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The warming effect of black carbon must be reassessed in light of observational constraints

Highlights

- We constrain warming estimates by BC using recent observations and emission inventories
- We find BC warming due to aerosol-radiation interaction spans a factor of three
- Rapid atmospheric adjustments reduce the instantaneous radiative forcing by nearly 50%

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In brief

Warming from BC stays uncertain despite observational constraints.

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The warming effect of black carbon must be reassessed in light of observational constraints

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SCIENCE FOR SOCIETY Incomplete combustion of fossil fuels, biofuels, and biomass leads to emissions of black carbon (BC). BC adversely impacts air quality and contributes to climate change. The climate effect of BC has been debated for decades and remains much more uncertain than that of greenhouse gases. This is due to its inhomogeneous distribution in the atmosphere; uncertainties in how strongly it absorbs sunlight; and its complex influence on temperature, water vapor, and clouds.

We use observational constraints and four climate models to uncover a factor of three difference in surface temperature response to BC-induced warming. This, combined with recent satellite-based information, highlights the need for a community effort to evaluate climate models against a broader set of observations in order to reduce the uncertainty associated with the climate impact of BC.

SUMMARY

Anthropogenic emissions of black carbon (BC) aerosols are generally thought to warm the climate. However, the magnitude of this warming remains highly uncertain due to limited knowledge of BC sources; optical properties; and atmospheric processes such as transport, removal, and cloud interactions. Here, we assess and constrain estimates of the historical warming influence of BC using recent observations and emission inventories. Based on simulations from four climate models, we show that the current global mean surface temperature change from anthropogenic BC due to aerosol-radiation interaction spans a factor of three—from +0.02 ± 0.02 K to +0.06 ± 0.05 K. Rapid atmospheric adjustments reduce the instantaneous radiative forcing by nearly 50% (multi-model mean), substantially lowering the net warming. Yet, recent satellite constraints suggest a stronger effect, highlighting the need for a more comprehensive reassessment of BC's climate influence.

INTRODUCTION

Atmospheric black carbon (BC) aerosols, emitted from incomplete combustion of fossil fuel, biofuel, and biomass burning, can both scatter and absorb incoming solar radiation.[1–4] Anthropogenic BC emissions are generally thought to exert a positive net radiative forcing and were assessed by the Intergovernmental Panel on Climate Change (IPCC) 6th Assessment Report

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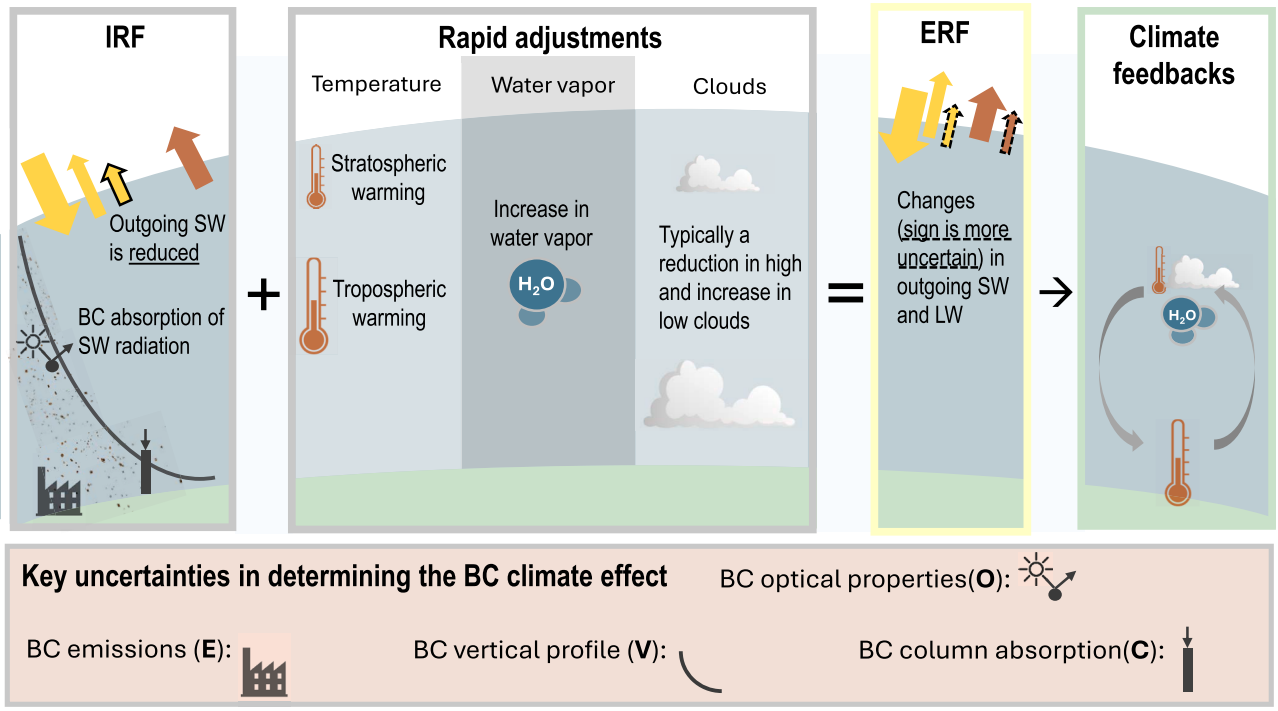

Figure 1. Illustration of BC impact on climate

Schematic illustration of the instantaneous change in top-of-the-atmosphere radiative fluxes, rapid adjustments, and feedback processes. Yellow arrows are for shortwave radiation and red for longwave radiation. The thinnest lines (one for shortwave and one for longwave) are perturbations to the radiation budget by BC.

