Pyrogenic carbon decomposition critical to resolving fire's role in the Earth system

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Recently identified post-fire carbon fluxes indicate that in order to understand if global fires represent a net carbon source or sink, one must consider both terrestrial carbon retention through pyrogenic carbon production, and carbon losses via multiple pathways. Here, these legacy source and sink pathways are quantified using a CMIP6 land surface model to estimate Earth's fire carbon budget. Over 1901-2010, global pyrogenic carbon drives annual soil carbon accumulation of 337 TgCyr^{-1}, offset by legacy carbon losses totalling -248 TgCyr^{-1}. The residual of these values constrains maximum annual pyrogenic carbon mineralisation to 89 TgCyr^{-1}, and pyrogenic carbon mean residence time to 5387 years, assuming steady state. The residual is negative over forests and positive over grassland-savannahs (implying a potential sink), suggesting contrasting roles of vegetation in the fire carbon cycle. Paucity of observational constraints for representing pyrogenic carbon mineralisation mean that without assuming steady state, we are unable to determine the sign of the overall fire carbon balance. Constraining pyrogenic carbon mineralisation rates, particularly over grassland-savannahs, is a critical research frontier that would enable fuller understanding of fire's role in the earth system and inform attendant land use and conservation policy.

Wildfires are a key driver of disturbance-recovery cycles in many regions of the world. While fires emit large quantities of CO_2-C to the atmosphere (~2 PgC yr^{-1}, hereafter E^{-}_{Fire})[1], subsequent vegetation recovery re-captures the emitted C on decadal timescales[2–4] and results in an uncertain but likely small net impact on atmospheric C in the long run[5], and is insignificant compared to other biogeochemical feedbacks in geological time[6–8]. Natural shifts in fire regimes and vegetation occur infrequently[9] and current changes are largely driven by climatic[10] and human[11] perturbations. However, even in the absence of global fire regime changes, a range of long-term 'legacy' post-fire C fluxes lead to either C accumulation or loss by land ecosystems locally, with their balance as yet undetermined[12].

On the terrestrial legacy C sink side, the charring of biomass by fire creates a by-product known as pyrogenic C (PyC) (~10-20% annual fire CO_2 emissions)[12,13] which is significantly more resistant to biochemical oxidation than bulk soil organic C (SOC)[14–17]. Most studies find that PyC degrades with a highly uncertain mean residence time (MRT), ranging from decades to thousands of years [18–23] (1-3 orders of magnitude higher than non-PyC SOC), suggesting that its production drives a sequestration flux from the atmosphere which exceeds the temporal boundaries of the fire-recovery cycle in most fire regimes, resulting in long-term terrestrial PyC accumulation (SOC^{+}_{PyC}). In addition to the production of refractory PyC accumulating in soils (SOC^{+}_{PyC}), there is also a lightweight 'labile' component that is likewise readily mobilised, hereafter denoted (PyC^{+}_{LW}, Supplementary Text S2).

On the terrestrial 'legacy C loss' side, like other forms of SOC, PyC is liable to mineralisation to the atmosphere (E^{-}_{PyC}), and to export from land to oceans via rivers (SOC^{-}_{PyCExp}) in particulate or dissolved form (Py-POC and Py-DOC, respectively), totalling > 40 TgPyC-C yr^{-1} [18,24]. A fraction of this river-transported PyC is eventually deposited to the ocean floor up to 10,000 years[18,21] after its initial production, with some presently unknown proportion of photo-oxidation occurring en route in fresh and marine surface waters and in sediments[25]. The steady state condition of the terrestrial fire C cycle thus has the following formulation:

$$\boldsymbol{E^{-}_{Fire} + E^{-}_{PyC} + SOC^{-}_{PyCExp} = U^{+}_{VCO_2} + SOC^{+}_{PyC} + PyC^{+}_{LW}} \qquad \textbf{(1)}$$

Where E^{-}_{Fire} is the fire C emissions due to vegetation combustion, E^{-}_{PyC} represents refractory and light-weight PyC mineralisation in the terrestrial domain[25], and U_{VCO_2} is uptake of atmospheric CO_2 by post-fire vegetation recovery, poles referring to flux direction (gain (+)/loss (-)) with respect to C stocks in the terrestrial biosphere.

The production rate of PyC is intimately linked with vegetation type, mean climate and climate variability[6,26]. Bio-climatic zones determine the rate of biomass (fuel) build-up as well as probable time between fire events, referred to here as fire return interval (FRI), with a positive relation between fuel accumulation and FRI across a gradient of increasing FRI from e.g. grassland-savannah to dry forest and rainforest biomes (Fig. 1a). FRI in turn proxies biome-scale PyC production rates (Fig. 1d), while increasing dry fuel accumulation per unit area enables greater combustion, heat release and flame temperatures, all else (fuel and climate conditions) equal (model H_1, Fig.1c).

Less is known about how the MRT of PyC is affected by FRI. One plausible conceptual model is that MRT is a positive function of flame temperature[14,20], such that low FRI biomes will tend to generate PyC of lower MRT (inverse curves, Fig. 1d), all else equal. However, flame temperatures are also determined by climate over the mid-length (drought and fuel moisture) and the short (e.g. wind conditions) cumulative timescales of fire drivers[27,28], as well as by human suppression, meaning that other conceptual models whereby low FRI results in higher-MRT PyC are plausible (e.g. models H_2, H_3 in Figs.1c,d).

To constrain the overall terrestrial fire C balance, several mechanisms which impose long-term C deficits on the terrestrial biosphere must be considered: First, the return of biomes to their pre-fire biomass state (Fig.1a) requires a stable fire regime, in which the biomass recovery interval (BRI; the time period of complete vegetation recovery) is shorter than the FRI. Violation of this condition (BRI < FRI) entails a natural or man-made change in the fire regime and an overall C-deficit, representing a step-wise decrease in biomass C ($VC^{-}_{\Delta FiReg}$)

