

Supplement of Atmos. Chem. Phys., 19, 11887–11910, 2019
<https://doi.org/10.5194/acp-19-11887-2019-supplement>
© Author(s) 2019. This work is distributed under
the Creative Commons Attribution 4.0 License.



Supplement of

Exploring the impacts of anthropogenic emission sectors on PM_{2.5} and human health in South and East Asia

Carly L. Reddington et al.

Correspondence to: Carly L. Reddington (c.l.s.reddington@leeds.ac.uk)

The copyright of individual parts of the supplement might differ from the CC BY 4.0 License.

S1 Health impact estimation

Equation S1 expresses premature mortality (M) from disease endpoint (j) in grid cell (i) as a function of the population of the grid cell (P), the baseline mortality rate (I) and relative risk (RR) at the $PM_{2.5}$ concentration (c). Regional estimates were then calculated through summing all disease endpoints (j) over all grid cells (i), and split by state/province using shapefiles.

$$5 \quad M_{i,j} = P_i I_j (RR_{j,c} - 1) / RR_{j,c} \quad (S1)$$

To be consistent with the Global Burden of Diseases, Injuries, and Risk Factors Study 2015 (GBD2015), we used country- and disease-specific baseline mortality rates from the GBD2015 in 5-year groupings for both genders combined (Institute for Health Metrics and Evaluation, 2016). This was done for mean, upper and lower confidence intervals.

Years of life lost (YLL) are estimated following Eq. S2 (Devleesschauwer et al., 2014), where the number of deaths per disease and grid cell ($M_{i,j}$) is multiplied by the age-specific life expectancy (LE) remaining at the age of death from the standard reference life table from GBD2015 (GBD Collaborative Network, 2016).

$$10 \quad YLL_{i,j} = M_{i,j} LE \quad (S2)$$

This study estimates health impacts from long-term exposure of whole populations to annual mean ambient $PM_{2.5}$. This study does not account for indoor exposure to pollution, and the health impacts resulting from ambient $PM_{2.5}$ exposure therefore do not represent the total $PM_{2.5}$ related premature mortality burden. Household air pollution is a serious issue and there is a need to address this in conjunction with ambient air pollution both in India (Balakrishnan et al., 2013) and China (Du et al., 2018).

S1.1 Uncertainties

We estimate an error in each term, and then combine the fractional errors in quadrature (i.e. square root of the sum of squares). Uncertainty intervals at the 95% level (95UI) were determined reflecting the statistical uncertainty of the parameters in Eq. S1 (Lelieveld et al., 2013). This includes the population data having an uncertainty range of $\pm 2\%$ (GPWv4, 2016). The GBD2015 baseline mortality estimates (Institute for Health Metrics and Evaluation, 2016) have defined upper and lower uncertainty values. For India, the 95UI in annual mean $PM_{2.5}$ concentrations was estimated for each grid cell through assuming a Gaussian distribution and applying ± 2 standard deviations from weekly $PM_{2.5}$ concentrations. The uncertainties in $PM_{2.5}$ were then applied to the derived uncertainties in the IER for the RR at both 5% and 95% confidence levels for India as in Conibear et al. (2018a).

Supplementary tables

- Table S1.** Summary of mass concentrations ($\mu\text{g m}^{-3}$) of non-refractory particulate matter species, including organics (Org), sulfate (SO_4), nitrate (NO_3), and ammonium (NH_4) in China measured with aerosol mass spectrometer (AMS) systems. Regions are: North China Plain (NCP), Yangtze River Delta (YRD), Pearl River Delta (PRD) and North West China (NWC).
- 5 Table is modified from Li et al. (2017) (Table S3). Please see Qin et al. (2017) for information and data from the Guangzhou field campaign and references in Li et al. (2017) for all other individual field campaigns. AMS measurements from two campaigns that took place in Beijing during January 2013 only were removed from the dataset prior to comparison and are not included in the Table due to the anomalously high mass concentrations observed during this month.

