#### The Climate Response to Emissions Reductions due to COVID-19: Initial Results 1 from CovidMIP 2

- 3
- 4
- 5
- 6
- 7
- Chris D. Jones<sup>1</sup>, Jonathan E. Hickman<sup>2</sup>, Steven T. Rumbold<sup>3</sup>, Jeremy Walton<sup>1</sup>, Robin D. Lamboll<sup>4</sup>, Ragnhild B. Skeie<sup>5</sup>, Stephanie Fiedler<sup>6,7</sup>, Piers M. Forster<sup>8</sup>, Joeri Rogelj<sup>4,9</sup>, Manabu Abe<sup>10</sup>, Michael Botzet<sup>11</sup>, Katherine Calvin<sup>12,13</sup>, Christophe Cassou<sup>14</sup>, Jason N.S. Cole<sup>15</sup>, Paolo Davini<sup>16</sup>, Makoto Deushi<sup>17</sup>, Martin Dix<sup>18</sup>, John C. Fyfe<sup>15</sup>, Nathan P. Gillett<sup>15</sup>, Tatiana Ilyina<sup>11</sup>, Michio Kawamiya<sup>10</sup>, Maxwell Kelley<sup>19,2</sup>, Slava Kharin<sup>15</sup>, Tsuyoshi Koshiro<sup>17</sup>, Hongmei Li<sup>11</sup>, Chloe Mackallah<sup>18</sup>, Wolfgang A. Müller<sup>11</sup>, Pierre Nabat<sup>20</sup>, Twan van Noije<sup>21</sup>, Paul Nolan<sup>22,23</sup>, Rumi Ohgaito<sup>10</sup>, Dirk Olivié<sup>24</sup>, Naga Oshima<sup>17</sup>, Jose Parodi<sup>25</sup>, Thomas J. Reerink<sup>21</sup>, Lili Ren<sup>26</sup>, Anastasia Romanou<sup>2</sup>, Roland Séférian<sup>20</sup>, Yongming Tang<sup>1</sup>, Claudia Timmreek<sup>11</sup>, Jorry Tiiputro<sup>27</sup>, Etiepne Tourigny<sup>28</sup>, Kostes Tsigeridis<sup>29,2</sup>, Haileng 8
- 9
- 10
- Claudia Timmreck<sup>11</sup>, Jerry Tjiputra<sup>27</sup>, Etienne Tourigny<sup>28</sup>, Kostas Tsigaridis<sup>29,2</sup>, Hailong Wang<sup>12</sup>, Mingxuan Wu<sup>12</sup>, Klaus Wyser<sup>30</sup>, Shuting Yang<sup>31</sup>, Yang Yang<sup>26</sup>, Tilo Ziehn<sup>18</sup>. 11
- 12
- <sup>1</sup>Met Office Hadley Centre, Exeter, UK. 13
- <sup>2</sup>NASA Goddard Institute for Space Studies, New York, NY, USA. 14
- <sup>3</sup>National Centre for Atmospheric Science, University of Reading, UK. 15
- <sup>4</sup>Grantham Institute for Climate Change and the Environment, Imperial College London, 16
- London, UK. 17
- <sup>5</sup>CICERO Center for International Climate Research, Oslo, Norway. 18
- <sup>6</sup>University of Cologne, Institute of Geophysics and Meteorology, Cologne, Germany. 19
- <sup>7</sup>Hans-Ertel-Centre for Weather Research, Climate Monitoring and Diagnostics, Bonn/Cologne, 20
- 21 Germany.
- 22 <sup>8</sup>Priestley International Centre for Climate, University of Leeds, UK.
- <sup>9</sup>International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria. 23
- <sup>10</sup>Japan Agency for Marine-Earth Science and Technology, 3173-25 Showamachi, Kanazawa-24
- ward, Yokohama, 236-0001, Japan. 25
- <sup>11</sup>Max Planck Institute for Meteorology, Hamburg, Germany. 26
- <sup>12</sup>Pacific Northwest National Laboratory, Richland, WA, USA. 27
- <sup>13</sup>Pacific Northwest National Laboratory, College Park, MD, USA. 28
- <sup>14</sup>CECI, Université de Toulouse, CNRS, CERFACS, Toulouse, France. 29
- <sup>15</sup>Canadian Centre for Climate Modelling and Analysis, Environment and Climate Change 30
- Canada, Victoria, BC, Canada. 31
- <sup>16</sup>Istituto di Scienze dell'Atmosfera e del Clima, Consiglio Nazionale delle Ricerche (CNR-32
- ISAC), Torino, Italy. 33
- <sup>17</sup>Meteorological Research Institute, Japan Meteorological Agency, 1-1 Nagamine, Tsukuba, 34
- Ibaraki, 305-0052, Japan. 35
- <sup>18</sup>CSIRO Oceans and Atmosphere, Aspendale, VIC, Australia. 36
- <sup>19</sup>SciSpace LLC, New York, NY, USA. 37

- <sup>20</sup>CNRM, Université de Toulouse, Météo-France, CNRS, Toulouse, France. 38
- <sup>21</sup>Royal Netherlands Meteorological Institute (KNMI), 3730 AE De Bilt, the Netherlands. 39
- <sup>22</sup>Irish Centre for High-End Computing (ICHEC), 2, 7/F, The Tower, Trinity Technology & 40
- Enterprise Campus, Grand Canal Dock, Dublin 2, Ireland. 41
- <sup>23</sup>Research and Applications Division, Met Éireann, Dublin, Ireland. 42
- <sup>24</sup>NORCE Norwegian Meteorological Institute, Oslo, Norway. 43
- <sup>25</sup>Spanish State Meteorological Agency (AEMET), DT Murcia, Avda de la Libertad 11, 30107 44 Murcia, Spain. 45
- <sup>26</sup>Jiangsu Key Laboratory of Atmospheric Environment Monitoring and Pollution Control, 46
- Jiangsu Collaborative Innovation Center of Atmospheric Environment and Equipment 47
- Technology, School of Environmental Science and Engineering, Nanjing University of 48
- Information Science and Technology, Nanjing, China. 49
- <sup>27</sup>Norwegian Research Centre and Bjerknes Centre for Climate Research, Bergen, Norway. 50
- <sup>28</sup>Earth Sciences Department, Barcelona Supercomputing Center (BSC), C/ Jordi Girona 29, 51
- 08034 Barcelona, Spain. 52
- <sup>29</sup>Center for Climate Systems Research, Columbia University, New York, NY, USA. 53
- <sup>30</sup>Rossby Centre, Swedish Meteorological and Hydrological Institute (SMHI), 601 76 54

#### Norrköping, Sweden. 55

- <sup>31</sup>Danish Meteorological Institute (DMI), 2100 Copenhagen, Denmark. 56
- 57
- Corresponding author: Chris D. Jones (chris.d.jones@metoffice.gov.uk) 58
- 59

#### 60 **Key Points:**

- Lockdown restrictions during COVID-19 have reduced emissions of aerosols and 61 • greenhouse gases 62
- 12 CMIP6 Earth system models have performed coordinated experiments to assess the 63 impact of this on climate 64
- Aerosol amounts are reduced over southern and eastern Asia but there is no detectable 65 • change in annually averaged temperature or precipitation 66
- 67

## 68 Abstract

- 69 Many nations responded to the COVID-19 pandemic by restricting travel and other activities
- during 2020, resulting in temporarily reduced emissions of CO<sub>2</sub>, other greenhouse gases and
- ozone and aerosol precursors. We present the initial results from a coordinated Intercomparison,
- 72 CovidMIP, of Earth system model simulations which assess the impact on climate of these
- ra emissions reductions. Twelve models performed multiple initial-condition ensembles to produce
- 74 over 300 simulations spanning both initial condition and model structural uncertainty. We find
- 75 model consensus on reduced aerosol amounts (particularly over southern and eastern Asia) and
- <sup>76</sup> associated increases in surface shortwave radiation levels. However, any impact on near-surface
- temperature or rainfall during 2020-2024 is extremely small and is not detectable in this initial
   analysis. Regional analyses on a finer scale, and closer attention to extremes (especially linked to
- changes in atmospheric composition and air quality) are required to test the impact of COVID-
- 80 19-related emission reductions on near-term climate.

