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Supporting information for

The Contribution of Emission Sources to the Future Air Pollution Disease Burden in China

Luke Conibear*[,1], Carly L. Reddington[1], Ben J. Silver[1], Stephen R. Arnold[1], Steven T. Turnock[2,3], Zbigniew Klimont[3], and Dominick V. Spracklen[1]

[1] Institute for Climate and Atmospheric Science, School of Earth and Environment, University of Leeds, Leeds, UK

[2] Met Office Hadley Centre, Exeter, UK

[3] University of Leeds Met Office Strategic (LUMOS) Research Group, School of Earth and Environment, University of Leeds, UK

[4] International Institute for Applied Systems Analysis, Laxenburg, Austria

* Corresponding author: Luke Conibear (L.A.Conibear@leeds.ac.uk)

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Additional Supporting Information (Files uploaded separately)

The trained emulators per grid cell in China that support the findings of this study are available in Conibear *et al* (2022a).

Supplementary Methods

Emulators and simulators of air quality

The version of WRFChem used here (version 3.7.1) was described and evaluated in our previous work (Reddington *et al* 2019, Silver *et al* 2020, Conibear *et al* 2021b, 2021a).

We developed separate emulators for each grid cell across China in our WRFChem (Weather Research and Forecasting model online–coupled with Chemistry) domain. Hence, the emulators provided spatial information of air quality across China. The emulators were trained on data from 50 separate annual WRFChem simulations, and independently tested on 5 separate years of data. Simulations were selected to train and test the emulators across the entire parameter space of inputs. Each simulation was identical apart from having different fractional changes in anthropogenic emissions. The fractional changes for each sector were determined from separate maxi−min Latin hypercube space–filling designs for the training and test data (Conibear *et al* 2022b).

Each simulation was for the whole of 2015 with one–month spin–up. The domain covered the whole of China at 30 km × 30 km horizontal resolution. The anthropogenic emissions in China were from the MEIC (Multi–resolution Emission Inventory for China) emission inventory for 2015 at 0.25° × 0.25° horizontal resolution (Li *et al* 2017b, MEIC Research Group and Tsinghua University 2019, Zheng *et al* 2018, Li *et al* 2017a). Gas phase chemistry was simulated using the extended MOZART (Model for Ozone and Related Chemical Tracers) scheme (Emmons *et al* 2010, Knote *et al* 2014, Hodzic and Jimenez 2011). Aerosol physics and chemistry was simulated using the updated MOSAIC (Model for Simulating Aerosol Interactions and Chemistry) scheme with aqueous chemistry (Hodzic and Knote 2014, Zaveri *et al* 2008). Secondary organic aerosol (SOA) formation was based on an updated volatility basis set mechanism (Knote *et al* 2015).

To provide the closest match with observations, we scaled the emulated fine particulate matter ($PM_{2.5}$) and ozone (O_3) concentrations to measurements (Silver *et al* 2018, Jin *et al* 2020). Scalings were applied by prefecture if observations were available, otherwise scalings were applied by province (administrative division). The scaling was applied to all emulators to allow us to accurately predict the spatial pattern and magnitude of $PM_{2.5}$ (annual−mean) concentrations and O_3 (maximum 6−monthly−mean daily−maximum 8−hour, 6mDM8h) concentrations across China.

Compared to measurements, the simulators had low bias and error for both annual−mean $PM_{2.5}$ concentrations (normalised mean bias factor, NMBF = 0.02 and normalised mean absolute error factor, NMAEF = 0.10) and 6mDM8h O_3 concentrations (NMBF = 0.03 and NMAEF = 0.11). The emulators were then independently evaluated on the unseen test simulations from WRFChem to predict air quality concentrations from only emission changes. The emulators accurately predicted the unseen simulated test data, with a coefficient of determination (R^2) value for both $PM_{2.5}$ and O_3 concentrations of 0.999. These evaluations showed that the simulators accurately represented the spatial pattern and magnitude of measured $PM_{2.5}$ and O_3 concentrations across China, and that the emulators accurately predicted the simulator. The emulators are detailed in full in Conibear *et al* (2022c).

These outputs were chosen as they are the metrics used in the health impact assessment.

The emulators do not account for any future changes in the O_3 chemical regime due to emission changes.

Future emission scenarios

The ECLIPSE (Evaluating the Climate and Air Quality Impacts of Short–Lived Pollutants) scenarios are state−of−the−art scenarios for future global emissions (Klimont *et al* 2022, 2017, Stohl *et al* 2015). The ECLIPSEv6b emissions were produced using the GAINS (Greenhouse gas – Air pollution Interactions and Synergies) model (Amann *et al* 2011, Klimont *et al* 2017, Höglund−Isaksson *et al* 2020). Detailed descriptions of the ECLIPSEv6b emissions were provided by Höglund−Isaksson *et al* (2020) for methane and Klimont *et al* (2022) for other species.

These scenarios include activity projections from the World Energy Outlook (WEO) 2018 (International Energy Agency 2018). These activity projections combine various short−term activities, such as the Three–Year Action Plan in China, alongside possible long−term future projections of energy use, demand, and activity.

