbations. The model is most sensitive overall to the Theta fire constraint, but the overall range of sensitivity is just +-4.4%. Key: AFR = Anthropogenic fire regime, Vegetation = Vegetation constraint, VC = Vegetation Clearance

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