CORRESPONDENCE:

Upward adjustment needed for aerosol radiative forcing uncertainty

To the Editor — Recently, major known inconsistencies between observationally constrained and unconstrained model-based estimates of the global mean direct aerosol radiative forcing (DARF) have been resolved[1]. However, there is still considerable debate about the magnitude of DARF uncertainty[2–8]. A recurring question is whether current aerosol models adequately cover the full range of uncertainties[6,9]. There are several ways to calculate DARF from reported aerosol model results. Here we show that calculating DARF using a simple Monte Carlo technique, which accounts for the variance in relevant input parameters, provides an estimate of DARF with a significantly larger uncertainty range. The expanded range is close to observation-based uncertainty estimates. This suggests that an upward adjustment of modelled direct aerosol radiative forcing uncertainty may be needed to account for the limited number of models used in recent assessments. A doubling of the estimated uncertainty range for DARF, as described here, would have a substantial impact on the uncertainty in climate sensitivity[10–12].

DARF between 1750 and 2010 was recently estimated as −0.35 W m^{-2}, based on 16 state-of-the-art aerosol models[7]. We hereafter refer to this study as M13. The 5–95% uncertainty range, based on values taken from the models, was −0.65 to −0.03 W m^{-2}. This range is in stark contrast with other recent publications that employ satellite and ground-based observations and reanalysis (Fig. 1c).

In global climate models, a wide range of processes that can affect the final estimate of DARF are simulated. Several recent studies have pointed out that emissions levels — in particular, of carbonaceous aerosols — may be systematically underestimated by models[13,14], but it is hard to pinpoint other processes that are simulated with insufficient variance across the model sample. In addition, a recent idealized study showed that forcing-efficiencies in the models used in M13 are relatively insensitive to the aerosol schemes of the individual models[15].