Site	Measurement time	Characteristics	Region	Org	SO_4	NO_3	NH_4
Beijing	Jul. 2006	urban	NCP	28.1	20.3	17.3	13.1
Yufa	Aug. – Sep. 2006	suburban	NCP	10.8	8.2	2.9	4.1
Beijing	Jan. – Oct. 2008	urban	NCP	34.8	16.5	16.1	10
Mt. Tai	Jun. 2010 – Jan. 2012	mountainous	NCP	11.2	9.2	7.2	5.8
Tianjin	Sep. 2010	urban	NCP	15.7	14.4	16.2	13.6
Beijing	Jul. – Sep. 2008	urban	NCP	23.9	16.8	10	10
Beijing	Sep. 2012 – Jan. 2013	urban	NCP	21.2	9.7	9.1	8.6
Beijing	Oct. – Dec. 2014	urban	NCP	33.1	10.3	16.2	8.4
Changdao	Mar. – Apr. 2011	receptor	NCP	14.1	8.9	13.1	7.1
Beijing	Jun. – Aug. 2011	urban-summer	NCP	20	9	12	8
Beijing	Nov. 2011 – Jan. 2012	urban-winter	NCP	34.4	9.3	11	8.6
Beijing	Sep. 2012	urban-autumn	NCP	17.1	6.4	8.1	5.1
Beijing	Oct. – Dec. 2012	urban-winter	NCP	34.1	9.9	9.9	6.1
Beijing	Dec. 2013 – Jan. 2014	urban-winter	NCP	29.5	6.5	5.9	4
Beijing	Oct. – Nov. 2014	urban-autumn	NCP	20.6	5.8	12.5	4.1
Xianghe	Jun. 2013	suburban-winter	NCP	28.3	13	14	8.8
Lanzhou	Jul. – Aug. 2012	urban	NWC	11.5	3.9	2.5	2.7
Menyuan	Sep. – Oct. 2013	background-autumn	NWC	4.9	3.2	1.2	1.4
Xi'an	Dec. 2012 – Jan. 2013	urban-winter	NWC	73.8	18.3	13.6	16.7
Xinzhou	Jul. – Sep. 2014	suburban-summer	NWC	11.7	11	5.1	4.2
Qingyuan	Jul. 2006	rural	PRD	13.6	10.8	1.4	3.7
Heshan	Nov. 2010	urban outflow	PRD	17.4	10	6.2	4.6
Hong Kong	2011 – 2012	suburban	PRD	4.8	7.4	0.8	2.3
Kaiping	Oct. – Nov. 2008	rural	PRD	11.2	11.2	3.5	4.6
Shenzhen	Oct. – Dec. 2009	urban	PRD	17.7	10.9	4.5	4.5
Shenzhen	Jan. – Feb. 2009	urban	PRD	27	13	7.3	7.7
Hong Kong	Sep. – Dec. 2013	urban-winter	PRD	15.1	6	1.7	3
Guangzhou	Nov. 2014 – Jan. 2015	suburban	PRD	25.0	12.4	6.1	4.9
Lin'an	Mar. 2013	background	YRD	17.7	8.1	9.8	6.9

Lin'an	Nov. – Dec. 2013	background	YRD	29	10	15	7.7
Shanghai	May – Jun. 2010	urban	YRD	8.4	9.7	4.8	3.9
Jiaxing	Jun. – Dec. 2010	suburban	YRD	11.7	7.7	6.7	4.5
Nanjing	Jan. 2013	urban-winter	YRD	22.5	8.6	12.8	8

5

10

15

20

25

30

35

Table S2. Comparison of sector-specific averted or attributed annual premature mortality estimates for China from this study and previous studies. Sector-specific mortality estimates are split into those calculated using the substitution approach (i.e. the number of averted premature mortalities resulting from complete mitigation of each sector) and those calculated using the attribution approach (i.e. the number of premature mortalities attributed to each sector). To compare with previous studies that have used the mortality-attribution method (see Table 3) we have calculated the number of annual premature mortalities attributed to each emission sector for this study. Emission sectors are: agriculture (AGR), open biomass burning (BBU), power generation (ENE), industrial non-power (IND), residential energy use (RES) and land transport (TRA).

