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Editor summary:

The authors combine fire-vegetation models, a chemical transport model and health risk model to link human mortality from fire emissions to climate change. They estimate that 12.8% of mortalities 2010 are climate change related, with South America, Australia, Europe and Boreal forests most impacted.

Peer review information:

Nature Climate Change thanks Hamish Clarke, Jennifer Stowell and the other, anonymous, reviewer(s) for their contribution to the peer review of this work.

Inventory of Supporting Information

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1. Extended Data

Figure or Table # Please group Extended Data items by type, in sequential order. Total number of items (Figs. + Tables) must not exceed 10.	Figure/Table title One sentence only	Filename Whole original file name including extension. i.e.: Smith_ED_Fig1.jpg	Figure/Table Legend If you are citing a reference for the first time in these legends, please include all new references in the main text Methods References section, and carry on the numbering from the main References section of the paper. If your paper does not have a Methods section, include all new references at the end of the main Reference list.
Extended Data Fig. 1	Fire organic carbon emissions from three	ED_Fig1.jpg	Annual total organic carbon (OC) emissions from three fire models (CLASSIC (a), SSiB4 (b), and JULES (c)) and observation-based

	fire-vegetation models		reference data (GFED4.1s [Global Fire Emissions Database version 4.1] for 1997–2019 (d) and together with GFAS [CAMS Global Fire Assimilation System] for 2003–2019 (e)). OC is the predominant particulate carbon from fire. Three fire-vegetation models (a, b, and c) have two simulation results (factual simulation (1) and counterfactual simulation (2)) and the attribution of climate change (ACC) (3). JULES considered fires in both cropland and pastureland as agricultural fires, while CLASSIC considered only fires in cropland.

1. Supplementary Information:

A. PDF Files

Item	Present?	Filename Whole original file name including extension. i.e.: Smith_SI.pdf. The extension must be .pdf	A brief, numerical description of file contents. i.e.: *Supplementary Figures 1-4, Supplementary Discussion, and Supplementary Tables 1-4.*
Supplementary Information	Yes	Supplementary_Information.pdf	Supplementary Notes1-3, Supplementary Figures 1-9, Supplementary Tables1-2, and References.
Reporting Summary	Yes	Reporting summary.pdf	

3. Source Data

Parent Figure or Table	Filename Whole original file name including extension. i.e.: *Smith_SourceData_Fig1.xls*, or *Smith_ Unmodified_Gels_Fig1.pdf*	Data description i.e.: Unprocessed western Blots and/or gels, Statistical Source Data, etc.
Source Data Fig. 1	Fig1.csv	Source data for bar chart
Source Data Fig. 2	Fig2.csv	Source data for mapping changes
Source Data Fig. 3	Fig3.csv	Source data for bar chart

Source Data Fig. 4	Fig4.csv	Source data for mapping changes
Source Data Fig. 5	Fig5.csv	Statistical source data
Source Data Extended Data Fig./Table 1	ExtFig.1.csv	Source data for plotting

Title: Attributing human mortality from fire $PM_{2.5}$ to climate change

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Abstract

Climate change intensifies fire smoke, emitting hazardous air pollutants that impact human health. However, the global influence of climate change on fire-induced health impacts remains unquantified. Here, we used three well-tested fire-vegetation models in combination with a chemical transport model and health risk assessment framework to attribute global human mortality from fire fine particulate matter ($PM_{2.5}$) emissions to climate change. Of the 46401 (1960s) –to 98748 (2010s) annual fire $PM_{2.5}$ mortalities, 669 (1.2%, 1960s) –to 12566 (12.8%, 2010s) were attributed to climate change. The most substantial influence of climate change on fire mortality occurred in South America, Australia, and Europe, coinciding with decreased

relative humidity, and in boreal forests with increased air temperature. Increasing relative humidity lowered fire mortality in other regions, like South Asia. Our study highlights the role of climate change in fire mortality, aiding public health authorities in spatial targeting adaptation measures for sensitive fire-prone areas.

Main text

Increasing forest fires and resultant smoke pose significant public health concerns. The record-breaking forest fires in Canada in 2023[1] impacted the US and Canada, raising emergency department visits[2]. Australian megafires during 2019–2020 incurred over nine times smoke-related health costs than the average of the past 19 years[3]. Fire smoke includes fine particulate matter with a diameter of ≤2.5 µm ($PM_{2.5}$). $PM_{2.5}$ is a major environmental risk[4], contributing to 4.1–8.9 million annual global deaths[5,6]. Recently, fire smoke represented 4.4–5% of the global $PM_{2.5}$ mortality[7–9]. The mortality associated with annual fire-$PM_{2.5}$ was estimated at 339000–677745 deaths[10,11] and additionally contributed to 130000 annual infant deaths[12] in the 2000s and 2010s.

In recent decades, human activities, such as increasing landscape fragmentation and fire suppression, have reduced fire activity in the tropical savannas of South America and Africa and in the grasslands of the Asian steppe[12,13]. However, climate change has simultaneously increased burned areas, especially in regions where the primary limiting factor for fires is weather, such as boreal and tropical forests[14,15]. In addition, climate change has intensified both the severity and frequency of fire weather[16]. Drought and increased air temperature influence fuel dryness, a significant driver of flammability[17]. Decreased surface moisture increases rates of fire spread, making fire suppression more challenging and resulting in extensive fire activity in the recent past[18,19].