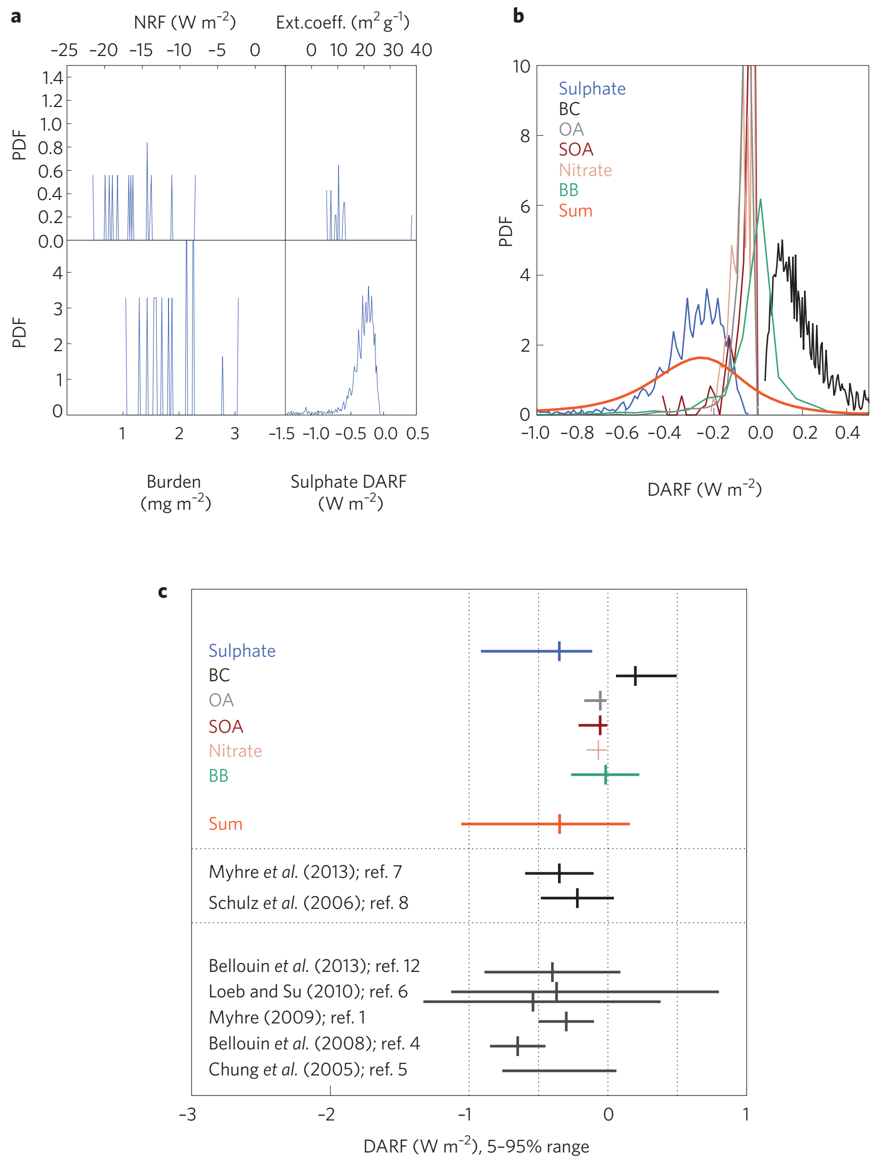

Figure 1 | Revised direct aerosol radiative forcing (DARF) uncertainty ranges using a Monte Carlo approach. **a**, Parameter-based estimation of a probability density function (PDF) for DARF from sulphate. PDFs for normalized forcing (NRF), extinction coefficient and burden are shown, in addition to the PDF resulting from multiplying values taken from these three distributions (lower right). **b**, PDFs for the six aerosol species treated in M13: sulphate (blue), black carbon (BC; black), organic aerosols (OA; grey), secondary organic aerosols (SOA; brown), nitrate (peach), biomass burning (BB; green) and the PDF derived for total DARF by adding the estimates for component DARF (orange). **c**, DARF mean and 5–95% confidence ranges for aerosol species as calculated in this study, aside ranges in the purely model based studies, and recent studies where models and observational data are combined using various methods.

When trying to understand differences in model diversity, alternative derivations of the same quantity are very useful. An alternative approach to estimating DARF is to derive it from other modelled parameters:

$$\mathrm{DARF} = \frac{\overline{\mathrm{DARF}}}{\overline{\mathrm{AOD}}} \times \frac{\overline{\mathrm{AOD}}}{\overline{\mathrm{Bd}}} \times \overline{\mathrm{Bd}} = \mathrm{NRF} \times \mathrm{ext.coeff.} \times \overline{\mathrm{Bd}} \qquad (1)$$

Here AOD is the aerosol optical depth (dimensionless), Bd is the burden (g m^{-2}), ext.coeff. is the extinction coefficient (m^2 g^{-1}) and NRF is the forcing, normalized to unit AOD (W m^{-2}). The bars over variables indicate global, annual mean values.

Using values from M13 as inputs to equation (1), we performed a simple Monte Carlo-based analysis[16] to calculate the mean and spread in aerosol species and total DARF (Fig. 1). Assuming that the three parameters are independent, we collected a large number of combinations of NRF, ext.coeff. and Bd from the model sample, which was sufficient to construct probability density functions (PDF) for aerosol species DARF (Supplementary Information). Figure 1a illustrates the procedure for sulphate. The mean values from each PDF were taken as new estimates of DARF for each of the six aerosol species treated in M13: sulphate, primary black carbon and organic aerosols from fossil fuel and biofuel, nitrate, aerosols from biomass burning, and secondary organic aerosols. These estimates are consistent with the M13 multi-model means for each species, but have wider spreads (Fig. 1c). For each Monte Carlo pull, the component DARFs were also added, yielding a PDF for the total DARF. The mean was –0.35 W m^{-2}, again consistent with M13, but with a 5–95% uncertainty range of –1.06 to 0.18 W m^{-2}.

An even simpler approach calculates DARF as the product of the burden and the normalized forcing with respect to burden. This yielded a mean of –0.29 W m^{-2} and a smaller 5–95% uncertainty range of –0.74 to 0.22 W m^{-2} — mainly due to a reduction in the estimated range for sulphate — indicating that the AOD of this component has high model-diversity. This is expected, as sulphate AOD depends on hygroscopic growth, which in turn relies on modelled relative humidity.

