

IAM-FIRE: a Climate Emulator–Based Framework to Project Wildfire Impacts and Risks for Integrated Assessment Models

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Abstract

Most Integrated Assessment Models (IAMs) underrepresent dynamic feedbacks from climate-driven disturbances such as wildfires, potentially overestimating the permanence of land-based carbon sinks. In particular, representing the impacts of forest fires is becoming increasingly important, as these are expected to intensify in the coming years. We introduce IAM-FIRE (Integrated Assessment Model – Fire Impacts & Risks Emulator), a novel framework that enables the projection of wildfire burned area (BA) and carbon emissions (CE) directly from IAM outputs. IAM-FIRE combines a spatial climate emulator, land-use downscaling, vegetation productivity modelling, and an empirical fire model to generate global annual wildfire impacts for arbitrary socioeconomic and emissions scenarios at 0.5° resolution for the period 2020–2100.

Calibrated against GFEDv5 observations and using inputs from the Global Change Analysis Model (GCAM), we report projections BA and CE derived from IAM-FIRE for four scenarios: SSP1-2.6, SSP2-4.5, SSP3-6.6 and SSP5-7.6. The model reproduces historical global trends for total BA, including the observed global decline since the early 2000s, and for forest BA. Projected fire trajectories differ strongly among scenarios: total BA range from declines under SSP1-2.6 ($-3.36 \text{ Mha yr}^{-1}$) to increases under SSP3-6.6 ($+1.6 \text{ Mha yr}^{-1}$). Corresponding total CE show a similar divergence ranging from -15 to $+10.6 \text{ TgC yr}^{-1}$. Socioeconomic development exerts a dominant suppressing effect on wildfire impacts while climate change and CO_2 -driven increases in vegetation productivity amplify fire risk, particularly under high-emissions pathways.

Compared with CMIP6 fire-enabled Earth System Models, IAM-FIRE exhibits greater sensitivity to radiative forcing and a stronger role for human-driven fire suppression, highlighting substantial structural uncertainties in future fire projections. By providing a computationally efficient and internally consistent approach to represent wildfire impacts within IAMs, IAM-FIRE enables systematic exploration of fire–climate–land feedbacks and supports improved assessments of mitigation permanence and climate risks in future integrated scenarios.

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) often relies on a framework combining Integrated Assessment Models (IAMs), Earth System Models (ESMs), and impact models (IPCC, 2023) to explore future mitigation pathways and their implications for climate, ecosystems, and society. IAMs project greenhouse gas (GHG) emissions and removals under different socioeconomic scenarios, providing inputs to ESMs, which in turn generate climate projections for impact models. This linear structure neglects climate feedbacks (processes amplifying or dampening an initial change in radiative forcing) and reduces the internal consistency of projections, which has implications for a wide range of biophysical and socioeconomic dynamics (C. G. Jones et al., 2024). Accordingly, IPCC AR6 called for improved representation of biophysical climate effects in IAMs to better assess concerns of mitigation permanence (Nabuurs et al., 2022).

Among climate-driven risks, improving the representation of wildfires is of growing importance given their growing impact on forests carbon sinks (Anderegg et al., 2020). Related permanence risks are expected to intensify through the 21st century, leading to losses in forest area and carbon stocks (Hermoso et al., 2021). Wildfires pose a worsening threat due to more frequent and severe fire weather, both observed (Bedia et al., 2015; M. W. Jones et al., 2022) and projected (Son et al., 2021). Shifts in regional fire regimes can significantly affect the feasibility of large-scale and long-term carbon sequestration and the net forest-based mitigation potential (Fesenmyer et al., 2025). While an explicit representation of fire dynamics within IAMs is vital to avoid overestimating the potential of forests as a climate mitigation strategy on a warming planet, few established IAMs currently capture the climate feedbacks of worsening fire weather on forests-based mitigation (Jäger et al., 2024).

Dynamically integrating climate impacts like wildfires into IAMs remains challenging due to technical constraints in the current model chain, particularly the dependency on ESM outputs. While IAM-generated emissions and land-use trajectories feed into ESMs to simulate climate and vegetation dynamics, the high computational and labour demands of ESMs restrict simulations to a standardized set of scenarios, most recently following the SSP–RCP framework (Eyring et al., 2016; O’Neill et al., 2017). As a result, only a narrow set of climate responses can currently be passed back into IAMs, making it difficult to ensure a consistent two-way coupling in which climate change and its impacts meaningfully influence IAM trajectories. Hence a broader and more flexible range of climate simulations is required to assess how scenario-dependent climate feedbacks could alter socio-economic and emission pathways within IAMs.

Spatial climate emulators (SCEs) have been developed to overcome these barriers by providing ESM-like outputs for arbitrary future scenarios of anthropogenic forcing (Tebaldi et al., 2025). SCEs have become increasingly complex, evolving from simple pattern scaling of temperature and precipitation to reproducing the multidimensional variability and temporal dynamics of full ESM outputs. They derive climate information consistent with the temperature trajectory endogenously produced by simple climate models (SCMs) from IAM outputs (Fig. 1). The Fast Assessment for Scenario Trajectories Multi-emulator Intercomparison Project (FASTMIP) (Seneviratne et al., 2024), a new experimental protocol allowing the fast derivation of climate projections for new emissions scenarios, actively builds on the novel capacities of existing SCEs such as MESMER (Beusch et al., 2020), PRIME (Mathison et al., 2024) or STITCHES (Tebaldi et al., 2022).

Beyond climatic factors, fire regimes are also driven by land use and land use changes (LULUC), topography, vegetation productivity, and human activities (Haas, Keeping, et al., 2024). Most fire-enabled ESMs estimate burned area (BA) and carbon emissions (CE) using process-based models which differ in their underlying equations, calibration, and treatment of human drivers. While they reproduce global totals of BA reasonably well, they fail to capture the historic global decline, largely due to underrepresented human suppression (Li et al., 2024). In parallel, empirical approaches using statistical methods like Generalized Linear Models (GLMs) (Forrest et al., 2024; Haas et al., 2022; Kavhu et al.,

2025) have been used in previous studies to predict BA and provide highly interpretable results (Bistinas et al., 2014) but, to our knowledge, have not yet been combined with climate projections from SCEs.

This study introduces IAM-FIRE (Integrated Assessment Model - Fire Impacts & Risks Emulator), a novel method designed to predict fire impacts and risks on land systems dynamically through IAM simulations. IAM-FIRE predicts BA and CE directly from IAM outputs by employing the STITCHES climate emulator to generate the climate variables needed to model fire dynamics. We demonstrate the efficiency and flexibility of this approach to derive consistent outputs using inputs from the Global Change Analysis Model (GCAM) (Calvin et al., 2019). Focusing on fire impacts and risks across multiple SSP–RCP scenarios, we estimate BA and CE at annual resolution on a $0.5^{\circ} \times 0.5^{\circ}$ grid (the resolution of ISIMIP3b output variables for fire) for the 2020–2100 period. Additionally, we perform a factorial decomposition to assess the contribution of different drivers and compare results with CMIP6 benchmarks. This methodology provides a computationally rapid and adaptable tool for projecting fire impacts and risks that can facilitate future representation of wildfire feedbacks on land and climate systems within the IAM framework.

2. Methods

2.1. Modelling framework

IAM-FIRE predicts spatially-explicit BA and CE for arbitrary IAM scenarios at global scale. The framework combines the climate emulator STITCHES, the land use downscaling tool Demeter, the vegetation productivity model P-model and a GLM (Fig. 2 illustrates the modelling processes of IAM-FIRE). The framework is calibrated using the fire activity data from the Global Fire Emission Database version 5.1 (hereafter referred to as GFEDv5) (van der Werf et al., 2025). In the following sections, we provide an overview of each methodological steps while further details can be found in the Supplementary Material (SM).

2.2. Land and temperature: GCAM & Hector

In this study the inputs for IAM-FIRE are derived from the Global Change Analysis Model (GCAM). GCAM (v8.2) is a dynamic recursive model representing the complex interactions between five major systems—energy, water, land, climate, and the economy (Calvin et al., 2019). GCAM has been widely used for studying climate change mitigation from the land use sector (Rouhette et al., 2024; X. Zhao et al., 2024), as well as climate impacts on agriculture (A. Snyder et al., 2020; X. Zhao et al., 2021), and water systems (Turner et al., 2017). The land and water systems are subdivided into 235 water basins and 32 geopolitical regions structure the economic and energy systems, resulting in a total of 384 distinct land-water regions (called land use units, LUTs).

To represent the climate system response to its emissions and land use, GCAM integrates the simple climate model Hector (Dorheim et al., 2024) which projects future GHG concentrations based on a given

emissions pathway while simulating the carbon cycle, estimates global mean radiative forcing from these concentrations and short-lived climate forcers, and translates the radiative forcing into global mean temperature and other Earth system variables (Calvin et al., 2019).

2.3. IAM-FIRE

Three inputs are required to run IAM-FIRE: the temperature trajectory, the CO₂ concentration and the land use projections (grassland, shrubland, cropland and forest). In parallel, historic data of fire activity and predictors are compiled over the 2002–2019 period to fit the relationship between observed total BA and the predictors in the statistical model (Table 1 provides the list and sources of the data used in IAM-FIRE).

Table 1

Sources of fire response data and predictor variables used for both the historic (2002–2019) and the simulated periods (2020–2100). Detailed processing steps are provided in the SM.

