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LETTER

The contribution of emission sources to the future air pollution disease burden in China

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Abstract

Air pollution exposure is a leading public health problem in China. Despite recent air quality improvements, fine particulate matter ($PM_{2.5}$) exposure remains large, the associated disease burden is substantial, and population ageing is projected to increase the susceptibility to disease. Here, we used emulators of a regional chemical transport model to quantify the impacts of future emission scenarios on air pollution exposure in China. We estimated how key emission sectors contribute to these future health impacts from air pollution exposure. We found that $PM_{2.5}$ exposure declines in all scenarios across China over 2020–2050, with reductions of 15% under current air quality legislation, 36% when exploiting the full potential of air pollutant emission reduction technologies, and 39% when that technical mitigation potential is combined with emission controls for climate mitigation. However, population ageing means that the $PM_{2.5}$ disease burden under current legislation (CLE) increases by 17% in 2050 relative to 2020. In comparison to CLE in 2050, the application of the best air pollution technologies provides substantial health benefits, reducing the $PM_{2.5}$ disease burden by 16%, avoiding 536 600 (95% uncertainty interval, 95UI: 497 800–573 300) premature deaths per year. These public health benefits are mainly due to reductions in industrial (43%) and residential (30%) emissions. Climate mitigation efforts combined with the best air pollution technologies leads to an additional 2% reduction in the $PM_{2.5}$ disease burden, avoiding 57 000 (95UI: 52 800–61 100) premature deaths per year. Up to 90% of the 2020–2050 reductions in $PM_{2.5}$ exposure are already achieved by 2030, assuming efficient implementation and enforcement of currently committed air quality policies in key sectors. Achieving reductions in $PM_{2.5}$ exposure and the associated disease burden after 2030 will require further tightening of emission limits for regulated sectors, addressing other sources including agriculture and waste management, and international coordinated action to mitigate air pollution across Asia.

1. Introduction

Air pollution exposure is a leading cause of the loss of life in China (GBD 2019 Risk Factors Collaborators 2020, Yin *et al* 2020, Cai *et al* 2021). Measured ambient fine particulate matter ($PM_{2.5}$) concentrations across China have decreased by 26% over 2015–2020, from 48.1 to 35.4 $\mu g\ m^{-3}$ (Silver *et al* 2018, 2020a, 2020b, Conibear *et al* 2022c). These recent reductions in $PM_{2.5}$ concentrations have provided large public health benefits that have mainly been attributed to decreasing anthropogenic emissions (Ministry of Environmental Protection of China 2013, Jiang *et al* 2015, Zheng *et al* 2017, Guo *et al* 2018, Huang *et al* 2018, Zheng *et al* 2018, Cheng *et al* 2019, Ding *et al* 2019, Li *et al* 2019a, Silver *et al* 2020a). However, despite these recent improvements, $PM_{2.5}$ exposure remains high across China, exceeding the National Air Quality Standard (NAQT) (35 μg m^{-3}) in many areas, and the loss of healthy life from air pollution exposure remains substantial (Conibear *et al* 2022b). Over this same time frame, some air pollutant concentrations have increased, for example, ozone (O_3) (Silver *et al* 2018, 2020b). Population ageing is projected to increase the disease susceptibility from air pollution exposure in China (Rafaj *et al* 2021). Future reductions in the disease burden will require large improvements in air quality to offset the impacts from population ageing (Yue *et al* 2020).

These air quality improvements can be achieved by reducing air pollutant emissions either through the application of dedicated mitigation technologies (e.g. filters, scrubbers, catalysts) or as a co-benefit of climate policy (e.g. reducing fossil fuel use, improving clean energy access, improving efficiency) (Amann *et al* 2020). Some measures could provide large benefits to both air quality and climate. For example, replacing residential solid fuels with clean electricity could reduce emissions of both air pollutants and greenhouse gases (Cai *et al* 2021). The public health benefits from air quality improvements are often local and near-term relative to the global and long-term benefits from climate mitigation (Shindell *et al* 2018, Watts *et al* 2018). Previous studies have analysed the air quality impacts of possible future scenarios in China (Kan *et al* 2012, Woodward *et al* 2019). Some studies have focused on specific measures, such as variations in carbon pricing (Li *et al* 2018), transitions to synthetic natural gas (Qin *et al* 2017, 2018), transitions away from residential solid fuel use (Meng *et al* 2020), impacts from the National Determined Contributions (NDCs) for a single emission sector (Cai *et al* 2018), and a combination of air quality, development, and climate measures (UNEP 2019, Amann *et al* 2020). Other studies have focused on the impacts from broad national policies, such as the NDCs overall (Li *et al* 2019b, Xing *et al* 2020), the best air pollution technologies (GBD MAPS Working Group 2016, Xie *et al* 2018, Li *et al* 2019b, Xing *et al* 2020), carbon neutrality (Cheng *et al* 2021), shared socioeconomic pathways (Dong *et al* 2015, Xie *et al* 2018, Xu *et al* 2021), and the representative concentration pathways (RCP) (Wang *et al* 2021). Some global studies extract the impacts in China from broad global policies, such as those of the Paris Agreement (Markandya *et al* 2018, Vandyck *et al* 2018, Sampedro *et al* 2020), pathways to 2 °C and 1.5 °C (Shindell *et al* 2018, Rafaj *et al* 2021), and fossil fuel phase outs (Shindell and Smith 2019). None of these previous studies estimated the source-contributions to the air quality and human health impacts from these possible future scenarios.

Here, we used emulators of a chemical transport model to quantify the impacts of air pollution and climate mitigation emission scenarios on $PM_{2.5}$ and O_3 exposure in China over 2015–2050. These new emulators enabled us to separate the contribution of individual emission sectors to exposure and health impacts, providing information on the contribution of different sectors to future air pollution trajectories. The key novelty of this work is estimates of the source-contributions to the future air pollution disease burden in China.