Assuming total independence of the parameters in equation (1) is not likely to be correct. For example, a model with a high aerosol lifetime can be expected to give high burdens for all species and, due to broad dispersion, strong forcing efficiencies for all species. Supplementary Table 1 lists correlations between the parameters used above, taken from data in M13. The few correlations found to be significant at $p = 0.05$ are between parameters estimated from the same model results, for example, the mass extinction coefficient (AOD per burden) and the forcing per burden.

There is an interesting significant correlation between forcing per AOD for black carbon and organic aerosols. To test the sensitivity of our results to this and other possible correlations, we repeated the analysis with various correlations included (Supplementary Information). For example, assuming full correlation between black carbon and sulphate burdens in the second, simplified calculation preserves the mean and yields a smaller range from –0.72 to 0.18 W m^{-2}. This is still significantly wider than in M13, as is the case when using all correlations indicated in Supplementary Table 1.

We conclude that current purely model-based estimates of the uncertainty in DARF may be biased low. When allowing for the full diversity between modelled burdens, optical parameters and radiative sensitivity to aerosol optical depth, which come from a unified experiment reported in M13, an uncertainty range is found that is not only significantly wider, but similar to those reported in observationally based studies (Fig. 1c).

A number of factors may contribute to the increase in forcing range reported here. One concern is whether our conclusions also hold locally. We repeated the analysis for constrained geographical regions around Europe and North America, and again found that the Monte Carlo method yields increased uncertainty ranges while preserving the means (Supplementary Information). Another factor is whether local enhancements in one component of equation (1) may introduce spurious variability when combined with results from other models. Our usage of global mean values from M13 is partly a guard against this. Also, constraining the Monte Carlo method to yield only values of global mean AOD < 0.10 — taken as an approximate bound on anthropogenic AOD as indicated by remote sensing measurements[2,17] — does not significantly impact the ranges found in the present work. However, constraining to AOD < 0.05, as suggested by the models in M13, reduces the range to –0.62 to 0.15 W m^{-2}, which is a smaller elevation relative to M13. This indicates that better observational constraints on anthropogenic AOD, when implemented in models, could yield significant reductions in the modelled DARF range.

Our uncertainty estimate is high if major positive correlations exist among the parameters we assumed to be independent, and is low if the models fail to span the full range of parameter values. Assuming that component forcings are globally additive is a further approximation, and total aerosol forcing is likely to be less negative than the sum of individual forcings[18]. Furthermore, the role of uncertainty in emissions, the aerosol anthropogenic fraction and modelled vertical distributions are parameters that we are unable to investigate with the present method and available data[6].

The significant elevation of the DARF uncertainty range, even after excluding global correlations and testing on two different spatial scales, may indicate that the ensemble of opportunity used in AeroCom Phase II was too small. We suggest that global aerosol forcing should be further analysed using stochastic methods, perturbing critical parameters in multiple models in a systematic way, designed to explore the impact of the likely range of relevant parameters.

A statistical analysis allows efficient sampling of a wide range of physically possible values of the intermediate model parameters[19]. However, it also replaces physical process formulations with simple factorial assumptions, removing some physical understanding. Further work is needed to understand the difference between statistical emulation and process-based models, and also to constrain individual model processes and their combined simulation results, through global and regional, temporally resolved, aerosol and atmospheric observations.

Achieving a better understanding of both DARF and its spread has broad implications, for example, for the analysis of Coupled Model Intercomparison Project Phase 5 simulations where the direct aerosol effect can contribute more to diversity than previously thought[20], and for constraining climate sensitivity[21]. Climate sensitivity estimated from energy constraints is a sharply rising function of the total aerosol cooling over the industrial era[10,11]. An increase in the uncertainty on aerosol forcing therefore translates into a relatively larger increase in the uncertainty on climate sensitivity. ❐

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Additional information
Supplementary information is available in the online version of the paper.