Variable	Data source for historic period (2002–2019)	Model used for projection (2020–2100)
Fire Response Variable		
Burned area (BA)	Global Fire Emissions Database (GFED5.1) (van der Werf et al., 2025)	GLM + Post-processing steps
Carbon emissions (CE)		
Climate Predictors		
Vapor Pressure Deficit (VPD)	W5E5 v2.0. ISIMIP Repository (Lange, Stefan et al., 2021)	STITCHES (A. C. Snyder et al., 2024)
Number of dry days (NDD)		
Wind speed		
Precipitation (30-day rolling sum)		
Land use Predictors		
Forest	European Space Agency (ESA) Climate Change Initiative (CCI) Plant Functional Types (Harper et al., 2023)	DEMETER (Vernon et al., 2018)
Grassland		
Shrubland		
Cropland		
Grazing pressure	Perkins, Haas, & Millington, (2025)	
Vegetation Predictor		
Gross Primary Productivity (GPP)	P-Model (Stocker et al., 2020; Wang et al., 2017)	
- Temperature	W5E5 v2.0. ISIMIP Repository (Lange, Stefan et al., 2021)	GCAM & HECTOR (Calvin et al., 2019; Dorheim et al., 2020)
- Vapor Pressure Deficit (VPD)		STITCHES
- Solar Radiation		
- Atmospheric CO ₂ concentration	GCAM & HECTOR	
- Atmospheric pressure	GMTED2010 Digital Elevation Model (Danielson & Gesch, 2011)	
- Fraction of absorbed photosynthetically active radiation (fAPAR)	GIMMS FPAR4g (W. Zhao et al., 2024)	

Variable	Data source for historic period (2002–2019)	Model used for projection (2020–2100)	
Fire Response Variable			
Socio-economic Predictor			
Human Development Index (HDI)	Kummu et al., (2018)	Perkins et al., (2024)	
Topographic Predictors			
Topographic Position Index (TPI)	Amatulli et al., (2018)		
Vector ruggedness measure (VRM)			
Fuel consumption			
Fuel load (FL)	ECMWF Fuel Characteristics V1 (McNorton & Di Giuseppe, 2024)		
Combustion completeness (CC)	Ranges per biomes and fuel pools (van Wees et al., 2022)		

2.3.1 Climate emulator: STITCHES

The global average temperature projections of Hector are fed into the climate emulator STITCHES (A. C. Snyder et al., 2024). STITCHES utilizes existing archives of Earth system models’ (ESMs) scenario experiments to generate ESM-like outputs for new scenarios or to enhance existing initial-condition ensembles. It preserves the key characteristics of the ESM output it aims to replicate (multivariate, spatially detailed, and high-frequency) while capturing both the forced response and the surrounding internal variability (Tebaldi et al., 2022).

STITCHES follows a time-slicing approach which takes several time windows of gridded, multivariate outputs from ESMs and recombines them into new instances of transient trajectories for future periods by stitching them together on the basis of the global surface air temperature (GSAT) derived from the GCAM scenario. We selected two ESMs that provided enough experiments in the Pangeo database at the daily scale required for the analysis: CanESM5 (Swart et al., 2019) and MPI-ESM1-2-LR (Gutjahr et al., 2019) (Table S1). We use STITCHES to derive five variables in the period 2015–2100: temperature (tas), relative humidity (hurs), precipitation (pr), wind speed (sfcWind) and solar radiation (rsds). We use the ESM-derived projections to derive the final climatic drivers: monthly temperature and relative humidity are used to compute the vapor pressure deficit (VPD), daily precipitation is used to compute the monthly number of dry days (NDD) and we finally compute the mean wind speed of the hottest month. Solar radiation is used to model gross primary productivity (GPP), as described below.

In order to remove systematic biases from the climate simulation data of the ESMs relative to the observation data, we perform a bias adjustment which involves two distinct procedures: (i) the actual

bias adjustment at the spatial resolution of the simulation data and (ii) a statistical downscaling to the spatial resolution of the observation data. The method used for both bias adjustment and statistical downscaling (BASD) are based on the approach described by Lange (2019). The observational data used for the BASD procedure is the W5E5 v2.0 dataset compiled to support the bias adjustment of climate input data for the Phase 3b of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) (Frieler et al., 2024).

2.3.2 Vegetation projection: P-Model

Mean annual GPP is used as an index of vegetation productivity (Krause et al., 2022) and is derived from the P-Model (Stocker et al., 2020; Wang et al., 2017). Using the inputs described in Table 1, it estimates GPP as the product of light use efficiency (LUE) of photosynthesis and absorbed radiation. These variables represent the key environmental controls on photosynthesis: light availability determines the energy input for carbon fixation, while temperature, VPD, and CO₂ concentration regulate stomatal behaviour and biochemical efficiency. Together, they capture the eco-physiological constraints that govern LUE and therefore GPP.

The P-Model is used for both the historic and simulated period to ensure consistency between both periods. CO₂ concentrations are extracted from Hector while the VPD and solar radiation are emulated with STITCHES. Solar radiation is converted to photosynthetic photon flux density using established constants (Haas et al., 2022) and elevation to atmospheric pressure using a dedicated function of the P-Model. We assumed a constant fAPAR by using monthly climatological means from the historical period, meaning that potential future increases in canopy density or vegetation greenness are not represented. As a result, our projections reflect changes driven solely by environmental controls on LUE, and may underestimate future GPP in regions where fAPAR is expected to increase.

To account for periods of high vs. low GPP, the seasonality index is estimated for each year and grid cell as the relative intra-annual amplitude of the mean GPP in each calendar month (see equation in SM).

2.3.3 Land use downscaling: Demeter

To represent the role of land use in fire regimes, the aggregated land use projections of GCAM are downscaled at the grid level (0.5-deg resolution) with Demeter (Vernon et al., 2018). Demeter is an open-source spatial disaggregation model providing gridded and land cover change (LULCC) products derived directly from IAMs in a variety of formats and resolutions commonly used by ESMs. Demeter has been used to generate a new global gridded LU dataset at a high spatial resolution (M. Chen et al., 2020). Demeter utilizes a base land cover map at a target resolution as a reference and strategically distributes projected land type area changes from models (e.g., GCAM) to target grid cells according to a set of user-defined rules and spatial constraints (M. Chen et al., 2019).

In this study, we update the base map of Demeter with the ESA CCI Land Cover data (Figure S1, Table S2-3). Since CGAM land module is calibrated on HYDE 3.2 (Klein Goldewijk et al., 2017), we employ an established methodology to reproject GCAM land use outputs onto the novel ESA basemap (M. Chen et

al., 2020). The downscaled results are grouped into broad land use categories: forest, grassland, shrubland, cropland and other land (tundra, rock, ice, desert and urban) at the 0.5-degree resolution and linearly interpolated from a 5-year time step to annual time step for the period 2015–2100.

2.3.4 Statistical modelling of burned area: GLM

To predict future BA, a statistical model is trained on historical data over 2002–2019. Following previous studies (Haas et al., 2022; Kavhu et al., 2025), we use a generalized linear model (GLM) to estimate BA fractions from a range of predictors. BA and CE are derived from GFED5 which provides data at $0.25^\circ \times 0.25^\circ$ resolution for the period from 1997 to 2022 (van der Werf et al., 2025).

For the drivers of burned area, predictor variables are grouped in five categories: climatic, land use, vegetation, topographic and socio-economic. To represent climatic drivers, we use VPD, NDD, the 30-day precipitation rolling sum and wind speed. For the simulated period (2020–2100), these drivers are estimated from the bias-adjusted and statistically downscaled projections from STITCHES for the selected ESMs. For drivers related to vegetation and land uses, we use GPP, grazing pressure (average computed over the 2002–2014 period) from Perkins, Haas, & Millington (2025) and fractions of grassland, shrubland, forestland and cropland from the ESA CCI product for Plant Functional Types aggregated at 0.5-degree resolution by Harper et al., (2023). For topography, we use topographic positioning index (TPI) and vector ruggedness measure (VRM) which are static during the simulated period. For human influence, Human Development Index (HDI) is selected as it captures the country's social and economic development levels. HDI projections were obtained per SSPs from Perkins et al. (2024).

To reduce skewedness, we log-transform VPD, NDD, wind speed, precipitation rolling sum and GPP. We run the GLM using a quasi-binomial function with a logit-link function adapted to the nature of the response variable (BA fraction) ranging from 0 to 1. Different models are evaluated and compared using the coefficient of determination (R^2), the normalized mean error (NME) and root mean square error (RMSE). Details and equations are provided in SM.

In GLMs, the relative importance of each predictor is assessed using absolute t-values (the fitted regression coefficient of each predictor divided by its standard error) which are reported along with summary metrics for the best model. We perform multicollinearity analysis looking at variance inflation factors (VIF) to assess redundancy between predictor variables.

Forest BA is derived from total BA based on the average proportion of forest BA per grid cell from GFEDv5 historical data. It is assumed that this proportion remains constant over the simulated period (Figure S2).

2.3.5 Modelling of carbon emissions

CE from biomass combustion are calculated by projecting fuel consumption (FC) which is then multiplied by BA (SM Section 1.2.6). FC depends on the biomass available to burn (fuel load, FL) and the

fraction of the biomass that is combusted (combustion completeness, CC). FL data is obtained from the global fuel characteristic dataset (McNorton & Di Giuseppe, 2024) and CC values from van Wees et al., (2022) (Table S4). CC was then scaled linearly by VPD values to account for the impact of dryness/wetness of the fuel. By combining FL data with the scaled CC factors, we derive spatially-explicit and climate-responsive FL values for the four fuel types (leaf, stem, litter and coarse wood debris) over the simulated period (Figure SM3). Forest FL is obtained by summing all four fuel types and non-forest FL by summing litter and leaf.

To ensure consistency between our values and GFEDv5 FC values (Figure S3-4), which are constrained by field measurements and broadly accepted references for CE, we estimate a change ratio for our projected FC and multiply the GFEDv5 FC values in 2019 by the ratio per year for both land use categories in IAM-FIRE (forests and non-forests) (Zhao et al., 2025). This implies that FC projections are aligned with the GFEDv5 historical benchmark used in the GLM and maintains dynamic changes under diverging future climate conditions. Trends of global FC are presented in the results with weighted averages using the fixed BA data for 2019 in order to isolate the FC signal across scenarios with different future BA trajectories.

2.4. Scenario design

The estimates of BA and CE are computed for four scenarios ranging from low to high emissions. We run SSP1-2.6 and SSP2-4.5 reference scenarios as well as reference scenarios for SSP3 and SSP5, which in GCAM8.2 only reach radiative forcings of 6.6 and of 7.6 by 2100, respectively (Figure S5). Since STITCHES emulates specific ESMs, we model each scenarios using the 2 ESMs presented above, addressing structural uncertainties in the modelling of the climate system. Our main results report the multi-model mean (MME) along with range across the 2 ESMs.

2.5. Factorial decomposition

To assess the relative importance of predictors on the total BA per scenarios, we run factorial simulations following the approach of Wu et al., (2021) which differentiates limiting factors and drivers (Table S5). We grouped the predictors into climatic (VPD, NDD, wind speed, precipitation), land use (grassland, shrubland, cropland, grazing pressure), vegetation (GPP) and socio-economic (HDI) groups. For each group, we test its role as a driver of BA – by allowing the variables of the group to vary while fixing at the 2020-value all the other groups –; and as a limiting factor of BA – by fixing its value at the 2020-value while allowing the other groups to vary.

