Earth's Future

Supporting Information for

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

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Introduction

This supplementary information provides further context to the calibration of the WHAM-INFERNO model ensemble presented in the main text. Specifically, it describes the set-up of the perturbed parameter ensembles used to define model free parameters and how these parameter values relate to results presented in the main text. It then briefly describes the setup of a baseline model used to benchmark performance of WHAM-INFERNO, before showing how free parameters vary across parameter spaces.

Text S1.

1. Definition of perturbed parameter ensemble

Four categories of model parameter were included in the perturbed ensemble. These are firstly parameters whose values were defined heuristically in the first version of INFERNO (Mangeon et al., 2016). These comprise the burned area per fire for each plant functional type in the model (seven parameters; Table SI1). Burned area for cropland PFTs was set to 0, as WHAM! represents anthropogenic cropland burning. The second set of parameters included were those that were required to integrate WHAM! with JULES-INFERNO either structurally or ontologically. These are the Φ parameter for accounting for differences in conceptualisation of anthropogenic ignitions (INFERNO) vs anthropogenic fires (WHAM!) and parameters accounting for previous fires within a given calendar year (α, β).

Thirdly, parameters are included for aspects of WHAM! for which no initial external verification was possible, as presented in Perkins et al., (2023). For example, whilst assessment of WHAM! crop residue burning outputs was possible with the new GFED5 crop fires algorithm (Hall et al., 2023), assessment of managed pasture fires and managed vegetation fires (comprising crop field preparation, hunting and gathering, pyrome management and vegetation clearance) was not possible with currently available remote sensing data products or other data sources. As such, two free parameters were added reflecting the unexplored uncertainty in these WHAM outputs. No free parameter was added to the rate of escaped fires (Main text, section 2.2.1) because the rate of escaped fires is implicitly changed with the rate of managed burned area and altering both processes would have led to implausibly high rates of escaped fire in some model parameter sets. Other WHAM! outputs to which free parameters were applied were the rates of background and arson fires, as well as fire suppression.

Fourthly, and finally, free parameters were included in the perturbed parameter ensemble relevant to representations of landscape fragmentations described in the main text. These are a scaling parameter for the impact of road density in reducing fire size (ρ) and for the impact of logging in increasing flammability of tropical forests (Λ).

2. Setup of the perturbed parameter ensembles

2.1 Defining and sampling parameter distributions

Having defined the variables to be included in the perturbed parameter ensembles, probability distributions for their values were defined. Given the large degree of uncertainty surrounding initial values for parameters, these were set as uniform distributions with upper and lower bounds +- 50% of the initial value. Where possible, parameter values were taken from previously defined estimates – as such parameter values for burned area per fire per PFT were taken from Burton et al., (2019). Whilst in the INFERNO baseline model, initial parameter values for anthropogenic and lightning ignitions were those given in Mangeon et al. (2016). Furthermore, WHAM! parameters for fire suppression could be defined on a narrower range than other parameter values, as the impact of limited and moderate fire suppression must ontologically be less than that of intensive fire suppression (see Perkins et al., 2023 for details). Similarly, it was not logically consistent for the role of logging to reduce flammability of tropical forests, and hence values <1 were excluded. Elsewhere, parameters for WHAM! were defined heuristically. For example, the initial value of the road density scaling parameter (ρ) was the global maximum of its own natural logarithm; whilst the initial value of the fire-ignitions scaling parameter (Φ) was defined from the reciprocal of the global mean flammability in JULES-INFERNO.

Having defined sampling distributions for model parameters, a Latin Hypercube sampling strategy was taken using a minmax sampling design (Carnell 2022). Such a sampling design allows for robust exploration of the model parameter space in a computationally efficient way (Florian, 1992). 10,000 parameter sets were defined for WHAM-INFERNO and INFERNO offline, and model runs were conducted for each parameter set.

2.2 Assessing model outputs from the perturbed ensemble

Model outputs were assessed in two ways. Firstly, a process of history matching was conducted to remove implausible parameter sets from consideration. Secondly, a pareto-optimal parameter space was defined, which then became the basis of analysis presented in the main text.

2.2.1 History matching for implausibility assessment

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 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:

$$I = \left| \frac{y_{mod} - y_{obs}}{\sqrt{({\sigma_{mod}}^2 + {\sigma_{obs}}^2)}} \right| \qquad (S1)$$

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 non-independence of observations and model outputs (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 (Kennedy & O'Hagan 2001; McNeall et al., 2016). 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).