(Fig. 1a). Second, tropical rainforests exposed to drought[29] are vulnerable to episodes of vegetation-C (VC) mortality in the decades following fires (mortality can be up to 25% of VC[30,31]) and may not fully recover prior to the next fire event, so that C is lost from this biome (VC_{Mort}^{-}). Third, in areas where fire regime shifts to higher fire frequencies than the average for that vegetation type, large fractions of SOC can be lost through combustion, erosion and microbial mineralisation (SOC_{hfloss}^{-})[32]. Average topsoil SOC losses of >20% through this mechanism has been observed in grasslands and broadleaf forests globally[33]. Finally, PyC loss occurs through soil-atmosphere mineralisation (E_{PyC}^{-}), and is the principal 'unknown' of this study. Equation 1 can then be expanded to include legacy fluxes from these changes in fire regimes, to arrive at the net balance of post-fire C with respect to the terrestrial biosphere (Supplementary Text S1a,b):

$$\boldsymbol{E_{Fire}^{-} + E_{PyC}^{-} + SOC_{PyCExp}^{-} + VC_{\Delta FiReg}^{-} + VC_{Mort}^{-} + SOC_{hfloss}^{-} = U_{VCO_2}^{+} + SOC_{PyC}^{+} + PyC_{LW}^{+}} \tag{2}$$

Mechanistic models of the terrestrial C-cycle have thus far omitted these collective fire legacy-C sinks and sources[34,38]. Here, we integrate them into a global land surface model (*Methods,* Fig. S1) to provide an estimate of the annualised components of the fire legacy C cycle represented by Eq. 2. Specifically, we incorporate dynamic PyC production by fires into ORCHIDEE-MICT (Figs. S1,S2)[39,40,41] and run the model globally over 1901-2010 with prescribed vegetation and anthropogenic land use changes (LUC), variable climate and historical CO_2 forcing (*Methods, SI Text S7*). We investigate the spatio-temporal dynamics of the legacy fluxes over the 20th Century and quantify a fire C balance for global biomes (*Methods*). C loss terms on the left side of Eq. 2 are derived offline from model output (*Methods*). The FRI is determined for each grid cell and plant type (Figs. S2,S3,S4, Table S1), as is vegetation-specific BRI (Fig. S5, *Methods*). We did not attempt to estimate global mean PyC mineralisation (E_{PyC}^{-}) due to a critical paucity of information on PyC residence times, their drivers, and measurement across biomes[36,42,43]. Instead, we infer the maximum value of PyC mineralisation that would lead to mass balance in Eq. 2. From this we infer a constraint on global terrestrial PyC MRT ($\mathrm{MRT_{Terr.}}$) (*Methods, Supplementary Text*).

20th Century Patterns of PyC Production

Over 1901-2010, we estimate average annual $SOC_{PyC}^{+}$of 281 TgC-PyC yr^{-1} (min.-max. range 188-424, TgC yr^{-1}, see *Methods*), similar to a previous estimate for the period 1997-2016 driven by satellite observations of fire (256 (196-340) TgC yr^{-1})[13]. Large interannual variations found (251-345 TgC yr^{-1}, σ=18 TgC yr^{-1}) are symptomatic of trends over the 20thC [44,45], when PyC production declined from an average of 298 to 269 TgC yr^{-1} between the first and last 3 decades (*Methods, SI Text S7*). Distribution of PyC production is consistent with that of fires generally, with the bulk occurring in the range 20°N-30°S (Fig. 2a,b)[13]. However, 20thC declines in PyC production occurred mostly in the northern hemisphere, reflecting grassland LUC (Fig. 2b), while most localised PyC production gains were modelled in the southern tropics, resulting from increasing aridity and FRI (Figs. S6-9).

Globally, fires affect biomes disproportionately, as ~80% of burning occurs in grassland-savannah dominated regions[46], with 73-79% and 13-17% of modelled PyC production taking place in C4 and C3 (13-17%) grasslands, respectively, despite these accounting for ~30-40% of the global land surface[47,48]. This mismatch is caused by the evolutionary fire adaptations of grasslands, which preferentially allocate biomass to belowground organs, allowing them to rapidly recover from disturbance [49,50] (BRI <1-3 yr[27,51]). This enables the rapid return of fire events almost as soon as vegetation has recovered (FRI≅BRI) since tropical grassland-savannah fires are particularly fuel-limited[52], enabling them to thrive where tree cover is limited by environmental conditions[53]. This feature of grassland-savannah biomes is important to Eq. 2, since whereas loss terms VC_{Mort}^{-} and $VC_{\Delta FiReg}$ are dependent on relative FRI:BRI, the production of refractory SOC_{PyC}^{+} is an absolute quantity, meaning simply that the more fire there is the more PyC is injected into the global soil mass (Fig.1). Low FRI and BRI values mean that we find grassland-savannahs to be both the main PyC source (~250 TgCyr^{-1}), and, compared to other vegetation types, pull the relative sink and source terms of Eq. 2 towards the former, in agreement with the relatively high PyC proportion of bulk SOC (5-30%) found in global grassland soils[54].

Our vegetation maps drive a -21% (-1.16 Mkm^2) and -12% (-3.6 Mkm^2) net decline in C3 and (tropical) grassland-savannah area between the first and last decades of simulation (Fig. S6). These changes lead to global decreases in PyC production (Fig. 2, Fig S7) during 1901-2010 in spite of global forest PyC production doubling (Fig. S10), as is consistent with a marked decrease in 20thC forest FRI (Fig. S8). These PyC dynamics can be explained by bioclimatic and human factors that impact global patterns of burned area and fire emission (Figs. S7, S9). In grassland-savannah regions where fire emissions and PyC production decreased, reduced fuel loading through conversion to agriculture where burning is suppressed is likely a factor[2,44,55].

Conversion of native grassland to cultivation is visible in our simulated PyC production trends (Fig. S7), consistent with global-scale[2,44,55] and localised observations in Argentina[56,57], northern Turkey[58,59], post-Soviet European and west Asian steppe[60], India[61,62], north-eastern China[63,64], south-eastern Australia[65,66], the Great Plains region[67], central and northern Mexico[68]. PyC gain/loss is thus modulated by human management[69,70], largely responsible for an apparent decrease in fires in recent decades[44] and over the past century[45], as captured by modelled declines in global PyC production, mean fire radiation and duration (Fig. S12). The net effect of these dynamics has been to approximately halve the partial fire C sink over the 20th Century (Fig. S12).

