

Fossil fuels dominate future warming but not the past or present

Nathaniel Tarshish^{1,*}, David M. Romps^{2,3}, and Inez Fung²

¹*Center for the Environment, Harvard University, Cambridge, MA 02138, USA*

²*Department of Earth and Planetary Science, University of California, Berkeley, CA 94720, USA*

³*Climate and Ecosystem Sciences Division, Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA*

**Corresponding author. E-mail: ntarshish@g.harvard.edu*

September 30, 2026

Abstract

Fossil fuels have long been considered the primary driver of global warming, but this claim has not been rigorously demonstrated. Here, we quantify the impact of fossil fuels on historical warming with an ensemble of climate emulators that account for aerosol cooling and other key uncertainties. Contrary to conventional wisdom, we find that the majority of present-day anthropogenic warming likely stems from non-fossil sources, particularly agriculture and land-use change. Moreover, fossil fuels likely caused net cooling before 1980, as high rates of sulfate emissions from coal increased Earth’s reflectivity enough to offset the associated greenhouse-gas warming. Although fossil fuels are likely responsible for less than half of present-day warming, they have dominated emissions of long-lived carbon dioxide, and so fossil fuels are expected to dominate global warming by mid-century and for millennia thereafter.

Keywords: fossil fuels; climate change; warming attribution; aerosols; land use

It is widely asserted that fossil fuels are the primary cause of anthropogenic warming, as stated by the U.S. National Climate Assessment, the EPA, NASA, and the United Nations [1–4]. Fossil fuels are indeed the dominant source of carbon dioxide, which is by far the single largest source of radiative forcing [5]. Since roughly 90% of current CO₂ emissions come from fossil fuels [6], it would seem reasonable to assume that the vast majority of the warming is attributable to fossil fuels. Here, “warming” refers to the global mean temperature increase since 1750 due to human activities, currently about 1.3 °C [5].

However, this attribution overlooks that fossil fuels also emit sulfate aerosols, which presently cool the planet by approximately 0.5 °C [5]. Consider a simplified climate in which CO₂ and sulfate aerosols are the only anthropogenic forcings. The 1.3 °C of current warming then implies that aerosol cooling is offsetting 1.8 °C of CO₂-driven warming. Much of this CO₂-driven warming, however, is not due to fossil fuels. CO₂ warming scales with cumulative rather than current emissions [7], and only two thirds of cumulative CO₂ emissions are from fossil fuels, with the remainder from land use [6]. Therefore, fossil-fuel CO₂ is responsible for $1.8\text{ °C} \times \frac{2}{3} \approx 1.2\text{ °C}$. In net, fossil fuels then contribute only $1.2\text{ °C} - 0.5\text{ °C} = 0.7\text{ °C}$, no longer the vast majority of current warming. Notably, this attribution is still an overestimate, as it neglects the warming from CH₄ and N₂O emissions, which are primarily from non-fossil sources.

Although crude, this back-of-the-envelope estimate suggests that fossil fuels are not the dominant driver of historical warming. A rigorous assessment would include all of the emitted gases and also account for uncertainty in historical emissions and in the climate response. Here we provide such an assessment. We find that, of the 1.3 °C of warming in 2019 assessed by the IPCC [5], fossil fuels were responsible for a median estimate of 0.42 °C with a 90% confidence interval of [0.13–0.64] °C. Extending this analysis to 2025 increases the fossil-fuel share of warming, but it remains likely less than half.

Both the back-of-the-envelope estimate and our detailed calculation point to the same fundamental conclusion: fossil fuels are likely responsible for a *minority* of the present-day global-mean temperature anomaly. This result hinges on two often overlooked facets of historical climate change [8, 9]: the cumulative impact of centuries of land-use emissions, and the masking of fossil-fuel greenhouse warming by co-emitted aerosols.

From cooling to minority of warming

Here we extend the methodology of the IPCC AR6 report to assess the contribution of fossil fuels to global warming over the industrial era. Warming attribution in AR6 links temperature change to individual greenhouse gases and aerosols [10]. Since emissions of these species are due to both fossil fuels and other activities, the impact of fossil fuels alone is unclear. The present study fills this gap by providing a probabilistic evaluation of the total warming due to fossil fuels consistent with the state of the science as reflected in AR6.

In particular, we assess fossil-fuel warming with the Finite-amplitude Impulse Response (FaIR) emulator, a simple climate model that is prominently featured in recent IPCC reports [11–13] and was developed to provide probabilistic estimates of the global-mean climate variations caused by greenhouse gas and aerosol emissions [14–16]. Experiments are performed here with an ensemble of 841 configurations of FaIR, designed to span the current physical uncertainty in the climate system [17]. The ensemble is calibrated to reproduce historical observations and AR6-assessed ranges for key climate metrics, including uncertainty in the magnitude of aerosol cooling (see Materials and Methods).

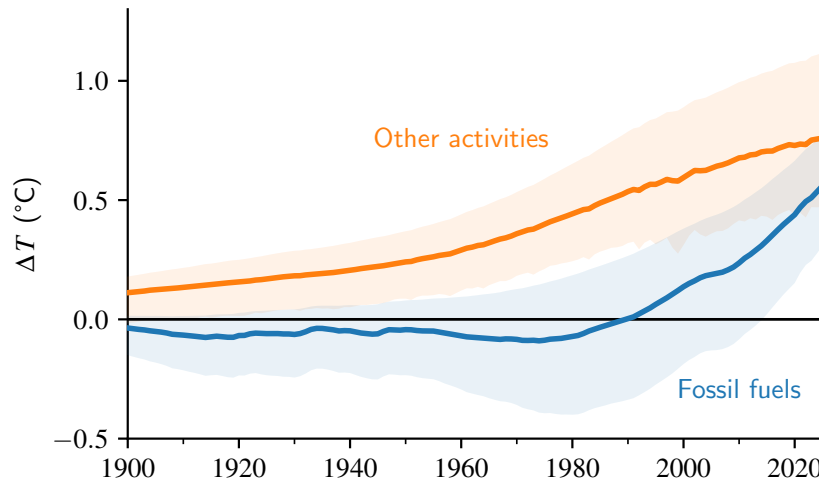


Figure 1. Origins of historical warming. Warming attributed to burning fossil fuels (blue) versus all other activities (orange) over 1900–2025. Solid lines are the medians of the climate model ensemble and shading indicates the 90% confidence interval.

Historical emissions data are sourced from the same datasets used in AR6 [18, 19], updated to the present day as per the 2023 Indicators of Global Climate Change (IGCC) report [6, 20–23]. Gaps in the historical data, arising from reporting delays, are filled by linear extrapolation of the past decade’s emissions for each species and activity. When all emission sources are considered, the FaIR ensemble agrees with the consensus estimates and uncertainties for the per-species radiative forcings and resultant warming (refer to Fig. S4 and Table S4, respectively).

Anthropogenic warming is attributed here using two separate experiments with FaIR: one driven solely by historical fossil-fuel emissions, and another driven by historical emissions from all other activities. Those other activities are agriculture, forestry, and other land uses (AFOLU), cement calcination, biomass combustion, certain mineral and chemical processes, waste handling, landfills, and emissions of halogenated gases. Reporting practices make it unclear whether certain industrial processes originate from fossil fuels [24]: these ambiguous processes are included with the fossil fuels here, but our findings are not sensitive to this choice (Fig. S10). Uncertainty in reported emissions is sampled with a quasi–Monte Carlo algorithm, yielding 128 realizations of historical emissions. For each realization, FaIR is run forward to compute concentrations, radiative forcing, and the global-mean temperature response across 841 calibrated physical parameter sets, for a total of $128 \times 841 = 107,648$ simulations. For a detailed breakdown of the emissions sources, classification, and uncertainties, refer to Materials and Methods and the Supplementary Information.

Due to nonlinear effects (primarily from atmospheric chemistry), the sum of the temperature anomalies from the separate fossil and non-fossil experiments exceeds the anomaly due to all emissions by 12% in 2025 (see Fig. S6). Since this nonlinear component of the warming is generated if and only if both sets of emissions are present, it is attributed in equal parts to fossil fuels and other activities following the Shapley procedure [25]. The temperature time series for the two separate experiments are reduced by equal (yet time-varying) amounts so that their sum matches the temperature time series resulting from when FaIR is driven by all emissions combined (see Materials and Methods).

Fig. 1 shows the resultant temperatures for the fossil-fuel experiment (blue) and for other activities (orange). The median estimate of the temperature change induced by fossil-fuel emissions is negative, averaging -0.1°C , up until around 1990. This suggests that fossil fuels contributed to a weak global-cooling effect during much of the 20th century, partially offsetting warming from other sources. From 1990 onward, the temperature anomaly due to fossil fuels has increased sharply, rising by 0.16 [0.11 – 0.22] $^{\circ}\text{C}$ per decade and culminating in a net anomaly of 0.56 [0.31 – 0.78] $^{\circ}\text{C}$ in 2025; here and throughout, the central number is the median and the range in brackets is the 90% confidence interval.

In contrast, the temperature anomaly attributable to other activities (primarily AFOLU; Fig. S1) was positive throughout the 20th century, increasing at a more consistent and gradual rate of 0.05 [0.04 – 0.08] $^{\circ}\text{C}$ per decade, amounting to 0.76 [0.47 – 1.12] $^{\circ}\text{C}$ in 2025. For 78% of the ensemble members, other activities are responsible for a larger fraction of present-day warming than fossil-fuel emissions. Therefore, our analysis indicates that fossil-fuel emissions are likely responsible for only a minority of warming to date.

Uncertainty in this analysis is dominated by uncertainty in the physical response of the climate system rather than uncertainty in the underlying emissions (Fig. S8). Aerosol cooling uncertainty, in particular, obscures whether fossil fuels were a net source of warming or cooling over much of the 20th century: restricting to the quartile of ensemble members with the weakest present-day aerosol cooling shifts the transition to net warming from 1990 to 1930 (Fig. S9). This sensitivity reflects genuine disagreement among CMIP6 models on the strength of aerosol-cloud cooling, rather than a deficiency of the global emulator used here (Materials and Methods). Calibrated against each of 13 CMIP6 models, FaIR’s global-mean aerosol parameterization successfully reproduces the historical aerosol–cloud forcing trajectory, despite regional shifts in aerosol sources over time (Fig. S7).

Over recent decades, the net effect of fossil fuels has emerged from this shroud of aerosol uncertainty and grown rapidly. Fossil fuels are now poised to overtake other activities to become the dominant source of realized warming. Linear extrapolation of the decadal temperature trends in Fig. 1 suggests that fossil fuels will be the primary source of warming by mid-century (2037 [2009–2065]). The exact timing of fossil-fuel dominance, however, depends on the details of future emissions and is not further explored here.

These results sharpen earlier approximations of the net impact of fossil fuels [8, 9]. While IPCC assessments quantify sectoral contributions to warming [5, 11], they rely on pulse experiments with present-day emissions, which by construction cannot address the historical origins of observed warming. Ref. [8] addresses this question by weighting each species’ current radiative forcing by the fossil-fuel share of its cumulative emissions, concluding that 19% of the warming in 2015 is due to fossil fuels. That approximation does not account for natural sinks, the timescales of those sinks, or the time series of emissions—all of which are accounted for here, along with their respective uncertainties. Accounting for these factors raises the fossil-fuel share of warming to 32% [2–54%] in 2015 and 42% [23–60%] at present.

Our work also resolves an ambiguity in ref. [9], which found that non-AFOLU emissions became the dominant source of anthropogenic forcing in the 1980s. Because that broad category lumped fossil fuels together with cement production, halocarbons, and other industrial emissions, it left open whether fossil fuels themselves had become the dominant driver of warming. We show that fossil fuels, considered in isolation, were near-zero net contributors at that time and remain a minority contributor today.

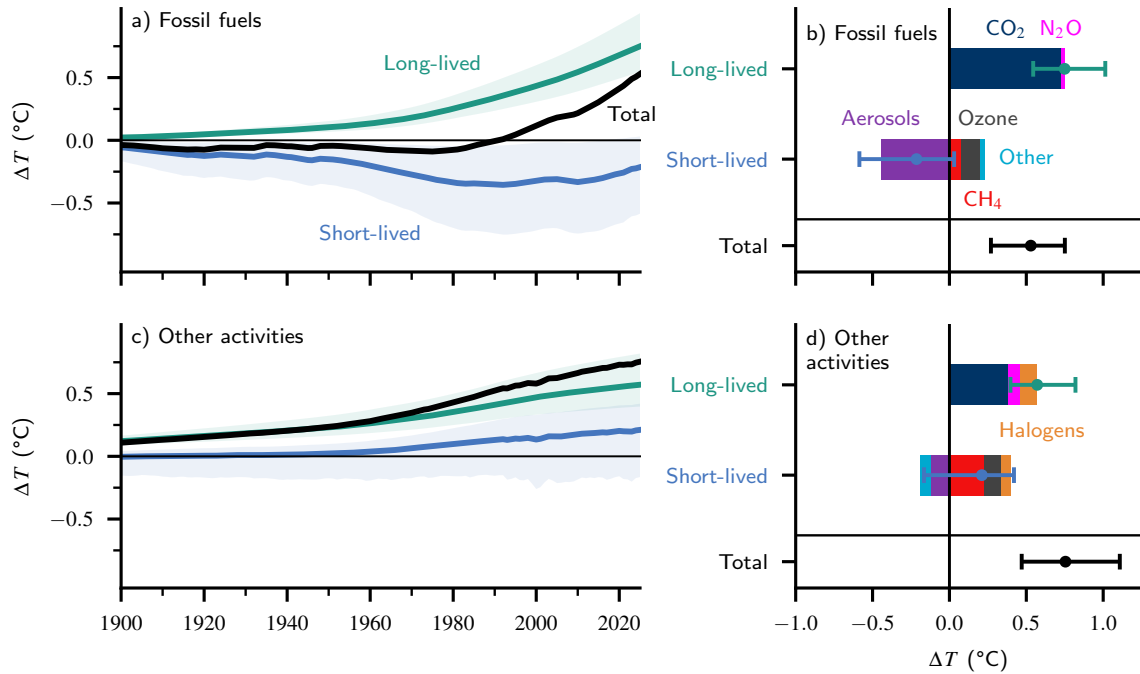


Figure 2. Warming sorted by activity, lifetime, and chemical species. (A) Warming from long-lived fossil-fuel greenhouse gases (green) has accumulated over 1900–2025, overcoming cooling due to co-emitted short-lived species (blue) around 1990. (B) The long-lived component of fossil fuels in 2025 is predominantly from CO_2 , while aerosols have dominated the short-lived species. (C) Warming from other activities (primarily agriculture and land use) has grown relatively slowly over the industrial period and has never been substantially masked by short-lived cooling. (D) The short- and long-lived warming due to other activities in 2025 are both positive and involve a variety of species. Shadings and whiskers indicate the 90% confidence interval. For total warming, refer to Fig. 1 for the relevant confidence interval. The “other” contribution (turquoise) aggregates the contributions from land-use albedo changes, particles on ice and snow, and stratospheric water vapor (see Table S3).

