Environment International 175 (2023) 107972

Contents lists available at ScienceDirect

Environment International

journal homepage: www.elsevier.com/locate/envint

Full length article

Air pollution and child health impacts of decarbonization in 16 global cities: Modelling study

James Milner[a,b,*], Robert Hughes[a,c], Sourangsu Chowdhury[d,e], Roberto Picetti[a,c], Rakesh Ghosh[f], Shunmay Yeung[g,h], Jos Lelieveld[d,*], Alan D. Dangour[a,c], Paul Wilkinson[a,b]

[a] Centre on Climate Change and Planetary Health, London School of Hygiene & Tropical Medicine, London, UK
[b] Department of Public Health, Environments and Society, London School of Hygiene & Tropical Medicine, London, UK
[c] Department of Population Health, London School of Hygiene & Tropical Medicine, London, UK
[d] Department of Atmospheric Chemistry, Max Planck Institute for Chemistry, Mainz, Germany
[e] CICERO Center for International Climate Research, Oslo, Norway
[f] Institute for Global Health Sciences, University of California San Francisco, San Francisco, USA
[g] Department of Clinical Research, London School of Hygiene & Tropical Medicine, London, UK
[h] Department of Global Health and Development, London School of Hygiene & Tropical Medicine, London, UK

A R T I C L E I N F O

Handling Editor: Dr. Hanna Boogaard

Keywords:
Decarbonization
Air pollution
Child health
Asthma
Low birthweight
Pre-term birth

A B S T R A C T

Most research on the air pollution-related health effects of decarbonization has focused on adults. We assess the potential health benefits that could be achieved in children and young people in a global sample of 16 cities through global decarbonization actions. We modelled annual average concentrations of fine particulate matter ($PM_{2.5}$) and nitrogen dioxide (NO_2) at 1x1 km resolution in the cities using a general circulation/atmospheric chemistry model assuming removal of *all* global combustion-related emissions from land transport, industries, domestic energy use and power generation. We modelled the impact on childhood asthma incidence and adverse birth outcomes (low birthweight, pre-term births) using published exposure–response relationships. Removal of combustion emissions was estimated to decrease annual average $PM_{2.5}$ by between 2.9 μg/m^3 (8.4%) in Freetown and 45.4 μg/m^3 (63.7%) in Dhaka. For NO_2, the range was from 0.3 ppb (7.9%) in Freetown to 18.8 ppb (92.3%) in Mexico City. Estimated reductions in asthma incidence ranged from close to zero in Freetown, Tamale and Harare to 149 cases per 100,000 population in Los Angeles. For pre-term birth, modelled impacts ranged from a reduction of 135 per 100,000 births in Dar es Salaam to 2,818 per 100,000 births in Bhubaneswar and, for low birthweight, from 75 per 100,000 births in Dar es Salaam to 2,951 per 100,000 births in Dhaka. The large variations chiefly reflect differences in the magnitudes of air pollution reductions and estimated underlying disease rates. Across the 16 cities, the reduction in childhood asthma incidence represents more than one-fifth of the current burden, and an almost 10% reduction in pre-term and low birthweight births. Decarbonization actions that remove combustion-related emissions contributing to ambient $PM_{2.5}$ and NO_2 would likely lead to substantial but geographically-varied reductions in childhood asthma and adverse birth outcomes, though there are uncertainties in causality and the precision of estimates.

1. Introduction

There is strengthening evidence that, among other effects, exposure to ambient fine particulate matter ($PM_{2.5}$) and nitrogen dioxide (NO_2) can affect children's lung development, the incidence of asthma and, through maternal exposure, the risk of premature birth and low birthweight babies (Landrigan et al., 2019; Chen et al., 2015). The evidence for these effects in children is not as conclusive as for many outcomes in adults but is supported by high quality systematic reviews published in the last decade (Johnson et al., 2021; Perera et al., 2019; Volk et al., 2021). Various mechanisms have been proposed to explain how air pollution exposure may affect child health, including oxidative stress, airway and systemic inflammation, epigenetic factors and DNA damage (Esposito et al., 2014).

* Corresponding authors at: Department of Public Health, Environments and Society, London School of Hygiene & Tropical Medicine, London, UK (J. Milner). Department of Atmospheric Chemistry, Max Planck Institute for Chemistry, Mainz, Germany (J. Lelieveld).
E-mail addresses: james.milner@lshtm.ac.uk (J. Milner), jos.lelieveld@mpic.de (J. Lelieveld).

https://doi.org/10.1016/j.envint.2023.107972
Received 3 February 2023; Received in revised form 25 April 2023; Accepted 8 May 2023
Available online 12 May 2023

Since air pollution shares many common emission sources with greenhouse gases (GHGs), action to decarbonize economies can be expected to reduce air pollution (Chang et al., 2017; Gao et al., 2018). Following the 2021 United Nations Climate Change Conference (COP26) in Glasgow, as of March 2022, almost 50 countries have now committed either in law or policy to reducing their GHG emissions to attempt to meet the ambition of the 2015 Paris Agreement to restrict the global average temperature rise to no more than 1.5 °C above pre-industrial levels. In practice, this entails many countries working towards 'net zero' emissions – the state in which GHG emissions are balanced by removal through GHG sinks – by 2050, with other nations having ambitions for similar emissions reductions by later dates (ECIU, 2022).

Despite a growing body of literature on the air pollution-related consequences for health of reducing GHG emissions (Lelieveld et al., 2019; Markandya et al., 2018; Hamilton et al., 2021; Vandyck et al., 2018), the impact on the children and adolescents has been much less studied. One study by Perera et al. (2020) of the US Regional Greenhouse Gas Initiative, found that the associated reductions in air pollution would have substantial benefits for several aspects of child health. We aimed to add to this literature by assessing, as an 'upper limit' indication of the air pollution-related impact of decarbonization, the reductions of $PM_{2.5}$ and NO_2 levels that could be achieved in 16 cities of the world through removal of combustion-related emissions and the resulting impact on the health of children and young people. Given the large uncertainties in the data used for analyses of this type, to help improve future modelling studies we also systematically assess the limitations of currently-available data.

2. Material and methods

We selected 16 global cities with a global distribution and variations in population size, socioeconomic development and current air pollution levels using a combination of convenience and purposive sampling: Bhubaneswar (India), Dar es Salaam (Tanzania), Dhaka (Bangladesh), Freetown (Sierra Leone), Glasgow (UK), Harare (Zimbabwe), Jaipur (India), Lahore (Pakistan), London (UK), Los Angeles (USA), Manila (Philippines), Mexico City (Mexico), Milan (Italy), Nairobi (Kenya), Quito (Ecuador) and Tamale (Ghana).