2. Methods

2.1. Emulators and simulators of air quality

We used emulators to predict air quality across China from changes in emissions. The emulators were developed and evaluated in Conibear *et al* (2022c a, 2021a c). In Conibear *et al* (2021a), we developed the emulator approach for predicting short-term (1 month) $PM_{2.5}$ exposure from emission changes in China. In Conibear *et al* (2022c), we extended the emulator approach for long-term (annual) exposure, multiple air pollutants ($PM_{2.5}$ and O_3), and chronic health impacts. The emulators and simulators of air quality are fully described and evaluated in these companion papers.

The emulators were machine learning models trained and tested on simulator data from WRFChem (Weather Research and Forecasting model online-coupled with Chemistry) (Grell *et al* 2005, Skamarock *et al* 2008). The emulators were computationally efficient proxies of the simulator, enabling many more sensitivity experiments to be explored. The inputs to the emulators were fractional changes in anthropogenic emissions from the residential (RES), industrial (IND), land transport (TRA), agricultural (AGR), and power generation (ENE) sectors, averaged across all species. The emulators output annual-mean $PM_{2.5}$ concentrations and maximum 6-monthly-mean daily-maximum 8 h (6mDM8h) O_3 concentrations. For more details, see the supplementary methods (available online at stacks.iop.org/ERL/17/064027/mmedia).

The emulators only account for future changes in the five anthropogenic emission sectors used as inputs. Hence, the impacts of future changes in other sectors and sources are not considered in this study. The emulators were developed using meteorology from 2015. Hence, we do not account for the air quality impacts from future climate change (Jacob and Winner 2009, von Schneidemesser *et al* 2015), which are likely to be smaller than those from emission changes (supplementary discussion, Horton *et al* 2014, Hong *et al* 2019). A large additional ensemble of simulations would be required to quantify the air quality impacts from future climate change. Therefore, we focused this study on the impacts on exposure and public health from changes in emissions and the underlying population. The future impacts of climate change on air quality are an important research question for future work.

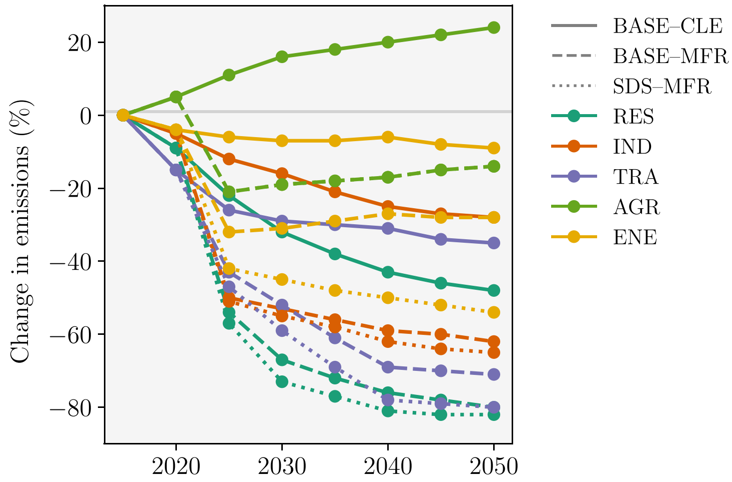

Figure 1. Fractional air pollution emission changes in China from 2015 to 2050 under the baseline activity projection with CLE air pollution storyline (BASE-CLE), baseline activity projection with MFR air pollution storyline (BASE-MFR), and SDS activity projection with MFR air pollution storyline (SDS-MFR). Emission changes are averaged over all species from the residential (RES), industrial (IND), land transport (TRA), agricultural (AGR), and power generation (ENE) sectors.

2.2. Future emission scenarios

The future emission scenarios covered 2020–2050 and used the Evaluating the Climate and Air Quality Impacts of Short-Lived Pollutants (ECLIPSE) emissions version 6b (Stohl *et al* 2015, Klimont *et al* 2017, 2022). The emission scenarios we used were the combination of one of two activity projections (baseline or sustainable development (SDS)) and one of two air pollution storylines (current legislation (CLE) or maximum feasible reduction).

The baseline (BASE) activity projections draw on the New Policy Scenario from the World Energy Outlook 2018 (International Energy Agency 2018). The SDS activity projections were based on the similarly named scenario from the World Energy Outlook 2018 (International Energy Agency 2018). The CLE air pollution storyline assumes effective implementation of air quality legislation committed up to 2018. The maximum technically feasible reduction (MFR) air pollution storyline assumes the implementation of the best available emission reduction technologies for all pollutants defined in the Greenhouse gas – Air pollution Interactions and Synergies (GAINS) model. For more details, see the supplementary methods.

To represent likely current trends, the BASE activity projection was combined with CLE air pollution storyline (BASE-CLE). To represent the maximum air quality improvements achievable from employing the best known emission reduction technologies, the BASE activity projection was combined with the MFR air pollution storyline (BASE-MFR). To represent the air quality co-benefits that could be achieved from climate mitigation efforts, the SDS activity projection was combined with the MFR air pollution storyline (SDS-MFR). Our climate mitigation scenario therefore includes both changes in activity and technological measures (see supplementary methods for more detail). To assess the benefits of the implementation of the best available air pollution technologies, we compared the BASE-MFR against the BASE-CLE. To assess the additional benefits from emission changes implemented for climate mitigation, on top of those achieved from the implementation of the best air pollution technologies, we compared the SDS-MFR against the BASE-MFR.