Competition between short-lived and long-lived gases

To understand the changes in warming over time, Fig. 2 categorizes chemical species as either long-lived or short-lived. All species, except for CO_2 , N_2O , and halogenated gases that have atmospheric lifetimes of a century or more, are considered short-lived. Short-lived gas concentrations are proportional to recent emissions levels, while long-lived gas concentrations are determined by cumulative emissions over the entire industrial period.

At the turn of the 20th century, annual CO_2 emissions from fossil fuels and other activities were the same order of magnitude (Fig. S1). However, the warming from fossil-fuel CO_2 was minimal because not enough time had passed since the start of industrialization for those emissions to accumulate significantly. In contrast, CO_2 from non-fossil sources had been accumulating from deforestation over the prior centuries, resulting in a substantial temperature anomaly by 1900.

Sulfate concentrations, however, depend only on recent emissions, meaning that aerosol cooling from fossil fuels had a substantial influence even at the onset of industrialization. Additionally, the fuel mix in the early 20th century had a higher sulfur content than present-day [19], further enhancing the relative importance

of aerosol cooling. As a result, fossil fuels yielded a net cooling over much of the 20th century: short-lived cooling outweighed the gradual buildup of long-lived greenhouse gases, primarily CO₂. This dynamic shifted around 1990 when fossil-fuel CO₂ had finally accumulated to sufficient levels to overcome aerosol cooling and produce net warming.

The sharp increase in fossil-fuel-related warming since then can be attributed to a significant rise in long-lived greenhouse gas emissions, alongside a reduction in short-lived cooling effects, primarily from a decrease in sulfate aerosols (Fig. S1). Stricter emissions standards, which led to the adoption of flue-gas desulfurization at coal-fired power plants and lowered the sulfur content of liquid fuel, are responsible for this decline in aerosols [26]. The net temperature effect of short-lived species from fossil fuels is near -0.2°C in 2025, as the cooling from aerosols is largely balanced by warming from ozone and methane (Fig. 2B). Therefore, the net rate of warming generated by *present-day* fossil-fuel infrastructure can be thought of, to first approximation, as entirely long-lived and due to CO₂.

Committed warming dominated by fossil fuels

While fossil fuels do not yet dominate the total warming to date, the long-lived component of warming has been primarily due to fossil fuels since the early 2000s. Today, in 2025, the long-lived warming from fossil fuels is roughly 50% larger than that of other activities (see green curves in Fig. 2A,C). Here a timescale of a century was used to distinguish short-lived from long-lived species, but it is possible to consider warming over much longer timescales. In the centuries beyond 2100, “long-lived” species like N₂O and many types of halogens are effectively removed from the atmosphere, leaving CO₂ responsible for the vast majority of warming. The cumulative emissions of CO₂ due to fossil fuels surpassed other activities in the late 1980s, meaning that fossil fuels have been the leading contributor to multi-century committed warming since that time.

Furthermore, the nature of the warming committed by CO₂ emissions from fossil fuels is fundamentally different from that committed by CO₂ emissions from AFOLU. If future food production shifts away from land-intensive practices, CO₂ from past land-use emissions would largely be removed from the atmosphere due to ecosystem regrowth on a centennial timescale [27]. By contrast, carbon released from geologic fossil reservoirs has no direct path back to its former state, and must rely instead on slower oceanic pathways [28]. From this perspective, since the onset of industrialization, fossil-fuel emissions have imposed a stronger commitment to multi-century warming than all other activities.

Fig. 3 probes these differing warming commitments with experiments in which emissions are ceased in 2025. Physical rather than emissions uncertainty again dominates (Fig. S8). The median temperature anomaly due to fossil fuels remains essentially constant over the coming centuries. Radiative forcing in this fossil-fuel experiment, on the other hand, is roughly halved over the following centuries due to CO₂ uptake by natural carbon sinks (Fig. S5). However, this decline in radiative forcing is balanced by a weakening of the deep-ocean heat sink, which substantially moderates surface temperatures at present. The compensation between the declining source and sink of heat results in a nearly time-invariant temperature response to the cessation of fossil-fuel emissions [29, 30].

In contrast, the temperature change due to other activities declines steeply after emissions cessation, particularly under the assumptions of strong regrowth (Materials and Methods). Large declines in radiative

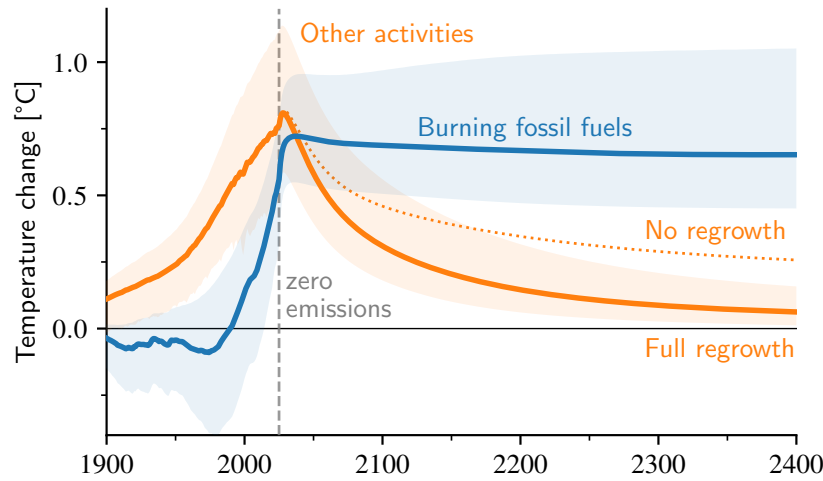


Figure 3. Fossil fuels dominate committed warming. The temperature response to presently ceasing emissions in scenarios driven solely by burning fossil fuels (blue) and all other activities (orange), respectively. In the latter case, the fate of agriculture and land-use CO_2 emissions is illustrated by scenarios with no (dashed) and full (solid) regrowth from ecosystem restoration. Solid lines are the medians of the climate model ensemble and shading indicates the 90% confidence interval.

forcing due to the shorter atmospheric lifetimes of these species dominate over the waning oceanic heat sink (Fig. S5), leading to a global-average temperature anomaly from other activities that approaches zero on a multi-century timescale. As a result, around two thirds of the warming in 2100 already committed by historical emissions is due to fossil fuels.

Discussion

These findings challenge the prevailing view that fossil-fuel combustion has been the dominant driver of historical warming [1–4]. A full accounting shows that much of the greenhouse warming from fossil fuels was offset by their co-emitted sulfate aerosols, and that 20th-century warming was driven instead by agriculture and land use. Despite its secondary contribution at present, fossil-fuel warming has risen sharply in recent decades and, unlike land-use emissions, is effectively permanent on civilizational timescales absent negative-emissions technologies. Extrapolating current trends, the warming from fossil-fuel emissions will likely exceed that from other activities by mid-century. In addition, even if all emissions ceased immediately, the warming by fossil fuels would still overtake other sources in the coming decades (Fig. 3). Therefore, although fossil fuels are not the primary cause of warming to date, projections indicate that fossil fuels will dominate warming from the near future onward.

Materials and Methods

Separating fossil-fuel emissions from other activities

Emissions of greenhouse gases and aerosols from 1750 to the present are compiled using the methodology described in ref. [17], which relies on the same datasets employed in AR6, updated to reflect current emissions as reported in the latest IGCC report [23]. In addition to replicating the total emissions reported in ref. [17], we use supplemental data to distinguish between emissions from fossil fuels and those from non-fossil-fuel sources.

Fossil-fuel emissions include all sources except those from agriculture, forestry, and other land uses (AFOLU); cement calcination and other material processes; specific industrial chemical and mineral processes; biomass fires and waste-to-energy; waste management; landfills; and halogenated gases. Guided by the IPCC’s common reporting framework [24], the fossil-fuel category defined here covers all energy sector emissions except for biomass combustion and includes a subset of the emissions due to industrial processes (Sector 2), waste (Sector 6), and other activities (Sector 7).

All CO₂ emissions data are taken from the 2023 Global Carbon Project (GCB) [31]. Fossil-fuel CO₂ emissions are taken from the fossil-only category of the GCB dataset, while non-fossil-fuel CO₂ emissions are sourced from GCB’s land-use-change and calcination datasets.

The Community Emissions Database (CEDS) [19, 22] is used to source emissions from 1750 to 2019 of black carbon (BC), organic carbon (OC), NH₃, NO_x, SO₂, and volatile organic compounds (VOC). CEDS does not capture changes in natural biogenic VOC emissions from land-use change; this missing pathway yields a short-lived-climate-forcer warming effect of order 0.1 W m⁻² for complete global deforestation [32]. Including this AFOLU warming effect, which is considerably smaller for historical deforestation, would cut in the direction of strengthening our conclusion that most historical warming is likely not due to fossil fuels. From 2019 to 2022, the CEDS data are projected forward using emission factors based on mobility data from the two-year blip scenario of COVIDMIP [33] following the methodology of ref. [17]. CEDS covers all activities except for biomass fires. The CEDS dataset categorizes fossil-fuel emissions by sector, detailed in Table S2. Biomass combustion emissions are excluded from the energy sector using data from the alternative “by fuel” CEDS dataset. The role of fossil fuels in emissions from certain industrial sectors remains ambiguous due to the diverse chemical processes aggregated within these sectors. While some of these processes undoubtedly use fossil fuels as feedstocks, precise attribution is not available in the CEDS dataset. In the primary results and figures, these ambiguous sectors are grouped with fossil fuels. However, attributing these ambiguous emissions to non-fossil activities instead does not affect the conclusions (see Fig. S10).

The primary source for CH₄ and N₂O emissions is PRIMAP-Hist (i.e., the “third-party” version) [20, 34], supplemented by CEDS data where necessary. PRIMAP data are grouped at the IPCC sectoral level, necessitating a further breakdown for the waste and industrial sector emissions, which include fossil, biogenic, and ambiguous sources. CEDS, which provides data at the finer subsector level, is used to estimate the fractional contribution of the above sources to the PRIMAP sector totals. The CEDS record, however, only goes back to 1970. To disaggregate the PRIMAP waste emissions before 1970, the fraction of PRIMAP sectoral emissions due to waste combustion is assumed to be constant prior to 1970. A similar approach is used to categorize non-fossil and ambiguous activities within the Industrial Process and Product Use (IPPU)

sector based on CEDS subsector data, with these respective emissions fractions assumed constant before 1970.

Emissions from biomass burning of all species other than CO₂ (i.e., BC, CH₄, CO, NH₃, NO_x, OC, and SO₂) are sourced from the Global Fire Emissions Dataset [21] and from BB4CMIP [18]. Halogenated gas emissions (F-gases) come from ref. [17] and are inverted from observed concentrations using IPCC assessed lifetimes, except for SF₆ and NF₃, which are available in the PRIMAP-Hist dataset. Future emissions and historical data gaps due to reporting delays are addressed by linear extrapolation based on per-species decadal emissions trends.

Climate emulator

Reduced-complexity models are well-suited to attributing warming to specific activities because they can be used in large ensembles that span key uncertainties and can be calibrated against observed data and other climate metrics [15, 17]. Specifically, the AR6 WG1 report included a detailed calibration of several such models, including the Finite-amplitude Impulse Response (FaIR) model, used in this study [35]. Simulations are performed here with the latest version (2.1.0) [16], which has been calibrated to observations updated through 2022 in ref. [17] to provide an 841-member AR6-consistent ensemble (v1.4.1). The complete calibration process is documented in [17] and summarized here for clarity.

FaIRv2.1 simulates global-average quantities with a three-box ocean model and a basic carbon-cycle parameterization with four uptake timescales [14, 16, 36]. Those four atmospheric lifetimes of CO₂ vary based on atmospheric levels, global-mean temperature, and the cumulative uptake by land and oceans.

In addition to CO₂, methane's lifetime is prognosed, as a function of the global-mean temperature and the concentrations of other chemically active species, including methane itself. All other greenhouse gases (GHGs) decay at a constant rate over a predefined timescale. The model also simulates interactive ozone levels—combined tropospheric and stratospheric—and parameterizes aerosol direct and indirect effects using functional fits (see section below). Changes in albedo from land-use are assumed to scale linearly with cumulative AFOLU CO₂ emissions (see ref. [14] for details).

The 841-member ensemble of physical configurations used in this study is a subset of an initial 1.6-million-member ensemble sampled from AR6 probability distributions [17], chosen as follows. Each of the 1.6-million model instances has 45 free parameters. Parameters related to energy balance, the carbon cycle, ozone, and aerosol-cloud interactions are sampled from kernel-density estimates of CMIP6 results [37–40]. The other forcing parameters are sampled from IPCC AR6 ranges [41]. The resultant forcings agree closely with the extensions of the AR6 WGI estimates to present-day in the latest IGCC report (see Fig. S4). Models that fail to replicate historical global-mean surface temperatures (GMST) within a root-mean-square error (RMSE) of less than 0.2 °C are excluded, eliminating 86% of the original ensemble. From the remaining models, 841 are selected that together optimally reproduce the AR6 distributions for equilibrium climate sensitivity (ECS), transient climate response (TCR), and aerosol forcing, as well as historical observations of GMST, ocean heat content, and CO₂ levels [17].

Partitioning land uptake

The treatment of the land sink follows the convention of the Global Carbon Budget [6]: FaIR’s carbon sink represents the land uptake due to climate change (e.g., CO₂ fertilization) on both managed and unmanaged land, while management-induced changes to land carbon stocks (e.g., deforestation and afforestation) are incorporated into the AFOLU emissions.

