The global drivers of wildfire: Supplementary Information

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This Supplementary Information contains the following figures and tables:

Supplementary Table 1. Details of the empirical fire models

Supplementary Table 2. Details of the predictor variables used in the global analyses of the controls on burnt area. The category column indicates how these variables were grouped in our analyses. The second column gives details of the specific variable used for prediction. The third column gives the references to the studies using these predictors. References are listed at the end of the Supplementary Information.

Supplementary Table 3. Details of the individual empirical analyses of the global controls on fire.

Supplementary Figure 1. Outcome of systematic variable selection, where the y-axis indicates the initial variable included in the model and the colour coding indicates the frequency with which other variables are selected in the final suite of models. (See Figure 3 in main text for summary)

Supplementary Table 1. Details of the empirical fire models

Model	Fire drivers	Concept	Input datasets	Parameter	Training period	Fire datasets
Glob-FIRM						
Thonicke et al., 2001	Climate, Vegetation	Annual burnt area derived from summing daily fire occurrence over a year (a function of fuel load and litter moisture)	CRU05; FAO soil dataset; length fire season field measurements (central Portugal, southern California. Kakadu NP)	PFT fire resistance	1901-1998	no global data
Kloster et al., 2012	Climate, Vegetation	Annual burnt area derived from sub-daily fire occurrence probability (a function of fuel load and soil moisture as a fraction of plant-available water content) Temperature threshold of zero degree Celsius.	CRU05; FAO soil dataset; length fire season field measurements (central Portugal, southern California. Kakadu NP)	PFT fire resistance	1901-1998	no global data
Séférian et al., 2019	Climate, Vegetation	Annual burnt area derived from summing daily fire occurrence over a year (a function of fuel load and litter moisture) No fires where cropland fraction is above 20%.	CRU05; FAO soil dataset; length fire season field measurements (central Portugal, southern California. Kakadu NP)	PFT fire resistance	1901-1998	no global data
SIMFIRE						
Knorr et al., 2014	Climate, Vegetation, Suppression	Fire frequency as a function of land cover, fAPAR, Nestrov index and population density	FAPAR SeaWiFS and MERIS (Gobron et al., 2002); WATCH ERA (1999 to 2010; Weedon et al., 2011); HYDE 3.1 (KleinGoldewijk et al., 2010)	IFBP landcover aggregation (Friedl et al., 2010)	1999-2010	L3JRC (Tansey et al., 2008); GFEDv3 (Giglio et al., 2010); MCD45 (Roy et al., 2008)
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Mangeon et al., 2016	Climate, Ignitions (anthropogenic and natural), Suppression	Burnt area as a function of ignitions (which include suppression, flammability and PFT burnt area	LIS-OTD (2013; Christian et al., 2003); HYDE (Hurtt et al., 2011); CRU NCEP (https://crudata.uea.ac.uk/cru/data/ncep/); WFDEI (Weedon et al., 2014); GPCC (Schneider et al., 2013)	PFT per burnt area	1997-2010	GFEDv3 (Giglio et al., 2010), FINNv1 (Wiedinmyer et al., 2011), GFAS (Kaiser et al., 2012), GFEDv4 (Giglio et al., 2013), GFEDv4s (Randerson et al., 2012)

Supplementary Table 2. Details of the predictor variables used in the global analyses of the controls on burnt area. The category column indicates how these variables were grouped in our analyses. The second column gives details of the specific variable used for prediction. The third column gives the references to the studies using these predictors. References are listed at the end of the Supplementary Information.

