



OSCAR-fire v1.0: A fire bookkeeping module for the OSCAR compact Earth system model

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Abstract. Wildfires represent a major natural driver of the land carbon cycle. Although their instantaneous combustion emissions are increasingly well captured by Earth system models (ESMs), the associated legacy carbon dynamics and post-fire ecosystem recovery remain largely absent from reduced-complexity ESMs and hard to isolate in fully fledged ones. Here we present OSCAR-fire v1.0, a wildfire carbon dynamics module developed within the OSCAR compact ESM. The module extends OSCAR's land carbon bookkeeping framework by introducing two new prognostic pools for coarse woody debris (CWD) and pyrogenic carbon (PyC) produced by incomplete combustion, alongside the existing living biomass and soil pools. A fire event induces a three-phase carbon cycle response in the OSCAR-fire module: instantaneous combustion emissions accompanied by dead biomass transfer, legacy dead carbon release, and gradual post-fire ecosystem recovery. The module's performance is assessed using prescribed burned area from GFED4.1s and GFED5.1 datasets, and parametric uncertainty is characterised using a Monte Carlo (MC) ensemble of 2000 configurations. Simulated global instantaneous fire emissions are in good agreement with both reference products, differing from reference totals by about 6% under GFED4.1s and 3% under GFED5.1. Legacy CWD emissions in boreal regions under GFED4.1s are broadly consistent with references but substantially higher under GFED5.1, and simulated PyC production under GFED4.1s falls below published estimates and exceeds them under GFED5.1. Besides, simulated post-fire recovery timescales reproduce the latitudinal gradient in ecosystem productivity. OSCAR-fire v1.0 provides a process-based and computationally efficient framework for quantifying wildfire contributions to the land carbon budget within a probabilistic modelling context, with broad applicability to historical carbon cycle attribution studies and assessments of fire-climate feedbacks under future climate scenarios.



30 1 Introduction

Wildfire is a critical regulator of carbon–climate interactions in the Earth system (Kelly et al., 2020). The global annual burned area is estimated to have averaged 758.5 Mha yr⁻¹ and fire carbon emissions amounted to 3.4 Pg C yr⁻¹ during 2002–2022 (Van Der Werf et al., 2025). Wildfires reshape land-atmosphere carbon exchange and accelerate climate change through immediate combustion emissions (Zheng et al., 2023), decomposition of fire-killed biomass (Santin et al., 2020), and reduced ecosystem carbon storage (Archibald et al., 2018; Pausas and Ribeiro, 2017). In turn, climate change intensifies wildfire activity by promoting fire weather, lengthening fire seasons, and increasing the frequency and severity of extreme fire events (Harrison et al., 2018; Di Virgilio et al., 2019; Abatzoglou et al., 2019). Therefore, wildfire modules in ESMs need to be improved to more accurately represent wildfire-driven carbon dynamics and their interactions with climate to deepen our understanding of carbon–climate interactions (Jones et al., 2022; Hantson et al., 2016).

Wildfire modules in ESMs have evolved from simplified empirical approaches to increasingly sophisticated representations of biophysical processes (Or et al., 2023). In CMIP5 models, burned area was generally represented using the GlobFIRM scheme, which describes it as a probabilistic function of climatic drivers such as temperature, precipitation, and humidity (Thonicke et al., 2001). Subsequent refinements incorporated natural and anthropogenic constraints through regression-based approaches (Kloster and Lasslop, 2017), but these models are limited in capturing the spatiotemporal heterogeneity of burned area and associated emissions. In contrast, CMIP6 models widely adopted the Li scheme or SPITFIRE module, which simulate wildfire occurrence, spread, and suppression processes (Li et al., 2024; Thonicke et al., 2010; Li et al., 2012). These approaches more effectively reproduce the spatiotemporal variability of fires and their emissions by quantifying the mechanistic relationships between environmental conditions and fire activities (Lasslop et al., 2014). Their coupling with land surface biogeochemical and atmospheric transport components in ESMs enables dynamic feedback among fire, ecosystems, and the atmosphere, improving the representation of climate-vegetation-fire interactions (Hantson et al., 2020; Arora and Melton, 2018). More recently, machine learning has been integrated into wildfire modules to capture nonlinear relationships between fire activity and its environmental and anthropogenic drivers (Liu et al., 2025; Di Giuseppe et al., 2025; Zhang et al., 2025). Such hybrid frameworks enable more effective incorporation of human influences, such as agricultural practices and fire management and suppression policies that were previously difficult to capture (Zhu et al., 2022).

These developments in wildfire modules have so far focused on the accurate simulation of instantaneous combustion emissions, as these are critical for quantifying the immediate impacts of wildfires on atmospheric carbon dioxide (CO₂) concentrations and aerosol burdens (Thonicke et al., 2010; Knorr et al., 2016). But the carbon legacy of fire extends beyond the moment of combustion, encompassing two distinct post-fire processes that are not yet represented in current modeling frameworks. First, fire-induced vegetation mortality leaves behind carbon residues that decompose over decades, gradually releasing CO₂ (Santín et al., 2015). In most dynamic global vegetation models (DGVMs) and ESMs, this fire-killed biomass is transferred into soil and coarse woody debris (CWD) pools and subsequently released through first-order heterotrophic



decomposition, with decomposition rates depending on climate and residue type (Li et al., 2025). The fire-specific legacy signal cannot be separated from the broader background decomposition flux, limiting the ability to attribute delayed emissions to fire as opposed to other disturbances.

65 Second, during post-fire regeneration and succession, ecosystems gradually reabsorb atmospheric CO₂, driving carbon sequestration over multi-decadal timescales (Su et al., 2025; Archibald et al., 2018). In most ESMs, this recovery emerges implicitly from the standard vegetation growth formulation, whereby surviving and regenerating plant functional types reallocate carbon into leaf, root, and stem pools as net primary productivity resumes, without a dedicated fire-specific carbon pool to isolate these signals (Li et al., 2025). As a result, the legacy carbon signal cannot be disentangled from the broader
70 land carbon sink, making it difficult to attribute and quantify fire-driven carbon fluxes spanning from burning to post-fire ecosystem recovery. This limitation introduces uncertainties into simulated ecosystem carbon sinks and reduces the reliability of climate-carbon feedback assessments under a warming climate (Teckentrup et al., 2019). A modeling framework that tracks fire-induced carbon fluxes as a distinct bookkeeping pathway is therefore needed.

The simplified Earth system model OSCAR is a computationally efficient, modular framework designed for ensemble-based
75 simulations of global climate and biogeochemical processes (Gasser et al., 2020). It has been applied in the Reduced Complexity Model Intercomparison Project (RCMIP) and several CMIP6-coordinated MIPs (e.g., CDRMIP, LUMIP) to investigate carbon–climate feedbacks (Zhu et al., 2025; Gasser et al., 2017a; Quilcaille et al., 2023). However, the latest version of OSCAR represents wildfire only as instantaneous emissions, parameterized as a function of CO₂, temperature, and precipitation (Gasser et al., 2017b). Owing to its modular structure, OSCAR is well suited to incorporating fire-related
80 ecological processes. When coupled with OSCAR's existing land surface and atmospheric chemistry modules, such extensions can represent fire-climate feedback dynamically.

This study develops and introduces the OSCAR wildfire carbon module and assesses its performance in simulating both instantaneous and legacy carbon dynamics associated with wildfires, with the recovery timescales calibrated against observational records and multi-model ensemble estimates. Driven by prescribed burned area, the module represents three
85 phases of fire-induced land carbon dynamics: immediate combustion emissions, delayed emissions from the decomposition of fire-killed biomass, and post-fire ecosystem recovery. It provides annual estimates of regionally annual wildfire carbon fluxes with associated uncertainty ranges, disaggregated by carbon pool, biome type, and region. By representing all aspects of the wildfire carbon cycle, the module supports probabilistic assessments of fire-driven carbon fluxes and their role in the land carbon budget.



90 2 Model description and parameterization

2.1 Overview of OSCAR

OSCAR (v3.3) is a compact Earth system model designed to simulate natural biogeochemical cycles and the climate system response to anthropogenic forcings (Gasser et al., 2017b; He et al., 2024). Its core carbon framework represents major pools in the ocean, land, permafrost, and the atmosphere, linked by fluxes including land-atmosphere exchange, ocean uptake, and carbon release from permafrost thaw. The carbon modules are coupled to representations of non-CO₂ greenhouse gases (i.e., methane, nitrous oxide, halogenated compounds), short-lived climate species (i.e., ozone and aerosols), and surface albedo changes. The modules feed into radiative forcing and climate response modules that simulate temperature, precipitation, and ocean heat content. This structure enables OSCAR to represent key feedbacks among human activities, biogeochemical cycles, and the climate system. In this study, only the terrestrial carbon cycle and land-use-related components of OSCAR are used, while other Earth system components are not activated.

The OSCAR land carbon cycle is represented by a regionalized two-box model composed of vegetation and soil carbon pools (Gasser et al., 2020). Carbon enters the vegetation pool through net primary productivity (NPP), which responds dynamically to atmospheric CO₂ concentration, temperature, and precipitation. Vegetation carbon is lost through wildfire, crop harvest, grazing, and natural mortality. Soil carbon is released to the atmosphere through heterotrophic respiration, which is parameterized as a function of temperature and precipitation.

The land module is coupled to a bookkeeping framework that tracks carbon stock changes associated with land-use and land-cover change (LULCC), including land-cover transitions, wood harvest, and shifting cultivation. Carbon removed during land-use change is partitioned among direct emissions, soil slash pools, and harvested wood product pools, each with distinct decay timescales. The bookkeeping equations are consistent with the underlying vegetation and soil turnover dynamics, enabling simulation of both environmentally and land-use-driven terrestrial carbon fluxes. Within this framework, wildfire acts as a natural carbon loss process in the intact land carbon cycle, while the wildfire module developed here extends this bookkeeping structure to represent fire-induced carbon dynamics, as described in the following section.

2.2 Structure of the OSCAR-fire module

The wildfire module operates at an annual timestep resolved by region and biome, and is organised around four prognostic carbon pools (Table 1). Two of these pools are inherited from the existing OSCAR land carbon framework: (i) the vegetation carbon pool C_{veg} , partitioned into leaf, stem, and root sub-pools derived from biomass allocation fractions; and (ii) the soil carbon pool C_{soil} , which is similarly partitioned to isolate the litter fraction. Two additional pools are newly introduced in this module: (iii) the coarse woody debris pool C_{CWD} , representing fire-killed woody biomass undergoing slow temperature-sensitive decay; and (iv) the pyrogenic carbon pool C_{pyC} , representing the refractory black carbon fraction produced by



incomplete combustion. In this version, the CWD pool receives inputs from fire-induced stem mortality only, while background stem mortality is not represented as a source of woody debris because such a process is not described by OSCAR v3.3, which will be improved in OSCAR v4.0. Carbon fluxes among these four pools in the current version are illustrated in Fig. 1.

