Response to Referees for Westervelt et al. (2020):

Reviewer 1

This is a nice study. It's great to see some numbers on these effects, especially in the context of a multi-model study. This paper is clearly important, not only for its additions to the scientific literature, but also for policy at the intersection of climate and air quality, as well as for negotiations of allowable greenhouse gas emissions. The paper is also quite well written. I am recommending minor revisions.

We thank the reviewer for the nice comments and suggestions.

Comments: I really appreciate your careful attention to your statistical tests, particularly the number of degrees of freedom.

GISS ModelE has a configuration (TOMAS) that could allow you to prognostically simulate aerosol size distribution, like CESM1. It would be useful to say why you chose not to use that configuration.

TOMAS introduces an extra ~200 or so advected tracers for aerosol size, so running 200 to 400 year simulations with it is currently not computationally efficient. It is worth noting that the first author (Westervelt) is a TOMAS developer and did his PhD on TOMAS.

In your introduction, a reference to Murphy (2013) seems relevant: <u>https://www.nature.com/articles/ngeo1740</u>

Good point, added to manuscript. The following sentence has been edited to include radiatve forcing and a citation was added for Murphy (2013):

"Recently, additional studies have quantified mean surface temperature responses and radiative forcing to *regional* emissions changes of aerosol (Murphy, 2013)."

Section 2.3: It would be helpful to spell things out a little more when computing the ETCCDI metrics. For your baseline, did you use the entire 400-year control run? Did you throw out any of that period for spinup? For the perturbed case, did you throw out any of the 160 years or did you use the whole thing? (This sort of thing really matters for TX90p, but to some degree for the others as well.)

This is a good point. We remove about the first 200 years or so of the control runs and treat that as spin up. Then we also remove the 20 of the 160 years in the perturbation to allow for equilibration. The years are matched between the control and perturbation such that we difference the same year. We have added the following text:

"We discard the first 20 years of each perturbation simulation (as with the mean surface temperature analysis), and use the corresponding matching years in the control run when creating the differences."

Page 6, lines 24-25: In light of Malavelle et al. (2018)

(https://www.nature.com/articles/nature22974), it might be worth making a comment as to whether the cloud lifetime effect is actually something that should be included.

While the point about the uncertainty of the cloud lifetime effect and whether it should be included in models is well taken, the results of our paper are not authoritative on this subject, so any statement on the worthiness of inclusion of the cloud lifetime effect would be too speculative to be included in the paper.

Page 6, lines 24-29: Your results bear a striking similarity to those of Seneviratne et al. (2018): https://www.nature.com/articles/s41561-017-0057-5 Your choice, but could be worth a comment?

Yes, cited and added to the manuscript: "The response pattern is also similar to regional modifications of land surface albedo as reported in Seneviratne et al. (2018)."

Page 10, lines 1-3: Is there a statistical test you could use? Anything better than simply eyeballing the change?

In lieu of another statistical test on the dataset (we note that the t-test for significance has already been applied), we have changed the text to be more descriptive and precise regarding shape:

"For the spatial average over the eastern US, the shape of the distributions remains unimodal and not skewed in GISS-E2 and GFDL-CM3, except for CESM1 which is not skewed in the control simulation but skewed in the perturbation. Global mean temperature distributions are consistently bimodal in the control and perturbation and generally not skewed. Overall, distribution shapes are mostly consistent, indicating that a mean shift is the statistical mechanism behind the increased temperature extremes."

Figure 1: The results here say some interesting things about aerosol transport. In particular, the bottom row indicates that Wang et al. (2014)

(https://agupubs.onlinelibrary.wiley.com/doi/full/10.1002/2014JD022297) and subsequent related studies might be relevant. The point being, your discussion about common patterns of temperature change is good, but it's not necessarily the entire story.

Interesting point. We have added a citation to the Wang paper and the following sentence to the manuscript:

"The role of transport of BC from source regions remote to the Arctic may also be a contributor to the Arctic temperature response (Wang et al., 2014)"

Figure 2: I'd recommend getting rid of the red color and just leaving it white. It doesn't say much that two models agree on the sign but without statistical significance.

Done.

In Figure 4, CESM1 clearly has some different Southern Hemisphere behavior from the other two models (which doesn't show up in Figure 5, possibly due to cancellation). Any hypotheses as to what might be going on here?

There is indeed some different behavior, such as cooling over Australia, in CESM1 in the TXx response. The extreme temperature response is mostly not statistically significant in any simulation in CESM1 in the southern hemisphere, so this is most likely just internal variability.

Reviewer 2

Review of "Local and remote mean and extreme temperature response to regional aerosol emissions reductions" by Westervelt at al.

Summary

This paper quantifies the temperature response, including extremes, due to removal of aerosol emissions in six different geographical regions, with three different climate models. Such removal generally leads to warming, with the Arctic region particularly vulnerable. Similar changes occur in temperature extremes. The authors also update Regional Temperature Potentials, which are useful for estimating regional climate impacts due to regional aerosol changes in Integrated Assessment Models. Overall, the paper is well written and contains interesting and novel results. I recommend publication with minor revision.

We thank the reviewer for the useful review and comments.

Comments P2 L12. See also "Emerging Asian aerosol patterns" Nature Geosci. 12 (2019) by Samset et al.

Good point. Added and cited.

There are also several PDRMIP papers that are relevant to the discussion, that should probably be cited. For example, "Rapid Adjustments Cause Weak Surface Temperature Response to Increased Black Carbon Concentrations" by Stjern et al. JGR 2017.

Added and cited. Refer to the comment below which also references this paper.

Also, "Arctic Amplification Response to Individual Climate Drivers" by Stjern et al. JGR 2019. Looks like the Arctic Amplification paper is eventually mentioned on Page 6.

Yes, this is already cited and discussed.

P4 L33. Naik reference parentheses typo.

Fixed, thanks.

Model Description Section. Please include some brief information of each of these model's aerosol ERF (e.g., PD-PI). For example, in "A 21st century northward tropical precipitation shift

caused by future anthropogenic aerosol reductions" by Allen JGR 2015, CESM yields - 1.52; GFDL yields -1.60; and GISS yields -0.76 W/m². So GISS has a much smaller aerosol ERF. Based on this alone, I would expect any temperature response to similar aerosol perturbations to be weakest in GISS. You may also want to mention why this is. For example, GISS lacks aerosol-cloud second indirect effects (aerosol-cloud lifetime effect). Looks like this is eventually mentioned on Page 6. Might be beneficial to mention here as well. Although, it is interesting that GISS also has a smaller climate sensitivity to CO2, relative to GFDL and NCAR. This could also contribute to a weaker surface temperature response in GISS.

Good points. We have added the following text:

"For comparison, the present day minus pre-industrial aerosol ERF in CESM1, GFDL-CM3, and GISS-E2 is -1.52, 1.60, and 0.76 W m⁻², respectively (Allen et al., 2015). This version of the GISS-E2 model does not include the aerosol-cloud lifetime effect, resulting in a smaller ERF, as discussed below."

The sensitivity to regional aerosol reductions in GISS-E2 is about the same or larger than GFDL-CM3 and CESM1 (Figure 8), suggesting that the weaker CO2 climate sensitivity is not a major factor in the GISS-E2 weaker temperature response.

Methods Section. These simulations are designed for an instantaneous removal of aerosol emissions. Thus, there is no time evolution of the aerosol emission reductions, which would be more realistic. How does this impact the results? Maybe a few comments on this are necessary.

These are idealized simulations, meant to establish the maximum potential impact of phasing-out of aerosols on climate. The temperature response would be a bit weaker overall assuming a ~ 100 year drawdown of aerosols. If only the years after the time evolving anthropogenic aerosol emissions approached 0 (or close to it) were included in the hypothetical analysis, then I expect the results to be similar to what we are showing here. We have added a line clarifying this in the manuscript:

"Aerosol emissions removals are instantaneous and we do not consider the effect of a long timeevolving drawdown."