2.6. CMIP6 Comparison

We compare the total BA results with BA projections from CMIP6 runs. We select the total BA outputs from four ESMs listed in Li et al. 2024: CESM2, CESM2-WACCM, CMCC-ESM2, Nor-ESM2-LM. For each ESM we extract BA for the following experiments: historical, SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5 (although GCAM 8.2 produces baseline scenarios for SSP3 and SSP5 that end up at intermediate levels of radiative forcing, as SSP3-6.6 and SSP5-7.6). We compare the IAM-FIRE BAs with the CMIP6 BAs

looking at global totals and at temporal linear trends computed by ordinary least square OLS (and tested for significance using the Mann-Kendall test).

3. Results

3.1. Historical burned area and carbon emissions

BA and CE predictions for historical periods are shown in Fig. 3. Predicted total BA adequately captures the decline reported by GFED5 in the 2002–2019 period (Fig. 3 (a)). The spatial distribution is well captured by the GLM with minor differences in latitudinal bands (Fig. 4 (a-c)). Aggregated per GFED regions, higher estimates are observed in SHSA (South Hemisphere South America) (47 Mha.yr⁻¹ observed vs 98 Mha.yr⁻¹ predicted) (Fig. 3 (b)). For total CEs, both the predictions and observations of total CE show an absence of trend in historic period, and IAM-FIRE captures well global totals (3.0 TgC.yr⁻¹ predicted vs. 2.9 TgC.yr⁻¹ observed) (Fig. 3 (e-f)).

For forests, predicted BA captures the absence of trend in the 2002–2019 period (Fig. 3 (c)). On average, global forest BA is higher by 10 Mha (30 in GFED vs. 40 in IAM-FIRE), due to the higher values in SHSA and despite lower estimates in boreal regions (BOAS, Boreal Asia and BONA, Boreal North America) (Fig. 3 (d)). For forests CE, both predictions and observations report no statistically significant trend. Despite the agreement on global totals, IAM-FIRE has higher forest CE in the SHSA region (0.07 TgC.yr⁻¹ observed vs 0.31 TgC.yr⁻¹ predicted) and lower in boreal regions (0.32 TgC.yr⁻¹ observed vs 0.08 TgC.yr⁻¹ predicted across BONA and BOAS) (Fig. 3 (g-h)).

The regional discrepancies highlighted can be explained by several factors (Figures S6-9). Contemporary fires in boreal forests are dominated by very large and intense fire years (such as 2003 and 2016 – see SM). In common with many fire models, IAM-FIRE cannot fully capture these dynamics (Hantson et al., 2024). In turn, the results in SHSA could be explained by an underrepresentation of suppressing effects like moisture constraints which strongly limit BA in tropical forests. Due to the multiplicative nature of the CE calculations, moderate gaps in total BA can result in large difference in CE estimates through error propagation in each step.

The GLM performs well with high predictive power: a pseudo R^2 of 0.71, NME of 0.48 and RMSE of 0.07. Table 2 provides the summary statistics. From the initial set of predictors, the forest variable was removed due to a high correlation with GPP as well as the GPP seasonality index because it did not improve the model's performance. Final VIF values ($VIF_{\max} = 4.4$) demonstrate a low level of multicollinearity among predictors. Complementary details on the final GLM including the partial residual plots are provided in SM Section 2.1.

Table 2

Summary statistics of the final GLM model used to predict burned area. Predictors included were all significant at $Pr(>|t|) < 1.97e-11$. VPD: Vapor Pressure Deficit, NDD: Number of Dry Days, GPP: Gross Primary Productivity, TPI: Topographic Position Index, VRM: Vector ruggedness measure, HDI: Human Development Index

Group	Variable	Coefficient	t-value	VIF
Intercept		-35.17	-65.31	
Climatic factors	VPD	0.43	33.77	2.17
	NDD	4.19	39.67	2.04
	NDD Seasonality	0.00	0.30	2.88
	Wind Speed	-0.12	-5.41	2.35
	Precipitation (30-Day rolling sum)	0.85	34.29	4.44
Vegetation productivity	GPP	0.89	46.28	2.74
Topography	TPI	0.13	7.06	1.75
	VRM	-115.31	-19.83	2.23
Socioeconomic development	HDI	-2.92	-58.43	1.56
Land use	Grassland	2.76	59.42	1.69
	Shrubland	1.26	15.86	1.14
	Cropland	0.78	14.93	2.22
	Grazing pressure	-6.42	-44.84	1.89

Positive relationships (t-value) are observed for VPD, NDD, NDD-seasonality, precipitation, GPP, TPI, grassland, shrubland and cropland while negative relationships are observed for wind speed, VRM, HDI, and grazing pressure. Grassland area is the strongest predictor (59) closely followed by HDI (-58), GPP (46) and grazing pressure (-45). High levels of human development and grazing activity play a crucial role in counteracting the increasing risks posed by climate change which materialize directly through both drier and hotter conditions (reflected by climatic factors) and indirectly through increasing biomass through CO₂ fertilization (reflected by vegetation productivity).

3.2. Future burned area and carbon emissions

We report future global BA and CE trends for total fires and forest fires as ensemble means across the 2 ESMS used to emulated climate variables (CanESM and MPI) for the four scenarios over the 2020–2100 period.

The scenarios show strongly diverging trends of total BA at the global level (Fig. 5 (a,b)). SSP1-2.6 shows a sharp decline in BA, with a trend of $-3.36 \text{ Mha.yr}^{-1}$ for total BA and $-0.28 \text{ Mha.yr}^{-1}$ for forest BA, due

to high economic development and strong mitigation of GHG emissions. African regions (NHAF and SHAF) drive the decline for both total and forest BA, with declining trends in all regions (Fig. 6 (a-b)). SSP2-4.5 has a trend of -1.9 Mha.yr^{-1} for total BA and -0.1 Mha.yr^{-1} for forest BA due to lower HDI improvements and higher GHG emissions. Multiple regions will not experience declines compared to SSP1-2.6 (BONA, AUST and EQAS) (Fig. 6 (a-b)). SSP5-7.6 closely follows the declining trends observed in SSP2-4.5 up until mid-century due to a similar HDI increases, but stabilizes as climate impacts worsen in later periods. Total BA declines at a much lower pace ($-0.34 \text{ Mha.yr}^{-1}$) than in SSP2-4.5 and forest BA globally increases at 0.17 Mha.yr^{-1} globally. This scenario is marked by strong divergences in regional trends due to both high human development and climate impacts. SSP3-6.6 shows a strong positive trend for total BA with 1.6 Mha.yr^{-1} and global increases of forest BA with 0.28 Mha.yr^{-1} , due to the combined effect of high climate change impacts and the lowest HDI increases among the four scenarios due to underlying regional rivalry assumptions. All regions but EQAS will see increases in total BA, with forest BA strongly increasing in South America (Fig. 6 (a-b)).

IAM-FIRE projects changes in FC (biomass burned annually per m^2 of burned area) depending on the meteorological conditions as CC increases along with VPD – the indicator used as a proxy of fuel dryness in this study. FC is projected to increase in all scenarios albeit with different magnitude depending on the climate trajectory (Fig. 5 (c, d)). For total fires, the results range from $0.02 \text{ gC.m}^2.\text{yr}^{-1}$ for SSP1-2.6 to $0.13 \text{ gC.m}^2.\text{yr}^{-1}$ for SS5-7.6. For forest fires, IAM-FIRE reports an increase in FC ranging from $0.06 \text{ gC.m}^2.\text{yr}^{-1}$ for SSP1-2.6 to $0.71 \text{ gC.m}^2.\text{yr}^{-1}$ for SSP5-7.6. Unlike BA results, SSP5-7.6 has higher increases in FC than SSP3-6.6 since FC is only impacted by VPD and independent from fire suppression processes such as HDI or LULUC.

The CE projections arise from both the BA and the FC trends (Fig. 5 (e, f)). The low and medium emission scenarios have statistically significant declines in CE from fires globally. SSP1-2.6 shows the sharpest decline with a trend of -15 TgC.yr^{-1} in total CE and -4 TgC.yr^{-1} for forest CE, while SSP2-4.5 has a trend of -7.4 TgC.yr^{-1} for total CE and -1.3 TgC.yr^{-1} for forest CE (Fig. 6 (c-d)). On the contrary, high emission scenarios have increasing CE for both total and forest wildfires. SSP5-7.6 shows a trend of 1.72 TgC.yr^{-1} for total CE and of 2.7 TgC.yr^{-1} for forest CE globally. SSP3-6.6 shows the sharpest trend for total CE (10.6 TgC.yr^{-1}) and of forest CE (4.7 TgC.yr^{-1}) through moderate HDI increases and higher FC increases. Total CE are expected to significantly increase in most regions in these scenarios, in sharp contrast with SSP1-2.6 and SSP2-4.5. South America (both SHSA and NHSA) is the region with the highest potential increase in forest CE (Fig. 6 (c-d)).

3.3. Contributions of the drivers of burned area

We performed a factorial decomposition analysis of the drivers of total BA projections (Fig. 7) to better understand how changes in climate, vegetation, land use, and socio-economic factors influence the projected fire impacts. Details on time series of predictors (Figure S15) and on the factorial decomposition (Figures S16-18) are provided in SM Section 2.5.

Socio-economic development

HDI is the main driver of total BA results, which reflects the high t-value of the GLM for the historic period and the significant range of projections from the SSP assumptions. Large differences in human development patterns between SSPs lead to significant divergence in the relative strength of fire suppression processes in IAM-FIRE. To illustrate this, fixing all drivers but HDI leads to significant reduction of global total BA compared to baseline values at 2020 under all scenarios. SSP1-2.6 and SSP5-7.6 yields similar values as they share similar HDI projections (-247 Mha.yr^{-1} and -239 Mha.yr^{-1} relative to 2020, respectively) while SSP3-6.6, which project the lowest increases in HDI across SSPs, has much lower suppressing effects with -110 Mha.yr^{-1} relative to 2020. On the contrary, stagnant HDI coupled with high emission (SSP5-7p6) would lead to significant increases in total BA reaching $+300 \text{ Mha.yr}^{-1}$ (Figure S17) relative to 2020.

