Historical (1700–2012) Global Multi-model Estimates of the Fire Emissions from the Fire Modeling Intercomparison Project (FireMIP)

Fang Li1*, Maria Val Martin2, Stijn Hantson3,4, Meinrat O. Andreae5, Almut Arneth4, Gitta Lasslop6, Chao Yue7,8, Dominique Bachelet6, Matthew Forrest6, Johannes W. Kaiser10,5, Erik Kluzek11, Xiaohong Liu12, Joe R. Melton13, Daniel S. Ward14, Anton Darmenov15, Thomas Hickler6,16, Charles Ichoku17, Brian I. Magi18, Stephen Sitch19, Guido R. van der Werf20, Christine Wiedinmyer21

1 International Center for Climate and Environment Sciences, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing, China
2 Leverhulme Center for Climate Change Mitigation, Department of Animal & Plant Sciences, Sheffield University, Sheffield, UK
3 Geospatial Data Solutions Center, University of California, Irvine, CA, USA
4 Karlsruhe Institute of Technology (KIT), Institute of Meteorology and Climate research, Atmospheric Environmental Research, Garmisch-Partenkirchen, Germany
5 Max Planck Institute for Chemistry, Mainz, Germany
6 Senckenberg Biodiversity and Climate Research Institute (BiK-F), Senckenberganlage, Germany
7 Laboratoire des Sciences du Climat et de l’Environnement, LSCE/IPSL, CEA-CNRS-UVSQ, Université Paris-Saclay, Gif-sur-Yvette, France
8 State Key Laboratory of Soil Erosion and Dryland Farming on the Loess Plateau, Northwest A&F University, Yangling, Shanxi, China
9 Biological and Ecological Engineering, Oregon State University, Corvallis, OR, USA

10 Deutscher Wetterdienst, Offenbach, Germany

11 National Center for Atmospheric Research, Boulder, CO, USA

12 Department of Atmospheric Science, University of Wyoming, Laramie, WY, USA

13 Climate Research Division, Environment and Climate Change Canada, Victoria, BC, Canada

14 Karen Clark and Company, Boston, MA, USA

15 Global Modeling and Assimilation Office, NASA Goddard Space Flight Center, Greenbelt, MD, USA

16 Department of Physical Geography, Goethe University, Frankfurt am Main, Germany

17 Howard University, NW, Washington, DC, USA

18 Department of Geography and Earth Sciences, University of North Carolina at Charlotte, Charlotte, NC, USA

19 College of Life and Environmental Sciences, University of Exeter, Exeter, UK

20 Faculty of Science, Vrije Universiteit, Amsterdam, The Netherlands

21 University of Colorado Boulder, Boulder, CO, USA

*Correspondence to: Fang Li (lifang@mail.iap.ac.cn)
Abstract

Fire emissions are critical for carbon and nutrient cycles, climate, and air quality. Dynamic Global Vegetation Models (DGVMs) with interactive fire modeling provide important estimates for long-term and large-scale changes of fire emissions. Here we present the first multi-model estimates of global gridded historical fire emissions for 1700–2012, including carbon and 33 species of trace gases and aerosols. The dataset is based on simulations of nine DGVMs with different state-of-the-art global fire models that participated in the Fire Modeling Intercomparison Project (FireMIP), using the same and standardized protocols and forcing data, and the most up-to-date fire emission factor table from field and laboratory studies over various land cover types. We evaluate the simulations of present-day fire emissions by comparing them with satellite-based products. Evaluation results show that most DGVMs simulate present-day global fire emission totals within the range of satellite-based products, and can capture the high emissions over the tropical savannas, low emissions over the arid and sparsely vegetated regions, and the main features of seasonality. However, most of the models fail to simulate the interannual variability, partly due to a lack of modeling peat fires and tropical deforestation fires. Historically, all models show only a weak trend in global fire emissions before ~1850s, consistent with multi-source merged historical reconstructions. The long-term trends among DGVMs are quite different for the 20th century, with some models showing an increase and others a decrease in fire emissions, mainly as a result of the discrepancy in their simulated responses to human population density change and land-use and land-cover change.
Our study provides a basic dataset for developing regional and global multi-source merged historical reconstructions and merging methods, and analyzing historical changes of fire emissions and their uncertainties as well as their role in the Earth system. It also highlights the importance of accurately modeling the responses of fire emissions to LULCC and population density change in reducing uncertainties in historical reconstructions of fire emissions and providing more reliable future projections.

1. Introduction

Fire is an intrinsic feature of terrestrial ecosystem ecology globally, and has emerged soon after the appearance of terrestrial plants over 400 million years ago (Scott and Glasspool, 2006; Bowman et al., 2009). Fire emissions are a key component of the global and regional carbon budgets (Bond-Lamberty et al., 2007; Ciais et al., 2013; Kondo et al., 2018), and also a major source of greenhouse gases (Tian et al., 2016) and the largest contributor of primary carbonaceous aerosols globally (Andreae and Rosenfeld, 2008; Jiang et al., 2016). By changing the atmospheric composition, fire emissions can have resultant effects on global and regional radiation balance and climate (Ward et al., 2012; Tosca et al. 2013; Jiang et al., 2016; Grandey et al., 2016; McKendry et al., 2018; Hamilton et al., 2018; Thornhill et al., 2018), terrestrial nutrient and carbon cycles (Mahowald et al., 2008; Chen et al., 2010; McKendry et al., 2018; Yue and Unger, 2018), and air quality (Val Martin et al., 2015; Knorr et al., 2017), which is a major human health hazard and has been estimated to result in at
least ~165,000, and more likely ~339,000 premature deaths per year globally (Johnston et al., 2012; Marlier et al., 2013; Lelieveld et al., 2015).

To date, only emissions from individual fires or small-scale fire complexes can be directly measured from laboratory experiments and field campaigns (Andreae and Merlet, 2001; Yokelson et al., 2013; Stockwell et al., 2016). Regionally and globally, fire emissions are estimated based on satellite observations, fire proxies, or numerical models. Satellite-based fire emission estimates are derived from satellite observations of burned area, active fire counts, fire radiative power, and/or constrained by satellite observations of aerosol optical depth (AOD), CO, or CO$_2$ (Wiedinmyer et al., 2011; Kaiser et al., 2012; Krol et al., 2013; Konovalov et al., 2014; Ichoku and Ellison, 2014; Darmenov and da Silva, 2015; van der Werf et al., 2017; Heymann et al., 2017). Data are available globally, but only cover the present-day period. Fire proxies include records of CH$_4$, black carbon, levoglucosan, ammonium, and CO concentration trapped in the air enclosed in ice cores (Ferretti et al., 2005; McConnell et al., 2007; Wang et al., 2012; Zennaro et al., 2014), site-level sedimentary charcoal records (Marlon et al., 2008, 2016), visibility records (van Marle et al., 2017a), and aerosol indices (Duncan et al., 2003). These fire proxies cover decades to millennia, but are of limited spatial extent, cannot be directly related to emission amount, and have large uncertainties and discrepancies in their referred regional or global long-term trends due to limited sample size or/and often unclear representative area and time period of fire emissions (Pechony and Shindell, 2010; van der Werf et al., 2013; Legrand et al., 2016).
Dynamic Global Vegetation Models (DGVMs) that include fire modeling are indispensable for estimating fire carbon emissions at global and regional scales and for past, present, and future periods (Hantson et al., 2016). These models represent interactions among fire dynamics, biogeochemistry, biogeophysics, and vegetation dynamics at the land surface in a physically and chemically consistent modeling framework. DGVMs also constitute the terrestrial ecosystem component of Earth System models (ESMs) and are applied to global change research (Levis et al., 2004; Li et al., 2013; Kloster and Lasslop, 2017). Using fire carbon emissions simulated by DGVMs and fire emission factors, fire emissions of trace gases and aerosols can be derived (Li et al., 2012; Knorr et al., 2016).