The modelled child health outcomes were selected as those likely to be affected by changes in air pollution following a 'balance-of-probabilities' assessment of evidence from the epidemiological literature and the recommendations of a previous review (Perera et al., 2019). The three included outcomes were: asthma incidence, low birthweight and pre-term birth.

For each city, using published exposure–response relationships, we estimated the burden of child and adolescent asthma incidence and adverse birth outcomes (pre-term birth and low birthweight) attributable (i) to current $PM_{2.5}$ (birth outcomes) and NO_2 (asthma incidence) annual average *ambient* (outdoor) concentrations and (ii) to levels corresponding to a decarbonization scenario in which *all* combustion-related emissions contributing to these air pollutant concentrations are removed. Although this is an ambitious target, nevertheless it represents a stated policy aim in many countries around the world.

2.1. Air pollution exposure

We used observation-constrained, model-derived estimates of annual average $PM_{2.5}$ and NO_2 concentrations at 1x1 km resolution in each city based on methods used in Hammer et al (2020) and Chowdhury et al (2021) respectively. The estimates of $PM_{2.5}$ were based on gridded data for 2019 using methods from Hammer et al. (2020) that combine information from satellite retrievals of aerosol optical depth (AOD), $PM_{2.5}$ and the ratio of $PM_{2.5}$ to AOD simulated by GEOSChem (Bey et al., 2001), with available ground measurements to produce $PM_{2.5}$ exposure at 1x1 km spatial resolution with high confidence. Further detail on the methods can be found elsewhere (Hammer et al., 2020; van Donkelaar et al., 2021; Chowdhury et al., 2022).

For NO_2, the ECHAM/MESSy Atmospheric Chemistry (EMAC) general circulation model was used at a spatial resolution of roughly 1.1x1.1° and the bias towards low values (in particular over densely populated areas) was corrected using a publicly available land-use regression model at 1x1 km spatial resolution that employs measurement data from globally-distributed monitoring sites and predictor variables including distance from major and minor roads, satellite retrieved active fires, tree cover, population density, elevation, satellite retrieved NO_2, water mask and elevation (Larkin et al., 2017). The modelled $PM_{2.5}$ and NO_2 have been shown to perform well against ground measurements and satellite retrievals. Please see Chowdhury et al. (2022), Chowdhury et al. (2021) and Hammer et al. (2020) for more details on comparison with ground measurements.

To determine the sector contributions, concentrations of ambient $PM_{2.5}$ and NO_2 were simulated using the EMAC model with all emission sources based on 2014 emissions taken from the Community Emissions Data System (CEDS) anthropogenic emission inventory at 0.5x0.5° resolution for primary emitted $PM_{2.5}$ species, NO_X, SO_2, CO and volatile organic compounds (Hoesly et al., 2018). The sources include land transportation, industries, domestic energy use, energy generation by power plants, agricultural soils, agricultural waste and residue burning, emissions from ships and other water navigation, biomass burning, and biogenic and natural emissions. For India, we augmented the CEDS anthropogenic emissions data with a regional emission inventory (Venkataraman et al., 2020). Biomass burning emissions were obtained from the Global Fire Assimilation System (GFAS) inventory (Kaiser et al., 2012). The emission data were pre-processed by distributing them over six emission heights as described elsewhere (Pozzer et al., 2009). Concentrations of ambient $PM_{2.5}$ and NO_2 were first estimated by running EMAC with all emission sources, and then the individual source sectors were removed one at a time, and the results linearized, to determine their contribution to ambient levels. See Chowdhury et al (2022) (Chowdhury et al., 2022) and Chowdhury et al (2021) (Chowdhury et al., 2021) for further details on modelling exposure and sources of $PM_{2.5}$ and NO_2 respectively.

We calculated the population-weighted average of $PM_{2.5}$, NO_2 and the sectoral contributions to both across all 1x1 km grid squares in each city. To define city boundaries, city extents were obtained from the Global Human Settlement Layer (GHSL) Urban Centre Database GHS-UCDBR 2019A (European Commission, 2018). Our decarbonization scenario assumed removal of the (population-weighted) contribution from all global emissions in land transport, industries, domestic energy use and power generation.

2.2. City populations

Population estimates (for age-groups 0–4, 5–9, 10–14 and 15–19 years) for the year 2020 at 1x1 km spatial resolution within each city's boundaries were based on downscaled population projections from the Shared Socioeconomic Pathway, SSP2, from Gao (2020).

2.3. Estimation of attributable health burdens

We calculated the burden of incident asthma cases attributable to NO_2 and the burdens of pre-term and low birthweight births attributable to $PM_{2.5}$.

For asthma calculations, we used 2019 estimates of age- and country-specific asthma incident cases (expressed as incidence rates) from the 2019 Global Burden of Disease (GBD) study (IHME, 2019). For four cities (London, Los Angeles, Nairobi, Mexico City) these were available at sub-national level. We applied the rates at ages 1–4, 5–9, 10–14 and 15–19 to our population data to estimate baseline incident asthma cases in each city in those age groups.

For birth outcomes, we used country-specific counts of total live births, pre-term births and low birthweight births from GBD 2019

(IHME, 2019) and available from Ghosh et al. (2021). We downscaled the birth counts to city level using the ratio of city to national populations using national population estimates from GBD 2019 (IHME, 2019).

The health burdens were calculated using standard methods for the population attributable fraction (PAF):

$$PAF = \frac{RR - 1}{RR}$$

where *RR* is the relative risk of the health outcome at the given exposure level.

The PAFs at each exposure level were calculated by applying exposure–response functions (ERFs) obtained from recent high quality meta-analyses of the effects of air pollution on child health, which covered the range of modelled exposure levels (Table 1). For asthma incidence, we assumed the ERF for NO_2 was log-linear and used a counterfactual (low cut-off) concentration of 2 ppb in accordance with the original meta-analysis and other modelling analyses (Achakulwisut et al., 2019; Khreis et al., 2017; Khreis et al., 2019). For birth outcomes, we used the meta-regression–Bayesian regularized trimmed (MR-BRT) model for $PM_{2.5}$ from Ghosh et al. (2021). We calculated and applied median risk functions from 1,000 draws of each function provided by Ghosh et al. (2021). In accordance with the source study, we normalized the RRs by the RR at the theoretical minimum risk exposure level (TMREL) (we used the median of 1,000 estimates, TMREL = 4.2 $\mu g/m^3$) and set RR = 1 at $PM_{2.5}$ exposures below TMREL. There is minimal risk for these outcomes below this population level exposure.