(AR6) to be currently (year 2019) responsible for 0.07°C of global annual mean surface warming.[5]

This estimate is, however, highly uncertain, and has varied strongly in recent assessments due to a range of factors that are challenging both to observe and to represent in global climate models. These include the efficiency of the direct interaction of BC with sunlight, notably how strongly it absorbs radiation and transfers the energy to the surrounding air; the change of BC concentrations with altitude, which affects its warming because absorption is more efficient above a high albedo surface such as a cloud[1]; the transport, aging, and removal mechanisms of BC aerosols; and the overall amount of anthropogenic BC emissions. Further, although the energy absorption by BC occurs almost entirely in the solar spectrum, the resulting atmospheric heating triggers responses with impacts also on thermal infrared radiation.[6] These so-called rapid adjustments (RAs) include changes in atmospheric temperature,[7,8] in water vapor concentration,[7,8] and to cloud formation and properties.[9,10] RAs are initiated within hours after a BC particle is emitted[11] and have recently been shown to be critical in determining the total influence of absorbing aerosols on the atmospheric energy budget.[8,12–14]

In the current study, we present a set of climate model simulations, and a range of scaling exercises, to quantify the influence of these key uncertainties on estimates of the climate influences of BC emissions. First, however, we illustrate and discuss the current understanding of the progress from the emission of a BC particle, through to its influence on surface temperatures, and where the key uncertainties come in (see Figure 1).

The first important factor is the absolute volume of emissions, which varies among available datasets.[15,16] Observations indicate a reduction of global BC emissions in recent years, with a current best estimate of around 4.9 Tg yr^{-1}.[17] Recent modeling exercises, such as Coupled Model Intercomparison Project Phase 6 (CMIP6),[18] have generally used higher emissions than previous multi-model exercises,[19] leading to challenges in comparing modeling studies over time. Naturally, misrepresenting the level of emissions will influence the estimate of the climate effect of BC. In addition, the so-called representativeness error, where measurements of the BC concentrations close to an emission site are taken to be representative of a large, coarse climate model grid box when tuning climate models, has been shown to result in a positive bias.[20]

Next, we need to know how far, and how high up, BC particles are transported after emission. In recent modeling studies, the concentration of BC in the middle and upper troposphere is typically lower than in the previous generation of global aerosol models.[21–23] This has been related to the lifetime of BC, which is, in turn, primarily related to how models age the particles after emission and how effectively the particles are removed by precipitation. Comparisons with observations indicate that the CMIP5 generation of global models overestimated the concentrations of BC in the upper troposphere, likely leading to elevated radiative forcing due to the increased forcing efficiency with altitude.[24]

We also need to know the absorptive properties of BC, which are typically quantified by the mass absorption coefficient

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Table 1. BC experiments, their temperature response, and description.

Experiments	Global mean ΔT	Description of constraint/scaling
BC-E	0.05 ± 0.02	Scaled to account for updated emission inventories.
BC-EVO	0.02 ± 0.02	In addition to the emission scaling (E), BC profiles are vertically (V) constrained prior to simulation by reducing models' BC lifetime to better match observed BC profiles. Constraining the optical properties (O) by scaling MAC.
BC-EVOC	0.06 ± 0.05	In addition to the EV constraint, responses are further scaled to satellite data of column (C) absorption by BC. This scaling is vertically uniform and thus only constitutes an increased magnitude of BC-EVO responses.
IPCC AR6	0.07	Central estimate from the latest IPCC report.

Temperature change numbers are averages over all four models. As all experiments as based on BC×10 simulations (see Methods), all responses are scaled so that they represent responses to a BC concentration increase corresponding to the increase from preindustrial until present day. Further, all responses are scaled to account for updated knowledge of the typical optical properties of BC. See Methods and Figure 1.