Modeling fire and fire emissions within DGVMs started in the early 2000s (Thonicke et al., 2001), and has rapidly progressed during the past decade (Hantson et al., 2016). The Fire Model Intercomparison Project (FireMIP) initiated in 2014 was the first international collaborative effort to better understand the behavior of global fire models (Hantson et al., 2016), where a set of common fire modeling experiments driven by the same forcing data were performed (Rabin et al., 2017). Nine DGVMs with different state-of-the-art global fire models participated in FireMIP. All global fire models used in the upcoming 6th Coupled Model Intercomparison Project (CMIP6) and IPCC AR6 were included in FireMIP, except for the fire scheme in GFDL-ESM (Rabin et al., 2018; Ward et al., 2018) which is similar to that of CLM4.5 (Li et al., 2012) in FireMIP. Furthermore, GlobFIRM (Thonicke et al., 2001) in FireMIP was the most commonly-used fire scheme in CMIP5 (Kloster and Lasslop, 2017).
Earlier studies provided only one single time series of fire emissions for global grids or regions (Schultz et al., 2008; Mieville et al., 2010; Lamarque et al., 2010; Marlon et al., 2016; van Marle et al., 2017b; and references therein), limiting their utility for quantifying the uncertainty in global and regional reconstructions of fire emissions and its subsequent impacts on estimated historical changes in carbon cycle, climate, and air pollution. A small number of studies also investigated the drivers of fire carbon emission trends (Kloster et al., 2010; Yang et al., 2014; Li et al., 2018; Ward et al., 2018). However, because only a single DGVM was used in these studies, they could not identify the uncertainty source in recent model-based reconstructions or help understand the inter-model discrepancy in projections of future fire emissions.

Our study provides a new dataset of global gridded fire emissions, including carbon and 33 species of trace gases and aerosols, over the 1700–2012 time period, based on the nine DGVMs with different state-of-the-art global fire models that participated in FireMIP. The dataset provides the basis for developing multi-source (satellite-based products, model simulations, and/or fire proxies) merged fire emission reconstructions and methods. It also, for the first time, allows end users to select all or a subset of model-based reconstructions that best suits their regional or global research needs, and importantly, to quantify the uncertainty range of past fire emissions and their resulting impacts. In addition, the model-based estimates of fire emissions are comprehensively evaluated through comparison with satellite-based products, including amounts, spatial distribution, seasonality, and interannual variability, providing information on the limitations of recent model-based
reconstructions. We also analyze long-term trends of the model-based reconstructions, and the forcing drivers of these trends for each DGVM and for inter-model discrepancy.

2 Methods and datasets

2.1 Models in FireMIP

Nine DGVMs with different fire modules participated in FireMIP: CLM4.5 with CLM5 fire module, CTEM, JSBACH-SPITFIRE, JULES-INFERNO, LPJ-GUESS-GlobFIRM, LPJ-GUESS-SIMFIRE-BLAZE, LPJ-GUESS-SPITFIRE, MC2, and ORCHIDEE-SPITFIRE (Table 1, see Rabin et al., 2017 for detailed description of each model). JSBACH, ORCHIDEE, and LPJ-GUESS used the variants of SPITFIRE (Thonicke et al., 2010) with updated representation of human ignitions and suppression, fuel moisture, combustion completeness, and the relationship between spread rate and wind speed for JSBACH (Lasslop et al., 2014), combustion completeness for ORCHIDEE (Yue et al., 2014, 2015), and human ignition, post-fire mortality factors, and modifications for matching tree age/size structure for LPJ-GUESS (Lehsten et al., 2009; Rabin et al., 2017).

The global fire models in the nine DGVMs have diverse levels of complexity (Rabin et al., 2017). SIMFIRE is a statistical model based on present-day satellite-based fire products (Knorr et al., 2016). In CLM4.5, crop, peat, and tropical deforestation fires are empirically/statistically modeled (Li et al., 2013). The scheme for fires outside the tropical closed forests and croplands in CLM4.5 (Li et al., 2012;
Li and Lawrence, 2017) and fire modules in CTEM (Arora and Boer, 2005; Melton and Arora, 2016), GlobFIRM (Thonicke, 2001), and INFERNO (Mangeon et al., 2016) are process-based and of intermediate-complexity. That is, area burned is determined by two processes: fire occurrence and fire spread, but with simple empirical/statistical equations for each process. Fire modules in MC2 (Bachelet et al., 2015; Sheehan et al., 2015) and SPITFIRE variants are more complex, which use the Rothermel equations (Rothermel, 1972) to model fire spread and consider the impact of fuel composition on fire behavior.

The way in which humans affect fire is treated differently among these global fire models (Table 1), influencing the simulations of fire emissions. GlobFIRM does not consider any direct human effect on fires, and MC2 fire model only considers human suppression on fire. CLM4.5 includes crop fires, fires caused by man-made deforestation in tropical closed forests, and human ignitions and suppression on both fire occurrence and spread area for fires outside tropical closed forests and croplands. Burned area in SIMFIRE and human influence on fire occurrence in other models are a non-linear function of population density. CTEM and JSBACH-SPITFIRE also consider human suppression on fire duration. All models, except for CLM4.5, set burned area zero over cropland. Models treat pasture fires as natural grassland fires by using the same parameter values if they have pasture plant functional types (PFTs) or lumping pastures with natural grasslands otherwise. Note that biomass harvest is considered in pastures in LPJ-GUESS-GlobFIRM and
LPJ-GUESS-SIMFIRE-BLAZE, which decreases fuel availability for fires, and that JSBACH-SPITFIRE sets high fuel bulk density for pasture PFTs. Only CLM4.5 simulates peat fires, although only emissions from burning of vegetation tissues and litter are included in outputs for FireMIP (i.e. burning of soil organic matter is not included).

In the FireMIP models, fire carbon emissions are calculated as the product of burned area, fuel load, and combustion completeness. Combustion completeness is the fraction of live plant tissues and ground litter burned (0.0–1.0). It depends on PFT and plant tissue type in GlobFIRM and in the fire modules of CLM4.5 and CTEM, and also a function of soil moisture in INFERNO. Combustion completeness depends on plant tissue type and surface fire intensity in SIMFIRE, fuel type and wetness in the SPITFIRE family models, and fuel type, load, and moisture in MC2 fire module.

2.2 FireMIP experimental protocol and input datasets

Fire emissions in this study are estimated using the model outputs of PFT-level fire carbon emissions and vegetation characteristics (PFTs and their fractional area coverages) from the FireMIP historical transient control run (SF1) (Rabin et al., 2017). SF1 includes three phases (Fig. 1): the 1700 spin-up phase, the 1701–1900 transient phase, and the 1901–2012 transient phase. In the 1700 spin-up phase, all models are spun up to equilibrium, forced by population density and prescribed land-use and land-cover change (LULCC) at their 1700 values, 1750 atmospheric CO$_2$ concentration, and the repeatedly cycled 1901–1920 atmospheric forcing.
(precipitation, temperature, specific humidity, surface pressure, wind speed, and solar radiation) and lightning data. The 1701–1900 transient phase is forced by 1701–1900 time-varying population and LULCC, with constant CO$_2$ concentration at 1750 level until 1750 and time-varying CO$_2$ concentration for 1750–1900, and the cycled 1901–1920 atmospheric forcing and lightning data. In the 1901–2012 transient phase, models are driven by 1901–2012 time-varying population density, LULCC, CO$_2$ concentration, atmospheric forcing, and lightning data. Unlike all other models, MC2 and CTEM run from 1901 and 1861, respectively, rather than 1700.

The nine DGVMs are driven with the same forcing data (Rabin et al., 2017). The atmospheric forcing is from CRU-NCEP v5.3.2 with a spatial resolution of 0.5° and a 6-hourly temporal resolution (Wei et al., 2014). The 1750–2012 annual global atmospheric CO$_2$ concentration is derived from ice core and NOAA monitoring station data (Le Quéré et al., 2014). Annual LULCC and population density at a 0.5° resolution for 1700–2012 are from Hurtt et al. (2011) and Klein Goldewijk et al. (2010, HYDE v3.1), respectively. Monthly cloud-to-ground lightning frequency for 1901–2012, at 0.5° resolution, is derived from the observed relationship between present-day lightning and convective available potential energy (CAPE) anomalies (Pfeiffer et al., 2013, J. Kaplan, personal communication, 2015).

Six FireMIP models (CLM4.5, JSBACH-SPITFIRE, JULES-INFERN0, LPJ-GUESS-SPITFIRE, LPJ-GUESS-SIMFIRE-BLAZE, and ORCHIDEE-SPITFIRE) also provide outputs of five sensitivity simulations: constant climate, constant atmospheric CO$_2$ concentration, constant land cover, constant
population density, and constant lightning frequency throughout the whole simulation period. The sensitivity simulations are helpful for understanding the drivers of changes in reconstructed fire emissions.

