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Global Air Quality Inequality over 2000-2020

Abstract

Air pollution generates vast health burdens and economic costs around the world. Pollution exposure varies greatly, both between countries and within them. But the degree of air quality inequality and its' trajectory have not been quantified at a global level. I use economic inequality indices to measure global inequality in exposure to ambient fine particles smaller than 2.5 microns (PM2.5). I find high and rising levels of global air quality inequality. The global PM2.5 Gini Index rose from 0.30 in 2000 to 0.35 in 2020, exceeding levels of income inequality in many countries. Air quality inequality is mostly driven by differences between countries and less so by variation within them, as decomposition analysis shows. A large share of those facing the highest levels of PM2.5 exposure live in only a few countries. Building on the Global Burden of Disease framework, I find that mortality associated with PM2.5 exposure is even more unequal than pollution exposure itself. The findings suggest that the common focus on inequality within countries overlooks an important global dimension of environmental justice.

JEL-Codes: D630, I140, Q530.

Keywords: air pollution, inequality, health, environmental justice.

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1 Introduction

Elevated levels of air pollution generate vast damages to human health (Landrigan et al., 2018; Murray et al., 2020) and productivity (Aguilar-Gomez et al., 2022) worldwide. Lowering pollution levels is increasingly recognized as a key step towards achieving the United Nation's Sustainable Development Goals (Sachs et al., 2019). At the same time, exposure to ambient air pollution varies substantially within countries, often in ways that correlate with socio-demographic characteristics (Jbaily et al., 2022; Currie et al., 2023; Sager and Singer, 2024). Research efforts and the public discourse around environmental justice tend to focus on these within-country differences (Mohai et al., 2009; Banzhaf et al., 2019; Drupp et al., 2024). But pollution exposure also varies greatly between countries (Southerland et al., 2022; Sicard et al., 2023) and is often worse in poorer countries (Apte et al., 2021; Rentschler and Leonova, 2023).

Less is known about how unequal air quality is distributed globally, and how differences between and within countries shape the global air pollution exposure distribution. In this article, I investigate global air quality inequality between 2000 and 2020 by combining gridded population data with annual concentration estimates of fine particles with 2.5 microns or less in diameter ($PM_{2.5}$). $PM_{2.5}$ is one of the pollutants most strongly linked to premature deaths and other damages (Landrigan et al., 2018; Murray et al., 2020; Aguilar-Gomez et al., 2022). The final sample covers 85% of the world population in 2020 spread across 80.1 million grid cells in 231 countries or territories.

To quantify global air quality inequality, I employ indices typically used to measure economic inequality. I calculate the ratio of the 90th to the 10th percentile of the global $PM_{2.5}$ exposure distribution (R9010), the global $PM_{2.5}$ Gini Index (Gini, 1921), and three Generalized Entropy measures including the common Theil Index (Shorrocks, 1980). Some of these indices have been used in previous work to characterize the distribution of air pollution levels within countries (Clark et al., 2014; Boyce et al., 2016; Rosofsky et al., 2018; Pisoni et al., 2022) and to study the distribution of benefits from air quality regulation (Levy et al., 2007; Fann et al., 2011; Holland et al., 2019; Mansur and Sheriff, 2021). Here, I use them to quantify air quality inequality at the global level, accounting for variation both between and within countries.

By calculating indices to describe global air quality inequality, I contribute a new perspective to a literature that has thus far focused on describing exposure differences between countries, regions and cities (Southerland et al., 2022; Sicard et al., 2023; Apte et al., 2021; Rentschler and Leonova, 2023). In particular, the indices allow me to assess whether and by how much global air quality inequality has increased between 2000 and 2020. As some indices allow for sub-group decomposition (Shorrocks, 1984; Mookherjee and Shorrocks, 1982), I can further quantify the relative contributions of between-country and within-country differences in shaping global air quality inequality.