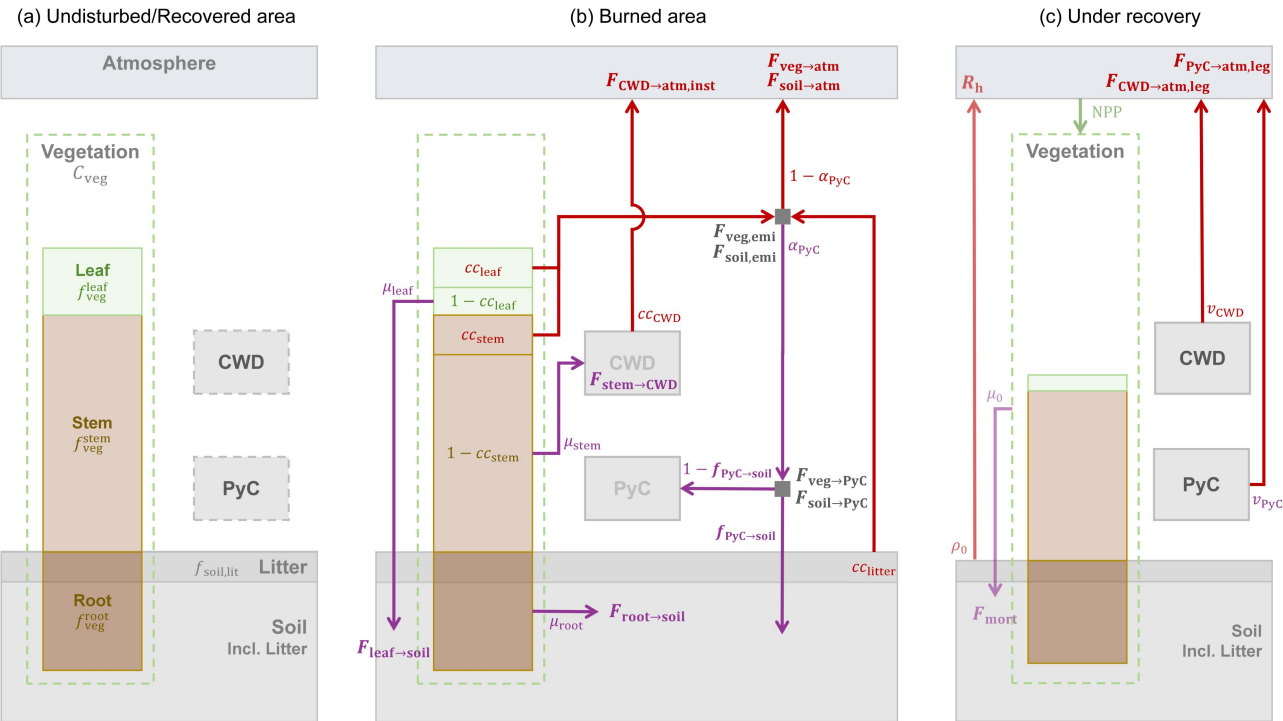


Fig. 1. Structure of the OSCAR-fire module. (a) Carbon pools under undisturbed or fully recovered conditions. Vegetation is subdivided into leaf, stem, and root components, and litter (excluding coarse woody debris, CWD) is part of the soil carbon pool. CWD and pyrogenic carbon (PyC) pools are absent in areas with no fire history. Note that CWD in OSCAR-fire comprises only fire-induced inputs. (b) Carbon emissions and mortality fluxes occurring within burned areas during wildfire events. (c) Post-fire recovery dynamics, showing background vegetation and soil turnover processes alongside delayed carbon release from CWD and PyC pools. Polygons represent carbon pools and arrows denote carbon fluxes, with adjacent parameters indicating the fraction of the source pool transferred through each flux. Red arrows indicate carbon emissions to the atmosphere, purple arrows represent mortality biomass transfers, and green arrows denote carbon uptake. Lighter arrows represent background fluxes (e.g., NPP, vegetation mortality, and soil heterotrophic respiration), whereas darker arrows indicate wildfire-related processes.



135 **Table 1. List of variables of the model.**

Notation	Definition
<i>Pool</i>	
C_{veg}	Bookkeeping vegetation carbon stock
C_{soil}	Bookkeeping soil carbon stock
C_{CWD}	Carbon stock of CWD
C_{PyC}	Carbon stock of PyC
<i>Flux</i>	
$F_{\text{veg,emi}}$	Carbon emissions from vegetation combustion
$F_{\text{soil,emi}}$	Carbon emissions from litter combustion
$F_{\text{veg} \rightarrow \text{PyC}}$	Pyrogenic carbon formation flux into PyC pool from vegetation combustion
$F_{\text{soil} \rightarrow \text{PyC}}$	Pyrogenic carbon formation flux into PyC pool from litter combustion
$F_{\text{leaf} \rightarrow \text{soil}}$	Fire-induced leaf mortality flux to soil
$F_{\text{root} \rightarrow \text{soil}}$	Fire-induced root mortality flux to soil
$F_{\text{stem} \rightarrow \text{CWD}}$	Fire-induced stem mortality flux to CWD pool
$F_{\text{veg} \rightarrow \text{atm}}$	Instantaneous vegetation carbon flux to the atmosphere
$F_{\text{soil} \rightarrow \text{atm}}$	Instantaneous litter carbon flux to the atmosphere
$F_{\text{CWD} \rightarrow \text{atm,inst}}$	Instantaneous re-combustion flux from legacy CWD to the atmosphere
$E_{\text{fire,inst}}$	Total instantaneous fire emission
$F_{\text{CWD} \rightarrow \text{atm,leg}}$	Legacy CWD decomposition flux to the atmosphere
$F_{\text{PyC} \rightarrow \text{atm,leg}}$	Legacy PyC decomposition flux to the atmosphere
$E_{\text{fire,leg}}$	Legacy fire emissions
E_{fire}	Total fire carbon emissions (instantaneous + legacy)
ΔNPP	Bookkeeping net primary productivity
ΔF_{mort}	Background mortality flux from vegetation to soil
ΔR_h	Heterotrophic respiration flux from soil
$F_{\text{veg,rcv}}$	Vegetation recovery flux under bookkeeping



Notation	Definition
$F_{\text{soil,rcv}}$	Soil recovery flux under bookkeeping
$F_{\text{land,rcv}}$	Net ecosystem recovery flux under bookkeeping
F_{net}	Net fire-related carbon flux (emission + recovery)
F_{veg}	Net fire-related carbon flux from the bookkeeping vegetation pool
F_{soil}	Net fire-related carbon flux from the bookkeeping soil pool

2.3 Process Descriptions

2.3.1 Carbon redistribution

For each region–biome unit, the combustion carbon emissions from biomass and soil organic matter are:

$$F_{\text{veg,emi}}^{r,b,i} = c_{\text{veg}}^{r,b} A_{\text{burn}}^{r,b} f_{\text{veg}}^{r,b,i} cc^{r,b,i}, \quad (1)$$

$$F_{\text{soil,emi}}^{r,b} = c_{\text{soil}}^{r,b} A_{\text{burn}}^{r,b} f_{\text{soil,lit}}^{r,b} cc^{r,b,\text{litter}}, \quad (2)$$

where f_{veg}^i is the biomass fraction of component i ($i \in \{\text{leaf, stem}\}$), cc^i is the corresponding combustion completeness, and $f_{\text{soil,lit}}^{r,b}$ is the biomass fraction of litter in soil. A portion of $F_{\text{veg,emi}}^{r,b,i}$ and $F_{\text{soil,emi}}^{r,b}$ is subsequently allocated to the PyC pool:

$$F_{\text{veg} \rightarrow \text{PyC}}^{r,b} = \sum_{i \in \{\text{leaf, stem}\}} F_{\text{veg,emi}}^{r,b,i} \alpha_{\text{pyc}}^i, \quad (3)$$

$$F_{\text{soil} \rightarrow \text{PyC}}^{r,b} = F_{\text{soil,emi}}^{r,b} \alpha_{\text{pyc}}^{\text{leaf}} \quad (4)$$

where α_{pyc}^i is the fraction of fire carbon emissions converted to the PyC pool.

Fire additionally transfers partially combusted or fire-killed biomass to soil organic matter and CWD. Three redistribution pathways operate in parallel, each depending on c_{veg} , A_{burn} , and the biomass fractions f_{veg}^i . First, the fraction of leaf carbon that escapes combustion but is killed by fire enters the soil organic carbon pool:

$$F_{\text{leaf} \rightarrow \text{soil}}^{r,b} = c_{\text{veg}}^{r,b} A_{\text{burn}}^{r,b} f_{\text{veg}}^{r,b,\text{leaf}} (1 - cc^{r,b,\text{leaf}}) \mu^{r,b,\text{leaf}}. \quad (5)$$

Second, root biomass is not subject to direct combustion, and fire-induced heat damage and plant death transfer root carbon to the soil pool via the mortality factor alone:

$$F_{\text{root} \rightarrow \text{soil}}^{r,b} = c_{\text{veg}}^{r,b} A_{\text{burn}}^{r,b} f_{\text{veg}}^{r,b,\text{root}} \mu^{r,b,\text{root}}. \quad (6)$$



Third, partially burned or fire-killed stem biomass is transferred to the CWD pool:

$$F_{\text{stem} \rightarrow \text{CWD}}^{r,b} = c_{\text{veg}}^{r,b} A_{\text{burn}}^{r,b} f_{\text{veg}}^{r,b,\text{stem}} (1 - c c^{r,b,\text{stem}}) \mu^{r,b,\text{stem}}. \quad (7)$$

2.3.2 Instantaneous emissions

150 Fire transfers carbon directly to the atmosphere during burning from three processes: living vegetation (i.e., leaf and stem), surface litter, and fire-induced CWD accumulated from prior fire events. Root biomass is excluded from direct combustion, as it is assumed to be physically shielded from surface fire.

$F_{\text{veg,emi}}^{r,b,i}$ and $F_{\text{soil,emi}}^{r,b}$ are the carbon emissions from vegetation and soil combustion, respectively, as defined in Sect. 2.3.1.

Not all of this emitted carbon reaches the atmosphere, as a fraction is diverted to the PyC pool. The net vegetation-to-atmosphere and soil-to-atmosphere fluxes during burning are therefore:

$$F_{\text{veg} \rightarrow \text{atm}}^{r,b} = \sum_{i \in \{\text{leaf}, \text{stem}\}} F_{\text{veg,emi}}^{r,b,i} - F_{\text{veg} \rightarrow \text{PyC}}^{r,b} \quad (8)$$

$$F_{\text{soil} \rightarrow \text{atm}}^{r,b} = F_{\text{soil,emi}}^{r,b} - F_{\text{soil} \rightarrow \text{PyC}}^{r,b}. \quad (9)$$

Residual CWD that has accumulated from previous fire events can be partially combusted during subsequent fires. The re-burning flux is proportional to the CWD carbon density per unit land area:

$$F_{\text{CWD} \rightarrow \text{atm,inst}}^{r,b} = \frac{C_{\text{CWD}}^{r,b}}{A_{\text{land}}^{r,b}} A_{\text{burn}}^{r,b} c c^{\text{CWD}}, \quad (10)$$

where $C_{\text{CWD}}^{r,b}/A_{\text{land}}^{r,b}$ is the CWD carbon density of each region-biome unit.

Summing contributions from vegetation, litter, and fire-induced CWD gives the total instantaneous fire emission:

$$E_{\text{fire,inst}}^{r,b} = F_{\text{veg} \rightarrow \text{atm}}^{r,b} + F_{\text{soil} \rightarrow \text{atm}}^{r,b} + F_{\text{CWD} \rightarrow \text{atm,inst}}^{r,b}. \quad (11)$$

160 2.3.3 Legacy decomposition of CWD and PyC

Carbon pools generated by fire, including CWD and PyC, continue to release carbon to the atmosphere over years to centuries under post-burning recovery. The CWD stock $C_{\text{CWD}}^{r,b}$ decays via first-order kinetics with a temperature-dependent rate:

$$F_{\text{CWD} \rightarrow \text{atm,leg}}^{r,b} = v_{\text{CWD}}^{r,b} C_{\text{CWD}}^{r,b}, \quad (12)$$

165 where $v_{\text{CWD,pi}}^{r,b}$ is the decay rate (Sect. 2.4.4) based on temperature. The exponential factor produces accelerated CWD decomposition under warming, analogous to a Q_{10} -style temperature dependence (Harmon et al., 2020).



The PyC pool is decomposed to the atmosphere through independent first-order decay:

$$F_{\text{PyC} \rightarrow \text{atm}, \text{leg}}^{r,b} = v_{\text{PyC}}^{r,b} C_{\text{PyC}}^{r,b}, \quad (13)$$

where $v_{\text{PyC}}^{r,b}$ is the decomposition rate (Sect. 2.4.4). The total fire legacy emissions are thus:

$$E_{\text{fire}, \text{leg}}^{r,b} = F_{\text{CWD} \rightarrow \text{atm}, \text{leg}}^{r,b} + F_{\text{PyC} \rightarrow \text{atm}, \text{leg}}^{r,b}, \quad (14)$$

and the combined fire instantaneous and legacy emission is:

$$E_{\text{fire}}^{r,b} = E_{\text{fire}, \text{inst}}^{r,b} + E_{\text{fire}, \text{leg}}^{r,b}. \quad (15)$$

2.3.4 Post-fire ecosystem recovery

170 Within OSCAR's bookkeeping framework, post-fire recovery is not simulated by tracking the absolute magnitude of vegetation and soil carbon pools. Instead, each disturbed area is represented by the deviation of vegetation and soil carbon from their pre-fire levels. Recovery is then expressed as the gradual relaxation of these anomalies back toward zero, denoting a return to pre-disturbance carbon stocks.

Following the standard bookkeeping assumption (Hansis et al., 2015), the net primary production (NPP) anomaly of the
 175 disturbed area is set to zero at all times:

$$\Delta NPP^{r,b} = 0. \quad (16)$$

This assumption means that NPP, vegetation mortality rate ($\mu_0^{r,b}$), and soil heterotrophic respiration rate ($\rho_0^{r,b}$) are held constant (i.e., age-independent) regardless of time since disturbance. This simplification allows ecosystems disturbed in different years to be aggregated within the same bookkeeping pool, rather than tracked individually by stand age. This method is a substantial simplification relative to reality, but one that greatly reduces computational and bookkeeping
 180 complexity.