2.2.2 Defining a pareto optimal parameter space

From the set of parameters 'not ruled-out yet' by the implausibility assessment (hereafter NROY), the pareto optimal parameter set was 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:

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

$$y_i(x_1) \geq y_i(x_2) \quad (S2)$$

Hence in a pareto parameter space, no parameter sets would satisfy the inequality in $(S2)$.

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.

2.2.3 Understanding the pareto optimal parameter space

In order to understand how model parameters were contributing to defining the pareto parameter spaces, Kruskall-Wallis tests were used to assess which parameters differed significantly across NROY and pareto optimal parameter sets. Significant differences were set as those with p-values <0.0025: 0.05 with a Bonferroni correction applied to reflecting multiple testing across 20 parameters. Furthermore, to understand if there were parameters with small impacts on global burned area, but nonetheless meaningful impacts in capturing observed patterns of fire, correlations between parameter values and the correlation of outputs with GFED5 were calculated, and divided by the correlation of parameter values to the amplitude of global burned area:

$$cor\_weighted_i = \frac{cor\_correlation_i}{cor\_BA_i} \quad (S3)$$

where $cor_BA_i$is the correlation coefficient between the values of parameter i and the amplitude of burned area in model outputs; $cor\_correlation_i$ is the correlation coefficient of the values of parameter i and the model correlation with GFED5, and $cor\_weighted_i$ is a measure of how far a given parameter impacts model performance relative to its overall impact on model outputs. This ensured that identification of the role of model parameters in defining the pareto parameter space was not merely an exercise in understanding sensitivity of the model structure, but also which processes may be most pertinent to capturing the distribution of global fire regimes.

2.3 Setup and evaluation of INFERNO baseline model

INFERNO v1.0 (Mangeon et al., 2016) calculates burned area as:

$$BA_{INFERNO} = Ignitions * Suppression * Flammability * \widehat{BA}_{PFT} \; (S4)$$

Therefore, flammability and burned area per PFT ($\widehat{BA}_{PFT}$) were taken from the same sources as WHAM-INFERNO (Main text; Table 1). As in the WHAM-INFERNO integration, lightning ignitions were calculated following Mangeon et al., (2016) as:

$$I_L = 7.7 \times Lightning \times (1 - Suppression) \qquad (S5)$$

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. Similarly, as in Mangeon et al., (2016), anthropogenic ignitions and suppression were calculated respectively as:

$$Ignitions_A = (6.8 * PD^{-0.6}) * (0.03 * PD) \qquad (S6)$$

$$Supression = 1 - 7.7 * (0.05 + 0.9 * e^{-0.05*PD}) \qquad (S7)$$

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 S2).

As in WHAM-INFERNO, equations in the main text (7) and (8) were used to account for prior fires restricting the connectivity and availability of vegetation. Outputs from 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 the two versions of WHAM-INFERNO in this pareto space was then compared.

The parameters in the perturbed ensemble for the baseline version of INFERNO – INFERNO v1.0 recalibrated to GFED5 – were as follows (Table S2). Parameters from the WHAM-INFERNO ensemble that related to uncertain aspects of WHAM! outputs and vegetation fragmentation were removed. These were replaced with two additional parameters, which allowed recalibration of INFERNO fire counts to GFED5 (σ_1, λ, Sup). The original values of these parameters were derived from calibrating lightning strikes and human population density to fire counts observed in GFED v4. As such, with much greater capacity to detect anthropogenic fires in GFED5, these each need recalibration. Further, as WHAM! crop fires did not contribute to the baseline model, burned area parameters per PFT were reintroduced for cropland PFTs.

3. Characteristics of parameter spaces in the perturbed parameter ensembles

Based-on Wilcox tests between pareto and other parameter sets, across the three model setups there are five parameters with significantly different values in the pareto sets (Figure S1). For both WHAM-INFERNO and WHAM-EO, road density shows a strong difference, with pareto parameter sets (mean = 6.00, 6.51) showing lower values than other sets (mean = 9). This has the effect of lowering the threshold at which road density effects apply, and hence increasing its constraint on burned area. Similarly, values for the scaling parameter that corrects for the double counting of flammability effects in the model ensemble are weighted towards the upper end of the parameter range in the perturbed ensemble (Figure S1). Overall, this suggests that increasing the impact of climate (through vegetation flammability) and vegetation fragmentation (through road density) are important in defining the pareto parameter spaces for the two coupled models.

However, when individual parameter correlations with overall WHAM!-GFED5 correlation are calculated and weighted by their respective impact on burned area, a more complex picture emerges (Figure S2). Weighted by impact on overall burned area, for logging, suppression, shrub PFT burned area per fire, and previous fires have the most impact on correlations between WI-JULES, WHAM-EO and GFED5. 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.