A key motivation in studying the distribution of pollution exposure is the association with health damages and overall welfare loss. As the relationship between exposure and damages may be non-linear and mediated by other factors, the level of inequality in the final health burden may differ from the inequality in pollution exposure. That is why, in addition to measuring pollution exposure inequality, I also measure inequality of the resulting health burden. Specifically, I rely on the Global Burden of Disease (GBD) 2019 assessment of mortality that can be attributed to $PM_{2.5}$ exposure (Murray et al., 2020; Vos et al., 2020). I first replicate the country-level GBD 2019 mortality estimates for six leading causes and then extend the analysis to include within-country variation. The results confirm the highly unequal mortality burden from $PM_{2.5}$ exposure, which for certain exceed the inequality in pollution exposure itself.

Finally, I investigate the dimension of absolute, instead of relative, deprivation in the global air quality distribution. I find that a large share of people exposed to the highest levels of $PM_{2.5}$ levels live in just a few countries, especially in South Asia. Taken as a whole, the results from using inequality indices to quantify global air quality inequality showcase the highly unequal and geographically concentrated nature of pollution exposure and health burdens.

2 Data and methods

To quantify global air quality inequality between 2000 and 2020, I calculate inequality indices based on a gridded data set combining population counts with estimates of fine particle ($PM_{2.5}$) concentrations.

2.1 Data

Population counts are from Gridded Population of the World (GPW v4.11) from CIESIN (2018). I use UN WPP-adjusted population counts for 241 countries/territories in 2000, 2005, 2010, 2015 and 2020 at a 30 arc-second (0.0083 degree) resolution. $PM_{2.5}$ data are from Van Donkelaar et al. (2021) [V5.GL.04], using annual mean surface-level $PM_{2.5}$ concentrations in 2000, 2005, 2010, 2015 and 2020 at a 0.01 arc-degree resolution.[1]

The spatial unit of analysis is the grid cell from the GPW v4.11 population data. In each year and for each population grid cell, $PM_{2.5}$ is assigned as follows: Where available, I assign the $PM_{2.5}$ level at the pollution grid point closest (in arc-degrees) to the centroid of the population grid cell. When that $PM_{2.5}$ level is missing, I use the mean of the non-missing values from the 8 surrounding points in arc-degree space. Doing so extends sample coverage, but does not significantly alter the results, as shown in Appendix Table A1 where I limit my sample to only cells matched to the nearest $PM_{2.5}$ reading.

Due to computational constraints, I further limit the sample as follows. First, grid cells with population estimates below 1 are dropped. This reduces the number of grid cells by over 50% but maintains 99.7% of the population coverage. Second, I omit 10 countries/territories with populations smaller than 10,000 in 2020.[2] Finally, the sample only includes grid cells that can be matched to a $PM_{2.5}$ estimate using the procedure described above. This final sample contains N=80,109,345 grid cells in 231 countries/territories and covers 85% of the world population as shown in Figure 1.[3]