Bjørn H. Samset[1*], Gunnar Myhre[1] and Michael Schulz[2]
[1]CICERO Center for International Climate and Environmental Research, PO Box. 1129 Blindern, N-0318 Oslo, Norway, [2]Norwegian Meteorological Institute, Postboks 43 Blindern, N-0313 Oslo, Norway.
*e-mail: b.h.samset@cicero.oslo.no

CORRESPONDENCE:

Climate adaptation in India

To the Editor — The United Nations Framework Convention on Climate Change (UNFCCC) has established the green climate fund, the adaptation fund and the fund for least developed countries (LDCs) to support developing countries and LDCs in their efforts to adapt to climate change. However, accessing these funds is challenging mainly because the interested countries have limited technical capacity to prepare effective proposals for fund applications. Further adaptation is not easily measurable, which makes it difficult to disburse the funds in a transparent, equitable and efficient manner. The 17th conference of the parties to the UNFCCC established the National Adaptation Plan (NAP) process as a way to facilitate effective adaptation planning in LDCs and developing countries. NAPs should reduce vulnerability to the impacts of climate change, by building adaptive capacity and resilience, and should facilitate the integration of climate change adaptation in the countries' plans for economic development.

At present, India is implementing the State Action Plan on Climate Change (SAPCC) — a set of strategies for adaptation and mitigation at the subnational and local level. In terms of adaptation, the SAPCC is like a NAP that operates at the local level. Many state governments have initiated the SAPCC, thanks to the technical and financial support from multilateral development agencies. The estimation of the costs of implementing the SAPCC is cumbersome. A study has observed that existing estimates of costs for both adaptation and mitigation, which are in the range of US$3–5 billion over a five-year period for states of similar size and climate change challenges, are inconsistent mainly because of variation in the methodologies adopted for vulnerability assessment, development of adaptation plans and mitigation targets[1]. As the UNFCCC has not standardized the procedure for vulnerability assessment, preparation of adaptation plans and estimation of adaptation costs, the difficulties with the SAPCC are likely to reverberate in the national action plans of many developing countries and LDCs.

The SAPCC operates locally and, with a typical bottom-up approach, helps to build resilience at the national level. Hence, it is fundamental for local communities to understand their vulnerabilities to climate change and get involved in the adaptation planning[2]. Lessons should be learned from existing schemes in India — such as the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) — that aim at decentralized governance and empowering local institutions and that have already generated success stories[3]. Like the MGNREGA scheme, the SAPCC could be taken a step further and involve local governing institutions in the preparation of the local adaptation plan, even on a microscale such as districts and blocks, with support from scientific communities, given the importance of including local knowledge in adaptation planning[4]. After translating the SAPCC into workable local adaptation programmes, two steps are required. One is capacity building of stakeholders, mainly members of local governing institutions and government officials. The other is addressing hard adaptation initiatives — those that, according to the World Bank, usually imply the use of specific technologies and actions involving capital goods (infrastructure) as opposed to soft adaptation that focuses on information, capacity building, policy and strategy development, and institutional arrangements.

Once local challenges are understood, the adaptation process needs to move towards measurement and planning. The key measures here are the vulnerability of the region and the capacity of stakeholders to efficiently implement the adaptation project[5]. In the case of soft adaptation, financial support will have to be used to train local government body representatives and line department officials. This training may comprise vulnerability assessment methodology, assessing adaptive capacity and exposure to good practices on adaptation. With this training, the stakeholders must be able to develop and implement an appropriate adaptation plan for the region.

Measuring adaptation is difficult, but as vulnerability is a function of adaptive capacity, it may be used as an indicator to measure success of adaptation. A number of publications and indicators on vulnerability assessment are now available[6]. However, fixing benchmarks for vulnerability assessment universally is difficult, owing to uncertainty in indicators[7]. This makes it difficult to standardize the disbursement of funds for hard adaptation, given varying vulnerability assessment techniques, as well as geographically and socio-economically varying adaptation needs and costs. Overall, the implementation of NAPs such as the SAPCC in India will succeed only if the local stakeholders are adequately trained and the preparation of adaptation plans is done in a participatory manner. The UNFCCC and other adaptation funding agencies must first set up funds for soft adaptation, such as capacity building of key stakeholders[8], then develop a standard procedure for baseline vulnerability assessment and estimation of adaptation costs across developing countries and LDCs, for equitable and efficient allocation of funds. Hopefully, the example of the SAPCC in India will help LDCs and developing countries in local adaptation planning and to access global funds, should the SAPCC succeed in obtaining them. ❐

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