Understanding the historical impact of climate change on fire health burden is crucial for adapting to present and future risks. However, a literature gap exists in studying the historical impact of climate change on global, long-term trends in fire health burden. Recently, extreme droughts and heatwaves have resulted in large fires that significantly increased the number of short-term (i.e., daily) $PM_{2.5}$ mortalities compared with the number during previous weather conditions[3,20,21]. In the hot and dry summer of 2005, 403 more people than in the regular year

2008 were estimated to have died due to daily $PM_{2.5}$ emissions from vegetation fires in southern Europe[20]. In Equatorial Asia in 2015 during an extreme smoke event, $PM_{2.5}$ emissions were 2.2 times than the 2002–2014 mean[22], resulting in approximately million mortalities, which was more than double of the number in the regular year of 2006[21]. The substantial impacts of fire on health and their relationship with extreme weather suggest that climate change has already affected fire mortality. Nevertheless, estimates of the contribution of long-term climate change, the evident and trend in the 20th century[23], to the global fire $PM_{2.5}$ health burden are missing so far.

This study explored the attribution of fire-$PM_{2.5}$ mortality to climate change over the past 60 years, focusing on long-term decadal variability. The simulations were conducted under factual and detrended climate forcings to reveal the impact of climate change on historical fire mortality. We used fire simulations from state-of-the-art coupled fire-vegetation models provided by the Intersectoral Impact Model Intercomparison Project Phase 3a (ISIMIP3a)[24] to drive a chemical transport model and health risk assessment framework. Conceptually, we follow the IPCC AR6 WGII attribution framework that focuses on attributing impacts to observed climate change to disentangle climatic from socioeconomic signals[25,26].

Results

We used three global fire-vegetation models (CLASSIC, SSiB4, and JULES, Supplementary Note 1) to calculate the gas and aerosol emissions from fires between 1960 and 2019. The factual simulations showed a population-weighted concentration (PWC) of global fire $PM_{2.5}$ was 1.4 μg m^{-3} for the last 60 years and led to 46401 annual deaths in the 1960s and 98748 annual deaths in the 2010s (Fig. 1). The contribution of fire to all-cause $PM_{2.5}$ and its mortality decreased until 1990, then increased again. More details are provided in Supplementary Note 2. To isolate the effect of climate change, we compared the results of the factual and counterfactual simulations (attribution to climate change, ACC). While factual simulations reproduce historical climate observations as closely as possible, counterfactual simulations aim to capture the impacts in a hypothetical world without historical climate change[26]: CO_2 and their fertilization effect on biomass and CH_4 concentrations were kept constant at 1901 levels. The two simulations induced changes in fuel characteristics and fire spread. However, other inputs, including land cover changes, population, and GDP, were the same in both simulations following historical trends (Table 1). All other inputs for $PM_{2.5}$ exposure and mortality calculations remained equal between the simulations, including anthropogenic emissions, meteorological conditions in atmospheric chemical transport, and baseline mortality.

Global attribution to climate change

We found that global fire risks in $PM_{2.5}$ and related mortality over the past six decades were higher in the factual simulations compared to the counterfactual simulations. The ACC of PWC of global annual fire $PM_{2.5}$ increased from a model-average of 1.8% (representing individual model results for CLASSIC, SSiB4, and JULES, which were -1.3, 4.6, and 2.2%, respectively, in the 1960s) to 15% (-1.9, 36.8, and 10.1%, respectively, in the 2010s) (Fig. 1e). This led to an increase in excess annual mortality from 669 (-398, 1773, 632 in the 1960s) to 12566 (3481, 30126, 4092 in the 2010s), which equals to 1.2–12.8% ACC (Fig. 1f). The ACC of fire mortality showed considerable variation depending on the fire-vegetation model; particularly, CLASSIC simulated a negative ACC of fire mortality until the 2000s. This is because CLASSIC simulated a significantly lower fire $PM_{2.5}$ level in the northern hemisphere of Africa (NHAF) and South America (NHSA), Middle East, and India in the factual simulations, while the other models simulated either higher or only slightly lower levels than counterfactual simulations (Fig. 2).

The positive ACC of $PM_{2.5}$ and related mortality was led by higher fire emissions in the factual simulations compared to the counterfactual simulations. The annual global fire organic carbon emissions in the 2010s were in the range of 20, 28, and 17 Tg for CLASSIC, SSiB4, and JULES, respectively, with the ACC being 6, 42, and 21%, respectively (Extended Data. 1). Note that global terrestrial net primary production sequesters around 60 Pg of organic carbon from the atmosphere to biomass annually[27]. Especially, tropical forests and grasslands, temperate forests in North America, Mediterranean forests in Europe, and boreal forests had higher ACC of fire emissions in 2010s (Fig. 2).

Regional attribution to climate change

The ACC of fire $PM_{2.5}$ and related mortality was most prominent in South America (SHSA, NHSA), the NHAF, Europe (EURO), and boreal forests (Fig. 3, Supplementary Fig. 1). While most areas showed increased fire mortality due to climate change, Central Asia (CEAS) and South and East Asia (SEAS) had similar or lower fire mortality under climate change. Many of the areas where mortality increased were drier and hotter in the factual simulations, as evidenced by the decreased relative humidity and increased air temperature in the factual simulations compared to counterfactual simulations (Supplementary Fig. 2, 3).