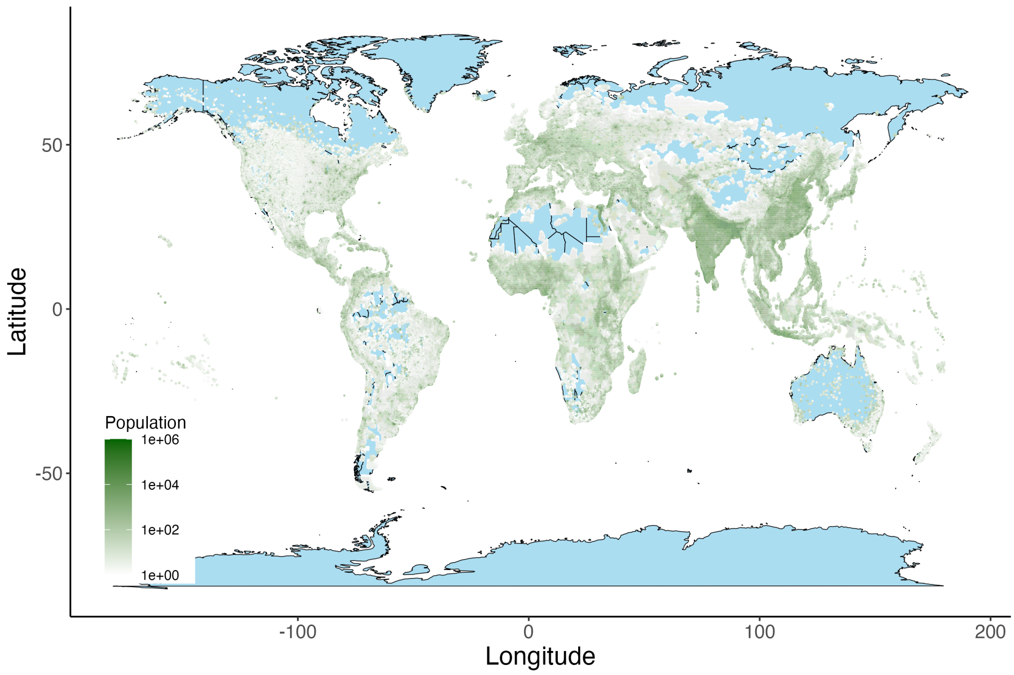
[1] GPW v4.11 is available at https://doi.org/10.7927/H4F47M65. WUSTL ACAG Surface $PM_{2.5}$ version V5.GL.04 is available at https://sites.wustl.edu/acag/datasets/surface-pm2-5.

[2] The 10 omitted territories are: Falkland Islands, Holy See, Montserrat, Niue, Norfolk Islands, Pitcairn, Saint Helena, Saint Pierre and Miquelon, Svalbard and Jan Mayen Islands, and Tokelau.

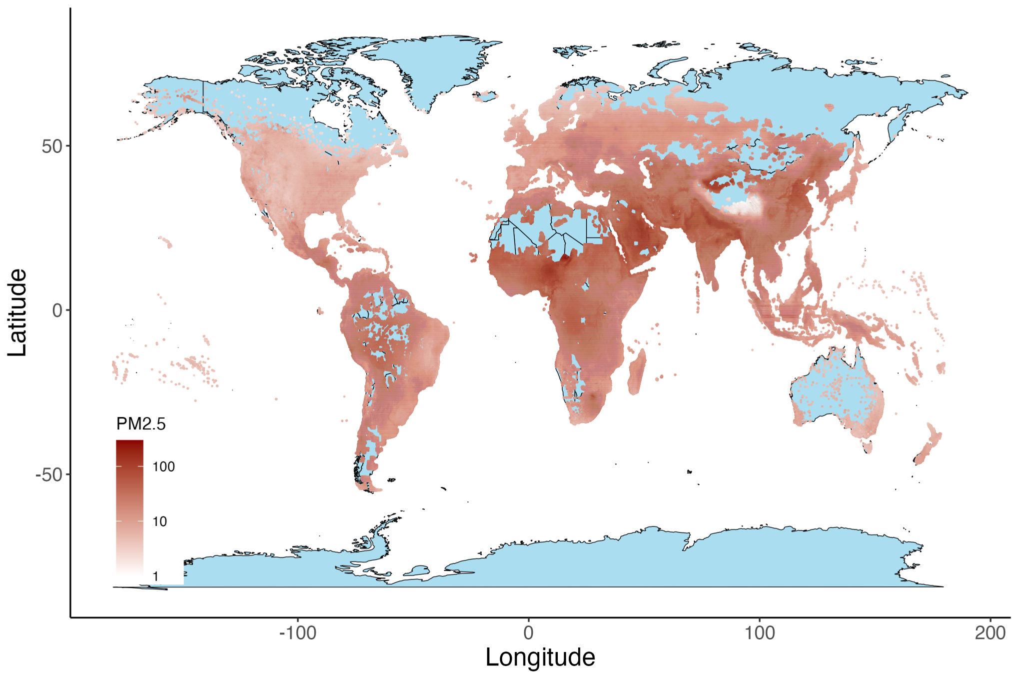
[3] GPW v4.11 contains a total population of 7,758,982,599 in 2020, of which I match 6,570,286,387 to $PM_{2.5}$ levels. Countries and territories are based on the classification in CIESIN (2018) and population counts are UN WPP-adjusted versions from GWP v4.11. The full list of countries/territories is shown in Appendix Table A2.