2.3 Estimates of fire trace gas and aerosol emissions

Based on fire carbon emissions and vegetation characteristics from DGVMs and fire emission factors, fire emissions of trace gas and aerosol species $i$ and the PFT $j$, $E_{ij}$ (g species m$^{-2}$ s$^{-1}$), are estimated according to Andreae and Merlet (2001):

$$E_{ij} = EF_{ij} \times CE_{j} / [C],$$

where $EF_{ij}$ (g species (kg dry matter (DM))$^{-1}$) is a PFT-specific emission factor (EF), $CE_{j}$ denotes the fire carbon emissions of PFT $j$ (g C m$^{-2}$ s$^{-1}$), and $[C]=0.5 \times 10^3$ g C (kg DM)$^{-1}$ is a unit conversion factor from carbon to dry matter.

The EFs used in this study (Table 2) are based on Andreae and Merlet (2001), with updates from field and laboratory studies over various land cover types published during 2001–2018 (see Andreae (2019) for details). The EFs are used for all simulations of FireMIP models in the present study.

DGVMs generally simulate vegetation as mixture of PFTs in a given grid location to represent plant function at global scale, instead of land cover types. In Table 3, we associate the PFTs from each DGVM to the land cover types shown in Table 2. Grass, shrub, savannas, woodland, pasture, tundra PFTs are classified as grassland/savannas; tree PFTs as forests and crop PFTs as cropland, similar to Li et al. (2012), Mangeon et al. (2016), and Melton and Arora (2016). PFTs of other broadleaf
deciduous tree in CTEM, extra-tropical evergreen and deciduous tree in JSBACH, and
broadleaf deciduous tree and needleleaf evergreen tree in JULES are divided into
tropical, temperate, and boreal groups following Nemani and Running (1996).

We provide two versions of fire emission products with different spatial
resolutions: the original spatial resolution for each FireMIP DGVM outputs (Table 1),
and a 1x1 degree horizontal resolution. For the latter, fire emissions are unified to 1
degree resolution using bilinear interpolation for CLM4.5, CTEM, JSBACH, and
JULES which have coarser resolution, and area-weighted averaging-up for other
models whose original resolution is 0.5 degree. The 1x1 degree product is used for
present-day evaluation and historical trend analyses in Sects. 3 and 4.

2.4 Benchmarks

Satellite-based products are commonly used as benchmarks to evaluate present-day
fire emission simulations (Rabin et al., 2017, and references therein). In the present
study, six satellite-based products are used (Table 4). Fire emissions in
GFED4/GFED4s (small fires included in GFED4s) (van der Werf et al., 2017),
GFAS1 (Kaiser et al., 2012), and FINN1.5 (Wiedinmyer et al., 2011) are based on EF
and CE (Eq. 1). CE is estimated from MODIS burned area and VIRS/ATSR active
fire products in the GFED family, MODIS active fire detection in FINN1.5, and
MODIS fire radiative power (FRP) in GFAS1. Fire emissions from FEER1 (Ichoku
and Ellison, 2014) and QFEDv2.5 (Darmenov and da Silva, 2015) are derived using
FRP, and constrained with satellite AOD observations. Satellite-based present-day fire
emissions for the same region can differ by a factor of 2–4 on an annual basis (van der Werf et al., 2010) and up to 12 on a monthly basis (Zhang et al., 2014). The discrepancy among them mainly comes from the satellite observations used, the methods applied for deriving fire emissions, and emissions factors.

2.5 Multi-source merged historical reconstruction

We also compared the simulated historical changes with historical reconstructions merged from multiple sources used as forcing data for CMIPs. Fire emission estimates for CMIP5 and CMIP6 were merged from different sources (Table 4). For CMIP5 (Lamarque et al., 2010), the decadal fire emissions are available from 1850 to 2000, estimated using GFED2 fire emissions (van der Werf et al., 2006) for 1997 onwards, RETRO (Schultz et al., 2008) for 1960–1900, GICC (Mieville et al., 2010) for 1900-1950, and kept constant at the 1900 level for 1850–1900. RETRO combined literature reviews with satellite-based fire products and the GlobFIRM fire model. GICC is based on a burned area reconstruction from literature review and sparse tree ring records (Mouillot et al., 2005), satellite-based fire counts, land cover map, and representative biomass density and burning efficiency of each land cover type.

For CMIP6, monthly fire emission estimates are available from 1750 to 2015 (van Marle et al., 2017b). The CMIP6 estimates are merged from GFED4s fire carbon emissions for 1997 onwards, charcoal records GCDv3 (Marlon et al., 2016) for North America and Europe, visibility records for Equatorial Asia (Field et al., 2009) and central Amazon (van Marle et al., 2017b), and the median of six FireMIP models.
(CLM4.5, JSBACH-SPITFIRE, JULES-INFERNO, LPJ-GUESS-SPITFIRE, LPJ-GUESS-SIMFIRE-BLAZE, and ORCHIDEE-SPITFIRE) for all other regions. Then, based on the merged fire carbon emissions, CMIP6 fire trace gas and aerosols emissions are derived using EF from Andreae and Merlet (2001) with updates to 2013 and Akagi et al. (2011) with updates for temperate forests to 2014, and a present-day land cover map.

3 Evaluation of present-day fire emissions

The spatial pattern and temporal variability of different fire emission species are similar, with slight discrepancies resulting from the estimated fire carbon emissions over the land cover types that have different emission factors (Table 2). Therefore, we focus on several important species as examples to exhibit the performance of FireMIP models on the simulations of present-day fire emissions.

3.1 Global amounts and spatial distributions

As shown in Table 5, FireMIP models, except for MC2 and LPJ-GUESS-GlobFIRM, estimate present-day fire carbon, CO₂, CO, CH₄, BC, OC, and PM₂.₅ annual emissions to be within the range of satellite-based products. For example, the estimated range of fire carbon emissions is 1.7–3.0 Pg C yr⁻¹, whereas they are 1.5–4.2 Pg C yr⁻¹ for satellite-based products. Low fire emissions in MC2 result from relatively low simulated global burned area, only about 1/4 of satellite-based observations (Andela et al., 2017), whereas high emissions in LPJ-GUESS-GlobFIRM are mainly due to the
higher combustion completeness of woody tissues (50-90% of stem and coarse woody debris burned in post-fire regions) than those used in other FireMIP models (Rabin et al., 2017) and the satellite-based GFED family (van der Werf et al., 2017). FireMIP DGVMs, except for MC2, represent the general spatial distribution of fire emissions evident in satellite-based products, with high fire BC emissions over tropical savannas and low emissions over the arid and sparsely vegetated regions (Fig. 2). Among the nine models, CLM4.5, JULES-INFERNO, and LPJ-GUESS-SIMFIRE-BLAZE have higher global spatial pattern correlation with satellite-based products than the other models, indicating higher skill in their spatial-pattern simulations. It should also be noted that, on a regional scale, CTEM, JULES-INFERNO, LPJ-GUESS-SPITFIRE, and ORCHIDEE-SPITFIRE underestimate fire emissions over boreal forests in Asia and North America. LPJ-GUESS-GlobFIRM and LPJ-GUESS-SIMFIRE-BLAZE overestimate fire emissions over the Amazon and African rainforests. CLM4.5 and JSBACH-SPITFIRE overestimate fire emissions over eastern China and North America, respectively. MC2 underestimates fire emissions over most regions, partly because it allows only one ignition per year per grid cell and thus underestimates the burned area.

We further analyze the spatial distribution of inter-model difference. As shown in Fig. 3, the main disagreement among FireMIP models occurs in the tropics, especially over the tropical savannas in Africa, South America, and northern Australia.
3.2 Seasonal cycle

FireMIP models reproduce similar seasonality features of fire emissions to satellite-based products, that is, peak month is varied from the dry season in the tropics to the warm season in the extra-tropics (Fig. 4).

For the tropics in the Southern Hemisphere, fire PM2.5 emissions of satellite-based products peak in August–September. Most FireMIP models can reproduce this pattern, except ORCHIDEE-SPITFIRE and LPJ-GUESS-SPITFIRE peaking two months and one month earlier, respectively, and JSBACH-SPITFIRE with much lower amplitude of seasonal variability.

For the tropics in the Northern Hemisphere, most FireMIP models exhibit larger fire emissions in the northern winter, consistent with the satellite-based products.

In the northern extra-tropical regions, satellite-based products show two periods of high values: April–May resulting mainly from fires over croplands and grasslands, and July mainly due to fires over the boreal evergreen forests. Most FireMIP models can reproduce the second one, except for LPJ-GUESS-SPITFIRE which peaks in October. CLM4.5 is the only model that can captures both peak periods.