We applied the calculated PAFs to the baseline health data to estimate numbers of attributable incident cases at present day air pollution levels and air pollution levels corresponding to the decarbonization scenario.

2.4. Uncertainty analysis

To assess the effect of parameter uncertainties in our estimates, we used Monte Carlo simulation based on 10,000 simulations sampling from the distributions of input parameters, conservatively assuming uniform distributions. For the ERFs and asthma incidence rates, we used the 95% confidence intervals (CIs) from the original sources. For air pollution exposures, we compared the estimated annual average $PM_{2.5}$ levels for each city to those reported in the WHO's air pollution database to obtain an indication of the likely uncertainty in our estimates (WHO, 2018). The average difference between our estimates and the WHO database was −3.7% but with relatively large differences for some cities (range: −52.8%–39.9%). Based on this comparison, we assumed a uniform distribution of ± 40% around the central estimates for both $PM_{2.5}$ and NO_2.

We also performed a semi-quantitative assessment of confidence in the model inputs. We judged the quality of model inputs for each city against the author-defined criteria shown in Appendix A (Table A1). We combined these ratings to estimate a level of confidence in the modelled health impacts for each city based on an overall assessment across the model inputs.

Table 1
Summary of exposure–response functions used in modelling analysis.

Summary measure	Asthma incidence	Adverse birth outcomes
Source	(Khreis et al., 2017)	(Ghosh et al., 2021)
Air pollutant	NO_2	$PM_{2.5}$
Outcomes	Diagnosis of asthma at ages 0–18 years	Pre-term birth (gestation less than 37 completed weeks) and low birthweight (birth weight less than 2,500 g)
Model	Log-linear, RR = 1.26 (1.10 to 1.37) per 10 ppb*	Meta-regression–Bayesian regularized trimmed (MR-BRT) (non-linear)
Evidence	Systematic review and meta-analysis of 21 studies	Systematic review and meta-regression of 40 studies

*converted to RR per 10 ppb by Achakulwisut et al. (2019).

3. Results

Current population-weighted $PM_{2.5}$ in the 16 cities varied from 7.5 $\mu g/m^3$ in Dar es Salaam to 74.2 $\mu g/m^3$ in Jaipur (Table 2). Decreases in $PM_{2.5}$ under the decarbonization scenario were generally large, ranging from 2.9 $\mu g/m^3$ (8.4% reduction) in Freetown to 45.3 $\mu g/m^3$ (63.7% reduction) in Dhaka, with the largest absolute reductions in Dhaka (45.3 $\mu g/m^3$), Bhubaneswar (43.0 $\mu g/m^3$) and Jaipur (27.9 $\mu g/m^3$) and the smallest in Dar es Salaam (1.8 $\mu g/m^3$), Freetown (2.9 $\mu g/m^3$) and Harare (2.9 $\mu g/m^3$). For NO_2, the lowest current exposure was in Dar es Salaam (2.8 ppb, approximately 5.3 $\mu g/m^3$) and the highest exposure in Mexico City (20.4 ppb, 38.3 $\mu g/m^3$). The range of reductions under decarbonization was again large for NO_2, ranging from 7.9% in Freetown to 92.3% in Mexico City. Absolute reductions varied from 0.3 ppb (0.7 $\mu g/m^3$) in Freetown to 18.8 ppb (35.4 $\mu g/m^3$) in Mexico City.

Between-city variations were correspondingly large for modelled incident asthma cases, pre-term births and low birthweight births averted in one year attributable to the reductions in $PM_{2.5}$ and NO_2 under the decarbonization scenario (Table 3). For asthma incidence, the difference between the city with the lowest and highest rate per 100,000 population averted by decarbonization was greater than two orders of magnitude. Our estimates of reduced asthma incidence in Freetown, Tamale and Harare were close to zero. On the other hand, we estimated 149 averted cases per 100,000 in Los Angeles and 62 per 100,000 in London and Mexico City. In absolute terms, the largest number of averted cases were in Los Angeles (6,765 cases), Mexico City and (5,309) and Manila (3,601).

There were also very large differences between cities for estimated reductions in adverse birth outcomes under the decarbonization scenario (Table 3). For pre-term birth, the modelled impacts ranged from 135 per 100,000 live births in Dar es Salaam to 2,818 per 100,000 live births in Dhaka. For low birthweight, the impacts ranged from 75 per 100,000 live births in Dar es Salaam to 2,951 per 100,000 live births in Dhaka. In absolute terms, the impacts ranged from 8 in Tamale to 10,674 in Dhaka for pre-term births, and from 6 in Tamale and Freetown to 11,180 in Dhaka for low birthweight. However, the ranges of uncertainty around the central estimates were large, particularly for pre-term birth due primarily to the wide confidence interval around the exposure–response function. Although the central estimates show positive numbers of averted cases of pre-term birth (i.e. health benefits), it is worth noting that the lower bound estimates suggest the possibility that decarbonization may have no or even adverse impacts for this outcome.

In total, summed over all 16 cities, the mean modelled impacts represent reductions to the current disease burdens of 19,098 cases (22%) for asthma, 22,029 (9%) for pre-term birth and 19,818 (8%) for low birthweight.

Fig. 1 shows that much of the *per capita* variation in impacts is due to the estimated absolute reductions in $PM_{2.5}$ and NO_2 under decarbonization with, for example, large reductions in NO_2 in Los Angeles and Mexico City, which had the largest corresponding reductions in asthma incidence (Fig. 1A). Similar findings apply to pre-term and low birthweight births per 100,000 live births in relation to $PM_{2.5}$ reduction (Fig. 1B and 1C). The other major factor contributing to variations in impacts was variation in baseline estimates of underlying disease rates, as indicated in Fig. 2, with cities with the highest number of cases having the greatest impacts.

4. Discussion

This work illustrates the theoretical potential of ambitious global action to remove combustion-related GHG emissions on the health of

Table 2
Summary of modelled current air pollution exposures and exposures under decarbonization scenario.