The emulators used the fractional changes in emissions per sector as inputs (figure 1). Under the BASE-CLE scenario, emissions in all sectors gradually declined to 2050, except for the agricultural sector where emissions continued increasing. Under the BASE-MFR scenario, emissions steeply declined in the coming decade for all key sources, with further reductions in residential, land transport, and industrial emissions through to 2050. The SDS-MFR scenario further reduced residential, land transport, and power generation emissions, with a smaller reduction in industrial emissions, and little change in agricultural emissions. Overall, the best air pollution technologies provided large reductions to air pollutant emissions, with additional reductions in air pollutant emissions from climate mitigation efforts.

2.3. Health impact assessment

The health impact assessment for $PM_{2.5}$ exposure used the global exposure mortality model (GEMM, Burnett *et al* 2018). The health impact assessment for O_3 exposure followed the methodology of the Global Burden of Diseases, Injuries, and Risk Factors Study (GBD) for 2017 (GBD 2017 Risk Factor Collaborators 2018). For more details, see the supplementary methods.

3. Results and discussion

3.1. Impacts of future emission scenarios on air quality and human health in China

In 2020, $PM_{2.5}$ exposure in China is estimated at 43.3 μg m^{-3} (table 1 and supplementary figure

Table 1. The impacts of future emission scenarios on air quality and human health 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 feasible reduction (MFR) air pollution storyline (BASE-MFR), and sustainable development activity projection with MFR air pollution storyline (SDS-MFR). Exposure is from fine particulate matter ($PM_{2.5}$, annual-mean) and ozone (O_3, maximum 6-monthly-mean daily-maximum 8 h (6mDM8h)). Premature mortalities (MORT) are estimated per year.

		BASE-CLE			BASE-MFR			SDS-MFR		
	2020	2030	2040	2050	2030	2040	2050	2030	2040	2050
$PM_{2.5}$ exposure (μg m^{-3})	43.3	39.7	37.5	36.7	30.0	28.2	27.5	28.9	27.0	26.6
O_3 exposure (ppb)	42.0	41.2	40.7	40.5	39.3	38.4	38.1	39.0	37.8	37.5
$PM_{2.5}$ MORT (millions deaths yr^{-1})	2.89 (2.65–3.10)	3.22 (2.96–3.48)	3.39 (3.12–3.67)	3.38 (3.10–3.65)	2.73 (2.50–2.96)	2.86 (2.62–3.10)	2.84 (2.60–3.08)	2.67 (2.45–2.89)	2.84 (2.60–3.08)	2.79 (2.55–3.02)
O_3 MORT (millions deaths yr^{-1})	0.07 (0.05–0.09)	0.09 (0.06–0.11)	0.10 (0.08–0.13)	0.12 (0.09–0.15)	0.07 (0.05–0.09)	0.08 (0.06–0.10)	0.10 (0.07–0.12)	0.07 (0.05–0.09)	0.08 (0.06–0.10)	0.09 (0.07–0.11)

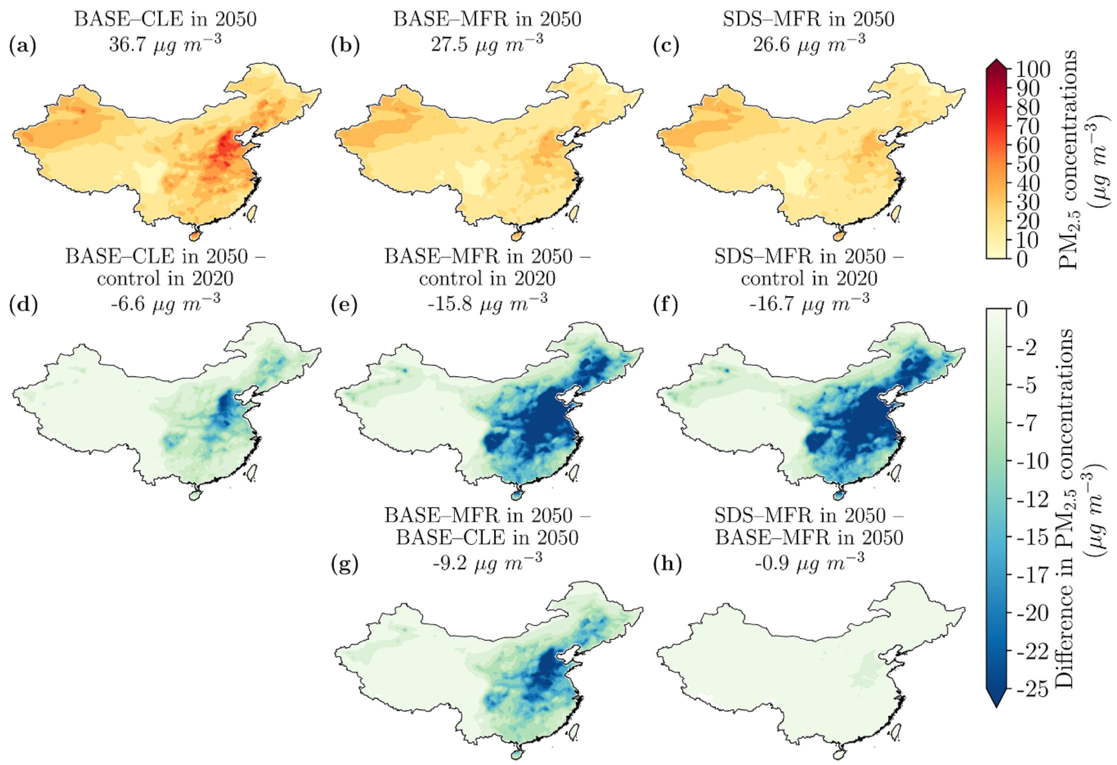

Figure 2. The impacts of future emission scenarios on fine particulate matter ($PM_{2.5}$, annual-mean) exposure in China from 2020 to 2050. Scenarios are the baseline activity projection with current legislation air pollution storyline (BASE-CLE), baseline activity projection with maximum feasible reduction (MFR) air pollution storyline (BASE-MFR), and sustainable development activity projection with MFR 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.