Methods Section. It is stated perturbation simulations are conducted for 160-200 years. What years are actually analyzed? I assume the first several decades (hopefully more) are not used, since the model is not yet in some sort of quasi-equilibrium?

We discard the first 20 years of the perturbation simulation. This has been added to the manuscript. Also for the 400 year control simulation, the first 200 years are discarded as spin up. There is a tradeoff between years analyzed and likelihood that the model is in equilibrium. In order to generate robust statistics, we need a long sample size, so this is part of the reason why we only discard the first 20 years.

Added to manuscript:

"The first 20 years of the perturbation simulations are discarded in the response calculation."

P6 L26. "Surface temperature response is strongest in the US SO2 and Europe SO2 simulations in all three models, with annual mean local and remote temperature increases of up to 1 K or higher." I assume this is related to the magnitude of the aerosol emission reduction. What if you normalize by this perturbation? I guess you eventually normalize by ERF, which would be similar.

Yes, we normalize by effective radiative forcing, which provides the same effect (with different units). In a forthcoming paper in preparation, we plan to present some results normalized by emissions, so we leave that analysis for later.

P7 L10. Regarding the weak and inconsistent BC temperature response. Again, this appears to be consistent with the Stjern PDRMIP paper above. Also, this may be related the resulting rapid adjustments. See, for example, Smith, C. J. et al. "Understanding rapid adjustments to diverse forcing agents". Geophys. Res. Lett. 45, 12023–12031 (2018). And in particular, the impact of the vertical profile of absorbing aerosol on the rapid adjustments. For example, Allen, R. J. et al. "Observationally constrained aerosol cloud semi-direct effects" npj Climate and Atmospheric Science (2019) showed very different surface temperature responses to absorbing aerosol dependent on the vertical absorbing aerosol profile. Models tend to have a vertically-uniform profile, and this leads to a negative adjustment, associated with high cloud reductions. However, a vertical profile that resembles CALIPSO observations (more absorption in the lower troposphere) yields low/mid-level cloud reductions, a positive adjustment, and surface warming. Looks as if this is eventually discussed near P11.

Yes, the Smith et al. (2018) paper is already cited and discussed on page 11. However, we have added another reference to it, as indicated below. We agree with the reviewer that rapid adjustments could explain some of the weaker responses for BC reductions. We have added the following to the text:

"The weak forcing in the black carbon simulations may reflect the role of rapid adjustments (Stjern et al., 2017; Smith et al., 2018), including the semi-direct effect of BC on clouds (Allen et al., 2019)."

Figure 2. Can the "Robustness %" be defined in the figure caption.

Yes, done. Added to caption:

"Robustness indicates percentage of the surface area that has all 3 models in sign agreement."

Near Page 8 L10. Can you explain why BC reductions lead to surface warming (despite having a positive RF) in nearly all cases?

This is likely a symptom of internal variability swamping the signal from BC reductions. For example, BC reductions in India yield very little statistical significance in temperature response.

How do tropical emission reductions drive Arctic warming? Is it due to direct transport of aerosol to the Arctic, or due to changes in atmospheric/oceanic circulation that then leads to

Arctic warming? Are these responses robust across the three models? Perhaps this is outside the scope of the current study.

We believe that the majority of the impact is due to atmospheric and ocean circulation that then causes Arctic warming. The first reviewer pointed out that transport of BC to the Arctic is possible even from the tropics, though Wang et al. (2014 suggests that tropical regions such as Southeast Asia seem to contribute less than 10% to the BC burden in the Arctic, so we do not expect this to be the dominant pathway for Arctic temperature changes. Figure 3b shows the Arctic temperature response, and for some of the tropical aerosol emissions pertubations (such as India SO2, Africa BB, etc), there is some minor degree of robustness. For example, for India SO2 and South America BB, all three models agree on sign.

Local and remote mean and extreme temperature response to regional aerosol emissions reductions

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Abstract. The climatic implications of regional aerosol and precursor emissions reductions implemented to protect human

- 15 health are poorly understood. We investigate the mean and extreme temperature response to regional changes in aerosol emissions using three coupled chemistry-climate models: NOAA GFDL-CM3, NCAR-CESM1, and NASA GISS-E2. Our approach contrasts a long present-day control simulation from each model (up to 400 years with perpetual year 2000 or 2005 emissions) with fourteen individual aerosol emissions perturbation simulations (160-240 years each). We perturb emissions of sulfur dioxide (SO₂) and/or carbonaceous aerosol within six world regions and assess the statistical significance of mean and
- 20 extreme temperature responses relative to internal variability determined by the control simulation and across the models. In all models, the global mean surface temperature response (perturbation minus control) to SO₂ and/or carbonaceous aerosol is mostly positive (warming), statistically significant, and ranges from +0.17 K (Europe SO₂) to -0.06 K (US BC). The warming response to SO₂ reductions is strongest in the US and Europe perturbation simulations, both globally and regionally, with Arctic warming up to 1 K due to a removal of European anthropogenic SO₂ emissions alone; however, even emissions from
- 25 regions remote to the Arctic, such as SO₂ from India, significantly warm the Arctic by up to 0.5 K. Arctic warming is the most robust response across each model and several aerosol emissions perturbations. The temperature response in the northern hemisphere mid-latitudes is most sensitive to emissions perturbations within that region. In the tropics, however, the temperature response to emissions perturbations is roughly the same in magnitude from emissions perturbations either within or outside of the tropics. We find that climate sensitivity to regional aerosol perturbations ranges from 0.5 to 1.0 K per W m⁻²
- 30 depending on the region and aerosol composition, and is larger than the climate sensitivity to a doubling of CO₂ in two of three models. We update previous estimates of Regional Temperature Potential (RTP), a metric for estimating the regional temperature responses to a regional emissions perturbation that can facilitate assessment of climate impacts with integrated assessment models without requiring computationally demanding coupled climate model simulations. These calculations indicate a robust regional response to aerosol forcing within the northern hemisphere mid-latitudes, regardless of where the
- 35 aerosol forcing is located longitudinally. We show that regional aerosol perturbations can significantly increase extreme

temperatures on the regional scale. Except in the Arctic in the summer, extreme temperature responses largely mirror mean temperature responses to regional aerosol perturbations through a shift of the temperature distributions and are mostly dominated by local rather than remote aerosol forcing.

1 Introduction

- 5 Understanding regional climate responses to present and future anthropogenic forcing agents remains a key challenge of direct relevance to human and natural systems. Emissions of aerosols and their precursors are spatially heterogeneous and short-lived, and thereby expected to exert complex responses as emissions of air pollutants are reduced through policies enacted to protect human health. Emissions of sulfur dioxide (SO₂), black carbon (BC), and organic carbon aerosol (OA) have decreased throughout the United States and Europe for several decades (Leibensperger et al., 2012; Tørseth et al., 2012). On
- 10 the other hand, emissions have largely increased in recent decades in countries such as China, India, and others in the Global South; however, since 2013, emissions of SO₂ are beginning to decline at least in China, while emissions in India continue to increase (Fontes et al., 2017; Li et al., 2017; Lu et al., 2011; <u>Samset et al. 2019</u>). As emissions of anthropogenic aerosols and their precursors are reduced in high-emitting regions such as China, their reduction is expected to perturb regional and global temperatures (Kasoar et al., 2016). To improve future climate projections, a deep understanding of the magnitude, spatial
- 15 pattern, statistical significance, and physical mechanisms of the temperature response to a phasing out of both scattering and absorbing anthropogenic aerosols is needed. Here we address this need by simulating the local and remote mean and extreme surface temperature responses to removal of different components of anthropogenic aerosols from six world regions in three distinct earth system models.
- The net effect of removal of global emissions of all anthropogenic aerosols is a surface warming, as decreases in aerosol scattering result in additional solar energy reaching the surface of the Earth (Myhre et al., 2013). Removal or reduction of scattering aerosols on the regional scale will also result in surface warming on average. However, removal of global and regional emissions of black carbon or other absorbing aerosol is generally expected to induce a cooling at the surface, due to a net reduction in the absorption of incoming solar radiation (Bond et al., 2013; Ramanathan and Carmichael, 2008; Samset et al., 2018). In addition to influencing surface temperature directly by scattering or absorbing incoming solar radiation (aerosol
- 25 direct effect), aerosols also indirectly influence surface temperature by modulating cloud properties such as brightness and lifetime (aerosol indirect effects) (Albrecht, 1989; Twomey, 1977). Regional emissions perturbations of both scattering and absorbing aerosols also exert significant local and remote precipitation responses (Westervelt et al., 2017, 2018), though here we focus primarily on mean and extreme surface temperature responses.