City	Population-weighted annual average air pollution					
	$PM_{2.5}$ (μg/m^3)			NO_2 (ppb)		
	Current	Decarbonization	**% change**	**Current**	Decarbonization	**% change**
Bhubaneswar	70.9	28.0	−60.6%	7.4	2.9	−60.3%
Dar es Salaam	7.5	5.7	−24.1%	2.8	1.5	−48.0%
Dhaka	71.2	25.8	−63.7%	11.8	4.7	−60.1%
Freetown	34.6	31.7	−8.4%	3.3	3.0	−7.9%
Glasgow	11.2	6.4	−42.8%	11.7	2.7	−76.9%
Harare	7.8	4.9	−37.2%	5.0	3.4	−31.5%
Jaipur	74.2	46.3	−37.6%	10.3	5.0	−51.5%
Lahore	50.3	31.2	−38.0%	11.3	4.7	−58.3%
London	14.9	8.2	−45.1%	15.7	4.1	−74.0%
Los Angeles	10.7	6.5	−38.7%	19.8	2.0	−90.0%
Manila	23.7	10.3	−56.3%	10.4	2.2	−78.7%
Mexico City	21.1	9.9	−53.2%	20.4	1.6	−92.3%
Milan	20.5	10.5	−48.9%	16.1	1.4	−91.3%
Nairobi	8.0	5.0	−38.2%	8.1	3.0	−62.4%
Quito	15.7	11.0	−29.5%	8.7	2.2	−75.0%
Tamale	52.3	42.9	−17.9%	5.1	4.2	−16.8%

Table 3
Modelled health impacts (averted cases in one year) for asthma incidence, pre-term birth and low birthweight attributable to removal of combustion-related emissions from land transport, industries, domestic energy use and power generation by city.

City	Averted cases or rate in one year (95% CI)					
	Total number averted			**Rate per 100,000 population (asthma) or live births (birth outcomes)**		
	Asthma incidence	**Pre-term birth**	**Low birthweight**	**Asthma incidence**	**Pre-term birth**	**Low birthweight**
Bhubaneswar	11 (8–50)	193 (−267–379)	248 (28–452)	6 (4–25)	2,283 (−3,159–4,484)	2,934 (331–5,347)
Dar es Salaam	92 (17–223)	93 (−86–304)	52 (4–127)	8 (1–19)	135 (−125–441)	75 (6–184)
Dhaka	307 (106–706)	10,674 (−15,706–(21,829)	11,180 (1,269–21,415)	5 (2–10)	2,818 (−4,146–5,763)	2,951 (335–5,653)
Freetown	1 (0–1)	10 (−13–23)	6 (1–12)	1 (0–1)	174 (−226–400)	104 (17–209)
Glasgow	102 (29–187)	37 (−34–112)	17 (2–38)	33 (9–60)	244 (−225–740)	112 (13–251)
Harare	8 (4–18)	40 (−36–131)	18 (1–45)	3 (1–6)	222 (−199–726)	100 (6–249)
Jaipur	42 (23–165)	316 (−511–593)	439 (54–754)	7 (4–28)	1,241 (−2,007–2,329)	1,724 (212–2,961)
Lahore	311 (164–1,003)	3,428 (−4,314–7,027)	2,377 (256–4,540)	7 (4–23)	1,341 (−1,687–2,749)	930 (100–1,776)
London	1,685 (594–3,861)	446 (−411–1,286)	202 (19–443)	62 (22–142)	339 (−312–977)	153 (14–337)
Los Angeles	6,765 (3,343–18,833)	682 (−600–2,083)	244 (21–542)	149 (74–416)	347 (−305–1,059)	124 (11–276)
Manila	3,601 (1,056–6,913)	3,406 (−3,533–9,407)	3,580 (349–7,591)	39 (11–75)	852 (−884–2,353)	896 (87–1,899)
Mexico City	5,309 (2,312–15,345)	2,255 (−2,255–6,308)	1,245 (117–2,702)	62 (27–178)	550 (−550–1,537)	303 (29–659)
Milan	318 (95–639)	176 (−170–490)	74 (7–163)	41 (12–83)	544 (−525–1,514)	229 (22–504)
Nairobi	273 (70–543)	174 (−164–589)	76 (6–184)	19 (5–38)	235 (−222–796)	103 (8–249)
Quito	272 (84–1,007)	91 (−86–253)	54 (4–126)	35 (11–131)	228 (−216–635)	136 (10–316)
Tamale	1 (0–4)	8 (−12–16)	6 (1–12)	2 (0–9)	292 (−438 584)	219 (37–438)

Table A1
Summary of criteria for semi-quantitative assessment of confidence in model input data.

Model input	Estimated confidence		
	Low Low confidence. Uncertainty likely to be large	**Medium** Medium confidence. Uncertainty likely to be in mid-range	**High** High confidence. Uncertainty likely to be small
Modelled air pollution (NO_2, $PM_{2.5}$)	• Very limited or poor quality local air pollution emissions data • Very limited or poor quality local air pollution monitoring data for model calibration • Other factors that may adversely affect modelled estimates, such as close proximity to large bodies of water	• Some, though limited, local air pollution emissions data • Some, though limited, local air pollution monitoring data for model calibration	• Availability of high quality local air pollution emissions inventories • Network of high quality local air pollution monitoring data for model calibration
Baseline health data	• Very limited or poor quality local health data • Extrapolation of health data from other settings	• Some, though limited, local health data • Extrapolation of health data from other relevant settings (e.g. national data)	• Routine local health data or data from high quality local studies
Exposure-response functions	• Very limited or poor quality epidemiological evidence appropriate to the local conditions, air pollution and population	• Based on evidence (meta-analysis or local evidence) that may not entirely reflect the local conditions, air pollution and population	• Comprehensive meta-analysis or high quality epidemiological evidence from local setting • Based on evidence that is likely to accurately reflect the local conditions, air pollution and population