3). Under the BASE-CLE scenario, $PM_{2.5}$ exposure reduces by 15% in 2050, down to 36.7 μg m^{-3} (figure 2(a)). The BASE-MFR scenario reduces $PM_{2.5}$ exposure by 36% in 2050 (figure 2(b)), down to 27.5 μg m^{-3}, achieving the NAQT (35 μg m^{-3}), equivalent to the 2021 World Health Organization (WHO) Interim Target 1 (World Health Organization 2021). These air quality improvements are mostly obtained by 2030, where $PM_{2.5}$ exposure is already less than 30.0 μg m^{-3}. The SDS-MFR scenario reduces $PM_{2.5}$ exposure by 39% in 2050, down to 26.6 μg m^{-3} (figure 2(c)). Owing to the already stringent air pollution legislation in China and pursued strategy to strongly reduce the use of solid fuels (coal and biomass) for household cooking and heating (reflected in the BASE activity projection), the SDS-MFR scenario provides a reduction in $PM_{2.5}$ exposure of approximately 1.0 μg m^{-3}, which is largely achieved by 2030. None of the emission scenario's reductions in the five emission sectors enable the attainment of the 2021 WHO Interim Target 2 (25 μg m^{-3}) by 2050, due to remaining air pollution from other sources such as from natural sources, anthropogenic emissions outside China, and from other sectors.

In 2020, the disease burden associated with $PM_{2.5}$ exposure is 2885 300 (95% uncertainty interval, 95UI: 2652 700–3111 100) premature deaths per year (figure 3(b)). Under the BASE-CLE scenario in 2050, the $PM_{2.5}$ disease burden increases by 17% compared to 2020, an additional 494 200 (95UI: 447 500–540 900) premature deaths per year. This is despite the 15% reduction in $PM_{2.5}$ exposure, and is largely due to future population ageing significantly increasing the susceptibility to disease. If the population age groupings are kept fixed at 2020 levels (POP2020), then the $PM_{2.5}$ disease burden reduces by 46% in 2050, avoiding 1326 000 (95UI: 1221 200–1427 400) premature deaths per year compared to 2020. However, future improvements in baseline health provide important public health benefits, where without them the $PM_{2.5}$ disease burden would increase by 80% in 2050 (BM2020), an additional 2322 300 (95UI: 2124 400–2516 400) premature deaths per year compared to 2020. If the $PM_{2.5}$ exposure reductions are isolated from all other changes (i.e. population, age, and baseline health kept are at 2020 levels, POPAGEBM2020), then the $PM_{2.5}$ disease burden would reduce by 9% in 2050, avoiding 267 400 (95UI: 249 400–284 100) premature deaths per year compared to 2020.

Compared to the BASE-CLE scenario in 2050, the BASE-MFR scenario reduces the $PM_{2.5}$ disease burden by 16%, avoiding 536 600 (95UI: 497 800–573 300) premature deaths per year. Over 90% of these public health benefits are already obtained by