FaIR’s carbon sink is calibrated to reproduce the observed CO₂ record given total historical emissions. Because this sink incorporates climate-change impacts on managed land, the strength of the tuned sink reflects the historical trajectory of managed land. Applying this historically-tuned sink to the fossil-fuel-only case—where no AFOLU has occurred and more forest is available for fertilization—underestimates the counterfactual carbon sink. Under a preindustrial land-cover counterfactual, the cumulative historical sink would be ~40 GtC larger—a quantity known as the “Loss of Additional Sink Capacity” (LASC) [42]. By carrying this LASC-reduced sink into the fossil case, FaIR overestimates the fossil-fuel warming by roughly 0.07 K (assuming 1.65 K per 1000 GtC [41]). Adjusting for this bias, therefore, further strengthens the claim that fossil fuels are likely not the dominant source of warming.

Independent of this conservative bias, we note that the carbon sink is nonlinear in atmospheric CO₂, temperature, and cumulative uptake. As a result, the CO₂ concentrations from the isolated fossil and non-fossil experiments sum to 8 ppm less than in the combined-emissions experiment in 2025 (Fig. S12). This small residual, along with all other nonlinearities in FaIR, is attributed equally to fossil and non-fossil activities under the Shapley procedure (see *Nonlinearity* subsection below).

Aerosol-cloud interaction

We follow the treatment of aerosol forcing adopted in AR6 [43] and earlier IPCC assessments [11], in which global-mean aerosol effects are related to global emissions. Specifically, the effective radiative forcing from aerosol–cloud interactions (ERF_{aci}) is parameterised as a logarithmic function of the global emissions of SO₂, BC, and OC, following refs. [44, 45] and implemented in FaIR per Eq. 8 of ref. [17]. The resulting ensemble produces a present-day ERF_{aci} of -0.73 [-1.33 to -0.26] W m⁻², in close agreement with the IGCC estimate of -0.77 [-1.35 to -0.23] W m⁻² [23] (Table S3).

Expressing global-mean aerosol forcing as a function of global emissions may be questioned given the regional heterogeneity of both clouds and aerosol sources. The global-mean expression, however, provides a close fit to the aerosol forcing timeseries diagnosed in 13 CMIP6 models (Fig. S7, reproduced from Figure 5 of ref. [17] for completeness). We emphasize that the forcing trajectories are accurately reproduced despite cloud fields differing across models and aerosol sources that migrate regionally over time. Therefore, the regional structure of the aerosol–cloud responses does not appear to be a key limitation of the global treatment used in AR6 and reproduced here. Finally, while the global expression captures the response within any given model, a factor-of-two difference persists in the total magnitude of cooling across CMIP6 models. The FaIR ensemble inherits this uncertainty and propagates it through the entire analysis.

Emissions uncertainty

Uncertainty in partitioning emissions between fossil-fuel sources and all other activities is detailed here. The default FaIR AR6 ensemble is tuned to reproduce the AR6 forcing distributions given a single best estimate

of historical emissions. For CO₂, FaIR reproduces observed annual concentrations by adjusting the modeled carbon sinks. For the non-CO₂ greenhouse gases, FaIR assumes fixed atmospheric lifetimes and multiplies the inventory emissions by a single constant factor chosen to minimize the difference between simulated and observed concentrations. In effect, FaIR aligns the *total* emissions with the observed historical concentrations, yielding a calibrated ensemble that is largely insensitive to systematic errors in the total emissions. To use this calibration, but additionally account for uncertainty in the apportioning of emissions between fossil fuels and other activities, we keep total emissions fixed while statistically sampling the fossil-fuel and other-activities components, as described below.

Let $T_i(t) = F_i(t) + O_i(t)$ denote the total emissions of species i at time t , with $F_i(t)$ (fossil-fuel) and $O_i(t)$ (all other) emissions treated as time-dependent, log-normally distributed random variables. We take the means of the random variables to be the central values reported in the underlying emissions inventories and used in the FaIR calibration. The standard deviation is determined by the uncertainties reported in the emissions inventories (see the Supplementary Information and Table S1 for the per-species uncertainty estimates).

From these distributions, we generate rescaled samples $\tilde{F}_i(t)$ and $\tilde{O}_i(t)$ that preserve the total, $\langle T_i(t) \rangle = \tilde{F}_i(t) + \tilde{O}_i(t)$, by drawing the fossil-fuel emissions fraction,

$$\phi_i(t) = \frac{F_i(t)}{F_i(t) + O_i(t)}, \quad (1)$$

from the logit-normal distribution implied by the log-normal parameters of F_i and O_i (Fig. S11). Finally, we compute the rescaled emissions as

$$\tilde{F}_i(t) = \phi_i(t) \langle T_i(t) \rangle, \quad \tilde{O}_i(t) = [1 - \phi_i(t)] \langle T_i(t) \rangle. \quad (2)$$

Because $\tilde{F}_i$ and $\tilde{O}_i$ are perfectly anti-correlated, this approach maximizes uncertainty when attributing warming to fossil fuels versus other activities. Even with this conservative treatment, we still robustly find (probability 78%) that fossil fuels were not the dominant driver of historical warming (Fig. 1).

There are ten species emitted by both fossil-fuel and non-fossil-fuel activities (as detailed in Table S1) and modeled by FaIR. To sample the emissions of a given species across time, we draw a quasi-random quantile $q_i \in [0, 1]$ and then use the quantile function of each year's logit-normal distribution to compute the corresponding $\phi_i(t)$ holding that same quantile fixed across time. Quantile samples are generated as a quasi-Monte Carlo Sobol sequence on the unit hypercube in ten dimensions [46, 47]. The main results draw samples independently for each species; supplemental calculations, detailed in the Supplementary Information, consider the existence of correlations across species. With a Sobol sequence of length 128, median values of all results converge to two significant figures and 5–95% uncertainty bounds on temperature contributions stabilize to within 0.01 °C. (Standard Monte Carlo requires approximately 500 samples to converge; not shown.) Combined with the original 841 member AR6 ensemble (which spans uncertainty in the physical climate response) the full experiment comprises $128 \times 841 = 107,648$ realizations.

Fig. S8 partitions the total uncertainty in the fossil-fuel-driven temperature change between uncertainty in the emissions and uncertainty in the physical response. The latter dominates. Consider that the 90% confidence range of the aerosol forcing spans roughly $\pm 70\%$ [23], whereas SO₂ emissions—the main aerosol precursor—are uncertain by only $\pm 10\%$ [19]. Likewise, total CO₂ emissions are uncertain at the $\pm 10\%$ level (mostly from AFOLU), yet the transient climate response (TCR) to a doubling in CO₂ in the ensemble spans

$\pm 50\%$.

Because physical uncertainty is so much larger than the emissions uncertainty, our results are only weakly sensitive to correlation in emissions uncertainty between species. Fig. S10 shows that enforcing perfect correlation or anti-correlation between aerosol and greenhouse-gas emissions does not significantly impact our findings. The fossil-fuel share of warming in 2025 remains near 42% across correlation assumptions, but the 90% confidence interval is [23%–60%] with no correlation, [24%–58%] given a perfect positive correlation between greenhouse-gas and aerosol uncertainties, and [21%–64%] given a perfect negative correlation. Because emissions inventories compute emissions by multiplying activity data by emissions intensities [22], greenhouse-gas and aerosol emissions likely co-vary positively, so reality should lie between the uncorrelated case and the more constrained, positively correlated case. We conservatively report the results from the no-correlations experiment in the main text and figures.

In summary, we find that emissions uncertainty, whether independent or correlated, is of second-order importance and does not alter our main conclusions, as the dominant source of uncertainty is instead linked to the physical climate response.

Simulations

Changes in temperature and forcing are assessed relative to their levels in 1750. The “fossil fuel” experiments are driven by the changes in emissions since preindustrial (1750) due solely to fossil-fuel activity. In these fossil-fuel experiments, emissions from non-fossil-fuel activities are held constant at their preindustrial baselines. Their inclusion is necessary to apply the aerosol forcing formulae in FaIR [17], which are tuned relative to the total preindustrial emissions. The “other activities” experiments are likewise driven by the historical changes in the emissions since preindustrial due solely to non-fossil-fuel activities, holding fossil-fuel emissions constant at their 1750 levels.

The first set of experiments (shown in Fig. 1) is driven by historical emissions from 1750 to 2025. Emissions for 2023–2025 are estimated by linearly extrapolating per-activity emissions over the previous decade (2012–2022). In addition to the temperature anomaly, the per-species radiative forcings are recorded for experiments driven by emissions from fossil fuel, other activities, and all activities combined. The time series for these radiative forcings are then adjusted to remove non-linear components due to cross-activity interactions using the procedure detailed in the next section. In a second set of experiments, the per-species, per-activity forcings are applied one at a time as external radiative forcings to FaIR’s energy-balance model, yielding the warming decomposition in Fig. 2. Because each species’ forcing is extracted from a multi-species simulation with interactive chemistry, the resulting warming contributions include cross-species interactions, consistent with concentration-based warming attributions [43]. In a third set of experiments (shown in Fig. 3), historical emissions abruptly end in 2025, probing the zero-emissions commitment [48] out to 2500.

We explore contrasting futures of land activity after emissions cessation with the “no regrowth” and “full regrowth” scenarios. In the no-regrowth scenario, managed lands are held fixed at their present state, with no changes in carbon storage or albedo forcing. In the full-regrowth scenario, managed ecosystems are allowed to recover: we include an additional carbon sink to account for regrowth on abandoned land, removing AFOLU emissions from the atmosphere and relaxing the land-use albedo forcing to zero on an e -folding timescale of one century. This simple treatment of carbon uptake by soil and biomass from post-agricultural succession is relatively conservative. Over half of historical land-use emissions originate from tropical regions [49], where

ecosystems typically regrow over several decades, according to biomass versus age studies of abandoned land [50]. However, we conservatively use the regrowth timescale of boreal forests, which is closer to a century, as found in studies of regrowth after disturbances [51]. Note that the no-regrowth temperature in 2400, as shown in Fig. 3, is slightly below the CO₂ warming for other activities reported in Fig. 2D because of the additional long-term influence of land-use albedo forcing, which is fixed at its 2025 value (-0.2 W m^{-2} ; Fig. S3) in this scenario to be consistent with no ecosystem recovery.

Nonlinearity

Summing the temperature from the separate fossil-fuel and other-activities experiments results in a value that is 12% greater than when FaIR is driven by all emissions combined, as displayed in Fig. S6. All nonlinearities in this calculation arise from the relationship between emissions and forcing, as the energy-balance model in FaIR that computes the temperature from the total forcing is linear. Since the non-linear component arises fundamentally from the interplay between fossil-fuel and non-fossil-fuel emissions, it must be attributed equally to each. This equal division is the unique solution prescribed by Shapley theory for fairly attributing interaction effects between two contributors [25]. Thus, half of the (negative) temperature anomaly due to these nonlinear effects (shown in Fig. S6) is added to the temperature anomaly time series of the fossil-fuel and other-activities experiments. This process ensures that the total temperature anomaly resulting from the sum of the separate experiments is scaled to match that of FaIR when driven by all emissions combined. This same procedure is applied to the per-species radiative forcing time series, such that any nonlinear component is attributed equally to the fossil-fuel and other-activities experiments in the isolated-forcing experiments.

As shown in Fig. S6, methane exhibits the strongest nonlinearity ($0.11 \text{ }^{\circ}\text{C}$ in 2025). AerChemMIP [39] found that changes in methane chemistry are largely driven by NO_x. Because FaIR's methane cycle was calibrated to those AerChemMIP experiments, the nonlinearity identified here primarily reflects FaIR's sensitivity to NO_x (not shown). The magnitude of this nonlinear effect remains uncertain due to the difficulty of representing methane chemistry with a simple parameterization and incomplete constraints on historical anthropogenic methane sources and wetland sinks [17].

Data availability

All data and code used in this study are deposited in a Zenodo repository (<https://doi.org/10.5281/zenodo.13743384>).

Acknowledgments

The authors thank A. Match, N. Jeevanjee, E. Ignaszewski, and A. Williams for their valuable feedback on an earlier version of this work. N.T. acknowledges support from the Kernan Brothers Fund at the Harvard University Center for the Environment.

Author contributions

N.T. conceived the study, performed the analysis, and wrote the initial manuscript. N.T. and D.M.R. co-designed the methodology. All authors contributed to revising the manuscript.

Competing interests

The authors declare no competing interests.

References

- [1] AK Jay, et al., Chapter 1: Overview (Fifth National Climate Assessment) (2023).
- [2] U.S. Environmental Protection Agency, Causes of climate change (2024) Accessed: 2024-06-14.
- [3] NASA, Scientific consensus: Earth's climate is warming (2024) Accessed: 2024-06-14.
- [4] United Nations, What is climate change? (2024) Accessed: 2024-06-14.
- [5] S Szopa, et al., Short-lived climate forcers in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, eds. V Masson-Delmotte, et al. (Cambridge University Press, Cambridge, UK and New York, NY, USA), pp. 817–921 (2021).
- [6] P Friedlingstein, , et al., Global Carbon Budget 2023. *Earth Syst. Sci. Data* **15**, 5301–5369 (2023).
- [7] MR Allen, et al., Warming caused by cumulative carbon emissions towards the trillionth tonne. *Nature* **458**, 1163–1166 (2009).
- [8] GB Dreyfus, Y Xu, DT Shindell, D Zaelke, V Ramanathan, Mitigating climate disruption in time: A self-consistent approach for avoiding both near-term and long-term global warming. *Proc. Natl. Acad. Sci.* **119**, e2123536119 (2022).
- [9] NM Mahowald, DS Ward, SC Doney, PG Hess, JT Randerson, Are the impacts of land use on warming underestimated in climate policy? *Environ. Res. Lett.* **12**, 094016 (2017).
- [10] IPCC, Summary for policymakers in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, eds. V Masson-Delmotte, et al. (Cambridge University Press, Cambridge, UK and New York, NY, USA), pp. 1–31 (2021).
- [11] G Myhre, et al., *Anthropogenic and Natural Radiative Forcing*, eds. TF Stocker, et al. (Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA), pp. 659–740 (2013).
- [12] V Masson-Delmotte, et al., eds., *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty*. (Cambridge University Press, Cambridge, UK and New York, NY, USA), p. 616 (2018).
- [13] P Forster, et al., The earth's energy budget, climate feedbacks, and climate sensitivity supplementary material in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, eds. V Masson-Delmotte, et al. (Cambridge University Press, Cambridge, UK and New York, NY, USA), pp. 1–35 (2021).
- [14] CJ Smith, et al., FAIR v1.3: a simple emissions-based impulse response and carbon cycle model. *Geosci. Model. Dev.* **11**, 2273–2297 (2018).
- [15] ZRJ Nicholls, et al., Reduced Complexity Model Intercomparison Project Phase 1: introduction and evaluation of global-mean temperature response. *Geosci. Model. Dev.* **13**, 5175–5190 (2020).