The baseline (BASE) activity projections were developed with the GAINS (Greenhouse gas – Air pollution Interactions and Synergies) model (Amann *et al* 2011) and draw on the WEO 2018 New Policy Scenario (NPS) energy projections (International Energy Agency 2018). The BASE activity projections included the proposed national energy programs, the commitments of the NDCs, the Three–Year Action Plan in China (Ministry of Environmental Protection of China 2018), and the Clean Heating Plan for North China (Ministry of Environmental Protection of China 2017). The BASE activity projections included China's plans for growth in gas demand, a reduction in coal demand, and an increase in electricity demand and energy efficiency. The Three–Year Action Plan required emission reductions of 15% in sulphur dioxide (SO_2), 15% in nitrogen oxides (NO_X), and 10% in volatile organic compounds (VOCs). The Three–Year Action Plan required all cities that exceeded the National Air Quality Standard (35 $\mu g\ m^{-3}$) for annual–mean $PM_{2.5}$ concentrations in 2015 to achieve 18% reductions by 2020. The projected carbon dioxide (CO_2) emissions under the BASE activity projections were comparable to Shared Socioeconomic Pathways (SSP) 2–4.5 (Eyring *et al* 2016, Riahi *et al* 2017). Agricultural forecasts in the BASE activity projections were derived from the United Nations Food and Agriculture Organization (Alexandratos and Bruinsma 2012) and from the European Union (EU) funded First Clean Air Outlook for the EU 28 countries (European Commission 2019).

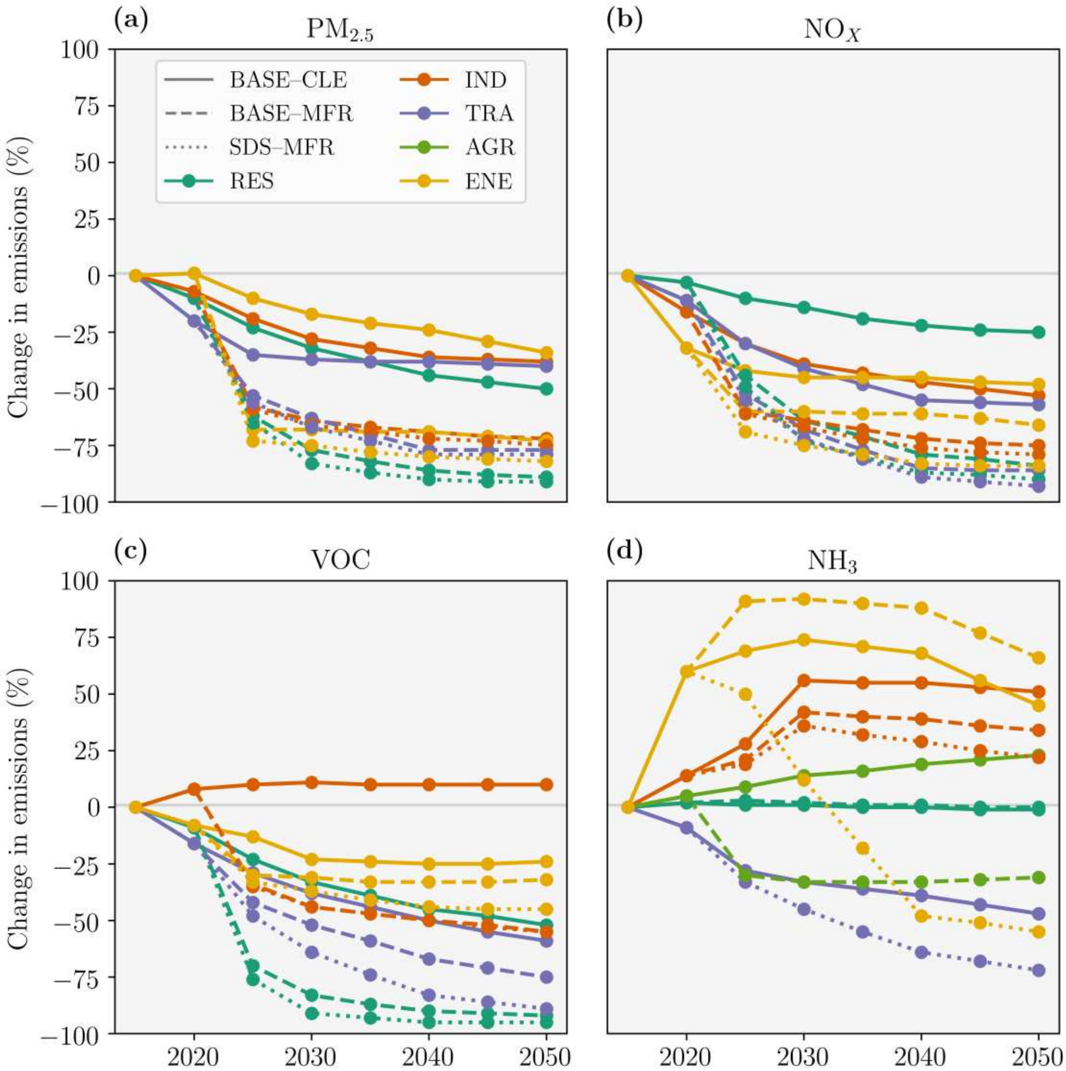
The sustainable development (SDS) activity projections were developed with the GAINS model and adapted the SDS energy scenario from the WEO 2018 (International Energy Agency 2018). The SDS activity projections included China's plans for substantial reductions in coal demand, with increases in land transport electrification, nuclear energy, renewables, carbon capture and storage, and of the emissions trading scheme. The actions to tackle climate change were for energy–related CO_2 emissions to peak and decline in line with the Paris Agreement objectives and to be consistent with a global average temperature rise of 1.7–1.8 °C. The SDS activity projection focused on the energy–related components of the Sustainable Development Goals (SDGs). The energy–related components of the Sustainable Development Goals (SDGs) included tackling climate change (SDG 13), universal access to clean cooking and electricity (SDG 7), and substantial reductions in the disease burdens from ambient and household air pollution exposure (SDG 3). The projected CO_2 emissions under the SDS activity projections were comparable to SSP1–2.6 (Eyring *et al* 2016, Riahi *et al* 2017). Forecasts of agricultural activities were the same as in the BASE activity projections.