Within this assumption, the vegetation carbon can only decay through the constant background mortality flux, which transfers carbon from the vegetation anomaly to the soil anomaly at the constant turnover rate $\mu_0^{r,b}$:

$$\Delta F_{\text{mort}}^{r,b} = \mu_0^{r,b} \cdot \Delta C_{\text{veg}}^{r,b}. \quad (17)$$

The soil carbon anomaly receives this input from vegetation while simultaneously losing carbon through heterotrophic respiration at the constant turnover rate $\rho_0^{r,b}$:

$$\Delta R_h^{r,b} = \rho_0^{r,b} \cdot \Delta C_{\text{soil}}^{r,b}. \quad (18)$$



185 The net vegetation, soil, and total ecosystem recovery fluxes are then:

$$F_{\text{veg,rcv}}^{r,b} = \Delta NPP^{r,b} - \Delta F_{\text{mort}}^{r,b}, \quad (19)$$

$$F_{\text{soil,rcv}}^{r,b} = \Delta F_{\text{mort}}^{r,b} - \Delta R_h^{r,b}, \quad (20)$$

$$F_{\text{land,rcv}}^{r,b} = \Delta NPP^{r,b} - \Delta R_h^{r,b}. \quad (21)$$

The net biome carbon flux associated with wildfire disturbance is defined as the balance between total fire emissions and post-fire land recovery:

$$F_{\text{net}}^{r,b} = E_{\text{fire}}^{r,b} - F_{\text{land,rcv}}^{r,b}. \quad (22)$$

A positive $F_{\text{net}}^{r,b}$ indicates net carbon release to the atmosphere, while a negative value reflects ecosystem recovery exceeding cumulative fire losses.

190 2.3.5 Bookkeeping carbon pools

The net fire-driven carbon loss from the bookkeeping vegetation pool combines combustion emissions and fire-induced mortality (Sects. 2.3.1–2.3.2):

$$F_{\text{veg}}^{r,b} = \sum_{i \in \{\text{leaf,stem}\}} F_{\text{veg,emi}}^{r,b,i} + F_{\text{leaf} \rightarrow \text{soil}}^{r,b} + F_{\text{root} \rightarrow \text{soil}}^{r,b} + F_{\text{stem} \rightarrow \text{CWD}}^{r,b}. \quad (23)$$

For the soil pool, the net fire-related flux is defined as the balance between litter combustion losses and inputs from leaf mortality, root mortality, and PyC transferring to the soil pool:

$$F_{\text{soil}}^{r,b} = F_{\text{soil,emi}}^{r,b} - F_{\text{leaf} \rightarrow \text{soil}}^{r,b} - F_{\text{root} \rightarrow \text{soil}}^{r,b} - (F_{\text{veg} \rightarrow \text{PyC}}^{r,b} + F_{\text{soil} \rightarrow \text{PyC}}^{r,b}) f_{\text{PyC} \rightarrow \text{soil}}. \quad (24)$$

195 A positive $F_{\text{soil}}^{r,b}$ indicates net carbon removal from the soil pool (combustion exceeds inputs), while a negative value indicates net accumulation. The two bookkeeping stocks then evolve as:

$$\frac{dC_{\text{veg}}^{r,b}}{dt} = -F_{\text{veg}}^{r,b} + F_{\text{veg,rcv}}^{r,b}, \quad (25)$$

$$\frac{dC_{\text{soil}}^{r,b}}{dt} = -F_{\text{soil}}^{r,b} + F_{\text{soil,rcv}}^{r,b}. \quad (26)$$

The CWD stock $C_{\text{CWD}}^{r,b}$ accumulates fire-killed stem biomass $F_{\text{stem} \rightarrow \text{CWD}}^{r,b}$ and is depleted by both legacy decomposition and instantaneous re-combustion:

$$\frac{dC_{\text{CWD}}^{r,b}}{dt} = F_{\text{stem} \rightarrow \text{CWD}}^{r,b} - F_{\text{CWD} \rightarrow \text{atm,leg}}^{r,b} - F_{\text{CWD} \rightarrow \text{atm,inst}}^{r,b}. \quad (27)$$



The $F_{\text{CWD} \rightarrow \text{atm}, \text{inst}}^{r,b}$ represents re-combustion of accumulated CWD during subsequent fire events (Sect. 2.3.2), while legacy
 200 flux $F_{\text{CWD} \rightarrow \text{atm}, \text{leg}}^{r,b}$ follows the temperature-dependent first-order decay described in Sect. 2.3.3.

The PyC pool gains carbon from the vegetation combustion and loses it through first-order transfer to the atmosphere:

$$\frac{dC_{\text{PyC}}^{r,b}}{dt} = (F_{\text{veg} \rightarrow \text{PyC}}^{r,b} + F_{\text{soil} \rightarrow \text{PyC}}^{r,b})(1 - f_{\text{PyC} \rightarrow \text{soil}}) - F_{\text{PyC} \rightarrow \text{atm}, \text{leg}}^{r,b} \quad (28)$$

where $F_{\text{veg} \rightarrow \text{PyC}}^{r,b}$ and $F_{\text{soil} \rightarrow \text{PyC}}^{r,b}$ are the PyC formation fluxes (Sect. 2.3.1) and $F_{\text{PyC} \rightarrow \text{atm}, \text{leg}}^{r,b}$ is the first-order legacy emission to the atmosphere (Sect. 2.3.3).

2.4 Model parameters and data sources

205 The wildfire carbon bookkeeping module in OSCAR is parameterized by pre-industrial carbon density, background ecosystem turnover rates, fire-related combustion and mortality efficiencies, and post-fire legacy carbon decomposition characteristics (Table 2). These parameters are either diagnosed from multi-model land surface ensembles or drawn from peer-reviewed literature. Where applicable, parameters are spatially resolved by region (r) and biome land type (b).

Table 2. Drivers and parameters of the OSCAR-fire module.

Notation	Description	Unit	Dimension	Temporal type
<i>Indices</i>				
r	OSCAR region index	-	-	-
r_0	GFED region index	-	-	-
b	Biome land type index (including forest and non-forest)	-	-	-
i	Biomass component index (including leaf, stem, root, litter, and CWD)	-	-	-
c	MC configuration index	-	-	-
<i>Natural background</i>				
$c_{\text{veg},0}$	Pre-industrial vegetation carbon density	PgC Mha ⁻¹	r, b	Constant
$c_{\text{soil},0}$	Pre-industrial soil carbon density	PgC Mha ⁻¹	r, b	Constant
Δc_{veg}	CO ₂ - and climate-driven anomaly in vegetation carbon density relative to pre-industrial baseline	PgC Mha ⁻¹	r, b	Time-varying
Δc_{soil}	CO ₂ - and climate-driven anomaly in soil carbon density relative to pre-industrial baseline	PgC Mha ⁻¹	r, b	Time-varying
μ_0	Pre-industrial vegetation mortality rate to soil	-	r, b	Constant



Notation	Description	Unit	Dimension	Temporal type
ρ_0	Pre-industrial heterotrophic respiration rate	-	r, b	Constant
$f_{\text{veg}}^i, i \in \{\text{leaf, stem, root}\}$	Vegetation biomass fraction for leaf, stem, and root	-	r, b, i	Constant
$f_{\text{soil, lit}}$	Fraction of litter carbon within total soil carbon pool	-	r, b	Constant
T_{pi}	Pre-industrial surface air temperature	K	r	Constant
ΔT	Surface air temperature anomaly relative to pre-industrial baseline	K	r	Time-varying
A_{land}	Regional biome area	Mha	r, b	Time-varying
<i>Fire activities</i>				
A_{burn}	Burned area	Mha yr ⁻¹	r, b	Time-varying
$cc^i, i \in \{\text{leaf, stem, litter, CWD}\}$	Combustion completeness for leaf, stem litter, and CWD	-	r, b, i	Constant
$\mu^i, i \in \{\text{leaf, stem, root}\}$	Fire-induced mortality rate for leaf, stem, and root	-	r, b, i	Constant
$v_{\text{CWD, pi}}$	Baseline CWD decomposition rate at 10 °C	yr ⁻¹	r	Constant
g_{CWD}	Temperature sensitivity coefficient of CWD decomposition	°C ⁻¹	r	Constant
v_{CWD}	Effective CWD decomposition rate at ambient temperature	yr ⁻¹	r	Time-varying
α_{PyC}	Fraction of fire carbon emissions converted to PyC pool	-	-	Constant
$f_{\text{PyC} \rightarrow \text{soil}}$	Fraction of annually produced PyC transferred to the soil carbon pool	-	-	Constant
v_{PyC}	Decomposition rate of PyC pools	yr ⁻¹	-	Constant

210 2.4.1 Carbon pool

Pre-industrial baseline carbon densities for vegetation ($c_{\text{veg},0}$) and soil ($c_{\text{soil},0}$) are derived from the TRENDYv12 multi-model ensemble (Sitch et al., 2024), using the S0 experiment in which atmospheric CO₂, climate forcing, and land use are all held at 1700 conditions. Carbon densities are obtained by normalising the simulated carbon stocks by the corresponding regional biome area:

$$c_{\text{veg},0}^{r,b} = \frac{C_{\text{veg}}^{r,b}(\text{S0})}{A_{r,b}}. \quad (29)$$



215 The climate-driven anomalies Δc_{veg} and Δc_{soil} are diagnosed from the difference between the S2 experiment (varying CO₂ and climate, fixed land use) and the S0 experiment, normalised by area:

$$\Delta c_{\text{veg}}^{r,b} = \frac{C_{\text{veg}}^{r,b}(\text{S2}) - C_{\text{veg}}^{r,b}(\text{S0})}{A_{r,b}}. \quad (30)$$

The vegetation carbon density is then calculated as:

$$c_{\text{veg}}^{r,b} = c_{\text{veg},0}^{r,b} + \Delta c_{\text{veg}}^{r,b}, \quad (31)$$

while soil carbon density is calculated analogously. This approach isolates the combined effect of historical CO₂ and climate change on ecosystem carbon storage, while excluding the influence of LULCC. All TRENDYv12-derived parameters are
 220 computed from a consistent subset of five land surface models (i.e., JSBACH, OCN, CABLE-POP, ORCHIDEE, and CLASSIC) that report carbon pools and fluxes at the plant functional type (PFT) level (Friedlingstein et al., 2023). PFT-level output is required to distinguish between forest and non-forest biomes in our framework.

Vegetation structural fractions, defined as the proportional contribution of each component to total vegetation carbon, are:

$$f_{\text{veg},i}^{r,b} = \frac{C_i^{r,b}}{C_{\text{veg}}^{r,b}}, \quad (32)$$

where C_i denotes the carbon stock of vegetation component i ($i \in \{\text{leaf}, \text{stem}, \text{root}\}$) and C_{veg} is the total vegetation
 225 carbon. These fractions are estimated as multi-year climatological means from historical simulations of the CLASSIC land surface model. The fraction of litter carbon within the total soil pool, $f_{\text{soil},\text{lit}}$, is defined as:

$$f_{\text{soil},\text{lit}}^{r,b} = \frac{C_{\text{litter},\text{ag}}^{r,b}}{C_{\text{soil}}^{r,b} + C_{\text{litter},\text{ag}}^{r,b}}, \quad (33)$$

where litter carbon is represented by the above-ground litter variable $C_{\text{litter},\text{ag}}$. Both C_{soil} and $C_{\text{litter},\text{ag}}$ are drawn from the ISIMIP3a historical simulations of the CLASSIC land surface model (Frieler et al., 2024). Together, $f_{\text{veg},i}$ and $f_{\text{soil},\text{lit}}$ are used to partition fire-induced carbon fluxes across vegetation components and soil sub-pools.

230 2.4.2 Background turnover

Background carbon turnover parameters are also derived from the S0 experiment. The pre-industrial vegetation mortality rate μ_0 is defined as the first-order rate at which vegetation carbon is transferred to the soil pool:

$$\mu_0^{r,b} = \frac{f_{\text{veg} \rightarrow \text{soil}}^{r,b}(\text{S0})}{C_{\text{veg}}^{r,b}(\text{S0})}. \quad (34)$$

The vegetation biomass recovery timescale is thus $\tau = 1/\mu_0$.



For forest biomes, μ_0 is calibrated against observation-based post-disturbance recovery trajectories from Xu et al. (in
 235 preparation). These trajectories were reconstructed at 1° resolution from 30 m Landsat disturbance records and high-
 resolution regional above-ground carbon (AGC) maps using a space-for-time substitution (Xu et al., 2026; Xu et al., 2023).
 National Forest Inventory data were additionally used to constrain recovery beyond the approximately 30-year Landsat
 record. In each grid cell, recovery is fit with a Chapman-Richards curve and normalized by AGC_{max} . For each GFED region
 r_0 , the pointwise median of these curves defines a reference recovery time $t_{ref}^{r_0}$, the first year at which the median curve
 240 reaches 90% of AGC_{max} .