Reference	PM _{2.5} -mortality (all sources)	RES	IND	ENE	TRA	BBU	AGR
Substitution Approach							
Silva et al. (2016) ^a	1,060,000 (696,000- 1,440,000)	223,000 (158,000- 299,000)	178,000 (127,000- 239,000)	117,000 (84,500- 156,000)	48,000 (34,700- 62,500)	-	-
Butt et al. (2016)	-	121,075 (44,596 – 195,443)	-	-	-	-	-
Aunan et al. (2018)	1,146,000 (1,088,000- 1,181,000)	397,000 (340,000- 442,000)	-	-	-	-	-
Butt et al., <i>in prep.</i> (2019)	-	187,472 (153,938 - 224,457)	-	-	-	-	-
This study	1,046,900 (846,100- 1,286,900)	187,900 (140,700- 250,300)	203,600 (152,300- 271,100)	22,300 (16,500- 30,400)	14,800 (10,800- 20,500)	7,300 (5,600- 9,300)	-
Attribution Approach							
Lelieveld et al. (2015) ^b	1,357,000	434,240	108,560	244,260	40,710	13,570	393,530
Archer- Nicholls et al. (2016)	916,000 (821,000- 933,000)	341,000 (306,000- 370,000)	-	-	-	-	-
GBD- MAPS (2016) ^c	915,898 (821,470- 993,077)	177,494 (159,160- 192,519)	250,374 (224,455- 271,509)	86,531 (77,654- 93,804)	137,395 (123,182- 148,899)	70,228 (63,006- 76,067)	-
Hu et al. (2017) ^d	1,300,000 (594,000- 1,777,000)	282,000 (129,000- 386,000)	397,000 (181,000- 542,000)	134,000 (61,000- 183,000)	74,000 (34,000- 101,000)	64,000 (29,000- 87,000)	159,000 (72,000- 217,000)
Gao et al. (2018)	1,331,100 (824,800- 1,914,600)	-	-	520,000 (324,300- 747,300)	-	-	-
Gu et al. (2018) ^b	1,143,000 (168,000- 1,796,000)	229,000 (34,000- 354,000)	414,000 (61,000- 640,000)	183,000 (27,000- 288,000)	73,000 (11,000- 115,000)	-	129,000 (19,000- 203,000)
Butt et al., <i>in prep.</i> (2019)	-	406,560 (234,305- 598,285)	-	-	-	-	-
This study	1,046,900 (846,100- 1,286,900)	398,600 (322,200- 490,000)	451,500 (364,900- 555,000)	55,000 (44,400- 67,600)	39,400 (31,800- 48,400)	10,100 (8,100- 12,400)	-

^a Values are for all of East Asia (including China).

^b Values show total and attributed premature mortality due to exposure to PM_{2.5} and ozone air pollution combined.

^c Values taken from Table 7 of GBD-MAPS (2016). ENE = Powerplant coal; IND = Industrial coal + Non-coal industrial; RES = Domestic coal + Domestic biomass burning.

5 ^d Values calculated from total premature mortality estimates in Table S2 and relative source contributions in Table 1 of Hu et al. (2017).

Table S3. Comparison of sector-specific averted or attributed annual premature mortality estimates for India from this study and previous studies. Sector-specific mortality estimates are split into those calculated using the substitution approach (i.e. the number of averted premature mortalities resulting from complete mitigation of each sector) and those calculated using the attribution approach (i.e. the number of premature mortalities attributed to each sector). To compare with previous studies that have used the mortality-attribution method (see Table 3) we have calculated the number of annual premature mortalities attributed to each emission sector for this study. Emission sectors are: agriculture (AGR), open biomass burning (BBU), power generation (ENE), industrial non-power (IND), residential energy use (RES) and land transport (TRA).