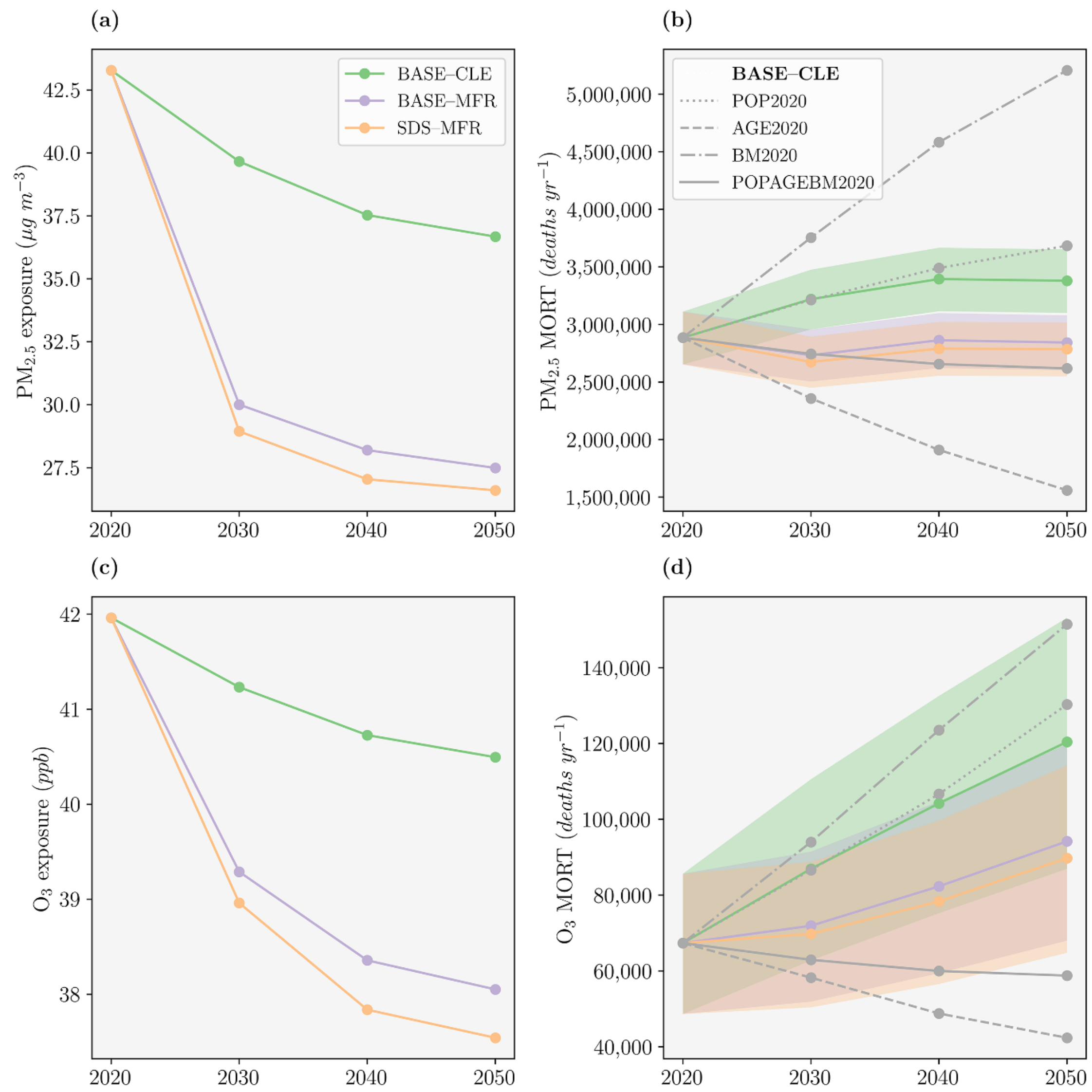

Figure 3. The impacts of future emission scenarios on air quality and human health in China from 2020 to 2050. Scenarios are the baseline activity projection with current legislation air pollution storyline (BASE-CLE), baseline activity projection with maximum feasible reduction (MFR) air pollution storyline (BASE-MFR), and sustainable development activity projection with MFR air pollution storyline (SDS-MFR). Results are for (a) fine particulate matter ($PM_{2.5}$) exposure, (b) annual premature mortalities (MORT) from $PM_{2.5}$ exposure, (c) maximum maximum 6-monthly-mean daily-maximum 8 h (6mDM8h) ozone (O_3) exposure, and (d) annual MORT from O_3 exposure. Sensitivity health impacts are shown for the BASE-CLE for 2050 using 2020 data for population count individually (POP2020), population age groupings individually (AGE2020), baseline mortality rates individually (BM2020), and all three of these variables combined (POPAGEBM2020).

2030. Compared to the BASE-MFR scenario in 2050, the SDS-MFR scenario avoids 57 000 (95UI: 52 800–61 100) premature deaths per year. Relative to the baseline in 2020, the BASE-MFR scenario reduces the $PM_{2.5}$ disease burden by 1% in 2050 avoiding 42 300 (95UI: 32 400–50 400) premature deaths per year, and the SDS-MFR scenario reduces the $PM_{2.5}$ disease burden by 3% in 2050 avoiding 99 400 (95UI: 93 500–103 100) premature deaths per year. The changes in $PM_{2.5}$ disease burden are less than the changes in $PM_{2.5}$ exposure due to the non-linear exposure-outcome association.

These results highlight that the best air pollution technologies can substantially avoid additional future premature loss of life in China. Most of these public health benefits are from large reductions in $PM_{2.5}$ exposure and are obtained by 2030. Climate mitigation efforts further reduces air pollution exposure, providing additional co-benefits to public health. Our analysis suggests that the disease burden associated with O_3 exposure is challenging to reduce and likely to increase in the future, due to the large sensitivity to population ageing (supplementary results). Future work should analyse the interacting impacts from changes in emissions, demographics, baseline health, and urbanisation across different regions in China.

3.2. Sector contributions to air quality under future emission scenarios

The future emission scenarios were emulated with each emission sector individually removed to quantify the sector contributions to future air quality

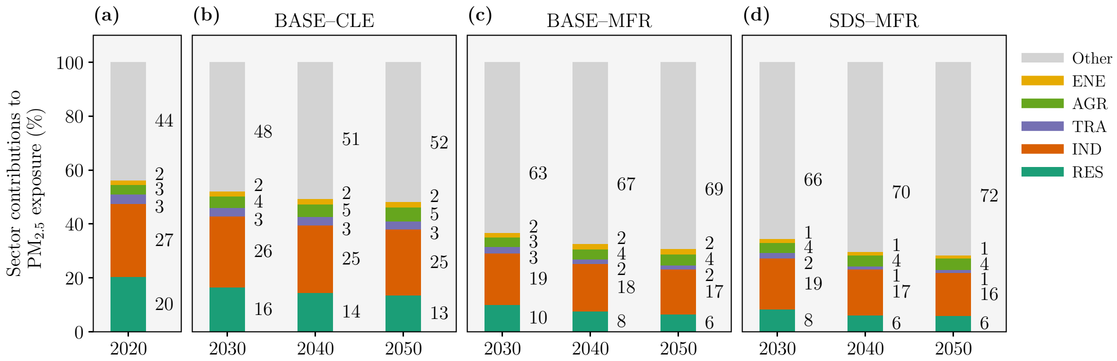

Figure 4. Sectoral contributions to annual-mean fine particulate matter ($PM_{2.5}$) exposure in China over 2020–2050. Results are for (a) all emission scenarios in 2020, (b) the baseline activity projection with current legislation air pollution storyline (BASE-CLE) over 2030–2050, (c) the baseline activity projection with maximum feasible reduction (MFR) air pollution storyline (BASE-MFR) over 2030–2050, and (d) the sustainable development activity projection with MFR air pollution storyline (SDS-MFR) over 2030–2050. Sectors are residential (RES), industrial (IND), land transport (TRA), agricultural (AGR), and power generation (ENE) emissions. Other includes shipping, aviation, and agricultural fires, anthropogenic emissions outside China, and natural emission sources such as vegetation fires, dust, sea spray, and biogenic volatile organic compounds leading to secondary organic aerosols.

(figure 4). This was undertaken for $PM_{2.5}$ concentrations only, due to the approximately linear response of $PM_{2.5}$ concentrations to emission reductions (Conibear *et al* 2022c).