The corresponding model recovery time $t_{mod}^{r_0}$ is computed by aggregating OSCAR regions r with above-ground carbon
 weights and solving the post-disturbance recovery equations analytically (Sect. 3.3). $t_{mod}^{r_0}$ is taken from the median across
 Monte Carlo (MC) parameter sets. A region-specific scaling factor $\mu_{factor}^{r_0}$ is determined by bisection such that $t_{mod}^{r_0} = t_{ref}^{r_0}$,
 yielding the calibrated rate:

$$\mu_0^{r_0, ideal} = \mu_0^{r_0} \cdot \mu_{factor}^{r_0}. \quad (35)$$

245 Then the forest μ_0^r for all OSCAR regions within the GFED region r_0 are replaced by $\mu_0^{r_0, ideal}$. For Australia (AUST),
 where calibration data are currently lacking, forest μ_0 is set to the per-parameter-set mean of μ_0^{ideal} across the remaining 13
 GFED regions.

Since the vegetation-to-soil carbon flux $f_{veg \rightarrow soil}$ is not directly reported by all TRENDY models, it is inferred from the soil
 carbon mass balance under steady-state S0 conditions, where the net soil carbon tendency is approximately zero:

$$f_{veg \rightarrow soil}^{r,b} = \frac{dC_{soil}^{r,b}(S0)}{dt} + Rh_{r,b}(S0). \quad (36)$$

250 The pre-industrial heterotrophic respiration rate ρ_0 is defined as the ratio of heterotrophic respiration flux Rh to soil carbon
 stock (including litter carbon where available) under S0 conditions:

$$\rho_0^{r,b} = \frac{Rh_{r,b}(S0)}{C_{soil}^{r,b}(S0) + C_{litter}^{r,b}(S0)}, \quad (37)$$

where Rh and C_{soil} are reported directly by the TRENDY models, and C_{litter} is set to zero for models that do not report
 litter carbon. This formulation imposes a first-order decay structure on soil carbon dynamics, consistent with the OSCAR
 land carbon module.

255 2.4.3 Fire process

Combustion completeness (cc) and fire-induced mortality (μ) are specified at OSCAR regions across forest and non-forest
 biome types. These two parameters differ in their pool coverage: cc applies to leaf, stem, litter, and CWD pools, while μ
 applies to leaf, stem, and root pools.



Parameters are derived by combining two independent sources. Field-based cc estimates are taken from Van Wees et al. (2022), in which site-level measurements were aggregated to the 14 GFED basis regions by biome type and subsequently mapped to OSCAR regions. DGVM-derived cc and μ are extracted from two fire schemes (SSiB4/TRIFFID-Fire and CLM-Li) (Huang et al., 2020; Rabin et al., 2017), with PFT-specific parameters spatially aggregated to OSCAR regions via the ESACCI PFT cover map. The adopted simulation parameters combine the field-based cc product with two DGVM schemes representing the range of mainstream fire model parameterizations. Parametric uncertainty is represented by triangular distributions at each OSCAR region. For cc , the most likely value (mode) is the field-based regional estimate with bounds defined by the spread across field and DGVM values. For μ , the mode is the two-model mean with bounds defined by the model range. Detailed cc and μ adopted in the OSCAR-fire module are provided in Table 3.

Table 3. Global means of adopted triangular combustion completeness and fire-induced mortality (min, mode, max) by biome type and vegetation pool.

Biome type	Vegetation pool	Combustion completeness (min)	Combustion completeness (mode)	Combustion completeness (max)	Fire-induced mortality (min)	Fire-induced mortality (mode)	Fire-induced mortality (max)
Forest	Leaf	0.69	0.76	0.90	0.70	0.75	0.80
Forest	Stem	0.10	0.28	0.31	0.12	0.31	0.49
Forest	Root	0.00	0.00	0.00	0.11	0.12	0.13
Forest	Litter	0.35	0.86	0.86	0.00	0.00	0.00
Forest	CWD	0.32	0.49	0.52	0.00	0.00	0.00
Non-Forest	Leaf	0.74	0.83	0.92	0.78	0.79	0.80
Non-Forest	Stem	0.44	0.83	0.89	0.45	0.62	0.78
Non-Forest	Root	0.00	0.00	0.00	0.20	0.24	0.28
Non-Forest	Litter	0.42	0.85	0.88	0.00	0.00	0.00
Non-Forest	CWD	0.33	0.48	0.49	0.00	0.00	0.00

2.4.4 Post-fire legacy carbon decomposition

The decomposition of legacy CWD is represented using a temperature-sensitive first-order decay formulation. The baseline decomposition rate at a reference temperature of 10 °C is set to $k_{10} = 0.061 \text{ yr}^{-1}$, with a temperature sensitivity of $Q_{10} = 2.5$, based on field decay studies compiled by Harmon et al. (2020). The decomposition rate v_{CWD} is derived from the land surface air temperature T (°C):

$$v_{\text{CWD}}^{r,b} = k_{10} \cdot Q_{10}^{(T^{r,b}-10)/10}. \quad (38)$$

The parameter α_{pyC} defines the fraction of combusted biomass converted to pyrogenic carbon. Following Jones et al. (2019), α_{pyC} is differentiated by biome type and vegetation component. For forest ecosystems, the underlying parameter α_{pyC} takes modal values of 9.1% and 18.1% for leaf and stem material, respectively, with triangular uncertainty distributions



spanning minima of 7.4% and 12.0% and maxima of 11.4% and 27.1%. For non-forest ecosystems, modal values are 9.1% and 10.0% for leaf and stem material, respectively, with minima of 7.4% and 6.4% and maxima of 11.4% and 15.3%. Since the total emission factor is the sum of combustion completeness cc and the pyrogenic carbon fraction, directly using α_{PyC} would yield $cc + \alpha_{PyC}$, which can exceed unity when $cc \approx 1$. The parameter stored in the model is therefore the transformed fraction:

$$\alpha_{PyC} \leftarrow \frac{\alpha_{PyC}}{1 + \alpha_{PyC}}, \quad (39)$$

which ensures that $cc + \alpha_{PyC}$ remains bounded between 0 and 1. The fraction of annually produced PyC transferred to the soil carbon pool ($f_{PyC \rightarrow soil}$) is set to 0.74. This value is derived as the ratio of non-mineralized PyC to total PyC production from the global PyC budget of Bowring et al. (2022). The remaining fraction ($1 - f_{PyC \rightarrow soil}$) is retained in the PyC pool and is gradually released to the atmosphere through slow decomposition. The loss rate of the PyC pool v_{PyC} is derived from the pool-weighted mean residence time (MRT) of the slow-cycling (300 yr) and passive (3000 yr) sub-pools in Bowring et al. (2022), using a slow-to-passive pool ratio of 28.5:67. This yields an effective MRT of approximately 2194 yr.

2.5 Uncertainty analysis

2.5.1 Monte Carlo framework

Parametric and structural uncertainties in the OSCAR-fire are quantified using an MC sampling framework that propagates uncertainty from multiple sources through the OSCAR simulations, including land surface model structural variability, literature-based parameter ranges, and compositional constraints. A total of $N=2000$ MC configurations are generated. Five sampling strategies are employed, each tailored to the type and source of the parameter. These are described in turn below.

The first strategy is multi-model weighted averaging, applied to parameters derived from the TRENDY and ISIMIP3a ensembles. Parameters $c_{veg,0}$, $c_{soil,0}$, Δc_{veg} , Δc_{soil} , μ_0 and ρ_0 are sampled as weighted combinations of the five TRENDY models. For each MC configuration, a set of model weights is drawn from a symmetric Dirichlet distribution with equal concentration parameters ($sum = 1$), which assigns equal prior probability to all models while spanning the full range of model outputs. This preserves inter-parameter correlations among parameters from the same land surface model. The parameter $f_{soil,lit}$ is treated analogously, with MC configurations generated as Dirichlet-weighted combinations of the ISIMIP3a CLASSIC land surface model simulations. A single set of Dirichlet weights is generated per ensemble source (TRENDY and ISIMIP3a separately) and shared across all parameters from that source.

The second strategy is compositional sampling, applied to vegetation biomass fractions. Vegetation biomass fractions f_{veg}^i ($i \in \{\text{leaf}, \text{stem}, \text{root}\}$) are subject to the compositional constraint that component fractions must remain non-negative and sum to unity. These parameters are therefore sampled using a Dirichlet distribution parameterized by the multi-model mean



(ISIMIP3a CLASSIC) fractions, which act as the concentration parameter vector. This guarantees that sampled fractions are strictly positive and sum to unity by construction.

The third strategy uses triangular distributions for fire process parameters, including combustion completeness (cc), fire-induced mortality fraction (μ), and pyrogenic carbon production fraction (α_{pyc}). A triangular distribution is defined by three parameters: a minimum value, a most likely value (mode), and a maximum value. This formulation captures both process-based model spread and literature-based parameter ranges. Where the minimum and maximum bounds are identical, a small Gaussian perturbation (standard deviation = 0.1) is applied to avoid degenerate point-mass distributions.

The fourth strategy applies stochastic perturbation to post-fire decomposition parameters. Parameters governing reburn frequency and post-fire legacy carbon decomposition (v_{CWD}) are perturbed by a multiplicative noise term drawn from a Von Mises-based symmetric distribution with a relative standard deviation of 0.1.

The fifth strategy uses a lognormal distribution for PyC decomposition parameters. A lognormal distribution is used for v_{pyc} , parameterized by the mean and standard deviation of the effective pool loss rate. MC samples are drawn as $v_{pyc} = \exp(\bar{v}_{pyc} + \sigma_{pyc} \cdot \mathcal{N})$, where $\mathcal{N} \in (0,1)$ and $\bar{v}_{pyc}$ and σ_{pyc} are the lognormal shape parameters derived from the prescribed mean and standard deviation.

2.5.2 Results constraining

Each MC configuration is assigned a likelihood weight based on its simulated instantaneous wildfire carbon emissions ($E_{fire,inst}$), assessed against the GFED dataset over the overlapping observational period (2001–2016 for GFED4.1s and 2002–2022 for GFED5.1). Simulated and observed emissions are first aggregated from OSCAR regions r to the 14 GFED regions r_0 . For region r_0 and biome b , the Gaussian likelihood of configuration c is:

$$w^{r_0,b,c} = \frac{1}{\sigma^{r_0,b} \sqrt{2\pi}} \exp\left(-\frac{(\sum_{r_0,b} E_{fire,inst}^{r_0,b,c} - \bar{x}^{r_0,b})^2}{2\sigma_{r_0,b}^2}\right), \quad (40)$$

where $\bar{x}^{r_0,b}$ is the annual mean emission from the GFED dataset and $\sigma_{r,b}$ is the standard deviation calculated by $\sigma^{r_0,b} = \bar{x}^{r_0,b}/3$. OSCAR regions r inherit the weight of their parent GFED region r_0 .

These weights are used to compute likelihood-weighted ensemble statistics. For any simulated variable X , the weighted ensemble mean is calculated as:

$$\bar{X}^{r,b} = \frac{\sum_c X^{r,b,c} w^{r,b,c}}{\sum_c w^{r,b,c}}, \quad (41)$$

and the corresponding weighted standard deviation is:

$$\sigma_{\bar{X}}^{r,b} = \sqrt{\frac{\sum_c (X^{r,b,c} - \bar{X}^{r,b})^2 w^{r,b,c}}{\sum_c w^{r,b,c}}}. \quad (42)$$



3 Applications with GFED burned area and evaluation

3.1 Experimental design

The historical simulations evaluate the OSCAR-fire module under two burned area forcings, applied separately: GFED4.1s over 2001–2016 and GFED5.1 over 2002–2022.

Initial conditions for the fire bookkeeping pools are obtained analytically. For each ensemble member, the four prognostic pools C_{veg} , C_{soil} , C_{CWD} , and C_{PyC} are initialised at steady state by analytically solving the governing equations under constant 2001–2010 mean burned area forcing. This approach is necessary because the characteristic residence times of the CWD and PyC pools extend to centuries (Sect. 2.4.3), making it impractical to spin them up within the observational record. The historical integration is then run from 2001 to 2022 under time-varying burned area forcing.

An MC ensemble of 2000 parameter configurations is generated following Sect. 2.5.1. Each ensemble member is run under both GFED4.1s and GFED5.1 burned area forcings. A likelihood weight is then assigned to each member according to how well its instantaneous fire emissions match the corresponding GFED estimates. Uncertainty is parameterized as proportional to the reported multi-year mean emission, with standard deviation $\sigma = \epsilon \cdot \bar{E}_{ref}$, where ϵ is a prescribed relative uncertainty coefficient. The resulting weighted ensemble constitutes a posterior that accounts for both prior parameter uncertainty and consistency with the benchmarks.

3.2 Diagnostic comparison

Model performance is assessed against independent references corresponding to the three major carbon components of the module:

First, simulated instantaneous emissions $E_{fire,inst}$ are compared directly against GFED4.1s (Van Der Werf et al., 2017) and GFED5.1 (Van Der Werf et al., 2025) emission estimates at global and regional scales, with respect to multi-year means, interannual variability, and spatial patterns. As the module does not represent peatland and agricultural fires, both simulated and reference emissions exclude these two source types throughout the comparison. Note that although the model uses burned area from these datasets as forcing, other key parameters such as carbon densities differ, so the comparison is not circular and retains diagnostic value.