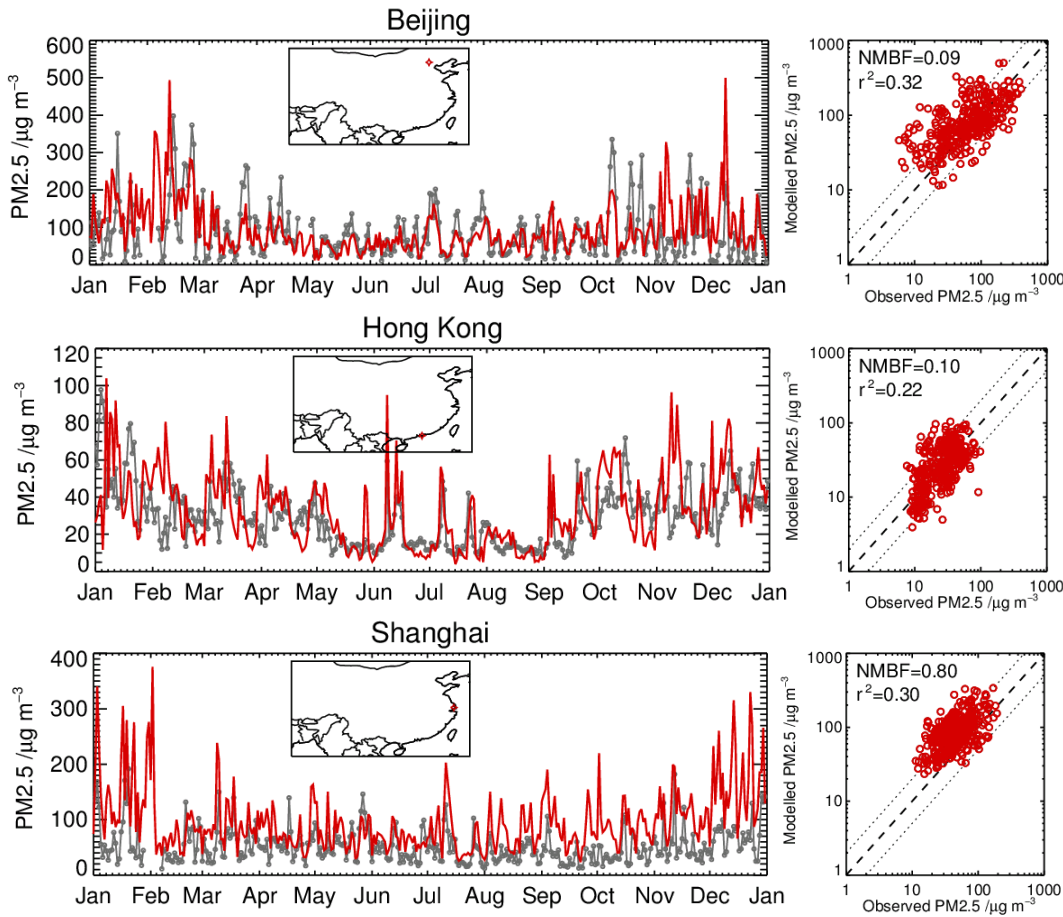
Reference	PM _{2.5} -mortality (all sources)	RES	IND	ENE	TRA	BBU	AGR
Silva et al. (2016)	392,000 (129,000-590,000)	173,000 (88,000-253,000)	36,400 (18,900-52,500)	39,200 (18,900-57,100)	19,900 (11,100-28,800)	-	-
Butt et al. (2016)	-	72,890 (26,891-117,360)	-	-	-	-	-
Upadhyay et al. (2018)	793,985	378,295 (175,002-575,293)	45,999 (20,682-70,021)	18,201 (7,777-27,786)	28,180 (12,459-42,934)	-	-
Butt et al., <i>in prep.</i> (2019)	-	141,757 (122,960 - 170,933)	-	-	-	-	-
This study & Conibear et al. (2018a)	990,000 (660,200-1,350,800)	255,600 (161,800-339,700)	66,500 (44,700-89,600)	90,400 (59,600-121,500)	43,000 (28,900-57,900)	12,300 (8,400-16,450)	1,000 (700-1,400)
Lelieveld et al. (2015) ^a	644,993	322,497	45,150	90,299	32,250	45,150	38,700
Gao et al. (2018)	803,800 (493,300-1,135,200)	-	-	267,900 (165,600-377,600)	-	-	-
GBD-MAPS (2018) ^b	1,090,400 (939,600-1,254,600)	267,700 (230,000-315,000)	106,200 (91,100-121,700)	82,900 (71,600-94,700)	23,100 (19,900 - 26,400)	66,200 (56,700-76,800)	-
Guo et al. (2018) ^c	1,040,000 (530,000-1,540,000)	577,200 (294,150-854,700)	204,880 (104,410-303,380)	70,720 (36,040-104,720)	19,760 (10,070-29,260)	-	123,760 (63,070-183,260)
Butt et al., <i>in prep.</i> (2019)	-	324,301 (197,379-464,012)	-	-	-	-	-
This study & Conibear et al. (2018a)	990,000 (660,200-1,350,800)	510,500 (340,500-696,700)	161,000 (107,300-219,600)	207,700 (138,500-283,400)	102,100 (68,100-139,300)	27,700 (18,500-37,800)	3,500 (2,300-4,700)

^a Values show total and attributed premature mortality due to exposure to PM_{2.5} and ozone air pollution combined.

^b Values taken from Table 3 of GBD-MAPS (2018). ENE = Powerplant coal; IND = Industrial coal + Brick production.

^c Sector-specific values calculated from total excess mortality and source contribution fractions in Table 2 of Guo et al. (2018).