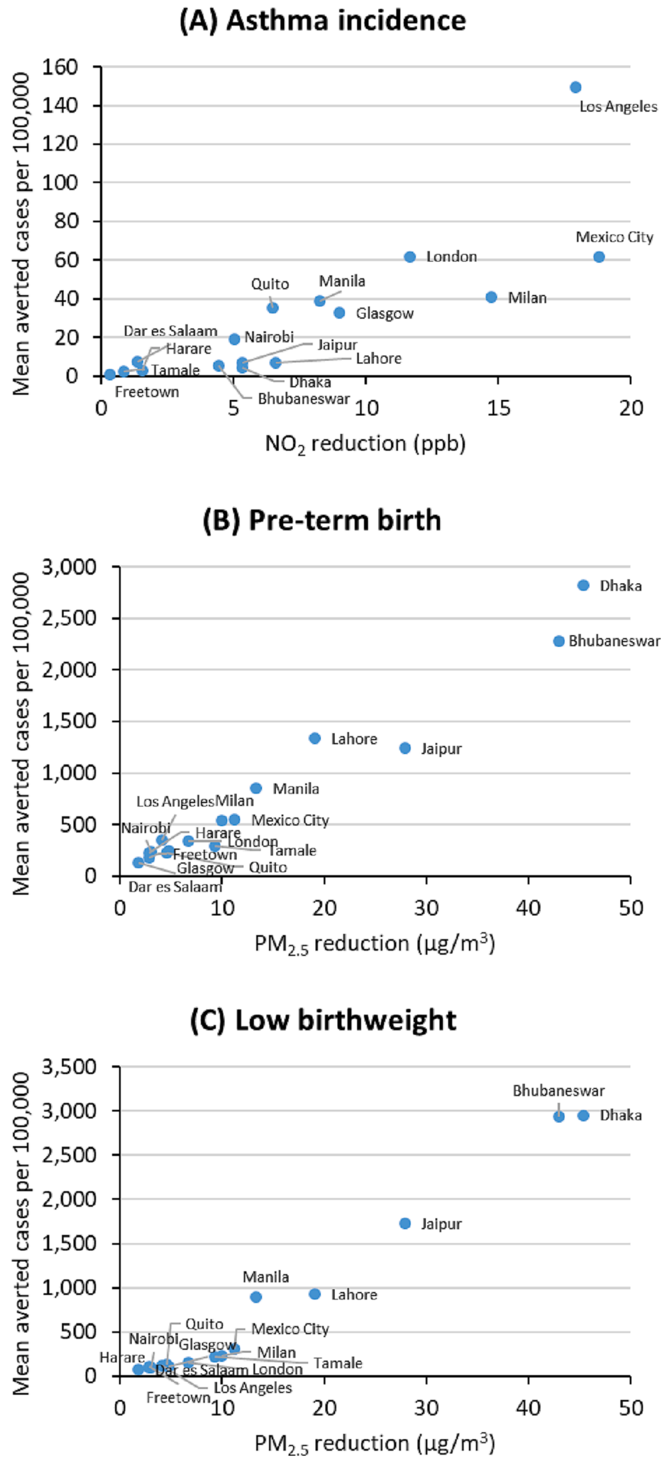

Fig. 1. Relationship between modelled air pollution reductions and modelled averted cases per 100,000 for [A] asthma incidence, [B] pre-term birth and [C] low birthweight.

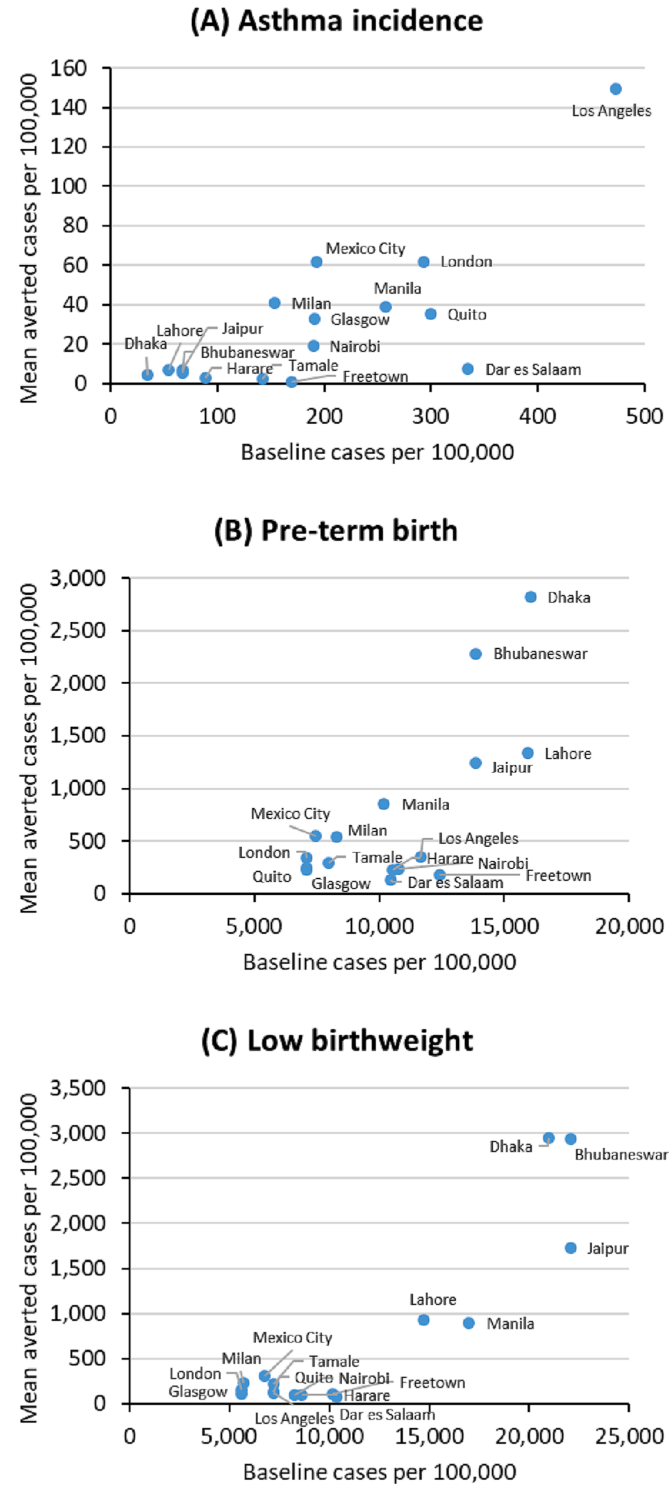

Fig. 2. Relationship between baseline cases per 100,000 and modelled averted cases per 100,000 for [A] asthma incidence, [B] pre-term birth and [C] low birthweight.

children and young people in terms of reduced incidence of asthma and adverse birth outcomes (pre-term and low birthweight births) as a result of lowered urban air pollution exposure. Although there were wide variations across the 16 cities we considered, all would be likely to see appreciable reductions in either asthma cases or adverse birth outcomes. In combination, the total reduction in asthma incidence across these 16 cities would represent roughly one-fifth of the current (2019) burden and there would be a reduction of almost 10% in the burden of adverse birth outcomes. The very wide variation in estimated impacts across cities reflects genuine differences in exposure and underlying disease rates (which vary by setting), but it may also in part reflect differences in the quality and completeness of input data, both with regard to disease outcome and local air pollution emissions. The ten-fold variation in underlying asthma incidence per 100,000 population is particularly noteworthy.