Second, simulated annual mean legacy CWD emissions ($F_{CWD \rightarrow atm, leg}$) over 1985–2020 are compared against boreal delayed CWD decomposition estimates for boreal North America (BONA) and boreal Eurasia (BOAS). The reference estimates are derived from a grid-based bookkeeping model that tracks post-fire dead biomass decay using region-specific exponential decay rates (Xu et al., 2023). The simulated CWD flux includes only fire-induced inputs, as natural turnover-driven CWD is not represented in the current model version. Since the reference estimates include CWD from both fire and natural mortality, this comparison should be interpreted with caution and serves only as an order-of-magnitude check.

Third, simulated annual mean PyC production ($F_{veg \rightarrow PyC} + F_{soil \rightarrow PyC}$) is evaluated against two independent estimates: Jones et al. (2019) combined a global database of PyC production factors with GFED to estimate a global flux of 256 (196–340) Tg C



yr⁻¹ over 1997–2016, while Bowring et al. (2022) estimated 337 (233–514) Tg C yr⁻¹ over 1901–2010 using a CMIP6 land surface model.

3.3 Post-fire carbon recovery diagnostics

365 Post-fire ecosystem recovery is diagnosed through a separate analytical experiment, using the first simulation year (2002 for GFED5.1) as the reference state. At this reference year t_0 , the above-ground vegetation and soil litter carbon stocks exposed to burning are defined as:

$$F_{\text{veg,ag}}^{r,b} = (f_{\text{leaf}}^{r,b} + f_{\text{stem}}^{r,b}) c_{\text{veg}}^{r,b} A_{\text{burn}}^{r,b} \quad (43)$$

$$F_{\text{soil,lit}}^{r,b} = f_{\text{soil,lit}}^{r,b} c_{\text{soil}}^{r,b} A_{\text{burn}}^{r,b} \quad (44)$$

Each pool is partitioned into a lost fraction and a surviving fraction. The lost fractions are:

$$F_{\text{veg,ag,loss}}^{r,b} = F_{\text{veg,emi}}^{r,b} + F_{\text{leaf} \rightarrow \text{soil}}^{r,b} + F_{\text{stem} \rightarrow \text{CWD}}^{r,b} \quad (45)$$

$$F_{\text{soil,loss}}^{r,b} = F_{\text{soil,emi}}^{r,b} \quad (46)$$

370 where the vegetation loss term includes direct combustion emissions and fire-induced transfers to litter and CWD. The surviving fractions are:

$$F_{\text{veg,ag,remain}}^{r,b} = F_{\text{veg,ag}}^{r,b} - F_{\text{veg,ag,loss}}^{r,b} \quad (47)$$

$$F_{\text{soil,remain}}^{r,b} = F_{\text{soil,lit}}^{r,b} - F_{\text{soil,loss}}^{r,b} \quad (48)$$

Within each GFED region, carbon pools are summed across all OSCAR regions, and the normalised loss and surviving fractions are then computed as:

$$r_{\text{loss}}^{r_0,b} = \frac{\sum_{r \in r_0} F_{\text{loss}}^{r,b}}{\sum_{r \in r_0} F_{\text{target}}^{r,b}}, \quad (49)$$

$$r_{\text{remain}}^{r_0,b} = \frac{\sum_{r \in r_0} F_{\text{remain}}^{r,b}}{\sum_{r \in r_0} F_{\text{target}}^{r,b}}, \quad (50)$$

where F_{target} denotes $F_{\text{veg,ag}}$ or $F_{\text{soil,lit}}$ respectively. The normalised post-fire recovery trajectory is then:

$$f_{\text{rcv}}^{r_0,b}(t) = r_{\text{remain}}^{r_0,b} + r_{\text{loss}}^{r_0,b} (1 - e^{-\lambda_{r_0,b} t}), \quad (51)$$

375 where λ is μ_0 for vegetation or ρ_0 for soil litter. At $t = 0$, $f_{\text{rcv}} = r_{\text{remain}}$, corresponding to the immediate post-fire carbon state. As t approaches ∞ , $f_{\text{rcv}}^{r_0,b}$ is approaching 1, meaning the pool fully recovers to its pre-fire stock. The recovery

trajectories are computed over a 300-year time horizon. Recovery time $t_{\text{mod}}^{r_0,b}$ is defined as the first year t at which $f_{\text{rcv}}^{r_0,b}$ permanently reaches or exceeds 90% of its pre-fire value, identified on the ensemble median trajectory across MC configurations.

For forest above-ground vegetation, modelled recovery curves are compared against the reference trajectories derived from remote-sensing-based estimates. Since forest μ_0 was calibrated to match the 90% recovery time of these curves (Sect. 2.4.2), this comparison serves as a consistency check. Soil carbon and non-forest vegetation trajectories are unconstrained by calibration and thus represent model predictions, because observational data for their validation are currently lacking.

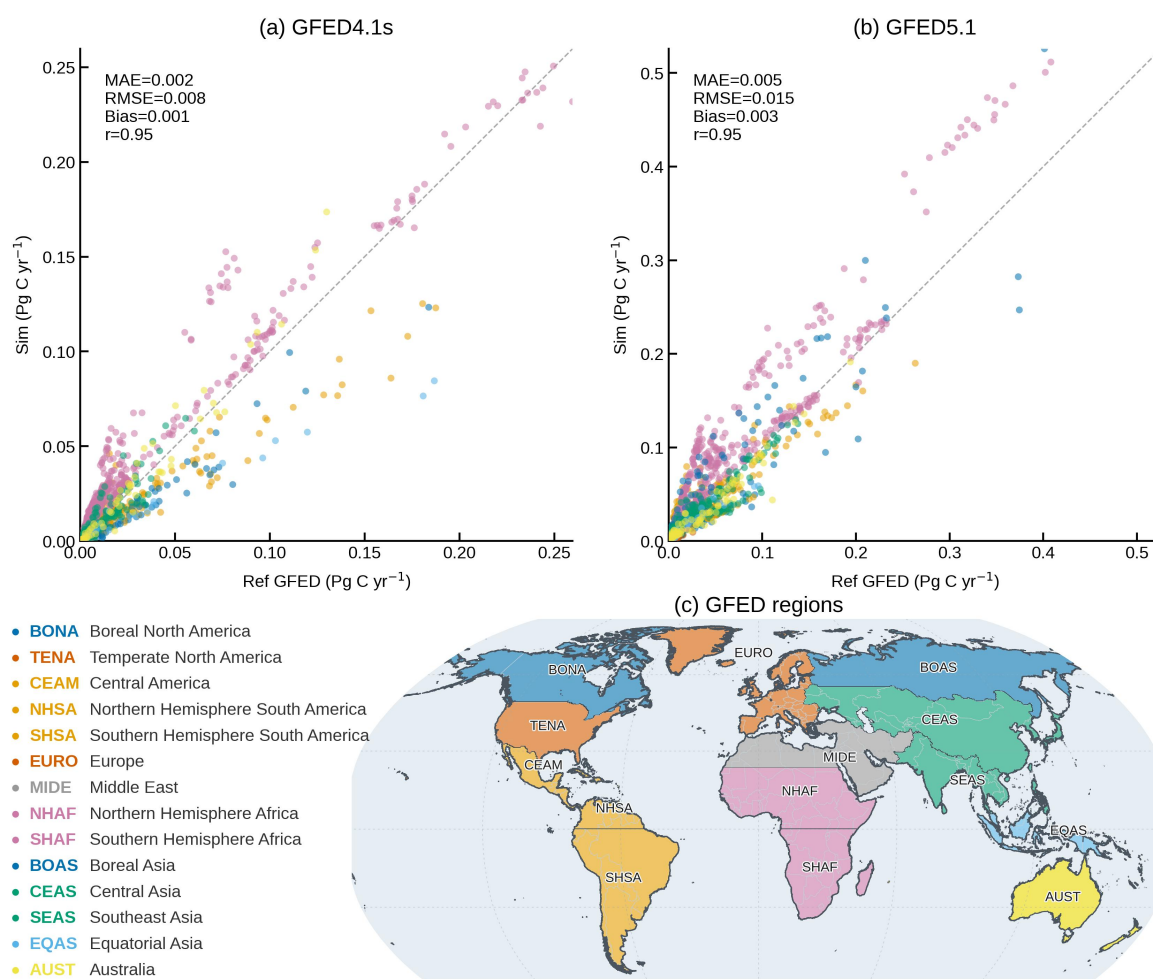


Fig. 2. GFED basis regions and evaluation of simulated instantaneous fire carbon emissions against GFED observations. (a, b) Scatter comparisons of OSCAR-region annual instantaneous fire emissions (Sim) versus GFED reference emissions (Ref), for (a) GFED4.1s (2001–2016) and (b) GFED5.1 (2002–2022). Each point is one OSCAR region; colors denote the corresponding GFED basis region. The dashed gray line is the 1:1 line. Inset statistics are mean absolute error (MAE), root-mean-square error (RMSE), mean bias (Sim-Ref), and Pearson's correlation coefficient (r), all in Pg C yr^{-1} except r . (c) Map of the 14 GFED basis regions.



390 3.4 Results

3.4.1 Instantaneous fire carbon emissions

The following analysis only includes forest and non-forest vegetation fires, while peatland and agricultural fires are not represented in the current OSCAR-fire. The model reproduces global fire emission magnitudes and inter-annual variability well under both datasets (MAE = 2.1 Tg C yr⁻¹ under GFED4.1s and MAE = 3.2 Tg C yr⁻¹ under GFED5.1, Fig. 2a and Fig. 2b). Simulated global annual fire emissions average 1.8 ± 0.2 Pg C yr⁻¹ under GFED4.1s and 3.2 ± 0.3 Pg C yr⁻¹ under GFED5.1 (Table 4). Because OSCAR is driven by the same prescribed burned area as each respective GFED product, these differences must come from the fuel load and the emission factor applied to burned area. OSCAR uses TRENDY-derived carbon densities directly and does not include natural turnover-driven CWD inputs or the effect of reburning on carbon density. Both of these omissions introduce structural uncertainty in available fuel carbon, particularly in forests. OSCAR's combustion completeness parameters combine field-based estimates from Van Wees et al. (2022) with two DGVM fire schemes (Huang et al., 2020; Rabin et al., 2017) rather than being taken directly from the GFED products, which contributes to the residual differences in emissions.

Table 4. Evaluation of simulated fire carbon emissions against GFED4.1s and GFED5.1 across the globe and 14 GFED basis regions. Values represent multi-year mean burned area and fire carbon emissions. Simulation results are reported as the ensemble mean $\pm$ one standard deviation.

Region	BA GFED4.1s (Mha yr ⁻¹)	BA GFED5.1 (Mha yr ⁻¹)	GFED4.1s Ref (Tg C yr ⁻¹)	GFED4.1s Sim $\pm$ SD (Tg C yr ⁻¹)	GFED5.1 Ref (Tg C yr ⁻¹)	GFED5.1 Sim $\pm$ SD (Tg C yr ⁻¹)
Global	397.4	694.8	1872.9	1760.9 $\pm$ 182.6	3116.9	3218.8 $\pm$ 293.2
BONA	2.7	3.0	58.3	35.5 $\pm$ 7.0	85.6	57.3 $\pm$ 11.3
TENA	1.7	3.4	15.2	13.6 $\pm$ 2.1	23.1	25.8 $\pm$ 4.2
CEAM	1.5	9.9	24.3	18.3 $\pm$ 3.5	80.1	64.4 $\pm$ 13.6
NHSA	3.3	7.8	23	20.8 $\pm$ 4.6	26.7	30.5 $\pm$ 6.0
SHSA	20.3	51.0	274.4	205.5 $\pm$ 37.4	394.9	392.9 $\pm$ 61.1
EURO	0.3	1.4	2.9	2.5 $\pm$ 0.4	8.4	11.7 $\pm$ 1.5
MIDE	0.3	0.5	0.6	0.8 $\pm$ 0.1	1.7	1.7 $\pm$ 0.3
NHAF	132.9	215.4	365.9	429.4 $\pm$ 88.5	623.6	723.1 $\pm$ 150.9
SHAF	163.2	250.9	694.6	697.6 $\pm$ 151.1	1018.5	1059.8 $\pm$ 225.7
BOAS	5.1	25.6	99.5	66.2 $\pm$ 12.4	277.3	300.2 $\pm$ 49.1
CEAS	10.3	24.4	33.2	29.0 $\pm$ 4.5	54.5	80.9 $\pm$ 10.0
SEAS	8.9	46.1	104.9	95.8 $\pm$ 17.8	326.2	296.1 $\pm$ 67.3
EQAS	1.2	2.6	67.3	38.2 $\pm$ 11.2	35.4	30.5 $\pm$ 5.8
AUST	45.6	52.8	108.8	107.7 $\pm$ 24.5	160.8	143.9 $\pm$ 32.8



Simulated non-forest emissions broadly agree with GFED references (Fig. 3). Non-forest vegetation dominates global fire emissions in both GFED products, and African savannas (NHAF, SHAF, Fig. 2c) account for over half of the global non-forest emissions. Simulated and reference non-forest global emissions both show a declining trend under GFED4.1s (Sim -23.3 ± 4.7 Tg C yr⁻², Ref -19.3 Tg C yr⁻²). Under GFED5.1, the simulated non-forest trend remains strongly negative (Sim -30.6 ± 4.9 Tg C yr⁻²) while the GFED5.1 reference trend is much weaker (Ref -8.2 Tg C yr⁻²). This suggests that OSCAR's fixed combustion completeness parameters cause simulated emissions to track burned area trends more closely than the GFED5.1 reference indicates. Forest global emission trends are weak and not statistically significant under any configuration (Fig. 4). Forest fires contribute a smaller but regionally significant share of global fire emissions. Simulated forest emissions broadly agree with GFED references in most regions, with the notable exceptions of BONA and BOAS.