Supplementary figures

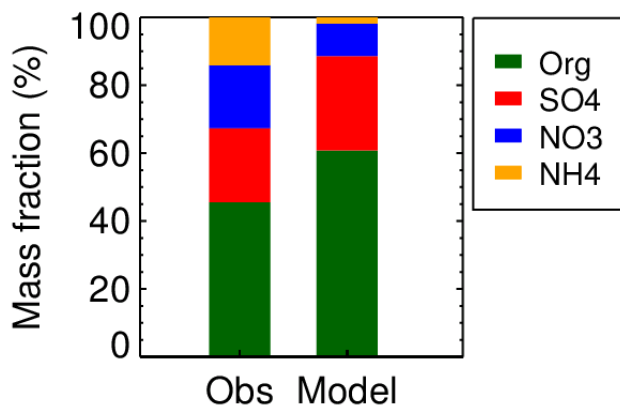


5

Figure S1. Simulated (red) and measured (grey) daily mean surface PM_{2.5} concentrations during 2014 in three megacities in China (top panel: Beijing municipality; middle panel: Hong Kong Special Administrative Region (SAR); bottom panel: Shanghai municipality). The location of each megacity is indicated with a red point on the map inset. The normalised mean bias factor (NMBF; Yu et al., 2006) and Pearson's correlation coefficient (r^2) between modelled and observed daily mean PM_{2.5} concentrations are shown in the upper left corner of the plots on the right. Measured PM_{2.5} concentrations for each megacity are averages of measurement data from multiple stations within the city boundaries. The monitoring stations are operated by the China National Environmental Monitoring Center (CNEMC) for Mainland China and the Environmental Protection Department for the Government of Hong Kong SAR. Measurement data for Beijing and Shanghai were downloaded from <http://beijingair.sinaapp.com/> and data for Hong Kong was downloaded from the Hong Kong Environmental Protection Department website (<https://cd.epic.epd.gov.hk/EPICDI/air/station/>) (see Silver et al. (2018) for further details).

10

15



5 **Figure S2.** Simulated (“Model”) and measured (“Obs”) average aerosol composition in China. Shown is the mass fractions of non-refractory particulate matter species (organics (Org), sulphate (SO₄), nitrate (NO₃), and ammonium (NH₄)). Measurement data are from Y.J. Li et al. (2017) and Qin et al. (2017). Measurement locations, time periods and references are detailed in Table S1.