- [16] NJ Leach, et al., FaIRv2.0.0: a generalized impulse response model for climate uncertainty and future scenario exploration. *Geosci. Model. Dev.* **14**, 3007–3036 (2021).
- [17] C Smith, et al., fair-calibrate v1.4.1: calibration, constraining and validation of the FaIR simple climate model for reliable future climate projections. *EGUsphere* **2024**, 1–36 (2024).
- [18] MJE van Marle, et al., Historic global biomass burning emissions for CMIP6 (BB4CMIP) based on merging satellite observations with proxies and fire models (1750–2015). *Geosci. Model. Dev.* **10**, 3329–3357 (2017).
- [19] RM Hoesly, et al., Historical (1750–2014) anthropogenic emissions of reactive gases and aerosols from the Community Emissions Data System (CEDS). *Geosci. Model. Dev.* **11**, 369–408 (2018).
- [20] J Gütschow, et al., The PRIMAP-hist national historical emissions time series. *Earth Syst. Sci. Data* **8**, 571–603 (2016).
- [21] GR van der Werf, et al., Global fire emissions estimates during 1997–2016. *Earth Syst. Sci. Data* **9**, 697–720 (2017).
- [22] R Hoesly, S Smith, CEDS v2024-04-01 Release Emission Data (Zenodo) (2024).
- [23] PM Forster, et al., Indicators of Global Climate Change 2023: annual update of key indicators of the state of the climate system and human influence. *Earth Syst. Sci. Data* **16**, 2625–2658 (2024).
- [24] Intergovernmental Panel on Climate Change, 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (<https://www.ipcc-nggip.iges.or.jp/public/2019rf/index.html>) (2019).
- [25] LS Shapley, A value for n -person games in *Contributions to the Theory of Games, Volume II*, Annals of Mathematics Studies, eds. HW Kuhn, AW Tucker. (Princeton University Press, Princeton, NJ) No. 28, pp. 307–317 (1953).
- [26] F Liu, et al., A new global anthropogenic SO₂ emission inventory for the last decade: a mosaic of satellite-derived and bottom-up emissions. *Atmospheric Chem. Phys.* **18**, 16571–16586 (2018).
- [27] GJ Nabuurs, et al., Agriculture, forestry and other land uses (afolu) in *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, eds. P Shukla, et al. (Cambridge University Press, Cambridge, UK and New York, NY, USA), (2022).
- [28] D Archer, H Kheshgi, E Maier-Reimer, Multiple timescales for neutralization of fossil fuel CO₂. *Geophys. Res. Lett.* **24**, 405–408 (1997).
- [29] HD Matthews, K Caldeira, Stabilizing climate requires near-zero emissions. *Geophys. Res. Lett.* **35** (2008).
- [30] S Solomon, GK Plattner, R Knutti, P Friedlingstein, Irreversible climate change due to carbon dioxide emissions. *Proc. Natl. Acad. Sci.* **106**, 1704–1709 (2009).
- [31] P Friedlingstein, et al., Global carbon budget 2023. *Earth Syst. Sci. Data* **15**, 5301–5369 (2023).
- [32] CE Scott, et al., Impact on short-lived climate forcers increases projected warming due to deforestation. *Nat. Commun.* **9**, 157 (2018).
- [33] RD Lamboll, et al., Modifying emissions scenario projections to account for the effects of COVID-19: protocol for CovidMIP. *Geosci. Model. Dev.* **14**, 3683–3695 (2021).
- [34] J Gütschow, M Pflüger, The PRIMAP-hist national historical emissions time series (1750–2022) v2.5 (Zenodo) (2023).
- [35] IPCC, Scenarios and modelling methods in *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, eds. C Guivarch, et al. (Cambridge University Press, Cambridge, UK and New York, NY, USA), (2022).
- [36] RJ Millar, ZR Nicholls, P Friedlingstein, MR Allen, A modified impulse-response representation of the global near-surface air temperature and atmospheric concentration response to carbon dioxide emissions. *Atmospheric Chem. Phys.* **17**, 7213–7228 (2017).
- [37] RB Skeie, et al., Historical total ozone radiative forcing derived from CMIP6 simulations. *npj Clim. Atmospheric*

- Sci.* **3**, 32 (2020).
- [38] G Thornhill, et al., Climate-driven chemistry and aerosol feedbacks in CMIP6 earth system models. *Atmospheric Chem. Phys.* **21**, 1105–1126 (2021).
- [39] GD Thornhill, et al., Effective radiative forcing from emissions of reactive gases and aerosols – a multi-model comparison. *Atmospheric Chem. Phys.* **21**, 853–874 (2021).
- [40] VK Arora, et al., Carbon–concentration and carbon–climate feedbacks in CMIP6 models and their comparison to CMIP5 models. *Biogeosciences* **17**, 4173–4222 (2020).
- [41] JY Lee, et al., *Future Global Climate: Scenario-Based Projections and Near-Term Information*, eds. V Masson-Delmotte, et al. (Intergovernmental Panel on Climate Change, Geneva, Switzerland), (2021).
- [42] WA Obermeier, et al., Modelled land use and land cover change emissions – a spatio-temporal comparison of different approaches. *Earth Syst. Dyn.* **12**, 635–656 (2021).
- [43] P Forster, et al., The earth’s energy budget, climate feedbacks, and climate sensitivity in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, eds. V Masson-Delmotte, et al. (Cambridge University Press, Cambridge, UK and New York, NY, USA), pp. 923–1054 (2021).
- [44] B Stevens, Rethinking the lower bound on aerosol radiative forcing. *J. Clim.* **28**, 4794–4819 (2015).
- [45] N Bellouin, et al., Bounding global aerosol radiative forcing of climate change. *Rev. Geophys.* **58**, e2019RG000660 (2020).
- [46] IM Sobol’, The distribution of points in a cube and the accurate evaluation of integrals. *USSR Comput. Math. Math. Phys.* **7**, 86–112 (1967).
- [47] P Virtanen, R Gommers, TE Oliphant, et al., Scipy 1.0: Fundamental algorithms for scientific computing in python. *Nat. Methods* **17**, 261–272 (2020).
- [48] S Palazzo Corner, et al., The Zero Emissions Commitment and climate stabilization. *Front. Sci.* **1** (2023).
- [49] RA Houghton, A Castanho, Annual emissions of carbon from land use, land-use change, and forestry from 1850 to 2020. *Earth Syst. Sci. Data* **15**, 2025–2054 (2023).
- [50] E Marín-Spiotta, DF Cusack, R Ostertag, WL Silver, *Trends in Above and Belowground Carbon with Forest Regrowth After Agricultural Abandonment in the Neotropics*. (Springer New York, New York, NY), pp. 22–72 (2008).
- [51] P Tompalski, et al., Developing aboveground biomass yield curves for dominant boreal tree species from time series remote sensing data. *For. Ecol. Manag.* **561**, 121894 (2024).
- [52] M Saunio, et al., Global methane budget 2000–2020. *Earth Syst. Sci. Data* **17**, 1873–1958 (2025).
- [53] H Tian, et al., A comprehensive quantification of global nitrous oxide sources and sinks. *Nature* **586**, 248–256 (2020).
- [54] LHC Tippett, On the extreme individuals and the range of samples taken from a normal population. *Biometrika* **17**, 364–387 (1925).
- [55] DC Montgomery, *Introduction to Statistical Quality Control*. (Wiley, Hoboken, NJ), 8th edition, (2020).
- [56] SJ Smith, et al., Anthropogenic sulfur dioxide emissions: 1850–2005. *Atmos. Chem. Phys.* **11**, 1101–1116 (2011).
- [57] RJ Andres, et al., A synthesis of carbon dioxide emissions from fossil-fuel combustion. *Biogeosciences* **9**, 1845–1871 (2012).
- [58] E Hansis, SJ Davis, J Pongratz, Relevance of methodological choices for accounting of land use change carbon fluxes. *Glob. Biogeochem. Cycles* **29**, 1230–1246 (2015).
- [59] T Gasser, et al., Historical CO₂ emissions from land use and land cover change and their uncertainty. *Biogeosciences* **17**, 4075–4101 (2020).
- [60] RA Houghton, A Castanho, Annual emissions of carbon from land use, land-use change, and forestry from 1850

- to 2020. *Earth Syst. Sci. Data* **15**, 2025–2054 (2023).
- [61] AHW Beusen, AF Bouwman, PSC Heuberger, G Van Drecht, KW Van der Hoek, Bottom-up uncertainty estimates of global ammonia emissions from global agricultural production systems. *Atmospheric Environ.* **42**, 6067–6077 (2008).
- [62] W Meng, B Zheng, Q Zhang, K He, , et al., Improvement of a global high-resolution ammonia emission inventory for combustion and industrial sources. *Environ. Sci. & Technol.* **51**, 10228–10236 (2017).
- [63] TC Bond, et al., A technology-based global inventory of black and organic carbon emissions from combustion. *J. Geophys. Res. Atmospheres* **109**, D14203 (2004).
- [64] K Miyazaki, et al., Updated tropospheric chemistry reanalysis and emission estimates, tcr-2, for 2005–2018. *Earth Syst. Sci. Data* **12**, 2223–2259 (2020).
- [65] R Xu, H Ma, J Li, D Tong, , et al., A technology-based global non-methane volatile organic compounds (nmvoc) emission inventory under the meic framework. *Atmospheric Chem. Phys.* **25**, 12675–12699 (2025).
- [66] MD Zelinka, CJ Smith, Y Qin, KE Taylor, Comparison of methods to estimate aerosol effective radiative forcings in climate models. *Atmospheric Chem. Phys.* **23**, 8879–8898 (2023).

Supplementary Information

Fossil fuels dominate future warming but not the past or present

Nathaniel Tarshish, David M. Romps, and Inez Fung

Estimating uncertainty in historical emission sources

We model the time-varying emissions of each species i as the sum of two log-normally distributed random variables,

$$T_i(t) = F_i(t) + O_i(t), \quad (\text{S1})$$

where $F_i(t)$ and $O_i(t)$ are the fossil-fuel and other-activity components, respectively. For each year t , the means of each component are set equal to the central values reported in the underlying inventories [6, 22, 52, 53].

As reviewed in ref. [22], a current limitation of emissions inventories is their lack of detailed uncertainty estimates. To overcome this limitation, we compile existing uncertainty estimates from various sources here and use the methods described below to fit log-normal emissions distributions to the available data. In general, we err on the side of broad, conservative uncertainties. The computed uncertainty estimates are tabulated in Table S1, plotted in Fig. S1, and detailed in separate sections for each species below.

Log-normal distributions are fit to the uncertainty data using the following methods. If confidence intervals for the emissions of a given species are reported in the literature, we fit the standard deviation of a log-normal distribution to these intervals as follows:

For notational convenience, we suppress the time coordinate and species index. Let emissions of a given species be log-normal, $X \sim \text{LogNormal}(\mu, \sigma^2)$, such that $U = \ln X \sim \mathcal{N}(\mu, \sigma^2)$. We are interested in deriving the standard deviation of X given a confidence interval in the form of two reported quantiles. Let X_α and X_β denote the α -th and β -th quantiles of X (with $0 < \alpha < \beta < 1$), such that $P(X \leq X_\alpha) = \alpha$ and $P(X \leq X_\beta) = \beta$. These quantiles can be related to quantiles of a unit normal because $\ln X = \mu + \sigma Z$ with $Z \sim \mathcal{N}(0, 1)$, yielding the relation,

$$\frac{X_\beta}{X_\alpha} = \exp[\sigma(z_\beta - z_\alpha)], \quad (\text{S2})$$

where z_α and z_β are the corresponding quantiles of the standard normal distribution (e.g., $z_{0.05} \approx -1.645$ and $z_{0.95} \approx 1.645$). Isolating for σ yields

$$\sigma = \frac{\ln(X_\beta/X_\alpha)}{z_\beta - z_\alpha}. \quad (\text{S3})$$

The standard deviation of X then follows from the log-normal identity,

$$\text{StdDev}(X) = \mathbb{E}[X] \sqrt{e^{\sigma^2} - 1}. \quad (\text{S4})$$

Instead of confidence intervals, literature reviews (e.g., ref. [53]) often report min-max ranges across

different emissions inventories. In this case, given min-max ranges across N inventories, we take each inventory to be an independent and identically distributed (i.i.d.) sample of the true emissions distribution. The standard deviation of the log-normal can then be approximated given the sample size and min-max range using the following method:

Let $X_1, \dots, X_N$ be i.i.d. samples with order statistics $X_{(1)} = \min X_i$ and $X_{(N)} = \max X_i$, and define the log-range $R = \ln X_{(N)} - \ln X_{(1)}$. Given that $\ln X = \mu + \sigma Z$ with $Z \sim \mathcal{N}(0, 1)$, the expected log-range simplifies to

$$\mathbb{E}[R] = (\mu + \sigma \mathbb{E}[Z_{(N)}]) - (\mu + \sigma \mathbb{E}[Z_{(1)}]) \quad (\text{S5})$$

$$= \sigma (\mathbb{E}[Z_{(N)}] - \mathbb{E}[Z_{(1)}]) \quad (\text{S6})$$

$$= 2\sigma \mathbb{E}[Z_{(N)}], \quad (\text{S7})$$

where $Z_{(N)}$ is the maximum of N samples from a standard normal distribution, and the third step follows by symmetry. Writing the expected range of N unit-normal draws as $d_2(N) \equiv 2 \mathbb{E}[Z_{(N)}]$ (tabulated in the literature, e.g., refs. [54, 55]), we estimate

$$\sigma = \frac{\ln X_{(N)} - \ln X_{(1)}}{d_2(N)}. \quad (\text{S8})$$

With σ in hand, we compute the standard deviation on the original scale via the log-normal identity (Eq. S4), using the sample mean as the estimate of $\mathbb{E}[X]$.

These methods enable us to estimate the log-normal distributions for each species and activity. When both top-down (e.g., satellite-based data assimilation) and bottom-up emissions estimates are available, we estimate an overall uncertainty as follows. The top-down (TD) and bottom-up (BU) methods are approximated as independent, and the between-method component (taken as $\sigma_{\text{between}} = \frac{1}{2}|\bar{X}_{\text{TD}} - \bar{X}_{\text{BU}}|$) is combined with the average within-method components, such that

$$\sigma_{\text{combined}}^2 = \sigma_{\text{between}}^2 + \frac{1}{2}(\sigma_{\text{TD}}^2 + \sigma_{\text{BU}}^2), \quad (\text{S9})$$

gives the standard deviation of the emissions distribution used here.