(MAC). The MAC magnitude is crucial for the BC radiative effect[19] and has been measured to be, on average, around 7.5 ± 1.2 $m^2\ g^{-1}$ (at 550 nm) for freshly generated particles.[3] MAC is, however, enhanced when BC particles age and are coated by non-BC aerosols. The efficiency of non-BC aerosols in enhancing the absorption of BC is debated,[25–27] but most recent observations, taking low-volatility organics into account, indicate an aged MAC of around 10 $m^2\ g^{-1}$ (at 550 nm).[27] However, the aging enhancement factor depends on the morphology assumption on the BC core,[28] and the average enhancement over time and space is uncertain.[29] Table S1 shows a range of measurements of MAC, illustrating a substantial range, likely due to regional differences and different measurements techniques.[30] Meanwhile, global models have shown a tendency to underestimate the MAC by about 25%–50%[31] compared with regional measurements.[30]

In all, the emissions, geographical distribution, vertical profile, and MAC broadly determine the instantaneous forcing (IRF) of BC aerosols (left panel in Figure 1). This is, however, where the RAs come in, altering the net influence of BC on the energy balance. For instance, based on idealized experiments with CMIP5 generation models, Smith et al.[8] showed RAs to be strongly negative for BC, with cloud changes as one of the main contributors. Whether the cloud response enhances or counteracts the direct influence on the radiation budget, however, differs between various studies.[19,32] The sign of the BC influence on clouds is mainly dependent on whether BC is located above or below clouds,[33–35] whereas the strength of the impact depends on atmospheric conditions and cloud properties.[34] Available estimates of BC-induced cloud changes come from models with spatial resolutions ranging from hundreds of kilometers (global scale models) to tens of meters (large eddy simulations)[32,35,36] and are partly based on satellite retrievals.[37,38]

After RAs, the remaining net influence of BC on the global energy balance is termed the effective radiative forcing (ERF).[19,39,40] ERF has been found to be more directly related to subsequent surface temperature change than IRF. For BC, ERF is typically found to be markedly lower than IRF due to the RAs (see results below); this insight is one reason the estimated relative importance of BC in anthropogenic climate change was markedly lower in the IPCC AR6 (0.07 C, based on an ERF estimate) than in the AR5 (which used IRF estimates but did not give a temperature estimate for BC separately).

In this study, we use a set of recent modeling studies, combined with observational constraints, to provide a revised estimate for the influence of current anthropogenic BC emissions on global annual mean surface temperature. Our main aim is to illustrate the individual and combined importance of a set of three uncertainties: the level of emissions, the vertical profile of BC in the atmosphere, and the total amount of shortwave absorption stemming from the MAC of aged BC. We also discuss how our revised estimates compare to previous and more recent estimates from the IPCC. Our results are based on four climate models with BC responses that are initially typical of the previous CMIP5 generation of global models. Some of these simulations are already thoroughly documented in previous studies.[8,31,41] Here, we scale these results to match recent emission estimates and then compare the responses to new simulations, where the vertical profile of BC has been constrained by observations in the upper troposphere as well as recent constraints based on satellite data of column absorption by BC (see Methods). Our best estimates of ERF and surface temperature change of BC from aerosol-radiation interactions are both lower than those arrived at in IPCC AR6, and we conclude by discussing the reasons for, and implications of, this result.

RESULTS

The model experiments used in this paper, and the scalings to observational constraints, are summarized in Table 1 and described in full in Methods. Briefly, we have three sets. BC-E denotes simulations from four models (ECHAM-HAM-M7, GISS-E2, NCAR-CESM-CAM4, and NorESM1) where BC concentrations (or, in one case, emissions) have been increased by 10x. These have previously been analyzed as part of the Precipitation Driver Response Model Intercomparison Project (PDRMIP).[31] Relative to the PDRMIP 10 model mean, two of our current models showed high sensitivity to BC emissions and two showed weak sensitivity (see further discussion in the Supplement). Here, in BC-E, we have scaled these results to reflect the most updated emission inventories of anthropogenic BC (4.9 Tg yr^{-1}; CEDS v2024.04.01).[17]

Next, in BC-EVO, we have performed additional 10× BC experiments with the same models but where the vertical profile (V) of BC has been tuned to match updated knowledge on

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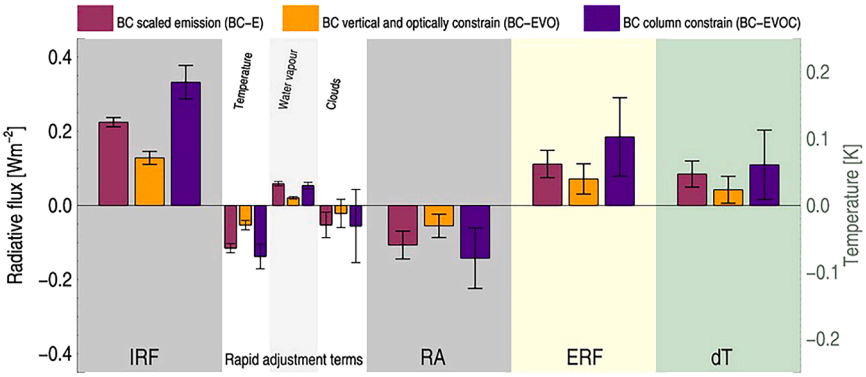

Figure 2. Forcing and temperature change due to BC

Calculated global mean values from the three experiments, BC-E, BC-EVO, and BC-EVOC, showing instantaneous radiative forcing (IRF), rapid adjustments (RAs), effective radiative forcing (ERF), and surface temperature change (dT). Surface temperature change has a y axis on the right-hand side. Uncertainty ranges are taken as one standard deviation among the four climate models. All three experiments are scaled to current BC inventories, see further description in Table 1.

abundancies in the upper vs. lower troposphere.[21,22] This is done by either prescribing a BC concentration distribution from a model with tuned BC removal or by tuning the removal in the model itself (ECHAM); see Methods. In addition, we have scaled the simulations to match observations of optical properties (O) of BC, specifically the MAC, as the observed value of 10 m^2 g^{-1} is higher than the multi-model mean of this study (7.3 m^2 g^{-1} ± 10% at 550 nm).