81

## 82 Plain Language Summary

- 83 Many nations responded to the COVID-19 pandemic by restricting travel and other activities
- during 2020. This caused a temporary reduction in emissions of CO<sub>2</sub> and other pollutants. We
- compare results from twelve Earth system models to see if the emissions reductions affected
- climate. These twelve models performed over 300 experiments using multiple initial-conditions.
- We find a consensus that aerosol amounts were reduced, especially over southern and eastern
- Asia, during 2020-2024. This led to increases in solar radiation reaching the surface in this
- region. However, we could not detect any associated impact on temperature or rainfall. We
- 90 recommend more analyses on regional scales. We also suggest that analysis of extreme weather
- and air quality would be useful to test the impact on climate of emission reductions due to
- 92 COVID-19.

#### 93 **1 Introduction**

94

#### 1.1 Impact of COVID-19 lockdown on emissions

95 96

97

98

The COVID-19 pandemic led to widespread measures restricting travel, industrial, and commercial activity during 2020. The effects of these changes in socioeconomic activity on atmospheric composition have been widely studied including estimates of emissions and

99 concentrations of species that directly or indirectly affect climate.100

The impacts of COVID-19 measures on long-lived greenhouse gases have been inferred 101 from both bottom-up estimates using activity data and top-down analysis of atmospheric 102 observations. Bottom-up estimates using sector activity have estimated global CO<sub>2</sub> emissions 103 reductions of 8.8% during the first 5 months of 2020 (Liu et al., 2020) and annual reductions 104 105 from 4% to 7% (Le Quéré et al., 2020). Top-down assessments have found some indications of a decrease in CO<sub>2</sub> growth rate during 2020 (Buchwitz et al., 2020), with examples of substantial 106 local and regional CO<sub>2</sub> and methane (CH<sub>4</sub>) emissions reductions inferred from surface 107 108 observations (Tohjima et al., 2020; Turner et al., 2020). However, existing satellite products could not provide the required coverage to reliably detect changes in CO<sub>2</sub> column densities at the 109 magnitude expected to be occurring in 2020 (Buchwitz et al., 2020; Chevallier et al., 2020). 110 Expected growth rates in atmospheric CO<sub>2</sub> fractions vary too much from year to year due to 111 internal climate variability (Jones and Cox, 2005; Betts et al., 2016) for the effects of emission 112 113 reductions on the order of 8% to be clearly detected from observations of CO<sub>2</sub> column densities (Sussmann and Rettinger, 2020; Tohjima et al., 2020). The long lifetime of CO<sub>2</sub>, and to a lesser 114 extent CH<sub>4</sub>, means that the small impact of emissions reductions is likely to be long-lived, and 115 may still exert a non-negligible climate impact on decadal timescales (Forster et al., 2020). 116

117

118 The largest changes in observed composition attributed to COVID-19 restrictions were for nitrogen dioxide (NO<sub>2</sub>), with concentration reductions at both national- and city-scales 119 typically on the order of 20-60% in China, India, Europe, and the United States (Goldberg et al., 120 121 2020; Keller et al., 2020; Menut et al., 2020; Miyazaki et al., 2020; Ordóñez et al., 2020; Venter et al., 2020; Zhao et al., 2020). The NO<sub>2</sub> decreases have been attributed largely to changes in the 122 transport sector (Bao and Zhang, 2020; Diamond and Wood, 2020; Lian et al., 2020b; Venter et 123 124 al., 2020). The rapid changes in emissions and complex dynamics of short-lived pollutants have complex and non-uniform implications for climate. In areas where background NO<sub>x</sub> 125 concentrations were high, reduced  $NO_x$  emissions led to increased tropospheric ozone (O<sub>3</sub>) 126 127 concentrations in many regions and cities (Keller et al., 2020; Le et al., 2020; Lian et al., 2020a; Ordóñez et al., 2020; Sicard et al., 2020; Venter et al., 2020). Elsewhere, tropospheric ozone may 128 have decreased during lockdowns leading to short-term estimated changes of radiative forcing by 129 -33 to -78 mWm<sup>-2</sup> (Weber et al., 2020). 130

131

Some studies report substantial decreases in particulate matter (PM) on the order of 1030% (Filonchyk et al., 2020; Le et al., 2020; Silver et al., 2020; Venter et al., 2020; Xu et al.,
2020), but analyses accounting for long-term trends generally found no lockdown impacts on
aerosol optical depth (AOD) or PM concentrations (Diamond and Wood, 2020; Field et al.,
2020; Zangari et al., 2020). In some regions, PM concentrations increased as a result of altered
dust or biomass burning emissions or as a consequence of changes in emissions and meteorology

(Le et al., 2020; Venter et al., 2020). Notably, northern China experienced an increase in haze
 during the spring lockdown due to enhanced formation of ozone, which, in combination with

140 favorable meteorological conditions and changes in heterogeneous chemistry, contributed to

- 141 enhanced secondary aerosol formation (Chang et al., 2020; Le et al., 2020; Wang et al., 2020b).
- 142

## 143 **1.2 Impact of emissions reductions on climate**

The reduction in emissions is expected to have regional impacts on atmospheric composition, and therefore could have implications for weather and climate. Different species have very different lifetimes from hours-to-days for aerosols, to decades or longer for long-lived greenhouse gases, and very different spatial scales, with some being very localized and others globally well-mixed.

149 For example, Yang et al. (2020) examined climate responses to aerosol emission reductions during the COVID-19 lockdown, back-to-work and post-lockdown stages throughout 150 the year 2020 based on CESM1 model simulations. They reported that an anomalous surface 151 152 warming appeared over the Northern Hemisphere continents due to the fast climate response to aerosol reductions. Fyfe et al. (2021) examine a large ensemble of simulations with CanESM5 153 under an idealized modelling framework of the COVID emission reduction and conclude that 154 any signal from such short-lived emissions changes is likely to be small or even undetectable. 155 Forster et al. (2020) developed a two-year COVID-19 emissions reduction scenario for long- and 156 short-lived species based on mobility data and the bottom-up approach of Le Quéré et al. (2020) 157 158 for some sectors and then assumed a recovery over the subsequent two years. Using the FaIR climate emulator, they simulated the effect of these emissions reductions and found a rapid short-159 term warming due to reduced aerosols, which was offset by a slightly slower, but also near-term 160 cooling due to reduced tropospheric ozone. On longer timescales, well-mixed GHGs, especially 161 CO<sub>2</sub> became important, and their simulations showed that the net effect of these emissions 162 changes by 2030 was negligible: a global cooling of about  $0.01 \pm 0.005$  °C. 163 However, because FaIR cannot capture regional climate effects, internal variability or 164 complex interactions of atmospheric composition and biogeochemistry, there remain unanswered 165 questions about the possible climatic impact of emissions reductions on regional air quality and 166

climate. These are beginning to be addressed by single model studies (e.g. Yang et al., 2020
 analyse an atmospheric model with prescribed sea surface temperature, and ; Fyfe et al, 2021

analyse a large ensemble of coupled atmosphere-ocean simulations with the CanESM5 model),

but would benefit greatly from being analyzed across an ensemble of Earth system models

171 (ESMs) run under a common protocol. Hence it was decided that this scenario would form the

basis of a multi-Earth system model intercomparison project (MIP). This paper presents an initial

analysis of the first results coming from this new activity, called CovidMIP. The emissions

estimates and modelling protocol used are described in section 2, results shown in section 3 and

175 discussed in section 4 in the context of ongoing climate change.

176 177

## 178 2 Materials and Methods

## 179 **2.1 CovidMIP protocol**

The emissions estimates assembled by Forster et al. (2020) were collated and gridded, and made available in Inputs4MIPs data format for use by CMIP Earth system models (Lamboll et al., 2020). A modelling protocol was agreed, and is incorporated into DAMIP (the Detection and Attribution MIP; Gillett et al., 2016), which is also described in Lamboll et al. (2020), but the main points are noted here for convenience.