Land use and land use changes

LULUC, which refers to the way specific areas of land are used or managed by humans and their alterations through time, has diverging net effects on global fire projections depending on the scenario. SSP1-2.6 and SSP2-4.5 are the scenarios with net suppressing impacts of LULUC due to large decreases in grassland and shrubland areas, which have a positive effect on BA. The effects of LULUC are moderated in SSP5-7.6 due to relatively lower decrease in grassland while in SSP3-6.6 LULUC has a net positive effect on total BA with 31 Mha.yr^{-1} due to large increase in cropland. High deforestation is observed for SSP3-6.6, while SSP1-2.6 yields significant afforestation/reforestation, with both SSP2-4.5 and SSP5-7.6 maintaining global forest areas around 2020 values (Figure S15).

Climatic factors

Climatic factors capture the combined effects of VPD, NDD, wind speed and precipitation on future BAs. Globally, the average maximum VPD will increase proportionally to the RCP levels. VPD will only decreases in SSP1-2.6, going back to historical levels (2020 baseline) in the second half of the century. While climatic impact on BA is small and highly uncertain for SSP1-2.6 (-28 Mha.yr^{-1}), it is the largest positive driver of total BA across the factorial decomposition, reaching 140 Mha.yr^{-1} by 2100 in SSP5-7.6. Climatic factors are the main drivers in northern latitude regions (BONA, TENA, Europe) at high emissions levels (Figure S16), although the effect is associated with relatively high uncertainty across the two ESMs.

Vegetation productivity

Like climatic factors, vegetation productivity is driven by changes in CO_2 concentration and has a positive impact on total BA. GPP growth is enhanced by CO_2 fertilization and higher RCP levels lead to increases in weighted average GPP values across ecosystems. SSP1-2.6 is the only scenario where vegetation productivity has a moderately suppressing impact on total BA. CO_2 fertilisation is a stronger

driver of total BA than climate change in intermediate levels of warming (RCP 4.5 and 6.6). Only in SSP5-7.6 climatic factors become a stronger driver, illustrating the complex relationships between fuel load and fuel dryness dynamics as driving factors of BA.

3.4. CMIP6 Comparison

To shed light on the differences between IAM-FIRE and process-based fire models in ESMs, we compare existing projections from CMIP6 with the results of IAM-FIRE for the four scenarios closest to the ones we ran in GCAM (SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5).

During the historical period (2002–2019 for IAM-FIRE, 2002–2015 for CMIP6), global BA simulated by CMIP6 are substantially lower than those of IAM-FIRE, which is calibrated against GFEDv5 observations (477 Mha yr⁻¹ and 695 Mha yr⁻¹, respectively) (Fig. 8). The two ensembles also exhibit opposite historical trends: IAM-FIRE reproduces the observed decline in global BA (– 5.17 Mha yr⁻²), while CMIP6 indicates a weak increasing trend (+ 2.34 Mha yr⁻²).

Over the projected period (2020–2100), CMIP6 models suggest a modest rise in total BA, ranging from + 0.51 Mha yr⁻² under SSP2-4.5 to + 2.22 Mha yr⁻² under SSP5-8.5. IAM-FIRE projects diverging trends with rates from 1.61 Mha yr⁻² (SSP3-6.6) to – 3.36 Mha yr⁻² (SSP1-2.6) (Fig. 8 (a)). This suggests that the fire suppressing mechanisms in IAM-FIRE are significantly stronger than in CMIP6 models at low and medium levels of emissions and highlights the structural uncertainties (cross-model) associated to wildfire drivers.

In addition, IAM-FIRE simulations show a strong and statistically significant sensitivity to radiative forcing (RCP level), while CMIP6 display a weaker and non-significant response (Fig. 8 (b-e)). In IAM-FIRE, total BA in 2100 increases by approximately + 65 Mha per W m⁻² of forcing ($p = 0.005$), and the interannual BA trend strengthens by + 0.81 Mha yr⁻¹ per W m⁻² ($p = 0.009$). In contrast, the CMIP6 ensemble exhibits much lower sensitivities (+ 10 Mha per W m⁻² and + 0.21 Mha yr⁻¹ per W m⁻², respectively), both statistically non-significant. These findings underscore the critical role of climate forcing in intensifying wildfire risk, with IAM-FIRE indicating a markedly more pronounced and robust increase in fire activity under stronger forcing.

4. Discussion

We presented BA and CE outputs from the novel IAM-FIRE modelling framework. This section elaborates on the insights and limitations of the proposed framework in relation to previous studies, while outlining potential avenues for future research.

4.1. Implications for modelling fire impacts and risks

Historic prediction of fire impacts

IAM-FIRE reproduces observed totals and temporal trends of global BA and CE for both total and forest fires over the 2002–2019 period. Overall global performance is good and slightly superior to similar GLMs: $R^2 = 0.71$ against $R^2 = 0.69$ in Haas et al. (2022) and $R^2 = 0.57$ in Kavhu et al. (2025). Nonetheless, regional discrepancies remain. In the SHAS region, IAM-FIRE projects higher values possibly due to limitations in modelling fuel and soil moisture and the current representation of suppressing effects from livestock grazing (assumed constant). Historically, deliberate and planned pastoral burning of grasslands and pastures was associated with positive residuals in previous GLMs, contributing to higher BA in regions like the Brazilian Cerrado and Caatinga (Perkins, Haas, & Millington, 2025). In contrast, the lower values of IAM-FIRE in boreal regions may be caused by the high short-term interannual variability of boreal fires since extreme fires cannot be adequately captured by a statistical model focused on mean long-term rates of fire drivers (Chuvieco et al., 2021; Haas, Prentice, et al., 2024).

Role of climate change through climate and vegetation

IAM-FIRE captures the impacts of climate change on future BA and CE in two ways: (1) changing climatic conditions make fuel drier and more flammable, and (2) higher GHG concentrations increase fuel load through CO_2 fertilization (e.g., GPP). Our study confirms that these two mechanisms could substantially increase global BA, particularly in high emission scenarios. Among regions, South America appears to be the most sensitive to changes in predictor signals, confirming the region's vulnerability to climate-driven fire risk captured through fire weather projections (Quilcaille et al., 2023). Non-tropical regions, particularly boreal North America and Europe, are also highly sensitive. Despite large uncertainties of ESM outputs, our results align with regional analyses that predict higher fire impacts due to fire weather even at lower latitudes, such as the Mediterranean (El Garroussi et al., 2024). Our results also show that CO_2 fertilization increases both fuel loads and BA by enhancing plant growth (GPP), although these effects could be limited by nutrient availability (Terrer et al., 2019). Despite the assumed constant fAPAR, this mechanism highlights the potential of fuel load control, such as prescribed burning or grazing, as effective fire management strategies (Perkins, Haas, & Millington, 2025; Puig-Gironès et al., 2025).

Role of socio-economic development and land use change

While human factors can significantly modulate fire regimes and override climate-driven effects (Fernández-García et al., 2023), fire models often represented them simplistically – through function of population density or based on cropland cover – and tend to disagree on their relative impacts (Haas, Keeping, et al., 2024; Perkins, Haas, Kasoar, et al., 2025). In contrast, IAM-FIRE incorporates human influence through both HDI and land conversions. HDI emerges as a dominant factor, highlighting that future socio-economic development can counteract climate-driven impacts on fire regimes. This has been observed historically (Burton et al., 2024) and aligns with recent studies showing that higher development levels reduce wildfire economic damages (Hwong et al., 2025) and are associated with more intensive fire suppression (Perkins, Haas, Kasoar, et al., 2025). Still, the SSP framework does not

account for climate impacts and hence HDI projections could be overestimated, especially in the high-emission scenarios. These projections also have equity implications as unequal HDI developments could lead to different readiness to manage fire across regions (Hwong et al., 2025). Strong fire suppression programs in highly-developed countries could also lead to rebound effects through excessive management, leading to accumulation of fuel and increased likelihoods of extreme fires (Kreider et al., 2024). While they remain challenging to model, future extreme fires may dampen human-driven suppressing effects and hence increase total BA projections, particularly in northern latitudes with worsening fire weather (Hantson et al., 2024).

LULUC also plays a significant role, having a varying effect on fires depending on the extent of grassland and shrubland conversion vs cropland expansion. Grassland is the largest predictor of the GLM as herbaceous plants and shrubs are the dominant vegetation that burn globally, mostly located in Africa (Y. Chen, Hall, van Wees, et al., 2023). Grazing pressure has a mitigating effect on BAs by reducing fuel load, consistent with the literature (Andela et al., 2017). Our results confirm that LULUC effects are particularly pronounced in regions with high projected cropland expansion under SSP2 and SSP3, such as the USA and southern Africa (SHAF). While IAM-FIRE does not cover anthropogenic fire types like agricultural burning or deforestation fires, it illustrates that LULUC and fragmentation effects can have divergent impacts across ecosystems (Rosan et al., 2022). The representation of these effects, which also depend on ecosystems adaptation to fires (Harrison et al., 2021), should be improved in fire models.

Impacts of fire on the carbon cycle

Our study suggests that FC is expected to continue increasing in the future, in line with the trends observed in recent decades (M. W. Jones et al., 2024). IAM-FIRE projects an increase in FC driven by fuel dryness, but does not fully account for growth in fuel load. Still, observations from 2010–2019 report a positive 10-year trend in fuel load, with an overall increase of + 4.5 Pg yr⁻¹ (McNorton & Di Giuseppe, 2024). As a result, our estimates of FC may still be conservative, particularly in scenarios with high CO₂ fertilization that enhance fuel accumulation.

In terms of CE, global carbon loss from fire can lead to shifts in vegetation cover and changes in carbon storage (Lasslop et al., 2020). IAM-FIRE does not explicitly model post-fire carbon sinks from regrowth and only provides gross CE. Warming and human development trajectories strongly determine whether future fire regimes reduce or enhance vegetation carbon stocks. While post-fire ecosystems can act as carbon sinks over decades, partially offsetting immediate emissions, ecosystem degradation may slow or prevent full recovery (Pereira et al., 2024; Zheng et al., 2021) and hence generate foregone emissions (Maxwell et al., 2019). Accounting for these dynamics would be required to assess the net impact of future fire regimes on the climate.