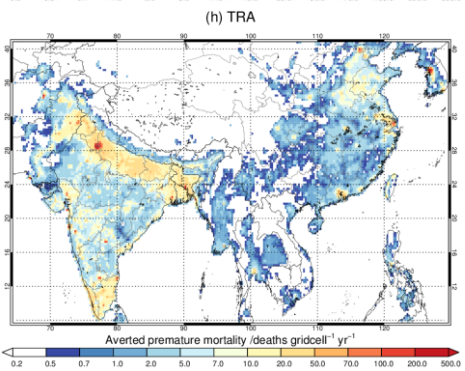
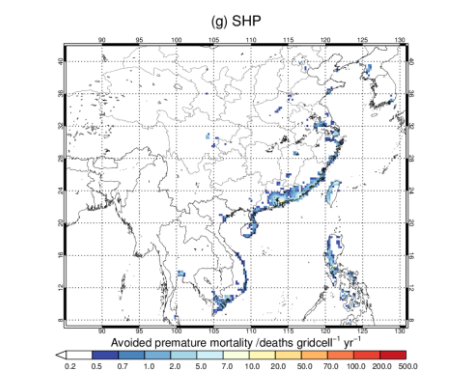
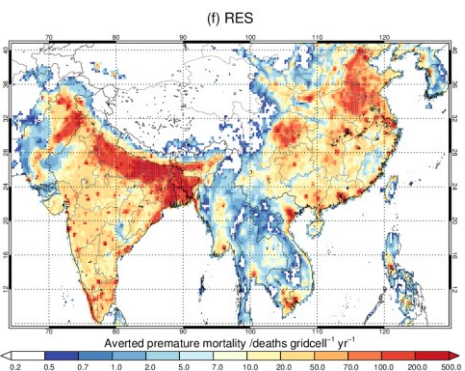
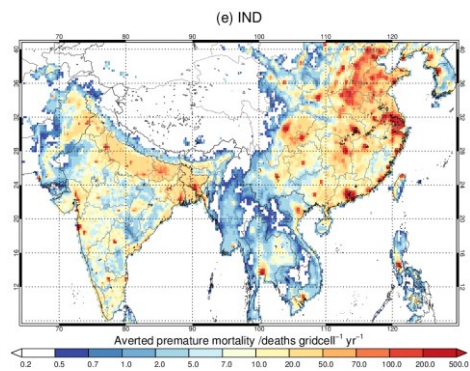
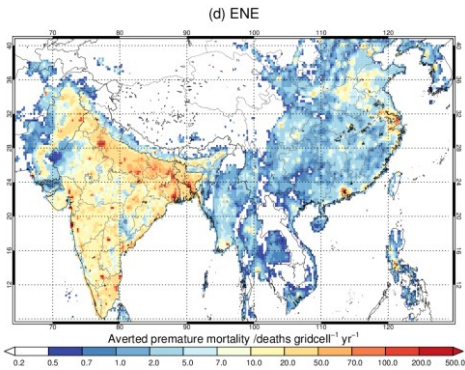
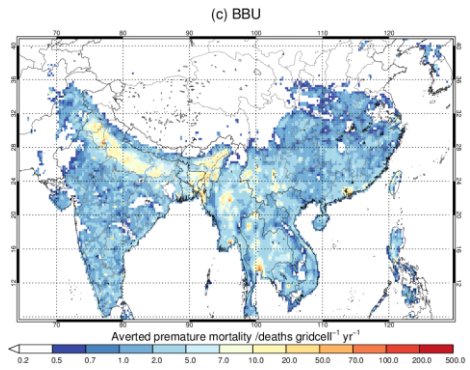
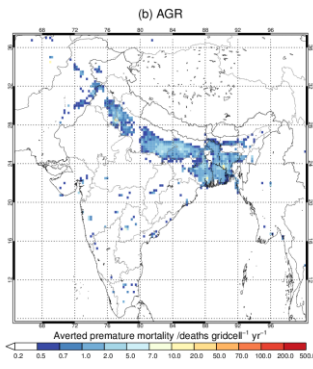
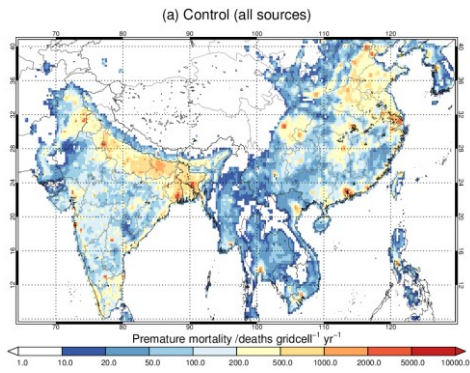
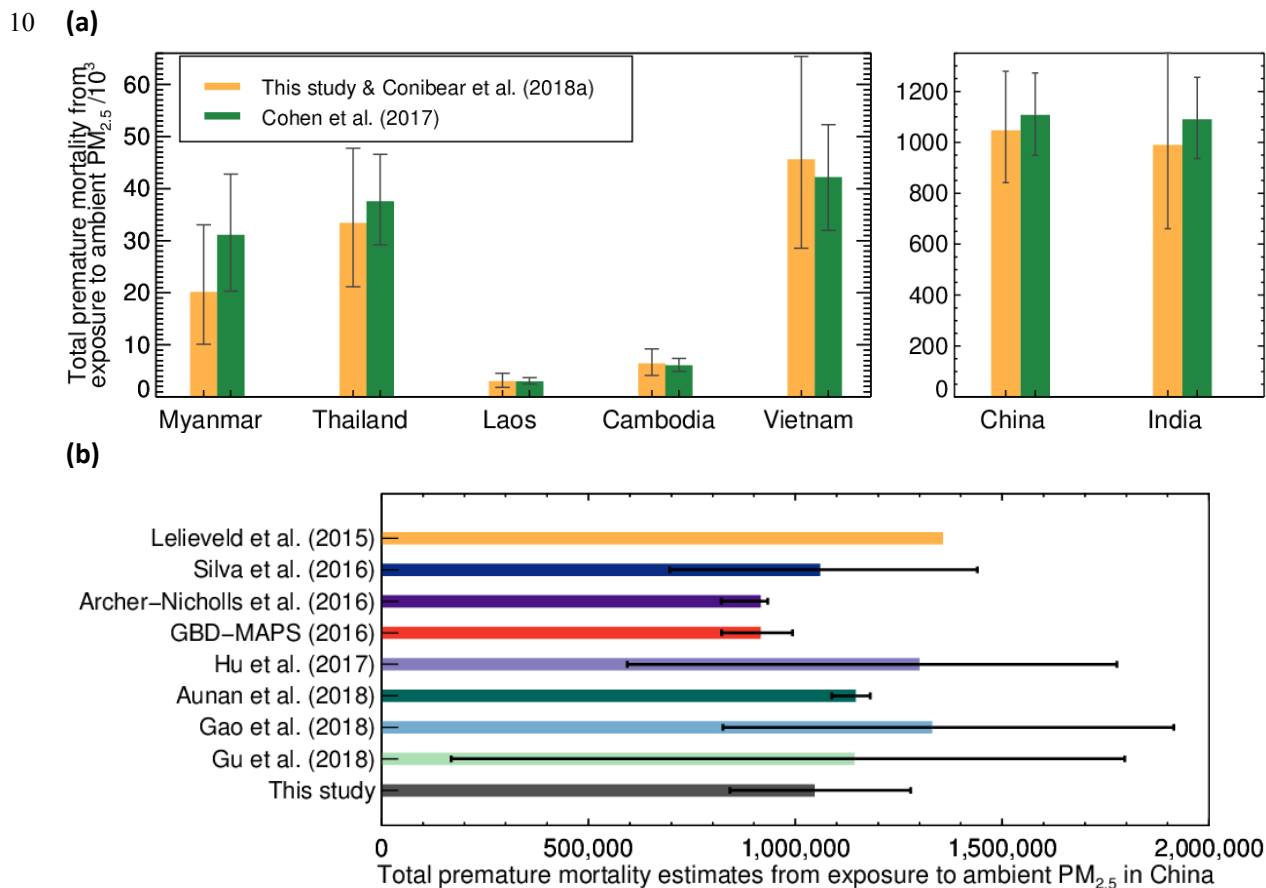