We modelled the effects of *global* decarbonization (i.e. actions across all nations) because of the inter-dependence among cities in their collective contribution to ambient air pollution. We did not quantify the likely effect of individual cities acting alone, but in such a scenario, it is reasonable to assume air pollution reductions would be appreciably smaller, especially for $PM_{2.5}$, because of the contributions of regional and other long-range sources (Kiesewetter et al., 2014). The results therefore emphasise the benefits of cities (and countries) acting together to mitigate climate change and reduce air pollution, since the air pollution concentration in one city will partly reflect emissions from surrounding areas, other regional cities and beyond.

Our findings are consistent with existing evidence that climate change actions that reduce ambient air pollution will have net beneficial effects on population health, but emphasize that those net benefits are likely for children as well as adults (Chang et al., 2017; Gao et al., 2018). In one of the few studies to focus explicitly on children, Perera et al.

Table A2
Estimated level of confidence (low, medium, high) in different components of modelling and modelled health impact estimates for each city.

City	Confidence			
	Modelled air pollution ($PM_{2.5}$, NO_2)	Baseline health data	Exposure-response functions	Modelled health impact estimates
Bhubaneswar	Medium	Low	Medium	**Medium** Mid-range uncertainty for air pollution and ERFs but baseline health data expected to be poor quality
Dar es Salaam	Low	Low	Low	**Low** Lack of local air quality and source apportionment data, poor quality health data and lack of local epidemiological evidence
Dhaka	Medium	Low	Medium	**Medium** Mid-range uncertainty for air pollution, poor quality health data, though some local epidemiological evidence
Freetown	Low	Low	Low	**Low** Lack of local air quality and source apportionment data, poor quality health data and lack of local epidemiological evidence
Glasgow	High	Medium	High	**High** Reasonably reliable air pollution estimates and high quality local epidemiological evidence but lower confidence in health data since based on assumptions/imperfect information
Harare	Low	Low	Low	**Low** Lack of local air quality and source apportionment data,

(*continued on next page*)

Table A2 (*continued*)

				poor quality health data and lack of local epidemiological evidence
Jaipur	Medium	Low	Medium	**Medium** Reasonable confidence in air pollution estimates and some local epidemiological evidence but poor quality local health data
Lahore	Medium	Low	Medium	**Medium** Reasonable confidence in air pollution estimates and some local epidemiological evidence but poor quality local health data
London	High	Medium	High	**High** Very reliable air pollution estimates and high quality local epidemiological evidence but lower confidence in health data since based on assumptions/imperfect information
Los Angeles	High	Medium	High	**High** Very reliable air pollution estimates and high quality local epidemiological evidence but lower confidence in health data since based on assumptions/imperfect information
Manila	Medium	Medium	Low	**Medium** Reasonable confidence in air pollution estimates and baseline health data but lack of local epidemiological evidence
Mexico City	High	Medium	Medium	**Medium** Good local air pollution data but

(*continued on next page*)

(2020) assessed the $PM_{2.5}$-related benefits of the Regional Greenhouse Gas Initiative to reduce GHG emissions from the electric power sector in the north-eastern USA, finding reductions in asthma cases, pre-term births, cases of autism spectrum disorder and low birthweight (Perera et al., 2020). Other studies have included child health in wider assessments of climate change mitigation health impacts. These include analyses showing improvements in respiratory health due to alternative transport scenarios aimed at reducing GHG emissions in Adelaide, Australia (Xia et al., 2015), reductions in infant mortality and improved respiratory health from climate mitigation policies in Europe (Schucht

Table A2 (*continued*)

				uncertainties in health data and ERFs likely to be in mid-range
Milan	High	Medium	High	**High** Reasonably reliable air pollution estimates and high quality local epidemiological evidence but lower confidence in health data since based on assumptions/imperfect information
Nairobi	Low	Low	Low	**Low** Lack of local air quality and source apportionment data, poor quality health data and lack of local epidemiological evidence
Quito	Medium	Medium	Low	**Medium** Reasonable confidence in air pollution estimates and baseline health data but lack of local epidemiological evidence
Tamale	Low	Low	Low	**Low** Lack of local air quality and source apportionment data, poor quality health data and lack of local epidemiological evidence

et al., 2015), reductions in infant mortality, health service contacts and acute bronchitis in children from the use of technologies to reduce fossil fuel emissions in Mexico City, Santiago, São Paulo and New York City (Cifuentes et al., 2001), and reductions in paediatric outpatient visits under energy scenarios in Shanghai, including scenarios of improved energy efficiency and a CO_2 tax (Kan et al., 2004). Further studies have considered child health impacts from isolated, local actions intended to reduce ambient air pollution but which may also lead to incidental reductions in GHG emissions (Adamkiewicz et al., 2021; Host et al., 2020; Malmqvist et al., 2018; Galvis et al., 2015).

Table A2 in Appendix A presents our semi-quantitative assessment of confidence in the model inputs and results. Overall, our confidence is greater for the high income cities of Europe and North America and lower for the lower income cities in Africa, Asia and South America. Uncertainties were generally largest for underlying disease rates because of differences or unknowns in the completeness of data recording and comparability of definitions/detection. Although we used well established data and methods of the Global Burden of Disease (GBD) initiative, those methods still rely on assumptions and imperfect data, for example using country-level estimates to represent cities. There may be particular concerns about underestimation of asthma prevalence due to under-reporting and differences in clinical definitions in Africa and South Asia, for example Asher et al. (2021).

Modelled air pollution estimates are most likely to be close to true ambient levels in higher income settings (e.g. Europe and North America) where local emissions inventories have been established and there is often extensive monitoring. But in many lower income settings, especially in sub-Saharan Africa, such inventories are less (Ostro et al., 2018). There is therefore an urgent need for improved health and air pollution data collection in many low income settings.