Several previous studies have considered the global and regional climate response to *global* reductions in aerosol and precursor emissions using transient future simulations (e.g. Gillett and Von Salzen, 2013; Levy et al., 2013; Samset et al., 2018; Westervelt et al., 2015), finding a robust increase of up to about 1 K of surface warming by 2100 in response to decreasing aerosol burden. Recently, additional studies have quantified mean surface temperature responses and radiative

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forcing to regional emissions changes of aerosol (Murphy, 2013). Kasoar et al. (2016) used three global climate models to estimate the global and regional surface temperature impacts from the removal of Chinese anthropogenic SO₂ emissions, finding hemispheric warming in two of the three models. Conley et al. (2018) also used three climate models to estimate the mean surface temperature response to a removal of SO₂ emissions from the United States alone, with warming over the United

- 5 States and in the Arctic found to be as high as 0.5 K. Persad and Caldeira (2018) used the NCAR CAM5 (Community Atmosphere Model 5) to show that climate responses to identical aerosol emissions changes are significantly different depending on the region where emissions are perturbed. Using a different model and a different emissions perturbation format, Kasoar et al. (2018) find similar patterns of mean surface temperature response to aerosols from different regions. Both Kasoar et al. (2018) and Persad and Caldeira (2018) used a single model to estimate the temperature responses to regional
- 10 anthropogenic aerosol emissions.

Reductions in regional aerosol emissions may also influence temperature extremes; however, the magnitude, statistical significance, and physical mechanisms of the greenhouse gas and aerosol impact on extreme events is also poorly understood (Horton et al., 2016). The Intergovernmental Panel on Climate Change Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (IPCC SREX; (IPCC, 2012)) identified forcing factors

- 15 that are important on regional scales (such as aerosols) as a key challenge to further understanding of the anthropogenic causes of extreme temperature change. Recent studies have found a role for global aerosol reductions in heat waves (Zhao et al., 2019) and also in temperature extreme indices (Mascioli et al., 2016; Samset et al., 2018) as defined by Expert Team of Climate Change Detection and Indices (ETCCDI) (Sillmann et al., 2013). To our knowledge, the extreme temperature response to regional aerosol emissions reductions has not been previously studied.
- 20 In addition to understanding the changes in mean and extreme surface temperature response to aerosol reductions, it is vitally important to understand the effective radiative forcing (ERF) induced by aerosols, and how ERF relates to temperature response. ERF includes the instantaneous top of atmosphere radiative forcing plus rapid adjustments, i.e. the radiative impacts to the top of atmosphere energy budget which are not related to surface temperature. Radiative forcing exerted by anthropogenic aerosols is far more spatially inhomogeneous than that from well-mixed greenhouse gases, making
- 25 generalization of the climate responses to anthropogenic aerosol emissions changes a more difficult task (Shindell, 2014). Additionally, radiative forcing in one region may result in different temperature response in local regions compared with remote regions. Shindell and Faluvegi (2009) began to address this by using an early version of the Goddard Institute for Space Studies ModelE chemistry-climate model to estimate temperature responses per unit radiative forcing for forcing perturbations in several wide latitude bands. Shindell (2012) also used these latitude bands to further develop the Regional Temperature
- 30 Potential (RTP), a temperature response metric normalized by aerosol ERF to provide estimates regional temperature change. More recently, Lewinschal et al. (2019) used NorESM (Norwegian Earth System Model) to calculate similar metrics based on emissions. Simple climate metrics such as RTP coefficients can be used in the Integrated Assessment Modelling (IAM) and climate impacts community to rapidly and easily calculate the climate impact of different energy or climate mitigation policies without requiring computationally expensive coupled climate model simulations. Thus far, metrics such as RTP incorporated



into IAMs have been based on simulations with a single climate model. Future climate projections can benefit and improve from a multi-model approach that enables more robust estimates of mean and extreme regional surface temperature responses per unit radiative forcing from a given region.

The relationship between surface temperature response and associated ERF is not well understood for individual 5 short-lived forcing agents such as regional aerosols. The climate sensitivity parameter, or the ratio between the temperature response to an external forcing and the forcing itself (K per W m⁻²), is a widely used metric essential for projecting future climate change (Myhre et al., 2013; Marvel et al., 2016; Previdi et al., 2013). Estimation of equilibrium climate sensitivity (ECS) using coupled models has mostly occurred in the context of a doubling (or quadrupling) of CO₂ concentrations (2xCO₂) (Arrhenius, 1896; Callendar, 1938; Cox et al., 2018; Huber et al., 2014; Knutti et al., 2017; Knutti and Hegerl, 2008; Knutti

- 10 and Rugenstein, 2015; Otto et al., 2013). A few studies estimating the ability of single forcing agents to change surface temperature (sometimes called "forcing efficacy") have found that anthropogenic aerosols have a greater forcing efficacy than CO₂ (Hansen, 2005; Marvel et al., 2016; Shindell, 2014). These findings, however, have come from single models using global reductions in aerosol and precursor emissions, despite substantial regional dependence and heterogeneity of aerosol forcing. Estimates of ECS based on modelling and modern and paleoclimatic observations should take into account the forcing efficacy
- 15 of regional aerosol perturbations, which our approach can help inform.

We improve on past work by conducting an extensive set of computationally demanding simulations in three (instead of one) Coupled Model Intercomparison Project Phase 5 (CMIP5) era chemistry-climate models in which emissions of SO₂, BC, OA, and a combination of all three are set to zero or significantly reduced in one of six world regions (instead of latitude bands). Using these simulations, we estimate the local and remote regional surface temperature responses to reduced or

20 removed aerosol and precursor emissions. We aggregate our results in each model to provide an estimate of robustness of the regional surface temperature response. In order to compare the surface temperature responses across models, regions, and forcing agents (including aerosols but also carbon dioxide), and to provide updated estimates of regional temperature response metrics as done in Shindell (2012), we estimate the climate sensitivity for a given region and forcing agent in each of our models, on a global and regional basis. We also report for the first time the extreme surface temperature response to regionally specific emissions reductions of aerosols and their precursors in three climate models.