There are important caveats regarding recently observed fire activity considering that our calibration period does not include 2020–2025. Recent fire-related carbon emissions increased strongly due to climate change despite below-average burned area, according to attribution analyses from the State of Wildfires 2024–2025 (Kelley et al., 2025). While IAM-FIRE shows a decoupling between BA and CE in

some scenarios and regions, the rapid acceleration of climate change in recent years suggests that projections may underestimate actual impacts (Potapov et al., 2025). By contrast, it is also possible that current boreal fires are secular events - the unique product of rapid warming after long-term fuel accumulation - and that future fire activity in the region will be limited by slow post-fire vegetation regrowth (Tepley et al., 2025). Overall, such complex climate-vegetation feedbacks are an inherent uncertainty in projecting future fire regimes, requiring detailed process-based ecosystem modelling beyond the scope of this study (Hantson et al., 2024).

4.2. Comparison with literature and CMIP6

Estimations of fire impacts vary widely across the literature, largely due to differences in benchmark datasets, predictor selection, and modelling frameworks. IAM-FIRE is parameterized with GFEDv5 which captures small fires more efficiently than previous datasets, resulting in significantly higher BA estimates than other lower-resolution BA datasets (Y. Chen, Hall, van Wees, et al., 2023). While CMIP6 models generally report a positive historical BA trend, our findings align with studies indicating an overall decline in global BA. For instance, Wu et al. (2021) found a decreasing BA at a rate of $-4.85 \text{ Mha.yr}^{-1}$ over the period 2000–2013 using a process-based global fire model (SEVER-FIRE), which is consistent with IAM-FIRE estimates of $-5.17 \text{ Mha.yr}^{-1}$ over 2002–2019. GFEDv5 confirms that the decline observed in 1997–2015 (Andela et al., 2017) has continued in the 2016–2020 period (Y. Chen, Hall, van Wees, et al., 2023). For future periods, Wu et al. (2021) reports increasing BA only in the scenario with high emissions, rapid population growth, and rapid urbanization (S4 with RCP 8.5), similarly to IAM-FIRE which reports increasing BA with high emissions and low human development (SSP3-6.6). A recent study also found diverging trends between low and high mitigation scenarios, highlighting the importance of human activities in reducing BAs through fragmentation and infrastructure (Haas, Prentice, et al., 2024).

The GFEDv5 global carbon emissions (2.9 Pg C yr^{-1}) are approximately 50% higher than those in GFED4s and slightly below IAM-FIRE's estimate of 3.0 Pg C yr^{-1} , which explains the gap with CMIP6 in historic periods. Major uncertainties also persist in FC modelling, primarily due to the high natural variability of combustion rates and inconsistencies among fuel load datasets. Recent evidence suggests that forest fire emissions have increased by 60% globally during 2001–2022 (Jones et al., 2024) while unprecedented high forest fires were observed in 2023 and 2024 (Kelley et al., 2025; Potapov et al., 2025). This contrasts with IAM-FIRE results and illustrate the importance of expanding the GLM's temporal coverage amid recent surges in global fire activity. For future periods, Park et al., (2023) found that global fire CE decreased in scenarios including for SSP3-6.0 and SSP3-8.5 due to increases in GDP per capita, which is aligned with the mitigating effect of HDI improvements found in this study.

4.3. Methodological insights and limitations

A key contribution of this study is the use of the novel STITCHES climate emulator, which offers advantages relative to using standard scenarios run by ESMs included in CMIP6. First, STITCHES allows the analysis of GCAM projections using SSP5 and SSP3 socio-economic assumptions while reaching two radiative forcing levels, 7.6 and 6.6, respectively, which would not be available from off-the-shelf

climate model experiments in the CMIP6 archive. Thus it enables a strictly consistent representation of climate impacts in IAMs for forcing levels more closely aligned with current expectations for high-emission scenarios (Burgess et al., 2020). Second, compared to ESMs that can take days or weeks to run, STITCHES and the BASD process run in only a few hours, reducing the computational cost. This modelling framework can further enable impact studies (assessed by WGII) based on climate projections (assessed by WGI), also reflecting the latest socio-economic trajectories (assessed in WGIII), thus supporting a more integrated approach across the three IPCC WGs. Third, unlike most emulators, STITCHES can emulate daily-scale variables, which is essential for including NDD and precipitation rolling sum predictors. However, STITCHES as a SCE has notable constraints that should be acknowledged. The time slicing approach hinders the emulation of path-dependent quantities and impacts lasting over a decade (Tebaldi et al., 2022). Therefore, STITCHES has not yet been thoroughly validated for scenarios involving large climate overshoots. Its application is also constrained by the availability of ESM outputs including all required variables at sufficient temporal resolution, which can limit the set of usable simulations in existing archives.

At the core of IAM-FIRE, the GLM predicts total BA fraction using an empirical approach that contrasts with the process-based fire modules of ESMs. The empirical setup allows flexible testing of different predictor combinations, facilitating model intercomparison and sensitivity analyses. It is also computationally efficient, which, when combined with STITCHES, enables seamless integration into IAMs without the heavy overhead associated with fire-enabled ESMs. Empirical models, however, come with trade-offs. Because they rely on historical data, they may fail to predict novel fire regimes not represented in past observations (Abalo et al., 2025). Emerging phenomena such as boreal (Corning et al., 2024; Hanes et al., 2025) or Amazonian (Bourgoin et al., 2025; Le Page et al., 2017; Pereira et al., 2024) extreme fires may therefore be underestimated. Moreover, empirical relationships implicitly assume stationarity (i.e., the links between drivers and impacts remain constant), which may not hold under strong climate forcing (Hwong et al., 2025). While GLMs have demonstrated reasonable skill in out-of-sample tests, caution is warranted when applying them to climates outside the historical envelope (Perkins, Haas, Kasoar, et al., 2025).

IAM-FIRE employs a process-based methodology to derive secondary variables from total BA. This introduces error propagation: moderate biases in total BA can lead to significant deviations from GFEDv5 benchmarks in regional forest CE (e.g., in SHAS and in boreal regions). IAM-FIRE does not currently differentiate between managed and unmanaged forest fires, does not cover peatland, agricultural, and deforestation fires and omits fire characteristics like fire size and intensity (Haas et al., 2022; He et al., 2025). Although the framework is optimized for wildfire dynamics, further disaggregation could expand its applicability to studies of LULUC, carbon feedbacks, and emissions accounting. Similarly, IAM-FIRE computes fire impacts at annual scale. Fires are inherently seasonal processes and some studies recommend the inclusion of sub-daily data for meteorological drivers (Matteo et al., 2025). This temporal aggregation limits the framework's precision for applications involving economic losses or air quality impacts sensitive to intra-seasonal fire variability.

4.4. Future work

Future research could focus both on both improvements and applications of IAM-FIRE. Improvements should address key gaps in model representation and scope, for instance, to incorporate missing drivers and to extend the historical period to include recent years of extreme fire activity. Enhancing the statistical framework to capture non-linear dynamics (Chuvienco et al., 2021) and benchmarking against alternative modelling approaches could strengthen predictive performance. Moreover, refining spatial resolution through land use (Forrest et al., 2024) or regional disaggregation (M. W. Jones et al., 2024) and expanding the climate emulation capabilities could improve robustness and reduce structural uncertainties across global fire projections.

Future applications of IAM-FIRE should expand its scenario coverage, assess broader fire impacts, and enhance integration of feedbacks in IAMs. As for scenario coverage, the new variants produced in the context of ScenarioMIP for the next IPCC assessment report (Dunne et al., 2025; van Vuuren et al., 2025) should be explored, as these will presumably yield different LULUC projections and land-based mitigation options, with potential justice and fairness implications (Zimm et al. 2024). As a computationally agile emulator, IAM-FIRE can be useful to characterize the effects of fire risk on these land-use trajectories at a small fraction of the substantial cost implied by running full ESMs. Furthermore, IAM-FIRE could be used to quantify the economic (Hwong et al., 2025), ecological (Lasslop et al., 2020), and health (Alari et al., 2025; J. Zhao et al., 2025) consequences of fires would strengthen its role in interdisciplinary assessments of future climate risks.

While IAM-FIRE demonstrates the potential of combining climate emulators and empirical models for rapid, transparent, and flexible impact assessments, incorporating fire-driven feedbacks between land and climate systems within IAMs would be needed to ultimately improve the understanding of land-based mitigation and adaptation dynamics (Jäger et al., 2024; Luo et al., 2025). To this aim, representing mechanisms such as dynamic carbon losses due to novel fire regimes and fire-responsive land allocation decisions are promising avenues for future research. In this way, IAM-FIRE could become an instrumental tool to support more internally consistent assessments of land-based mitigation and climate risks—an essential step toward reducing uncertainties in next-generation IAMs and CMIP7 frameworks.

Declarations

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Conflict of interest statement

The authors declare no conflict of interest.

Data availability statement

The Global Change Analysis Model (GCAM) version 8.2 is an open-source model that can be downloaded at <https://www.github.com/JGCRI/gcam-core>. GFEDv5 data was obtained from <https://doi.org/10.5281/zenodo.16794692>. W5E5v2.0 data web obtained from the ISIMIP repository at <https://data.isimip.org/10.48364/ISIMIP.342217>. ESA CCI Plant Functional Types Products was obtained from the CEDA archive at <https://catalogue.ceda.ac.uk/uuid/26a0f46c95ee4c29b5c650b129aab788/>. The ECMWF Fuel Characteristics V1 was obtained from the Copernicus Climate Data Store at cems_fuelmodel_data@aux.ecmwf.int.

Code available statement

The source code and instructions to run IAM-FIRE can be found in the online repository <https://github.com/bc3LC/IAM-FIRE> and input are provided in Zenodo <https://doi.org/10.5281/zenodo.18016585>. The source code used for the data analysis and the figure generation, both for the manuscript and the Supplementary Materials, can be found in the online repository https://github.com/LinoHub/IAM-FIRE_projections/ and <https://zenodo.org/records/17998286>.

Supporting information

Additional supporting information may be found online in the Supporting Information section.