Category	Variables used	Empirical study
Temperature	Annual mean temperature	Krawchuk et al., 2009
	Monthly mean temperature	Aldersley et al., 2011; Fan et al., 2023
	Monthly maximum temperature	Bistinas et al., 2014; Forkel et al., 2019; Zhang et al., 2023
	Monthly minimum temperature	Forkel et al., 2019; Zhang et al., 2023
	Daily mean temperature	Son et al., 2023
	Daily temperature anomaly	Son et al., 2023
	Mean daily maximum temperature	Forkel et al., 2019
	Mean daily minimum temperature	Forkel et al., 2019
	Annual temperature seasonality	Krawchuk et al., 2009
	Mean temperature of wettest month	Krawchuk et al., 2009
	Mean temperature of driest month	Krawchuk et al., 2009
	Mean temperature of warmest month	Krawchuk et al., 2009
	Mean temperature of coldest month	Krawchuk et al., 2009
	Annual temperature	Fernandez-Garcia et al., 2023
	Temperature annual range	Krawchuk et al., 2009, Fernandez-Garcia et al 2023
	Monthly diurnal temperature range	Krawchuk et al., 2009; Bistinas et al., 2014; Kuhn-Regnier et al., 2021; Haas et al., 2022
	Isothermality	Krawchuk et al., 2009
	Daily diurnal temperature range	Forkel et al., 2019
Atmospheric humidity	Daily mean specific humidity	Son et al., 2023
	Daily specific humidity anomaly	Son et al., 2023
	Monthly mean relative humidity	Fan et al., 2023
	Daily relative humidity	Son et al., 2023; Zhang et al., 2023
	Daily relative humidity anomaly	Son et al., 2023
	Climatic water deficit	Kuhn-Regnier et al., 2021
	Vapour pressure deficit	Kuhn-Regnier et al., 2021; Haas et al., 2022; Zhang et al., 2023
Precipitation	Daily total precipitation	Son et al., 2023

	Monthly total precipitation	Aldersley et al., 2011; Forkel et al., 2019; Kuhn-Regnier et al., 2021; Fan et al., 2023
	Cumulative precipitation over 13 months prior to peak burning	Aldersley et al., 2011
	Precipitation of driest month	Krawchuk et al., 2009
	Precipitation of warmest month	Krawchuk et al., 2009
	Annual precipitation	Krawchuk et al., 2009, Fernandez-Garcia et al., 2023; Yhang et al., 2023
	Monthly number of wet days	Aldersley et al. 2011; Forkel et al., 2019
	Monthly number of dry days	Bistinas et al., 2014; Kuhn-Regnier et al., 2021; Haas et al., 2022
Wind speed	Daily wind speed	Son et al., 2023
	Maximum wind speed of hottest month	Haas et al., 2022; Zhang et al., 2023
	Annual wind speed	Zhang et al., 2023
	Monthly 90th percentile of daily wind speed	Forkel et al., 2019
Lightning	Monthly lightning count	Bistinas et al., 2014; Kuhn-Regnier et al., 2021
	Lightning daily flashes	Krawchuk et al., 2009
	Lightning climatology (static)	Zhang et al., 2023
	Lightning climatology (varying)	Krawchuk et al., 2009; Aldersley et al., 2011; Kuhn-Regnier et al., 2021; Haas et al., 2022; Son et al., 2023
Soil moisture	Volume of water in 4 soil layers	Son et al., 2023
	Anomaly in the volume of water in 4 soil layers	Son et al., 2023
	Annual soil moisture	Zhang et al., 2023
	Monthly soil moisture	Bistinas et al., 2014; Kuhn-Regnier et al., 2021; Fan et al., 2023
Solar radiation	Short-wave radiation	Zhang et al., 2023
Vegetation amount	Daily leaf area index	Son et al., 2023
Vegetation amount	Monthly leaf area index	Forkel et al., 2019; Kuhn-Regnier et al., 2021
Vegetation amount	Daily leaf area index anomaly	Son et al., 2023
Vegetation amount	Daily leaf area index anomaly	Son et al., 2023
Vegetation amount	Above ground biomass	Forkel et al., 2019; Kuhn-Regnier et al., 2021
Vegetation amount	Above ground plant litter	Son et al., 2023
Vegetation amount	Annual net primary production	Krawchuk et al., 2009; Bistinas et al., 2014