There were two air pollution storylines applied to the BASE activity projection and one to the SDS activity projection (Supplementary Table 1). The current legislation (CLE) air pollution storyline assumes effective implementation of the currently committed environmental policies, and for China included the Three–Year Action Plan and the Clean Heating Plan. The maximum technically feasible reduction (MFR) air pollution storyline assumes the introduction of the best air pollutant reduction measures, considering constraints on how quickly measures achieve high market penetration, but were unconstrained by costs. Examples of the best available technologies for air pollution include selective catalytic/noncatalytic reduction, electrostatic precipitators, flue gas desulphurisation, stringent emission limit values for road and non−road vehicles, and improved nitrogen fertiliser use efficiency. Further discussion of the CLE and MFR assumptions and implementations in the GAINS model can be found in Amann *et al* (2013), Klimont *et al* (2022), and Höglund−Isaksson *et al* (2020). The global gridded emission datasets for the air pollutants from these scenarios are available from the dedicated website: iiasa.ac.at/web/home/research/researchPrograms/air/ECLIPSEv6b.html.

Supplementary Table 1: Summary of the future emission scenarios. Emissions were from ECLIPSE (Evaluating the Climate and Air Quality Impacts of Short–Lived Pollutants) version 6b.

Scenario	Activity Projection	Air Pollution Storyline
BASE–CLE	Baseline (BASE).	Current legislation (CLE).
BASE–MFR	Baseline (BASE).	Maximum technically feasible reduction (MFR).
SDS–MFR	Sustainable development (SDS).	Maximum technically feasible reduction (MFR).

The inputs to the emulators were fractional changes in anthropogenic emissions per sector, averaged across all species. Averaging over all species was chosen for computational reasons. For 5 inputs, 55 annual WRFChem simulations were required for training and testing data (Loeppky *et al* 2009). If the emulators used emissions per specie and per sector, then the computational burden would increase by up to a factor of 10. The results were similar when averaging over a key few species (i.e., NO_X, VOC, ammonia (NH_3), and $PM_{2.5}$) compared to averaging over all species. Individual specie changes were different in a few cases, for example, future changes in industrial VOC emissions and NH_3 emissions increased in the BASE–CLE scenario, as opposed to the reduction over all species (Supplementary Figure 1). These changes could influence the non–linear formation of O_3. Future research of these scenarios in terms of both species and sectors would provide additional insight into air quality.



Supplementary Figure 1: Fractional emission changes in China from 2015 to 2050 under the baseline activity projection with current legislation air pollution storyline (BASE–CLE), baseline activity projection with maximum technically feasible reduction air pollution storyline (BASE–MFR), and sustainable development activity projection with maximum technically feasible reduction air pollution storyline (SDS–MFR). Emission changes per specie of **(a)** fine particulate matter ($PM_{2.5}$), **(b)** nitrogen oxides (NO_X), **(c)** volatile organic compounds (VOC), and **(d)** ammonia (NH_3). Emissions changes from the residential (RES), industrial (IND), land transport (TRA), agricultural (AGR), and power generation (ENE) sectors.

Health impact assessment

The disease burden attributable to $PM_{2.5}$ and O_3 exposure was estimated using population attributable fractions of relative risk. Exposure variations were used to predict associated outcome variations. The estimated outcome was annual premature mortality (MORT).

The outcome associated with $PM_{2.5}$ exposure was non−accidental mortality (non−communicable disease, NCD, plus lower respiratory infections, LRI). The Global Exposure Mortality Model (GEMM) model used parameters that included the China cohort. The GEMM is one of the leading methods for health impact assessment, in part because it incorporates ambient air pollution data across the majority of the global exposure range owing to the inclusion of the China cohort (Yin *et al* 2017). The counterfactual exposure level of no excess risk for $PM_{2.5}$ exposure was 2.4 μg m^{-3}. The outcome associated with O_3 exposure was chronic obstructive pulmonary disease (COPD). The counterfactual exposure level of no excess risk for O_3 exposure was 35.7 ppb. Baseline mortality was for NCD directly, with LRI being for respiratory infections from communicable disease, and COPD being for non−communicable respiratory disease.