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Figures

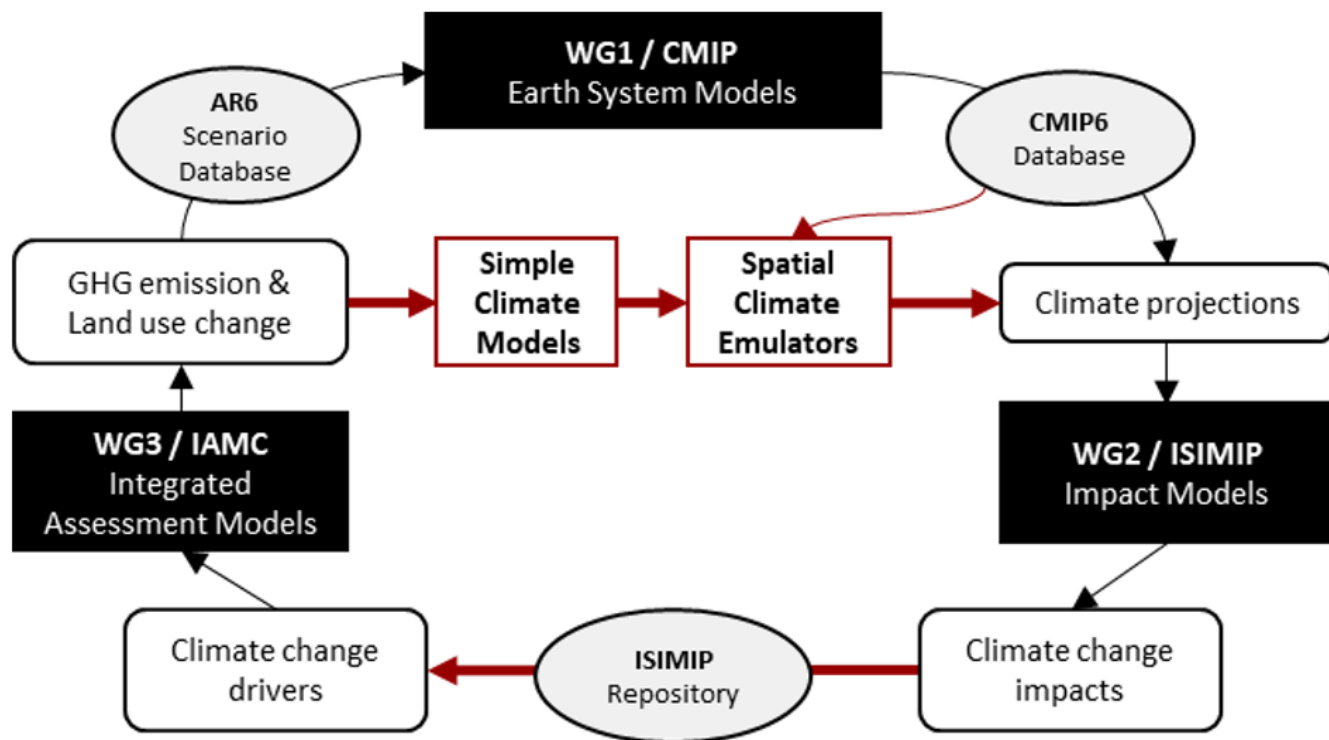


Figure 1

Representation of climate feedback effects in the modelling chain supporting a significant part of the IPCC assessment reports (black lines), where spatial climate emulators help closing the loop (red lines) between Integrated Assessment Models (IAMs, WG3/IAMC) and climate projections from Impact Models (WG2/ISIMIP). SCEs provide spatially resolved climate projections using endogenously derived temperature trajectories from simple climate models and existing climate projections of the Earth System Models (WG1/CMIP) from the CMIP6 database. This facilitates rapid scenario exploration, consistency across working groups, and integration of climate feedbacks.

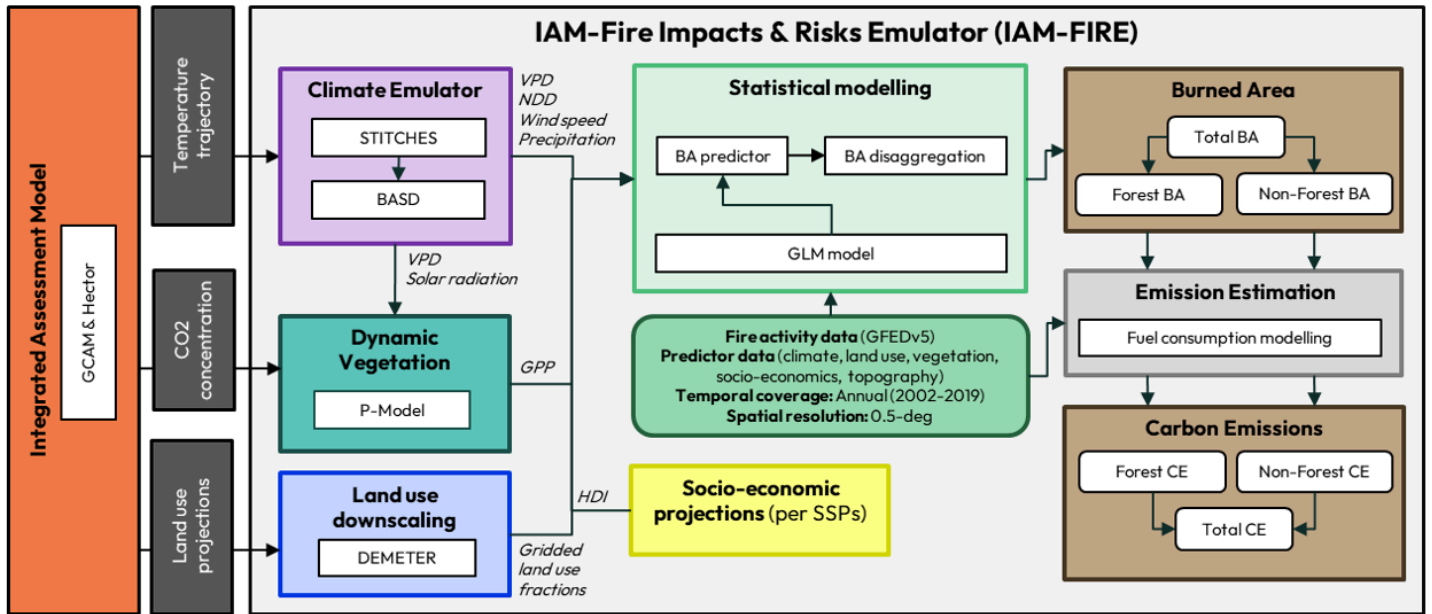


Figure 2

IAM-FIRE modelling framework to estimate burned area (BA) and carbon emissions (CE) in IAMs combining the Global Change Analysis Model (GCAM) (Section 2.2), the climate emulator STITCHES with Bias-Adjustment and Statistical Downscaling (BASD) procedure (Section 2.3.1), the vegetation productivity model P-Model (Section 2.3.2), the land use downscaling tool Demeter (2.3.3), and a Generalized Linear Model (GLM) (Section 2.3.4). VPD: Vapor Pressure Deficit, NDD: Number of Dry Days, GPP: Gross Primary Productivity, GFEDv5: Global Fire Emissions Database version 5.1.

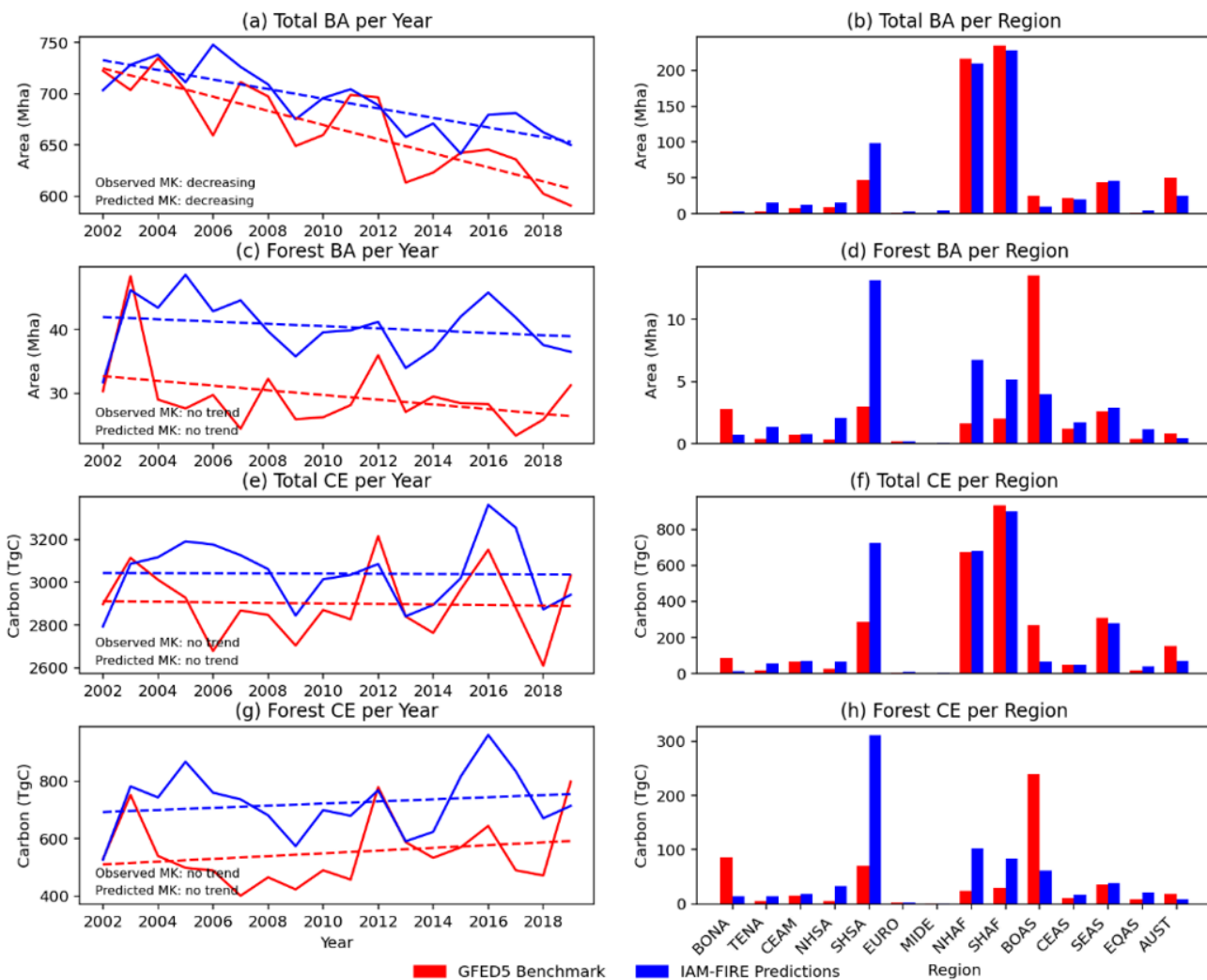


Figure 3

Temporal trend for total BA time series (a) and regional average (b), forest BA time series (c) and regional average (d), total CE time series (e) and regional average (f), and forest CE time series (g) and regional average (h). Regional averages are computed over 2002-2019 for burned areas and carbon emissions. BONA: Boreal North America; TENA: Temperate North America; CEAM: Central America; NHSA: Northern Hemisphere South America; SHSA: Southern Hemisphere South America; EURO: Europe; MIDE: Middle East; NHAF: Northern Hemisphere Africa; SHAF: Southern Hemisphere Africa; BOAS: Boreal Asia; CEAS: Central Asia; SEAS: Southeast Asia; EQAS: Equatorial Asia; AUST: Australia and New Zealand.