Finally, in BC-EVOC, we have applied a scaling to make the column average (C) absorbing aerosol optical depth (AAOD) match the recent satellite-based constraint by Chen et al.[42] Taken together, these three experiments represent a stepwise constraining of model results to match the current best estimates of the three key uncertainties in the quantification of the surface temperature impacts of BC emissions.

Figure 2 shows the IRF, RA, and ERF from all experiments, calculated as a combination of direct model output, double radiation calls, and application of radiative kernels, following Myhre et al., Smith et al., and Soden et al.[8,43,44] The global annual mean temperature change is also shown, quantified from fully coupled climate model simulations, as a mean over the years 51–100 after the 10× BC perturbation is applied.

In BC-E, we find a surface temperature change for current anthropogenic BC emissions of 0.05 (±0.02) °C, where the standard deviation is taken across the four models. We note that this gives the same relative standard deviation as using the full set of 10 PDRMIP models that performed the BC×10 experiment (see Table S2). This temperature influence is lower than the 0.07°C assessed by IPCC AR6[5] but consistent within errors; we discuss this further below.

In BC-EVO, where the vertical profile and optical parameters are constrained, we find a markedly lower temperature influence of 0.02 (±0.02) °C. This is mainly due to the lower BC total abundance in the upper troposphere, where its absorption is particularly efficient.[45–47] For example, Sand et al.[48] demonstrate, using two climate models, that IRF of BC is 2–3 times stronger in the upper troposphere compared with the lowest 2 kilometers of the atmosphere. We note that the IRF of 0.33 Wm^{-2} in BC-EVOC is 50% higher than BC-E and is identical to the estimate in Chen et al.,[42] even though we take into account the lower recent BC emissions over the last decade, as opposed to Chen et al.[42]

Finally, in BC-EVOC, we find a warming influence from BC of 0.06 (±0.05) °C. The strong increase here is because the satellite-derived constraint on BC AAOD from Chen et al.[42] is markedly higher than what is simulated by most models.

In Figure 3, we show the geographical distributions of the multi-model mean surface temperature change, displaying a strongly inhomogeneous pattern. Reflecting the proximity to the BC emission sources, the warming is much stronger in the Northern Hemisphere than the Southern Hemisphere—and stronger over continents than over oceans. However, many of the regions that have a high abundance of BC, such as Southeast Asia, show a very modest warming, or even a

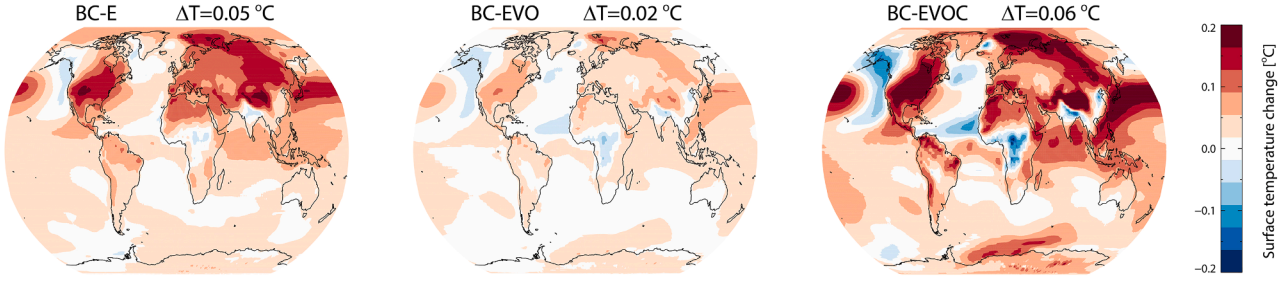

Figure 3. Temperature change due to BC

Multi-model annual mean surface temperature change for the BC-E, BC-EVO, and BC-EVOC experiments. The change is relative to model PDRMIP reference simulation.[49]