For a few minor species detailed below, the total emissions uncertainty is available, but data on per-activity uncertainties is limited. For these species, we make the parsimonious assumption that the sources of emissions have equal *relative* uncertainty. In other words, we equate the coefficients of variation ($\text{CV}[X] = \text{StdDev}[X]/\mathbb{E}[X]$) of the fossil-fuel F and other activity O distributions. Assuming F and O are independent log-normals with a common coefficient of variation, we have $\text{Var}[F] = (\text{CV} \mathbb{E}[F])^2$ and $\text{Var}[O] = (\text{CV} \mathbb{E}[O])^2$. Using $\text{Var}[T] = \text{Var}[F] + \text{Var}[O]$, we solve for the shared coefficient of variation as

$$\text{CV} = \sqrt{\frac{\text{Var}[T]}{\mathbb{E}[F]^2 + \mathbb{E}[O]^2}}. \quad (\text{S10})$$

Given this shared CV, we then compute $\text{Var}[F]$ and $\text{Var}[O]$ from their respective means, ensuring that the

per-activity log-normal emissions distributions are simultaneously consistent with the inventory means and variance of the total emissions. The application of these methods to specific species is detailed below.

CO₂ and SO₂

Emissions of fossil-fuel CO₂ and SO₂—the two species that have the greatest impact on our results—are known with the greatest certainty of all emissions [22]: following CEDS guidance [19], the 90% confidence interval for fossil-fuel sulfur is conservatively taken to be $\pm 14\%$ [56] and for CO₂ is taken to be $\pm 8\%$ [57].

Given this confidence interval and the mean fossil-fuel CO₂ estimate of 35.2 Gt CO₂ yr⁻¹, Eqs. S3–S4 yield a standard deviation of 1.7 Gt CO₂ yr⁻¹. Thus, we take the 1σ relative uncertainty of fossil-fuel CO₂ emissions to be 5%. For AFOLU CO₂ emissions, we compute a (time-varying) uncertainty (that averages to a 1σ relative uncertainty of 32% over the last hundred years) by taking the standard deviation of the three book-keeping datasets [58–60] used in the Global Carbon Budget [6].

For fossil-fuel sulfur emissions, the 90% confidence range of $\pm 14\%$ yields a standard deviation of 5.3 Mt SO₂ yr⁻¹. Compared to the mean present-day emissions of 62 Mt SO₂ yr⁻¹, this standard deviation gives a 1σ relative uncertainty of 9%. For simplicity, we apply this same relative uncertainty to the AFOLU sulfur emissions, which comprise less than 5% of total sulfur emissions (see Fig. S2).

Methane

For fossil-fuel methane, we estimate emissions uncertainty by comparing the top-down atmospheric inversions and bottom-up inventories reported in the Global Methane Budget. For the 2000–2009 period (more uncertain than the most recent decade), these methods yield 105 (88–115) Tg CH₄ yr⁻¹ for the inversion methods and 105 (97–123) Tg CH₄ yr⁻¹ for the bottom-up estimates, where the ranges indicate the min–max across 16 model inversions and 6 inventories, respectively [52]. The top-down estimates imply a standard deviation of approximately 8.0 Tg CH₄ yr⁻¹ given Eq. S8, while the bottom-up inventories imply a standard deviation of approximately 9.9 Tg CH₄ yr⁻¹ via the same method. Combining the top-down and bottom-up uncertainties via Eq. S9, we find a 1σ relative uncertainty of 9% for fossil-fuel methane.

For agricultural and biofuel methane, the results from approximately 16 top-down and 10 bottom-up estimates over the same period are 236 (219–252) Tg CH₄ yr⁻¹ and 224 (203–252) Tg CH₄ yr⁻¹ [52]. Applying the same methodology yields standard deviations of 9.4 and 15.8 Tg CH₄ yr⁻¹ for the top-down and bottom-up methods, respectively. Combining between- and within-method components as above gives a 1σ relative uncertainty of 6% for agricultural methane emissions.

Nitrous Oxide

For nitrous oxide, only bottom-up inventory-based estimates of the fossil fuel and other activity emissions are available. AR6, drawing on the Global N₂O budget (ref. [53]), reports fossil-fuel emissions of 1.0 (0.8–1.1) Tg N₂O yr⁻¹ and non-fossil emissions of 5.7 (3.3–9.3) Tg N₂O yr⁻¹ averaged over 2000–2009 [5]. The fossil-fuel estimate [53] comes from 2 inventories, yielding a standard deviation of 0.29 Tg N₂O yr⁻¹ via the min-max estimation method (Eq. S8). We, therefore, assume a 29% uncertainty on fossil-fuel N₂O emissions.

The non-fossil estimate aggregates approximately 30 bottom-up estimates [53] (using inventories, process models, and statistical approaches); with $N = 30$, the reported 5.7 (3.3 – 9.3) $\text{Tg N}_2\text{O yr}^{-1}$ implies a standard deviation of $1.5 \text{ Tg N}_2\text{O yr}^{-1}$ via the min-max estimation method, yielding a 1σ relative uncertainty of 26%.

NH₃

Confidence intervals for agricultural NH₃ emissions report a 10%–90% range of [33–46] $\text{Tg NH}_3 \text{ yr}^{-1}$ [61] for the year 2000. Fitting this interval to a log-normal distribution (Eq. S3) yields a relative 1σ uncertainty of about 13% for non-fossil emissions. For fossil-fuel emissions of NH₃, the interquartile range is estimated at [5–19] $\text{Tg NH}_3 \text{ yr}^{-1}$ [62], and fitting a log-normal distribution to this range implies a 1σ relative uncertainty of approximately 125%.

Black carbon and organic carbon

CEDS guidance indicates that global BC emissions have uncertainties of roughly a factor of two [19]. In particular, comparing bottom-up inventories [63] yields a best estimate of 8 Tg BC yr^{-1} in 1996, with a 95% confidence interval of 4.3 – 22 Tg BC yr^{-1} . Fitting a log-normal distribution to this 95% range (Eq. S3) yields a standard deviation of $3.5 \text{ Tg BC yr}^{-1}$. Distributing this uncertainty to the fossil and non-fossil emissions assuming equal coefficients of variation (Eq. S10) gives a 1σ relative uncertainty for each activity of approximately 60%. Repeating this process for the organic carbon emissions, given the 1996 emissions estimate of 33 Tg OC yr^{-1} with a 95% confidence interval of 17 – 77 Tg OC yr^{-1} [63], we infer a standard deviation of $13.56 \text{ Tg OC yr}^{-1}$ and a corresponding per-activity emissions uncertainty of 44%.

Carbon monoxide

Satellite retrievals combined with data assimilation estimate a global total emission rate of $1103 \pm 223.2 \text{ Mt CO yr}^{-1}$ averaged over 2005–2018 [64], whereas CEDS [19] gives $902 \text{ Mt CO yr}^{-1}$ over the same period. Using Eq. S9, we compute an overall uncertainty on the total emissions of 19%. Assuming equal coefficients of variation (Eq. S10), we project this total uncertainty onto the fossil-fuel and non-fossil components, finding a 1σ relative uncertainty of approximately 26% for each over the 2005–2018 period. Over the past hundred years (1924–2024), the average 1σ relative uncertainties are 25% for the per-activity emissions.

NO_x

For NO_x, the data-assimilation estimate of the global total emission is $161 \pm 9 \text{ Mt NO}_2 \text{ yr}^{-1}$ averaged over 2005–2018 [64], and CEDS [19] gives $150 \text{ Mt NO}_2 \text{ yr}^{-1}$ averaged over the same period. Repeating the above procedure yields an overall uncertainty (Eq. S9) on the total emissions of 6%. Assuming equal coefficients of variation (Eq. S10), the 1σ relative uncertainty is approximately 7% for the fossil and non-fossil distributions, respectively.

Table S1. Relative 1σ uncertainties (i.e., coefficients of variation) of the activity-based emissions. Results shown here are averaged over the past hundred years (1924–2024). See above sections for the per-species details.

Species	Fossil-fuel uncert.	Other uncert.
CO ₂	$\pm 5\%$	$\pm 32\%$
CH ₄	$\pm 9\%$	$\pm 6\%$
N ₂ O	$\pm 29\%$	$\pm 26\%$
Sulfur	$\pm 9\%$	$\pm 9\%$
BC	$\pm 60\%$	$\pm 60\%$
OC	$\pm 44\%$	$\pm 44\%$
NH ₃	$\pm 125\%$	$\pm 13\%$
NO _x	$\pm 7\%$	$\pm 7\%$
VOC	$\pm 51\%$	$\pm 51\%$
CO	$\pm 25\%$	$\pm 25\%$

NMVOCs

For non-methane volatile organic compounds (NMVOCs), ref. [65] estimates global emission uncertainties with 95% confidence intervals spanning -51% to $+107\%$ of the mean annual emissions in 1970 and -47% to $+87\%$ of the mean annual emissions in 2020. To err on the conservative side, we adopt the earlier, more uncertain 1970 figure, which implies a log-normal distribution with a 1σ relative uncertainty of 39% for the global total. Under the equal-coefficient-of-variation assumption (Eq. S10), this projects to per-activity 1σ relative uncertainties of approximately 54% for both fossil and non-fossil components in 1970, and near 51% when averaged over the past hundred years (1924–2024).

Computing the partition distribution

For each species i we define the fossil-fuel share as

$$\phi_i(t) = \frac{F_i(t)}{F_i(t) + O_i(t)}. \quad (\text{S11})$$

Writing $F = \exp(U)$ and $O = \exp(V)$ with $U \sim \mathcal{N}(\mu_F, \sigma_F^2)$, $V \sim \mathcal{N}(\mu_O, \sigma_O^2)$, we have

$$\phi = \frac{1}{1 + \exp(V - U)}, \quad (\text{S12})$$

such that $\text{logit}(\phi) = U - V$ is normal with

$$\text{logit}(\phi) \sim \mathcal{N}(\mu_F - \mu_O, \sigma_F^2 + \sigma_O^2), \quad (\text{S13})$$

assuming that F and O are independent. This formula specifies the logit-normal distribution of $\phi_i(t)$ used in the Monte-Carlo uncertainty analysis and plotted for each species in Fig. S11.

Table S2. Emissions categories. Assignment of CEDS [19] subsectors to fossil fuels and other activities. In the main figures, the ambiguous column is grouped with fossil fuels. Fig. S10 demonstrates the impact of alternatively associating these ambiguous emissions with other activities.

Fossil Fuels	Other	Ambiguous
1A1a_Electricity-autoproducer	2A1_Cement-production	2Ax_Other-minerals
1A1a_Electricity-public	2A2_Lime-production	2B2_Chemicals-Nitric-acid
1A1a_Heat-production	3B_Manure-management	2B3_Chemicals-Adipic-acid
1A1bc_Other-transformation	3D_Rice-Cultivation	2B_Chemical-industry
1A2a_Ind-Comb-Iron-steel	3D_Soil-emissions	2D_Chemical-products-manufacture-processing
1A2b_Ind-Comb-Non-ferrous-metals	3E_Enteric-fermentation	2D_Degreasing-Cleaning
1A2c_Ind-Comb-Chemicals	3F_Agricultural-residue-burning-on-fields	2D_Other-product-use
1A2d_Ind-Comb-Pulp-paper	3I_Agriculture-other	2D_Paint-application
1A2e_Ind-Comb-Food-tobacco	5A_Solid-waste-disposal	2H_Pulp-and-paper-food-beverage-wood
1A2f_Ind-Comb-Non-metalic-minerals	5D_Wastewater-handling	2L_Other-process-emissions
1A2g_Ind-Comb-Construction	5E_Other-waste-handling	
1A2g_Ind-Comb-machinery		
1A2g_Ind-Comb-mining-quarrying		
1A2g_Ind-Comb-other		
1A2g_Ind-Comb-textile-leather		
1A2g_Ind-Comb-transpequip		
1A2g_Ind-Comb-wood-products		
1A3ai_International-aviation		
1A3aii_Domestic-aviation		
1A3b_Road		
1A3c_Rail		
1A3di_International-shipping		
1A3di_Oil_Tanker_Loading		
1A3di_Oil_tanker_loading		
1A3dii_Domestic-navigation		
1A3eii_Other-transp		
1A4a_Commercial-institutional		
1A4b_Residential		
1A4c_Agriculture-forestry-fishing		
1A5_Other-unspecified		
1B1_Fugitive-solid-fuels		
1B2_Fugitive-petr		
1B2_Fugitive-petr-and-gas		
1B2b_Fugitive-NG-distr		
1B2b_Fugitive-NG-prod		
1B2d_Fugitive-other-energy		
2C_Metal-production		
5C_Waste-combustion		
6A_Other-in-total		
6B_Other-not-in-total		
7A_Fossil-fuel-fires		
7BC_Indirect-N2O-non-agricultural-N		

Table S3. Radiative forcings in the FaIR ensemble. Effective radiative forcing from 1750 to 2023. The latest radiative forcings estimates by the IGCC [23] are compared to the FaIR ensemble driven by all emissions, fossil fuels, and other activities. The second column differs from the sum of the third and fourth columns due to nonlinearities in FaIR (see Fig. S6). Median and 5th–95th interquantile ranges are shown. All quantities are in units of W m^{-2} .