The population count data was for the Shared Socioeconomic Pathways (SSP) 2 scenario (Jones and O'Neill 2016, 2020). Version 7.5.3 of the International Futures integrated modelling system was used for population age and baseline mortality rates (Frederick S. Pardee Center for International Futures 2021). Age groupings were for adults over 25 years of age in 5−year intervals. Population count was from a different data source to age groupings and baseline health rates due to data limitations. We ensured that population age and baseline health rates came from the same data source, as these two drivers have larger impacts on the air pollution disease burden relative to population count (see Figure 2b and 2d). Shapefiles were used to aggregate results at the country, province, and prefecture level (Hijmans *et al* 2020).

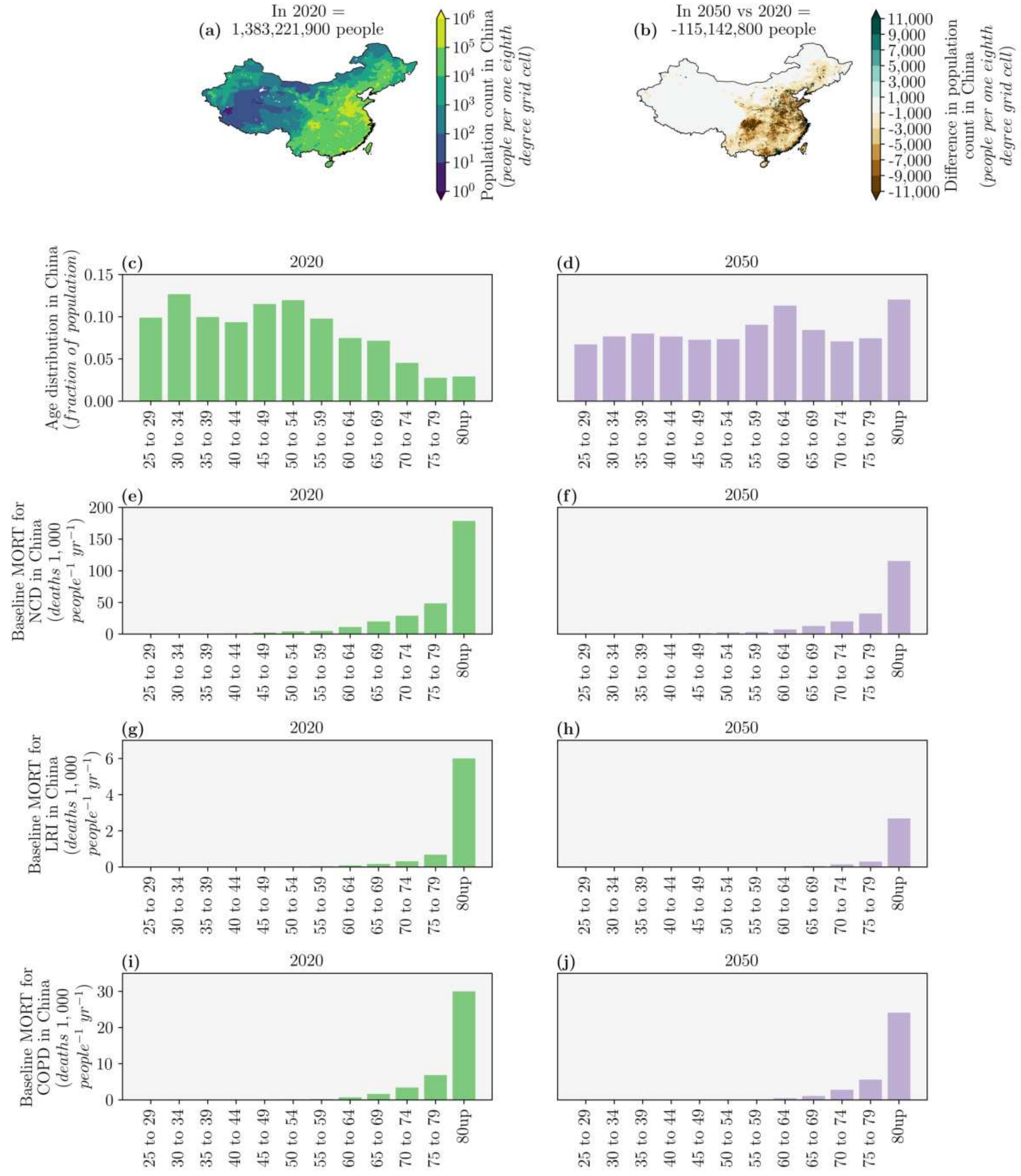
Uncertainty intervals at the 95% confidence level were estimated using the uncertainty intervals from the exposure−outcome associations. We acknowledge that other uncertainties exist, as we discuss below. However, it is common for health impact assessments to provide confidence intervals based on the given uncertainties in the exposure−outcome associations. The uncertainties between health impact assessments often do not overlap, in part because they use different exposure−outcome associations from independent epidemiological studies. Our 95% confidence interval estimates of the total air pollution disease burden were 8−9%. This is only slightly smaller than those from leading health impact assessments from the GEMM of 15−16% and from the Global Burden of Diseases, Injuries, and Risk Factors Study (GBD) of 18−19% (Burnett *et al* 2018, GBD 2019 Risk Factors Collaborators 2020).