3.3 Interannual variability

Global fire PM2.5 emissions from satellite-based products for 1997–2012 show a substantial interannual variability, which peaks in 1997–1998, followed by a low around 2000 and a decline starting in 2002/2003 (Fig. 5). The 1997–1998 high
emission values are caused by peat fires in Equatorial Asia in 1997 and widespread
drought-induced fires in 1998 associated with the most powerful 1997–1998 El Niño
event recorded in history (van der Werf et al., 2017; Kondo et al., 2018). Most
FireMIP models cannot reproduce the 1997–1998 peak, except CLM4.5 as the only
model that simulates the burning of plant-tissue and litter from peat fires (although
burning of soil organic matter is not included) and the drought-linked tropical
deforestation and degradation fires (Li et al., 2013, Kondo et al., 2018). CLM4.5,
CTEM, and LPJ-GUESS-SIMFIRE-BLAZE present the highest temporal correlation
between models and satellite-based products (0.55–0.79 for CLM4.5, 0.51–0.68 for
CTEM, and 0.39–0.72 for LPJ-GUESS-SIMFIRE-BLAZE), and thus are more skillful
than other models to reproduce the interannual variability observed from
satellite-based products (Table 6).

We use the coefficient of variation (CV, the standard deviation divided by the
mean, %) to represent the amplitude of interannual variability of fire emissions. As
shown in Fig. 5, for 1997–2012, all FireMIP models underestimate the variation as a
result of (at least) partially missing the 1997–1998 fire emission peak. For 2003–2012
(the common period of all satellite-based products and models), interannual variation
of annual fire PM\textsubscript{2.5} emissions in CLM4.5, CTEM, and LPJ-GUESS family models
lies within the range of satellite-based products (CV=6–12%). Other models present
weaker variation (CV=5%) except for MC2 (CV=24%) that has a much stronger
variation than all satellite-based products and other FireMIP models.
4 Historical changes

4.1 Historical changes and drivers

Figure 6 shows historical simulations of the FireMIP models and the CMIP reconstructions for fire carbon, CO₂, CO and PM₂.₅ species. We find similar historical changes for all the species, with the maximum global fire emissions given by LPJ-GUESS-GlobFIRM and the minima by LPJ-GUESS-SPITFIRE before 1901 and MC2 afterwards.

Long-term trends in modelled global fire emissions for all models are weak before the 1850s (relative trend <0.015% yr⁻¹), similar to CMIP6 estimates (Fig. 6).

After the 1850s, disagreement in the trends among FireMIP models begins to emerge. Fire emissions in LPJ-GUESS-SIMFIRE-BLAZE decline since ~1850, while fire emissions in LPJ-GUESS-SPITFIRE, MC2, and ORCHIDEE-SPITFIRE show upward trends from ~1900s. In CLM4.5, CTEM, and JULES-INFERNO, fire emissions increase slightly before ~1950, similar to the CMIP6 estimates, but CTEM and JULES-INFERNO decrease thereafter, contrary to CMIP5 and CMIP6 estimates and CLM4.5. JSBACH-SPITFIRE simulates a decrease of fire emissions before 1940s and an increase later, similar to the CMIP5 estimates. All the long-term trends described above are significant at the 0.05 level using the Mann-Kendall trend test.

Six FireMIP models also conducted sensitivity experiments, which can be used to identify the drivers of their long-term trends during the 20th century. As shown in Figs. 6 and 7, the downward trend of LPJ-GUESS-SIMFIRE-BLAZE is mainly caused by LULCC and increasing population density. Upward trends in
LPJ-GUESS-SPITFIRE and ORCHIDEE-SPITFIRE are dominated by LULCC and rising population density and CO$_2$ during the 20th century. In CLM4.5 and JULES-INFERNO, upward trends before ~1950 are attributed to rising CO$_2$, climate change, and LULCC, and the subsequent drop in JULES-INFERNO mainly results from the rising population density and climate change. Long-term changes in JSBACH-SPITFIRE are mainly driven by LULCC and rising CO$_2$.

4.2 Drivers for difference in simulated long-term changes

The discrepancy in long-term trends among FireMIP models mainly arises from the simulated anthropogenic influence (LULCC and population density change) on fire emissions (Fig. 7), as the standard deviation in simulated responses to LULCC (0.27 Pg C yr$^{-1}$) and population density (0.11 Pg C yr$^{-1}$) is much larger than the other drivers.

LULCC decreases fire emissions sharply in LPJ-GUESS-SIMFIRE-BLAZE during the 20th century, but increases fire emissions for the other models except for JSBACH-SPITFIRE. The response to LULCC in LPJ-GUESS-SIMFIRE-BLAZE is because it assumes no fire in croplands and accounts for biomass harvest (decreases fuel availability) in pastures (Table 1), the area of which expanded over the 20th century. The LULCC-induced increase in fire emissions for the other models are partly caused by increased burned area due to the expansion of grassland (pastures are lumped in grassland in these models) which burn much more easily than woody vegetation in the setup of all FireMIP models (Rabin et al., 2017). Additionally,
CLM4.5 models crop fires, which are estimated to increase during the 20th century. JSBACH shifts the sign of response to LULCC around ~1940s due to both assuming no fires over croplands and setting high fuel bulk density for pastures. Rising population density throughout the 20th century decreases fire emissions in CLM4.5 and LPJ-GUESS-SIMFIRE-BLAZE because they include human suppression on both fire occurrence and fire spread. Fire suppression increases with rising population density simulated explicitly in CLM4.5 and implicitly in LPJ-GUESS-SIMFIRE-BLAZE. On the contrary, rising population density increases fire emissions in LPJ-GUESS-SPITFIRE and ORCHIDEE-SPITFIRE because observed human suppression on fire spread found in Li et al. (2013), Hantson et al. (2015), and Andela et al. (2017) is not taken into account in the two models. The response to population density change for the other models is small, reflecting the compensating effects of human ignition and human suppression on fire occurrence (strongest in JULES-INFERNO in FireMIP models), and human suppression on fire duration (JSBACH-SPITFIRE).

All models simulate increased fire emissions with increased CO₂ since elevated CO₂ increases fuel load through increasing the carbon entering into the land ecosystems (Mao et al., 2009) and improving the water-use efficiency (Keenan et al., 2013). Such a CO₂-driven increase of fuel load is consistent with a recent analysis of satellite-derived vegetation indices (Zhu et al., 2016). FireMIP models also agree that impacts of changes in lightning frequency on long-term trends of fire emissions are small. Moreover, most FireMIP models agree that climate change tends to increase
fire carbon emissions during the first several decades and then falls, reflecting
co-impacts of climate on both fuel load and fuel moisture.

4.3 Regional long-term changes
We divided the global map into regions following the definition of the GFED family
(Fig. 8a). As shown in Fig. 8b, inter-model discrepancy in long-term changes are
largest in Southern Hemisphere South America (SHSA), southern and northern Africa
(NHAF and SHAF), and central Asia (CEAS). In other regions, long-term changes of
most FireMIP models are small, similar to CMIP5 or CMIP6 fire emission estimates,
except for equatorial Asia where only CLM4.5 partly reproduces the upward trend
shown in CMIP5 and CMIP6 estimates after 1950s (not shown).

Most FireMIP models reproduce the upward trends found also in the CMIP5 or
CMIP6 estimates since 1950s in SHSA and till ~1950 in Africa (Figs. 9a and b).
Long-term trends in regional fire emissions in SHSA, Africa, and central Asia can
broadly explain the upward trends in global fire emissions in LPJ-GUESS-SPITFIRE,
MC2, and ORCHIDEE-SPITFIRE, the downward trends in
LPJ-GUESS-SIMFIRE-BLAZE, and the rise followed by a drop in CTEM, whose
global fire emissions exhibit most obvious long-term trends in FireMIP models (Fig.
6).
Our study provides new multi-model reconstructions of global historical fire emissions for 1700–2012, including carbon and 33 species of trace gases and aerosols. Two versions of the fire emission product are available, at the original spatial resolution for outputs of each FireMIP model and at a unified 1x1 degree. The dataset is based on simulations of fire carbon emissions and vegetation distribution from nine DGVMs with state-of-the-art global fire models that participated in FireMIP and the most up-to-date emission factors over various land cover types. It will be available to the public at https://bwfilestorage.lsdf.kit.edu/public/projects/imk-ifu/FireMIP/emissions.