In 2020, the leading sectors contributing to $PM_{2.5}$ exposure are industrial (27%) and residential (20%) emissions, followed by agricultural (3%), land transport (3%), and power generation (3%) emissions. Under the BASE-CLE scenario in 2050 compared to 2020, the contributions decrease from residential emissions to 13% (−7%) and industrial emissions to 25% (−2%), and increase from agricultural emissions to 5% (+2%). Under BASE-MFR compared to BASE-CLE in 2050, the contributions decrease further from residential emissions to 6% (−7%) and industrial emissions to 17% (−8%). Under SDS-MFR compared to BASE-MFR in 2050, there are 1% point reductions in industrial (to 16%), land transport (to 1%), and power generation emissions (to 1%).

The contribution from other sources to $PM_{2.5}$ exposure increases from 44% in 2020, to 52% in 2050 under BASE-CLE, 69% under BASE-MFR, and 72% under SDS-MFR. By 2030 under the BASE-MFR scenario, other sources contribute 63% of $PM_{2.5}$ exposure. These other sources include anthropogenic emissions inside China from alternative sectors including shipping, aviation, and agricultural fires, anthropogenic emissions outside China, naturally occurring vegetation fires, and natural aerosols such as mineral dust, sea spray, and biogenic secondary organic aerosols (SOAs). Previous studies have estimated the contributions to national $PM_{2.5}$ concentrations in China from dust were up to 10% (Yang *et al* 2011, Shi *et al* 2017), fires were up to 8% (Shi *et al* 2017, Reddington *et al* 2019, 2021), biogenic SOA were up to 8% (Hu *et al* 2017, Shi *et al* 2017), anthropogenic emissions outside China were up to 3% (Liu *et al* 2020), shipping were up to 3% (Chen *et al* 2019, Dasadhikari *et al* 2019, Reddington *et al* 2019), aviation were 1% (Zhang *et al* 2017, Dasadhikari *et al* 2019), and sea salt were 1% (Shi *et al* 2017). Natural sources (fire, dust, biogenic SOA, and sea salt) could therefore contribute up to 27% of national $PM_{2.5}$ concentrations in China. Although these sources are natural, they are modified by land cover change and land management, providing opportunities for air quality mitigation (Heald and Spracklen 2015). Natural sources are also projected to change under future climate (Carslaw *et al* 2010).

These results suggest that future $PM_{2.5}$ exposure in China will continue to have large contributions from industrial emissions in 2050. Under CLE, the contribution from residential emissions decreases moderately by 2050. While under the best air pollution technologies, these reductions can be much larger, highlighting the potential of further action in this sector (Zhao *et al* 2018, Conibear *et al* 2021b). As the future contributions from these five sectors decreases, the proportional contribution from other sources increases. As much as 90% of the air quality improvement in these scenarios (BASE-MFR and SDS-MFR) is achieved by 2030, with limited reductions in pollution over 2030–2050. These findings highlight the future air quality improvements in China after 2030 may require further efforts across a wider range of sectors and that international collaboration to reduce emissions across the continent is likely to become more important.

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

To explore the individual role of different emission sectors, the future emission scenarios were emulated for each emission sector individually with all other sectors held at the baseline in 2020.

Under the BASE-CLE scenario, the 6.6 μg m^{-3} reduction in $PM_{2.5}$ exposure by 2050 is primarily from reductions in residential (55%) and industrial

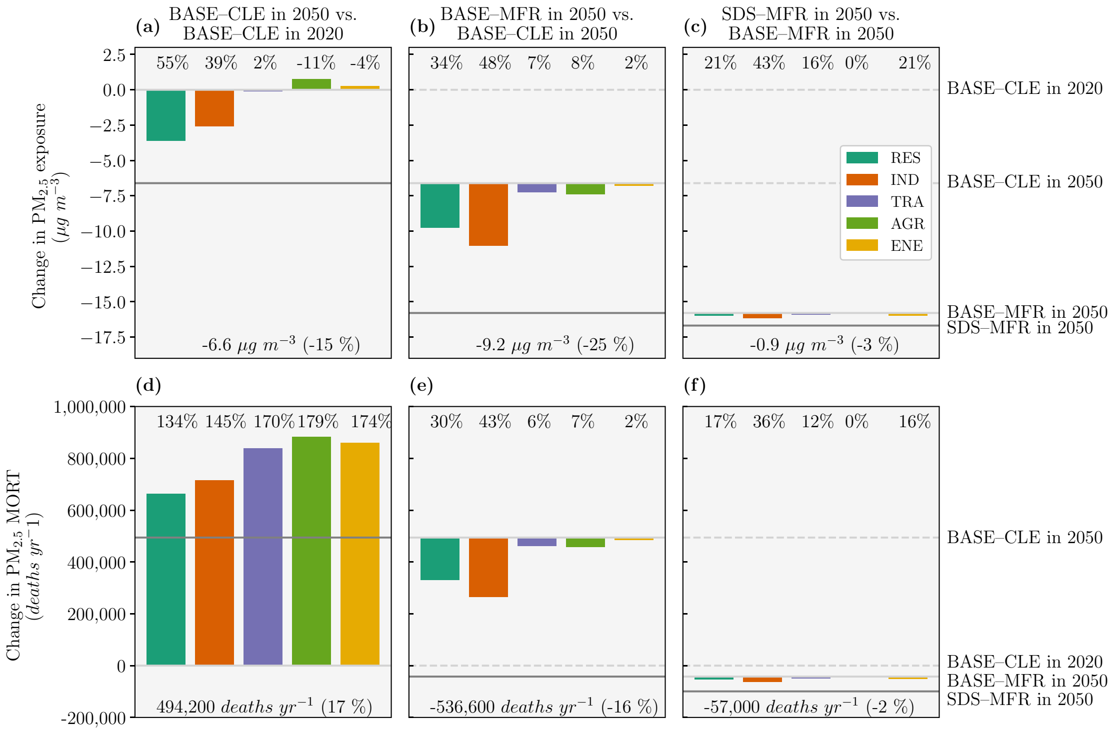

Figure 5. The relative impacts of individual sector changes on (a)–(c) annual-mean fine particulate matter ($PM_{2.5}$) exposure and (d)–(f) associated premature mortalities (MORT) from future emission scenarios in China. Scenarios are (a) and (d) the baseline activity projection with current legislation air pollution storyline (BASE-CLE) in 2050 compared to 2020, (b) and (e) the baseline activity projection with maximum feasible reduction (MFR) air pollution storyline (BASE-MFR) in 2050 compared to BASE-CLE in 2050, and (c) and (f) the sustainable development activity projection with MFR 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.