In SHSA, the ACC of fire mortality increased from a model-average of 35% (with individual model results of -3, 95, and 15% for CLASSIC, SSiB4, and JULES, respectively) to 71% (with individual model results of 13, 187, 14%, respectively) between the 1960s and 2010s. Fires mainly occurred in temperate grassland in the southern cone region with a high agreement across fire-vegetation models (Fig. 4). The southern cone region experienced a reduction of more than 10% in relative humidity under climate change in the 2010s, drying the fire fuel (Supplementary Fig. 2). The southern part of the Amazon basin also experienced higher fire emissions under climate change. However, its impact on $PM_{2.5}$ exposure was found to be negligible because of the intense meridional flow (northern wind), which transports smoke from the Amazon Basin to the southern cone region during the peak month of SHSA fires[28].

Excess fire mortality in Australia attributed to climate change increased steadily, with more than 20% of ACC since the 1970s. The fire-vegetation models agreed on a climate change-driven increase in fire $PM_{2.5}$ in the northern and southeastern part of Australia (Fig. 4c). The southeast had a higher risk than the north owing to its higher population density. Recent studies confirmed increased large and intense forest fires in southern Australia due to hotter and drier climate[29,30].

In EURO, the ACC of fire mortality increased from the 2000s onwards. The ACC of fire mortality in the 1990s was 10% (4, 18, 8%) but became 39% (12, 79, 26%) in the 2010s. The climate impact on fire emissions was evident in southern Europe, with a clear model agreement (Fig. 4b), which can mainly be explained by an increase in air temperature and a decrease in relative humidity. Previous studies also argued that fires in this region have become sensitive to warmer and drier conditions[31,32].

In boreal North America (BONA) and BOAS, the impact of climate change on fire mortality was negligible before the 21st century. Air temperature, the main driver of extreme wildfires in Canada's boreal forests[33], was significantly higher in the factual climate forcing than in the counterfactual forcing in boreal forests in the 2010s (Supplementary Fig. 3). High temperatures contribute to fires directly by increasing evapotranspiration which dries out fuel loads. The increase in air temperature may also decreased soil moisture, leading to drier and more flammable fuels and extending the vegetation growing season, potentially increasing the fuel loads[34].

In equatorial Asia (EQAS), the ACC of fire mortality steadily increased, from 4% (9, 0, 4%) in the 1960s to 16% (21, 10, 19%) in the 2010s. We observed a strong model agreement on the impact of climate change in Indonesia (Fig. 4a). Unlike the drier conditions in the factual climate forcing in previous regions, EQAS had higher relative humidity in the factual simulations. Nevertheless, since relative humidity after the peak fire month in EQAS was high (over 85% in both simulations), the difference in relative humidity between the two simulations might not affect the fuel dryness directly. Furthermore, increased relative humidity could increase vegetation by enabling plants to keep their stomata open, thus facilitating photosynthesis[35], which could increase fire activity by increasing biomass production and fuel load (Supplementary Fig. 4).

Asia exhibited lower or negative values in ACC of fire mortality with poor agreement between the fire-vegetation models (Fig. 3). However, models showed a strong agreement for increasing fire mortality in the factual climate forcing in the western part of China and Central Asia and decreasing fire mortality in Indochina such as Thailand (Fig. 4a). A previous study revealed a significant decreasing trend in fire weather in Indochina[17]. Similarly, our results showed that SEAS had 1.5–3.5% higher relative humidity in the factual simulation than in the counterfactual simulation, with values ranging below 60%.

Most areas in NHAF showed low model agreement in excess mortality under climate change. One previous study argued that climate change has no apparent effect on fire activity in Africa; dry and flammable fuels and increased temperatures might increase the ignition possibility; however, higher temperatures also drive increased evapotranspiration, which may reduce grass productivity and fuel loads[36]. However, Nigeria showed a high agreement in excess fire mortality from climate change (Fig. 4a). Another previous study revealed significant relationships of between maximum temperature (positive) and rainfall (negative) with fire occurrences in Nigeria[37].

We confirmed a strong relationship between increased ACC of fire mortality and decreased ACC of relative humidity or increased ACC of air temperature in certain regions (Fig. 5). The SHSA, EURO, and AUST regions suffered from a drier climate owing to climate change, and hence, fire mortality increased: a 1% decrease in ACC of relative humidity led to a 1.2–10.7% ACC of fire mortality increase. In addition to relative humidity, increased air temperature had significant relationships between fire mortality in BONA, BOAS, and EURO. Those regions had significant higher air temperature in the factual simulations, and a 1% increase in ACC of air temperature resulted in 6.5–33.8% ACC of fire mortality increase.

Other factors influencing fire mortality

We used a range of sensitivity tests to assess the influence of other factors on fire mortality. In the 2010s, climate change contributed to 12566 annual excess deaths globally. However, we also found that interannual variability in fire activity can lead to a greater increase in fire mortality than the long-term trend in climate: the difference between 2015 (maximum) and 2013 (minimum) was 32020 deaths. Regionally, EQAS showed the most significant difference since it had the highest fire emissions in 2015. However, the region with the greatest fire activity varied year by year. For example, in 2019 (the second-maximum), AUST showed the highest mortality.