Emerging Constraints on Fire's Role in the Carbon Cycle

This study has simulated the legacy impacts of PyC production and fire C losses, a significant advance on previous studies that considered these in isolation[13,32,71]. Over 1901-2010, average global legacy soil C sinks through refractory PyC production (SOC_{PyC}^{+}; 281 (188-424) TgC yr^{-1}) and lightweight PyC production (PyC_{LW}^{+} = 56 (45-90) TgC yr^{-1}) are partially countered by legacy C sources from incomplete post-fire vegetation recovery ($VC_{\Delta FiReg}^{-}$ = 129 (123-231) TgC yr^{-1}, Fig. S15;Table S4), high frequency topsoil degradation (SOC_{hfloss}^{-} = 57 (30-95) TgC yr^{-1}, Fig. S16; Table S4), PyC aquatic export (SOC_{PyCExp}^{-} = 44(28-59) TgC yr^{-1}, Figs.3,S17,18; Table 4), and tropical drought-induced post-fire mortality (VC_{Mort}^{-} = 21 (18-25) TgC yr^{-1}, Figs. 4,S19;Table S4). Excluding E_{PyC}^{-}, the legacy fluxes are imbalanced and indicate a partial terrestrial C sink in PyC of 89 (34-104) TgC yr^{-1} (Fig. 3; Table S4) assuming Eq.2 is in steady state, implying a potential net fire 'C-savings' rate of 0-4% of the ~2.2 PgC yr^{-1} in fire CO_2 emissions. The magnitude of E_{PyC}^{-} is solved as a residual of Eq (2), meaning that if E_{PyC}^{-} exceeds the net PyC accumulation of 89 (34-104) TgC yr^{-1} then wildfires result in terrestrial PyC losses, and if E_{PyC}^{-} is in balance with the net PyC accumulation (steady state), then we can constrain the global terrestrial mean residence time ($\mathrm{MRT}_{Terr.}$) of PyC to a value of ~5,370 (1,966-14,100) years (*Methods*, Text S1b, Table S8), longer than refs[20,22,23] but smaller than ref[19].

Field and laboratory studies of PyC MRT have been sparse and restricted to a subset of biomes and fuel types, providing inconsistent central estimates with impractically large uncertainty ranges[19,20]. The temperature sensitivity of PyC decomposition is another key parameter for PyC turnover which is poorly understood, and whether PyC degradation is primarily mechanical or metabolic remains an open question[17], with implications for model representation[18,72]. Ultimately, the lack of robust mechanistic description of PyC mineralisation rates and drivers, perhaps attributable to inconsistencies in their measurement and definition, lead to PyC MRT estimates that vary by at least 40-fold (see Text S1b). Our steady state constraint on PyC MRT (~5,370yrs) is in the range of values reported in a soil incubation experiment[19] and the radiocarbon age of riverine Py-POC[18]. Until addressed, the observational shortfall will frustrate efforts to reliably quantify or constrain the fire C balance (Text S1).

Regional Distribution of Legacy Carbon Fluxes

The global value of the residual C-sink from changes in fire regimes and PyC masks substantial variability at the biome level. The largest absolute fire C gains and losses are simulated in the tropics (Fig. 4a). The net legacy C gain associated with PyC production is greatest in the tropics (+83 $\mathrm{TgCyr^{-1}}$) although it is substantially offset by legacy C losses, most notably by incomplete vegetation recovery (VC^{-}_{Mort}), soil degradation (SOC^{-}_{hfloss}; Figs.4c, S8, S16) and riverine export (SOC^{-}_{PyCExp}). The ratio of gains to losses is 1.2 in the NH tropics and 1.7 in the SH tropics, signifying a potential for overall C sequestration depending on the magnitude of the PyC mineralisation flux in these regions. Gains exceed losses in the tropics predominantly due to tropical grassland-savannahs (gains:losses of 1.5 and 2.1. in the NH and SH respectively), whereas losses substantially exceed gains in tropical forests (Figure 4). Legacy C losses exceed legacy C gains in the southern extra-tropics even before the unconstrained losses of PyC are considered. Globally, the residual of the constrained fluxes is strongly on the sink side in grasslands (+148 $\mathrm{TgCyr^{-1}}$), but on the source side in forests (-43 $\mathrm{TgCyr^{-1}}$).

We show that most (73-79%) PyC production occurs in tropical grassland-savannah regions, through fires which also generate the highest mean global flame temperatures (~500°C, Table S2), implying that the majority of global PyC production may result in PyC with a high MRT, as conferred by the heat of charring (Fig. 1c,d; Table 1)[14,73]. In contrast, tropical and temperate forest fires produce the highest *maximal* but lower average flame temperatures, consistent with the greater dependence of fire on fuel moisture than fuel availability in these regions (Fig. 1c). Overall, the model simulates the highest flame temperatures in semi-arid and higher elevation regions in the 0-30°N/S range, implying we can expect a decreasing PyC-MRT gradient from tropics to poles.

Simulated fire temperatures(Table S2) increase across biomes over the gradient: boreal(188°C), C3 grass(335°C), tropical forest(353°C), temperate forest (404°C) and tropical grassland-savannah (501°C), indicating the relationship between flame temperature and fuel availability (Fig. 1c) is nonlinear and strongly modulated by climatic and fuel conditions[74], such that curves H_1-H_3 (Fig. 1c,d) cannot accurately represent the global relationship without additional dimensionality, such as plant trait impacts on flammability and flame intensity[75].

However, current understanding of PyC charring[14,73] allows us to propose that tropical grassland and savannah regions produce the greatest quantity of PyC of the greatest relative longevity, and that grassland and forest fires play contrasting functional roles in the terrestrial C balance, with tropical grassland-savannah fires conferring the greatest capacity to increase terrestrial C storage.

Towards a Holistic Understanding of Fire's Role in the Carbon Cycle

Legacy C sequestration fluxes driven by PyC production exceed legacy C losses through incomplete post-fire recovery, LUC and soil degradation. The overall impact of legacy C fluxes on the terrestrial C balance is nonetheless not constrained due to insufficient knowledge regarding PyC mineralisation. We note that the riverine export of PyC to the global oceans (SOC_{PyCExp}^{-}) is also a conservative flux with respect to the atmospheric C-balance, however rates of PyC mineralisation in oceanic pools are constrained at least as poorly as in the terrestrial domain[18,76]. The resolution of PyC mineralisation fluxes in soils and sediments across the land-to-ocean continuum is a critical research frontier for the coming decade if we are to constrain the overall impact of fires on the global C-cycle.