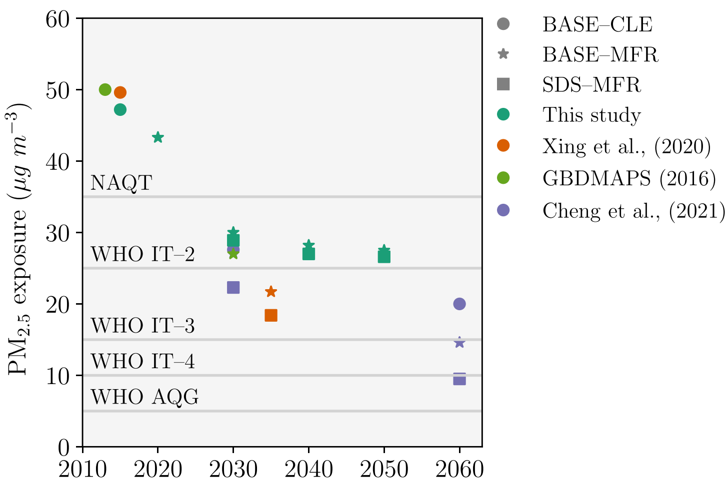

Figure 6. Comparison of annual-mean fine particulate matter ($PM_{2.5}$) exposure in China over 2010–2060 from our work to previous studies (GBD MAPS Working Group 2016, Xing *et al* 2020, Cheng *et al* 2021). Scenarios are the baseline activity projection with current legislation air pollution storyline (BASE-CLE), the baseline activity projection with maximum feasible reduction (MFR) air pollution storyline (BASE-MFR), and the sustainable development activity projection with MFR air pollution storyline (SDS-MFR). Horizontal lines are shown for the NAQT (35 $\mu g\ m^{-3}$), the 2021 WHO Interim Target 2 (IT-2, 25 $\mu g\ m^{-3}$), the WHO Interim Target 3 (IT-3, 15 $\mu g\ m^{-3}$), the WHO Interim Target 4 (IT-4, 10 $\mu g\ m^{-3}$), and the WHO air quality guideline (AQG, 5 $\mu g\ m^{-3}$).

(39%) emissions (figure 5(a)). The reduction in $PM_{2.5}$ exposure is partly offset from a rising contribution from agricultural emissions. Under the BASE-MFR scenario, the further 9.2 $\mu g\ m^{-3}$ reduction in $PM_{2.5}$ exposure by 2050 is mainly due to reductions in industrial (48%) and residential (34%) emissions (figure 5(b)). There are smaller contributions to $PM_{2.5}$ exposure reductions from agricultural (8%) and land transport (7%) emissions. Under the SDS-MFR scenario, the further 0.9 $\mu g\ m^{-3}$ reduction in $PM_{2.5}$ exposure by 2050 is mainly due to reductions in industrial (43%), residential (21%), and power generation (21%) emissions (figure 5(c)).

Under the BASE-CLE scenario, the $PM_{2.5}$ disease burden increases by 494 200 (95UI: 447 500–540 900) premature deaths per year, largely due to population ageing (figure 5(d) horizontal line and figure 5(b)). Under the BASE-MFR scenario, the $PM_{2.5}$ disease burden is reduced by 536 600 (95UI: 497 800–573 300) premature deaths per year in 2050 mainly due to reductions in industrial (43%) and residential (30%) emissions (figure 5(e)), with smaller contributions from agricultural (7%) and land transport (6%) emissions. Under the SDS-MFR scenario, the further 57 000 (95UI: 52 800–61 100) avoided premature deaths per year from $PM_{2.5}$ exposure in 2050 is mainly due to reductions in industrial (36%), residential (17%), and power generation (16%) emissions (figure 5(f)).

These results suggest that the substantial public health benefits from reduced $PM_{2.5}$ exposure under the best air pollution technologies is primarily from reduced industrial and residential emissions. The additional air quality co-benefits from climate mitigation efforts are spread across industrial, residential, power generation, and land transport emissions. It is now important to assess sub-sector level contributions to the air pollution disease burden. The complexities of reducing O_3 exposure are highlighted by some air pollution technologies and climate mitigation efforts increasing O_3 exposure, especially power generation emissions (supplementary results).

3.4. Comparison to previous studies

Figure 6 compares results from our work to previous studies over China (GBD MAPS Working Group 2016, Xie *et al* 2018, Li *et al* 2019b, Xing *et al* 2020, Cheng *et al* 2021).

Xing *et al* (2020) found that the best air pollution technologies can reduce $PM_{2.5}$ concentrations by up to 27.9 μg m^{-3} in 2035, a 56% reduction compared to 2015, which is larger than our reduction of 19.0 μg m^{-3} (40%) over 2015–2040. Cheng *et al* (2021) found that the best air pollution technologies reduced $PM_{2.5}$ exposure by 5.4 μg m^{-3} (27%) beyond current air quality legislation in 2060, similar to our reduction of 9.2 μg m^{-3} (25%) in 2050. The GBD MAPS Working Group (2016) found that the best air pollution technologies reduced $PM_{2.5}$ exposure by 12.0 μg m^{-3} (24%) over 2013–2030, smaller than our reduction of 17.2 μg m^{-3} (36%) over 2015–2030. Li *et al* (2019b) found in 2050 that the best air pollution technologies reduced the $PM_{2.5}$ disease burden by 29% beyond current air quality legislation, larger than our estimate of 16%.