2 Methods

2.1 Models and simulations

Our modeling framework has been previously described by Westervelt et al. (2018), Westervelt et al. (2017), and Conley et al. (2018). Briefly, we employ three coupled atmosphere-ocean-land-sea-ice climate models with fully interactive chemistry of aerosols and trace gases: 1) Geophysical Fluid Dynamics Laboratory Coupled Climate Model version 3 (GFDL-CM3) (Donner et al., 2011), 2) Goddard Institute for Space Studies ModelE2 (GISS-E2-R) (Schmidt et al., 2014), and 3) Community Earth System Model version 1 (CESM1) (Neale et al., 2012). The model configuration for each is very similar to that used for CMIP5. For further model description and model evaluation, we refer readers to Westervelt et al. (2017) and Naik

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- et al., (2013). Only CESM1 includes prognostic simulation of aerosol size distribution (Conley et al., 2018 and references therein). Of particular relevance for our results is the model treatment of black carbon. In GFDL-CM3, black carbon is internally mixed with only sulfate in the radiation code, whereas in CESM1, black carbon is internally mixed with all aerosol constituents within a given aerosol mode. In GISS-E2, black carbon is externally mixed with other aerosol species (Schmidt et al., 2014).
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We conduct for each model a long "present-day" control simulation of up to 400 years in length, forced by perpetual year 2000 (2005 for NCAR-CESM1) conditions, including all emissions of aerosols and their precursors and greenhouse gas concentrations. We also conduct individual regional aerosol perturbation simulations of at least 160 years and as long as 240 years in each model, in which the anthropogenic aerosol or aerosol precursor emissions for a certain region are completely 10 removed (100%) or reduced by the amount shown in Table 1. Aerosol emissions removals are instantaneous and we do not

- consider the effect of a long time-evolving drawdown. The first 20 years of the perturbation simulations are discarded in the response calculation. We choose the magnitude of relative emissions reductions in order to have roughly equivalent emissions decreases for a particular species across regions and models. As an example, "ISO2" refers to a simulation with perpetual year 2000 conditions (2005 for NCAR-CESM1), perturbed by setting all anthropogenic SO2 emissions over India to zero. Other
- 15 than the regional aerosol emissions perturbation, all other model settings remain identical to the control. Long control and perturbation simulations allow us to establish statistical significance and separate forced responses from internal climate variability.

We also conduct a set of simulations for each perturbation and control in each model using modeled climatological fixed sea surface temperatures (SST) and sea ice cover (SIC) in order to calculate ERF. These simulations only use the

atmosphere and land components of the climate models and are not coupled to the ocean and sea ice models but are otherwise 20 identical to our longer coupled model integrations. ERF is determined by differencing the perturbation simulation minus the control simulation. Estimates of ERF done in this manner include the instantaneous radiative forcing plus the rapid adjustments from the atmosphere and the land. For the aerosol perturbation simulations, the ERF is calculated based on 50 years of simulation data for CESM1, 80 years for GFDL-CM3, and 160 years for GISS-E2 (to allow detection of a smaller forcing 25 observed in that model). The ERF associated with a doubling of CO₂ (2xCO₂) is also calculated using the fixed-SST method

from simulations similar to 4xCO2 fixed-SST simulations conducted for the CMIP5 experiments. For comparison, the present day minus pre-industrial aerosol ERF in CESM1, GFDL-CM3, and GISS-E2 is -1.52, -1.60, and -0.76 W m², respectively (Allen et al., 2015). This version of the GISS-E2 model does not include the aerosol-cloud lifetime effect, resulting in a smaller ERF, as discussed below.

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2.2 Statistical methods

We estimate the change in surface temperature between the control and perturbation simulations as the cotemporal annual mean differences (perturbation minus control), and perform a paired sample modified Student t-test where the pairs are cotemporal samples of the perturbation and the control. The modified t-test accounts for autocorrelation in the model surface

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temperature time series by calculating an effective standard error, which utilizes an effective sample size based on the lag-1 autocorrrelation. A time series showing autocorrelation overestimates the number of independent samples when calculating statistical significance, but our approach, based on Conley et al. (2018) and Zwiers et al. (1995), corrects against this overestimation. We also use the False Discovery Rate procedure of Wilks (2016) on our t-tests over our gridded atmospheric data, which limits the fraction of erroneously rejected null hypotheses in a field of mutually correlated t-tests (at each grid

2.3 Extreme indices

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point).

To estimate extreme temperature responses to aerosol perturbations, we use the "FClimDex" Fortran package (http://etccdi.pacificclimate.org/software.shtml) developed by the Expert Team of Climate Change Detection and Indices (ETCCDI) to estimate 27 climate extreme indices. Daily minimum, maximum, and mean surface air temperature is input to the extremes package for each of our simulations for which daily data was available, including the control simulation. Cotemporal differences were then taken as for mean temperature, and we performed modified paired t-tests (perturbation and control) to assess significance. Extreme temperature analysis was not performed on all of our simulations, but rather a subset

- 15 of simulations that demonstrated the highest mean temperature response. Further, we only perform extreme analysis on simulations <u>conducted for at least</u> 160 years of daily data, as shorter time periods are not sufficient to build up robust statistics. We discard the first 20 years of each perturbation simulation (as with the mean surface temperature analysis), and use the corresponding matching years in the control run when creating the differences. We focus our analysis on the TXx index, one of the most commonly analyzed extreme index in the existing literature. TXx is defined as the maximum of the maximum
- 20 daily temperature in a given time period (e.g., over a model simulated year) (Sillmann et al., 2013). We explored results using other temperature indices and found the results to be qualitatively similar to the results for TXx, and thus do not include these additional indices in the main text (see Supplementary Information).

3 Global and regional mean surface temperature responses to regional aerosol emissions

25 3.1 Comparison across models

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Figure 1 shows the ~160-240 year annual mean surface temperature response in each of the three models for 6 regional aerosol perturbations. An analogous figure for all of the remaining simulations can be found in the Supplementary Fig. S1. The change in temperature in Fig. 1 and all following figures is the "perturbation minus control", representing the temperature response to a removal or reduction of emissions of anthropogenic aerosols and their precursors. Generally, the response is overwhelmingly positive (warming) with large regions of statistical significance in each of the three models for most simulations. We find a larger temperature response in GFDL-CM3 and CESM1 (first and second columns of Fig. 1) compared

lifetime effect in that model (Westervelt et al., 2017, 2018). In all three models, the largest remote temperature responses are 6

to GISS-E2, consistent with to the smaller magnitude of aerosol ERF in GISS-E2 (see Sect. 5) resulting from a lack of a cloud

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over the Arctic, owing to the well-established polar amplification phenomenon (Smith et al., 2019; Stjern et al., 2019). Surface temperature response is strongest in the US SO₂ and Europe SO₂ simulations in all three models, with annual mean local and remote temperature increases of up to 1 K or higher. Despite different regions of emissions perturbations, the salient features of the spatial distribution of surface temperature response are similar between the US SO₂, China SO₂, US ALL (SO₂, BC, and

- 5 OC combined), Europe SO₂, and EU ALL (Fig. S1) perturbations in all models, suggesting that aerosol forcing in northern hemisphere mid latitudes (NHML) induces a qualitatively consistent spatial response pattern. This pattern features strong Arctic warming, differential heating of the Northern Hemisphere compared to the Southern Hemisphere, strong local responses, and far-reaching remote responses across continents (e.g., European warming in response to US SO₂ emissions reductions). The response pattern is also similar to regional modifications of land surface albedo as reported in Seneviratne et
- 10 al. (2018). Climate responses to aerosol perturbations also can project onto known modes of climate variability, such as El Niño-Southern Oscillation (ENSO), as described in Westervelt et al. (2018). The temperature response to US SO₂ emissions removal in CESM1 (Fig. 1b) resembles an El Niño-like response, with cooling in the western tropical Pacific Ocean coupled with warming in the eastern tropical Pacific Ocean. In GFDL-CM3, most simulations regardless of region or aerosol species result in cooling (sometimes statistically significant) south of 60°S along the Antarctic coast starting roughly at the 180°
- 15 meridian coupled with surrounding statistically significant warming (e.g. EU SO₂, Fig 1d), suggesting interaction with the Amundsen Sea Low (ASL), which exerts significant influence on Antarctic climate (Raphael et al., 2016). However, this is also a region of strong climate variability in GFDL-CM3.