Because any climate signal due to COVID-19-induced emissions reductions was considered likely to be small, it is advantageous to carry out large initial-condition ensembles which have been shown to enable detection of even small regional climate signals (e.g. Banerjee et al., 2020). But cognizant of the computational cost and time required for producing such large ensembles, a pragmatic recommendation was made that model groups perform at least 10 initialcondition ensemble members. This was hoped to maximize the number of modelling groups participating but still produce enough members to enable meaningful analysis.

The protocol uses the SSP2-4.5 scenario (O'Neill et al., 2016) as a baseline against which 192 193 to apply the emissions reductions. Simulations are run parallel to ssp245, but branching from that simulation on 1 January 2020 and following the new forcing in line with emissions reductions. 194 The results will be published on the CMIP6 archive (Earth System Grid Federation) under 195 experiment name ssp245-covid. Forcing is provided as concentrations of greenhouse gases and 196 emissions of aerosols and aerosol and ozone precursors. For models with interactive chemistry, 197 198 ozone can be simulated otherwise it has been provided as concentrations. Similarly, models can simulate aerosols or they can be represented with the MACv2-SP parametrisation (Stevens et al., 199 200 2017; Fiedler et al., 2020).

In this manuscript we focus on the immediate term impact (from 2020-2024) of the "two 201 year blip" scenario under which emissions revert to the baseline levels by the end of 2022. In 202 addition to this, Forster et al. (2020) created a set of scenarios spanning possible future economic 203 recovery strategies: a reduction in anthropogenic CO<sub>2</sub> emissions post-2020 consistent with 204 enhanced investment in environmentally friendly technologies (moderate or strong "green 205 206 stimulus"), no effect after 2022 (continuation of "two year blip" studied here with emissions reverting to ssp245) or an increase in anthropogenic CO<sub>2</sub> emissions relative to ssp245 after 2020 207 consistent with an investment in more traditional fossil-fuel based energy production (or "fossil-208 fuelled recovery"). All of these scenarios have become part of the CMIP6 set of experiments, 209 under the detection and attribution activity (DAMIP: Gillett et al., 2016). 210

## 211 **2.2 Participating Earth system models**

The protocol is open to all models participating in CMIP6 and to date twelve models have provided data for analysis (Table 1). A particular value of a multi-model ensemble is being able to incorporate different levels of process complexity, but this also brings challenges of interpreting results.

Some models prescribe aerosols and ozone, either using their own climatology or MACv2-SP and/or prescribed ozone 3D concentrations taken from the OsloCTM3 chemical transport model (Lamboll et al., 2020). Others may simulate either aerosols or ozone interactively in response to their primary or secondary emissions. The MPI -ESM1-2-LR model simulated interactive CO<sub>2</sub> while the other models used prescribed CO<sub>2</sub> concentrations. Models have differing complexity and species richness of aerosols, representing both natural and anthropogenic species such as sulphates, black carbon, organic carbon, sea-salt and mineral-dust,
 but many still lack representation of nitrate aerosols.

In terms of biogeochemistry many ESMs now represent land and marine ecosystems and the carbon cycle (Boysen et al., 2020; Séférian et al., 2020; Thornhill et al., 2020). On the nearterm studied here, the carbon cycle is unlikely to have a large effect on climate but impacts of emissions reductions may show up in terms of changes in carbon fluxes, stores and partitioning across realms of the Earth system.

To generate initial conditions some models (ACCESS-ESM1-5, CanESM5, EC-Earth3, MIROC-ES2L, MPI-ESM1-2-LR, UKESM1-0-LL) drew on existing ssp245 simulations which followed on from initial-condition ensembles of the CMIP6 historical simulations. Others perturbed conditions at the end of the historical period (CESM1, E3SM-1-1, GISS-E2-1-G), or mixed the two approaches by inflating existing ensembles with additional perturbations applied (MRI-ESM2-0, CNRM-ESM2-1, NorESM2-LM) or by running on different super-computers (NorESM2-LM).

Future studies will be able to take into account the model complexity and how this affects 236 the simulated results. For example, are changes in atmospheric circulation or surface climate 237 affected differently between models with simulated and prescribed ozone and aerosols? How 238 does the model treatment of interactions between atmospheric composition (such as fraction of 239 diffuse light or surface ozone) affect vegetation productivity and carbon storage? In this analysis 240 241 such considerations are out of scope and we give an overview on each model's results for the climate response for 2020-2024. The reader is referred to Table 1, which documents the spatial 242 resolution and the process complexity of each participating model as well as the number of 243 ensemble members utilized in this study. 244

245

## 246 **3 Results**

## **3.1 Indicators of global change**

Our analysis draws on different sized ensembles from 12 ESMs. Throughout, we base analysis on ensemble mean anomalies from each model, calculated from a pair-wise difference between simulations with COVID-19-related emissions reductions ("ssp245-covid") and simulations using the standard, baseline SSP2-4.5 scenario ("ssp245").

Globally, for 2020, all models show a reduction in aerosol optical depth (at 550 nm) in their ensemble mean with 7 out of 11 models which reported this variable having a reduction greater than 1 standard deviation (Figure 1). In 2021, the AOD anomalies of 10 out of 11 models remain negative with ACCESS-ESM1-5 showing near-zero deviation. From 2022 onwards there is no robust global signal in AOD as emissions reductions in this simulation recover to levels in the baseline scenario and aerosol amounts quickly recover too.

This behavior is reflected in the amount of solar radiation reaching the surface, which is generally simulated to have increased, with all models (of the 11 for whom this variable was available for this analysis) having a positive anomaly in downwards shortwave (SW) radiation for both 2020 and 2021 (Figure 1, panel b). Although only MRI-ESM2-0 simulated an ensemble mean global increase greater than 1 standard deviation. As for AOD, the anomaly quickly recovers and becomes very small from 2022 onwards. We have not yet investigated the extent to
 which surface shortwave is directly affected by aerosol absorption or by aerosol-induced changes
 in cloud cover. Future studies will also assess impacts and implications of aerosol-cloud

266 interactions in driving the changes seen here.

267

268 Figure 1. Annual mean, ensemble average output from ESMs. Each panel shows anomalies from the simulations with COVID-19-

related emissions reductions compared to the baseline SSP2-4.5 simulations ("ssp245-covid" minus "ssp245"). (a) Global
 aerosol optical depth at 550nm; (b) downwards SW radiation at the surface; (c) Global surface air temperature; (d) Global

aerosol optical depth at 550nm; (b) downwards SW radiation at the surface; (c) Global surface air temperature; (d) Global
 precipitation. Coloured lines show ensemble average results from each model, and paler plumes show ensemble spread for each

272 model calculated here as  $\pm 1$  standard deviation across each model's ensemble. Vertical bars to the left of each panel show each

273 model spread (mean ±1 standard deviation) for the first year, 2020. Each model has performed a different number of ensemble

274 members as listed in Table 1 and shown in square brackets in the caption.

The impact of this, however, on surface climate at a global scale is very small. Figure 1 panels (c) and (d) show globally averaged surface air temperature and precipitation respectively. No model shows any significant change in either of these quantities at a global level for any year.

278

## **3.2 Patterns of regional changes**

Figure 2 shows the regional patterns of the changes in aerosol optical depth for each 280 model. It is apparent that models agree that the largest response is in Asia, predominantly over 281 India and China where almost all models show a marked decrease in aerosols as an average over 282 the 5-year period 2020-2024. Some models also show some patches of aerosol increases, for 283 284 example CanESM and E3SM-1-1 over the Himalayan region, and MIROC-ES2L over regions of North Africa. Reasons for these changes are not explored further here and we do not yet know if 285 they are caused by changes in anthropogenic or natural sources, such as dust, which can be very 286 287 sensitive to variations in windspeed. 288

289

- Figure 2. Model by model simulated changes in aerosol optical depth (at a wavelength of 550 nm). For each model we plot the
- 290 291 ensemble mean response from 2020-2024 inclusive. Blue colours denote a decrease in AOD. Each model has performed a
- 292 293 different number of ensemble members as listed in Table 1 and shown in square brackets in the caption. The black box shows the region analysed in Figure 3.