We also acknowledge that the strength of evidence of (avoidable) causal associations for child asthma incidence and birth outcomes is lower than for some other outcomes of air pollution exposure. We chose a select few child health outcomes where, in our judgement, the balance of evidence is clearly in favour of avoidable causal relationships with $PM_{2.5}$ or NO_2, supported by recent systematic reviews (Ghosh et al., 2021; Khreis et al., 2017). Our rationale is that decisions for climate action are needed now with less-than-perfect evidence, and that a 'balance of probabilities' assessment is an important component of that evidence. The evidence on which the exposure–response functions was based comes largely from higher income settings (particularly Europe and the USA), though there is growing evidence from settings with relatively higher ambient air pollution levels (e.g. east Asia). Because of differences in population vulnerability, source characteristics and exposure patterns, extrapolation of these exposure–response functions to other settings may not always be appropriate. Nonetheless, the exposure–response functions we used were from global meta-analyses and the GBD study, and all the functions have been previously applied globally in other studies.

Our analysis is the first to assess the impacts of climate change mitigation actions on the health of children in cities representing a wide range of settings, including cities in the Global South. Among the strengths of our analysis are that we employed a state-of-the-art atmospheric chemistry model and applied established health impact modelling methods based on the latest evidence of associations between air pollutants and important child and adolescent health outcomes. However, with any modelling exercise such as this, there are of course multiple uncertainties. In particular, removal of *all* combustion-related emissions is a theoretical scenario and probably unrealistic even for the distant future, and not needed for achievement of net zero targets. However, it seemed a reasonable 'upper limit' approximation of needed ambitions for the 2015 Paris Agreement and could help identify sectors to target emission reductions in the future. We did not attempt to capture the contribution of household exposure, which may be the dominant source of exposure in some settings (though we did account for the contribution of domestic emissions to ambient air pollution). It is also worth noting that there would likely be benefits for other child health outcomes that were not included in this analysis because of insufficient evidence or data, including lung and neurological development. The probable total health impact of decarbonization could therefore be appreciably greater than quantified in this study. There also remain uncertainties relating to data inputs and causality as described above, especially for cities in lower income countries.

5. Conclusion

In conclusion, achieving a global target of net zero GHG emissions would likely result in substantial reductions in ambient air pollution which would bring significant net beneficial effects on child asthma and adverse birth outcomes. There are important uncertainties in our estimates of these impacts, but we believe they provide a reasonable demonstration of some of the likely gains from an ambitious decarbonization agenda. Future work on the quantification of health impacts attributable to climate change mitigation actions would benefit from efforts to improve data quality.

Data sharing

All data and code used for this study will be made available on request following publication. Please email james.milner@lshtm.ac.uk.

CRediT authorship contribution statement

James Milner: Conceptualization, Methodology, Software, Writing – original draft. **Robert Hughes:** Conceptualization, Writing – review & editing, Funding acquisition. **Sourangsu Chowdhury:** Methodology, Resources, Writing – review & editing. **Roberto Picetti:** Resources, Writing – review & editing. **Rakesh Ghosh:** Methodology, Resources, Writing – review & editing. **Shunmay Yeung:** Conceptualization, Writing – review & editing. **Jos Lelieveld:** Writing – review & editing, Supervision. **Alan D. Dangour:** Conceptualization, Writing – review & editing, Supervision, Funding acquisition. **Paul Wilkinson:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: RCH has been a paid adviser to both the Children's Investment Fund Foundation and the Clean Air Fund charities.

Data availability

Data will be made available on request.

Acknowledgement

The authors are grateful for the support of other collaborators on the 'Children, Cities and Climate' project, in particular Ana Bonell, Rachel Juel, Sarah Sharpe and Martha Jennings.

Funding

This work was supported by Fondation Botnar (Grant ref: OOG-21-006).

References

Achakulwisut, P., Brauer, M., Hystad, P., et al., 2019. Global, national, and urban burdens of paediatric asthma incidence attributable to ambient NO_2 pollution: estimates from global datasets. Lancet. Planet. Health 3, e166–e178.

Adamkiewicz, L., Kryza, M., Mucha, D., et al., 2021. Estimating health impacts due to the reduction of particulate air pollution from the household sector expected under various scenarios. Appl. Sci 11, 272.

Asher, M.I., Rutter, C.E., Bissell, K., et al., 2021. Worldwide trends in the burden of asthma symptoms in school-aged children: Global Asthma Network Phase I cross-sectional study. Lancet 398 (10311), 1569–1580.

Bey, I., Jacob, D.J., Yantosca, R.M., et al., 2001. Global modeling of tropospheric chemistry with assimilated meteorology: Model description and evaluation. J. Geophys. Res. Atmos 106 (D19), 23073–23095.

Chang, K.M., Hess, J.J., Balbus, J.M., et al., 2017. Ancillary health effects of climate mitigation scenarios as drivers of policy uptake: a review of air quality, transportation and diet co-benefits modeling studies. Environ. Res. Lett 12 (11), 113001.

Chen, Z., Salam, M.T., Eckel, S.P., et al., 2015. Chronic effects of air pollution on respiratory health in Southern California children: findings from the Southern California Children's Health Study. J. Thorac. Dis 7 (1), 46–58.

Chowdhury, S., Haines, A., Klingmüller, K., et al., 2021. Global and national assessment of the incidence of asthma in children and adolescents from major sources of ambient NO2. Environ. Res. Lett 16, 035020.

Chowdhury, S., Pozzer, A., Haines, A., et al., 2022. Global health burden of ambient PM2.5 and the contribution of anthropogenic black carbon and organic aerosols. Environ. Int 159, 107020.

Cifuentes, L., Borja-Aburto, V.H., Gouveia, N., et al., 2001. Assessing the health benefits of urban air pollution reductions associated with climate change mitigation (2000–2020): Santiago, Sao Paulo, Mexico City, and New York City. Environ. Health. Perspect 109, 419–425.

ECIU. Net Zero Scorecard. Energy & Climate Intelligence Unit, 2022. https://eciu.net/netzerotracker [Accessed: 1 March 2022].

Esposito, S., Tenconi, R., Lelii, M., et al., 2014. Possible molecular mechanisms linking air pollution and asthma in children. Possible molecular mechanisms linking air pollution and asthma in children. BMC. Pulm. Med 14, 31.

European Commission, 2018. EC Urban Centre Database UCDB R2019A. https://ghsl.jrc.ec.europa.eu/ucdb2018Overview.php [Accessed: 1 October 2021].