Health impact assessments of the disease burden associated with air pollution exposure have many uncertainties (Nethery and Dominici 2019). Dedicated previous work has explored the current−day uncertainties in health impact assessments of total air pollution exposure in China (Giani *et al* 2020). This study quantified uncertainties in the three variables of $PM_{2.5}$ concentrations, baseline health rates, and exposure−outcome associations by sampling over assumed Gaussian distributions. They estimated that the total air pollution disease burden had 95% confidence intervals of 35−45%. However, it is unclear the uncertainties of these three variables are accurately captured by sampling Gaussian distributions. For example, annual $PM_{2.5}$ exposure was simulated using the simplified bulk aerosol scheme from GOCART (Global Ozone Chemistry Aerosol Radiation and Transport) (Chin *et al* 2000). This simplified scheme makes many assumptions relative to more sophisticated aerosol schemes, such as the updated sectional MOSAIC scheme with complex SOA formation mechanisms, as used in this study (Hodzic and Knote 2014, Zaveri *et al* 2008, Knote *et al* 2015).

There are many more uncertainties in health impact assessments, several of which are unquantifiable. These other uncertainties include ones in the scenarios (e.g., projections of future human action, future knowledge, future technologies), simulator (e.g., input data, parameterisations, grid aggregations, schemes of physics and chemistry, dynamical cores), exposure−outcome associations (e.g., confounding, induction, study variability, causality), generalisations (e.g., non−representative cohorts, population extrapolations), and population data (e.g., population count, age groupings). Future work should fully explore the quantifiable uncertainties in health impact assessments.

The population count, age groupings, and baseline health rates did not vary between the scenarios due to lack of data. The population count for the SSP1 was 3% smaller in China in 2050 compared to the SSP2. The air pollution disease burden is sensitive to population age and baseline health rates due to the influence on disease susceptibility (see Figure 2b and 2d). This study focused on the isolated impacts from emissions on air quality and human health. The full separation of drivers to the future air pollution disease burden should be explored in upcoming work.

There are large projected future changes in population and baseline health in China (Supplementary Figure 2). Over 2020−2050, the total population of China is projected to reduce by 8%. Urbanisation is projected to continue, with the percentage of people living in urban areas in China estimated to increase from 58% to 77% over 2017−2040 (International Energy Agency 2018). The population is projected to age substantially, with the percentage of the population over 60 increasing from 25% to 46% over 2020−2050. Baseline health rates are projected to improve considerably for non−communicable disease and lower respiratory infections, and slightly improve for chronic obstructive pulmonary disease. To explore the impacts of these changes on the future disease burden from air pollution exposure, we undertook sensitivity experiments where population count, population age groupings, and baseline mortality rates were kept at 2020 levels.



Supplementary Figure 2: Population count, age distributions, and baseline mortality rates in China from 2020 and 2050 (Frederick S. Pardee Center for International Futures 2021, Jones and O'Neill 2016, Jones and O'Neil 2020). Population count subplots are for **(a)** 2020 and **(b)** 2050 minus 2020. Age distribution subplots are for **(c)** 2020 and **(d)** 2050. Age−specific baseline mortality rate subplots are for **(e)** non−communicable disease (NCD) in 2020, **(f)** NCD in 2050, **(g)** lower respiratory infections (LRI) in 2020, **(h)** LRI in 2050, **(i)** chronic obstructive pulmonary disease (COPD) in 2020, and **(j)** COPD in 2050.

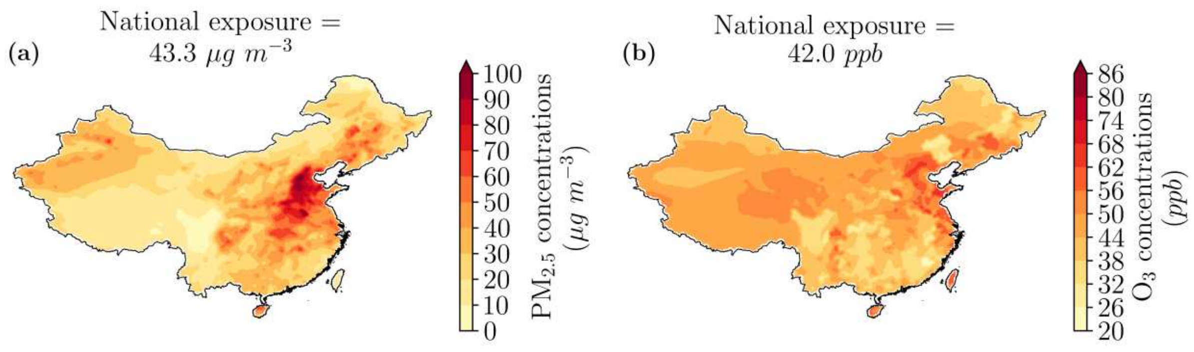
Sector−specific changes in the air pollution disease burden can either be calculated using the subtraction or attribution methods (Kodros *et al* 2016, Conibear *et al* 2018). The subtraction method estimates the change in the air pollution disease burden over time. The attribution method estimates the sector−specific contributions to the air pollution disease burden. In high−exposure regions, the sector−specific public health benefits from the subtraction method are smaller than those from the attribution method due to the non−linear exposure−outcome association for $PM_{2.5}$ concentrations (Kodros *et al* 2016, Conibear *et al* 2018). Here, we use the subtraction method to estimate the sector−specific change in the air pollution over time.