To see if these regional changes in aerosol loading affect regional climate properties, we 294 295 define a region bounded by 60-160°E and 0-50°N which has been chosen subjectively after considering all models to cover the main AOD anomalies across models (marked as black boxes 296 297 in Figure 2). We assess annual changes in surface SW radiation, temperature and precipitation in this region. Figure 3 shows a similar response to the global metrics shown in Figure 1 but with 298 greater magnitudes of average response. Again, there is a strong model agreement of reduced 299 aerosols, with all models agreeing on this in their ensemble mean for 2020 and 7 out of 11 300 having reductions greater than 1 standard deviation. Averaged across models, global AOD 301 reduction in 2020 is -0.0027±0.0012, while in southern and eastern Asia it is -0.0097±0.0034. 302 The associated increase in downwards SW radiation is also apparent, and stronger here: globally 303 models show an increase of  $0.21\pm0.10$  Wm<sup>-2</sup> while in southern and eastern Asia it is  $0.69\pm0.31$ 304  $Wm^{-2}$ . 305

Although most models simulate a slight warming signal in this region in their ensemble 306 mean (Figure 3, panel c), the magnitude is very small – less than 0.1 °C, and in all models smaller 307 than the standard deviation across ensemble members (typically of the order  $0.2^{\circ}$ C). 308

309 310

311 Figure 3. indicators of change in southern and eastern Asia (defined here as 60-160°E and 0-50°N). As for figure 1 results are

312 plotted as annual mean anomalies, with coloured lines denoting ensemble means from each model and grey shading 1-standard 313 deviation for each model. (a) Aerosol optical depth; (b) surface downwards shortwave radiation; (c) surface air temperature; (d) precipitation.

- 314
- 315

Outside of this region, models show patchy temperature changes, indicative of random 316 changes, and internal variability of modes such as NAO or ENSO. This residual signal of 317 internal variability is not eliminated in limited ensemble size and demonstrates the weak signal-318 to-noise ratio (see figure 1 in Supplementary Info). These changes do not appear to be 319 systematic, with some regions exhibiting both apparently strong warming and cooling signals in 320 different models. The region of northern East Asia often displays a strong temperature signal in 321 the model results, with CESM1 displaying a warming as reported in Yang et al. (2020), although 322 that study performed simulations with fixed sea-surface temperatures. GISS-E2-1-G and E3SM-323 1-1 also show strong warming patterns here and UKESM1-0-LL, MPI-ESM1-2-LR and 324 CanESM5 some warming too. But NorESM2-LM shows a strong cooling and ACCESS-ESM1-325 5, MIROC-ES2L and MRI-ESM2-0 having mixed signals. Models show marked differences 326 elsewhere e.g. MPI-ESM1-2-LR and MRI-ESM2-0 have opposite patterns of warming over 327 North America while in South America CanESM5 and UKESM1-0-LL show a cooling but 328 GISS-E2-1-G and NorESM2-LM show a warming. 329

When looking at regional patterns of precipitation and surface SW radiation (S.I. figures 330 2 and 3) there are no robust signals or consistent patterns of change across models. Even the 331 increase in surface SW radiation shown in Figure 3 is very hard to see by eye in the patterns of 332 change, due to the influence of clouds which can easily mask any signal from changes in 333 aerosols. This, and similar incoherent patterns of rainfall change, indicate the substantial 334 variability in these quantities and the challenges in detecting robust signals of change under 335 conditions of relatively small forcing. Despite a large number of ensembles, it is evident that at 336 these smaller regional scales, variability in meteorology prevents robust detection of signals in 337 clouds and rainfall. 338

- 339
- 340

#### 341 **4 Discussion and Conclusions**

Here we have only begun to scratch the surface of the results becoming available from 342 the CovidMIP simulations. We stress that this work has been the result of a very rapid response 343 of the Earth system modelling community. It often takes several years to design and perform 344 coordinated MIP experiments, and process the data for publication in a community archive. This 345 activity has taken place in only a matter of months. This paper is just the very first analysis of 346 initial results and therefore serves only as a first indication of how the climate system has 347 responded to the perturbations to emissions in response to the COVID-19 pandemic. It is not 348 possible at this stage to analyze all of the responses, nor the processes responsible for changes 349 across the whole system. But this study sets the scene and informs priorities for future analysis. 350 351

We have shown that the imprint of COVID-19-related changes in societal activity is 352 visible in atmospheric composition - notably aerosol optical depth over southern and eastern 353 Asia, and in the amount of solar radiation reaching the planet's surface. Over this most affected 354 region, the 2-year average effect was more than 0.5Wm<sup>-2</sup>. More locally and on shorter timescales 355 it could be substantially higher. However, despite these changes in the make-up of the 356 atmosphere, no detectable change in surface temperatures or rainfall could be found. We 357 conclude that the emissions reductions were too small in magnitude and time to have a 358 significant effect on global climate, and that larger, sustained changes on a much longer 359 timescale are required in order to have observable effects (Samset et al., 2020; Tebaldi et al., 360 2020). The CovidMIP protocol will be extended to include an additional "four year blip" 361 simulation so that future work can also consider the impact if lockdown restrictions were 362 prolonged or recovery delayed due to new strains of the Coronavirus. 363

364 365

366

Based on what we have found we recommend further analysis would be fruitful in the following areas:

- Effective radiative forcing (ERF) response to the emissions perturbations. The • 367 global patterns of downwards SW radiation anomalies are very noisy in these 368 369 simulations but the radiation signal would be improved in simulations with fixed-SSTs which reduce interannual variability in the climate system and allow 370 quantification of the ERF due to the emission changes (Pincus et al., 2016; Fiedler 371 et al., 2020). The CovidMIP protocol (Lamboll et al., 2020) defines additional 372 fixed-SST simulations to isolate the effects of ozone, aerosols and even separate 373 black carbon, organic carbon and sulphate aerosols. We recommend model groups 374 perform these complementary simulations to allow the radiative effects of 375 emissions reductions to be assessed more reliably. 376 Attribution of drivers of climate signals. As part of DAMIP, this activity has a 377 •
- Attribution of arivers of climate signals. As part of DAMIP, this activity has a strong interest in performing single-forcing simulations to enable understanding of different drivers and causes of the climate changes seen. Large ensembles have been shown to be successful in detecting and attributing changes, e.g., in recent southern hemisphere circulation changes to stratospheric ozone recovery (Banerjee et al., 2020). Similar techniques could be used here to separate the impacts of emissions reductions of GHGs and aerosols as explored in CanESM5 by Fyfe et al. (2021).
- Longer term implications of emissions reductions and options for economic
   recovery. Forster et al. (2020) compiled a set of hypothetical recovery scenarios

387	based on moderate or strong green stimulus packages or a fossil-fuel stimulus
388	rebound. The climate impacts by 2050 showed that how the world's economy
389	recovers after 2020 can have profound impacts on our ability to meet long-term
390	climate goals. Multi-model analysis of these simulations will enable clearer
391	understanding of the threats and opportunities arising from the current situation.
392	<i>Quantifying changes in extremes.</i> In addition to annual mean changes, the climate
393	response in terms of extremes – such as daily maximum or minimum
394	temperatures or daily precipitation rates – may also show important signals
395	(Seneviratne and Hauser, 2020).
396	Influence on atmospheric circulation. Studies have found a sensitivity of
397	monsoons to changes in emissions of aerosols (Meehl et al., 2008: Li et al., 2016:
398	Lau et al., 2017; Zhao et al., 2019). Analysis of these changes in a multi-model
399	study may be able to detect if COVID-19-related emissions reductions have had a
400	detectable impact on monsoon circulations, especially over Asia.
401 •	Response and impacts of atmospheric composition. The response of aerosols is
402	detectable in this ensemble, but we have not yet explored the role of other
403	chemically active components of the atmospheric composition. Especially, the
404	role of ozone and its response to changes in emissions of precursors, is a key
405	components of changes in air quality. Multiple studies have found increases in
406	ozone in populated urban areas during lockdown (e.g. Keller et al., 2020), in
407	contrast to a global decrease in tropospheric ozone (Weber et al., 2020). This MIP
408	provides an opportunity to shed process-level understanding on these changes in a
409	range of models of varying degrees of complexity with regards to atmospheric
410	chemistry.
<b>4</b> 11 •	Impact on the global carbon cycle. There is increasing interest in the ability to
412	make predictions from one year to the next of changes in atmospheric CO <sub>2</sub> (Betts
413	et al., 2016; Séférian et al., 2018; Lovenduski et al., 2019; Fransner et al., 2020;
414	Spring and Ilyina, 2020). These studies require knowledge of natural causes of
415	interannual variability – notable from ENSO (Watanabe et al., 2020), but they
416	also require knowledge of up to date estimates of anthropogenic CO <sub>2</sub> emissions.
417	These are normally expected to vary relatively little from year to year (Le Quéré
418	et al., 2018) but expected impacts from COVID-19-related emissions reductions
419	allow us to test out ability to forecast this most important metric of climate
420	change, and whether external forcing can affect its variability (McKinley et al.,
421	2020).