Forcing	IGCC	FaIR	FaIR: Fossil Fuels	FaIR: Other Activities
CO ₂	2.25 (1.98/2.52)	2.25 (1.98/2.52)	1.58 (1.31/1.86)	0.73 (0.53/0.96)
CH ₄	0.56 (0.45/0.67)	0.58 (0.47/0.69)	0.27 (0.21/0.33)	0.55 (0.44/0.66)
N ₂ O	0.22 (0.19/0.25)	0.22 (0.18/0.24)	0.05 (0.03/0.08)	0.17 (0.14/0.20)
Aerosols	−0.97 (−1.59/−0.39)	−0.93 (−1.54/−0.41)	−0.74 (−1.18/−0.32)	−0.20 (−0.84/0.02)
Aerosol-cloud	−0.77 (−1.35/−0.23)	−0.73 (−1.33/−0.26)	−0.55 (−1.02/−0.18)	−0.18 (−0.83/−0.00)
Aerosol-radiation	−0.20 (−0.41/0.01)	−0.20 (−0.40/0.01)	−0.19 (−0.37/0.01)	−0.03 (−0.09/0.07)
Ozone	0.48 (0.24/0.71)	0.45 (0.22/0.65)	0.27 (0.13/0.42)	0.26 (0.13/0.41)
Halogens	0.41 (0.33/0.49)	0.41 (0.33/0.48)	0.00 (0.00/0.00)	0.41 (0.33/0.48)
Land-use albedo	−0.20 (−0.30/−0.10)	−0.20 (−0.30/−0.09)	0.00 (0.00/0.00)	−0.19 (−0.31/−0.09)
Part. on snow + ice	0.07 (−0.00/0.16)	0.06 (−0.00/0.14)	0.03 (−0.00/0.10)	0.02 (−0.01/0.08)
Strat. water vapor	0.05 (−0.00/0.10)	0.05 (0.00/0.11)	0.02 (0.00/0.05)	0.05 (0.00/0.11)
Anthropogenic	2.91 (2.17/3.62)	2.88 (2.29/3.46)	1.50 (1.01/1.99)	1.76 (1.18/2.19)

Table S4. Attributed warming from 1750 to 2019. Attributed warming (in °C) by species from the AR6 assessment (WG1 Fig. 7.7) compared to the FaIR ensemble driven by all emissions, fossil fuels, and other activities, respectively. Medians and 5th–95th interquantile ranges are shown, pooled over emissions and physical uncertainty. The discrepancy in aerosol–cloud forcing is because issues were identified in the AR6 diagnosis of the radiative forcing in climate models [66], and then corrected in subsequent IGCC reports and the FaIR model used here [17, 23].

Forcing	AR6	FaIR	FaIR: Fossil Fuels	FaIR: Other Activities
CO ₂	1.01 (0.74/1.41)	1.02 (0.76/1.36)	0.64 (0.46/0.87)	0.37 (0.25/0.56)
CH ₄	0.28 (0.19/0.39)	0.29 (0.19/0.42)	0.07 (0.04/0.11)	0.22 (0.15/0.32)
N ₂ O	0.10 (0.07/0.14)	0.10 (0.07/0.14)	0.02 (0.01/0.04)	0.07 (0.05/0.11)
Aerosol-cloud	−0.38 (−0.77/−0.12)	−0.50 (−1.14/−0.14)	−0.36 (−0.80/−0.09)	−0.10 (−0.60/0.00)
Aerosol-radiation	−0.13 (−0.28/−0.01)	−0.14 (−0.36/0.00)	−0.13 (−0.33/0.01)	−0.01 (−0.06/0.05)
Ozone	0.23 (0.11/0.39)	0.23 (0.10/0.40)	0.13 (0.04/0.23)	0.10 (0.03/0.20)
Halogens	0.19 (0.14/0.27)	0.20 (0.13/0.27)	0.00 (0.00/0.00)	0.20 (0.13/0.27)
Land-use albedo	−0.11 (−0.18/−0.05)	−0.10 (−0.18/−0.05)	0.00 (−0.01/0.01)	−0.10 (−0.18/−0.04)
Part. on snow + ice	0.04 (0.00/0.10)	0.04 (0.00/0.10)	0.02 (0.00/0.07)	0.01 (0.00/0.05)
Strat. water vapor	0.02 (0.00/0.06)	0.03 (0.00/0.06)	0.01 (0.00/0.02)	0.02 (0.00/0.05)
Anthropogenic	1.27 (0.96/1.64)	1.12 (0.89/1.31)	0.39 (0.10/0.62)	0.72 (0.45/1.06)

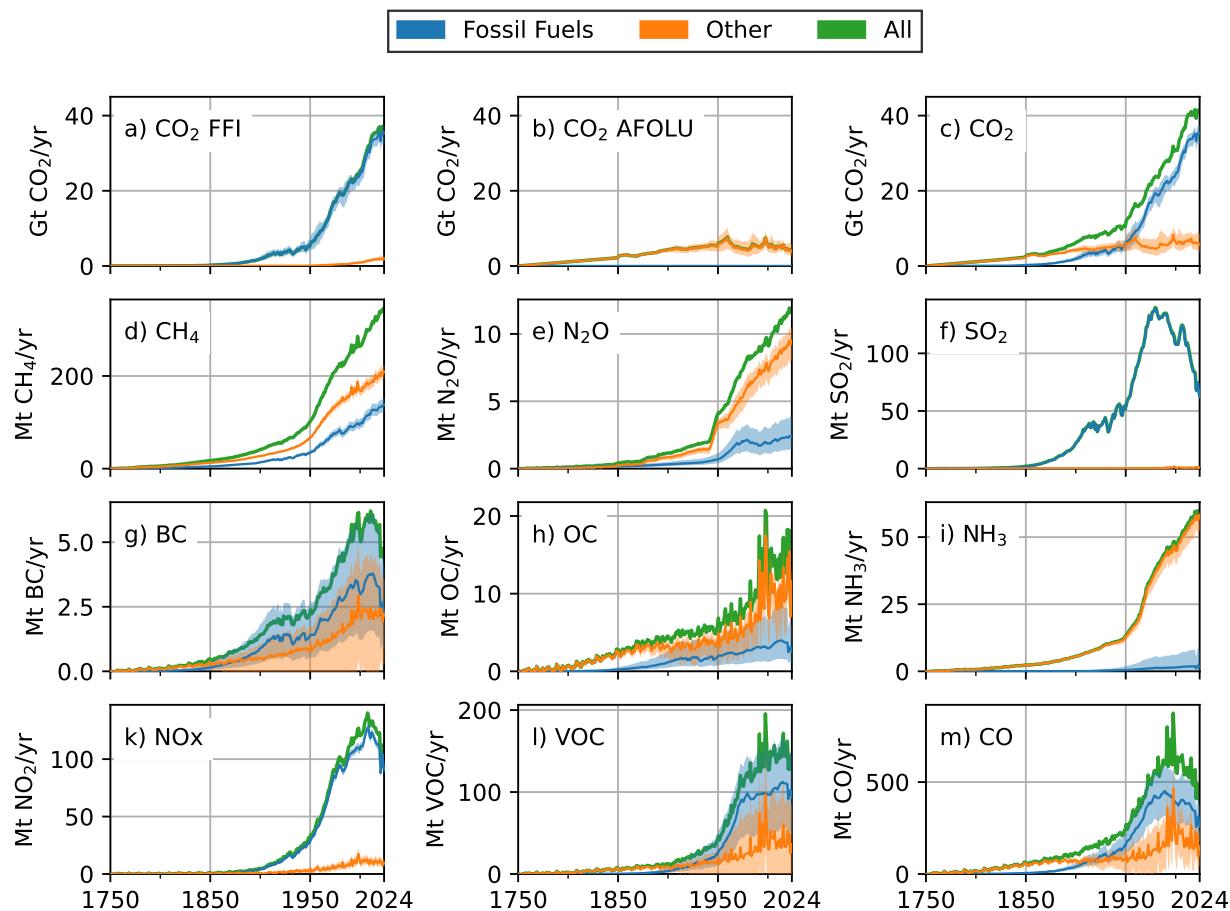


Figure S1. Historical emissions due to fossil fuels and other activities. The change in emissions from preindustrial due to fossil-fuel activities (blue), other activities (orange), and all activities combined (green) for various species. The changes due to all activities are identical to the results of ref. [17]. For CO₂, fossil-fuel and industrial emissions (FFI) are separated from agriculture, forestry, and land use (AFOLU) emissions. Solid lines indicate medians and shading represents the 90% confidence interval. Emissions are sampled from the partition distributions shown in Fig. S11.

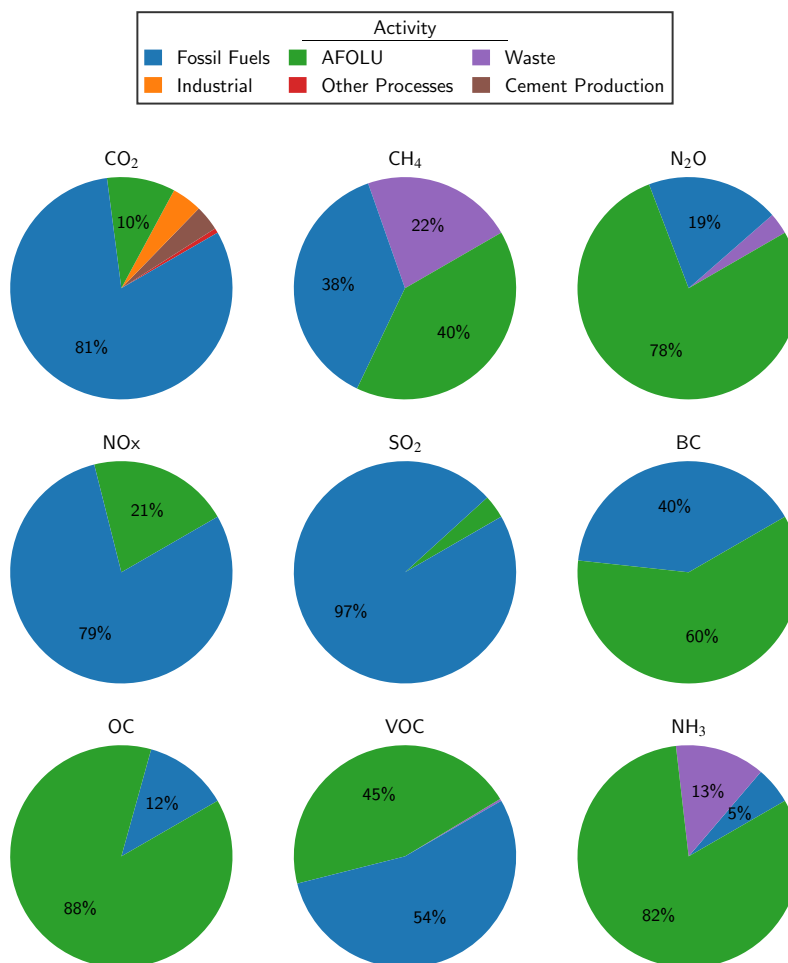


Figure S2. Sources of present-day emissions. The fractional contribution of different activities to the emissions of key species in 2022. Here, the blue “Fossil Fuels” activity encompasses all fossil-fuel emissions. Note that AFOLU here includes emissions from open biomass burning (GFED) and biomass combustion for energy purposes (CEDs).

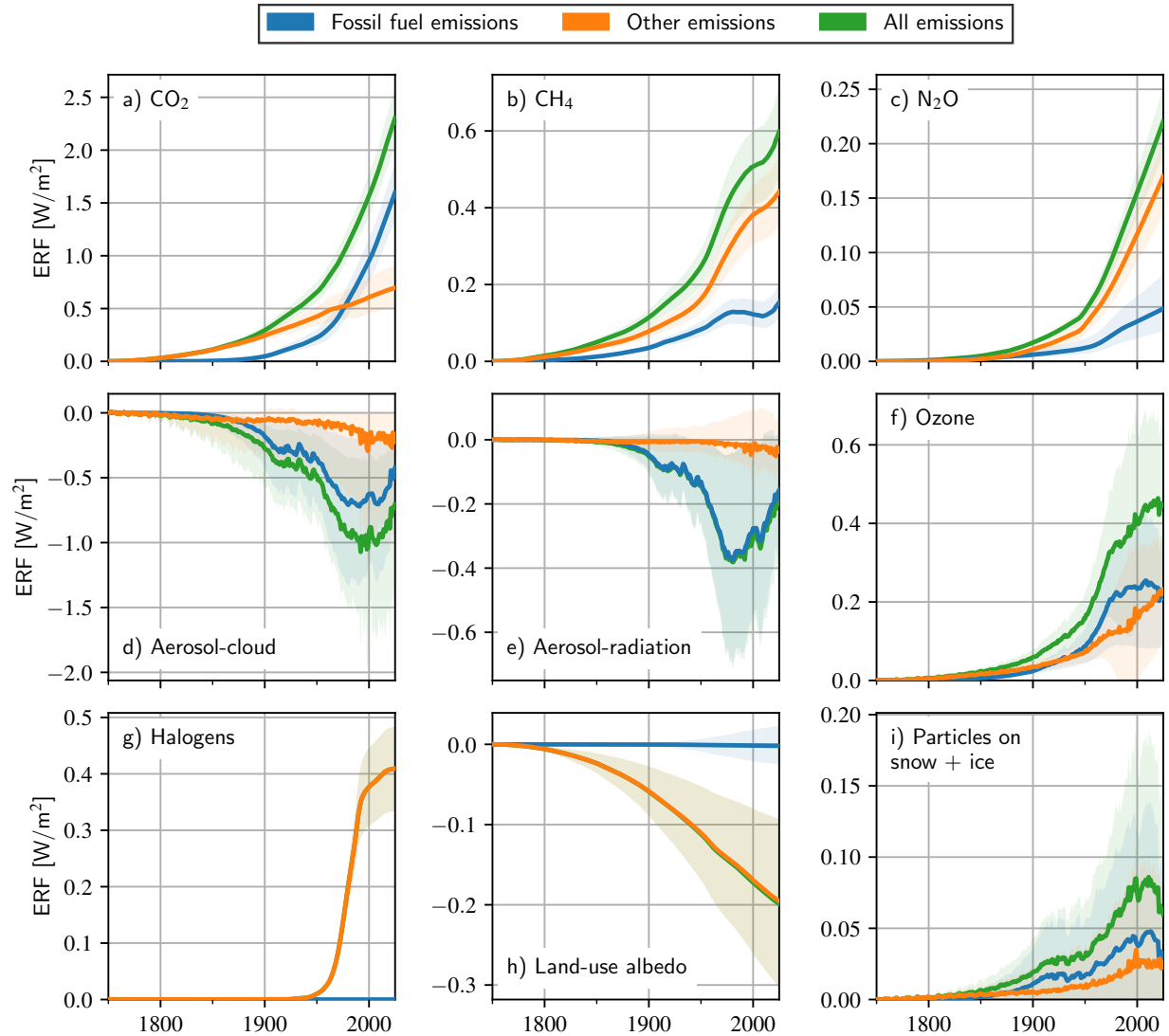


Figure S3. Attributing radiative forcings to human activities. Effective radiative forcings (ERFs) computed by the FaIR ensemble given the change in emissions since preindustrial due to all activities (green), solely fossil fuels (blue), and other activities (orange). Solid lines are median estimates and shading represents the 5th–95th interquartile range. The non-linear component has been removed such that the fossil-fuel and other experiments sum to the same value as the total emissions experiments (see Materials and Methods). A quirk of this non-linear adjustment is that it projects uncertainty in the land-use albedo forcing associated with AFOLU onto the fossil-fuel experiment.