Previous studies also find that climate mitigation efforts can provide additional reductions to $PM_{2.5}$ exposure. Cheng *et al* (2021) found that climate mitigation efforts can reduce $PM_{2.5}$ exposure by up to 5.1 μg m^{-3} beyond what can be achieved from the implementation of the best air pollution technologies in 2060, which is larger than our estimate of 0.9 μg m^{-3} in 2050. Xing *et al* (2020) found that climate mitigation efforts reduced $PM_{2.5}$ concentrations by an additional 3.3 μg m^{-3} in 2035, larger than our estimate of an additional reduction of 1.2 μg m^{-3} in 2040. Li *et al* (2019b) found that climate mitigation efforts further reduced the $PM_{2.5}$ disease burden in 2050 by 9%, larger than our estimate of a further 2% reduction. Xie *et al* (2018) found that climate mitigation efforts can avoid a further 225 000 premature deaths from air pollution exposure in 2050, larger than our estimate of a further 61 500 (95UI: 56 000–66 800) avoided premature deaths.

If the BASE and SDS activity projections are compared without the implementation of the MFR air pollution storyline, then the SDS activity projections would likely yield slightly larger air quality benefits. For example, the air quality benefits from the replacement of very well controlled modern power plants with renewable electricity generation (SDS with MFR) are not as large as the air quality benefits from replacing existing power plants with renewable capacity (SDS without MFR). Similarly, the air quality benefits from electric vehicles are smaller when the latest generation gasoline or diesel vehicles already fully comply with the strictest emission limits (SDS with MFR).

The differences in these estimates are likely due, in large part, to the different exposure estimation methods, scenarios, and health impact assessment methods, which are difficult to separate out. We expand on these differences in the supplementary discussion. In general, our results are in broad agreement with previous studies that the best air pollution technologies can provide substantial public health benefits in China, and that there are smaller additional air quality co-benefits from climate mitigation efforts.

4. Conclusion

We used emulators of a regional chemical transport model to quantify the impacts of future air pollution and climate mitigation emission scenarios on air quality in China, and estimated how key emission sectors contribute to the future disease burden from air pollution exposure.

We found that CLE can reduce $PM_{2.5}$ exposure by 15% over 2020–2050, but population ageing means that the disease burden increases by 17%, an additional 494 200 (95UI: 447 500–540 900) premature deaths per year by 2050. Application of the best air pollution technologies can provide substantial air quality improvements, reducing $PM_{2.5}$ exposure by 36% in 2050, attaining the NAQT (35 μg m^{-3}) by 2030. Despite a large reduction in $PM_{2.5}$ exposure over 2020–2050, an ageing population means that the best air pollution technologies only reduce the disease burden by 1% in 2050, avoiding 42 300

(95UI: 32 400–50 400) premature deaths per year. The application of climate mitigation efforts with the best air pollution technologies reduces $PM_{2.5}$ exposure by 39% in 2050, decreasing the $PM_{2.5}$ disease burden by 3%, and avoiding 99 400 (95UI: 93 500–103 100) premature deaths per year.

In comparison to CLE in 2050, application of the best air pollution technologies provides substantial health benefits, reducing $PM_{2.5}$ exposure by 25% and the $PM_{2.5}$ disease burden by 16% in 2050, avoiding 536 600 (95UI: 497 800–573 300) premature deaths per year. These public health benefits are mainly due to reductions in industrial (43%) and residential (30%) emissions. Climate mitigation efforts combined with the best air pollution technologies leads to an additional 3% reduction in $PM_{2.5}$ exposure by 2050, reducing the $PM_{2.5}$ disease burden by a further 2% and avoiding 57 000 (95UI: 52 800–61 100) premature deaths per year. These public health benefits are mainly due to a reduction in industrial emissions (36%).

The emulators only had information on emissions at the sector level due to computational constraints. Hence, we do not have the sub-sector attributions of specific policies and technologies. Policy makers require more detailed information on how interventions could impact air quality and disease burden. Future work is needed to assess the air quality impacts of specific interventions and technological solutions, and how societal changes such as urbanisation and changes to population will alter the health impacts. Further work is also needed to assess the health benefits of spatially specific emission reductions.

Of the five anthropogenic emission sectors studied here, $PM_{2.5}$ exposure in 2020 is primarily from industrial (27%) and residential (20%) emissions. Under all emission scenarios, we estimate that future $PM_{2.5}$ exposure in 2050 will continue to have large contributions from industrial emissions (16%–25%). The contribution from residential emissions in 2050 decreases to 13% under CLE and to 6% under the best air pollution technologies, highlighting the potential of stringent action in this sector. The proportional contribution from other emission sources, such as from other anthropogenic sources inside China, anthropogenic emissions outside China, and natural emissions, increases from 44% in 2020 to 52%–72% in 2050. Over 90% of the public health benefits achieved in 2050 are already obtained by 2030, highlighting the need for additional strategies to reduce pollution after 2030.

Data availability statement

The data that support the findings of this study are openly available. Code to setup and run WRF-Chem (using WRFotron version 2.0) is available through Conibear and Knote (2020). Emulator code and data is available through Conibear (2021; 2022a). The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.5518/1055.

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Author contributions

L C, C L R, S R A, and D V S designed the research. Z K and S T T provided ECLIPSEv6b emissions. B J S provided the measurements. C L R analysed the ECLIPSEv6b emissions and co-wrote section 2.2. L C developed the emulators and methods, conducted the data analysis and interpretation, created the figures, and wrote the manuscript. All authors comments on the manuscript.

Conflict of interest

The authors declare no conflicts of interest relevant to this study.

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