Varying 2010–2019 meteorological conditions with fixed emissions in GEOS-Chem revealed a maximum difference of 4179 deaths in fire mortality, reaching its peak in 2015 and the lowest point in 2010. The average fire mortality over the 10-year period of meteorological conditions in GEOS-Chem was similar to the value in 2016, supporting the validity of using that year in the main analysis. However, the results for 2016 tended to have higher $PM_{2.5}$ concentrations in NHSA, suggesting that dust-related $PM_{2.5}$ was highly influenced by meteorology.

Interpolating baseline mortality rates resulted in 16532 more deaths than employing a fixed rate in the 1980s, implying that the mortality is sensitive to socio-economic factors and emphasizing the need for higher quality baseline mortality data[38]. The difference was most significant in East Asia, and SHSA. The sensitivity results showed that modeling assumptions influenced fire mortality, inferring that health risk analysis requires careful parameterization based on observation. Further improvements in health data are needed to better understand the health burden.

Discussion

This study provides the first estimate of historical fire $PM_{2.5}$ and its associated mortality from climate change over the past six decades. At the global scale, determining a uniform climate change effect on fires is challenging due to its nonlinear dependency on fire weather, fuel moisture, and fuel availability across different regions. However, our results indicate a clear impact of climate change on fire mortality in certain regions. This is consistent with the existing evidence of climate change affecting regional fire activity; temperate grasslands and the Amazon Basin in South America[39,40], southern Australia[30], and southern Europe[31,32] have experienced increasing hot and dryness, rendering these regions more susceptible to fires and extreme droughts[41,42]. Hot and dry weather decreases fuel moisture, which increases fire risk[43].

Relative humidity indicates real-time climate conditions affecting fuel combustibility[44,45]. Over three-quarters of the trend in fire weather index were attributed to the trend in relative humidity in an analysis of observed climate data[17], supporting our results. SSiB4, which uses relative humidity as the fuel combustibility driver in the range of 30 to 70 %, showed the most sensitive impact of relative humidity on fire, especially in tropical and temperate forests (Supplementary Fig. 5a, b). This resulted in larger fire mortality in most regions compared to other fire-vegetation models, particularly a larger increase in SHAS.

Previous studies revealed that air temperature changed fire activity[17,46]. In our analysis, fire activities in tropical, temperate, and grassland areas steeply increased above 28 ºC (Supplementary Fig. 5c, d), consistent with a previous study[46]. The temperature rise directly increases fire flammability and indirectly influences fire activity by reducing soil moisture and increasing fuel load. Among the three fire-vegetation models, CLASSIC, utilizing root zone soil moisture as the sole climate driver for fuel combustibility, exhibited the lowest sensitivity to air temperature (Fig. 5), resulting in a lower ACC of fire mortality in BONA, BOAS, and EURO.

We used three well-established fire-vegetation models. We found that using three fire-vegetation models enhanced the validation of ambient $PM_{2.5}$ levels and their associated mortality (Supplementary Figs. 8 and 9). These models cover a wide range of the uncertainty defined by the larger ISIMIP3a fire-vegetation model ensemble used in a historical attribution study of burned area[47]. Despite significant variances in ACC among the three models we used, we found consistent trends in climate change impact on fire mortality in key fire regions: Long-term historical climate change robustly increased fire mortality in SHSA, AUST, EURO, BOAS, and BONA, and a decreased fire mortality in SEAS. However, it is essential to consider the challenges faced by the fire models in capturing spatial patterns and decadal trends in Central Asia, India, China, southern Amazonia, and eastern US regions, as evidenced by their poor agreement with satellite-based data (Supplementary Note 3, Supplementary Fig. 6, 7, Supplementary Table 1, 2). The differing usage of socioeconomic factors in fire-vegetation models could lead to poor model agreements in India, China, and Australia. Overestimated fire activity in recent years in southern Amazonia and Central Asia could be related to climate factors, and may therefore lead to uncertainty in the ACC. Enhancing the accuracy of spatiotemporal aspects in fire-vegetation models would improve our understanding in these regions.

Our analysis relies on several assumptions: we fixed a theoretical minimum risk exposure to account for the minimum risk level, not considering the health risk from the daily $PM_{2.5}$ exposure but focusing on annual $PM_{2.5}$ exposure, and calculated fire mortality using the fraction of the fire contribution to the $PM_{2.5}$ concentration. This assumes all $PM_{2.5}$ sources have the same toxicity as epidemiological studies on annual $PM_{2.5}$ exposure and its health impact have not differentiated the source of $PM_{2.5}$[4,9,48]. Though these assumptions are commonly used in health risk studies, we acknowledge that they may introduce underestimation of the health impact because the toxicity of particles originating from fire can be more severe than from other sources[49].

Climate change has increased fire $PM_{2.5}$ and mortality over the past six decades. With global temperature expected to surpass the 1.5 °C mark by 2040[25], adapting to the critical health impacts of fires is required. Many countries have enhanced emergency preparedness, developing fire monitoring systems and enhancing wildfire suppression funding[50]. These efforts, addressing extreme climate change risk, are crucial, given that interannual fire variation resulted in higher excess deaths in our study. However, policies and plans should also address increasing fire risks associated with long-term climate change. This involves resilient land-use planning and expanding fire-resilient housing and hospitals for treating illnesses associated with $PM_{2.5}$. Adaptation will be particularly relevant in South America, Europe, Australia, and boreal forests, the regions sensitive to high fire mortality from climate change.