Although the surface temperature response to Indian SO₂ and BC emissions reductions is small in all models, despite the tropical location of the emissions perturbation, changes in temperature still occur at both poles in all models, with some statistical significance. Removal of black carbon emissions (Fig. 1p, q, and r) elicits a very different temperature response in each of the three models in spatial distribution, sign, and magnitude, indicating a strong dependence of the surface temperature response to different model assumptions for black carbon, including different mixing state assumptions. Additionally, as

reported in Westervelt et al. (2018), aerosol ERF from India BC perturbations is small (ranging from -0.04 to 0.06 W m⁻²

across the three models) and statistically insignificant, resulting in climate responses that may be influenced by internal variability. The weak forcing in the black carbon simulations may also reflect the role of rapid adjustments (Stjern et al., 2017; Smith et al., 2018), including the semi-direct effect of BC on clouds (Allen et al., 2019). The climate response to BC perturbations in other regions, such as US BC (Fig S1 panel g and h), also is marked by disparate temperature responses, further highlighting the sensitivity of climate response to model physics, and in some cases representing noise when forcing signals are small. The role of transport of BC from source regions remote to the Arctic may also be a contributor to the Arctic 2016 temperature response (Wang et al., 2014).

3.2 Robustness across models

To estimate robustness of the surface temperature responses to regional aerosol perturbations, we use the sign (warming or cooling) and the statistical significance as a point of comparison between the three models. Figure 2 shows the

agreement between models in sign and statistical significance in each of the aerosol perturbations simulations that were conducted by all three models. We find widespread agreement in sign and significance in the US SO₂ (Fig. 2a), Europe SO₂ (Fig. 2b), China SO₂ (Fig. 2c), and US All (SO₂, BC, and OA combined, Fig. 2d) simulations. Using sign agreement in three models as a minimum for a qualification of robustness (light blue color), the most robust responses are to Europe SO₂ removal,

- 5 where 81 % of the Earth's surface qualifies as robust (values in the upper right of Fig. 2 panels). On the other hand, the response to India BC is robust across only 39 % of the Earth's surface. We conclude that climate responses to black carbon over India exhibit large variability between models compared to climate responses from source regions such as the US and Europe, likely due to the small forcing exerted by the BC perturbation simulations.
- The three models frequently agree in the sign and significance of Arctic warming, indicating that the Arctic surface temperature response is one of the most robust features of climate response to regional aerosol perturbations. Local responses are also robust, in particular the US SO₂ and US All perturbations show high levels of robustness (green and dark blue colors in Fig. 2a and 2d) over North America. The models agree in sign and significance in the remote Arctic temperature response even in the case of India BC and African biomass burning emissions perturbation, suggesting that the Arctic warming response is somewhat independent of emissions region or aerosol composition. Overall, all three models agree on sign and at least two
- 15 report statistical significance over 32 % of the Earth's surface (66 % when not including significance) in response to removal of US SO₂ emissions.

3.3 Local and remote responses by region

In Fig. 3, we present the global and regional mean surface temperature response to 14 different emissions perturbations in each of the three models. The emissions reductions forcing these temperature changes are roughly the same across models within a given perturbation scenario (Table 1). The global mean surface temperature response (Fig. 3a) indicates warming in 33 of the 34 simulations (US BC in GFDL-CM3 being the only example of global cooling) and is significant at the 95% confidence level in 30 of the 34 perturbation simulations. The Europe and US emissions perturbations (e.g., ESO2, EALL, USO2, etc.) cause the largest global mean temperature increases across all regions and aerosol compositions, resulting in a global mean warming of about 0.15 K. The SO₂ perturbations tend to result in greater warming than OA or BC (which can also result in global cooling). CESM1 and GFDL-CM3 tend to warm more than GISS-E2, although not for all simulations.

We break down the regional climate response into latitude bands, following the approach used by Shindell and Faluvegi (2009), by regionally averaging the temperature responses from 60 to 90°N (Arctic, Fig. 3b), 30 to 60°N (Northern Hemisphere Mid Latitudes, NHML, Fig. 3c), 30°S to 30°N (tropics, Fig. 3d), and 30 °S to 90°S (Southern Hemisphere, Fig. 3c). Surface temperature increases approach 1 K regionally averaged over the Arctic (60 to 90°N) in CESM1 and GFDL-CM3,

30 with GISS-E2 simulating smaller but still often statistically significant warming responses. The Arctic responds most strongly to European aerosol perturbations (e.g. ESO2, EALL), perhaps owing to the greater proximity of the European continent to the Arctic region. However, even remote regional aerosol perturbations, such as India SO₂ (ISO2), or South American biomass burning (SABB) lead to Arctic warming in all of the models (Fig. 2), with some statistical significance. NHML temperature

changes (Fig. 3c) are mostly dominated by these local perturbations. On the other hand, the temperature response to the emissions perturbations local to the tropics (red labels in Fig. 3d) are roughly the same in magnitude and significance as the response to some of the "remote" perturbations. Emissions perturbations local to the tropics exert a larger temperature response in the Arctic than they do either locally or in the closer NHML region. In the Southern Hemisphere (Fig. 3e), we find consistent, statistically significant warming in CESM1, but less warming in GFDL-CM3 and GISS-E2, owing to the localized Antarctic

5 statistically significant warming in CESM1, but less warming in GFDL-CM3 and GISS-E2, owing to the localized cooling in the case of GFDL-CM3. Overall, responses in the Southern Hemisphere are less statistically significant.

4. Extreme surface temperature responses to regional aerosol emissions

The response of temperature extremes (TXx, annual maximum of maximum daily temperature) averaged over the entire 160-240 simulation years is shown in Fig. 4 for each simulation in each model for which daily data were available. In addition to the TXx extreme index, we have also analyzed a series of other indices, however the results are qualitatively similar so we only present TXx here (see Supplementary Information for additional indices). In general, we find increases in extreme temperature nearly everywhere both locally and remotely in most simulations, with a few exceptions such as the BC aerosol perturbations. Increases in extreme temperature are as large as 1 K especially near the source region of the particular perturbation simulation. Remote increases in extreme temperature are observed for several perturbations, for example

- 15 European SO₂ in NCAR-CESM1 and GFDL-CM3. Statistical significance is less abundant in GISS-E2, though we find increases of similar magnitude in GISS-E2 and the other two models. Over land, extreme temperature (TXx) can be equally or more sensitive to regional aerosol forcing than mean temperature, which can be seen by comparing temperature changes in Fig. 1 and Fig. 4. For example, TXx response to US SO₂ is mostly similar in magnitude or slightly larger than mean temperature over the eastern US in all three models. In contrast, mean temperature changes are strong (up to 1 K) over the Arctic, whereas
- 20 extreme temperature changes (TXx) are much smaller (< 0.3 K) and statistically insignificant. This is likely caused by the seasonality of Arctic amplification, which is a robust response to external forcing in every season except summer. TXx values mostly reflect summer temperature changes, when the maximum temperature throughout the year is likely to occur in the northern hemisphere. We confirm this by showing extreme temperature response for the winter months December, Janaury, and February (DJF, Fig. S2), in which Arctic extreme temperature responses are larger and consistent with mean temperature</p>
- 25 responses. We conclude that the remote response relationship between mean and extreme temperatures is therefore strongly seasonally dependent.