Our results highlight the regional complexity of legacy C fluxes from fires and challenges the narrative that fires are solely catastrophic phenomena[77], suggesting that their severity and the long-term extent of their destructiveness is highly biome-dependent[78]. In forests, fire C losses can overwhelm PyC gains even without considering PyC mineralisation. This is not surprising, particularly in the humid tropics, where tree species are ill-adapted to disturbance[79] and massive post-fire mortality is commonplace[29–31,79](Fig. S19). Globally, forest fire-induced C losses are compensated by the dynamics of grassland ignition, in the absence of which fire phenomena would impose a net terrestrial C source irrespective of PyC production. Without widespread grassland-savannah coverage in the tropics, the legacy effects of fires could not feasibly enhance terrestrial C storage-a result afforded by grasses' capacity for fire recovery[80]. This emergent result coheres with studies suggesting that the co-evolution of grassland fire and herbivory, particularly in tropical grasslands, led to the formation of PyC-rich Mollisols that may have been central to climatic cooling in geological time[50], and that evolution of vegetation types with fire may have been central to the trajectory of Earth's C and O_2 cycles[81].

The dependency of the fire C residual on vegetation composition has important implications for projected increases[9,82,83] in climate extremes[84–86], potentially increasing all terms in Eq.2. The preservation/restoration of native grasslands may be an important vector for decreasing C losses from future fire activity in both temperate and tropical systems. Despite this, tropical grasslands have until recently been ignored in the landscape restoration and 'carbon farming' agenda[51,53,87,4,88].

This paper has attempted to further understanding of fire's role in the Earth's C-cycle by identification and first-order quantification of multiple legacy terms of the fire C budget in a land surface model. We provide a benchmark for the maximum global PyC mineralisation rate and show that without widespread grassland-savannah coverage, fires would be a net global source of atmospheric C. We call for significant investments in understanding of PyC degradation and its drivers[18,72], in addition to improved estimates of legacy fire C fluxes. Reliable quantification of PyC mineralisation and erosion, particularly over grasslands, remains the principal missing link in a holistic understanding of fire's role in the Earth system.

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Author contributions

S.P.K.B. and S.A designed the study. S.P.K.B. performed the code implementation in ORCHIDEE, set up the simulations and processed the output used for this study. M.W.J. provided access to data and insight to the PyC production factors used in the simulations. P.C. and B.G. provided additional input to the coding, study design and data processing. All authors contributed to the interpretation of the results. S.P.K.B. wrote the manuscript and produced the figures, M.W.J. made substantial additions to the text. All authors contributed to final modifications of the manuscript.

Competing interests

The authors declare no competing interests.

Figure Captions

Figure 1*: Schematic conceptual representation of the interrelation between plot or biome -scale:* ***(a)*** *Change of vegetation biomass carbon post-fire to steady state (VC_{SSn}) and its evolution with change in fire regime ($Fire\ Regime._T$), where subscript (T) refers to the specific fire regime as a f(time (x-axis)). Coloured shading indicates a hypothetical transition between stable vegetative states in a given biome or latitudinal bin along an environmental humidity and fire regime gradient. Included is vegetative C-loss term due to a change between fire regimes T and T+1 ($\Delta VC_{\Delta FiReg(T-T+1)}$), where FiReg. is an abbreviation of $Fire\ Regime._T$. The transition between vegetative states illustrates a shift from an idealised high BRI,FRI biome to a lower one.* ***(b)*** *is a graphic aid to mirror the y-axis in (a) onto the x-axis in* ***(c)****.* ***(c)*** *Fire temperature and terrestrial fuel accumulation (assumed here to be directly proportionate to ΔBiomass in* ***(a)****) The three curves denote different idealised possible relationships between the two variables, varying as a result of fuel conditions. Curve H_1 (black) describes a situation in which the conditions of fuel and fire (e.g. fuel moisture and wind velocity are equal across biomes). H_2 (dot-dash grey line) assumes that fuel condition differs with biome, and assumes that grassland fuels are driest and rainforest fuels wettest, such that fuel accumulation is inversely related to flame temperature. H_3 (dotted grey line)describes a situation in which flame temperatures are highest in tropical forests and grassland, under the situation that severe drought conditions (and hence dry fuel) are a prerequisite for tropical wildfires, while grassland fuels tend to be very dry, whereas temperate biomes support fires even if they are relatively wet and of a lower temperature.* ***(d)*** *Idealised PyC production (dashed pink) and its mean residence time ($MRT_{H1(black)\ -3(grey),}$) for different potential relationships between FRI, fuel accumulation and flame temperature in (c). PyC production is assumed to increase with decreasing environmental moisture and FRI. Black circles relate a specific level of PyC production for a given vegetative state to its corresponding MRT and flame temperature. Sub-graphs* ***(a,c,d)*** *are thus related to one another by the coloured dashed lines. Curves MRT_{H1}, MRT_{H2} and MRT_{H3} relate to the respective flame temperature/fuel accumulation curves in* ***(c)****. Refs.:* [13–15,27,34–37]

Figure 2: Simulated PyC production and change over 1901-2010. (a) Map of global PyC production averaged over the entire simulation period (log gC $m^{-2}yr^{-1}$), with global annual mean production and standard deviation

inset. (b) Simulation-averaged annual absolute PyC production summed per 0.5° latitude bin (TgC yr^{-1}*) in 1901-10 (orange) and 2001-10 (green), with the difference (latter-former) shown in yellow.*

Figure 3: Time averaged estimates for the source and sink terms in Eq. 2 (top), with the PyC mineralisation loss quantity unknown, but constrained by the net fire C balance. The PyC aquatic export flux (SOC_{PyCExp}^{-}) *is dotted to highlight that it is a terrestrial export flux, not an atmospheric flux. Bottom panel shows aggregations of (h) fire C losses relative to PyC production (sum of (c-f)) and (i) the fire C balance net of refractory PyC mineralisation, i.e. the sum of (a,b) and (c,d,e,f). Assuming steady state, maximum PyC mineralisation (g) is thus equal to the residual, (i), with the red, blue portions showing the range of maximum and minimum possible mineralisation respectively, and the arrows the possible mineralisation range according to the reported central estimate.*