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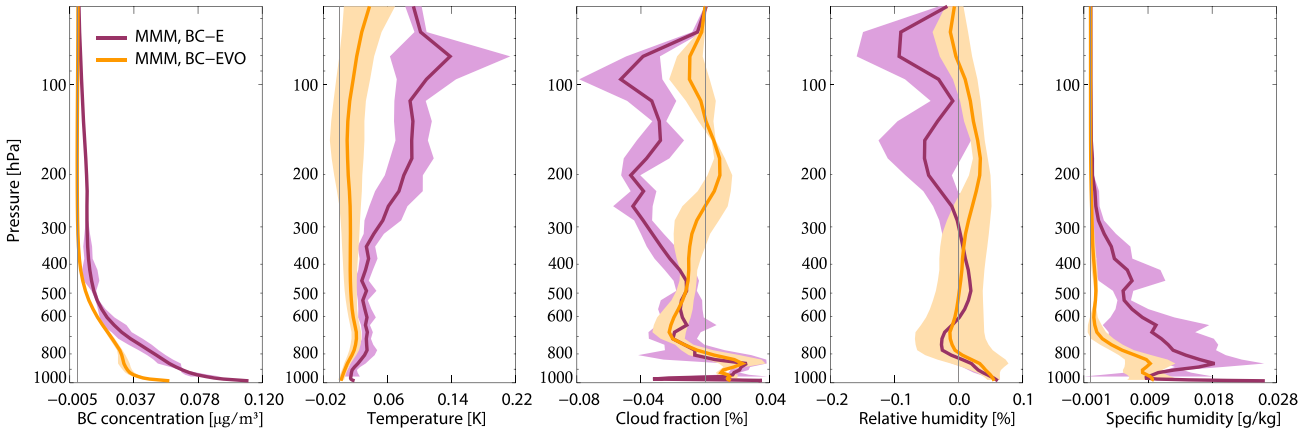

Figure 4. Global mean vertical profile and BC-induced changes

Atmospheric vertical profiles of changes in BC concentration, temperature, cloud fraction, and relative and specific humidity for the two experiments, BC-E and BC-EVO, from the fsst simulations. The model diversity is shown by the shading given as one standard deviation among the models.

cooling, suggesting the presence of compensating effects. The geographical pattern of warming is similar in BC-E and BC-EVO, even though the vertical and horizontal BC distributions are quite different. Note that BC-EVOC has an identical warming pattern to BC-EVO, as it only includes an additional column absorption scaling that enhances the magnitude of the response.

In Figure 4, we show the atmospheric vertical profiles of change in BC concentration (for individual models in Figure S1), temperature, cloud fraction, and relative and specific humidity. (BC-EVOC is omitted as it has the same profile as BC-EVO.) The profiles are markedly different in the upper troposphere for all models, where the unconstrained BC-E simulation shows strong changes whereas BC-EVO has almost none. In the lower troposphere, temperature changes and cloud changes are relatively similar for the two simulations. The cloud fraction changes largely follow the relative humidity profile. Specific humidity changes are positive throughout the troposphere, with much stronger increases in BC-E than in BC-EVO. The model diversity (shown as one standard deviation) is larger for BC-E than BC-EVO but varies vertically and is generally low for cloud changes. No particular model dominates the model spread, except for temperature changes around 100 hPa in BC-E, where NCAR-CESM1-CAM4 has a much larger temperature increase than the three other models (Figure S2).

BC typically reduces cloud cover in altitudes where it is present while increasing cloud cover at lower heights. This dynamic leads to a strong negative adjustment when BC is in the upper troposphere, characterized by a reduction in high clouds and an increase in middle and lower clouds.[48] In the BC-E experiment, the RA due to clouds is similar in magnitude to the sum of the other RA terms. For the BC-EVO and BC-EVOC experiments the RA of clouds is 40% of the total RA in a multi-model mean. Earlier studies have focused primarily on BC RA due to clouds,[32] but our results illustrate the importance of including all RA terms. We note, however, that the cloud RA has a strong inter-model standard deviation and is even positive in one of the models. The models used for the IPCC AR6 assessment also showed a large range in cloud adjustment, spanning strongly negative to slightly positive values.[50]

We find that the total RAs are negative in all three experiments. Recall that although the IRF quantifies the radiative impact only, the ERF incorporates the RAs and is thus sensitive to the magnitude of these adjustments. The negative RA of BC involves changes in (land) surface, tropospheric, and stratospheric temperatures caused by the atmospheric heating by BC, which increases the longwave radiation to space (Planck feedback). See further discussion in Smith et al.[8] on the impact on longwave radiation and how this differs among climate drivers. Water vapor change is a positive RA resulting from increased atmospheric temperatures. For BC-E the RA contributes to lowering the ERF by 50% relative to the IRF. For BC-EVO and BC-EVOC, the RA causes a 43% reduction from IRF to ERF (see Supplementary Note S1 and Figure S3 for split into longwave and shortwave contributions). In addition to the atmospheric RA terms, the prescribed sea-surface temperature simulations used to quantify ERF show small land surface temperature and albedo changes. We also note that Figure 2 shows a particularly strong change in the cloud RA between the BC-E and BC-EVOC experiments, indicating that cloud changes in the middle and upper troposphere are especially important.

Recently, the IPCC AR6 provided an updated estimate of the present-day climate warming due to BC emissions[50] of 0.07°C. This estimate was based on simulations, with a change in BC emission representative of a change between preindustrial and current conditions and simulated for 30 years. In the simulations, the CEDS v2016.07.16 (CMIP6 release) were used for year 2014, and these emissions are more than 50% higher compared with CEDS v2024.04.01 for year 2022. However, Forster et al.[51] showed that effective radiative forcings weaker than 0.1 Wm^{-2} involve large uncertainties in 30-year simulations because the signal is weak compared with natural variability. For several of the models involved in Thornhill et al.,[50] the ERF was weak and thus uncertainties in the ERF of BC are substantial.