Figure 5 shows the global (panel a) and latitude band averaged (panels b through e) extreme surface temperature response in each of the model simulations, analogous to Fig. 3 for mean surface temperatures. Another extreme temperature metric TX90p, or the percentage of days when the daily maximum temperature is greater than the 90th percentile, is shown in

30 Fig. S3 but is qualitatively similar to Figure 5. Global mean extreme surface temperature response is largest in GFDL-CM3 and CESM1 and in the Europe SO₂ (ESO2) and US SO₂ (USO2) simulations, in which the TXx response can approach about 0.2 K. Global mean TXx is only statistically significant for the ESO2 in GFDL-CM3 and CESM1, USO2 for CESM1, and ISO2 for GFDL-CM3. Changes in the extreme temperatures over the Arctic (Fig. 5b) are close to zero and statistically

insignificant, in contrast to Arctic mean temperature, which was heavily affected by many of the remote aerosol perturbations, though this is primarily caused by the seasonal dependence of Arctic amplification, as described above. TXx responses in the NHML (Fig. 5c) are dominated by local aerosol perturbations, reaching statistically significant increases of up to 0.4 K, while remote perturbations have no statistical significance. In the tropics and the Southern Hemisphere (Figs. 5d and 5e), there is almost no significant response in TXx to any aerosol perturbation. We conclude that although extreme temperature can be

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increased by remote aerosol perturbations in a few cases, in general the local forcing is a much greater control on extreme temperature, and remote responses are not nearly as large or significant for TXx compared to mean surface temperatures.

Figure 6 shows the eastern US and global mean surface temperature probability density function for each model for control and USO2. Each probability density function has been normalized such that the area under the curve is equal to unity.

- 10 The bars represent the actual probability density for each temperature value, whereas the dashed curve is a fitted Gaussian kernel density estimation of the probably density. In each model both globally and regionally, there is a clear shift in the mean of the distribution, resulting in additional occurrence of temperature extremes. Each mean shift is also statistically significant at the 95% confidence level, except for the eastern US regional temperature distributions in GISS-E2. For the spatial average over the eastern US, the shape of the distributions gemains unimodal and not skewed in GISS-E2 and GFDL-CM3, except for
- 15 CESM1 which is not skewed in the control simulation but skewed in the perturbation. Global mean temperature distributions are consistently bimodal in the control and perturbation and generally not skewed. Overall, distribution shapes are mostly consistent, indicating that a mean shift is the statistical mechanism behind the increased temperature extremes.

5. Effective radiative forcing and climate sensitivity

5.1 Effective radiative forcing and surface temperature response

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We use ~80 year fixed-SST and SIC atmosphere-only simulations in each of the three models to diagnose ERF due to each aerosol emissions perturbation. The global mean ERF from the 34 simulations ranges from about -0.1 to 0.3 W m², though all but 6 simulations (several of the BC emissions perturbations) have ERF greater than zero. In Fig. 7, we plot global mean surface temperature response from the ~200 year coupled model simulations against global mean ERF for every perturbation simulation. We find a strong positive correlation among all models (r = 0.64 for CESM1, r = 0.79 for GFDL-

25 CM3, and r = 0.76 for GISS-E2), consistent with previous studies (Liu et al., 2018; Marvel et al., 2016). There is substantial overlap and a similar slope for all three models (~0.4 K per W m⁻²), indicating that, on a global mean basis, the models are each similarly sensitive to regional aerosol forcing. We further analyze the climate sensitivity to aerosol forcing in the following section.

30 5.2 Global climate sensitivity to regional aerosol perturbations and global CO2 doubling

For a selection of simulations in which the aerosol ERF was statistically significant, we calculate in Fig. 8 the climate sensitivity parameter (K per W m⁻²) to the regional aerosol perturbations as the quotient between the equilibrium global surface temperature response from the coupled model simulations and global ERF using the fixed-SST approach, similar to the

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equilibrium climate sensitivity (ECS) approach used for CO₂. We also present the equilibrium climate sensitivity to a doubling of CO₂ ($2xCO_2$) in each of the three models using the same fixed-SST methodology for comparison to the aerosol climate sensitivity. We find that the climate sensitivity parameter for aerosol perturbations varies by model and by forcing, but mostly ranges from about 0.5 to 1.0 K per W m² in each of the three models, which is comparable to the values for CO₂ sensitivity of

- 5 approximately 1.0 K per W m⁻² in GFDL-CM3 and CESM1, and 0.5 K per W m⁻² in GISS-E2. Surface temperature appears to be most sensitive to European SO₂ emissions in GFDL-CM3, US SO₂ emissions in CESM1, and US ALL (SO₂, BC, and OA combined) emissions in GISS-E2. The 2xCO₂ climate sensitivity and the aerosol climate sensitivity for the European SO₂, European ALL, and US SO₂ are approximately equivalent at about 1.0 K per W m⁻² for GFDL-CM3 and CESM1. The aerosol climate sensitivity is also in good agreement (overlapping error bars in Fig. 8) for the US SO₂ emissions perturbation between
- 10 the three models. However, the aerosol climate sensitivity is often substantially greater than 2xCO₂ climate sensitivity in GISS-E2, consistent with results from Marvel et al. (2016), discussed further below. Differences between aerosol climate sensitivity and 2xCO₂ climate sensitivity can be explained by the differences in both the temperature response and the associated ERF for each perturbation. In particular, ERF may be quite different between heterogeneous, relatively smaller in magnitude forcing agents such as regional aerosols compared to more globally homogeneous, large forcing agents such as CO₂. Using 11 models
- 15 including GISS-E2, Smith et al. (2018) found that rapid adjustments reduce the ERF for BC aerosol, but increase the ERF for CO₂ forcing, consistent with the hypothesis that differences in ERF can explain differences in the temperature sensitivities shown in Fig. 8.

Previous work by Marvel et al. (2016) and Hansen et al. (2005) using only the GISS-E2 climate model found that the forcing efficacy of global aerosol reductions is greater than that of CO₂. We extend this finding for GISS-E2 to regional aerosol
emissions reductions, as the climate sensitivity parameter in all but one of our regional aerosol perturbation simulations in GISS-E2 is larger than the 2xCO₂ perturbation. In contrast, the aerosol climate sensitivity parameter in both GFDL-CM3 and CESM1 is smaller or about equal to that of 2xCO₂. We can conclude at minimum that aerosol forcing efficacy is model dependent, especially for regional aerosol perturbations, and this further highlights the importance of using multiple models to estimate or constrain estimates of ECS that includes forcing from a diverse set of agents. The CMIP6 experiments may be
used to shed further light on the relative efficacy of aerosol and greenhouse gas forcing, though not from regional perturbations.

5.3 Regional Temperature Potential

In addition to the global temperature response and global ERF, we also estimate the regional temperature sensitivities. We use the approach of Shindell (2012), which introduced Regional Temperature Potential (RTP) coefficients. These coefficients account for the spatial heterogeneity of aerosol forcing and temperature response and can be derived for any pair of response regions and forcing regions. Following the methods of Shindell (2012) and Lewinschal et al. (2019), we calculate, within each latitude band, the temperature response to regional aerosol perturbations as a function of the latitude band averaged ERF containing each aerosol perturbation region. We then normalize this quantity by the global mean equilibrium temperature

response to global mean forcing, resulting in a dimensionless coefficient giving the equilibrium temperature response in latitude band *x* to forcing in region *y*. The response latitude band *x* can be any of the bands defined in Fig. 2, whereas forcing regions *y* are the latitude bands containing each of our 14 regional aerosol perturbation locations, either 30-60°N (NHML) or 30° S- 30° N (tropics). As defined in Shindell (2012), RTP for a given pair of regions is:

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$$RTP = \frac{\frac{dT_x}{dF_y}}{\int \frac{dT_{global}}{dF_{global}}}$$

(Equation 1)

where dT is change in temperature and dF is change in ERF. Because of the normalization by global mean temperature and global mean ERF, the RTP coefficients are unitless.