422

The SARS-Cov-2 pandemic of 2020 has created one of the biggest health and economic crises of recent history, but it also presents a remarkable opportunity to study how the climate system responds to changes in emissions of radiatively active species. From regional air quality to global climate this database of ESM outputs will enable advances in our understanding of how the climate system responds to short-term perturbations.

428

429

430

manuscript submitted to Geophysical Research Letters

## 432 Acknowledgments, Samples, and Data

## 433 Acknowledgements

C.D.J., P.N., R.S. acknowledge support from the European Union's Horizon 2020 research and 434 innovation programme under grant agreement No 641816 (CRESCENDO). R.D.L., P.M.F., J.R., 435 R.B.S., P.N., R.S. acknowledge support from the European Union's Horizon 2020 research and 436 innovation programme under grant agreement No 820829 (CONSTRAIN). E.T., T.I. and H.L. 437 acknowledge support from the European Union's Horizon 2020 research and innovation 438 programme under grant agreement No 821003 (4C). C.T. is supported from the Deutsche 439 Forschungsgemeinschaft DFG (FOR2820, TI 344/2-1). MPI-ESM simulations were performed at 440 the German Climate Computing Center (DKRZ). We acknowledge DKRZ colleague Martin 441 Schupfner for cmorizing and publishing the MPI-ESM model simulations. S.R. was funded by 442 the National Environmental Research Council (NERC) national capability grant for the UK Earth 443 System Modelling project, grant NE/N017951/1. M.W., H.W. and K.C. acknowledge support by 444 the U.S. Department of Energy (DOE), Office of Science, Office of Biological and 445 Environmental Research, Earth and Environmental System Modeling program as part of the 446 Energy Exascale Earth System Model (E3SM) project. The Pacific Northwest National 447 Laboratory (PNNL) is operated for DOE by Battelle Memorial Institute under contract DE-448 AC05-76RLO1830. N.O., T.K., and M.D. were supported by the Japan Society for the 449 Promotion of Science (grant numbers: JP18H03363, JP18H05292, JP19K12312, and 450 JP20K04070), the Environment Research and Technology Development Fund 451 452 (JPMEERF20202003 and JPMEERF20205001) of the Environmental Restoration and Conservation Agency of Japan, the Integrated Research Program for Advancing Climate Models 453 (TOUGOU) grant number JPMXD0717935561 from the Ministry of Education, Culture, Sports, 454 Science and Technology (MEXT), Japan, and the Arctic Challenge for Sustainability II (ArCS 455 II), Program Grant Number JPMXD1420318865. S.F. acknowledges funding for the Hans-Ertel-456 Centre for Weather Research "Climate Monitoring and Diagnostic" (ID: BMVI/DWD 457 458 4818DWDP5A, https://www.herz.uni-bonn.de) and the Collaborative Research Centre "Earth evolution at the dry limit" (ID: DFG 68236062, https://sfb1211.uni-koeln.de). D.O. and J. T. 459 acknowledge the Research Council of Norway funded projects INES (270061) and KeyClim 460 (295046). Simulations of MIROC-ES2L are supported by the TOUGOU project "Integrated 461 Research Program for Advancing Climate Models" (grant number: JPMXD0717935715) of the 462 Ministry of Education, Culture, Sports, Science, and Technology of Japan (MEXT). MIROC-463 team acknowledges JAMSTEC for use of the Earth Simulator supercomputer. Simulations of 464 UKESM1 and analysis of data were supported by the Joint UK BEIS/Defra Met Office Hadley 465 Centre Climate Programme (GA01101). We gratefully acknowledge help from Martine Michou 466 for setting up the model configuration used in this work and for processing of data from CNRM-467 ESM2-1. P.N., C.C. and R.S., thank the support of the team in charge of the CNRM-CM climate 468 model. Supercomputing time was provided by the Meteo-France/DSI supercomputing center. 469 Simulations of GISS-E2-1-G were supported by NASA's Rapid Response and Novel Research in 470 Earth Science program. Resources supporting this work were provided by the NASA High-End 471 Computing (HEC) Program through the NASA Center for Climate Simulation (NCCS) at 472 Goddard Space Flight Center. We gratefully acknowledge Susanne Bauer, Gregory Faluvegi, 473 Kenneth Lo, and Reto Ruedy for their assistance in preparing simulations and processing output. 474 Y.Y. acknowledges the National Key Research and Development Program of China (grant 475 2019YFA0606800 and 2020YFA0607803). S.Y. acknowledges support from the Danish 476 National Centre for Climate Research (Nationalt Center for Klimaforskning, NCKF). This work 477

- used JASMIN, the UK's collaborative data analysis environment (<u>http://jasmin.ac.uk</u>, Lawrence
- et al., 2013). We are extremely grateful to the help and support of Martin Juckes, Alan Iwi, Ruth
- 480 Petrie, Ag Stephens, Charlotte Pascoe at the Centre for Environmental Data Analysis, Science
- and Technology Facilities Council, UK who facilitated the data sharing on JASMIN.
- 482

# 483 **Conflict of interest**

- 484 The authors declare no competing interests
- 485
- 486 **Data**
- 487 Model data is published on the CMIP6 archive available via the Earth System Grid Federation.
- 488 <u>https://esgf-index1.ceda.ac.uk/search/cmip6-ceda/</u>
- 489
- 490
- 491