Our study provides an important dataset with wide-ranging applications for the fire and Earth science research communities. First, it is the best multi-model-based reconstruction of fire emissions so far and for the next several years, and can serve as the basis for further developing multi-source merged products of global and regional fire emissions and the merging methodology. van Marle et al. (2017b) presented an example for using part of the dataset to develop a multi-source merged fire emission product as forcing dataset for CMIP6. In van Marle et al. (2017b), the median of fire carbon emissions from six FireMIP models was used to determine historical changes over most regions of the world. The merging method and merged product in van Marle et al. (2017b) are still preliminary, and need to be improved in the future, e.g. by weighting the different models depending on their global or regional simulation skills. Secondly, our dataset includes global gridded reconstructions for 300 years, thus can be used for analyzing global and regional historical changes in fire emissions.
on inter-annual to multi-decadal time scales and their interplay with climate variability and human activities. Third, the fire emission reconstructions based on multiple models provide, for the first time, a chance to quantify and understand the uncertainties in historical changes of fire emissions and their subsequent impacts on carbon cycle, radiative balance, air quality, and climate. Hamilton et al. (2018), for example, using fire emission simulations from two global fire models and the CMIP6 estimates to drive an aerosol model, quantified the impact of uncertainties in pre-industrial fire emissions in estimated pre-industrial aerosol concentrations and historical radiative forcing.

This study also provides significant information of the recent state of fire model performance by evaluating the present-day estimates based on FireMIP fire models (also those used in the upcoming CMIP6). Our results show that most FireMIP models can overall reproduce the amount, spatial pattern, and seasonality of fire emissions shown by satellite-based fire products, but fail to simulate the interannual variability partly due to a lack of modeling peat and tropical deforestation fires. In addition, Teckentrup et al. (in prep.) found that climate greatly affected interannual variability of burned area partly through affecting fire duration. However, all FireMIP models limit their fire duration of individual fire events within one day over natural vegetation regions, so they cannot skillfully model the drought-induced large fires that last multiple days (Le Page et al., 2015; Ward et al., 2018). Recently, Andela et al. (2018) derived a dataset of fire duration from MODIS satellite observations, which
provided a valuable dataset for developing parameterization of fire duration in global
fire models.

This study also identifies population density and LULCC as the primary
uncertainty sources in fire emission estimates. Therefore, accurately modeling these
responses remains a top priority to reduce uncertainty in historical reconstructions and
future projections of fire emissions, especially given that modeling is the only way for
future projections. For the response to changes in population density, many FireMIP
models have not included the observed relationship between population density and
fire spread (Table 1). Moreover, Bistina et al. (2014) and Parisien et al. (2016)
reported obvious spatial heterogeneity of the population density–burned area
relationship that is poorly represented in FireMIP models.

For the response to LULCC, improving the modeling of crop and pasture fires
and human indirect effect on fires (e.g. fragmentation of the landscape) is critical.
Earlier studies reported that the timing and emissions from crop fires were different
from natural vegetation fires, and that crop fires could be an important source of
greenhouse gas and air pollutant emissions (Magi et al., 2012; Tian et al., 2016; Wu et
al., 2017). In FireMIP, only CLM4.5 simulates crop fires, whereas the other models
assume no fire over croplands. For pasture fires, all FireMIP models assume that they
are as natural grassland fires and this needs to be verified by, for example,
satellite-based products. If fires over pastures and natural grasslands are significantly
different, adding the gridded coverage of pasture as a new input field in DGVMs
without pasture PFTs and developing a parameterization of pasture fires will be
necessary. In addition, Archibald (2016) and Andela et al. (2017) found that expansion of croplands and pastures decreased fuel continuity and thus reduced burned area and fire emissions. However, no FireMIP model parameterizes this indirect human effect on fires.

Author contribution. FL contributed to the processing and analyses of the fire emission dataset. SS and AA designed the FireMIP experiments and LF, SH, GL, CY, DB, MF, JM, and TH performed FireMIP simulations. MA compiled the EF table. JK, AD, CI, Gv, CW provided satellite-based and CMIP estimates of fire emissions. FL prepared the first draft of manuscript, and revised it with contributions from all co-authors.

Acknowledgements. This study is co-supported by the National Key R&D Program of China (2017YFA0604302), National Natural Science Foundation of China (41475099), and CAS Key Research Program of Frontier Sciences (QYZDY-SSW-DQC002). MVM is supported by the US Joint Fire Science Program (13-1-01-4) and the UK Leverhulme Trust through a Leverhulme Research Centre Award (RC-2015-029). AA acknowledges support from the Helmholtz Association, its ATMO programme and the Impulse and Networking fund which funded initial FireMIP activities. AA and SH acknowledge also the EU FP7 project BACCHUS (603445). BIM is supported by NSF (BCS-1436496). CI is supported by NASA (NNH12ZDA001N-IDS). We are grateful to Stéphane Mangeon for providing data of
JULES-INFERNO simulations, and R. J. Yokelson, Z.-D. Lin, S. Kloster, M. van Marle, B. Bond-Lamberty, and J. R. Marlon for helpful discussions.

Competing interests. The authors declare that they have no conflict of interest.

References


Ferretti, D. F., et al.: Unexpected changes to the global methane budget over the past


Hurtt, G. C., et al.: Harmonization of land-use scenarios for the period 1500–2100: 600 years of global gridded annual land-use transitions, wood harvest, and resulting secondary lands, Climatic Change, 109, 117–161,


https://doi.org/10.1289/ehp.1104422, 2012.


Klein Goldewijk, K., Beusen, A., and Janssen, P.: Long-term dynamic modeling of global population and built-up area in a spatially explicit way: HYDE 3.1,


Marlon, J. R., et al.: Climate and human influences on global biomass burning over the past two millennia, Nat. Geosci., 1, 697–702,


Mouillot, F. and Field, C. B.: Fire history and the global carbon budget: a 1°×1°fire
history reconstruction for the 20th century, Glob. Change Biol., 11, 398–420,

Nemani, R. R., and Running, S. W.: Implementation of a hierarchical global vegetation

Oleson, K., et al.: Technical Description of version 4.5 of the Community Land
Model (CLM), Tech. Rep. NCAR/TN-503+STR NCAR, Boulder, CO, USA,

Parisien, M., Miller, C., Parks, S. A., DeLancey, E. R., Robinne, F., and Flannigan, M.
D.: The spatially varying influence of humans on fire probability in North

Pechony, O., and Shindell, D. T.: Driving forces of global wildfires over the past
millennium and the forthcoming century, P. Natl. Acad. Sci. USA, 107,

Pfeiffer, M., Spessa, A., and Kaplan, J. O.: A model for global biomass burning in
preindustrial time: LPJ-LMfire (v1.0), Geosci. Model Dev., 6, 643–685,

Rabin, S. S., et al.: The Fire Modeling Intercomparison Project (FireMIP),
phase 1: experimental and analytical protocols with detailed model descriptions.

W.: A fire model with distinct crop, pasture, and non-agricultural burning: use of


Stockwell, C. E., et al.: Nepal Ambient Monitoring and Source Testing Experiment (NAMaSTE): emissions of trace gases and light-absorbing carbon from wood and


Yang, J., Tian, H., Tao, B., Ren, W., Kush, J., Liu, Y., and Wang, Y.: Spatial and temporal patterns of global burned area in response to anthropogenic and environmental factors: Reconstructing global fire history for the 20th and early


Table 1. Summary description of the Dynamic Global Vegetation Models (DGVMs) participated in FireMIP.

<table>
<thead>
<tr>
<th>Model</th>
<th>Acronym</th>
<th>Period</th>
<th>Spatial res.</th>
<th>Specific treat for pastures</th>
<th>crop fires</th>
<th>tropical human deforestation fires</th>
<th>human ignition fires</th>
<th>human suppression on fires</th>
<th>peat fires</th>
</tr>
</thead>
<tbody>
<tr>
<td>CLM4.5 and CLM5</td>
<td>Community Land Model version 4.5 and 5</td>
<td>monthly</td>
<td>~1.9° (lat) × 2.5° (lon)</td>
<td>1700–2012</td>
<td>yes yes</td>
<td>increase with PD</td>
<td>occurrence &amp; spread area</td>
<td>yes</td>
<td>d</td>
</tr>
<tr>
<td>CTEM</td>
<td>Canadian Terrestrial Ecosystem Model</td>
<td>monthly</td>
<td>2.8° 12.5’</td>
<td>1861–2012</td>
<td>no no</td>
<td>no increase with PD</td>
<td>occurrence &amp; duration</td>
<td>no</td>
<td>Arora &amp; Boer (2005)</td>
</tr>
<tr>
<td>JSBACH-SPITFIRE</td>
<td>Jena Schemefor Biosphere-Atmosphere Coupling in Hamburg: SPITFIRE</td>
<td>monthly</td>
<td>1.875°</td>
<td>1700–2012</td>
<td>no no</td>
<td>no increase with PD</td>
<td>occurrence &amp; duration</td>
<td>no</td>
<td>Lasslop et al. (2014)</td>
</tr>
<tr>
<td>JULES-INFERNO</td>
<td>Joint UK Land surface ecosystem model, INERGIE model</td>
<td>monthly</td>
<td>~1.2° (lat) × 1.9° (lon)</td>
<td>1700–2012</td>
<td>no no</td>
<td>no increase with PD</td>
<td>occurrence</td>
<td>no</td>
<td>Mangeon et al. (2016)</td>
</tr>
<tr>
<td>LPJ-GUESS-GlobFIRM</td>
<td>Landini et al. (2011), Global Forest Fire Emission Model (GlobFIRE)</td>
<td>annual</td>
<td>0.5°</td>
<td>1700–2012</td>
<td>harvest no no no no yes</td>
<td>Thonicke et al. (2001) Smith et al. (2014) Lindeskogen et al. (2013)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LPJ-GUESS-SPITFIRE</td>
<td>Landini et al. (2011), Global Forest Fire Emission Model (GlobFIRE)</td>
<td>monthly</td>
<td>0.5°</td>
<td>1700–2012</td>
<td>harvest no no no no yes</td>
<td>Smith et al. (2001) Ahlstrom et al. (2012)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Assume no fire in grid cell when pre-calculated rate of spread, fireline intensity, and energy release components are lower than thresholds.