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Author Contributions Statement

CYP contributed to analysis and writing. KT, SF, CR, and MM contributed to the design of the study. TJ, CB, HH, SKG, and EB ran the atmospheric model or fire-vegetation model simulations and contributed data. FL, SH, and CB coordinated the fire sector in ISIMIP with the support of CR. JT, DKL, and TH contributed to statistical analysis and reviewed the manuscript.

Competing Interests

The authors declare no competing interests.

Tables

Table 1. Input variables in the modeling framework and their forcing in the factual and counterfactual simulations.

	Climate	Socio-economic condition	Meteorological condition of atmospheric chemistry model
Variables	Air temperature, precipitation, wind speed, relative humidity	Population, gross domestic product, baseline mortality, land use, anthropogenic emissions	wind, cloud, surface fluxes, pressure, etc.
Factual	Historical climate forcing	Historical socioeconomic forcing	Fixed year (2016)
Counterfactual	Counterfactual climate forcing (CO_2 and CH_4 fixed at 1901values)	Historical socioeconomic forcing	Fixed year (2016)
Source	Inter-sectoral Model Inter-comparison Project (ISIMIP)3a (GSWP3-W5E5)[51,52]	ISIMIP3a (gridded population[53], land use[54]), United Nation (national population[55]), Institute for Health Metrics and Evaluation (baseline mortality[56]), Community Emissions Data System (anthropogenic emissions[57])	The Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) provided by the Global Modeling and Assimilation Office at NASA Goddard Space Flight Center[58]

Figure Legends/Captions

Figure 1. Global fire $PM_{2.5}$, its mortality, and attribution to climate change (ACC). Global population-weighted concentration (PWC) of fire $PM_{2.5}$ under factual simulations (a). Global fire mortality under factual simulations (b). The fire contribution to global PWC of $PM_{2.5}$ (c). The fire contribution to $PM_{2.5}$ mortality (d). ACC of global PWC of fire $PM_{2.5}$ (e). ACC of global fire mortality (f). The bar chart shows the mean value of three fire-vegetation models, and the asterisks show individual results (green: CLASSIC, orange: SSiB4, and blue: JULES).

Figure 2. The attribution to climate change (ACC) of fire emissions and their risk in the 2010s. Organic carbon emissions (a, e, h, k), fire $PM_{2.5}$ concentration (b, f, i, l), and fire mortality (c, g, j, n). a, b, c are the mean values of three fire-vegetation models (CLASSIC, SSiB4, and JULES), and e–n are the individual model values. Positive values (pink) indicate a larger value in the factual simulation, while negative values (green) indicate a larger value in the counterfactual simulation. Values below a threshold defined as 0.5 times the standard deviation of ACC are removed (white) ranged from 6 to 15%.

Figure 3. Regional attribution to climate change (ACC) of fire mortality. Regional ACC over six decades (a). Keymap of 14 regions (b). Top five regions with the highest ACC of fire mortality (c). For **(a)**, the bar charts show the mean value of three fire-vegetation models, and the error bars show the range of the three models. The Y-axis shows the percentage from -20 to 100%; the SHSA y-axis ranges from -20 to 220%. Supporting regional fire organic carbon emissions and $PM_{2.5}$ figures are in Supplementary Fig. 1. BONA: Boreal North America, TENA: Temperate North America, CEAM: Central America, NHSA: Northern Hemisphere South America, SHSA: Southern Hemisphere South America, EURO: Europe, MIDE: Middle East, NHAF: Northern Hemisphere Africa, SHAF: Southern Hemisphere Africa, BOAS: Boreal Asia, CEAS: Central Asia, SEAS: Southeast Asia, EQAS: Equatorial Asia, AUST: Australia and New Zealand.

Figure 4. Spatial model agreement in the 2010s. Global map and regional enlarged maps for fire mortality (a). Global map for fire carbon emissions (b). Global map for fire $PM_{2.5}$ (c). The red color indicates that the value is greater in the factual simulation (F), and blue indicates that the value is greater in the counterfactual simulation (C). A darker color means a strong agreement (all three models show F>C or F<C among the three), and a lighter color means an agreement (two models show F>C or F<C among the three). Yellow indicates that the models do not show agreement (only one model shows F>C or F<C among the three). We used the medium difference ($0.5\times std$ (standard deviation of the difference between two simulations)) as a threshold for identifying greater values.

Figure 5. The relation between ACC (attribution to climate change) of fire mortality and ACC of relative humidity or air temperature during the 1960s-2010s. We used 1,554,000 values (six decadal means, n=6 time ×

259,000 grid points). We determined a one-month time-lag for the relative humidity effect (mean relative humidity of the previous month of peak fire) (a) and no time-lag for air temperature (b). We partitioned relative humidity into 100 bins (-50% to 50%) and average values in each bin of ACC of fire mortality. Circles indicate the average in each bin with a sample size >15. We separated the data into two categories for (a): SHSA, EURO, and AUST (red) and other remaining regions (blue); for (b), BONA, BOAS, and EURO (red) and other remaining regions (blue). We plotted linear regressions using SHSA, EURO, and AUST, where relative humidity decreased by climate change for (a), and BONA, BOAS, and EURO, where air temperature increased by climate change for (b). Supplementary Fig. 6 shows the relationship between fire organic carbon emissions and climate variables.