#### 492 **References**

- Banerjee, A., Fyfe, J. C., Polvani, L. M., Waugh, D., and Chang, K. L. (2020). A pause in
  Southern Hemisphere circulation trends due to the Montreal Protocol. *Nature*.
  doi:10.1038/s41586-020-2120-4.
- Bao, R., and Zhang, A. (2020). Does lockdown reduce air pollution? Evidence from 44 cities in
  northern China. *Sci. Total Environ.* 731, 139052. doi:10.1016/j.scitotenv.2020.139052.
- Betts, R. A., Jones, C. D., Knight, J. R., Keeling, R. F., and Kennedy, J. J. (2016). El Nino and a
  record CO2 rise. *Nat. Clim. Chang.* 6, 806–810.
- Boysen, L. R., Brovkin, V., Pongratz, J., Lawrence, D. M., Lawrence, P., Vuichard, N., et al.
  (2020). Global climate response to idealized deforestation in CMIP6 models. *Biogeosciences* 17, 5615–5638. doi:10.5194/bg-17-5615-2020.
- Buchwitz, M., Reuter, M., Noël, S., Bramstedt, K., Schneising, O., Fuentes Andrade, B., et al.
  (2020). Can a regional-scale reduction of atmospheric CO 2 during the COVID-19
  pandemic be detected from space? A case study for East China using satellite XCO 2
  retrievals. *Atmos. Meas. Tech. Discuss.*
- Burrows, S. M., Maltrud, M., Yang, X., Zhu, Q., Jeffery, N., Shi, X., et al. (2020). The DOE
   E3SM v1.1 Biogeochemistry Configuration: Description and Simulated Ecosystem-Climate
   Responses to Historical Changes in Forcing. J. Adv. Model. Earth Syst. 12.
- 510 doi:10.1029/2019MS001766.
- Chang, Y., Huang, R. J., Ge, X., Huang, X., Hu, J., Duan, Y., et al. (2020). Puzzling Haze Events
  in China During the Coronavirus (COVID-19) Shutdown. *Geophys. Res. Lett.* 47, 1–11.
  doi:10.1029/2020GL088533.
- Chevallier, F., Zheng, B., Broquet, G., Ciais, P., Liu, Z., Davis, S. J., et al. (2020). Local
  anomalies in the column-averaged dry air mole fractions of carbon dioxide across the globe
  during the first months of the coronavirus recession. *Geophys. Res. Lett.*doi:10.1029/2020GL090244.
- Diamond, M. S., and Wood, R. (2020). Limited Regional Aerosol and Cloud Microphysical
   Changes Despite Unprecedented Decline in Nitrogen Oxide Pollution During the February
   2020 COVID-19 Shutdown in China. *Geophys. Res. Lett.* 47. doi:10.1029/2020GL088913.
- Fiedler, S., Wyser, K., Rogelj, J., and Noije, T. van (2020). Radiative effects of reduced aerosol
   emissions during the COVID-19 pandemic and the future recovery.
   doi:10.1002/ESSOAR.10504704.1.
- Field, R., Hickman, J., Geogdzhayev, I., Tsigaridis, K., and Bauer, S. (2020). Changes in satellite
   retrievals of atmospheric composition over eastern China during the 2020 COVID-19
   lockdowns. *Atmos. Chem. Phys. Discuss.* doi:10.5194/acp-2020-567.
- Filonchyk, M., Hurynovich, V., Yan, H., Gusev, A., and Shpilevskaya, N. (2020). Impact
  assessment of covid-19 on variations of so2, no2, co and aod over east China. *Aerosol Air Qual. Res.* 20, 1530–1540. doi:10.4209/aaqr.2020.05.0226.
- Forster, P. M., Forster, H. I., Evans, M. J., Gidden, M. J., Jones, C. D., Keller, C. A., et al.
  (2020). Current and future global climate impacts resulting from COVID-19. *Nat. Clim. Chang.* doi:https://doi.org/10.1038/s41558-020-0883-0.
- Fransner, F., Counillon, F., Bethke, I., Tjiputra, J., Samuelsen, A., Nummelin, A., et al. (2020).
  Ocean Biogeochemical Predictions—Initialization and Limits of Predictability. *Front. Mar. Sci.* 7. doi:10.3389/fmars.2020.00386.
- Fyfe, J.C., Kharin, V.V., Swart, N., Flato, G.M., Sigmond, M., Gillett, N. P. (2021). Quantifying
   the Influence of Short-term Emission Reductions on Climate. *Sci. Adv.* in press.

Gillett, N. P., Shiogama, H., Funke, B., Hegerl, G., Knutti, R., Matthes, K., et al. (2016). The 538 Detection and Attribution Model Intercomparison Project (DAMIP~v1.0) contribution to 539 CMIP6. Geosci. Model Dev. 9, 3685–3697. doi:10.5194/gmd-9-3685-2016. 540 Goldberg, D. L., Anenberg, S. C., Griffin, D., McLinden, C. A., Lu, Z., and Streets, D. G. 541 (2020). Disentangling the impact of the COVID-19 lockdowns on urban NO2 from natural 542 variability. Geophys. Res. Lett. doi:10.1029/2020GL089269. 543 Hajima, T., Watanabe, M., Yamamoto, A., Tatebe, H., Noguchi, M. A., Abe, M., et al. (2020). 544 Development of the MIROC-ES2L Earth system model and the evaluation of 545 biogeochemical processes and feedbacks. Geosci. Model Dev. 13, 2197-2244. 546 doi:10.5194/gmd-13-2197-2020. 547 Hurrell, J. W., Holland, M. M., Gent, P. R., Ghan, S., Kay, J. E., Kushner, P. J., et al. (2013). 548 The community earth system model: A framework for collaborative research. Bull. Am. 549 Meteorol. Soc. 94, 1339–1360. doi:10.1175/BAMS-D-12-00121.1. 550 Jones, C. D., and Cox, P. M. (2005). On the significance of atmospheric CO2 growth rate 551 anomalies in 2002-2003. Geophys. Res. Lett. 32. doi:10.1029/2005GL023027. 552 Kawamiya, M., Hajima, T., Tachiiri, K., Watanabe, S., and Yokohata, T. (2020). Two decades of 553 554 Earth system modeling with an emphasis on Model for Interdisciplinary Research on Climate (MIROC). Prog. Earth Planet. Sci. 7, 64. doi:10.1186/s40645-020-00369-5. 555 Keller, C. A., Evans, M. J., Knowland, K. E., Hasenkopf, C. A., Modekurty, S., Lucchesi, R. A., 556 557 et al. (2020). Global Impact of COVID-19 Restrictions on the Atmospheric Concentrations of Nitrogen Dioxide and Ozone. Atmos. Chem. Phys. Discuss., 1-32. 558 Lamboll, R. D., Jones, C. D., Skeie, R. B., Fiedler, S., Samset, B. H., Gillett, N. P., Rogelj, J., 559 and Forster, P. M. (2020). Modifying emission scenario projections to account for the 560 effects of COVID-19: protocol for Covid-MIP. Geosci. Model Dev. Discuss. 561 doi:doi.org/10.5194/gmd-2020-373. 562 Lau, W. K. M., Kim, K. M., Shi, J. J., Matsui, T., Chin, M., Tan, Q., et al. (2017). Impacts of 563 aerosol-monsoon interaction on rainfall and circulation over Northern India and the 564 Himalaya Foothills. Clim. Dyn. 49, 1945–1960. doi:10.1007/s00382-016-3430-y. 565 Lawrence, B. N., Bennett, V. L., Churchill, J., Juckes, M., Kershaw, P., Pascoe, S., et al. (2013). 566 Storing and manipulating environmental big data with JASMIN. in 2013 IEEE International 567 Conference on Big Data (IEEE), 68-75. doi:10.1109/BigData.2013.6691556. 568 Le Quéré, C., Andrew, R. M., Friedlingstein, P., Sitch, S., Hauck, J., Pongratz, J., et al. (2018). 569 570 Global Carbon Budget 2018. Earth Syst. Sci. Data 10, 2141–2194. doi:10.5194/essd-10-2141-2018. 571 Le Quéré, C., Jackson, R. B., Jones, M. W., Smith, A. J. P., Abernethy, S., Andrew, R. M., et al. 572 (2020). Temporary reduction in daily global CO2 emissions during the COVID-19 forced 573 confinement. Nat. Clim. Chang. 10, 647-653. doi:10.1038/s41558-020-0797-x. 574 Le, T., Wang, Y., Liu, L., Yang, J., Yung, Y. L., Li, G., et al. (2020). Unexpected air pollution 575 with marked emission reductions during the COVID-19 outbreak in China. Science (80-.). 576 369, 702-706. doi:10.1126/science.abb7431. 577 Li, Z., Lau, W. K. M., Ramanathan, V., Wu, G., Ding, Y., Manoj, M. G., et al. (2016). Aerosol 578 and monsoon climate interactions over Asia. Rev. Geophys. 54, 866-929. 579 doi:10.1002/2015RG000500. 580 Lian, X., Huang, J., Huang, R., Liu, C., Wang, L., and Zhang, T. (2020a). Impact of city 581 582 lockdown on the air quality of COVID-19-hit of Wuhan city. Sci. Total Environ. 742, 140556. doi:10.1016/j.scitotenv.2020.140556. 583