Figure 4: (a) Simulation-average (1901-2010) sources and sinks in the global fire C-cycle, summed per 30-degree latitudinal band, in Tg C yr^{-1}*. Note that fire regime change and high frequency fire SOC loss terms are disaggregated between forest (solid) and grass (dashed), and that the colour legend for each term is equivalent to that in Figure 3. Values appended to bars denote the ratio of C gain:loss (>1=C-sink). (b) Comparison of time-averaged grassland (left) and forest (right) fire C sources (red) and sinks (black) summed per 30° bin (as in (a)), in TgC* yr^{-1}*. Values appended to bars denote the ratio of C gain:loss (>1=partial C-sink, excluding* E_{PyC}^{-} *). (c) Global map of the time-averaged, vegetation-summed residual in Eq. 2 (gC* m^{-2} yr^{-1}*) for each pixel, where negative values indicate C-source, and positive a C-sink. The balance is calculated as the net sum of Eq. 2, excluding the PyC mineralisation term (*E_{PyC}^{-}*), which is constrained but unknown. A summary statistics table of the residual per plant type (mean, standard deviation and its %-mean value, concluding with the residual as a fraction of total* PyC_{SOC}*) are reported inset. In that table, EG, RG and SG refer to evergreen, rain-green and summer-green, respectively.*

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Methods

Model description:

Here we apply PyC production to the IPSL Earth System Model, ORCHIDEE-MICT revision number 5308, a widely used sub-branch of ORCHIDEE that is global in scope but includes some soil, hydrological and thermal processes specific to boreal regions [1–3] , whose use here will facilitate future assessments of PyC stocks in deep permafrost soils. At the core of the model is terrestrial biomass fixed by photosynthetic C uptake, performed by 13 plant functional types (PFTs) with distinct primary production, senescence and carbon dynamics[4]. Biomass is allocated to foliage, fruit, roots, above/below -ground sap, heart wood and carbon reserves which are transfered to two reactivity-differentiated litter pools. ORCHIDEE-MICT is integrated with a model-specific version (see ([5,6]))of the SPITFIRE fire module[5,7,8], which takes the aboveground portion of these biomass components and allocates them to potential fire fuel classes differentiated by their potential time to combustion/oxidation. ORCHIDEE-SPITFIRE has been involved in multiple phases of FireMIP[9] and its predictions found to be within the range of those from available fire models[10–13]. Fire ignitions are controlled by lightning strikes and human ignitions, the latter of which is determined as a positive logistic function of population density. Vegetation flammability is determined by fuel and climatic conditions (Nesterov Index and Fire Danger Index). Burned area is controlled by fire spread rate and fire duration, as influenced by vegetation flammability, and affects fire CO_2 emissions.

Modelled PyC Production:

PyC is produced in ORCHIDEE-MICT as a function of fuel class-specific fire CO_2 emissions using an adaptation of the apportioning between PyC production and fire CO_2 emissions estimate by Jones et al. (2019)[14], which posits central literature-based prediction of ratios $[SOC_{PyC}\colon E_{CO2}]$ of 0.261, 0.1 and 0.091 gPyC produced g^{-1} CO_2-C emitted, for the three fuel classes of Coarse Woody Fuels (CWF), Fine Woody Fuels (FWF), and Non Woody Fuels (NWF), respectively. Uncertainty in PyC production (Fig. 3) is based on the bootstrapped 95% confidence interval range in Jones et al. (2019), for PyC production ratios ($[SOC_{PyC}\colon E_{CO2}]$, gPyC-C g^{-1} CO_2-C) for CWF(0.176-0.389), FWF(0.064-0.153) and NWF(0.074-0.114) and applying the fractional difference of each bound from the central bound to PyC produced in the post-processing analysis. We apportion these to the four SPITFIRE fuel classes such that (1hr fuels→NWF), (10hr; 100hr fuels → FWF), (1000hr fuels → CWF), where the hour-term in SPITFIRE fuel classes refers to the order of magnitude of time required for the fuel to lose 63% of its moisture under idealized atmospheric conditions[8], determined effectively by the stem thickness of each biomass component of each PFT based on the 'average individual' of each woody PFT.

C mass balance is maintained by removing PyC produced from other C pools. PyC produced is first subtracted from the fraction of biomass going to litter pools in that SPITFIRE timestep (1 day). If PyC produced > biomass going to litter in that timestep, then the remaining quantity is taken from CO_2 emissions, whose reduction recursively reduces total PyC production. PyC is then introduced to the biosphere-pedosphere interface by its allocation to PyC-specific SOC reactivity pools, complementing the traditional CENTURY 3-pool model[15], with a 'Slow PyC' pool composed of (PyC_{10hr} + PyC_{100hr}), and a 'Passive PyC' pool (PyC_{1000hr}), where the subscript refers to the source fuel class of PyC. In the present configuration, PyC_{1hr} does not enter into either of the SOC pools and once produced, is instead added to the pool of dead biomass that becomes litter, which is then subject to normal model SOC dynamics (SI Text S2).

Once produced, the PyC SOC pools are immediately redistributed equally amongst the top 2.1cm of the model's vertically discretized soil layers to represent the initial translocation of PyC in the first year of production, following field observations from ref. ([16]). PyC pools are not exchanged with one another or with the other SOC pools, and are subjected to vertical bio- and cryo- turbation processes in the soil, and temperature and moisture -dependent mineralization Mineralisation rates are equivalent to bulk MRTs of ~300 and ~3000yrs for Slow and Passive PyC, respectively.

Simulation Configuration:

The simulations used for this study were forced with imposed historical 13-PFT vegetation (ESA-LUH2 v1.2), CRU-NCEP v8[17] climatology and atmospheric CO_2 concentrations at 0.5° resolution with SPITFIRE activated and hydrological river routing deactivated. Deforestation fires were deactivated and agricultural fires in the output ignored to simplify analysis. A 50 year 'spinup' run on a loop of the years 1901-1920 for the above input forcing datasets was first performed to bring the biosphere and fire cycle to a quasi-steady state under the closest pre-20th Century climatology we can approximate with our climate data. The same model was then run continuously over years 1901-2010. Fire C loss terms were estimated from derived variables in the simulation output. Deforestation fires were not activated for in these simulations as the legacy effects of these events remain poorly understood and quantified.