Two regions show simulated emissions consistently higher than both GFED products. NHAF consistently shows modestly higher values than the reference (Table 4). This pattern holds across both products and reflects that combustion completeness parameters for African savanna biomes are set slightly high. BONA and SEAS show the opposite behaviour, with simulated emissions consistently below both GFED references despite substantial increases in prescribed burned area under GFED5.1. This persistent gap points to structural deficiencies in OSCAR's region-averaged parameters. High biomass shrub and organic soil are not well captured in boreal zones and tropical transitional zones (Zheng et al., 2023; Van Gerrevink et al., 2026; Reddington et al., 2021), while combustion completeness values assigned to dense tropical forest fuels are low during intense burning events (Rabin et al., 2017; Huang et al., 2020; Van Wees et al., 2022).

CEAS and BOAS both move from simulated values below GFED4.1s to values above GFED5.1. In CEAS, burned area rises from 10.3 to 24.4 Mha yr⁻¹ between the two products, and simulated emissions move from modestly below GFED4.1s (29.0 vs. 33.2 Tg C) to clearly above GFED5.1 (80.9 vs. 54.5 Tg C). In BOAS, the burned area rises roughly fivefold, from 5.1 to 25.6 Mha yr⁻¹, and simulated emissions move from below the GFED4.1s reference (66.2 vs. 99.5 Tg C) to above the GFED5.1 reference (300.2 vs. 277.3 Tg C). Since carbon density and combustion completeness are unchanged between the two configurations, these reversals confirm that burned area uncertainty is the dominant source of emission uncertainty in these regions, with CEAS likely also reflecting the known sensitivity of GFED5.1 to small fire detection in agricultural and forest edge landscapes (Reddington et al., 2021; Field et al., 2016).

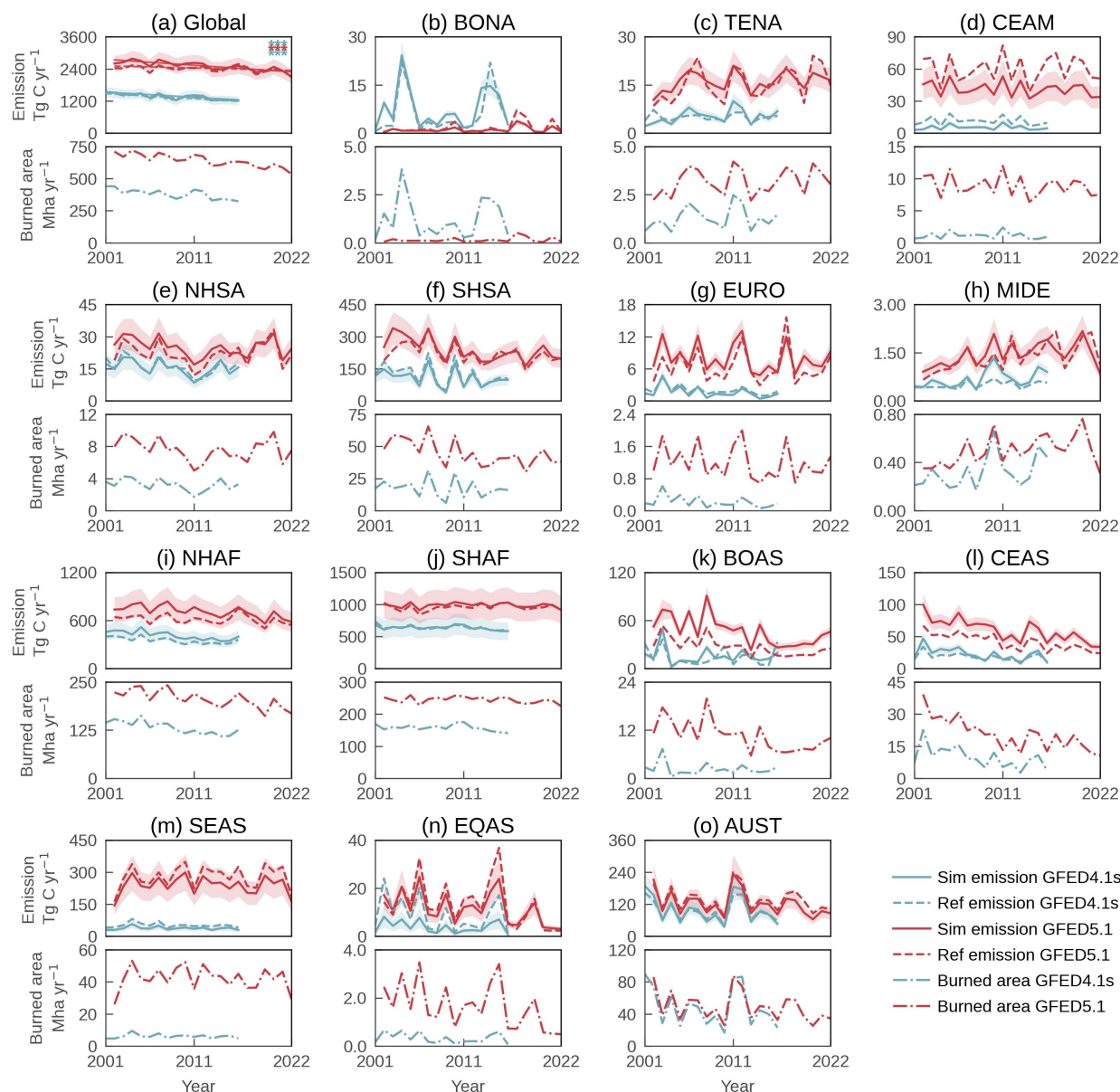


Fig. 3. Simulated and reference annual fire carbon emissions (Tg C yr⁻¹) and burned area (Mha) from non-forest vegetation for the global total and 14 GFED basis regions (panels a–o). In each panel, the upper subplot shows instantaneous fire carbon emissions, and the lower subplot shows the corresponding burned area. For emissions, solid lines indicate the OSCAR ensemble mean, shaded bands indicate ±1 standard deviation across ensemble members, and dashed lines indicate the GFED reference. Red and orange tones correspond to GFED4.1s (2001–2016) and GFED5.1 (2002–2022) configurations, respectively, for both simulation and reference. Blue tones show burned areas from GFED4.1s (dark blue) and GFED5.1 (light blue).

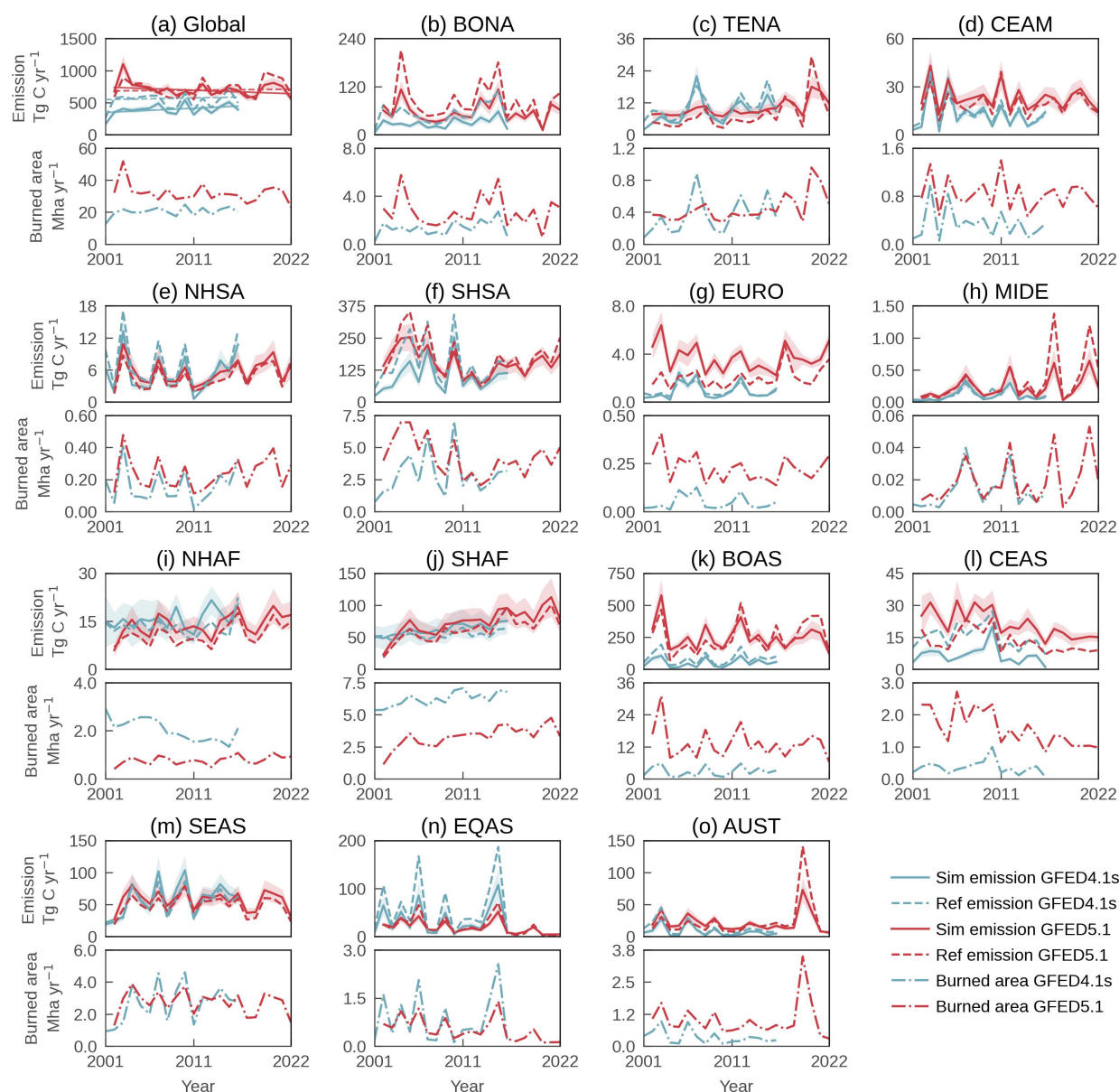


Fig. 4. Simulated and reference annual fire carbon emissions (Tg C yr^{-1}) and burned area (Mha) from forest vegetation for the global total and 14 GFED basis regions (panels a–o). In each panel, the upper subplot shows instantaneous fire carbon emissions, and the lower subplot shows the corresponding burned area. For emissions, solid lines indicate the OSCAR ensemble mean, shaded bands indicate ± 1 standard deviation across ensemble members, and dashed lines indicate the GFED reference. Red and orange tones correspond to GFED4.1s (2001–2016) and GFED5.1 (2002–2022) configurations, respectively, for both simulation and reference. Blue tones show burned areas from GFED4.1s (dark blue) and GFED5.1 (light blue).

3.4.2 Legacy fire carbon emissions

Since the CWD and PyC pools are initialized at their steady-state values under pre-simulation forcing (Sect. 3.1), legacy emissions during the simulation period reflect decomposition of both the pre-existing pool and the fire-induced inputs added during the simulation period. Global annual mean legacy fire emissions average $550.3 \pm 95.5 \text{ Tg C yr}^{-1}$ under GFED4.1s and $761.4 \pm 122.9 \text{ Tg C yr}^{-1}$ under GFED5.1 over the overlap period (2002–2016, Fig. 5).