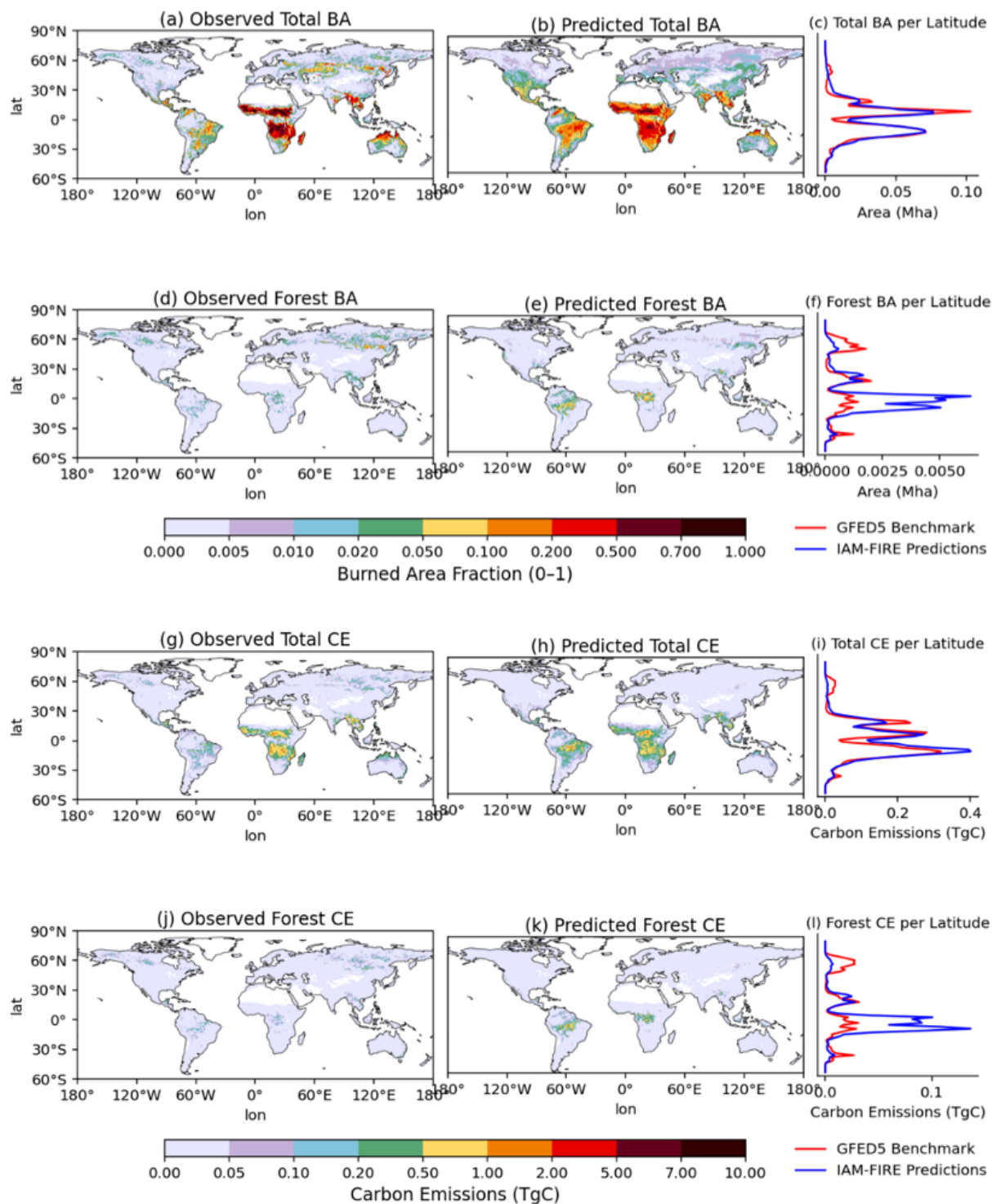


Figure 4

Average annual values of observed and predicted response variables and mean latitudinal distributions over historic period (2002-2019) for total BA (a-c), forest BA (d-f), total CE (g-i), and forest CE (j-l). Maps for BA are shown in fraction (0-1) and latitudinal bands in Mha. Carbon emissions are reported in TgC.

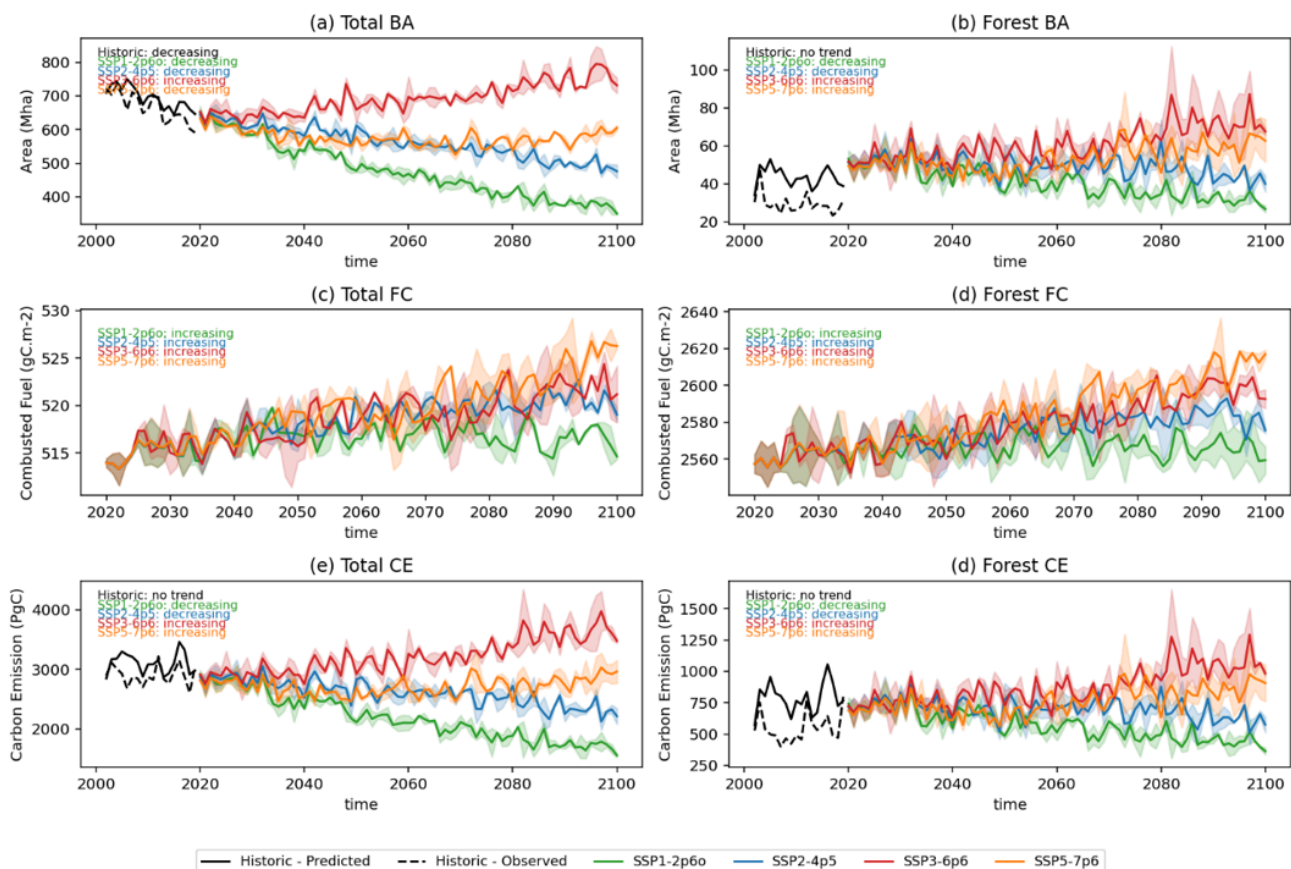


Figure 5

Observed and projected (2002 – 2100) burned area (top row) and carbon emissions (bottom row) and projected (2020 – 2100) fuel consumption (middle row) for total land (left column) and forests (right column). The shaded areas represent the range around the mean of the 2 ESMs (CanESM and MPI).