We did not calculate the household $PM_{2.5}$ disease burden and our estimates of the public health benefits from the residential sector are therefore likely underestimated given the major contribution of residential solid fuel emissions to total $PM_{2.5}$ exposure (Zhao *et al* 2018, Xing *et al* 2020).

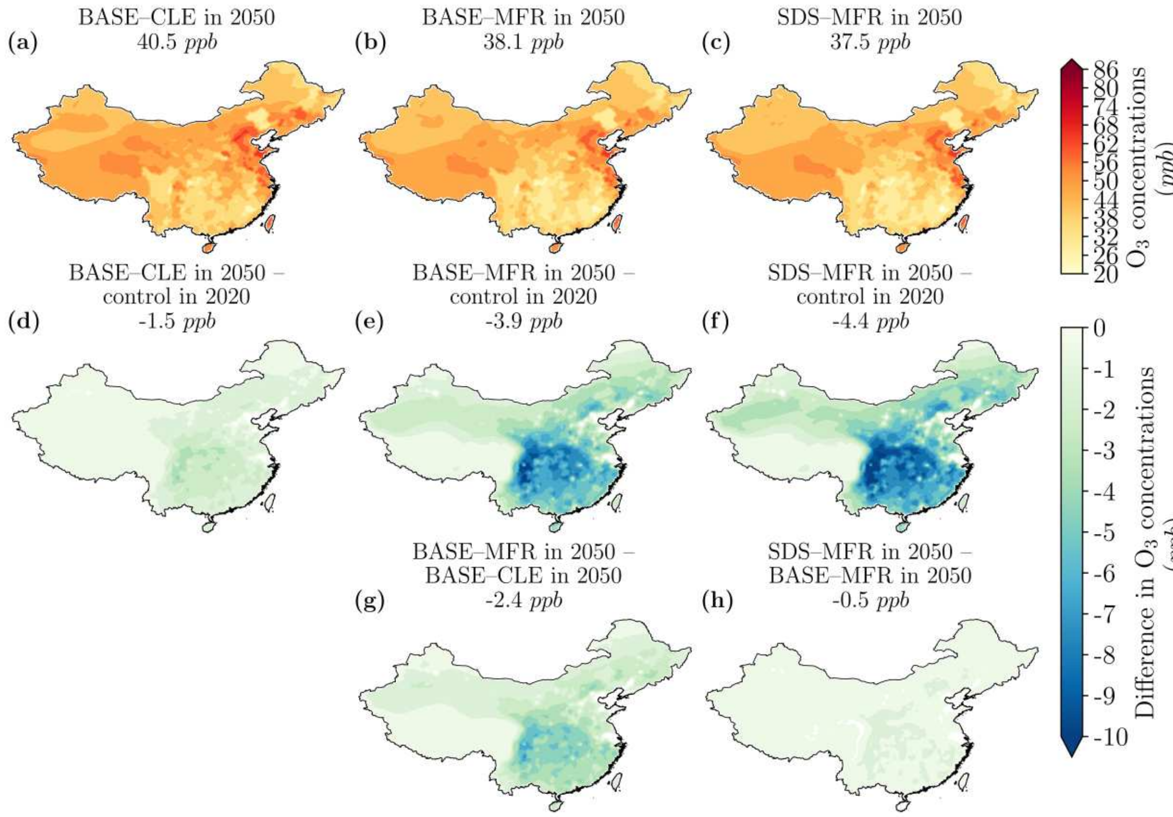
Supplementary Results

In the results and discussion, emulated $PM_{2.5}$ concentrations are ambient annual−means and emulated O_3 concentrations are ambient 6mDM8h. Exposures are population−weighted concentrations.

In 2020, O_3 exposure in China is 42.0 ppb (Supplementary Figure 3), attaining both the National Air Quality Target of 80 ppb and the 2021 WHO guideline of 50 ppb (World Health Organization 2021). Under the BASE–CLE scenario, O_3 exposure slightly reduces by 4% in 2050, down to 40.5 ppb (Supplementary Figure 4a). The BASE–MFR scenario reduces O_3 exposure by 9% in 2050, down to 38.1 ppb (Supplementary Figure 4b). The SDS–MFR scenario reduces O_3 exposure by 11% in 2050, down to 37.5 ppb (Supplementary Figure 4c). Despite the modest size of these air quality improvements, national O_3 exposure would then be close to the counterfactual exposure level no health risk (35.7 ppb). However, O_3 exposure remains high in some areas of China, for example, in Beijing O_3 exposure is 58.7 ppb.



Supplementary Figure 3: Control exposure in 2020 for (a) fine particulate matter ($PM_{2.5}$, annual−mean) and (d) ozone (O_3, maximum 6−monthly−mean daily−maximum 8−hour, 6mDM8h).



Supplementary Figure 4: The impacts of future emission scenarios on ozone (O_3, maximum 6−monthly−mean daily−maximum 8−hour, 6mDM8h) exposure in China from 2020 to 2050. Scenarios are the baseline activity projection with current legislation air pollution storyline (BASE–CLE), baseline activity projection with maximum technically feasible reduction air pollution storyline (BASE–MFR), and sustainable development activity projection with maximum technically feasible reduction air pollution storyline (SDS–MFR). Results are for **(a)** BASE–CLE in 2050, **(b)** BASE–MFR in 2050, **(c)** SDS–MFR in 2050, **(d)** BASE–CLE in 2050 minus the control in 2020, **(e)** BASE–MFR in 2050 minus the control in 2020, **(f)** SDS–MFR in 2050 minus the control in 2020, **(g)** BASE–MFR in 2050 minus BASE–CLE in 2050, and **(h)** SDS–MFR in 2050 minus BASE–MFR in 2050.