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Methods

Overview of the methods and simulation protocol

Fire $PM_{2.5}$ mortality was quantified in a three-step modeling chain: 1) fire emissions from three fire-vegetation models were fed into 2) an atmospheric chemistry transport model (Goddard Earth Observing System - Chemistry, GEOS-Chem[59]), the outputs of which drove 3) a health impact model (GBD 2019[60]). First and third steps were analyzed by using MATLAB 2024a. Fire emissions from three different fire-vegetation models that contributed to ISIMIP3a were used. ISIMIP provides a framework to compare climate change impact models at global and regional scales using community-agreed sets of simulation experiments and standardized input data and output variables[61]. GSWP3-W5W5 climate forcing data with (factual) and without climate change (counterfactual) were used, enabling us to quantify the contribution of climate change to observed long-term changes in fire health risk. Factual climate variables were derived from historical climate and socio-economic forcings, whereas counterfactual climate variables were generated by removing long-term climate change trends from the factual climate[26]. The detrending preserves the timing and rank of events in the climate data, that is, extreme fire weather at a certain time is also extreme in the counterfactual [26]. For the counterfactual simulations of the fire-vegetation model, CO_2 and CH_4 were kept constant at 1901 values, while for the factual simulations, they followed historical observations[24]. The factual and counterfactual simulations were both forced by the same historical socio-economic changes (population density, GDP, and land use)[53,54] and lightning frequency (LIS/OTD)[62], allowing us to single out the impact of climate change (Table 1). Finally, the attribution of fire impacts to climate change (hereafter, ACC of fire impacts) was calculated by subtracting the results of counterfactual simulation from those of factual simulation and dividing by the counterfactual results (Eq. 1).

$$ACC\ (\%) = \frac{x_{fact} - x_{c.fact}}{x_{c.fact}} \times 100 \qquad \text{(Eq. 1)}$$

where x can be fire emissions, fire $PM_{2.5}$ concentration, and its associated mortality.

Our analysis used a 0.5° × 0.5° spatial resolution, and decadal time step (converting monthly fire-vegetation model results to decadal monthly mean, then obtaining yearly mean $PM_{2.5}$ and annual mortality).

ISIMIP3a fire-vegetation models and estimation of fire emissions

We selected three fire-vegetation models (CLASSIC[63,64], SSiB4[65], and JULES[66]) from the fire-vegetation models that provided simulations in ISIMIP3a. The full ensemble of fire models was described previously[47]. Their analysis shows that CLASSIC, SSiB4, and JULES are among the models that perform best globally and yet cover different mechanisms relevant to simulate fire. The three models also showed differences between factual and counterfactual scenarios in total carbon emissions from fires (Extended Data 1), indicating that the models cover a wide range of uncertainties with regard to the climate change impact on fire. They incorporate sub-grid scale heterogeneity through a mosaic approach, wherein a heterogenous grid box is delineated by different land types and their respective fractional coverage area within the grid box (0.5-degree).

For inputs of GEOS-Chem, we converted the outcome of each fire-vegetation model into dry matter emissions for five land types: grassland and shrubland, agricultural areas, temperate forests, tropical forests, and boreal forests. For JULES and SSiB4, we converted burned area into fire dry matter emissions first and subsequently divided them into five land types. As the CLASSIC outcome includes fire carbon emissions by plant functional type (PFT), we converted carbon emissions into dry matter emissions by designating PFT into five land types.

To convert burned area into emissions, we used the biomass and soil moisture of each fire-vegetation model to calculate fuel consumption and combustion completeness (CC). Biomass and soil moisture were taken from ISIMIP3a under two simulations (i.e., factual and counterfactual). The CC was scaled linearly by using a soil moisture index. The 15th and 85th percentiles of the soil moisture index corresponded with the minimum and maximum CC values.

The minimum values of CC for leaf, stem, fine litter, and woody litter were 0.8, 0.2, 0.9, and 0.5, respectively, and maximum values were 1, 0.3, 1, and 0.6 [67]. The soil moisture index was calculated by soil moisture and soil type with MARS compute script (https://www.ecmwf.int/en/forecasts/documentation-and-support/evolution-ifs/cycles/change-soil-hydrology-scheme-ifs-cycle#implications).

The fire-vegetation models use climate variables to dynamically simulate fuel load (biomass), fuel combustibility (soil moisture, relative humidity, air temperature), fire spread (wind speed), and fuel consumption (soil moisture). The three fire-vegetation models considered the socio-economic impacts on global fire activity (i.e., fire management, suppression, land fragmentation) by using population density (SSiB4 uses GDP per capita together with population density). The brief description of each fire-vegetation model is provided in supplementary note 1.

Since fire-vegetation models have many structural differences, they often differ in simulated historical fire emission[68,69]. The spread in the global annual burned area across seven fire-vegetation models in ISIMIP3a is 350–750 Mha[47]. Modeling fire occurrence and its interaction with the atmosphere (i.e., gases and aerosol emitted from fire) at the global scale is still challenging. Given that the fire emissions from our three fire-vegetation models have not been evaluated, we assessed recent historical (1997–2019) fire organic carbon emissions, benchmarking them against satellite-based datasets.