Figure 1: Sample coverage of population and pollution data

(a) Population in 2020



(b) $PM_{2.5}$ concentrations in 2020



Notes: Sample of N=80,109,345 grid cells. Population data from CIESIN (2018). $PM_{2.5}$ exposure data from Van Donkelaar et al. (2021).

2.2 Inequality measures

While economic inequality indices usually describe the distribution of total income or wealth across the population, I use them here to describe the distribution of exposure to ambient $PM_{2.5}$ particles across the world population. In a given year, each geographic grid cell i is assigned $PM_{2.5}$ concentration P_i. Population counts of grid cells (n_i) are used as weights to quantify pollution exposure across the world population ($N = \sum_i n_i$). Population-weighted global mean $PM_{2.5}$ exposure is $\overline{P} = \frac{1}{N}\sum_i n_i P_i$ and higher moments of the distribution are calculated in a similar way.

Concentrations of $PM_{2.5}$ are measured in weight per volume ($\mu g m^{-3}$), averaged over the year. One interpretation of my approach is that, assuming all persons inhale similar volumes of outdoor air per year, I capture the global distribution of fine particles (by weight) inhaled. As inequality indices are generally derived from welfare economic principles, I also translate $PM_{2.5}$ exposure into mortality burdens that more directly measure the welfare costs of pollution exposure.

I employ five common inequality indices, which mainly differ in the weight they place on different characteristics of the pollution exposure distribution. R9010 is calculated as the ratio of the 90th and the 10th percentiles of the population-weighted global $PM_{2.5}$ distribution. The Gini Index is defined as a ratio of weighted sums across grid cells so that Gini $= \frac{\sum_i n_i \sum_j n_j |P_i - P_j|}{2\overline{P}N^2}$. The three remaining indices are members of the Generalized Entropy (GE) class with different values of the inequality aversion parameter α. When $\alpha = 0$, GE(0), also called the Mean Log Deviation (MLD), is defined as $GE(0) = \frac{1}{N}\sum_i \left[n_i log(\frac{\overline{P}}{P_i})\right]$. When $\alpha = 1$, GE(1), also called the Theil Index, is defined as $GE(1) = \frac{1}{N}\sum_i \left[n_i \frac{P_i}{\overline{P}} log(\frac{P_i}{\overline{P}})\right]$. And when $\alpha = 2$, GE(2), equal to half the square of the coefficient of variation, is defined as $GE(2) = \frac{1}{2}\left(\left[\sum_i \frac{n_i}{N}\frac{P_i}{\overline{P}}\right]^2 - 1\right)$.

The GE(α) measures are additively separable and can be decomposed into within- and between-country inequality (Shorrocks, 1980, 1984), such that $GE(\alpha) = GE_W(\alpha) + GE_B(\alpha)$. Here, inequality within countries (k) is defined as $GE_W(\alpha) = \sum_k \left[(\frac{N_k}{N})\left(\frac{\overline{P}_k}{\overline{P}}\right)^{\alpha} GE_k(\alpha)\right]$ where $GE_k(\alpha)$ is calculated as standalone inequality measure for country k. Gini Index decomposition is not exact when subgroup distributions overlap (Mookherjee and Shorrocks, 1982), which is why I do not focus on it here.