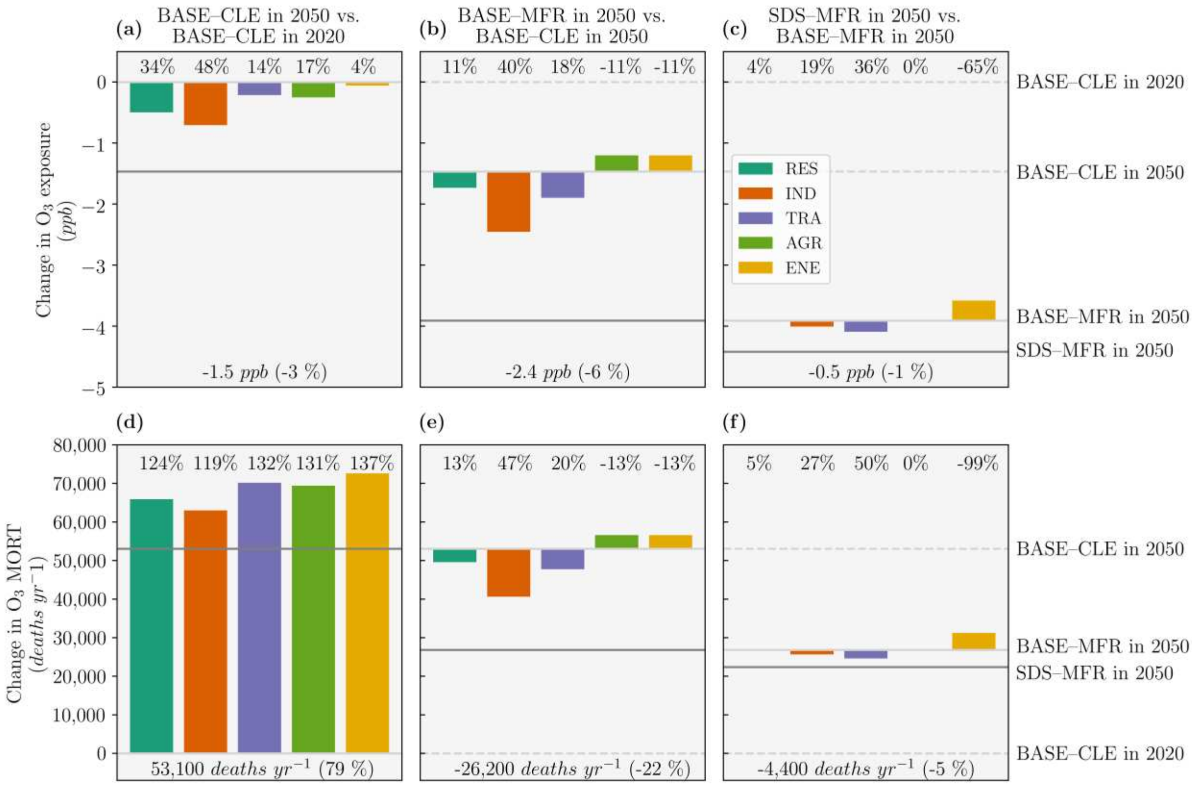
In 2020, the disease burden associated with O_3 exposure is 67,300 (95UI: 48,600–85,600) premature deaths per year (Figure 3d). Under the BASE–CLE scenario in 2050, the O_3 disease burden increases by 79%, an additional 53,100 (95UI: 38,300–67,500) premature deaths per year compared to 2020. This is despite the 3% reduction in O_3 exposure, and is driven by future population ageing significantly increasing the susceptibility to disease, with smaller improvements in baseline health for COPD. If the O_3 exposure reductions are isolated from all other changes (POPAGEBM2020), then the O_3 disease burden reduces by 13% in 2050, avoiding 8,600 (95UI: 6,200–10,900) premature deaths per year compared to 2020.

Compared to the BASE–CLE scenario in 2050, the BASE–MFR scenario reduces the O_3 disease burden by 22%, avoiding 26,200 (95UI: 19,000–33,300) premature deaths per year. Compared to the BASE–MFR scenario in 2050, the SDS–MFR scenario avoids 4,400 (95UI: 3,200–5,700) premature deaths per year. Relative to the baseline in 2020, the O_3 disease burden in 2050 increases by 40% under the BASE–MFR scenario and 33% under the SDS–MFR scenario, due to the large impacts from population ageing. The changes in O_3 disease burden are greater than the changes in O_3 exposure due to the high counterfactual exposure level of no excess risk (35.7 ppb). For example, O_3 exposure is 37.5 ppb in 2050 under the SDS–MFR scenario, where a further 5% reduction in exposure would remove 100% of the remaining disease burden.