- Lian, X., Huang, J., Zhang, L., Liu, C., Liu, X., and Wang, L. (2020b). Environmental indicator
   for COVID-19 non-pharmaceutical interventions. *Geophys. Res. Lett.* doi:10.1029/2020GL090344.
- Liu, Z., Ciais, P., Deng, Z., Lei, R., Davis, S. J., Feng, S., et al. (2020). Near-real-time
   monitoring of global CO2 emissions reveals the effects of the COVID-19 pandemic. *Nat. Commun.* 11, 5172. doi:10.1038/s41467-020-18922-7.
- Lovenduski, N. S., Bonan, G. B., Yeager, S. G., Lindsay, K., and Lombardozzi, D. L. (2019).
   High predictability of terrestrial carbon fluxes from an initialized decadal prediction system.
   *Environ. Res. Lett.* 14. doi:10.1088/1748-9326/ab5c55.
- Mauritsen, T., Bader, J., Becker, T., Behrens, J., Bittner, M., Brokopf, R., et al. (2019).
  Developments in the MPI-M Earth System Model version 1.2 (MPI-ESM1.2) and Its
  Response to Increasing CO2. J. Adv. Model. Earth Syst. 11, 998–1038.
  doi:10.1029/2018MS001400.
- McKinley, G. A., Fay, A. R., Eddebbar, Y. A., Gloege, L., and Lovenduski, N. S. (2020).
  External Forcing Explains Recent Decadal Variability of the Ocean Carbon Sink. *AGU Adv*.
  1. doi:10.1029/2019AV000149.
- Meehl, G. A., Arblaster, J. M., and Collins, W. D. (2008). Effects of black carbon aerosols on the
   Indian monsoon. J. Clim. 21, 2869–2882. doi:10.1175/2007JCL11777.1.
- Menut, L., Bessagnet, B., Siour, G., Mailler, S., Pennel, R., and Cholakian, A. (2020). Impact of
   lockdown measures to combat Covid-19 on air quality over western Europe. *Sci. Total Environ.* 741, 140426. doi:10.1016/j.scitotenv.2020.140426.
- Michou, M., Nabat, P., Saint-Martin, D., Bock, J., Decharme, B., Mallet, M., et al. (2020).
  Present-Day and Historical Aerosol and Ozone Characteristics in CNRM CMIP6
  Simulations. J. Adv. Model. Earth Syst. 12. doi:10.1029/2019MS001816.
- Miyazaki, K., Bowman, K. W., Sekiya, T., Jiang, Z., Chen, X., Eskes, H., et al. (2020). Air
  quality response in China linked to the 2019 novel Coronavirus (COVID-19) mitigation. *Geophys. Res. Lett.* 47, e2020GL089252. doi:10.1029/2020GL089252.
- O'Neill, B. C., Tebaldi, C., van Vuuren, D. P., Eyring, V., Friedlingstein, P., Hurtt, G., et al.
  (2016). The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. *Geosci. Model Dev.* 9, 3461–3482. doi:10.5194/gmd-9-3461-2016.
- 614 Ordóñez, C., Garrido-Perez, J. M., and García-Herrera, R. (2020). Early spring near-surface 615 ozone in Europe during the COVID-19 shutdown: Meteorological effects outweigh
- emission changes. *Sci. Total Environ.* 747, 141322. doi:10.1016/j.scitotenv.2020.141322.
   Oshima, N., Yukimoto, S., Deushi, M., Koshiro, T., Kawai, H., Tanaka, T. Y., et al. (2020).
- Oshima, N., Yukimoto, S., Deushi, M., Koshiro, T., Kawai, H., Tanaka, T. Y., et al. (2020).
   Global and Arctic effective radiative forcing of anthropogenic gases and aerosols in MRI ESM2.0. *Prog. Earth Planet. Sci.* 7, 38. doi:10.1186/s40645-020-00348-w.
- Pincus, R., Forster, P. M., and Stevens, B. (2016). The Radiative Forcing Model Intercomparison
- Project (RFMIP): experimental protocol for CMIP6. *Geosci. Model Dev.* 9, 3447–3460.
  doi:10.5194/gmd-9-3447-2016.
- Samset, B. H., Fuglestvedt, J. S., and Lund, M. T. (2020). Delayed emergence of a global
  temperature response after emission mitigation. *Nat. Commun.* 11, 3261.
  doi:10.1038/s41467-020-17001-1.
- Séférian, R., Berthet, S., and Chevallier, M. (2018). Assessing the Decadal Predictability of Land
   and Ocean Carbon Uptake. *Geophys. Res. Lett.* 45, 2455–2466.
- 628 doi:10.1002/2017GL076092.
- 629 Séférian, R., Berthet, S., Yool, A., Palmiéri, J., Bopp, L., Tagliabue, A., et al. (2020). Tracking

Improvement in Simulated Marine Biogeochemistry Between CMIP5 and CMIP6. Curr. 630 Clim. Chang. Reports. doi:10.1007/s40641-020-00160-0. 631 Séférian, R., Nabat, P., Michou, M., Saint-Martin, D., Voldoire, A., Colin, J., et al. (2019). 632 Evaluation of CNRM Earth System Model, CNRM-ESM2-1: Role of Earth System 633 Processes in Present-Day and Future Climate. J. Adv. Model. Earth Syst. 11, 4182-4227. 634 doi:10.1029/2019MS001791. 635 Seland, Ø., Bentsen, M., Seland Graff, L., Olivié, D., Toniazzo, T., Gjermundsen, A., et al. 636 (2020). The Norwegian Earth System Model, NorESM2 - Evaluation of theCMIP6 DECK 637 and historical simulations. Geosci. Model Dev. Discuss., 1-68. doi:10.5194/gmd-2019-378. 638 Sellar, A. A., Jones, C. G., Mulcahy, J., Tang, Y., Yool, A., Wiltshire, A., et al. (2019). 639 640 UKESM1: Description and evaluation of the UK Earth System Model. J. Adv. Model. Earth Syst. n/a. doi:10.1029/2019MS001739. 641 Seneviratne, S. I., and Hauser, M. (2020). Regional Climate Sensitivity of Climate Extremes in 642 CMIP6 Versus CMIP5 Multimodel Ensembles. Earth's Futur. 8. 643 doi:10.1029/2019EF001474. 644 Sicard, P., De Marco, A., Agathokleous, E., Feng, Z., Xu, X., Paoletti, E., et al. (2020). 645 Amplified ozone pollution in cities during the COVID-19 lockdown. Sci. Total Environ. 646 735, 139542. doi:10.1016/j.scitotenv.2020.139542. 647 Silver, B., He, X., Arnold, S. R., and Spracklen, D. V. (2020). The impact of COVID-19 control 648 649 measures on air quality in China. Environ. Res. Lett. 15. doi:10.1088/1748-9326/aba3a2. Skeie, R. B., Myhre, G., Hodnebrog, Ø., Cameron-Smith, P. J., Deushi, M., Hegglin, M. I., et al. 650 (2020). Historical total ozone radiative forcing derived from CMIP6 simulations. npj Clim. 651 Atmos. Sci. 3, 32. doi:10.1038/s41612-020-00131-0. 652 Spring, A., and Ilyina, T. (2020). Predictability Horizons in the Global Carbon Cycle Inferred 653 From a Perfect-Model Framework. Geophys. Res. Lett. 47. doi:10.1029/2019GL085311. 654 Stevens, B., Fiedler, S., Kinne, S., Peters, K., Rast, S., Müsse, J., et al. (2017). MACv2-SP: a 655 parameterization of anthropogenic aerosol optical properties and an associated Twomey 656 effect for use in CMIP6. Geosci. Model Dev. 10, 433–452. doi:10.5194/gmd-10-433-2017. 657 Sussmann, R., and Rettinger, M. (2020). Can we measure a COVID-19-related slowdown in 658 atmospheric CO2 growth? Sensitivity of total carbon column observations. *Remote Sens.* 659 12, 2387. doi:10.3390/RS12152387. 660 Swart, N. C., Cole, J. N. S., Kharin, V. V., Lazare, M., Scinocca, J. F., Gillett, N. P., et al. 661 662 (2019). The Canadian Earth System Model version 5 (CanESM5.0.3). Geosci. Model Dev. 12, 4823–4873. doi:10.5194/gmd-12-4823-2019. 663 Tebaldi et al (2020). Climate model projections from the Scenario Model Intercomparison 664 Project (ScenarioMIP) of CMIP6. doi:doi.org/10.5194/esd-2020-68. 665 Thornhill, G., Collins, W., Olivié, D., Archibald, A., Bauer, S., Checa-Garcia, R., et al. (2020). 666 Climate-driven chemistry and aerosol feedbacks in CMIP6 Earth system models. Atmos. 667 Chem. Phys., 1-36. doi:10.5194/acp-2019-1207. 668 Tjiputra, J. F., Schwinger, J., Bentsen, M., Morée, A. L., Gao, S., Bethke, I., et al. (2020). Ocean 669 biogeochemistry in the Norwegian Earth System Model version 2 (NorESM2). Geosci. 670 671 Model Dev. 13, 2393–2431. doi:10.5194/gmd-13-2393-2020. 672 Tohjima, Y., Patra, P. K., Niwa, Y., Mukai, H., Sasakawa, M., and Machida, T. (2020). Detection of fossil-fuel CO2 plummet in China due to COVID-19 by observation at 673 674 Hateruma. Sci. Rep., 1-9. doi:10.1038/s41598-020-75763-6. Turner, A. J., Kim, J., Fitzmaurice, H., Newman, C., Worthington, K., Chan, K., et al. (2020). 675