CLM4.5 outputs in FireMIP include biomass and litter burning due to peat fires, but don’t include burning of soil organic matter. Fire suppression increases with PD, but there’s a difference between tree PFTs and grass/shrub PFTs. PFT: plant functional type; PD: population density; P: prescribed; M: modeled; PD: population density.

ORCHIDEE: Organizing Carbon Hydrology In Dynamic Ecosystems.
GlobFIRM: fire module; Simple FIRE model; BLAZE: Blaze-Induced Land-Amosphere Flux Estimator.
JULES: Joint UK Land Environment Simulator; INFERNO: Interactive Fire and Emission Algorithm for Natural Environments; SMIFIRE: Simple FIRE model; INERNO: Interactive Fire and Emission Algorithm for Natural Environments.
Table 2. Emission factors (g specie (kg DM)^{-1}) for land cover types (LCTs).

<table>
<thead>
<tr>
<th>No.</th>
<th>Species</th>
<th>grassland/savanna</th>
<th>tropical forest</th>
<th>temperate forest</th>
<th>boreal forest</th>
<th>cropland</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>CO₂</td>
<td>1647</td>
<td>1613</td>
<td>1566</td>
<td>1549</td>
<td>1421</td>
</tr>
<tr>
<td>2</td>
<td>CO</td>
<td>70</td>
<td>108</td>
<td>112</td>
<td>124</td>
<td>78</td>
</tr>
<tr>
<td>3</td>
<td>CH₄</td>
<td>2.5</td>
<td>6.3</td>
<td>5.8</td>
<td>5.1</td>
<td>5.9</td>
</tr>
<tr>
<td>4</td>
<td>NMHC</td>
<td>5.5</td>
<td>7.1</td>
<td>14.6</td>
<td>5.3</td>
<td>5.8</td>
</tr>
<tr>
<td>5</td>
<td>H₂</td>
<td>0.97</td>
<td>3.11</td>
<td>2.09</td>
<td>1.66</td>
<td>2.65</td>
</tr>
<tr>
<td>6</td>
<td>NOₓ</td>
<td>2.58</td>
<td>2.55</td>
<td>2.90</td>
<td>1.69</td>
<td>2.67</td>
</tr>
<tr>
<td>7</td>
<td>N₂O</td>
<td>0.18</td>
<td>0.20</td>
<td>0.25</td>
<td>0.25</td>
<td>0.09</td>
</tr>
<tr>
<td>8</td>
<td>PM₂.₅</td>
<td>7.5</td>
<td>8.3</td>
<td>18.1</td>
<td>20.2</td>
<td>8.5</td>
</tr>
<tr>
<td>9</td>
<td>TPM</td>
<td>8.5</td>
<td>10.9</td>
<td>18.1</td>
<td>15.3</td>
<td>11.3</td>
</tr>
<tr>
<td>10</td>
<td>TPC</td>
<td>3.4</td>
<td>6.0</td>
<td>8.4</td>
<td>10.6</td>
<td>5.5</td>
</tr>
<tr>
<td>11</td>
<td>OC</td>
<td>3.1</td>
<td>4.5</td>
<td>8.9</td>
<td>10.1</td>
<td>5.0</td>
</tr>
<tr>
<td>12</td>
<td>BC</td>
<td>0.51</td>
<td>0.49</td>
<td>0.66</td>
<td>0.50</td>
<td>0.43</td>
</tr>
<tr>
<td>13</td>
<td>SO₂</td>
<td>0.51</td>
<td>0.78</td>
<td>0.75</td>
<td>0.75</td>
<td>0.81</td>
</tr>
<tr>
<td>14</td>
<td>C₂H₆ (ethane)</td>
<td>0.42</td>
<td>0.94</td>
<td>0.71</td>
<td>0.90</td>
<td>0.76</td>
</tr>
<tr>
<td>15</td>
<td>C₂H₅OH (methanol)</td>
<td>1.48</td>
<td>3.15</td>
<td>2.13</td>
<td>1.53</td>
<td>2.63</td>
</tr>
<tr>
<td>16</td>
<td>C₃H₈ (propane)</td>
<td>0.14</td>
<td>0.53</td>
<td>0.29</td>
<td>0.28</td>
<td>0.20</td>
</tr>
<tr>
<td>17</td>
<td>C₃H₂ (acetylene)</td>
<td>0.34</td>
<td>0.43</td>
<td>0.35</td>
<td>0.27</td>
<td>0.32</td>
</tr>
<tr>
<td>18</td>
<td>C₄H₄ (ethylene)</td>
<td>1.01</td>
<td>1.11</td>
<td>1.22</td>
<td>1.49</td>
<td>1.14</td>
</tr>
<tr>
<td>19</td>
<td>C₃H₆ (propylene)</td>
<td>0.49</td>
<td>0.86</td>
<td>0.67</td>
<td>0.66</td>
<td>0.48</td>
</tr>
<tr>
<td>20</td>
<td>C₅H₈ (isoprene)</td>
<td>0.12</td>
<td>0.22</td>
<td>0.19</td>
<td>0.07</td>
<td>0.18</td>
</tr>
<tr>
<td>21</td>
<td>C₁₀H₁₆ (terpenes)</td>
<td>0.10</td>
<td>0.15</td>
<td>1.07</td>
<td>1.53</td>
<td>0.03</td>
</tr>
<tr>
<td>22</td>
<td>C₆H₆ (toluene)</td>
<td>0.20</td>
<td>0.23</td>
<td>0.43</td>
<td>0.32</td>
<td>0.18</td>
</tr>
<tr>
<td>23</td>
<td>C₆H₆ (benzene)</td>
<td>0.34</td>
<td>0.38</td>
<td>0.46</td>
<td>0.52</td>
<td>0.31</td>
</tr>
<tr>
<td>24</td>
<td>C₈H₁₀ (xylene)</td>
<td>0.09</td>
<td>0.09</td>
<td>0.17</td>
<td>0.10</td>
<td>0.09</td>
</tr>
<tr>
<td>25</td>
<td>C₂H₃O (formaldehyde)</td>
<td>1.33</td>
<td>2.40</td>
<td>2.22</td>
<td>1.76</td>
<td>1.80</td>
</tr>
<tr>
<td>26</td>
<td>C₃H₄O (acetaldehyde)</td>
<td>0.86</td>
<td>2.26</td>
<td>1.20</td>
<td>0.78</td>
<td>1.82</td>
</tr>
<tr>
<td>27</td>
<td>C₄H₅O (acetone)</td>
<td>0.47</td>
<td>0.63</td>
<td>0.70</td>
<td>0.61</td>
<td>0.61</td>
</tr>
<tr>
<td>28</td>
<td>C₅H₇O₂ (hydroxyacetone)</td>
<td>0.52</td>
<td>1.13</td>
<td>0.85</td>
<td>1.48</td>
<td>1.74</td>
</tr>
<tr>
<td>29</td>
<td>C₄H₄OH (Phenol)</td>
<td>0.37</td>
<td>0.23</td>
<td>0.33</td>
<td>2.96</td>
<td>0.50</td>
</tr>
<tr>
<td>30</td>
<td>NH₃ (ammonia)</td>
<td>0.91</td>
<td>1.45</td>
<td>1.00</td>
<td>2.82</td>
<td>1.04</td>
</tr>
<tr>
<td>31</td>
<td>HCN (hydrogen cyanide)</td>
<td>0.42</td>
<td>0.38</td>
<td>0.62</td>
<td>0.81</td>
<td>0.43</td>
</tr>
<tr>
<td>32</td>
<td>MEK/2-butane</td>
<td>0.13</td>
<td>0.50</td>
<td>0.23</td>
<td>0.15</td>
<td>0.60</td>
</tr>
<tr>
<td>33</td>
<td>CH₃CN (acetonitrile)</td>
<td>0.17</td>
<td>0.51</td>
<td>0.23</td>
<td>0.30</td>
<td>0.25</td>
</tr>
</tbody>
</table>
Table 3. Attribution of plant function types (PFTs) in FireMIP DGVMs to land cover types (LCTs) for emission factors described in Table 2.