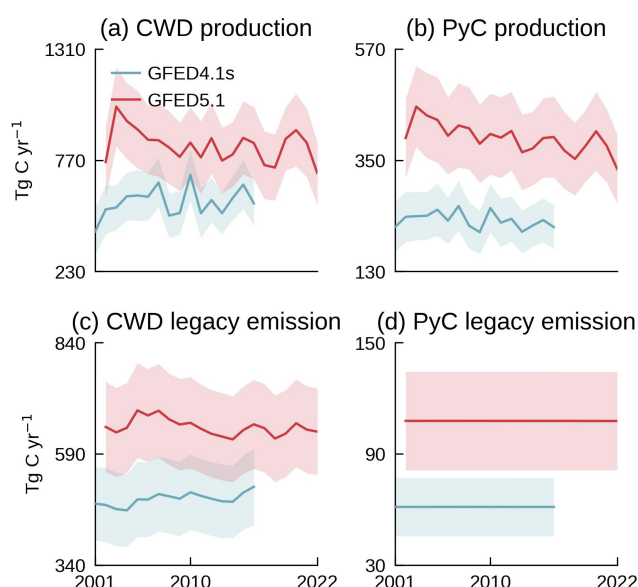


Fig. 5. Global time series of post-fire legacy carbon fluxes (Tg C yr^{-1}). (a) fire-killed stem to coarse woody debris (CWD), (b) pyrogenic carbon (PyC) production, (c) delayed CWD decomposition to the atmosphere, and (d) delayed PyC decomposition to the atmosphere.

The regional distribution of legacy emissions closely follows the spatial pattern of burned area in each dataset (Table 5). The largest inter-dataset differences occur in boreal regions, where GFED5.1 reports substantially higher burned area. BOAS legacy emissions increase by a factor of about 4.5, with similarly large increases in CEAS and EURO. The opposite holds in SHAF, NHAF, and EQAS, where GFED5.1 reports lower burned area and legacy emissions decline accordingly. These shifts closely track burned area differences, indicating that uncertainty in legacy emissions is driven primarily by the burned area inputs.

Simulated boreal CWD legacy emissions (BOAS and BONA combined) are $33.2 \pm 8.8 \text{ Tg C yr}^{-1}$ under GFED4.1s and $108.1 \pm 24.1 \text{ Tg C yr}^{-1}$ under GFED5.1. The reference estimate of 54 Tg C yr^{-1} from Xu et al. (in preparation) is closer to the GFED4.1s-driven result. The substantially higher GFED5.1-driven result is consistent with the larger burned area prescribed in this region. As discussed in Sect. 3.4.1, it is higher than under GFED4.1s partly due to differences in small fire detection between the two products (Van Der Werf et al., 2025). Simulated global annual mean PyC production is $232.2 \pm 46.0 \text{ Tg C yr}^{-1}$ under GFED4.1s and $404.4 \pm 79.1 \text{ Tg C yr}^{-1}$ under GFED5.1. The GFED5.1 result exceeds the range of 256 ($196\text{--}340$)



470 Tg C yr⁻¹ from Jones et al. (2019) and lies close to the upper end of the range implied by Bowring et al. (2022) (188–424 Tg C yr⁻¹, mean 281 Tg C yr⁻¹). The GFED4.1s result falls within the lower half of these reference ranges, because the smaller burned area prescribed under this dataset leads to proportionally lower PyC production.

Table 5. Annual mean legacy fluxes for the globe and 14 GFED basis regions under GFED4.1s (41s) and GFED5.1 (51) burned-area forcing during the overlapping period (2002–2016). Fluxes include production of coarse woody debris (CWD) and pyrogenic carbon (PyC), corresponding legacy emissions, and total legacy fire emissions (Tg C yr⁻¹).

Region	CWD production (41s)	PyC production (41s)	CWD legacy emissions (41s)	PyC legacy emissions (41s)	CWD production (51)	PyC production (51)	CWD legacy emissions (51)	PyC legacy emissions (51)
Global	575.7±113.0	232.2±46.0	489.0±83.5	61.4±15.8	856.2±173.6	404.4±79.1	653.6±101.1	107.8±26.6
BONA	19.1±6.4	4.3±0.9	15.2±4.4	0.9±0.2	35.5±10.6	6.9±1.5	29.5±7.5	1.6±0.3
TENA	4.9±1.3	1.9±0.4	4.1±1.0	0.4±0.1	7.5±2.2	3.2±0.6	7.1±2.0	0.8±0.2
CEAM	5.7±1.7	2.7±0.7	5.8±1.7	0.7±0.2	12.3±3.9	7.7±1.7	11.6±3.6	2.0±0.5
NHSA	7.3±2.8	2.6±1.0	7.1±2.6	0.7±0.3	11.1±5.3	4.9±2.1	10.8±4.9	1.4±0.6
SHSA	84.3±20.5	25.8±5.1	80.7±18.9	7.1±1.4	149.1±38.9	52.0±10.8	147.2±37.9	15.6±3.6
EURO	0.7±0.2	0.3±0.1	0.7±0.1	0.1±0.0	3.9±0.7	1.5±0.2	4.2±0.7	0.4±0.1
MIDE	0.1±0.1	0.1±0.0	0.1±0.0	0.0±0.0	0.2±0.1	0.2±0.0	0.2±0.1	0.0±0.0
NHAF	93.9±45.4	58.5±19.2	66.9±27.8	16.3±6.7	158.5±87.8	108.3±37.1	87.8±44.2	28.8±12.3
SHAF	160.3±60.7	80.6±18.8	131.2±52.1	21.0±5.6	182.3±85.7	119.6±38.7	121.0±46.4	30.4±11.6
BOAS	24.7±10.0	7.1±1.5	18.0±7.0	1.6±0.4	126.7±39.9	35.9±6.2	78.6±22.0	9.5±1.5
CEAS	5.9±1.5	3.5±0.8	6.4±1.3	1.0±0.3	28.1±6.3	11.3±1.8	28.3±6.1	3.4±0.5
SEAS	69.0±18.6	13.2±2.9	62.7±17.2	3.2±0.7	93.7±21.6	32.1±7.6	74.5±16.0	8.4±2.2
EQAS	35.7±15.0	5.6±2.0	33.0±13.8	1.3±0.4	27.3±10.0	5.1±1.5	27.4±10.0	1.3±0.4
AUST	15.0±11.6	10.6±3.4	14.6±10.0	2.9±0.9	26.2±15.2	14.4±4.2	23.3±12.5	3.8±1.0

3.4.3 Post-fire recovery

475 Forest vegetation recovery times range from 14 years to 100 years in the 14 GFED regions (Fig. 6). This range is governed primarily by the background vegetation turnover rate (μ_0), which was calibrated against Chapman-Richards post-fire regrowth curves derived from satellite observations (Sect. 2.4.2). The calibrated values follow a clear latitudinal gradient, reflecting the lower net primary productivity and biomass accumulation at higher latitudes (Zacharakis and Tsihrintzis, 2026). Tropical and subtropical regions recover in 24–30 yr, while boreal and temperate regions require 56–110 yr. Non-forest
 480 vegetation recovers within 2–3 yr across all regions (Hudiburg et al., 2023). Unlike forests, where slow turnover amplifies climate-driven productivity gradients, non-forest ecosystems turn over rapidly enough that regional differences in temperature and moisture have little effect on recovery timescales.



Post-fire soil carbon recovery is governed by two factors, including the heterotrophic respiration rate (ρ_0) and the fraction of the pre-fire litter carbon consumed by fire. The respiration rate follows a clear latitudinal thermal gradient and drives the dominant spatial pattern in soil recovery. Forest soil recovery times range from 16 yr in EQAS to 100 yr in BOAS. Unlike vegetation mortality rate to soil μ_0 , ρ_0 does not differ appreciably between forest and non-forest within the same region. Soil respiration rates are primarily controlled by temperature and soil moisture (Liang et al., 2024; Nissan et al., 2023), so climate is the dominant control on soil recovery timescales, with vegetation functional type playing a minor role.

Despite similar ρ_0 values, non-forest soils consistently require slightly longer recovery times than co-located forest soils (Fig. 7). The recovery timescale depends on the decomposition rate but also on the magnitude of the fire-induced deficit relative to the pre-fire litter pool. Non-forest litter has a higher combustion completeness in the model (Huang et al., 2020; Rabin et al., 2017; Van Wees et al., 2022), so a larger fraction of the pre-fire litter carbon is consumed per unit of area burned. Because non-forest soils start from a proportionally lower post-fire baseline, they take longer to reach 90% recovery even when decomposition rates are nearly identical. The effect is most pronounced in boreal regions, where slow decomposition amplifies differences in initial conditions (BOAS: +23 yr; BONA: +15 yr), and negligible in tropical regions, where rapid turnover makes recovery times insensitive to the initial deficit (EQAS: 0 yr; CEAM: +1 yr).

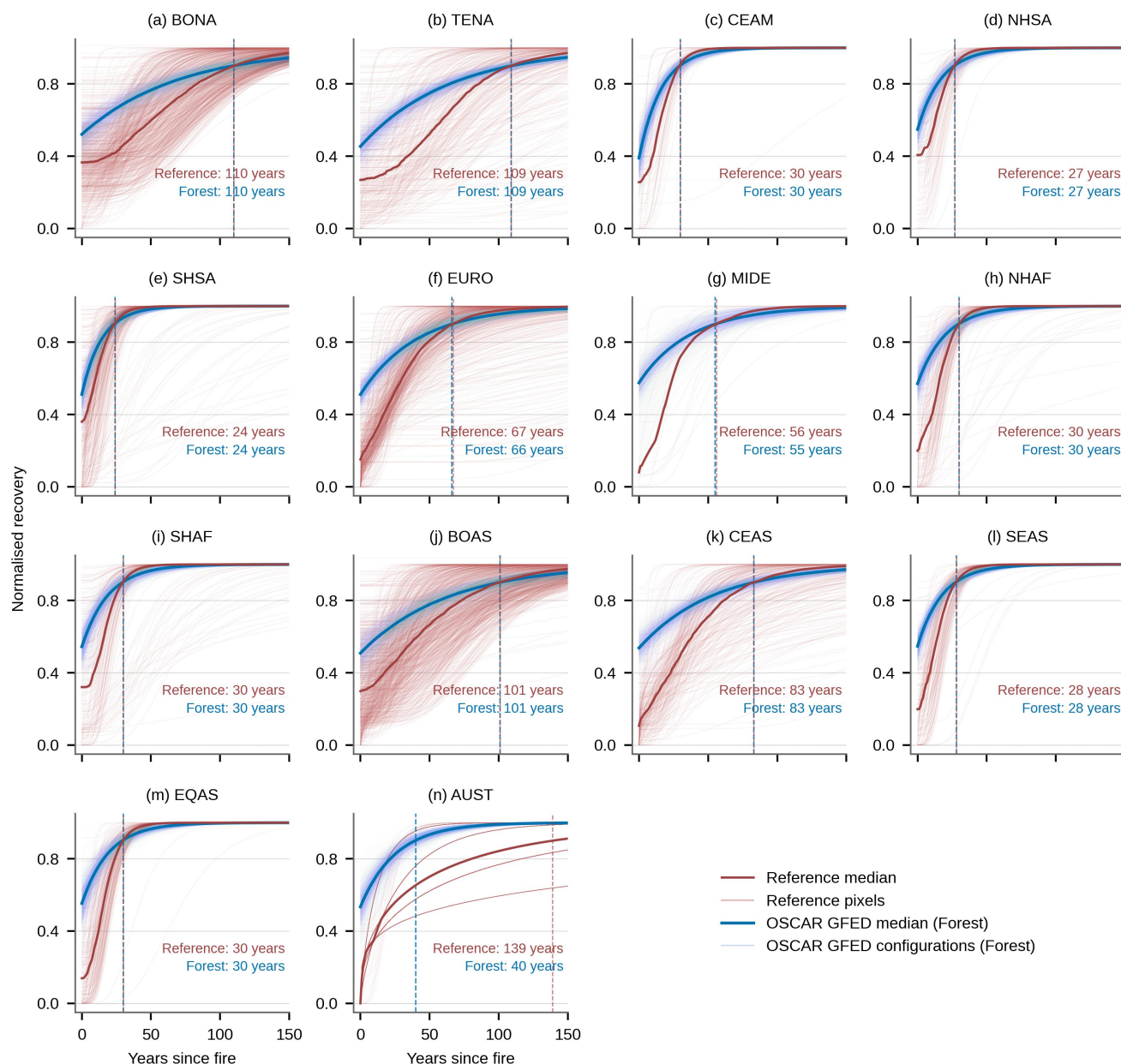


Fig. 6. Normalized post-fire recovery trajectories of above-ground vegetation carbon for forest biome across 14 GFED regions, simulated by OSCAR following an idealized fire event in year 2002. The y-axis shows the fraction of pre-fire above-ground vegetation carbon remaining. Recovery is tracked for 150 years post-fire. Blue solid lines show the OSCAR ensemble median, and faint blue lines show individual ensemble members. Maroon solid lines show the median of independent Chapman-Richards reference trajectories derived from satellite-based above-ground carbon observations. Faint maroon lines show individual pixel trajectories. Vertical dashed lines indicate the time at which each median trajectory first reaches and remains at or above 90% of pre-fire carbon (annotated in years).