- Observed impacts of COVID-19 on urban CO2 emissions. *Geophys. Res. Lett.*, 2–10.
  doi:10.1029/2020GL090037.
- Venter, Z. S., Aunan, K., Chowdhury, S., and Lelieveld, J. (2020). COVID-19 lockdowns cause
  global air pollution declines. *Proc. Natl. Acad. Sci. U. S. A.* 117, 18984–18990.
  doi:10.1073/pnas.2006853117.
- Wang, H., Easter, R. C., Zhang, R., Ma, P., Singh, B., Zhang, K., et al. (2020a). Aerosols in the
  E3SM Version 1: New Developments and Their Impacts on Radiative Forcing. J. Adv. *Model. Earth Syst.* 12. doi:10.1029/2019MS001851.
- Wang, P., Chen, K., Zhu, S., Wang, P., and Zhang, H. (2020b). Severe air pollution events not
   avoided by reduced anthropogenic activities during COVID-19 outbreak. *Resour. Conserv. Recycl.* 158, 104814. doi:10.1016/j.resconrec.2020.104814.
- Watanabe, M., Tatebe, H., Koyama, H., Hajima, T., Watanabe, M., and Kawamiya, M. (2020).
  Importance of El Niño reproducibility for reconstructing historical CO2 flux variations in the equatorial Pacific. *Ocean Sci.* 16, 1431–1442. doi:10.5194/os-16-1431-2020.
- Weber, J., Shin, Y. M., Sykes, J. S., and Archer-nicholls, S. (2020). Minimal climate impacts
   from short-lived climate forcers following emission reductions related to the COVID-19
   pandemic. *Geophys. Res. Lett.* doi:10.1029/2020GL090326.
- Ku, K., Cui, K., Young, L. H., Hsieh, Y. K., Wang, Y. F., Zhang, J., et al. (2020). Impact of the
  COVID-19 event on air quality in central China. *Aerosol Air Qual. Res.* 20, 915–929.
  doi:10.4209/aaqr.2020.04.0150.
- Yang, Y., Ren, L., Li, H., Wang, H., Wang, P., Chen, L., et al. (2020). Fast Climate Responses to
   Aerosol Emission Reductions During the COVID-19 Pandemic. *Geophys. Res. Lett.* 47.
   doi:10.1029/2020GL089788.
- YUKIMOTO, S., KAWAI, H., KOSHIRO, T., OSHIMA, N., YOSHIDA, K., URAKAWA, S.,
   et al. (2019). The Meteorological Research Institute Earth System Model Version 2.0, MRI ESM2.0: Description and Basic Evaluation of the Physical Component. J. Meteorol. Soc.
   Japan. Ser. II 97, 931–965. doi:10.2151/jmsj.2019-051.
- Zangari, S., Hill, D. T., Charette, A. T., and Mirowsky, J. E. (2020). Air quality changes in New
  York City during the COVID-19 pandemic. *Sci. Total Environ.* 742, 140496.
  doi:10.1016/j.scitotenv.2020.140496.
- Zhao, A. D., Stevenson, D. S., and Bollasina, M. A. (2019). The role of anthropogenic aerosols
  in future precipitation extremes over the Asian Monsoon Region. *Clim. Dyn.* 52, 6257–
  6278. doi:10.1007/s00382-018-4514-7.
- Zhao, Y., Zhang, K., Xu, X., Shen, H., Zhu, X., Zhang, Y., et al. (2020). Substantial Changes in
  Nitrogen Dioxide and Ozone after Excluding Meteorological Impacts during the COVID-19
  Outbreak in Mainland China. *Environ. Sci. Technol. Lett.* 7, 402–408.
- 712 doi:10.1021/acs.estlett.0c00304.
- Ziehn, T., Chamberlain, M. A., Law, R. M., Lenton, A., Bodman, R. W., Dix, M., et al. (2020).
  The Australian Earth System Model: ACCESS-ESM1.5. *J. South. Hemisph. Earth Syst. Sci.* doi:10.1071/es19035.
- 716
- 717
- 718
- 719

#### 720 Table 1. List of participating models, their main properties and number of ensemble members used in this study.

Model name	reference	Atmosphere resolution §	Ocean resolution §	ssp245- covid ensemble members	Aerosol processes #	Ozone forcing	Aerosol forcing
ACCESS- ESM1-5	Ziehn et al. (2020)	250km (N96), L38	100km, L50	30	5; CLASSIC	Prescribed <i>ssp245-covid</i> perturbation (Lamboll et al., 2020) *	interactive
CanESM5	Swart et al. (2019)	500km (T63), L49	100km, L45	50	5; Parameterized using a prognostic scheme for bulk concentrations	Prescribed <i>ssp245-covid</i> perturbation (Lamboll et al., 2020) *	interactive
CESM1	Hurrell et al. (2013)	250km (1.9x2.5), L30	100km (gx1v6), L60	10	6; MAM4	Prescribed without ssp245- covid perturbation	interactive
CNRM-ESM2-1	Séférian et al. (2019)	250km (TL127,1.4°) , L91	100km (eORCA1), L75	100	5; TACTIC (Michou et al., 2020)	Interactive above 560 hPa, prescribed below (Michou et al., 2020)	interactive
E3SM-1-1	Burrows et al. (2020)	100km (NE30), L72	60-30 km, L100	10	7; MAM4 (Wang et al., 2020a)	Prescribed without ssp245- covid perturbation	interactive
EC-Earth3		100km (T255), L91	100km (eORCA1), L75	30	n/a	Prescribed <i>ssp245-covid</i> perturbation (Lamboll et al., 2020)	MACv2-SP (Fiedler et al., 2020)
MIROC-ES2L	Hajima et al. (2020); Kawamiya et al. (2020)	500km (T42), L40	100km (360x256), L63	30	5; SPRINTARS	Prescribed <i>ssp245-covid</i> perturbation (Lamboll et al., 2020)	interactive
MPI-ESM1-2- LR	Mauritsen et al. (2019)	250km (T63), L47	150km, L40	10	n/a	Prescribed <i>ssp245-covid</i> perturbation (Lamboll et al., 2020)	MACv2-SP (Fiedler et al., 2020)
MRI-ESM2-0	Yukimoto et al. (2019); Oshima et al. (2020)	100km (TL159, 1.125°), L80	100km (tripolar 1° x 0.3° -0.5°), L61	10	5; MASINGAR mk-2r4c	interactive	interactive
GISS-E2-1-G	Kelley et al., 2020; Ito et al., 2020; Bauer et al., 2020	250km (2x2.5°), L40	100km (1x1.25°), L40	10	8; MATRIX	interactive	interactive

NorESM2-LM	Seland et al. (2020); Tjiputra et al. (2020)	250km (1.9° x 2.5°), L32	100km, L53	10	5; OsloAero6	Prescribed without ssp245- covid perturbation	interactive
UKESM1-0-LL	Sellar et al. (2019)	250km (N96), L85	100km (eORCA1), L75	16	5; UKCA MODE	interactive	interactive

721

522 § shown as CMIP "nominal resolution" in km, "L" denotes number of vertical levels. Grid name or information provided if available.

723 # number of aerosol species, and name/description of aerosol sub-model

\* These models used the first version of the ozone fields that had a small bug in the vertical interpolation of the ozone perturbation, stretching the ozone

perturbation to too high altitudes. The models weres not able to re-run the model simulations with the corrected ozone fields. Radiative kernel calculations

following Skeie et al. (2020) gave 0.6 mWm<sup>-2</sup> stronger total ozone radiative forcing in 2020 for the corrected fields compared to the incorrect ozone fields, that

are small compared to the total ozone radiative forcing of  $-37 \text{ mWm}^{-2}$  for *ssp245-covid* relative to *ssp245* in 2020.