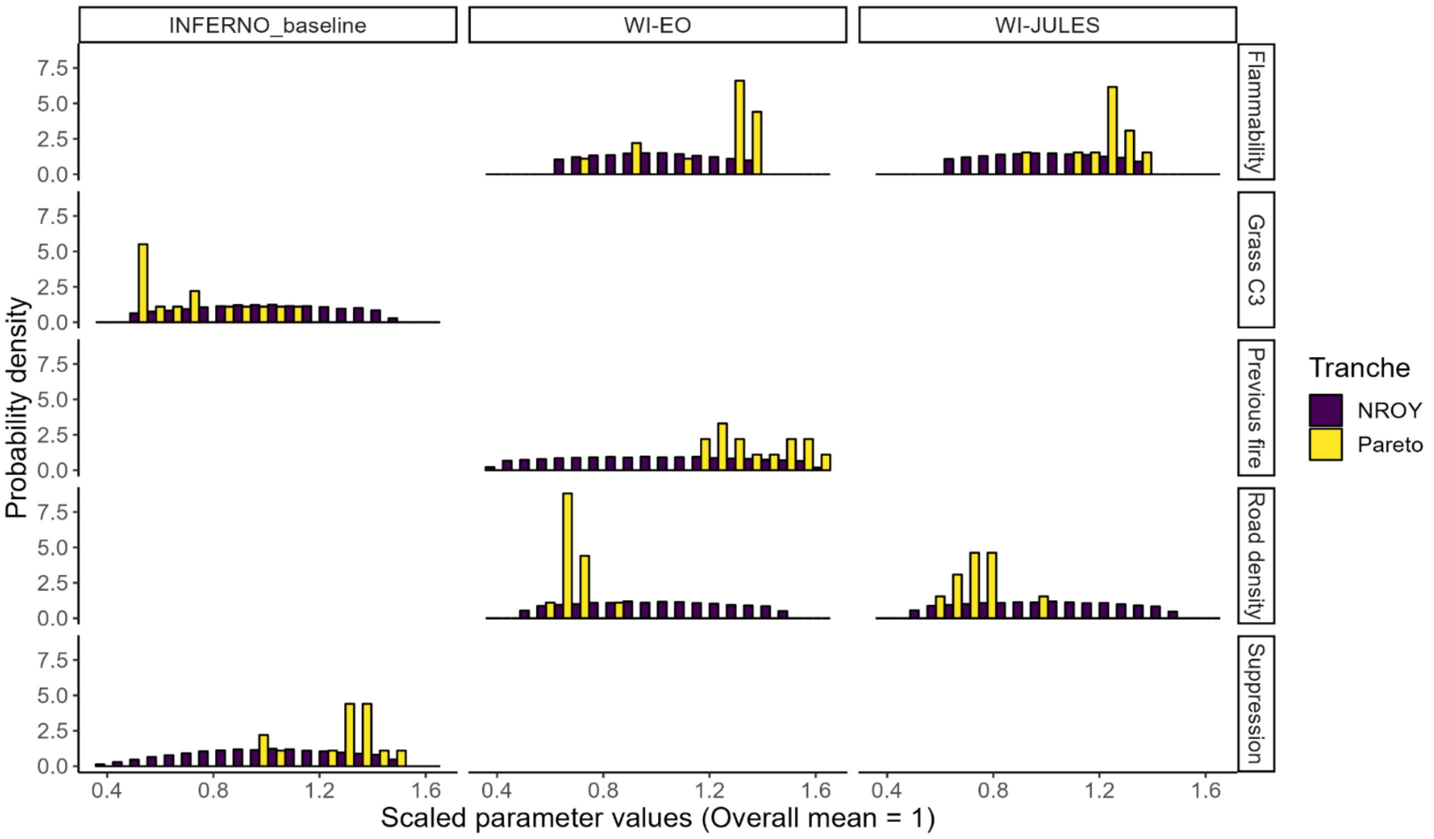

Figure S1: Comparison of parameter distributions across models and parameter tranches. Distributions shown had Wilcox tests with p<0.05 (Bonferroni correction applied). Under WHAM coupling, road density is important in constraining the distribution of fire in, but this effect is not captured in the baseline model (INFERNO_baseline).