Estimating PFT-specific Fire Return Interval (FRI):

PFT-specific FRI is defined as the interval between consecutive fires affecting a consistent area, which is not a standard output of ORCHIDEE and so was determined probabilistically. To do so, first we find the annual fractional fire contribution of each PFT ($fFire_{PFT}$) to total CO2 emissions:

$$\boldsymbol{fFire_{PFT} = EFire_{PFT} \, / \, \Sigma(EFire_{PFT})} \qquad \textbf{(3)}$$

From this the probabilistic fire incidence per PFT, pixel and year can be estimated:

$$\boldsymbol{p(Fire)_{PFT} = fPFT_{Pix} * fFire_{PFT} * BA_{Pix}} \qquad \textbf{(4)}$$

Where $p(Fire)_{PFT}$ is the annual probabilistic fire incidence per PFT and pixel, and $fPFT_{Pix}$ the fraction of each PFT occupied by vegetation from a given PFT ($\boldsymbol{fPFT_{Pix}}$). Global probabilistic FRI (yrs) for each pixel and PFT (FRI_{PFT}) over a given unspecifiable surface area (e.g. one hectare) can then be calculated by dividing $p(Fire)_{PFT}$ by PFT-specific vegetated area, giving the probability that a given hectare occupied by a given PFT in that pixel is the one that burned that year. This is summed over the simulation years then divided over the simulation length (110yrs). 1/ this value gives the FRI:

$$\boldsymbol{FRI_{PFT} = 1/((\textstyle\sum_{t=1}^{110}(\ p(Fire)_{PFT}/(fPFT_{Pix} * Area_{Pix})))/110)} \tag{5}$$

The resulting gridded PFT specific map is then adapted to set the maximum value of FRI at 1000 yrs across all PFTs, since this would largely result from insufficient sample size in time to adequately estimate the probabilistic FRI for these pixels/PFTs, resulting in strong potential skews in the FRI:BRI ratio, given that BRI itself rarely exceeds this value.

For estimating the average FRI value for each PFT, we employed a similar, yet PFT-specific approach. This was done for the same reasons as above, but with stricter thresholds for each PFT so as not to skew average values with unrealistic probabilistic values. We used expert judgement based on both the literature and authors' expertise to set maximum realistic FRI values for each PFT of 2000, 500, 200 and 100 years for tropical, temperate and boreal, C3 grass and C4 grasses, respectively, removing values above these for the mean estimate shown in the Supplementary Table.

Estimating PFT-specific Biomass Recovery Interval (BRI):

Biomass carbon recovery times (the time for which a given surface area recovers all of the biomass lost due to a disturbance event) are difficult to quantify, and to our knowledge no global gridded product estimating disturbance approximate PFT-specific BRI, modulated in space and time by the NPP of a pixel-specific PFT relative to the global median NPP of that PFT. We treated (a) C3 and C4 grasses, (b) all extra-tropical forest types, and (c) tropical forests, as separate categories. For (a) and (b), we assumed that for a given pixel and year, C losses from fire can be recovered by the completion of that time interval which itself varies by $\pm\beta$ as a function of the NPP experienced by that pixel relative to the global median NPP for that PFT:

$$\boldsymbol{BRI_{Pix}^{PFT} = BRI^{PFT} \pm (BRI^{PFT} * (\beta * NPP_{Pix}^{PFT}/\overline{NPPm_{Global}^{PFT}}))} \tag{6}$$

Where BRI_{Pix}^{PFT} is BRI per PFT, pixel and year, BRI^{PFT} is the central, global value of BRI, β is the fractional maximum variation of BRI_{Pix}^{PFT} from the central value, NPP_{Pix}^{PFT} the annual NPP of that PFT in a specific pixel and $\overline{NPPm_{Global}^{PFT}}$ is the time averaged global median NPP of that PFT. For C3 and C4 grasses, we set BRI^{PFT} at 2.5 and 1.5 years respectively, and β at ±25%, based on literature-based estimates and the assumption that tropical grasses have high NPP and recovery rates. For forests we set central BRI^{PFT} for all non-tropical forest PFTs to the value reported in a literature review -based study (fig. 4d of ref. [18]) of 133 years, which we then allow to vary (β) by ±50% as a function of NPP relative to $\overline{NPPm_{Global}^{PFT}}$ for each PFT. See the supplementary material for further discussion of parameter choices.

Estimating loss terms in Equation 2

Loss of biospheric C due to fire regime change ($\boldsymbol{VC_{\Delta FiReg}}$)

This loss term is calculated for each PFT and includes net C losses from areas where the biospheric disturbance steady state condition is not satisfied (BRI<FRI) as a result of a change in fire regime. We treat areas that experienced decreases in FRI of >10% between the first and last three decades of the simulation (Fig. S7), as having exhibited a fire regime shift. Then, we estimate the system biomass loss per fire event for these areas as the BRI:FRI ratio in the year of the event multiplied by the total CO_2 emissions from a given PFT in that year's fires:

$$\boldsymbol{VC_{\Delta FiReg} = (^{BRI_{PFT}}/_{FRI_{PFT}}) * E_{FCO2}} \qquad \textbf{(7)}$$

Unrecovered drought-induced tropical post-fire mortality ($\boldsymbol{VC^{-}_{Mort}}$)

Here, we extrapolate literature-derived estimates of tropical forest mortality losses derived from drought-induced fires to tropical forests globally and aggregate them annually. Existing literature estimates of this phenomenon are mostly drawn from the aftermath of El-Niño events, however given that drought is a continuous function of precipitation over time for a given biome, and that (a) not all droughts are El Niño driven and (b) not all tropical forests exist in zones whose interannual climate is strongly characterized by El-Niño activity, we extrapolate the findings of these field studies to all tropical forest regions characterized by severe or extreme drought according to a widely used drought index, tempering the index by taking only those regions where the index indicates these conditions on average over the course of a whole year. This gives a spatially-explicit timeseries of post drought-fire tree mortality conditions. The unrecoverable vegetative C losses from that mortality are calculated on the basis of the relative timescales of fire return and vegetative recovery, as detailed below.

For this annual estimate we do not consider belowground mortality losses, which are not estimated in the literature for this type of disturbance event. To get the *per-PFT* total aboveground fraction of biomass allocation (VC_{AG}^{PFT}), we extract annual gridded biomass allocation terms and sum them over the total biomass allocated to all vegetation C pools for each PFT (fVC_{AG}^{PFT}). The approximate total above and below -ground vegetative biomass C of tropical PFTs for each gridcell and year is obtained by weighting total vegetation C per pixel (VC_{Total}^{PFT}, a non-PFT specific variable) by the fractional vegetation coverage of that pixel by that PFT ($fPFT_{Pix}$) and the relative NPP of that pixel (NPP_{Pix}^{PFT}) versus that of the pixel mean NPP ($\overline{NPP_{Pix}}$). Multiplying this by (fVC_{AG}^{PFT}) gives an estimate of the total aboveground annual biomass of the two tropical PFTs per pixel:

$$\boldsymbol{VC_{AG}^{PFT} = [VC_{Total}^{PFT} * fPFT_{Pix} * (NPP_{Pix}^{PFT}/\overline{NPP_{Pix}})] * fVC_{AG}^{PFT}} \qquad \textbf{(8)}$$