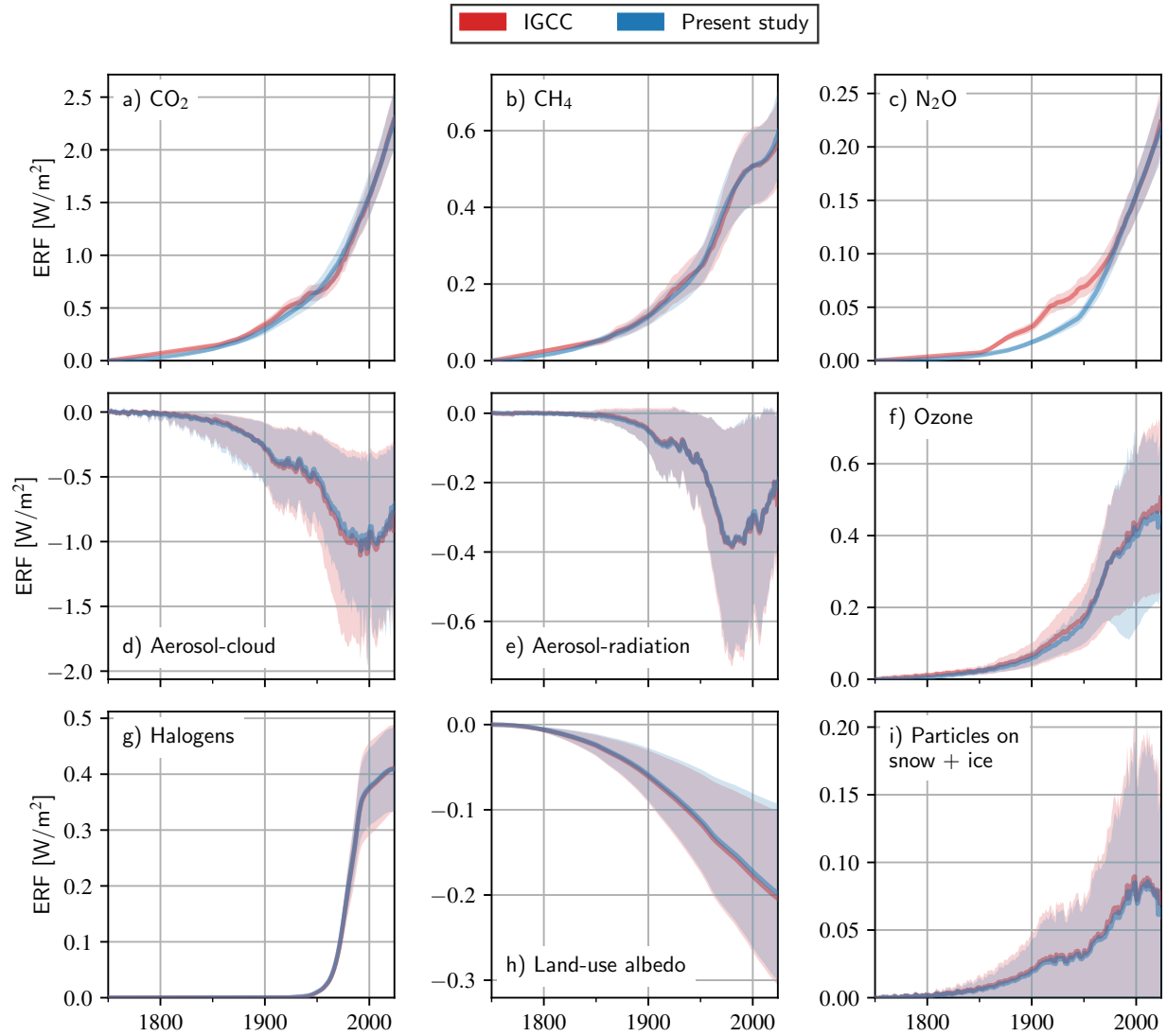


Figure S4. Comparing simulated radiative forcings to consensus estimates. Effective radiative forcing (ERF) computed by the FaIR ensemble given all historical emissions (blue) compared to the IGCC estimates (red) for various species. Solid lines are median estimates and shading represents the 5th–95th interquantile range. The IGCC estimates [23] extend the AR6 WGI ERF forcing time series given the most recent concentrations. Close agreement is found with the FaIR model because the FaIR forcing parameters are calibrated to the AR6 assessed ranges.

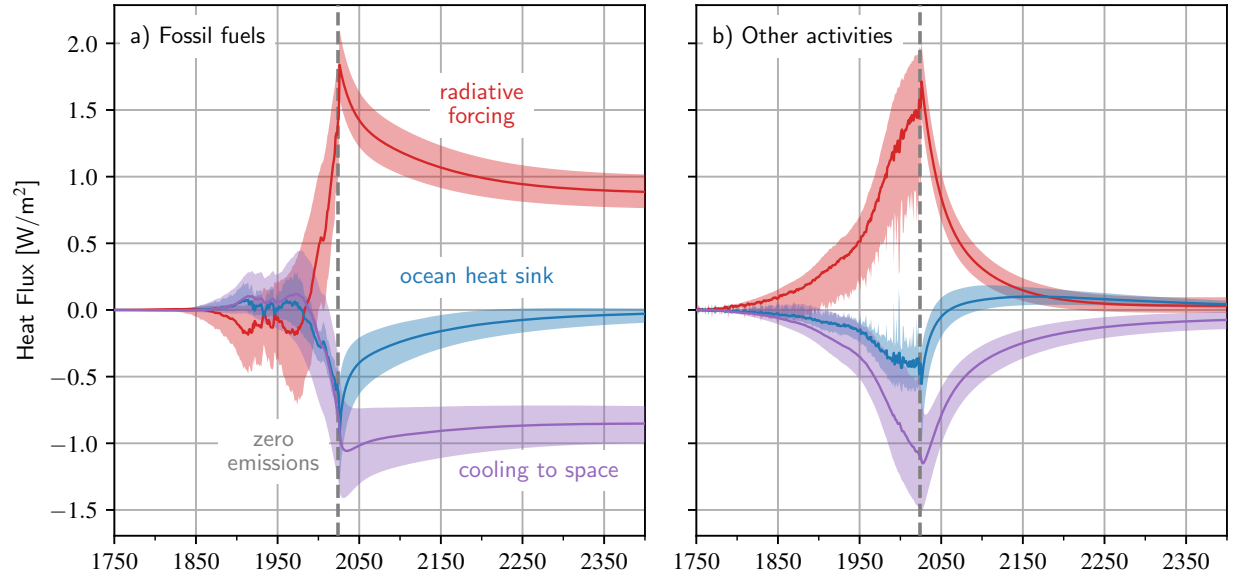


Figure S5. Surface energy budget in the abrupt cessation experiments. Heat fluxes contributing to the surface energy anomaly budget in the FaIR abrupt-cessation experiments given historical fossil-fuel emissions (A) and other activities (B), respectively. The latter experiment includes full ecosystem regrowth after AFOLU activities cease. After fossil-fuel emissions (A) end, the decline in radiative forcing (red) by roughly 1 W/m^2 is compensated for by a decrease in cooling to the deep ocean (blue) of equal magnitude. The surface temperature, which is proportional to the cooling to space (purple) in FaIR, exhibits a post-emissions plateau due to this cancellation. In the other activities experiment, uptake of AFOLU CO_2 given regrowth along with the disappearance of short-lived forcings results in a negligible forcing on multi-centennial timescales, yielding a dramatic temperature decline. Shading indicates 90% confidence interval.

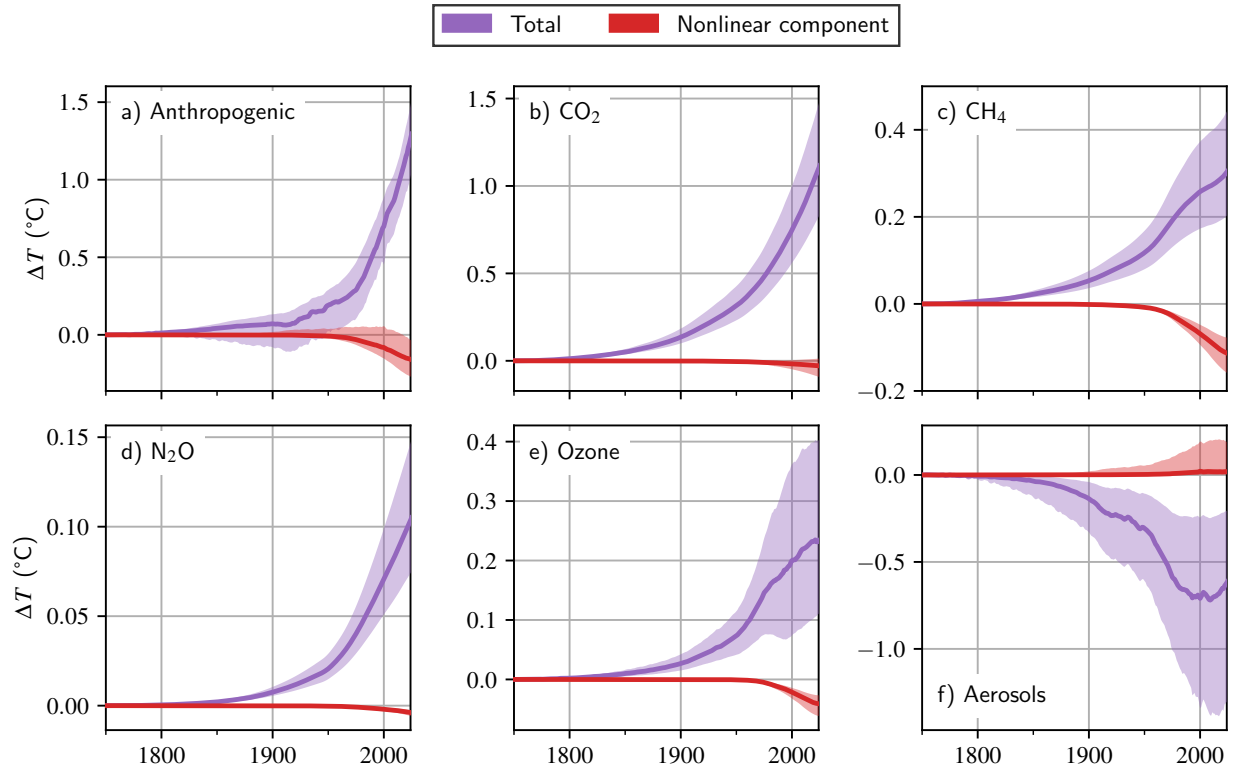


Figure S6. Nonlinear contributions. Temperature anomaly (purple) due to all human activity (A) and the emissions of specific species (B–F) in the FaIR all activities experiment. The nonlinear component (red) arises from the interaction between fossil-fuel emissions and emissions due to other activities. This nonlinearity makes the warming in the all-emissions experiment (purple) less than the sum of the temperature time series from the fossil-fuel and other-activities experiments. The nonlinear contribution (red) is calculated by subtracting the sum of the temperature anomaly from the fossil-fuel and other-activities experiments (not shown) from the temperature anomaly found when all emissions are considered together (purple). In the results presented in the main text, this nonlinear component has been removed in equal parts from the fossil-fuel and other-activities experiments (see Materials and Methods).

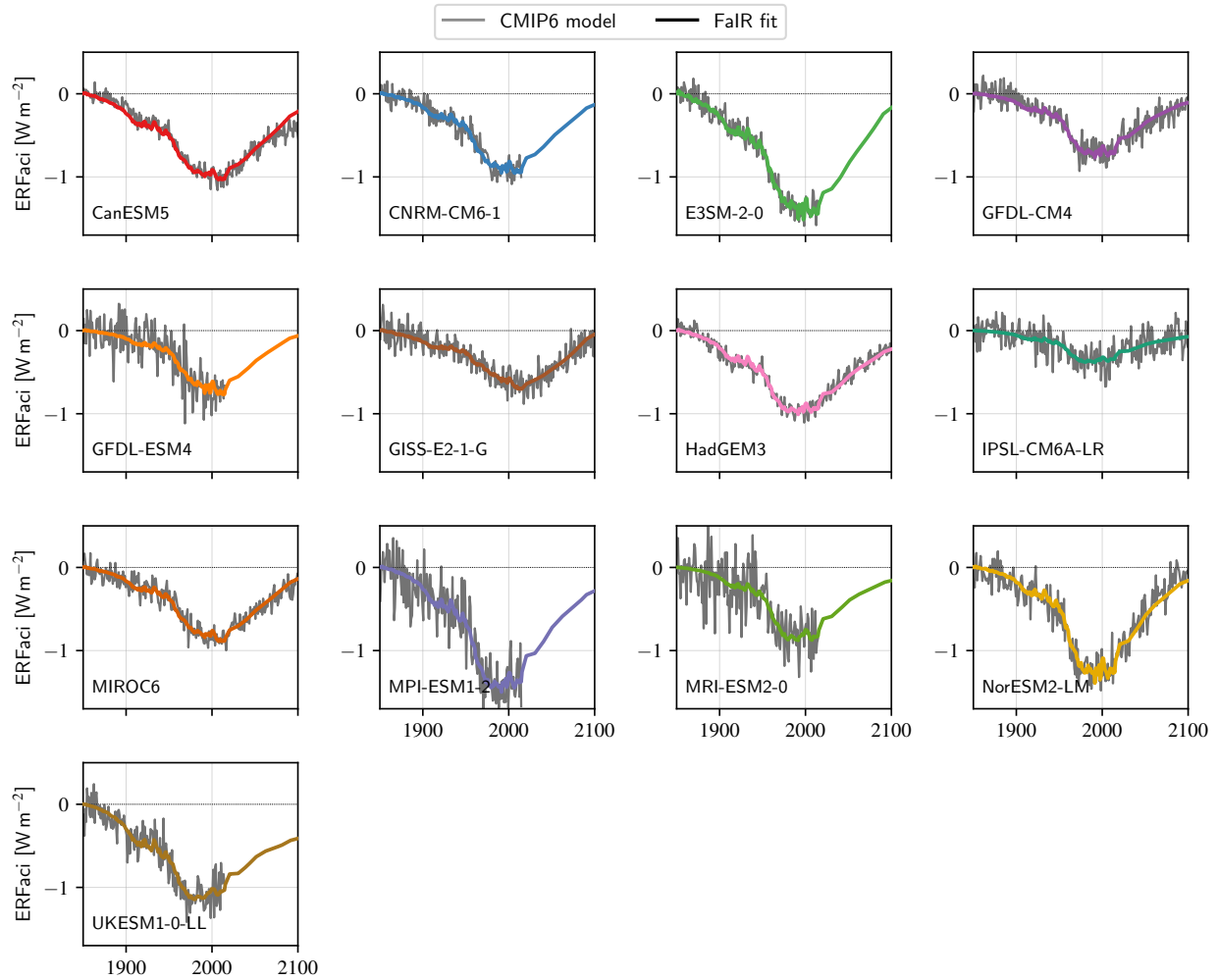


Figure S7. Calibration of the FaIR aerosol–cloud parameterisation against 13 CMIP6 models. Per-panel: ERFaci diagnosed from each CMIP6 model (grey) and the corresponding FaIR logarithmic fit (coloured), drawn from the calibration of ref. [17]. The global-mean concentration-based fit reproduces the century-long trajectory in each model, including the early industrial period when SO_2 emissions were concentrated in a handful of regions. This figure reproduces Figure 5 of ref. [17] and is included here for completeness.