Impacts of individual emission sectors on future air quality and public health

Under the BASE–CLE scenario, the 1.5 ppb reduction in O_3 exposure by 2050 is primarily from industrial (48%) and residential (34%) emissions (Supplementary Figure 5a). Under the BASE–MFR scenario, the further 2.4 ppb reduction in O_3 exposure by 2050 is mainly due to industrial (40%), land transport (18%), and residential (11%) emissions (Supplementary Figure 5b). Under the SDS–MFR scenario, the further 0.5 ppb reduction in O_3 exposure by 2050 is mainly due to land transport (36%) and industrial (19%) emissions (Supplementary Figure 5c).

Similar to the future $PM_{2.5}$ disease burden under the BASE–CLE scenario, projected population ageing substantially increases the O_3 disease burden beyond the impacts of individual emission sectors (Supplementary Figure 5d). This increase in disease susceptibility increases the O_3 disease burden by 53,100 (95UI: 38,300–67,500) premature deaths per year, which is partly offset from reductions in industrial and residential emissions. Under the BASE–MFR scenario, the reduction in O_3 disease burden by 26,200 (95UI: 19,000–33,300) premature deaths per year in 2050 is mainly due to industrial (47%), land transport (20%), and residential (13%) emissions (Supplementary Figure 5e). Under the SDS–MFR scenario, the further 4,400 (95UI: 3,200–5,700) avoided premature deaths per year from O_3 exposure in 2050 is mainly due to land transport (50%) and industrial (27%) emissions (Supplementary Figure 5f).



Supplementary Figure 5: The relative impacts of individual sector changes on **(a–c)** maximum 6−monthly−mean daily−maximum 8−hour (6mDM8h) ozone (O_3) exposure and **(d–f)** associated premature mortalities (MORT) from future emission scenarios in China. Scenarios are **(a and d)** the baseline activity projection with current legislation air pollution storyline (BASE–CLE) in 2050 compared to 2020, **(b and e)** the baseline activity projection with maximum technically feasible reduction air pollution storyline (BASE–MFR) in 2050 compared to BASE–CLE in 2050, and **(c and f)** the sustainable development activity projection with maximum technically feasible reduction air pollution storyline (SDS–MFR) in 2050 compared to BASE–MFR in 2050. The overall impact per scenario is shown by the horizontal lines and bottom estimates. The sector–specific impacts per scenario are shown by the top percentages.

Supplementary Discussion

The new knowledge that has been brought in by this study is the source–specific estimates to the future air pollution disease burden in China. These were across a range of projections from an updated version of the state–of–the–art ECLIPSE scenarios. These estimates were made possible by the novel machine learning emulators, which due to their low computational complexity, enabled much greater experimentation than numerical chemical transport models. Here, we compare our estimates of total air pollution exposure to relevant previous studies.

Recent studies of air quality exposure in China for 2019 vary in their estimates of $PM_{2.5}$ exposure between 33−48 μg m^{-3} and O_3 exposure between 48−69 ppb (Health Effects Institute 2020, Silver *et al* 2020, Zhang *et al* 2019, Liang *et al* 2020, Huang *et al* 2021, Yue *et al* 2020, Geng *et al* 2021b, Ma *et al* 2019, Zhai *et al* 2019, Kong *et al* 2021, Xue *et al* 2019, McDuffie *et al* 2021, Geng *et al* 2021a, Lu *et al* 2020). Our estimates of 43.3 μg m^{-3} for $PM_{2.5}$ exposure and 42.0 ppb for O_3 exposure in 2020 are similar to these previous studies.

The differences between our estimates and previous studies are likely due, in large part, to the different exposure estimation methods, scenarios, and health impact assessment methods, which are difficult to separate out. For example, Xing *et al* (2020) and Cheng *et al* (2021) both estimated emission projections using an Integrated Assessment Model (GCAM–China, Global Climate Assessment Model) and estimated exposure using WRF–CMAQ (Community Multiscale Air Quality). However, Xing *et al* (2020) tuned their Integrated Assessment Model with a bottom–up emission inventory, while Cheng *et al* (2021) incorporated a technology–based emission projection model (DPEC, Dynamic Projection for Emission in China) with hindcast $PM_{2.5}$ datasets, and both had different configurations for WRF–CMAQ. The GBD MAPS Working Group (2016) considered emissions projections from a 2012 baseline, before the legislation of the Three–Year Action Plan and the nationally determined contributions (NDCs), and estimated future exposure from scaling satellite–derived $PM_{2.5}$ concentrations by GEOS–Chem (Goddard Earth Observing System) simulations. For disease burden estimates, Li *et al* (2019b) used older exposure–outcome associations from the GBD 2013 Risk Factors Collaborators (2015) and Xie *et al* (2018) used linear exposure–outcome associations, in addition to other differences in estimation methods for emissions and exposure.

Our baseline $PM_{2.5}$ disease burden for 2020 is 4% larger than Conibear *et al* (2021d), due to the increased burden from larger baseline mortality rates and more recent estimates, partially offset by a decreased burden from scaling down simulated exposure to match measurements.

The air quality impacts from future climate change are likely to be smaller than those from emission changes. For example, Hong *et al* (2019) found that future climate change increased $PM_{2.5}$ exposure by 3% and O_3 exposure by 4% over 2010–2050, mainly due to changes in atmospheric stagnation and heat waves. Horton *et al* (2014) found that the air quality impacts from future changes in air stagnation in China primarily emerge after 2080. These air quality impacts from climate change are substantially smaller than the impacts from changes in emissions or population ageing (greater than 50%).

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