Vegetation amount	Annual gross primary production	Haas et al., 2022
Vegetation amount	Monthly gross primary production	Forkel et al., 2019
Vegetation amount	Fuelbed litter depth	Forkel et al., 2019
Vegetation amount	Secondary mean biomass carbon density	Son et al., 2023
Vegetation amount	Monthly fAPAR	Kuhn-Regnier et al., 2021
Vegetation amount	Monthly VOD	Kuhn-Regnier et al., 2021
Vegetation amount	Monthly SIF	Kuhn-Regnier et al., 2021
Vegetation amount	Total vegetation carbon	Forkel et al., 2019
Vegetation amount	Grass height	Forkel et al., 2019
Vegetation amount	Canopy height	Forkel et al., 2019
Vegetation type	Snow PFT	Son et al., 2023
	Tropical evergreen trees PFT	Son et al., 2023
	Tropical deciduous trees PFT	Son et al., 2023
	Extra-tropical deciduous trees PFT	Son et al., 2023
	Extra-tropical evergreen trees PFT	Son et al., 2023
	Broadleaved evergreen trees PFT	Forkel et al., 2019
	Needle-leaved deciduous trees PFT	Forkel et al., 2019
	Raingreen shrubs PFT	Son et al., 2023
	Deciduous shrubs PFT	Son et al., 2023
	Shrub needleleaved evergreen PFT	Forkel et al., 2019
	Shrub broadleaved evergreen PFT	Forkel et al., 2019
	Shrub broadleaved deciduous PFT	Forkel et al., 2019
	Bare land PFT	Son et al., 2023
	Shrub fraction	Haas et al., 2022; Zhang et al., 2023
	Grass fraction	Forkel et al., 2019 Haas et al., 2022; Son et al., 2023; Zhang et al., 2023
	Forest fraction	Zhang et al., 2023
	Non-tree cover	Bistinas et al., 2014
	Tree cover fraction	Aldersley et al., 2011; Bistinas et al., 2014; Haas et al., 2022
	Fuel woody 10h	Forkel et al., 2019
	Fuel woody 1h	Forkel et al., 2019
Topography	Elevation	Son et al., 2023; Zhang et al. 2023
	Slope	Son et al., 2023; Zhang et al., 2023

	Roughness	Son et al., 2023
	VRM	Haas et al., 2022
	TPI	Haas et al., 2022
Demographic	Population density	Bistinas et al., 2014; Forkel et al., 2019; Kuhn-Regnier et al., 2021; Haas et al., 2022; Zhang et al., 2023; Son et al., 2023
Economic	GDP per capita	Forkel et al., 2019; Zhang et al., 2023; Son et al., 2023
	Night-light development index	Forkel et al., 2019
	HDI	Aldersley et al., 2011; Son et al., 2023
Landscape Development	Total road density	Aldersley et al., 2011; Haas et al., 2022; Son et al., 2023
	Urban land	Son et al., 2023; Zhang et al., 2023
	Human Footprint Index	Krawchuk et al., 2009; Aldersley et al., 2011
Agricultural	Cropland	Aldersley et al., 2011; Bistinas et al., 2014; Forkel et al., 2019; Kuhn-Regnier et al., 2021; Haas et al., 2022; Son et al., 2023; Zhang et al., 2023
	C3 annual crops	Son et al., 2023
	C4 annual crops	Son et al., 2023
	C3 perennial crops	Son et al., 2023
	C4 perennial crops	Son et al., 2023
	C3 nitrogen-fixing crops	Son et al., 2023
	Managed pasture/Grazing	Aldersley et al., 2011; Bistinas et al., 2014; Son et al., 2023
	Rangeland	Son et al., 2023
	Cattle density	Forkel et al., 2019
Antecedent vegetation	Leaf area index pre-3 month and pre-6 month	Forkel et al., 2019; Kuhn-Regnier et al., 2021
	Leaf area index pre-1 year and pre-2 year	Zhang et al., 2023
	Gross primary production pre-3 month and pre-6 month	Forkel et al., 2019
	Leaf area index change 12M, 18M and 24M prior	Kuhn-Regnier et al., 2021
	Annual seasonality in gross primary production	Haas et al., 2022