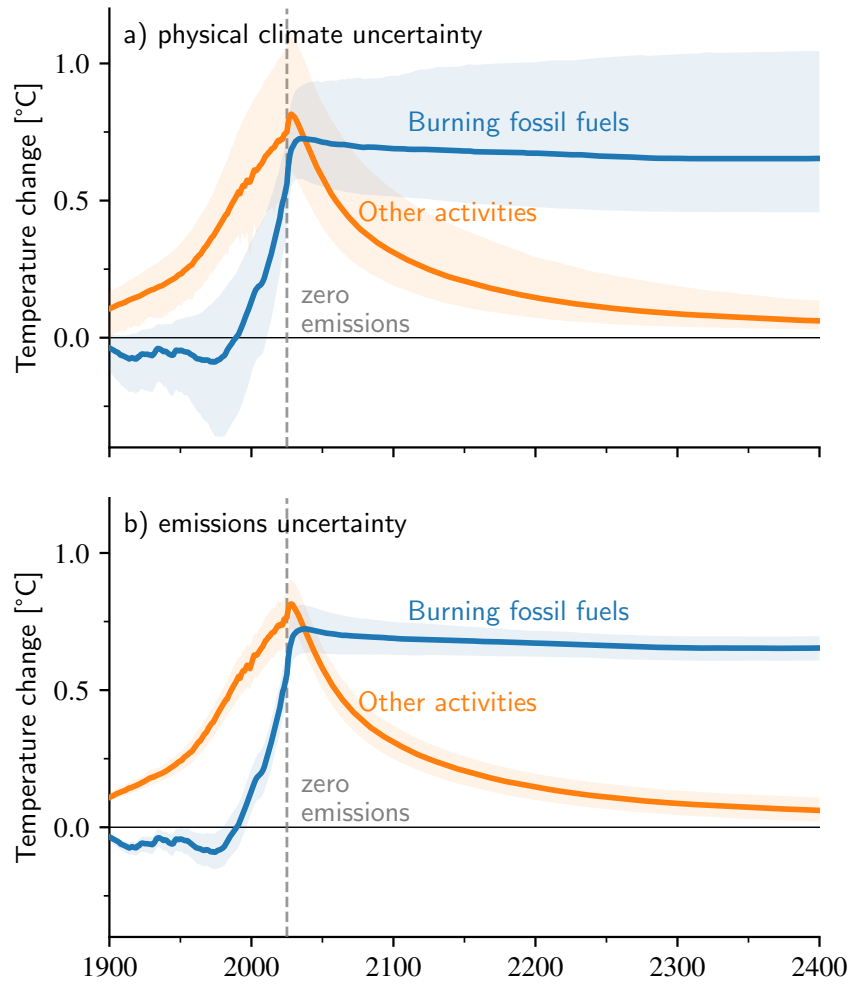


Figure S8. Uncertainty decomposition of committed warming. Same as Fig. 3 of the main text, but showing (A) only the physical-response uncertainty, computed by taking the median over all emissions samples, and (B) only the emissions uncertainty, computed by taking the median over all physical configurations.

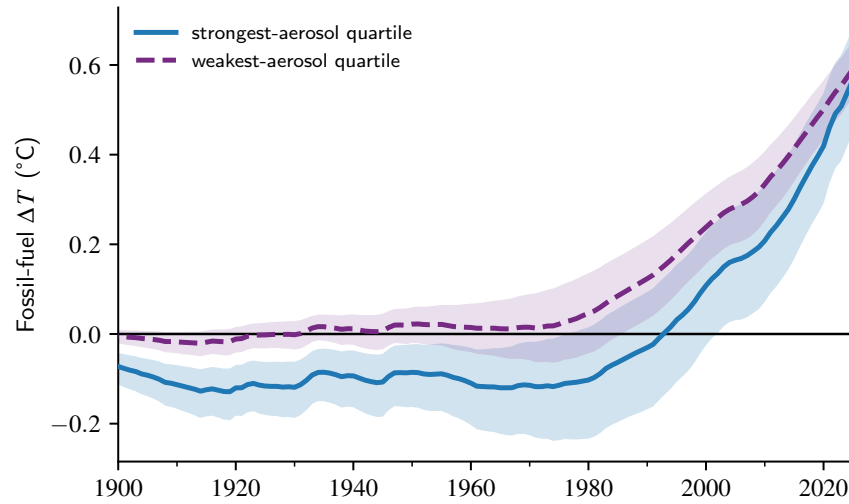


Figure S9. Sensitivity of the fossil-fuel temperature response to aerosol forcing strength. Same as the fossil-fuel warming timeseries in Fig. 1 of the main text, but with the ensemble grouped by the present-day aerosol effective radiative forcing. Trajectories are the medians over the weakest and strongest quartiles of aerosol forcing; shading shows the 5–95% range within the respective quartile.

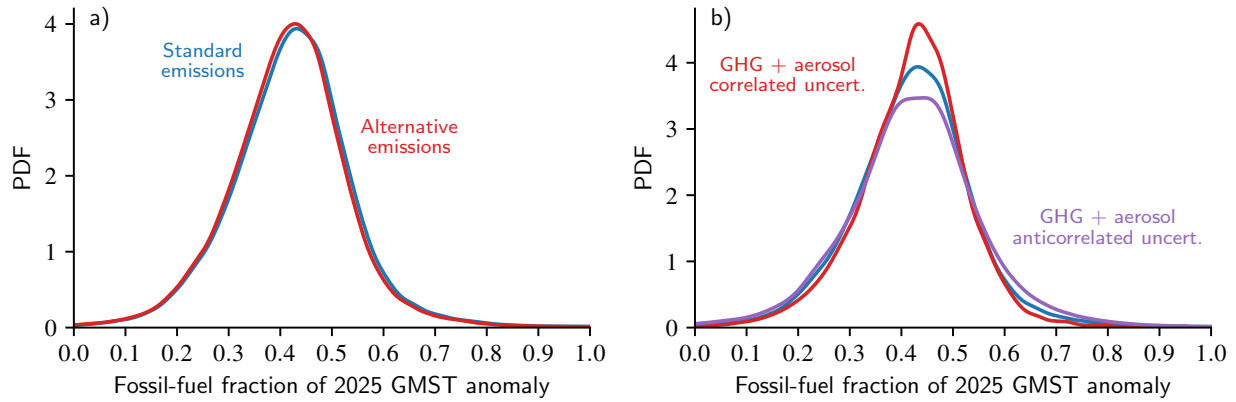


Figure S10. Sensitivity experiments. (A) Probability density functions (PDF) for the share of present-day warming due to fossil fuels assuming ambiguous IPPU emissions (see Table S2) are associated with fossil fuels (blue) or other activities (red). (B) Same as panel (A) but for experiments in which the uncertainty in greenhouse-gas emissions is assumed to be perfectly correlated (red) or anti-correlated (purple) with aerosol emissions uncertainty.

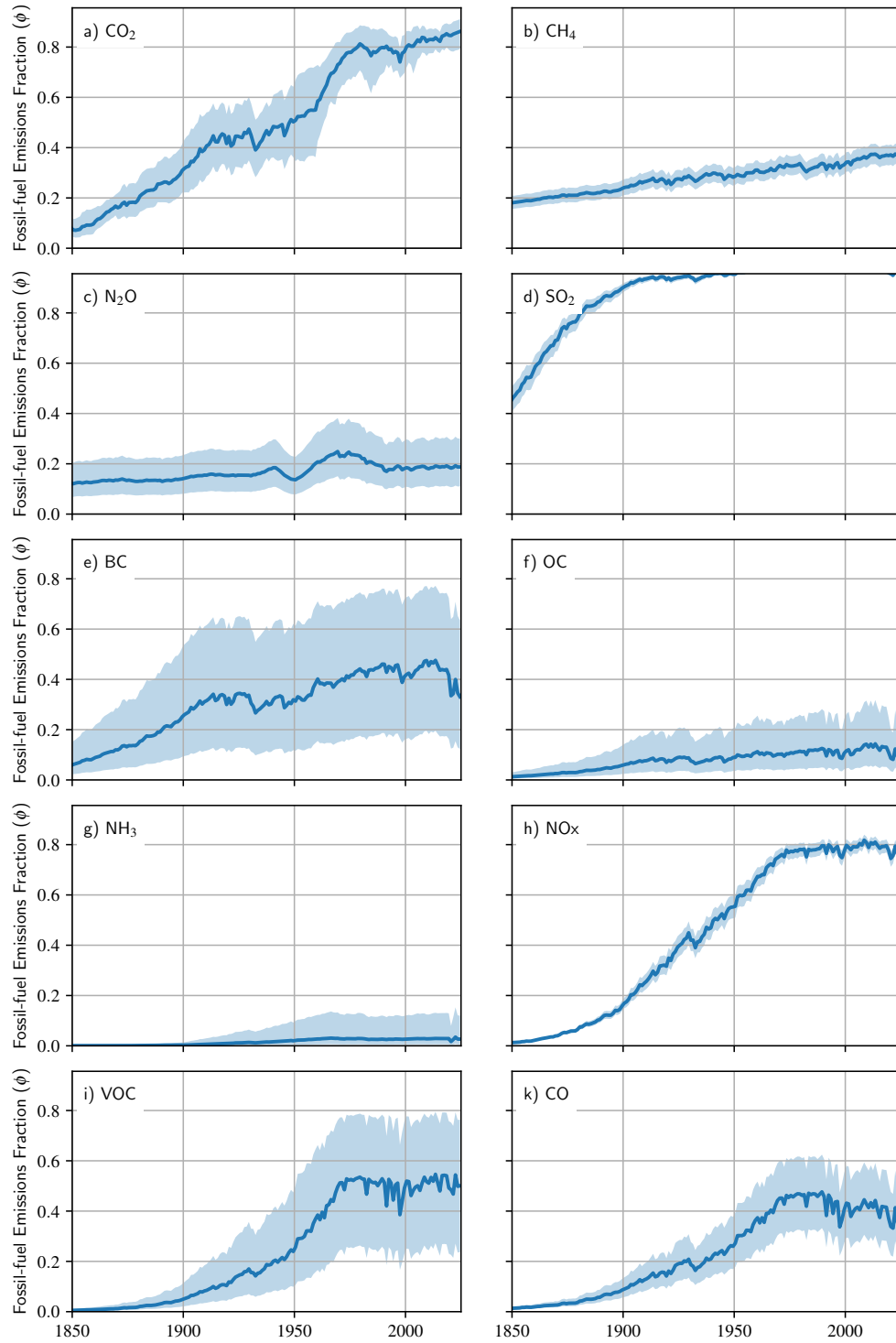


Figure S11. Fossil-fuel emissions uncertainty. The median (solid) and 90% confidence interval (shading) for the fraction of total emissions due to fossil fuels in each year (denoted as ϕ in Eq. S11). The probability distribution for each respective fraction is computed by propagating the uncertainties in the underlying fossil-fuel and non-fossil-fuel emissions inventories as described above.

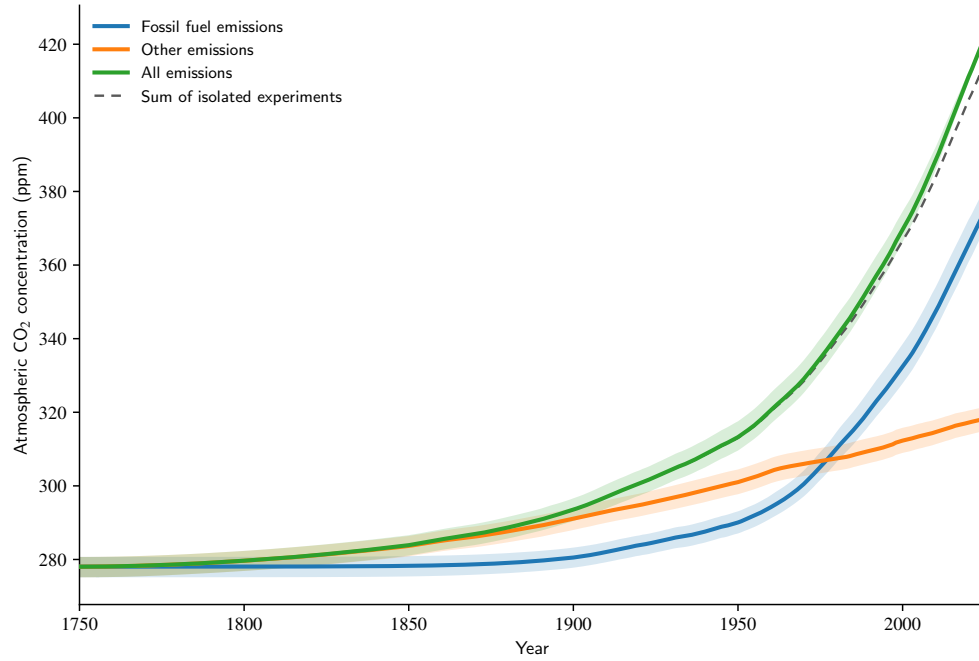


Figure S12. Atmospheric CO₂ from the isolated and combined FaIR experiments. Ensemble-median atmospheric CO₂ concentration in the combined-emissions experiment (red), the fossil-fuel-only experiment (blue), and the non-fossil-only experiment (green). The linear sum of the two isolated experiments (dashed grey) closely tracks the combined run, indicating that the nonlinearity in FaIR’s carbon sink is weak; the residual between the linear sum and the combined run is 8 ppm in 2025. Shading shows the 5–95% range.