Figure S3. Spatial distribution of **(a)** total estimated annual premature mortality due to long-term exposure to $PM_{2.5}$ concentrations from all sources and **(b-h)** averted annual premature mortality from eliminating different anthropogenic emission sectors over South and East Asia. Emission sectors are: **(b)** Agriculture (AGR) – only estimated for the South Asia domain; **(c)** Open biomass burning (BBU); **(d)** Energy/power generation (ENE); **(e)** Industry (IND); **(f)** Residential (RES); **(g)** Shipping (SHP) – only estimated for the East Asia domain; and **(h)** Land transport (TRA).



15 **Figure S4.** Estimated annual premature mortality due to long-term exposure to ambient $PM_{2.5}$ from all sources **(a)** by country – values from this study are compared to those from GBD2015 in Cohen et al. (2017); **(b)** in China – values from this study are compared to previous studies listed in Table 3 and Table S1.

References

- Archer-Nicholls, S., Carter, E., Kumar, R., Xiao, Q., Liu, Y., Frostad, J., et al.: The regional impacts of cooking and heating emissions on ambient air quality and disease burden in China, *Environ. Sci. Technol.* 50, 9416–9423 (2016).
- 5 Aunan, K., Ma, Q., Lund, M. T., and Wang, S.: Population-weighted exposure to PM_{2.5} pollution in China: An integrated approach, *Environment International* 120, 111-120, <https://doi.org/10.1016/j.envint.2018.07.042> (2018)
- Balakrishnan, K. et al.: State and national household concentrations of PM_{2.5} from solid cookfuel use: results from measurements and modeling in India for estimation of the global burden of disease, *Environ. Health* 12, 77 (2013).
- Butt, E. W., Rap, A., Schmidt, A., Scott, C. E., Pringle, K. J., Reddington, C. L., Richards, N. A. D., Woodhouse, M. T., Ramirez-Villegas, J., Yang, H., Vakkari, V., Stone, E. A., Rupakheti, M., S. Praveen, P., G. van Zyl, P., P. Beukes, J., Josipovic, M., Mitchell, E. J. S., Sallu, S. M., Forster, P. M., and Spracklen, D. V.: The impact of residential combustion emissions on atmospheric aerosol, human health, and climate, *Atmos. Chem. Phys.*, 16, 873-905, <https://doi.org/10.5194/acp-16-873-2016> (2016).
- 10 Butt, E. W., H. Pearce, Z. Kilmont, C. Heyes, J. McNorton, L. Conibear, C. L. Reddington, S. R. Arnold, and D. V. Spracklen: Near-term global and regional air quality and health benefits in 2050 due to widespread adoption of clean residential combustion technologies, *in preparation* (2019).
- 15 Cohen, A. J. et al.: Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global burden of Diseases Study 2015. *Lancet* 389, 1907–1918 (2017).
- Conibear, L., Butt, E. W., Knote, C., Arnold, S. R., and Spracklen, D. V.: Residential energy use emissions dominate health impacts from exposure to ambient particulate matter in India, *Nat. Commun.*, 9, 617, <https://doi.org/10.1038/s41467-018-02986-7> (2018a).
- 20 Devleeschauwer, B. et al.: Calculating disability-adjusted life years to quantify burden of disease. *Int. J. Public Health* 59, 565-569 (2014).
- Du, W., Li, X., Chen, Y., and Shen, G.: Household air pollution and personal exposure to air pollutants in rural China - a review, *Environ. Pollut.* 237, 625–638 (2018).
- 25 Gao, M., Beig, G., Song, S., Zhang, H., Hu, J., Ying, Q., Liang, F., Liu, Y., Wang, H., Lu, X., Zhu, T., Carmichael, G. R., Nielsen, C. P. and McElroy, M. B.: The impact of power generation emissions on ambient PM_{2.5} pollution and human health in China and India, *Environ. Int.* 121, 250-259, <https://doi.org/10.1016/j.envint.2018.09.015> (2018).
- GBD 2015 Risk Factors Collaborators: Global, regional, and national comparative risk assessment of 79 behavioural, environmental and occupational, and metabolic risks or clusters of risks, 1990-2015: a systematic analysis for the Global Burden of Disease Study 2015. *Lancet* 388, 1659–1724, DOI:[https://doi.org/10.1016/S0140-6736\(16\)31679-8](https://doi.org/10.1016/S0140-6736(16)31679-8) (2016).
- 30 GBD Collaborative Network. Global Burden of Disease Study 2015 (GBD2015) Reference Life Table. Available at: <http://ghdx.healthdata.org/record/global-burden-disease-study-2015-gbd-2015-reference-life-table>. Seattle, United States: Institute for Health Metrics and Evaluation (IHME), 2016.
- GBD-MAPS (Global Burden of Disease from Major Air Pollution Sources) Working Group: Burden of Disease Attributable to Coal-burning and Other Major Sources of Air Pollution in China. Special Report 20. Health Effects Institute, Boston, MA. <https://www.healtheffects.org/publication/burden-disease-attributable-coal-burning-and-other-air-pollution-sources-china> (2016).
- 35