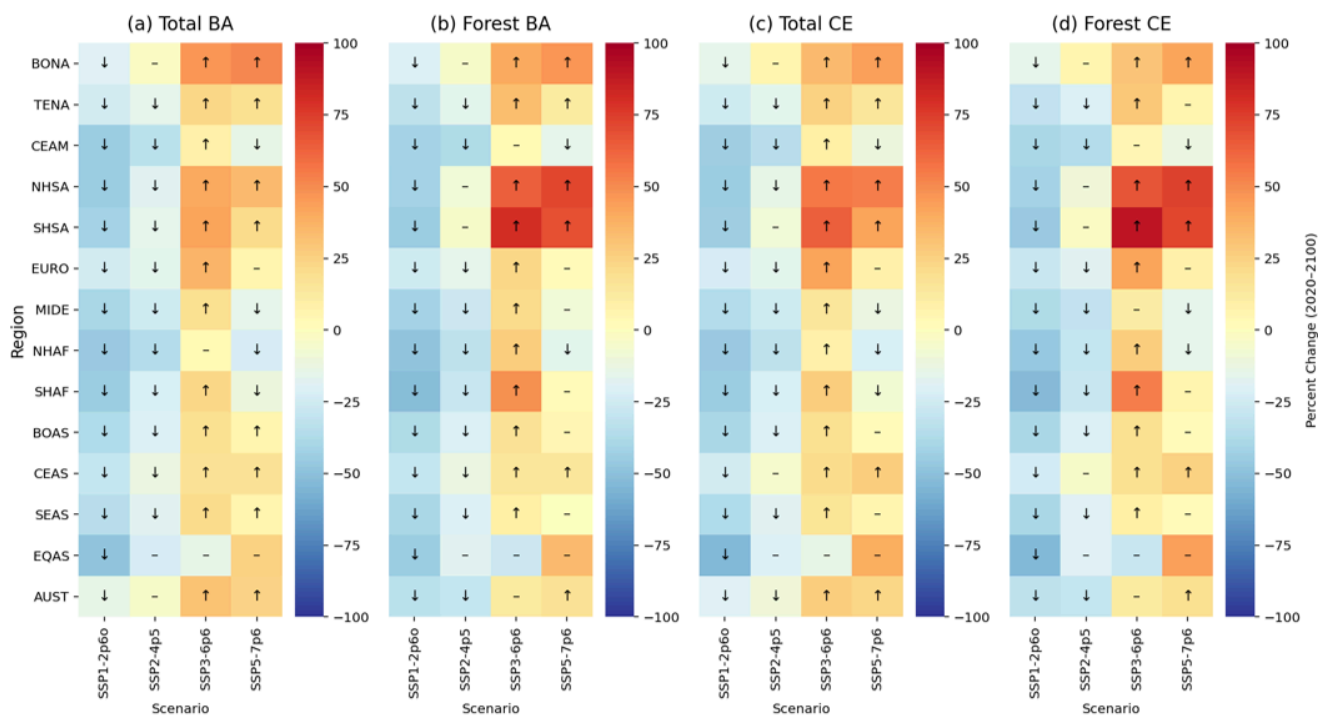


Figure 6

Heatmap of trends of total BA, forest BA, total CE and forest CE per region and scenarios in percent change in 2100 relative to 2020. Arrows represent the results of the Mann-Kendall test (statistically increasing, decreasing or no trends). BONA: Boreal North America; TENA: Temperate North America; CEAM: Central America; NHSA: Northern Hemisphere South America; SHSA: Southern Hemisphere South America; EURO: Europe; MIDE: Middle East; NHAF: Northern Hemisphere Africa; SHAF: Southern Hemisphere Africa; BOAS: Boreal Asia; CEAS: Central Asia; SEAS: Southeast Asia; EQAS: Equatorial Asia; AUST: Australia and New Zealand.

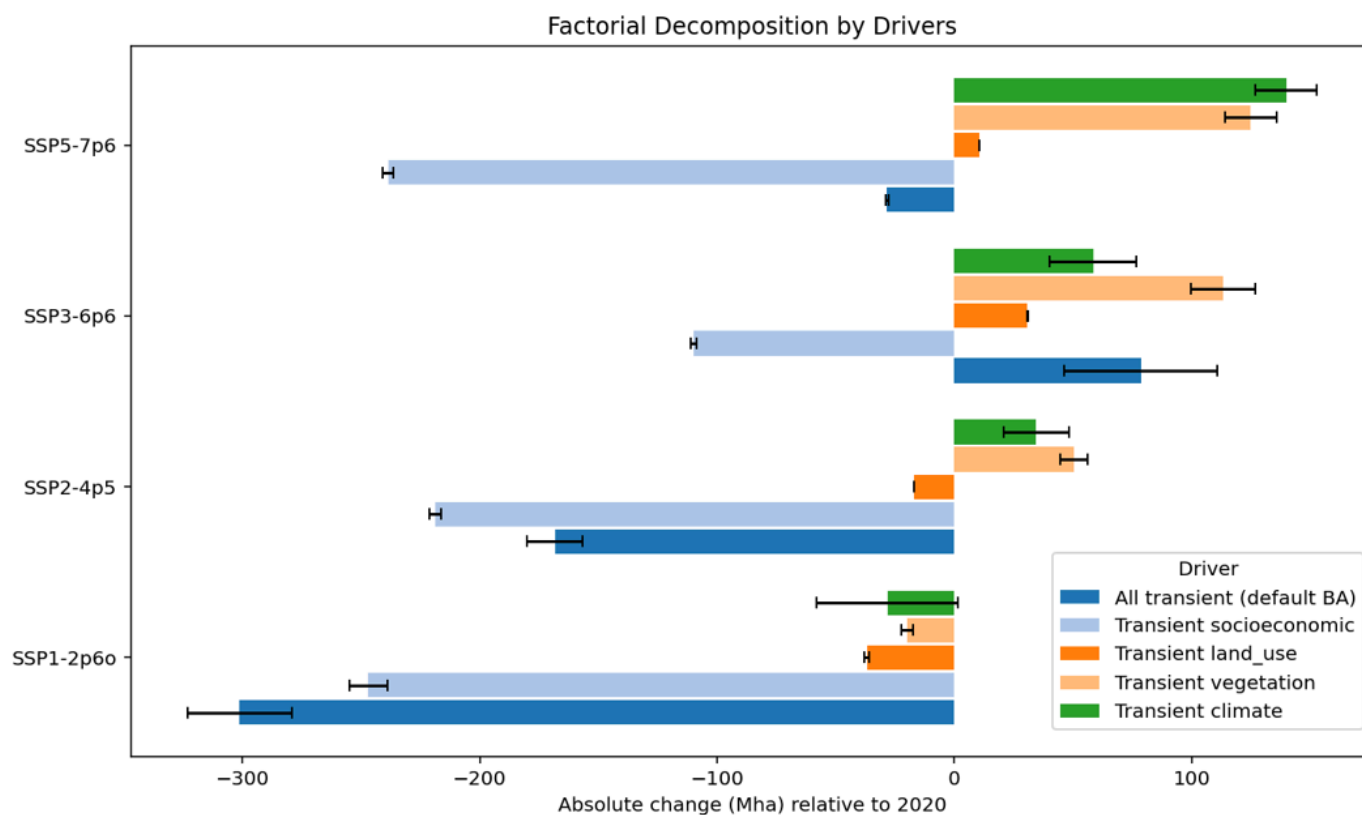


Figure 7

Factorial decomposition of drivers of total BA across scenarios. The absolute change of total BA (Mha) relative to 2020 is shown per scenario for default BA and four decomposition runs where only the group of driver is allowed to vary, keeping others fixed at 2020 value: transient socioeconomic (HDI), transient land use (cropland, grassland, shrubland), transient vegetation (GPP), and transient climate (VPD, NDD, NDD seasonality, wind speed and precipitation). Error bars show the range (maximum and minimum) from the two ESMs (CanESM and MPI).

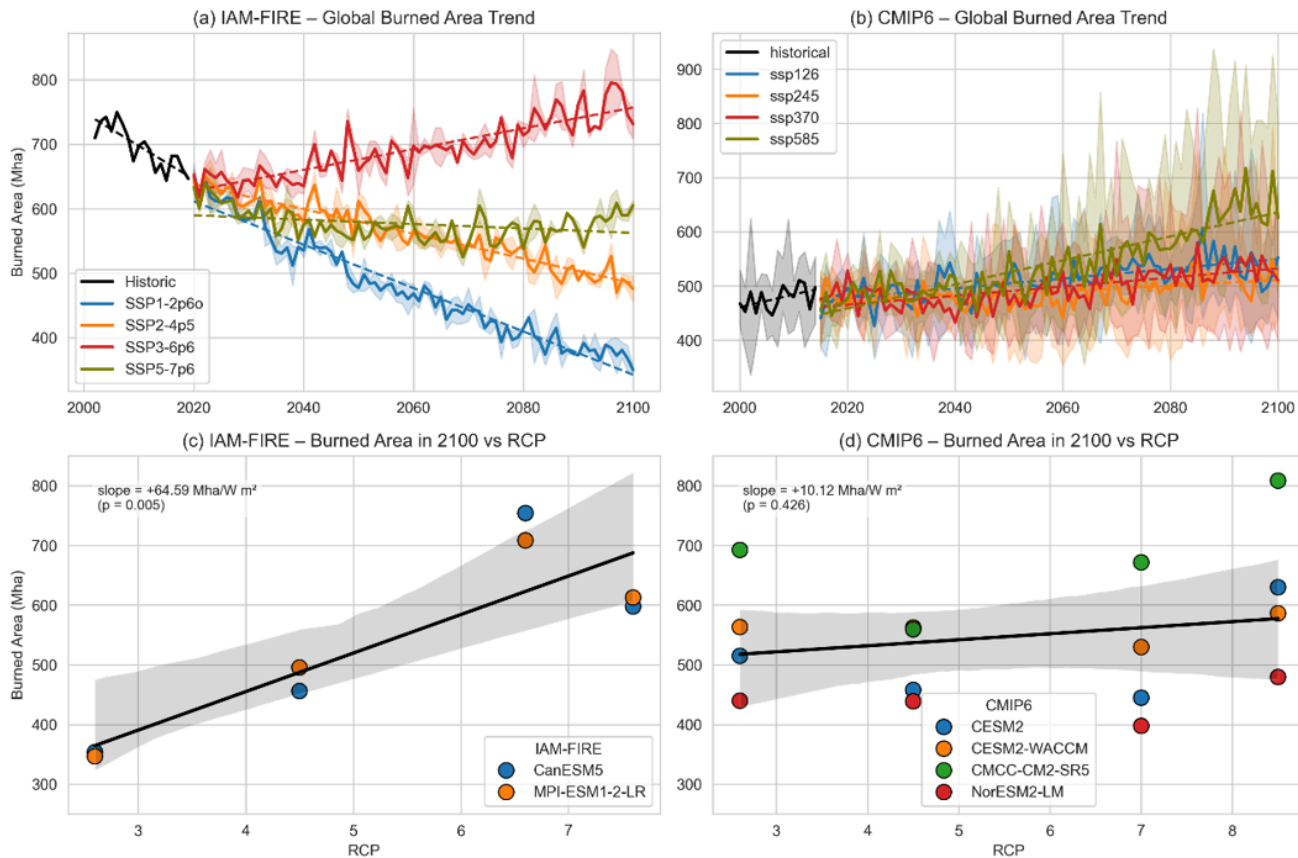


Figure 8

Comparison of time series from 2020-2100 for IAM-FIRE (a) and CMIP6 (b) projections and of the relationship between BA in 2100 and RCP levels for IAM-FIRE (c) and CMIP6 (d). (a-b) The shaded areas represent the range around the mean of the 2 ESMs (CanESM and MPI) for IAM-FIRE and the standard deviation for the 4 ESMs covered for CMIP6 (CESM2, CESM2-WACCM, CMCC-ESM2, Nor-ESM2-LM).