3 Results

The global distribution of ambient $PM_{2.5}$ exposure is plotted in Figure 2 (left panel). Population-weighted mean exposure stood at $34.7 \mu g m^{-3}$ in 2020, an increase of 16% relative to 2000 ($29.7 \mu g m^{-3}$). In 2020, over 99% of the sample population faced $PM_{2.5}$ levels exceeding the $5 \mu g m^{-3}$ guideline level set by the World Health Organization in 2021 and 91% faced levels exceeding the previous $10 \mu g m^{-3}$ threshold.[4]

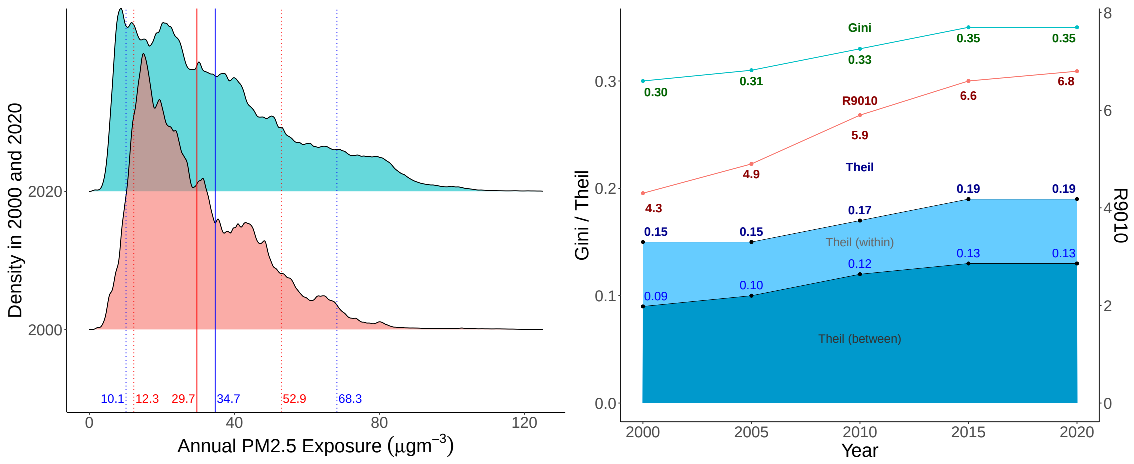
3.1 Global air quality inequality

Exposure to $PM_{2.5}$ is highly unequal and has become more unequal over time. Figure 2 (left panel) shows that the global $PM_{2.5}$ distribution has stretched, with the 90th percentile rising from $52.9 \mu g m^{-3}$ in 2000 to $68.3 \mu g m^{-3}$ in 2020. Meanwhile, the 10th percentile fell from 12.3 to $10.1 \mu g m^{-3}$. Consequently, the ratio of the 90th to the 10th percentile (R9010) increased from 4.3 to 6.8 (right panel). That means that the least-polluted member of the top decile in 2020 was exposed to seven times more air particulates than the most polluted member of the bottom decile. Similarly, the Global Air Quality Gini Index grew from 0.30 in 2000 to 0.35 in 2020. While this is much lower than the Global Income Gini Index, which stood at 0.67 in 2020 (Chancel and Piketty, 2021), global air quality is substantial. The global Gini Index for $PM_{2.5}$ exposure rose from 0.30 in 2000 to 0.35 in 2020, an increase comparable to moving from income inequality levels in France (0.31 in 2020) to those in Russia (0.36 in 2020) according to World Bank (2020). The Theil Index also increased, from 0.15 to 0.19, as did the other measures shown in Table 1. Lorenz curves shown in Appendix Figure A1 visually confirm the increase in inequality.

The changes are primarily driven by changing concentration levels rather than population movement. This can be seen when pairing 2020 $PM_{2.5}$ levels with 2000 population counts, as done in the bottom panel of Table 1, which yields similar mean exposure (33.6 μg^{-3}) and nearly identical inequality indices (R9010=6.8, Gini=0.35, Theil=0.20).

[4]WHO pollutant guidelines are based on a systematic review and meta-analysis of the literature linking long-term exposure to PM and all-cause and cause-specific mortality (WHO, 2021).

Figure 2: Global distribution of $PM_{2.5}$ exposure between 2000 and 2020.