In this study, we have chosen to base our analyses on strong 10-fold increases in BC, which we have thereafter scaled to

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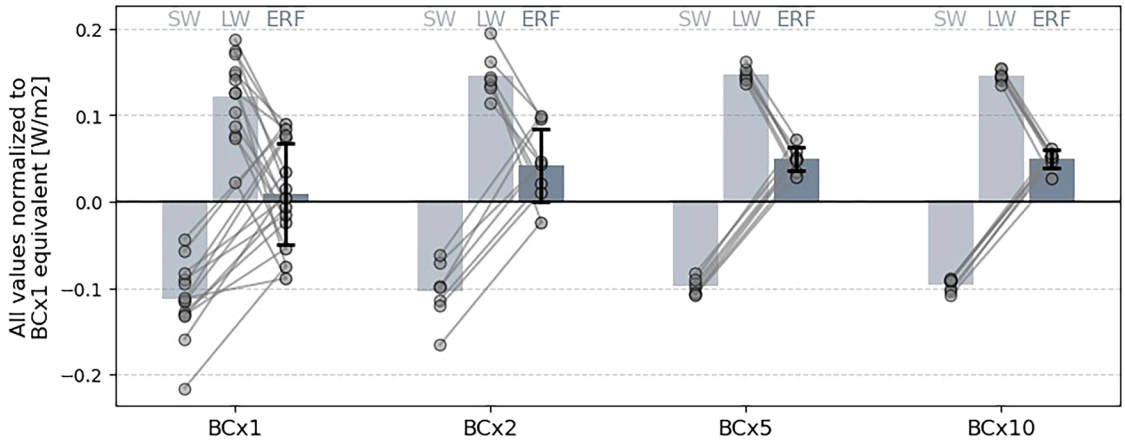

Figure 5. Linearity of BC ERF

Illustration of linearity of BC perturbations in simulations using CESM2-CAM4 with original (BC-E) profiles. Bars show the mean normalized shortwave (SW), longwave (LW), and net ERF for 200-year simulations with industrial era BC (BC×1) and 100-year simulations with twice the industrial era BC (BC×2), five times the industrial era BC (BC×5), and ten times the industrial era BC (BC×10), respectively. Circles show consecutive 15-year mean values, with lines connecting individual 15-year SW and LW values with the corresponding ERF value. Whiskers on ERF bars indicate +/− one standard deviation.

match the preindustrial to present-day increase in BC. We believe this method is more reliable for relatively short simulations of small perturbations and have performed an additional set of sensitivity simulations to illustrate this point. Figure 5 shows ERF of simulations, using one of the models, with industrial era BC (BC×1), industrial era BC multiplied by two (BC×2), five (BC×5), and ten (BC×10). The ERFs are normalized by the BC industrial era BC abundance to investigate the linearity of BC perturbation. The simulations were run for 100 years with fixed sea-surface temperatures for BC×2, BC×5, and BC×10 and for 200 years for BC×1. The bars indicate the mean over the full simulations, whereas the circles indicate all of the consecutive 15-year period included in the full simulations. The normalized mean full ERFs are very similar in the BC×2, BC×5, and BC×10, but the spread of the circles indicates reduced variability as the perturbation becomes stronger. In the BC×1 simulation, the 15-year means vary widely, ranging from negative to positive values. The forcing perturbation in BC×1 is weak compared with the internal variability, and very long simulations are required to get a representative ERF. Overall, the figure shows that the ERF exerted by BC is linear in concentration, up to ten times the change over the industrial era. This supports findings in Hodnebrog et al.[45] and validates our methodology of performing strong perturbations that are later scaled to match present-day levels. Consequently, we find that the AR6 estimate of historical era BC-induced warming may have had marked uncertainty and is fully consistent with the range of lower estimates we present here.

DISCUSSION

We have shown that estimates of climate impacts of BC vary strongly in the literature and that uncertainties in the climate effect of BC are particularly associated with emissions, atmospheric residence time (and thus the resulting vertical distribution), and optical properties such as absorption.[3,19,52]

BC emission data have previously been assessed to have a factor of two uncertainty.[53] We have mentioned the transition between emissions typically used in previous multi-model assessments (v2016.07.16 BC emissions CEDS[16]) compared with the most recent version of the CEDS data (v2024.04.01) used in newer studies. Although the most recent CEDS data have 8% higher emissions than older generations of multi-model studies, the previous CEDS version is 66% higher, partly because of higher emissions in 2,000 and partly as a result of an increase in BC emissions since 2,000. The lower discrepancy for the most recent CEDS version is mainly caused by a revisiting of emission before 2014 and a continued reduction after 2014. Although all our estimates are scaled to current emissions from CEDS, Zhao et al. (2024)[54] show that an earlier version of CEDS and other bottom-up emission inventories most likely underestimate BC emissions over China compared with a top-down approach. However, there are several limitations associated with the top-down approach, and more research is needed to robustly conclude that Chinese BC emissions are underestimated. In our analyses we scale the results to match the most recent CEDS emission. To illustrate the importance of that scaling, we show in Table S3 responses in ERF, IRF, and RAs for both versions 2024.04.01 and 2016–07.16.