RTP coefficients in each latitude band for a given aerosol perturbation region are reported in Table 2 for GFDL-CM3, Table 3 for GISS-E2, and Table 4 for CESM1. We present only RTP values for which the corresponding ERF and temperature response were statistically significant or for which data was available. The India, South America, and Africa entries in Tables 2-4 are based on a forcing average from the tropics since that region contains almost all of the statistically significant signal. All other values are based on NHML latitude band forcing average. Higher values of RTP indicate higher sensitivity of the particular response region to the aerosol forcing regions. RTP values from individual models provide a range of possible estimates. Figure 9 shows the multi-model mean RTP coefficients for a selection of regional aerosol perturbation simulations,

- 15 along with a mean of the NHML and tropics perturbations grouped together ("NHML tot.", "tropics tot."). Figure 9 indicates that the response to NHML forcing is consistent in all response regions regardless of where the aerosol forcing is longitudinally located within the NHML, as indicated by the similar RTP magnitudes in the first 4 clusters of bars (CSO2, ESO2, USO2, and UALL). Consistent with our earlier findings in Fig. 2, the Arctic always emerges as the most sensitive region to nonlocal aerosol forcing. After the Arctic, regional sensitivities are greatest for NHML, tropics, and Southern Hemisphere (SH) for
- 20 perturbations in the NHML (e.g. CSO2, ESO2, USO2, UALL). For tropical perturbations such as ISO2, SABB and AFBB, either the SH or the tropics are most sensitive, after the Arctic. Across each of the aerosol perturbations, the RTP coefficients are similar in magnitude when grouped by similar latitudinal forcing locations.

Our findings are similar to Shindell (2012), but we find a higher sensitivity in the Arctic to NHML forcing (1.49, Fig. 9 "NHML tot." versus RTP of 0.43 in Shindell (2012)). Shindell (2012) finds the Arctic is most sensitive to local forcing but

- 25 we lack a perturbation simulation to diagnose that response here. Shindell (2012) reported an Arctic RTP for tropical forcing of 0.36, close to that of NHML forcing, indicating that aerosol perturbations in the tropics is also important for Arctic climate response, which qualitatively agrees with our findings in Fig. 9. Averaging the RTP values corresponding to statistically significant ERF and temperature response within a single latitude band (for example, average RTP of USO2, ESO2, and CSO2) yields a close match with Shindell (2012) RTP values, especially in the NHML and tropics. Shindell (2012) report an RTP of
- 30 0.49 for NHML response to NHML forcing, very close to the average of our NHML forcings in Fig. 9, which is 0.46 (orange bar in Fig. 9 for "NHML tot."). The other response regions (tropics and southern hemisphere) compare moderately well with



Shindell (2012) for NHML forcing (0.25 versus 0.15 for the tropics and 0.1 versus 0.05 for the southern hemisphere). Shindell (2012) used an older model and an idealized forcing through an entire latitude band as opposed to our more realistic localized forcing, which may account for some of the differences in each region.

The uncertainty range in the final two clusters of bars in Fig. 9 give the range of RTP values for the total NHML 5 forcing using the model individual values to construct a high and low estimate. For the NHML forcing cases, which include USO2, CSO2, and ESO2, the responses are robust across our models and there is little intermodel variation, as indicated by the small uncertainty range in each of the four response regions under "NHML tot.". For the tropical forcing cases, the models diverge (uncertainty bars under "Tropics tot." in Fig. 9), especially in the regions remote to the tropics. These results imply that the use of RTP coefficients or similar simple climate response metrics for remote responses to forcing in NHML regions 10 are more robust and reliable than those for remote responses to forcing in tropical regions.

6. Summary and conclusions

Using three coupled chemistry-climate models, we conduct 160-240 year simulations in which aerosols of a specific type and from a specific region are set to zero (or greatly reduced) and compare to an otherwise identical control simulation in order to estimate the mean and extreme temperature response to regional aerosol emissions reductions. We estimate both the near-source local climate response and the remote response to regional aerosol emissions for both mean and extreme temperatures. Removal of regional aerosol emissions almost universally results in warming both globally and regionally, with some exceptions including perturbations of black carbon, an absorbing aerosol species. Surface warming is largest and most robust across models in response to SO₂ emissions reductions, particularly SO₂ from Europe and the US. Using a sign and

- 20 significance approach to assessing robustness, we estimate that about 81% of the global surface area has a robust surface temperature response to European SO₂ reduction. All perturbations except for Indian BC have a spatial robustness of greater than 50%. Furthermore, the magnitudes of the responses are in agreement (overlapping ranges in globally and regionally averaged temperature responses in most perturbation simulations) in CESM1 and GFDL-CM3, but temperature changes are smaller in GISS-E2 due to weaker aerosol forcing. We find both local and remote statistically significant regional climate
- 25 responses to regional aerosol emissions perturbations. Local emissions perturbations exert a strong warming response in the northern hemisphere mid latitude (NHML) regions including the US and Europe. Aerosol emission reductions from all world regions that we considered significantly increase mean temperature in the Arctic by up to 1 K (for emissions perturbations from Europe). Emissions reductions from the NHML exert a warming response in the tropics that rivals the magnitude of the response to emissions perturbations that are local to the tropics.
- 30 We assess the climate sensitivity to aerosol perturbations in each model and find a range from about 0.5 to 1.0 K per W m². The aerosol climate sensitivity varies by type of forcing (e.g. SO₂, OC, BC) and also magnitude of forcing, and can be
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different than the $2xCO_2$ climate sensitivity, due to differences between a heterogeneous, localized aerosol forcing and a more homogeneous CO_2 forcing. Though it has been argued that uncertainty in aerosol forcing is the major factor in uncertainty of estimates of climate sensitivity to CO_2 based on modern observations (Andreae et al., 2005), less attention has been given to the temperature sensitivity to aerosol forcing itself, both in response to global and regional aerosol perturbations. In contrast

- 5 to previous findings using global aerosol reductions (Hansen, 2005; Marvel et al., 2016), we find that the climate sensitivity to aerosol forcing is less than or equal to the climate sensitivity to a doubling of CO₂ in 2 of 3 models, indicating a strong dependence on both model choice and region of aerosol reduction. Future work using the CMIP6 simulations may shed light on forcing efficacy of global aerosol reductions using a large number of models.
- We estimate updated RTP coefficients in order to help facilitate estimation of climate impacts metrics at a sub-global scale. These updated RTP coefficients may be useful for integrated assessment modelling (IAM), such as the Long-range Energy Alternatives Planning system – Integrated Benefits Calculator (LEAP-IBC) (Heaps 2016), to calculate climate impacts across a range of emission scenarios quickly and efficiently. We improve on previous studies by providing RTP coefficients for multiple models and for a large variety of aerosol types and regional perturbations, and by narrowing the forcing region from latitudinal bands to specific countries or continents (e.g. US SO₂, European SO₂). We provide a multimodel mean RTP
- 15 as well as the range represented by individual models. We find that the regional temperature response to northern hemisphere mid-latitude forcing (NHML) is largely independent of longitudinal forcing location within the NHML. We also find a small range of intermodel variability in regional temperature response to NHML forcing, indicating robustness of the RTP coefficients. For aerosol forcing occurring in the NHML, our reported RTP coefficients are similar to those reported in Shindell (2012), except for the response in the Arctic, which we find to be more sensitive to NHML forcing. Our results indicate that
- 20 RTP coefficients for Arctic response to aerosol forcing in the Arctic may need to be revised upwards, which has implications for climate impacts and integrated assessment modelling applications. Further unexpected warming in the Arctic from the unmasking of aerosol forcing could bring about Arctic climate tipping points such as permafrost thawing even sooner than currently projected. Future work will link climate responses directly to emissions changes for each of our models, similar to what has been done for NorESM in Lewinschal et al. (2019).
- 25 We also consider the extreme temperature response to regional aerosol perturbations and find that by shifting the overall surface temperature distribution, aerosol perturbations increase the warming extremes (upper tail of the surface temperature distribution). The annual maximum of maximum daily temperatures, or TXx, increases by about 0.1 to 0.2 K globally, closely mirroring the global changes in mean surface temperature, suggesting a mean shift of the temperature distribution to warmer temperatures, with limited impact on the shape of the distribution mainly occurring in only one of our
- 30 models. We find the mean shift to be statistically significant on a global mean basis in all models, and regionally in two of the three models. Compared to mean surface temperatures, extreme temperatures are not very sensitive to remote aerosol perturbations, with a few exceptions.