- GBD-MAPS (Global Burden of Disease from Major Air Pollution Sources) Working Group: Burden of Disease Attributable to Major Air Pollution Sources in India. Special Report 21. Health Effects Institute, Boston, MA. <https://www.healtheffects.org/publication/gbd-air-pollution-india> (2018).
- 5 Gu, Y., Wong, T. W., Law, C. K., Dong, G. H., Ho, K. F., Yang, Y., and Yim, S. H. L.: Impacts of sectoral emissions in China and the implications: air quality, public health, crop production, and economic costs, *Environ. Res. Lett.* 13, 084008 (2018).
- Guo, H., Kota, S. H., Chen, K., Sahu, S. K., Hu, J., Ying, Q., Wang, Y., and Zhang, H.: Source contributions and potential reductions to health effects of particulate matter in India, *Atmos. Chem. Phys.*, 18, 15219-15229, <https://doi.org/10.5194/acp-18-15219-2018> (2018).
- 10 Hu, J., Huang, L., Chen, M., Liao, H., Zhang, H., Wang, S., Zhang, Q., and Ying, Q.: Premature mortality attributable to particulate matter in China: source contributions and responses to reductions, *Environ. Sci. Technol.*, 51, 9950-9959 (2017).
- Institute for Health Metrics and Evaluation (IHME): GBD Compare Data Visualization. Seattle, WA: IHME, University of Washington (2016). Available at: <http://vizhub.healthdata.org/gbd-compare>. (Accessed: 13th July 2016).
- Lelieveld, J., Evans, J. S., Fnais, M., Giannadaki, D. and Pozzer, A.: The contribution of outdoor air pollution sources to premature mortality on a global scale. *Nature* 525, 367–371 (2015).
- 15 Li, Y. J., Sun, Y., Zhang, Q., Li, X., Li, M., Zhou, Z., and Chan, C. K.: Real-time chemical characterization of atmospheric particulate matter in China: A review, *Atmos. Environ.*, 158, 270–304, <https://doi.org/10.1016/j.atmosenv.2017.02.027>, 2017.
- Qin, Y. M., Tan, H. B., Li, Y. J., Schurman, M. I., Li, F., Canonaco, F., Prévôt, A. S. H., and Chan, C. K.: Impacts of traffic emissions on atmospheric particulate nitrate and organics at a downwind site on the periphery of Guangzhou, China, *Atmos. Chem. Phys.*, 17, 10245-10258, <https://doi.org/10.5194/acp-17-10245-2017>, 2017.
- 20 Shi, Z., Li, J., Huang, L., Wang, P., Wu, L., Ying, Q., Zhang, H., Lu, L., Liu, X., Liao, H., Hu, J.,: Source apportionment of fine particulate matter in China in 2013 using a source-oriented chemical transport model. *Sci. Total Environ.* 601, 1476–1487 (2017).
- Silva, R. A., Adelman, Z., Fry, M. M. and West, J. J.: The impact of individual anthropogenic emissions sectors on the global burden of human mortality due to ambient air pollution. *Environ. Health Perspect.* 124, 1776–1784 (2016).
- 25 Upadhyay, A., Dey, S., Chowdhury, S. and Goyal, P.: Expected health benefits from mitigation of emissions from major anthropogenic PM_{2.5} sources in India: Statistics at state level, *Environmental Pollution* 242, 1817-1826, <https://doi.org/10.1016/j.envpol.2018.07.085> (2018).
- Yu, S., Eder, B., Dennis, R., Chu, S.-H. and Schwartz, S. E.: New unbiased symmetric metrics for evaluation of air quality models, *Atmosph. Sci. Lett.*, 7: 26–34. doi: 10.1002/asl.125 (2006).