We have also shown ERF due to BC over the industrial era to be lower than IRF (the direct BC aerosol effect) by around 50% in the multi-model mean. ERF has previously been found to be the most representative way to compare the surface temperature change from a perturbation to the Earth's energy budget for different climate drivers, including BC.[39] The total RA due to BC is strongly negative, and recent findings[8] underline the importance of atmospheric temperature increase and a negative cloud RA. Despite some model diversity in the IRF and in the magnitude of the cloud RA, we have found that, overall, the RA and ERF are consistent among four climate models, as are the underlying physical processes of vertical changes in

atmospheric temperature, water vapor, and clouds. This consistency includes simulations from three climate models using concentration fields of BC, and one model used emissions to derive the BC atmospheric concentration.

Note that the temperature change from the fully coupled climate model simulations is taken as a mean over the years 51–100. This means that our temperature response estimates are likely overstated compared with the current temperature change due to present-day anthropogenic BC because the model has had many decades to respond to the current levels, including a component from the deep ocean, unlike the real world. Therefore, we consider this an upper-bound from the four models. A lower bound, found by using a 5-year mean around year 20, is about 20% weaker than our upper-bound (see supplementary text for further discussion).

In conclusion, we find that there is a need for further work to provide an up-to-date estimate of the influence of anthropogenic BC emissions on global surface temperature over the historical era. Such efforts should ensure consistent treatment of emissions, and adherence to observational constraints of the vertical profile of BC in the atmosphere, its optical properties, and the total amount of absorption by BC in current satellite estimates.

METHODS

Concepts

IRF—instantaneous radiative forcing

The immediate energy imbalance at the top-of-atmosphere (TOA) caused by direct interactions between changed atmospheric BC burden and radiation, positive for increased energy input to the earth system.

RA—rapid adjustments

The short-term adjustments of atmospheric properties to the IRF that are not due to responses to surface temperature changes.

ERF—effective radiative forcing

The TOA radiative energy perturbation is due to the combination of IRF and the RAs. Thus, the TOA perturbation after RAs have taken place is positive for the increased energy input to the earth system.

Climate response

Any changes in climate variables in response to ERF, including the deep oceans. Ideally, a full climate response to an imposed ERF is the difference between climate states in long-term equilibrium, with and without the imposed ERF. The high inertia of the deep oceans hampers such estimates in practice. Instead, a *Transient Climate Response* is estimated after a given time for partial adjustment; in this case, we use 100-year-long coupled simulations.

Models

This study uses a subset of 4 PDRMIP models out of 10 Precipitation Driver Response Model Intercomparison Project (PDRMIP) models.[49] We use simulations from the four global climate models ECHAM-HAM-M7, GISS-E2-R, NCAR-CESM-CAM4, and NorESM1. In PDRMIP, atmosphere-land simulations with prescribed sea-surface temperatures (*AMIP-type*) and fully atmosphere-land-ocean-coupled (*CMIP-type*) simulations are applied for a large set of climate drivers and a reference simulation representing current climate conditions. The models include the atmospheric effect of absorption and scattering of BC but do not include any aerosol-cloud interactions and BC effect on snow and ice (with the exception of NorESM1, which includes the BC effect on snow and ice). For a further description of the PDRMIP models see Myhre et al.[49]

Simulations

The anthropogenic BC is scaled to its atmospheric change during the industrial era. Prescribed concentration fields are imported in three of the models (GISS, NCAR-CESM-CAM4, and NorESM1), which are thus run concentration driven without feedback between climate variables and BC concentrations. The fourth model (ECHAM) calculates BC concentrations from emissions and thus allows feedback between BC and atmospheric variables. Both 15-year-long AMIP-type (fixed sea-surface temperature) and 100-year-long CMIP-type simulations are performed (see also Supplementary Note S2).

Each model produces a standard set of climate response experiments (**BC-E**) based on importing BC data from the BC×10 (BC concentrations/emissions multiplied by 10) core set of PDRMIP simulations, see Figure S4 for ERF and Figure S5 for surface temperature change. Imported concentration fields in BC-E are multi-model mean fields from AeroCom.[52] A new set of simulations (**BC-EVO**) are performed by importing (in GISS, NCAR-CESM-CAM4, and NorESM1) or producing (in ECHAM) lifetime-adjusted BC×10 data to constrain the concentration profile to observations. We use a single model field for imported BC concentrations in the BC-EVO experiment.[45] The BC overabundance in the upper troposphere is reduced by increasing the wet removal of BC, which results in a shorter lifetime. Various sensitivity simulations are performed in Hodnebrog et al.[45] to achieve a realistic agreement with the aircraft measurements. In this study, the PERTBC simulation in Hodnebrog et al.[45] is adopted, but emissions are as in the standard case in Hodnebrog et al.[45] The vertical profiles for BC STD and BC-EVO are shown in Figure S1. The lifetime of BC in BC-EVO for the models GISS, NCAR-CESM-CAM4, and NorESM1 is 3.9 days[45] compared with 7.4 days in BC-E.[31] In the emission-driven simulations in ECHAM-HAM the wet removal tendencies of BC are scaled by a factor of 2, resulting in a change in the lifetime from 7.4 days (in BC-E) to 3.7 days (in BC-EVO). In **BC-EVOC**, we further scale the BC-EVO simulation with the ratio of absorption aerosol optical depth based on satellite data[42] of 0.0044 (550 nm) to 0.0017 (550 nm) in BC-EVO.