<table>
<thead>
<tr>
<th>LCT</th>
<th>Grassland/Savannas</th>
<th>Tropical Forest</th>
<th>Temperate Forest</th>
<th>Boreal Forest</th>
<th>Cropland</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Models</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CLM4.5</td>
<td>A C3/C3/C4 G</td>
<td>Tro BE T</td>
<td>Tem NE T</td>
<td>Bor NE T</td>
<td>Crop</td>
</tr>
<tr>
<td></td>
<td>Bor BD S</td>
<td>Tro BD T</td>
<td>Tem BE T</td>
<td>Bor ND T</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Tem BE/BD S</td>
<td>Tem BD T</td>
<td>Bor BD T</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTEM</td>
<td>C3/C4 G</td>
<td>BE T*</td>
<td>NE/BE T*</td>
<td>NET*, ND T</td>
<td>C3/C4 Crop</td>
</tr>
<tr>
<td></td>
<td>Other BD T*</td>
<td>Other BD T*</td>
<td>Cold BD T</td>
<td></td>
<td></td>
</tr>
<tr>
<td>JULES</td>
<td>C3/C4 G</td>
<td>Tro BE T</td>
<td>Tem BE T</td>
<td>BD/NE T*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>E/D S</td>
<td>BD T*</td>
<td>BD/NE T*</td>
<td>NDT</td>
<td></td>
</tr>
<tr>
<td>LGG*</td>
<td>C3/C4 G</td>
<td>Tro BE/BR T</td>
<td>Tem NSG/BSG/BE T</td>
<td>Bor NE T</td>
<td>R/I S/W Wheat</td>
</tr>
<tr>
<td></td>
<td>C3/C4 G in P</td>
<td>Tem SI BE T</td>
<td>Tem SI SG B T</td>
<td>Bor SI NE T</td>
<td>R/I Maize</td>
</tr>
<tr>
<td>LGS</td>
<td>C3/C4 G</td>
<td>Tro BE/BR T</td>
<td>Tem SI &amp; SG B T</td>
<td>Bor NE T</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Tro SI BE T</td>
<td>Tem B/N E T</td>
<td>Bor SI &amp; SG NE/NT</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LGBS*</td>
<td>C3/C4 G</td>
<td>Tro BE/BR T</td>
<td>Tem NSG/BSG/BE T</td>
<td>Bor NE T</td>
<td>R/I S/W Wheat</td>
</tr>
<tr>
<td></td>
<td>C3/C4 G in P</td>
<td>Tem SI BE T</td>
<td>Tem SI SG B T</td>
<td>Bor SI NE T</td>
<td>R/I Maize</td>
</tr>
<tr>
<td>MC2</td>
<td>Tem C3 G/S</td>
<td>Tro BE T</td>
<td>Maritime NE F</td>
<td>Bor NE F</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Sub-Tro C4 G/S</td>
<td>Tro D W*</td>
<td>Sub-Tro NE/BD/BE/M F</td>
<td>Subalpine F</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Tro S/G/Savanna</td>
<td></td>
<td></td>
<td>Cool N F</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Bor M W</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Tem/Sub-Tro NE/B/ M W</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Tundra Taiga-Tundra</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ORCHIDEE</td>
<td>C3/C4 G</td>
<td>Tro B/E/R T</td>
<td>Tem N/B E T</td>
<td>Bor N/E/D T</td>
<td>C3/C4 Crop</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Tem BD T</td>
<td>Bor BT T</td>
<td></td>
</tr>
</tbody>
</table>

Acronym: T: tree; S: shrub; W: woodland; F: forest; G: grass; P: pasture; Sava: Savanna; N: needleleaf; E: evergreen; B: broadleaf; D: deciduous; R: raingreen; SI: shaded-intolerant; SG: summer-green; M: mixed; I: irrigated; RF: rainfed; C/W: cool or warm; S/W: spring or winter, Tro: Tropical; Tem: Temperate; Bor: Boreal; Sub-Tro: subtropical; Ex-Tro: Extratropical; A: Arctic

* split tree PFTs into tropical, temperate, and boreal groups following rules of Nemani and Running (1996) that also used to make CLM land surface data by Peter et al. (2007; 2012) since CLM version 3

b LGG and LGBS did not outputs PFT-level fire carbon emissions, so land cover classified using its dominant vegetation type

c MC2 classifies tropical savannas and tropical deciduous woodland regions, and the latter mainly represents tropical deciduous forests
Table 4. Summary description of satellite-based products and historical constructions merged from multiple sources.

<table>
<thead>
<tr>
<th>Name</th>
<th>Method</th>
<th>Fire data sources</th>
<th>Peat burning</th>
<th>Start year</th>
<th>reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>GFED4</td>
<td>Bottom-up: fuel consumption, burned area &amp; active fire counts</td>
<td>MODIS, VIRS/ATSR</td>
<td>Y</td>
<td>1997</td>
<td>van der Werf et al. (2017)</td>
</tr>
<tr>
<td>GFED4s</td>
<td>(GFED4&amp;4s), FRP (GFAS1), active fire counts (FINN1.5), emis. factor</td>
<td>MODIS</td>
<td>Y</td>
<td>1997</td>
<td>Kaiser et al. (2012)</td>
</tr>
<tr>
<td>FINN1.5</td>
<td></td>
<td>MODIS</td>
<td>N</td>
<td>2003</td>
<td>Wiedinmyer et al. (2011)</td>
</tr>
<tr>
<td>FEER1</td>
<td>Top-down: FRP, satellite AOD constrained, emis. factor</td>
<td>MODIS, SEVIRI</td>
<td>Y</td>
<td>2003</td>
<td>Ichoku and Ellison (2014)</td>
</tr>
<tr>
<td>QFED2.5</td>
<td></td>
<td>MODIS</td>
<td>N</td>
<td>2001</td>
<td>Darmenov and da Silva (2015)</td>
</tr>
<tr>
<td>CMIP5</td>
<td>Merged decadal fire trace gas and aerosol emis.</td>
<td>GFED2, GICC, RETRO (model GlobFIRM used)</td>
<td>Y</td>
<td>1850</td>
<td>Lamarque et al. (2010)</td>
</tr>
<tr>
<td>CMIP6</td>
<td>Merged monthly fire carbon emis., present-day veg. dist., emis. factor</td>
<td>GFED4s, FireMIP models, GCDv3 charcoal records, WMO visibility obs.</td>
<td>Y</td>
<td>1750</td>
<td>van Marle et al. (2017)</td>
</tr>
</tbody>
</table>

Acronym: GFED4: Global Fire Emissions Dataset version 4; GFED4s: GFED4 with small fires; GFAS1.2: Global Fire Assimilation System version 1.2; FINN1.5: Fire Inventory from NCAR version 1.5; FRP: fire radiative power; FEER1: Fire emissions from the Fire Energetics and Emissions Research version 1; QFED2.5: Quick Fire Emissions Dataset version 2.5; AOD: aerosol optical depth; GFED2: GFED version 2; RETRO: REanalysis of the TROpospheric chemical composition; GICC: Global Inventory for Chemistry-Climate studies; GCDv3: Global Charcoal Database version 3.
**Table 5.** Global total of fire emissions from 2003 to 2008 for DGVMs in FireMIP and benchmarks. Unit: Pg (Pg=10^{15} g)