Simulation of surface $PM_{2.5}$ concentrations

We used the chemical transport model GEOS-Chem to simulate the surface-gridded yearly mean $PM_{2.5}$ concentration (v13-04[59], http://www.geos-chem.org). GEOS-Chem includes detailed global aerosol-oxidant chemistry[70,71]. We simulated the $PM_{2.5}$ concentration at 4° × 5° resolution with 72 vertical layers and downscaled it to 0.5° × 0.5° resolution using a first-order conservative remapping technique. This technique employs a conservative interpolation approach, ensuring the conservation of the integral of the field being remapped. A previous study had confirmed that GEOS-Chem results between nested (0.5° × 0.625° resolution) and non-nested (4° × 5° resolution) simulations were not significantly different when validated against observational data[72]. However, this downscaling process may introduce smoothing effects, potentially leading to a loss of fine-scale details and features in the original coarse grid data[73]. We used the monthly fire emissions averaged decadal mean from the 1960s to the 2010s under two simulations. Anthropogenic emissions data were derived from observational values for the years 1965, 1975, 1985, 1995, 2005, and 2015, obtained from the Community Emissions Data System Inventory[57]. We used the meteorological data fixed from the MERRA2 reanalysis product of the NASA Global Modeling Assimilation Office, specifically for the year 2016, which represented usual recent climate conditions without extreme events such as El Nino. Fixing the meteorological condition for a specific year allowed us to attribute the impact of climate change on fire activity.

We simulated $PM_{2.5}$ concentration with fire (PM_{wFire}) and without fire (PM_{woFire}) to calculate the fraction of fire contribution to $PM_{2.5}$ concentration by grid (Eq. 2). Here, two sets of PM_{wFire} with factual and counterfactual fire emissions simulations were used to calculate $frac$t ($fract_F, fract_C$). Since the functions of health risk and $PM_{2.5}$ concentration are non-linear, and they were developed without differentiation of the $PM_{2.5}$ composition or source, we calculated the total mortality using PM_{wFire} and multiplied it by $fract$ to obtain the contribution of fire to the total $PM_{2.5}$ mortality, as we assumed that all sources of $PM_{2.5}$ have the same risk.

$$fract = {}^{(PM_{wFire} - PM_{woFire})}\!\big/_{PM_{wFire}} \qquad \text{(Eq. 2)}$$

To calculate regional or global $PM_{2.5}$ concentration, we used PWC values, which is the averaged $PM_{2.5}$ of all grids within the region considering population (Eq. 3). where n is the number of grids in the region.

$$PWC = \sum_{i=1}^{n} \frac{PM_i}{Pop_i} \sum_{i=1}^{n} Pop \qquad \text{(Eq. 3)}$$

Estimation of $PM_{2.5}$ mortality

Mortality was estimated using meta-regression-Bayesian regularized trimmed (MRBRT) splines developed in the GBD 2019 study by country, diseases, and age group[60]. We selected six diseases, namely chronic obstructive pulmonary disease (COPD), lung cancer, ischemic heart disease (IHD), type II diabetes mellitus (DM), stroke, and lower respiratory infection (LRI), which have been considered by Southerland et al[74] and McDuffie et al.[9]. The relative mortality risk of annual PM2.5 exposure on these six diseases has been established through previous cohort studies conducted in many countries around the world. The splines for each disease are specific by age group: COPD, lung cancer, and DM for adults (>25 years, one group), IHD and stroke for adults (>25 years) with 5-year intervals (15 groups) because the relative risk of cardiovascular diseases decreases with age[75], and LRI for children (<5 years, one group). The mortality for each disease (d) and age group (a) was calculated at the grid level (0.5° × 0.5°) (Eq. 3).

$$Mort_{d,a,i} = Pop_{a,i} \times BM_{d,a,i} \times \frac{HR_{d,a,i} - 1}{HR_{d,a,i}} \qquad \text{(Eq. 3)}$$

where $Pop_{a,i}$ represents the population by age group in grid i. The age structure (population ratio by age group) of grid i follows the value of the country level to which the grid belongs. BM is the baseline mortality rate, and the BM of grid i follows the country-level value. HR is the hazard ratio, derived using MRBRT as in GBD 2019, and is a risk function corresponding to $PM_{2.5}$ exposure (= $MRBRT_{d,a,i}(PM_{wFire}) \Big/ MRBRT(TMREL)$). We used the mean values for the MRBRT outputs. $TMREL$ is the theoretical minimum risk exposure level, and we set it at 2.4 μg m^{-3}. We used two different $PM_{2.5}$ exposure sets from factual and counterfactual simulations in a risk function ($\mathrm{HR}_F, \mathrm{HR}_C$), while keeping the other socio-economic input based on observation data consistent for mortality analysis. We used gridded population data from ISIMIP3a (https://data.isimip.org/10.48364/ISIMIP.822480.2)[53] and country-level age structure data from the United Nations[55] for 1965, 1975, 1985, 1995, 2005, and 2015. BM has relatively larger yearly fluctuations than the population, and we used decadal mean values for the 2010s (2010–2019), 2000s (2000–2009), and 1990s (1990–1999) from the IHME[56]. Since BM was not available before 1990, we conservatively assumed that background disease rates remained constant at the 1990 levels. As a sensitivity test, we assumed that the BM between 1960 and 1980 followed a similar trend to that between 1980 and 1990 and interpolated BM between the 1960s and the 1980s using the 1980s–1990s change ratio.