Annual aboveground biomass maps are then filtered to mask out pixels where fire is absent in a given year. The resulting gridded VC_{AG}^{PFT} dataset is then used to estimate the proportion of tropical vegetation affected by fire by multiplying the probability that a fire in a given pixel comes from a given PFT by the burned fraction of that PFT ($\boldsymbol{fBurn_{Pix}}$):

$$\boldsymbol{FireVC_{AG}^{PFT} = VC_{AG}^{PFT} * p(Fire)_{PFT} * fBurn_{Pix}} \qquad \textbf{(9)}$$

To capture only those areas that may have experienced drought and hence drought induced fire mortality, we employ the standardised precipitation index (SPI)[19], which derives a generic wet-dry index for any location by fixing a gamma probability density function to a timeseries of precipitation for a given location (in this case a given pixel containing a tropical forest PFT). To calculate the SPI for all grid cells over the timeseries of the study simulation, we use a pre-existing SPI function available in the NCAR Command Language (NCL)[20]. The SPI defines different thresholds for wet and dry conditions according to a continuous positive and negative scale, in which all SPI values under SPI<-1.5 are indicative of a location experiencing severe to extreme drought. Averaging the SPI annually, we mask out pixels in the dataset $FireVC_{AG}^{PFT}$ which do not satisfy the SPI <-1.5 condition. We then assume that total post-fire mortality loss is approximated from the mean literature value of -24.8% (±6.9%)[21] and define this fraction as the total C-loss. However, since this biomass loss should be recoverable by the biosphere if BRI<FRI, only those pixels in which BRI>FRI are considered time-integrated losses, and only by the fraction given by the ratio of the two. To this loss is added the vegetative carbon-derived CO_2 emissions in the original drought-induced fire which is likewise reduced by the (BRI:FRI) ratio. Thus:

$$\boldsymbol{where\ SPI < -1.5\ and\ BRI > FRI}:$$

$$\boldsymbol{VC_{Mort}^{-}} = \left(\left(\boldsymbol{FireVC_{AG}^{PFT}} * \mathbf{0.248}\right) + \boldsymbol{E_{FCO2}}\right) * \left(\boldsymbol{BRI_{PFT}}/\boldsymbol{FRI_{PFT}}\right) \tag{10}$$

For the VC_{Mort}^{-} presented in the maps, figures and balance calculations, the total loss over the mortality period is calculated instantaneously for a given year, then spread into discrete annual loss terms over the cumulative period of dieback (see Supplementary Text S6) Note that online tree mortality calculations made by ORCHIDEE-SPITFIRE owing to crown and cambial scorching (Fig. S1) are excluded from the calculation of this metric as their time frame (quasi-instantaneous) is inconsistent with the phenomena measured and reported in the literature on which the VC_{Mort}^{-} term is based: drought induced fire leading to persistent, widespread and non-saturating dieback over several decades owing to a variety of fire and drought related physiological weaknesses. Likewise, instantaneously-killed biomass is a small fraction of the cumulative biomass loss instigated by drought-induced fires in tropical forests, according to the literature cited. Nevertheless, this quantity is in principle accounted for in the current iteration of VC_{Mort}^{-}.

Soil carbon loss in areas with high frequency fire ($\boldsymbol{SOC_{hfloss}^{-}}$)

These losses are based on a recent empirical study[22] which found that large topsoil SOC losses are apparent across multiple sites globally in areas with high fire frequency', defined therein as anywhere with roughly 4.3 times the mean fire frequency for a given vegetation type, with losses of 27% and 21% accruing in areas of broadleaf and grassland vegetation. Here, and for each PFT defined as broadleaf forest and grassland, we approximate this loss spatially first by isolating those pixels which have an FRI ≥4.3x that of the global average of that PFT (the threshold identified in ref. [22]). To account for the fact that the model simulation is transient and hence in the early years of simulation the topsoil carbon stocks will be unrealistically low, we only analyse SOC_{hfloss}^{-} for the last 30 years of simulation (1981-2010). The loss over the top 19cm of the soil column, based on the literature-derived soil loss parameters (27% ± 18% for broadleaf, 21% ± 12% for grassland)[22], is estimated for the relevant pixels during 1981-2010. Although SOC losses are not fully saturating in the Pellegrini et al. study, they are close enough that we assume that they represent total SOC losses due to high frequency fires. Our estimate is limited because the loss term is predicated on the last 30 years of simulation, whereas FRI is based on the temporal range of the simulation (110yrs; see above). Thus, once annualised, the SOC^{-}_{hfloss} estimate is constant over the whole simulation.

PyC export losses within the inland water network (SOC^{-}_{PyCExp})

A recent study has provided the first credible estimate to show that ~18 Tg of PyC in dissolved phase (Py-DOC) flushes out of the global terrestrial landmass into the inland aquatic network annually[23], while estimates of similar particulate PyC (Py-POC) aquatic export are thought to total ~25 TgC yr^{-1} [24]. Here, we use ORCHIDEE-MICT to construct the first gridded, PFT-specific and spatio-temporally dynamic estimate of outflux. Jones et al. (2020) estimated that boreal, tropical (<30° N/S) and temperate regions export 3.8 (± 0.6), 12.4 (± 4.9) and 1.8 (± 0.8) Tg Py-DOC yr^{-1}, respectively, providing observational constraints on the total export of Py-DOC for latitude bins ($\sum DOC_{Bin}$).