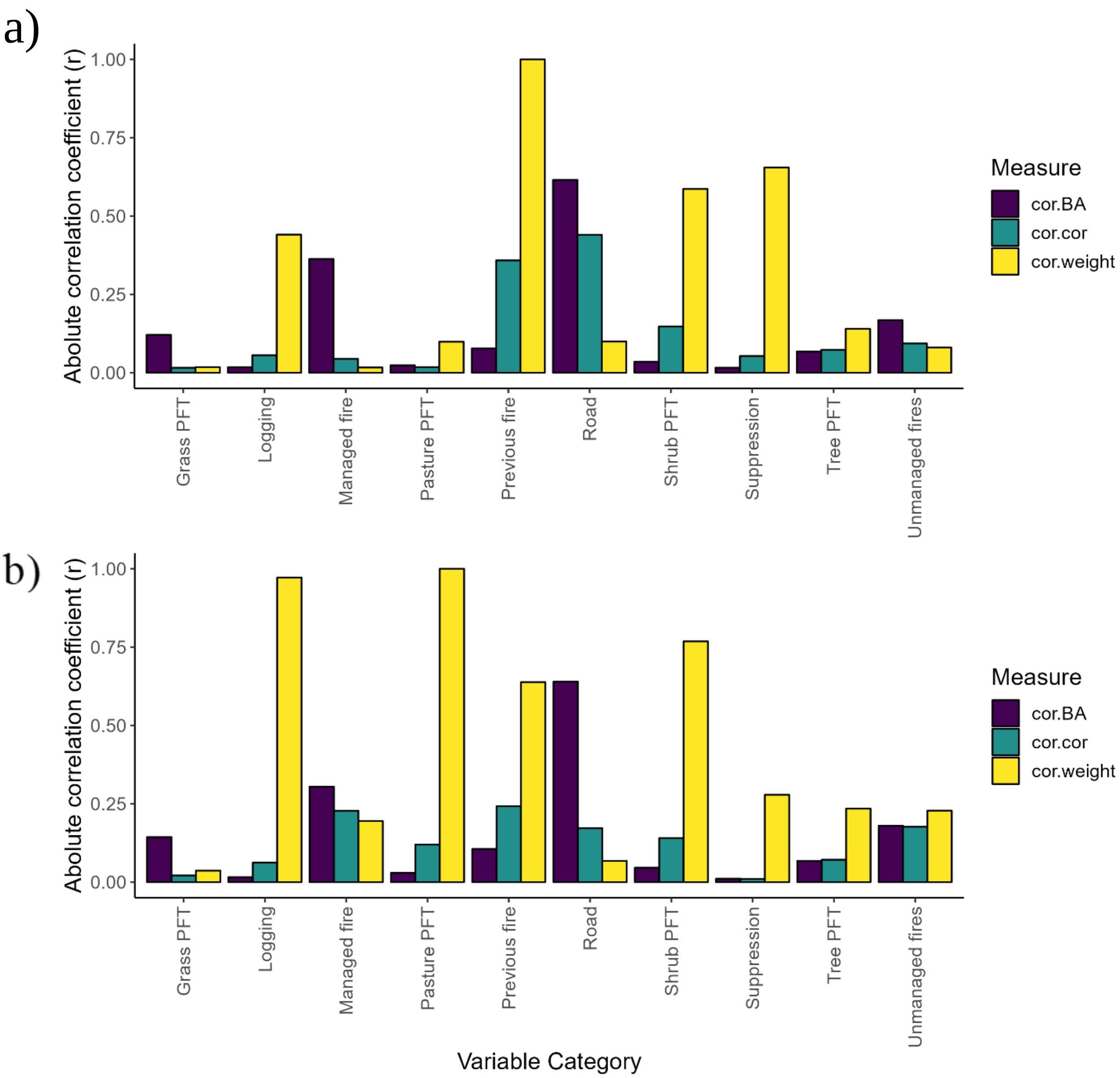

Figure S2: Effect of model parameters on model correlation with GFED5 across NROY & pareto runs for a) WI-EO and b) WI-JULES. Whilst they have limited impact on global burned area parameters for logging, suppression, shrub PFT burned area per fire, and previous fires are effective at capturing the relative spatio-temporal distribution of fire. By contrast, in WI-JULES, pasture PFTs prove useful in capturing the distribution of fire in GFED5, but this effect is not present in WI-EO.

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.

Table S1: 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, and 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	Rate of background ignitions	0.03	0.01	0.05
σ_2	Scaling arson fires	30	15	45
λ	Scaling parameter for lightning strikes	7.7	3.85	11.55
Φ	Harmonising model ontologies of ignitions & fires	650	400	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

Table S2: 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