The understanding of the major drivers of projected regional climate change is key information needed by the climate assessment and impacts community. Our results have the potential to provide a framework for a key methodological link

between physical science and impacts, adaptation, and vulnerability analysis. This work is a first step towards providing statistical relationships between the changes in regional aerosol emissions and the statistically significant changes in climate that can be attributed to them. Such relationships would allow for the generation of regional climate change scenarios without having to simulate computationally demanding chemistry-climate models.

5 Author Contributions

DMW wrote the manuscript and created all figures. NRM performed ERF simulations and contributed extremes analysis. AMF, DTS, and JFL originally conceived the project, with later input from DMW, AJC, MP, and LWH. GF, AJC, and GC conducted simulations and transferred data. All authors contributed to editing the manuscript.

Code Availability

10 The code for the atmospheric component of the GFDL-CM3 model is available here: https://www.gfdl.noaa.gov/am3/. NCAR-CESM1 model code is available here: http://www.cesm.ucar.edu/models/cesm1.0/. GISS-E2 model code is available here: https://simplex.giss.nasa.gov/snapshots/.

Data Availability

RTP coefficients have been provided here: <u>https://figshare.com/articles/RTP_coefficients_Westervelt_et_al_ACP/10669322</u> 15 (Westervelt, 2019). Global and regional temperature response model data used in the figures is provided here: <u>https://figshare.com/articles/Global_mean_T_by_latitude_band/10710722</u> (Westervelt, 2019). Contact the corresponding author for any other data requests.

Competing Interests

The authors declare no competing interests.

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Simulation	Region of emissions	Species perturbed	Perturbation amount (Tg yr ⁻¹), (%)
name	perturbation		
ESO2	Europe	Sulfur dioxide	18 (80%)
EBC	Europe	Black carbon	0.8 (100%)
EOC	Europe	Organic carbon	2 (100%)
EALL	Europe	Sulfur dioxide, black carbon, organic	(Sum of above)
		carbon	
USO2	United States	Sulfur dioxide	15 (100%)
UBC	United States	Black carbon	0.4 (100%)
UOC	United States	Organic carbon	0.8 (100%)
UALL	Unites States	Sulfur dioxide	(Sum of above)
CSO2	China	Sulfur dioxide	15 (80%)
ISO2	India	Sulfur dioxide	5.6 (100%)
IBC	India	Black carbon	0.6 (100%)
IOC	India	Organic carbon	2.78 (100%)
SABB	South America	Biomass burning sulfur dioxide, black	0.4 (SO ₂), 0.4 (BC), 4.7 (OA)
		carbon, organic carbon	(100%)
AFBB	Africa	Biomass burning sulfur dioxide, black	0.4 (SO ₂), 0.4 (BC), 5.3 (OA)
		carbon, organic carbon	(33%)

Table 1: Simulation description and labels, and amount of emissions perturbation (roughly the same for each model) in absolute terms and the percentage removed

 Table 2: Regional Temperature Potential (RTP) values for GFDL-CM3 for simulations with statistically significant ERF and temperature

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 response

	60-90°N (Arctic)	30-60°N (NHML)	30°S-30°N (Tropics)	30-90°S (SH)
CSO2	1.86	0.54	0.44	0.05
ESO2	2.26	0.58	0.24	0.12
EALL	1.29	0.38	0.18	0.16
USO2	1.43	0.42	0.21	0.09
UALL	1.87	0.32	0.22	0.11
ISO2	2.98	0.45	0.50	0.41
SABB	4.57	0.36	1.21	0.44
AFBB	2.15	0.34	0.26	0.17

	60-90°N (Arctic)	30-60°N (NHML)	30°S-30°N (Tropics)	30-90°S (SH)
CSO2	1.34	0.34	0.16	0.22
ESO2	0.62	0.43	0.23	0.12
USO2	0.87	0.37	0.16	0.12
UALL	0.80	0.44	0.15	0.04
SABB	0.97	0.61	0.42	0.37
AFBB	0.98	0.31	0.44	0.45

Table 3: Regional Temperature Potential (RTP) values for GISS-E2 for simulations with statistically significant ERF and temperature response

 Table 4:Regional Temperature Potential (RTP) values for CESM1 for simulations with statistically significant ERF and temperature

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 response

	60-90°N (Arctic)	30-60°N (NHML)	30°S-30°N (Tropics)	30-90°S (SH)
USO2	2.02	0.57	0.20	0.52
AFBB	1.29	0.72	0.97	2.37



Figure 1: 200-year annual mean temperature responses (K) to aerosol emissions decreases in each of the three models (GFDL-CM3, first column; NCAR-CESM1, second column; GISS-E2, third column) for several different regional emissions decreases

(simulations indicated in figure titles; see Table 1). Hatching represents statistical significance at the 95% level according to a Student's t-test with the False Discovery Rate method from Wilks (2016) applied.



Figure 2: Regions of robustness in surface temperature response to individual aerosol emissions perturbations (panels a-h). The different colors represent the number of models in agreement in sign (two or three) for a particular location, and asterisks indicate whether models agree that the response is statistically significant (** for significance in all three or both models, * for significance in two out of three models, and no asterisks for significance in 1 or no models). Robustness indicates percentage

of the surface area that has all 3 models in sign agreement.

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Figure 3: Global annual mean (panel a) and regional mean by latitude bands (panels b through e) surface temperature responses (K) to each of the 14 aerosol perturbation simulations. Error bars show ± 2 standard errors of the mean to assess statistical significance. Regions that are "local" to the given latitude band are in red. See Table 1 for definition of abbreviations. Note the different scales in each panel.



Figure 4: 200-year annual extreme temperature (TXx) responses (K) to aerosol emissions decreases in each of the three models (GFDL-CM3, first column; NCAR-CESM1, second column; GISS-E2, third column) for several different regional emissions decreases (simulations indicated in figure titles; see Table 1). Hatching represents statistical significance at the 95% level according to a Student's t-test with the False Discovery Rate method from Wilks (2016) applied.



Figure 5: Global annual mean (panel a) and regional mean by latitude bands (panels b through e) extreme temperature responses (K) to each of the 14 aerosol perturbation simulations. Error bars show ± 2 standard errors of the mean to assess statistical significance. See Table 1 for definition of abbreviations





10 Figure 6: Eastern US regional (top row) and global mean (bottom row) probability density function for control and perturbation simulations in each model (columns). Dashed line is the Gaussian kernel density estimation for the normalized probability density function.





Figure 7: Scatterplot of global mean surface temperature response (K) to regional aerosol perturbations (symbols) versus global mean effective radiative forcing in each model (green: GISS-E2, red: GFDL-CM3, blue: NCAR-CESM1).



Figure 8: Global climate sensitivity to regional aerosol emissions perturbations and to a doubling of CO_2 (2xCO₂) in each model. Error bars represent ±2 standard errors around the mean. See Table 1 for definition of abbreviations.



Figure 9: Regional Temperature Potential (RTP) coefficients (unitless) for the multi-model mean between GFDL-CM3, GISS-E2, and CESM1 for select simulations and the average by forcing region (e.g. "NHML tot." and "Tropics tot."). Uncertainty bars in the last two columns indicate the range of the RTP values as reported by the three models.

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