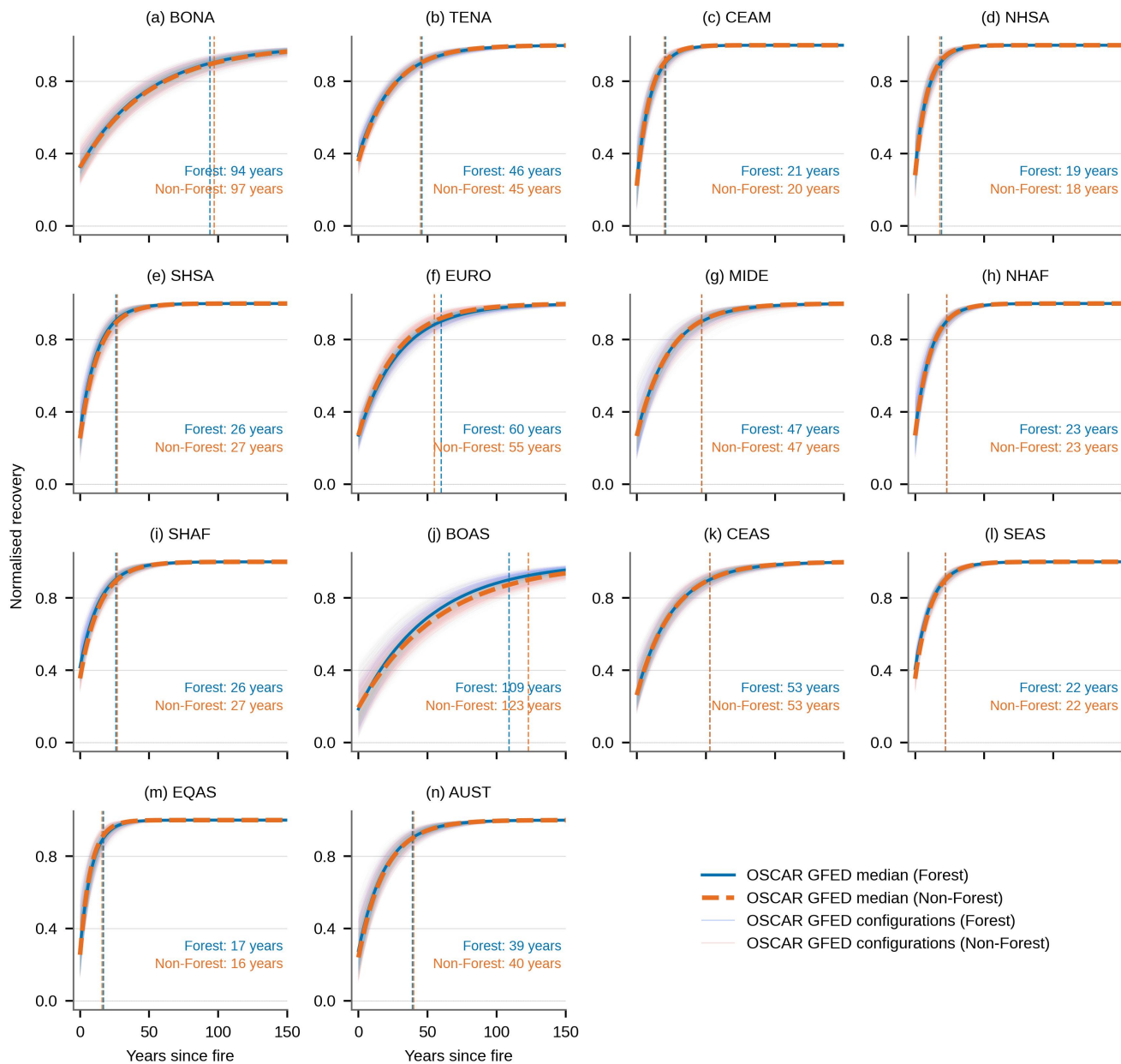


Fig. 7. Normalized post-fire recovery trajectories of soil carbon for forest (blue) and non-forest (orange) biomes across 14 GFED regions, simulated by OSCAR following an idealized fire event in the year 2002. The y-axis shows the fraction of pre-fire soil carbon remaining. Recovery is tracked for 150 years post-fire. Blue solid lines and orange dash lines show ensemble medians, and faint lines show individual ensemble members. Vertical dashed lines indicate the time at which each median trajectory first reaches and remains at or above 90% of pre-fire carbon (annotated in years).



4 Limitations and Future Directions

Prior to OSCAR-fire, the OSCAR framework represented wildfire as a simple carbon flux to the atmosphere akin to respiration, without tracking the fate of fire-affected biomass through legacy carbon pools or representing post-fire ecosystem recovery. The newly developed OSCAR-fire module addresses this by introducing bookkeeping pools for CWD, PyC, and fire-perturbed vegetation and soil carbon. These pools are governed by first-order decay or recovery dynamics, with parameters drawn from published literature and multi-model ensembles.

Several limitations stem from simplifications in the model's ecosystem process representation. First, burned area is prescribed as an external forcing, so residual discrepancies between simulated and reference emissions reflect differences in emission factors rather than in fire activities, and climate feedback also cannot be represented within the model. Second, the current implementation prescribes static regional biomass density values and does not account for the reduction in available fuel carbon between successive fire events. This is particularly relevant for fire-prone savannas and boreal forests, where reburning intervals are shortening under climate change (Van Gerrevink et al., 2026; Jones et al., 2022). Representing the age structure of post-fire stands and distinguishing burned areas between primary and secondary land would allow the model to track fuel carbon changes with time since the last fire. Third, the CWD pool currently accounts only for fire-induced inputs, while natural background CWD accumulation is not represented (Harmon et al., 2020; Xu et al., 2026), whereas reference datasets integrate both sources. This omission is most consequential in boreal regions, where the model's CWD legacy emissions are different from the reference depending on which burned area product is used. Fourth, post-fire recovery is governed by a first-order scheme, which reproduces the broad latitudinal gradient in recovery timescales but cannot capture successional dynamics (Tangney et al., 2022), permafrost feedback (Li et al., 2026), or non-linear moisture-decomposition interactions (Pellegrini et al., 2023), or within-region heterogeneity in disturbance history and species composition. Deviations in boreal regions reflect these structural omissions.

Other limitations arise from uncertainty in parameter values that could be reduced with additional observational or multi-model constraints. The emission factor in OSCAR is determined by carbon density and combustion completeness, each assigned as a single regionally averaged value. The model performs better in savanna-dominated regions, where fuel structure is relatively uniform and regionally averaged parameters adequately capture fire behaviour. Although a persistent positive difference in NHAf emissions under both forcing datasets suggests that combustion completeness for the African savanna biome may be set slightly higher relative to the emission factors implicit in the GFED products. In contrast, in boreal and tropical forest regions, a single mean biomass density differs substantially from local carbon density at individual fire locations, particularly in structurally heterogeneous environments such as primary forests or forest-agriculture margins (Zheng et al., 2023; Reddington et al., 2021).

Simulated boreal CWD emissions agree reasonably with independent estimates under GFED4.1s, lending some support to the calibrated CWD decay parameters. Simulated PyC production falls below literature-based ranges under GFED4.1s but exceeds or sits near the upper end of these ranges under GFED5.1, indicating that the model's PyC formation fractions are



sensitive to the burned area magnitude supplied by each forcing dataset. The structural uncertainty in PyC formation fractions is also less well constrained than that in vegetation biomass fractions, since no multi-model ensemble for PyC partitioning parameters currently exists. How representative the adopted formation fractions therefore remains difficult to assess with currently available observations. Similarly, the fourfold range in forest recovery times across regions is driven by turnover rates calibrated to follow a latitudinal gradient, and refining these rates would benefit from a broader observational basis than currently available.

Future development of OSCAR-fire will prioritize both structural extensions and improved parameter constraints. Replacing prescribed burned area with an internally prognostic fire scheme is the highest priority, as it would allow fire-climate feedback to be represented within the model. Representation of natural CWD turnover, planned for OSCAR v4, would give a more complete account of CWD carbon cycling and enable direct comparison with reference datasets that integrate both fire and non-fire sources. Introducing an age-dependent biomass density would allow the model to capture fuel legacy effects in re-burned areas, addressing the current limitation of static regional carbon density. Coupling with the peatland module of Zhu et al. (2025) would extend fire carbon accounting to high-latitude peat-burning emissions, and linking with the land-use module would represent deforestation fires, a major component of tropical fire emissions, alongside representation of crop residue burning to broaden coverage of anthropogenic fire regimes. Refining regional carbon density and recovery turnover rates with higher-resolution biomass and disturbance history products would further reduce parameter uncertainty without requiring structural changes to the model.

5 Conclusion

OSCAR-fire v1.0 extends the OSCAR compact Earth system model with a pool-based representation of fire-induced carbon cycling. The module tracks carbon through instantaneous combustion emissions, fire-killed fluxes into soil, CWD and PyC pools, legacy release via CWD and PyC decomposition, and post-fire recovery of vegetation and soil carbon, all within a MC probabilistic framework. Comparison against existing fire emission datasets and literature-based carbon flux ranges shows that the module reproduces global instantaneous fire emissions closely, yields boreal legacy CWD fluxes that are broadly consistent with references under GFED4.1s but higher under GFED5.1, produces PyC generally within literature-based constraints though exceeding that under GFED5.1, and captures the observed latitudinal gradient in post-fire recovery timescales. Regional differences in instantaneous emissions stem from regionally averaged carbon density and emission factors, while legacy emission differences between the two datasets reflect the divergence in their prescribed burned areas. OSCAR-fire v1.0 is thus well suited for large-ensemble applications exploring fire-driven carbon cycle variability.



Code and data availability

The OSCAR-fire source code used in this study is available at <https://doi.org/10.5281/zenodo.22705354> (Zhang, 2026), and the original OSCAR v3.3 code is available at <https://doi.org/10.5281/zenodo.10548477> (Gasser and Fu, 2024). Processed experiment drivers, parameters, and simulation outputs are archived in the Zenodo repository <https://doi.org/10.5281/zenodo.22701517> (Zhang et al., 2026). Burned area data are from the Global Fire Emissions Database <https://doi.org/10.1038/s41597-025-06127-w> (Van Der Werf et al., 2025). Vegetation and soil carbon densities are from TRENDY <https://doi.org/10.1029/2024GB008102> (Sitch et al., 2024). Litter and vegetation-part fractions are from ISIMIP3a Repository <https://doi.org/10.5194/gmd-17-1-2024> (Frieler et al., 2024). Land temperature is from CRU TS <https://doi.org/10.1038/s41597-020-0453-3> (Harris et al., 2020). Biome areas are from LUH2 <https://doi.org/10.5194/gmd-13-5425-2020> (Hurt et al., 2020). Combustion completeness and fire-induced mortality are derived from the GFED field synthesis <https://doi.org/10.5194/gmd-15-8411-2022> (Van Wees et al., 2022) and from fire-enabled DGVMs, including SSiB4-TRIFFID-Fire <https://doi.org/10.5194/gmd-13-6029-2020> (Huang et al., 2020) and CLM-Li <https://doi.org/10.5194/gmd-10-1175-2017> (Rabin et al., 2017), mapped with ESA CCI land cover <https://doi.org/10.24381/cds.006f2c9a> (Copernicus Climate Change, 2019). Coarse woody debris decay parameters follow <https://doi.org/10.1186/s13021-019-0136-6> (Harmon et al., 2020). Pyrogenic carbon production fractions follow <https://doi.org/10.1038/s41561-019-0403-x> (Jones et al., 2019). PyC turnover and the fraction transferred to soil follow <https://doi.org/10.1038/s41561-021-00892-0> (Bowring et al., 2022).

Author contributions

B. Zheng and T. Gasser conceived, designed, and supervised the study and secured funding. D. Zhang, B. Zheng, and T. Gasser designed the OSCAR-fire module framework. D. Zhang and T. Gasser developed and implemented the model code. D. Zhang conducted the simulations and analysis, produced the visualizations, and prepared the initial draft of the manuscript. B. Zhu provided burned area data in the early stage of the study and contributed to the methodology design. Y. Xu provided forest above-ground vegetation post-fire recovery curves. X. Liu contributed to climate data collection in the early stage of the study. N. Wang, L. Zhang, and J. Liang assisted with the processing and analysis of burned area data. D. Zhang, B. Zheng, Y. Xu, G. R. van der Werf, P. Ciais and T. Gasser reviewed and edited the manuscript.

Competing interests

At least one of the (co-)authors is a member of the editorial board of Geoscientific Model Development.



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