Evaluation of factual simulations

We evaluated the three-step modeling results with different benchmarking datasets. Fire organic carbon emissions (the major aerosol of secondary $PM_{2.5}$ from fire) were compared to the benchmark datasets Global Fire Emissions Database (GFED) 4.1s (1997–2019) and Global Fire

Assimilation System (GFAS) (2003–2019) organic carbon emissions. We evaluated spatial patterns with 2010s results using the normalized mean error (NME). NME is the benchmarking score for spatial agreement, with lower values indicating better agreement (Eq. 4)[76].

$$NME = \frac{\sum_i Area_i |B_i - S_i|}{\sum_i Area_i |B_i - \bar{B}|} \qquad \text{(Eq. 4)}$$

Where $Area_i$ is grid area and B_i and S_i are the benchmark dataset and simulated values over all grids i. We also calculated Step 3 NME (NME3), which uses $B_i/\bar{B}$ and $S_i/\bar{S}$ instead of B_i and S_i, which removes mean bias and absolute variance before comparison and assesses the models' ability to simulate regions of high and low burned area[77]. Third, temporal NME (NMEt) was calculated with anomalies normalized by the mean variation. In equation 4, grid i changes to year i (n=23 for GFED, 17 for GFAS), and the area is ignored to calculate NMEt. Third, we compared the long-term trends of fire organic carbon emissions by identifying the changes between the decadal mean of the 2010s and 2000s. We examined the spatial distributions of decadal changes using both fire-vegetation models and GFED4.1s and then checked the areas where both the model and GFED4.1s show an increasing or decreasing trend.

We validated the simulated surface annual $PM_{2.5}$ concentration (PM_{wFire}) with gridded $PM_{2.5}$ concentration data from GBD (Global Burden Disease) 2019. We validated the spatial pattern using linear regression models from our 2010s estimation and 2015 GBD data. Evaluation metrics were the scores of R-squared values and normalized mean bias (NMB, $\sum(B_i - A_i)/\sum A_i \times 100$). We also compared our PM2.5 estimation and GBD data for regions with greater fire proportion (over 30%) to identify whether GEOS-Chem generated reasonable fire-attributed $PM_{2.5}$. These spatial validations of PM2.5 concentration were carried out at 0.5°× 0.5° spatial resolution.

Finally, the mortality from annual $PM_{2.5}$ concentration was compared with country-level GBD 2019 results (from the six diseases outlined above)[56]. We used R-squared value and NMB evaluation metrics to compare GBD 2019 results and model output aggregated at the country level (n=204) in the 2010s. From $PM_{2.5}$ concentration analysis, we conducted simulations with decadal temporal steps and did not include temporal evaluations.

All the evaluation results of the simulations are provided in the Supplementary Note 3.

Sensitivity tests for assessing fire mortality

We conducted sensitivity tests to identify the attributable fire mortality to other influencing factors and climate change. We chose three key influencing factors that are closely related to uncertainty in the three-step modeling chains: [1] interannual variability in fire emissions from the fire-vegetation models, [2] meteorological condition of GEOS-Chem, and [3] baseline mortality assumption before 1990. We calculated X_a and X_b for each sensitivity test and calculated the difference between two Xs. For example, our main results showed the attributable fire mortality to climate change and designated X_a as the 2010s fire mortality under factual simulations, and X_b as the 2010s fire mortality under counterfactual simulations. For the first sensitivity test, we used GFED4.1s fire emissions in 2015 (the highest global fire mortality year during the 2010s) and 2013 (the smallest global fire mortality year during the 2010s) because the three fire-vegetation models could not reproduce interannual variability well. We designated X_a as the fire mortality in 2015 and designated X_b as the fire mortality in 2013. For the second sensitivity test, we identified the influence of meteorological conditions of GEOS-Chem because we fixed 2016-year meteorological conditions for producing our main results. We simulated GEOS-Chem with 2010–2019 meteorological conditions while fixing other emissions (2015 anthropogenic emissions and the 2010s fire emissions; fire emissions produced by CLASSIC exhibited the lowest NME values globally). For the third sensitivity test, we varied the baseline mortality rate assumption before 1990, for which data are unavailable. X_a was used as the fire mortality in the 1980s with temporally interpolated baseline mortality rates between 1980 and 1990 and X_b became the fire mortality in the 1980s with a fixed baseline mortality rate to the 1990s.

Data availability

Input data (climate and socio-economic forcing and the burnt area in the factual and counterfactual simulations) are available from the ISIMIP data repository (https://data.isimip.org/). Topographic data for making global map was driven from MathWorks and we used MATLAB R2024a for creating all figures. Intermediate and output data used in this analysis are available at the repository with MATLAB array format and NetCDF format (10.5281/zenodo.13231638[78]).

Code availability

All code to reproduce the analysis and figures is made available on the repository (10.5281/zenodo.13231638[78]).

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