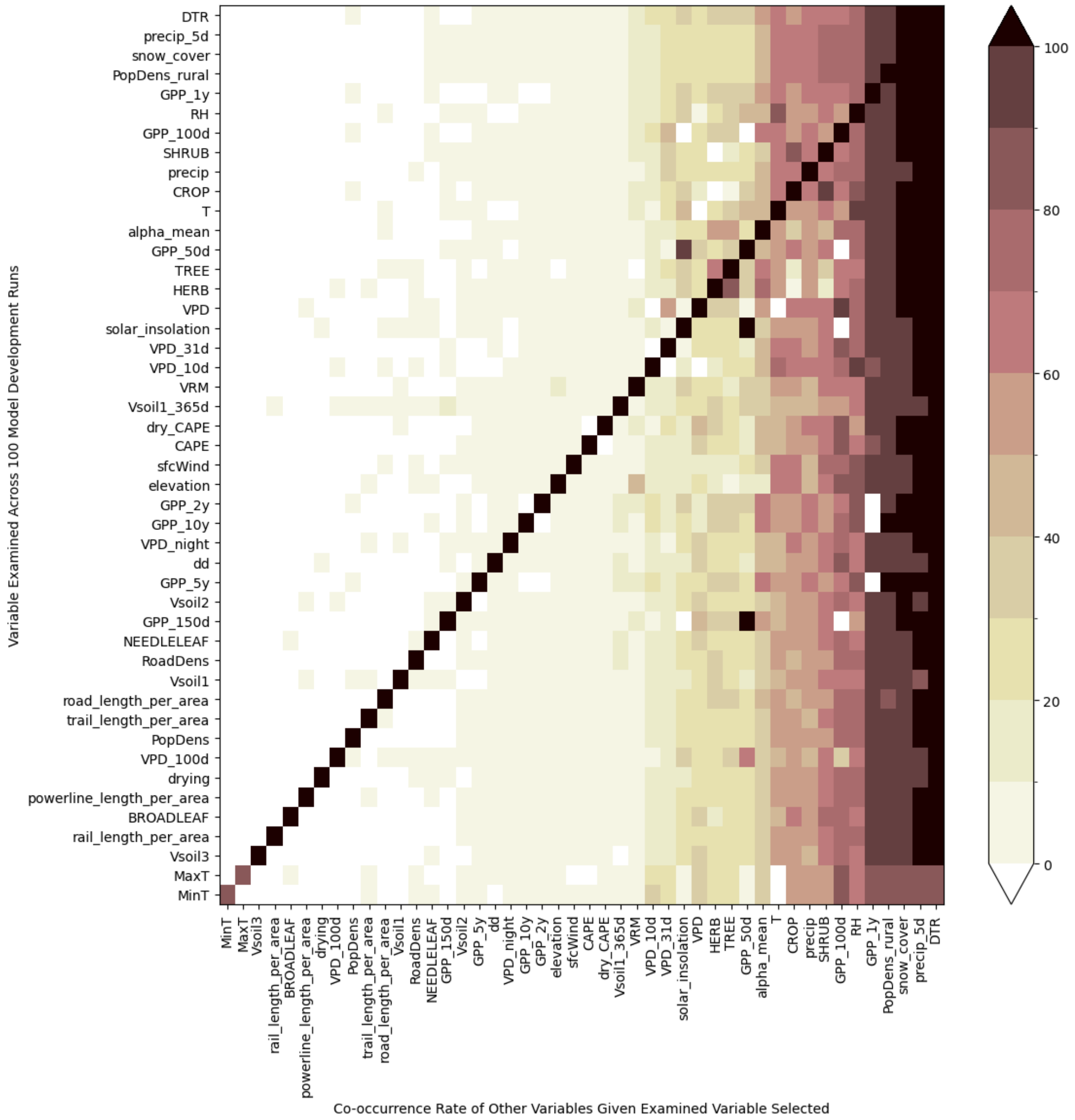
	Vegetation optical depth 12M, 18M, 24M	Kuhn-Regnier et al., 2021
	SIF change 12M, 18M and 24M prior	Kuhn-Regnier et al., 2021
	Vegetation optical depth 1M and 3M prior	Kuhn-Regnier et al., 2021
	Leaf area index 1M prior	Kuhn-Regnier et al., 2021
	Vegetation optical depth 9M prior	Kuhn-Regnier et al., 2021
	Vegetation optical depth 6M prior	Kuhn-Regnier et al., 2021
	fAPAR 9M	Kuhn-Regnier et al., 2021
	fAPAR 6M	Kuhn-Regnier et al., 2021
	fAPAR 1M	Kuhn-Regnier et al., 2021
	SIF 1M and 3M	Kuhn-Regnier et al., 2021
	SIF 9M prior	Kuhn-Regnier et al., 2021
	Leaf area index 9M prior	Kuhn-Regnier et al., 2021
Antecedent precipitation	Precipitation of wettest month	Krawchuk et al., 2009
	Precipitation seasonality	Krawchuk et al., 2009
	Precipitation of coldest month	Krawchuk et al., 2009
	Annual precipitation range	Fernandez-Garcia et al., 2023
	Number of dry days 1M and 3M prior	Kuhn-Regnier et al., 2021
	Change in number of dry days 12M, 18M and 24M prior	Kuhn-Regnier et al., 2021
	Number of dry days 6M and 9M prior	Kuhn-Regnier et al., 2021
	Seasonality of dry days	Haas et al., 2022