To integrate $\sum DOC_{Bin}$ with model output we estimate the contribution of each PFT to global PyC slow and PyC passive pool distributions and in doing so estimate the relative proportion of total DOC outflow originating from fires from each of these vegetation sources ($\sum DOC^{Pool}_{PFT}$). The relative global distribution of PyC produced are extracted from simulated global PyC soil pools in 1920, to approach historical distributions of PyC production. The fraction of total PyC per PFT and per PySOC pool ($f(PyC^{Pool}_{PFT})$) is calculated globally. The PFTs in $f(PyC^{Pool}_{PFT})$ are then split into boreal, temperate and tropical categories, and their fractional contribution to PyC of each bin to $PyC_{Slow}/PyC_{Passive}$ is calculated ($f(PyC_{PFT})^{Pool}_{Bin}$). C3 grasses incorporate temperate grasslands and tundra, so are split between by [temperate:boreal] surface area at 30-50° (~66%) and 50-90° N/S (~34%). Total mean absolute DOC flux (TgC yr^{-1}) per pool and PFT ($\sum \boldsymbol{DOC^{Pool}_{PFT}}$)is given by the following equation (Table S1):

$$\sum \boldsymbol{DOC^{Pool}_{PFT}} = \boldsymbol{f\left(PyC^{Pool}_{PFT}\right) * f(PyC_{PFT})^{Pool}_{Bin}} * \sum \boldsymbol{DOC_{Bin}} \qquad \textbf{(11)}$$

We assume that Py-POC export occurs proportionally to Py-DOC export based on their literature-reported global export rates, such that total Py-POC+DOC export occurs at a rate 2.39 (= (18+25)/25) times that of Py-DOC. The total Py-SOC that is hydrologically mobilized from each soil pool ($Hyd.PyC^{Pool}_{PFT}$) is thus given by:

$$\sum \boldsymbol{Hyd.PyC^{Pool}_{PFT}} = \sum \boldsymbol{DOC^{Pool}_{PFT}} * \mathbf{2.388} \qquad \textbf{(12)}$$

The global export quantities are then distributed spatially over the globe in proportion to soil PyC stocks. by a weighting based on the per-pixel fraction of the summed per-pool vertical PyC profile that is constituted by that pixel ($OUT^{Pool}_{PFT,Pixel}$):

$$\boldsymbol{OUT^{Pool}_{PFT,Pixel}} = \sum \boldsymbol{DOC^{Pool}_{PFT}} \;/ \boldsymbol{\left(\frac{\sum^{0m}_{3m} PyC^{Pool}_{Pix}}{\sum^{0m}_{3m} PyC^{Pool}_{Globe}}\right)} \qquad \textbf{(13)}$$

This generates gridded estimates for mean annual PFT-specific DOC+POC export that are constrained by the global latitude-specific estimates reported in ref.([23]). Interannual variability is implemented by allowing export to vary for each pixel by up 25% of the central value for each pixel in a manner that scales with deviation of annual precipitation from the median of the simulation period. Uncertainty is calculated by adjusting the DOC outflow values ($\sum DOC_{Bin}$) within the uncertainty ranges reported in ([23]).

Estimating Modelled Flame Temperature and Fire Radiative Power

Approximate flame temperatures for each fire event are calculated online within the ORCHIDEE-SPITFIRE code. There, the reaction intensity (see Eq. 9 in ref.[8]), i.e. the mean energy release rate per unit area of fire front (kJ m^{-2} min^{-1}), which is a measure of flame power, is converted to temperature using the classical Boltzmann equation:

$$\boldsymbol{Q = \mathcal{E} * k * T_F^4} \qquad \textbf{(14)}$$

where Q is flame power, Ɛ the emissivity of the combusting material (here assumed 0.9 for wood), k the Boltzmann constant and T_F flame temperature (K). The equation is solved for temperature and converted to Celsius. Given that this is the first time to our knowledge that wildfire flame temperatures are directly estimated by an earth system model, which are likewise not, to our knowledge, currently estimated by satellite products, we evaluate the flame temperature estimates simulated here by converting them to fire radiative power (FRP), a metric commonly employed by remote sensing practitioners for assessing fire intensity. For this purpose, we redeploy the equation proposed and employed by refs.[25,26] respectively, for returning FRP from MODIS satellite data to account for variations in pixel size:

$$\boldsymbol{FRP = A_s * \beta * \left(T_f^8 - T_b^8\right)} \qquad \textbf{(15)}$$

Where FRP (MWss) is fire radiative power, A_s is the nominal pixel area evaluated at scan or sample number, β is a coefficient relevant to the MODIS spectral response, while T_f and T_b are the temperature of the fire pixel and a 'representative' or neighbouring background pixel without fire, respectively. For our purposes, we convert each pixel to km^2, retain the beta coefficient, and use the calculated flame temperature T_F for T_f and the input climatological data for T_b, respectively. These are discussed in the Supplement.

Back-envelope estimation of PyC Bulk Mean Residence Time

The back-envelope estimates of minimum PyC MRT are made on the basis of a mix of existing stock and flow estimates, as well as the estimated maximum mineralisation rate found in this study. This is calculated using the maximum PyC mineralisation rate (E_{PyC}^{-} (PgC yr^{-1})), the estimated fraction of PyC in global SOC ($fPyC_{SOC}$), the estimated annual mineralisation of bulk SOC (E_{SOC} (PgC yr^{-1})) and the estimated bulk mean MRT of SOC globally (MRT_{SOC}, $(yrs.)$). PyC MRT (MRT_{PyC} (yrs.)) is estimated by:

$$\boldsymbol{MRT_{PyC} = (fPyC_{SOC}/(\frac{E_{PyC}^{-}}{E_{SOC}})) * MRT_{SOC}} \qquad \textbf{(16)}$$

For the central estimate, we use the central value of the residual found here and central values for the above variables found in the literature such that $fPyC_{SOC}$=13.7%[27], E_{SOC}=70 PgCyr^{-1})[28,29], and MRT_{SOC}=50 yrs[30]. For the range reported in the main text we varied the calculation by the calculated range of the residual and by the range of $fPyC_{SOC}$ in global grassland soils reported in ref.[31] and summarised in Table S8.

Code Availability:

The source code for this version of ORCHIDEE-MICT is available via https://forge.ipsl.jussieu.fr/orchidee/wiki/GroupActivities/CodeAvalaibilityPublication/ORCHIDEE_Biochar (DOI: https://doi.org/10.14768/054193dc-a5b0-4a51-bd11-3812e8f123079 Bowring, 2021). Please follow the online instructions for accessing the code -we suggest that interested parties contact the corresponding author for latest code versions containing bug fixes, improvements or cleaner code.

Data Availability

The data for Figure reconstruction in addition to data for tropical post drought-fire mortality and pyrogenic production and aquatic export are available online as figure source data and supplementary information, respectively, and are also deposited in the Zenodo digital repository [https://www.zenodo.org; DOI: https://doi.org/10.5281/zenodo.5789942], which is managed by the European Organization For Nuclear Research (CERN) and OpenAIRE. Due to file size limitations we are unable to deposit primary data (model output) online. These are archived on the Obelix cluster and repository managed by LSCE/IPSL that can be made available upon request by contacting the corresponding author.

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