In the BC-E PDRMIP experiment, the four selected models have a mean ERF within 1% of the mean of the 10 PDRMIP models, whereas the number is 25% lower for surface air temperature change.

Results after constraining to the observed MAC and emission data

All results are scaled to best match current BC emission estimates using the Community Emission Data System (CEDS) version 2024.04.01.[17] The CMIP6 BC emission in CEDS (version 2016.07.16) is 66% larger (from 4.6 to 7.6 Tg yr^{-1}) than the emissions used in AeroCom dataset (BC STD experiment) due to a strong increase in recent years and overall improved estimation of BC sources.[16] However, the most recent version of the CEDS data (version 2024.04.01) has only 8% (from 4.6 to 4.9 Tg yr^{-1}) higher emissions than used in previous multi-model studies.

This is mainly caused by a revisiting of emissions before 2014 and a continued reduction after 2014. In all Figures and numbers, the most recent CEDS data are used. In the Table S3, we report results from BC emissions of 4.9 and 7.6 Tg yr^{-1}. The concentration field applied in the BC-EVO experiment is derived from the EU project ECLIPSE emission dataset,[55,56] with a total BC emission of 7.1 Tg yr^{-1} (5.5 and 1.6 Tg yr^{-1}, respectively, from anthropogenic and natural sources).

Observations of MACs vary strongly,[3,30] see Table S1. Models have typically lower MAC values than observations. The mean MAC among the four models applied in this study is 7.3 m^2 g^{-1} ± 10% (550 nm). We scale this value to 10 m^2 g^{-1} (550 nm), which we find to be a representative value from the selected values in Table S1.

The scaling of the results by emissions and MAC is done on all post-processed GCM output. All results in this study thus represent a change in BC from preindustrial to present-day emissions of 4.9 Tg yr^{-1}. Scaling of the mass absorption coefficient of 10 m^2 g^{-1} (550 nm) is done for BC-EVO and BC-EVOC. The scaling is applied to the multi-model mean numbers.

Calculations of ERF and RAs

ERF and surface temperature changes are directly derived output from the PDRMIP models, respectively, from fixed sea-surface temperature simulations (AMIP-type) and fully coupled simulations (CMIP-type). Results from fixed sea-surface temperature simulations are taken as mean of years 6–15 and results from coupled simulations as mean of years 51–100.[41] Radiative kernel simulations[44] are applied for quantifications of the individual RA terms using a mean of 5 different radiative kernels.[8,43] Three of the models have implemented double radiation calls for quantification of IRF, whereas for NorESM1, IRF is taken as the difference between ERF and RA. When IRF is directly quantified, the residuals in the kernel simulations are discussed in the text. Similarly, BC IRF almost exclusively influences the SW radiation; therefore, the residual can be derived from LW ERF and kernel calculations, see Supplementary Note S3 and Figure S6.

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources should be directed to, and will be fulfilled by, the lead contact, Gunnar Myhre (gunnar.myhre@cicero.oslo.no).

Materials availability

The PDRMIP data are available through the World Data Center for Climate (WDCC) https://www.dkrz.de/up/systems/wdcc with https://doi.org/10.26050/WDCC/PDRMIP_2012-2021.

Data and code availability

- The PDRMIP data are available through the World Data Center for Climate (WDCC) https://www.dkrz.de/up/systems/wdcc with https://doi.org/10.26050/WDCC/PDRMIP_2012-2021. A code to read and make a summary of PDRMIP data is available at GitHub: https://github.com/ciceroOslo/PDRMIP_summary_codes

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AUTHOR CONTRIBUTIONS

Conceptualization, G.M., B.H.S., C.W.S., and Ø.H.; methodology, G.M., B.H. S., C.W.S., Ø.H., R.K., C.S., T.A., O.B., G.F., P.M.F., T.I., A.K., D.O., D.S., P.S., and D.W,-P.; investigation, G.M., B.H.S., C.W.S., Ø.H., R.K., C.S., T.A., O.B., G.F., P.M.F., T.I., A.K., D.O., D.S., P.S., and D.W.-P.; writing—original draft, G. M., B.H.S., and C.W.S.; writing—review & editing, G.M., B.H.S., C.W.S., Ø.H., R.K., C.S., T.A., O.B., G.F., P.M.F., T.I., A.K., D.O., D.S., P.S., and D.W.-P.; funding acquisition, G.M., T.A., P.M.F., and P.S.; resources, G.M., B.H.S., C. W.S., Ø.H., R.K., C.S., T.A., O.B., G.F., P.M.F., T.I., A.K., D.O., D.S., P.S., and D.W.-P.

DECLARATION OF INTERESTS

The authors declare no competing interests.

SUPPLEMENTAL INFORMATION

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