Galvis, B., Bergin, M., Boylan, J., et al., 2015. Air quality impacts and health-benefit valuation of a low-emission technology for rail yard locomotives in Atlanta Georgia. Sci. Total. Environ 533, 156–164.

Gao, J., Kovats, S., Vardoulakis, S., et al., 2018. Public health co-benefits of greenhouse gas emissions reduction: a systematic review. Sci. Total. Environ 627, 388–402.

Gao J. 2020. Global 1-km Downscaled Population Base Year and Projection Grids Based on the Shared Socioeconomic Pathways, Revision 01. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC) [Accessed 1: October 2021].

Ghosh, R., Causey, K., Burkart, K., et al., 2021. Ambient and household PM2.5 pollution and adverse perinatal outcomes: a meta-regression and analysis of attributable global burden for 204 countries and territories. PLOS. Med 18, e1003718.

Hamilton, I., Kennard, H., McGushin, A., et al., 2021. The public health implications of the Paris Agreement: a modelling study. Lancet. Planet. Health 5, e74–e83.

Hammer, M., van Donkelaar, A., Li, C., et al., 2020. Global estimates and long-term trends of fine particulate matter concentrations (1998–2018). Environ. Sci. Technol 54, 7879–7890.

Hoesly, R., Smith, S., Feng, L., et al., 2018. Historical (1750–2014) anthropogenic emissions of reactive gases and aerosols from the Community Emissions Data System (CEDS). Geosci. Model. Dev 11, 369–408.

Host, S., Honore, C., Joly, F., et al., 2020. Implementation of various hypothetical low emission zone scenarios in Greater Paris: assessment of fine-scale reduction in exposure and expected health benefits. Environ. Res 185, 109405.

IHME, 2019. GBD Results Tool. Institute for Health Metrics and Evaluation, Seattle, WA [Accessed: 1 October 2021].

Johnson, N., Hoffmann, R., a, C. Behlen J, et al., 2021. Air pollution and children's health—a review of adverse effects associated with prenatal exposure from fine to ultrafine particulate matter. Environ Health. Prev. Med 26, 72.

Kaiser, J.W., Heil, A., Andreae, M.O., et al., 2012. Biomass burning emissions estimated with a global fire assimilation system based on observed fire radiative power. Biogeosciences 9 (1), 527–554.
Kan, H.D., Chen, B.H., Chen, C.H., et al., 2004. An evaluation of public health impact of ambient air pollution under various energy scenarios in Shanghai. China. Atmos. Environ 38, 95–102.
Khreis, H., Kelly, C., Tate, J., et al., 2017. Exposure to traffic-related air pollution and risk of development of childhood asthma: a systematic review and meta-analysis. Environ. Int 100, 1–31.
Khreis, H., Cirach, M., Mueller, N., et al., 2019. Outdoor air pollution and the burden of childhood asthma across Europe. Eur. Respir. J 54, 1802194.
Kiesewetter, G., Borken-Kleefeld, J., Schöpp, W., et al., 2014. Modelling street level PM10 concentrations across Europe: source apportionment and possible futures. Atmos. Chem. Phys 15, 1539–1553.
Landrigan, P., Fuller, R., Fisher, S., et al., 2019. Pollution and children's health. Sci. Total. Environ 650, 2389–2394.
Larkin, A., Geddes, J., Martin, R., et al., 2017. Global land use regression model for nitrogen dioxide air pollution. Environ. Sci. Technol 51, 6957–6964.
Lelieveld, J., Klingmüller, K., Pozzer, A., et al., 2019. Effects of fossil fuel and total anthropogenic emission removal on public health and climate. Proc. Natl. Acad. Sci. USA 116, 7192–7197.
Malmqvist, E., Lisberg Jensen, E., Westerberg, K., et al., 2018. Estimated health benefits of exhaust free transport in the city of Malmo. Southern. Sweden. Environ. Int 118, 78–85.
Markandya, A., Sampedro, J., Smith, S., et al., 2018. Health co-benefits from air pollution and mitigation costs of the Paris Agreement: a modelling study. Lancet. Planet. Health 2, e126–e133.
Ostro, B., Spadaro, J.V., Gumy, S., et al., 2018. Assessing the recent estimates of the global burden of disease for ambient air pollution: Methodological changes and implications for low- and middle-income countries. Environ. Res. 166, 713–725.
Perera, F., Ashrafi, A., Kinney, P., et al., 2019. Towards a fuller assessment of benefits to children's health of reducing air pollution and mitigating climate change due to fossil fuel combustion. Environ. Res 172, 55–72.
Perera, F., Cooley, D., Berberian, A., et al., 2020. Co-benefits to children's health of the U.S. Regional Greenhouse Gas Initiative. Environ. Health. Perspect 128.
Pozzer, A., Jöckel, P., Van Aardenne, J., 2009. The influence of the vertical distribution of emissions on tropospheric chemistry. Atmos. Chem. Phys 9 (24), 9417–9432.
Schucht, S., Colette, A., Rao, S., et al., 2015. Moving towards ambitious climate policies: monetised health benefits from improved air quality could offset mitigation costs in Europe. Environ. Sci. Pol 50, 252–269.
van Donkelaar, A., Hammer, M.S., Bindle, L., et al., 2021. Monthly global estimates of fine particulate matter and their uncertainty. Environ. Sci. Technol 55 (22), 15287–15300.
Vandyck, T., Keramidas, K., Kitous, A., et al., 2018. Air quality co-benefits for human health and agriculture counterbalance costs to meet Paris Agreement pledges. Nat. Commun 9, 4939.
Venkataraman, C., Bhushan, M., Dey, S., et al., 2020. Indian network project on Carbonaceous Aerosol Emissions, Source Apportionment and Climate Impacts (COALESCE). Bull. Am. Meteorol. Soc 101 (7), E1052–E1068.
Volk, H., Perera, F., Braun, J., et al., 2021. Prenatal air pollution exposure and neurodevelopment: a review and blueprint for a harmonized approach within ECHO. Environ. Res 196, 110320.
WHO, 2018. WHO Air Quality Database (2018 Update). World Health Organization, Geneva, Switzerland.
Xia, T., Nitschke, M., Zhang, Y., et al., 2015. Traffic-related air pollution and health co-benefits of alternative transport in Adelaide, South Australia. Environ. Int 74, 281–290.