Supplementary Table 3. Details of the individual empirical analyses of the global controls on fire.

Model	Statistical method	Method for ranking importance	Top three variables	Number of predictors
Son et al., 2023	Deep-learning fire model using long short-term memory network approach (recursive neural network)	Layer-wise relevance propagation score	1. **PFT bare > 15%** 2. Fuel ~ 14% 3. Soil water content in layer 4 ~ 6%	50
Bistinas et al., 2014	Generalized linear modelling approach (quasi-binomial model)	*z*-scores	1. **Soil moisture z = -58.9** 2. Net primary production z=56.8 3. Dry days z=32.9	11
Forkel et al., 2019	Random-forest modelling approach	Variable importance score based on distance D, derived from fractional variance and Spearman correlation	1. **Maximum temperature (*mean > 0.5*)** 2. Tree (broadleaf deciduous) (*mean ~ 0.4*) 3. Gross primary production (previous 6-month) (*mean ~ 0.3*)	34
Haas et al., 2022	Generalized linear modelling approach (quasi-binomial model)	*t-values*	1. **Monthly number of dry days (*t-values = 70.23*)** 2. Annual gross primary production (*t-value = 63.00*) 3. Seasonality of dry days (*t-values = 59.26*)	16
Fan et al., 2023	Geographical Detector	*q* statistic	1. **Relative humidity (q statistic = 0.33)** 2. Temperature (q statistic = 0.24) 3. Soil moisture (q statistic = 0.20)	4
Yhang et al., 2023	Five machine learning approaches (Random Forest, CatBoost, XgBoost, LightGBM and Neural Network)	Calculated scores based on ensemble of machine learning methods (presented in discussion)	1. **Gross domestic product (13.1%)** 2. Past 1-year LAI (13.7%) 3. Vapour pressure deficit (12.5%)	17
Aldersley et al., 2011	Regression tree analysis and random forest modelling approach	Difference in mean square error (MSE) between the bootstrap sample and the test sample is determined and permuted, with differences averaged over all trees, normalised using the standard error	1. **Lightning** 2. GDP 3. Wet days	9
Kuhn-Regnier et al., 2021	Random forest modelling approach	Composite score derived from the Gini, PFI, LOCO, and SHAP metrics (divided each score by the sum of their	1. **Dry days** 2. fAPAR 3. Vegetation optical depth (1 month prior)	15

		absolute vale and then summed them		
Krawchuk et al., 2009	Generalized additive modelling approach	Ranked importance based on the number of times the explanatory variable was selected and the mean AIC value (which demonstrates relative amount of variance explained)	**1. Net primary production** 2. Mean temperature of the warmest month 3. Annual precipitation	20
Fernandez-Garcia et al., 2023	Polynomial regression modelling approach	Spearman correlations	**1. Annual temperature (p = 0.58)** 2. Annual temperature range (p = -0.36) 3. Annual precipitation (p =0.31)	4

Supplementary Figure 1. Outcome of systematic variable selection, where the y-axis indicates the initial variable included in the model and the colour coding indicates the frequency with which other variables are selected in the final suite of models. (See Figure 3 in main text for summary)



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