<table>
<thead>
<tr>
<th>Source</th>
<th>C</th>
<th>CO₂</th>
<th>CO</th>
<th>CH₄</th>
<th>BC</th>
<th>OC</th>
<th>PM₂.₅</th>
</tr>
</thead>
<tbody>
<tr>
<td>FireMIP</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CLM4.5</td>
<td>2.1</td>
<td>6.5</td>
<td>0.36</td>
<td>0.018</td>
<td>0.0021</td>
<td>0.020</td>
<td>0.042</td>
</tr>
<tr>
<td>CTEM</td>
<td>3.0</td>
<td>8.9</td>
<td>0.48</td>
<td>0.025</td>
<td>0.0028</td>
<td>0.030</td>
<td>0.060</td>
</tr>
<tr>
<td>JSBACH</td>
<td>2.1</td>
<td>6.5</td>
<td>0.32</td>
<td>0.013</td>
<td>0.0020</td>
<td>0.016</td>
<td>0.036</td>
</tr>
<tr>
<td>JULES</td>
<td>2.1</td>
<td>6.9</td>
<td>0.44</td>
<td>0.024</td>
<td>0.0022</td>
<td>0.020</td>
<td>0.039</td>
</tr>
<tr>
<td>LGG</td>
<td>4.9</td>
<td>15.4</td>
<td>0.90</td>
<td>0.047</td>
<td>0.0050</td>
<td>0.048</td>
<td>0.097</td>
</tr>
<tr>
<td>LGS</td>
<td>1.7</td>
<td>5.6</td>
<td>0.26</td>
<td>0.011</td>
<td>0.0017</td>
<td>0.012</td>
<td>0.027</td>
</tr>
<tr>
<td>LGSB</td>
<td>2.5</td>
<td>7.7</td>
<td>0.48</td>
<td>0.025</td>
<td>0.0025</td>
<td>0.024</td>
<td>0.047</td>
</tr>
<tr>
<td>MC2</td>
<td>1.0</td>
<td>3.1</td>
<td>0.18</td>
<td>0.008</td>
<td>0.0011</td>
<td>0.012</td>
<td>0.025</td>
</tr>
<tr>
<td>ORCHIDEE</td>
<td>2.8</td>
<td>9.2</td>
<td>0.44</td>
<td>0.018</td>
<td>0.0029</td>
<td>0.020</td>
<td>0.045</td>
</tr>
<tr>
<td>Benchmarks</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GFED4</td>
<td>1.5</td>
<td>5.4</td>
<td>0.24</td>
<td>0.011</td>
<td>0.0013</td>
<td>0.012</td>
<td>0.025</td>
</tr>
<tr>
<td>GFED4s</td>
<td>2.2</td>
<td>7.3</td>
<td>0.35</td>
<td>0.015</td>
<td>0.0019</td>
<td>0.016</td>
<td>0.036</td>
</tr>
<tr>
<td>GFAS1.2</td>
<td>2.1</td>
<td>7.0</td>
<td>0.36</td>
<td>0.019</td>
<td>0.0021</td>
<td>0.019</td>
<td>0.030</td>
</tr>
<tr>
<td>FINN1.5</td>
<td>2.0</td>
<td>7.0</td>
<td>0.36</td>
<td>0.017</td>
<td>0.0021</td>
<td>0.022</td>
<td>0.039</td>
</tr>
<tr>
<td>FEER1</td>
<td>4.2</td>
<td>14.0</td>
<td>0.65</td>
<td>0.032</td>
<td>0.0042</td>
<td>0.032</td>
<td>0.054</td>
</tr>
<tr>
<td>QFED2.5</td>
<td>----</td>
<td>8.2</td>
<td>0.39</td>
<td>0.017</td>
<td>0.0060</td>
<td>0.055</td>
<td>0.086</td>
</tr>
</tbody>
</table>
**Table 6.** Temporal correlation of annual global fire PM$_{2.5}$ emissions between FireMIP models and satellite-based GFED4 and GFED4s (1997–2012), GFAS1.2 and QFED2.5 (2001–2012), and FINN1.5 and FEER1 (2003–2012).

<table>
<thead>
<tr>
<th>DGVMs</th>
<th>GFED4</th>
<th>GFED4s</th>
<th>GFAS1.2</th>
<th>FINN1.5</th>
<th>FEER1</th>
<th>QFED2.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>CLM4.5</td>
<td>0.73***</td>
<td>0.70***</td>
<td>0.63**</td>
<td>0.62*</td>
<td>0.55*</td>
<td>0.58**</td>
</tr>
<tr>
<td>CTEM</td>
<td>0.51**</td>
<td>0.54**</td>
<td>0.63**</td>
<td>0.60*</td>
<td>0.52</td>
<td>0.68**</td>
</tr>
<tr>
<td>JSBACH</td>
<td>–0.18</td>
<td>–0.42</td>
<td>0.10</td>
<td>0.02</td>
<td>–0.04</td>
<td>0.32</td>
</tr>
<tr>
<td>JULES</td>
<td>0.33</td>
<td>0.31</td>
<td>0.31</td>
<td>0.56*</td>
<td>0.29</td>
<td>0.39</td>
</tr>
<tr>
<td>LGG</td>
<td>0.08</td>
<td>0.03</td>
<td>–0.15</td>
<td>0.01</td>
<td>–0.20</td>
<td>–0.03</td>
</tr>
<tr>
<td>LGS</td>
<td>0.12</td>
<td>0.04</td>
<td>–0.00</td>
<td>0.40</td>
<td>–0.01</td>
<td>0.08</td>
</tr>
<tr>
<td>LGSB</td>
<td>0.51**</td>
<td>0.64***</td>
<td>0.39</td>
<td>0.72**</td>
<td>0.56*</td>
<td>0.55*</td>
</tr>
<tr>
<td>ORCHIDEE</td>
<td>–0.13</td>
<td>–0.25</td>
<td>–0.16</td>
<td>0.29</td>
<td>–0.10</td>
<td>–0.10</td>
</tr>
</tbody>
</table>

*, **, and ***: Pearson correlation passed the Student’s t-test at the 0.1, 0.05, and 0.01 significance level, respectively.

**Figure 1.** FireMIP experiment design. Note that CTEM and MC2 start at 1861 and 1901 and spin-up using 1861 and 1901 CO$_2$, population density, and prescribed / modeled vegetation distribution, respectively.
Figure 2. Spatial distribution of annual fire black carbon (BC) emissions (g BC m$^{-2}$ yr$^{-1}$) averaged over 2003–2008. The range of global spatial correlation between DGVMs and satellite-based products is also given in brackets.
Figure 3. Inter-model standard deviation of 2003–2008 averaged fire BC emissions (g BC m$^{-2}$ yr$^{-1}$) in FireMIP models and the zonal average.
Figure 4. Seasonal cycle of fire PM$_{2.5}$ emissions normalized by the mean from FireMIP models and satellite-based products averaged over 2003–2008 in the Southern Hemisphere (SH) tropics (0–23.5ºS), Northern Hemisphere (NH) tropics (0–23.5ºN), and NH extra-tropics (23.5–90ºN). Fire emissions from LPJ-GUESS-GlobFIRM and MC2 are updated annually and thus are not included here.
Figure 5. Temporal change of annual global fire PM$_{2.5}$ emissions normalized by the mean from FireMIP models and satellite-based products. The numbers in the brackets are coefficient of variation (CV, the standard deviation divided by the mean, unit: %) for 1997–2012 and 2003–2012, respectively.

Figure 6. Long-term temporal change of fire emissions from DGVMs in FireMIP and CMIPs forcing. A 21-year running mean is used.
Figure 7. Change in global annual fire carbon emissions (Pg C yr⁻¹) in the 20th century due to changes in (a) climate, (b) lightning frequency, (c) atmospheric CO₂ concentration, (d) land use and land cover change (LULCC), and (e) population density (control run–sensitivity run). A 21-year running mean is used. The standard deviation (Std) of multi-model simulated long-term changes averaged over the 20th century is also given in the bracket.
Figure 8. a) GFED region definition (http://www.globalfiredata.org/data.html), and b) inter-model discrepancy (quantified using inter-model standard deviation) in long-term changes (a 21-year running mean is used, relative to present-day) of simulated regional fire CO emissions (Tg CO yr$^{-1}$) averaged over 1700–2012 (calculate long-term changes relative to present-day for each FireMIP model first, then the inter-model standard deviation, and lastly the time-average). Acronyms are BONA: Boreal North America; TENA: Temperate North America; CEAM: Central America; NHSA: Northern Hem. South America; SHSA: Southern Hem. South America; EURO: Europe; MIDE: Middle East; NHAF: Northern Hem. Africa; SHAF: Southern Hem. Africa; BOAS: Boreal Asia; CEAS: Central Asia; SEAS: South East Asia; EQAS: Equatorial Asia; AUST: Australia.
Figure 9. Long-term changes of annual regional fire CO emissions (Tg CO yr\(^{-1}\)) from FireMIP models and CMIPs for regions with highest inter-model discrepancy in long-term changes of regional fire emissions shown in Fig. 8. A 21-year running mean is used.