Notes: Left panel: Population-weighted Gaussian Kernel density estimates for $PM_{2.5}$ exposure in 2000 and 2020. Solid lines indicate global mean $PM_{2.5}$ exposure and dashed lines are 10th and 90th percentiles. Right panel: Inequality indices for global $PM_{2.5}$ exposure 2000-2020 in 5-year intervals, measured as ratio of 90th to 10th percentile (R9010, right axis), Gini and Theil Index (left axis). Theil Index decomposition into between- and within-country components following Shorrocks (1984). Population and pollution data from CIESIN (2018) and Van Donkelaar et al. (2021). Sample of N=80,109,345 grid cells in 231 countries/territories.

Table 1: Global $PM_{2.5}$ Exposure Inequality and Decomposition

	Mean	R9010	Gini	MLD	Theil	$0.5CV^2$
2000	29.7	4.3	0.30	0.15	0.15	0.15
between				0.11	0.09	0.09
within				0.05	0.05	0.07
2020	34.7	6.8	0.35	0.22	0.19	0.20
between				0.16	0.13	0.12
within				0.06	0.06	0.08
2020 (2000 pop)	33.6	6.8	0.35	0.22	0.20	0.21
between				0.17	0.14	0.13
within				0.06	0.06	0.08

Notes: Based on population data from CIESIN (2018) and $PM_{2.5}$ concentrations from Van Donkelaar et al. (2021). Sample of N=80,109,345 grid cells in 231 countries/territories. 'Mean' is population-weighted annual mean $PM_{2.5}$ exposure (in $\mu g m^{-3}$); 'R9010' is the ratio of the 90th to the 10th percentile; 'Gini' is the Gini Index; 'MLD' is the mean log deviation or GE(0); 'Theil' is the Theil Index or GE(1); $0.5CV^2$ is half of the squared coefficient of variation or GE(2). "2020 (2000 pop)" indicates that 2000 population weights are paired with 2020 $PM_{2.5}$ concentrations.

3.2 Decomposition analysis

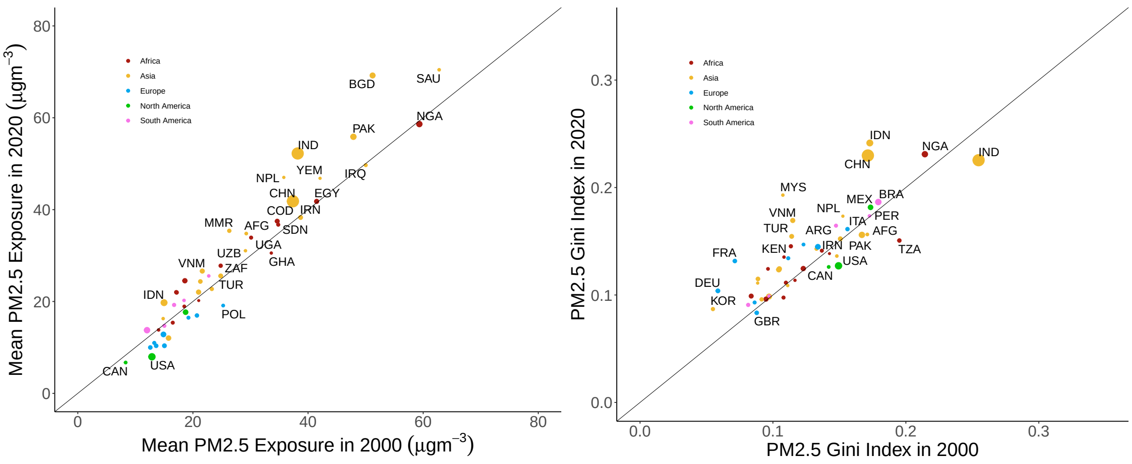
The bulk of global air quality inequality can be attributed to differences between countries rather than variation within them. Using the Theil Index, which is exactly decomposable (Shorrocks, 1984), in Figure 2 (right panel) we see that two thirds of global air quality inequality (0.14 out of 0.20) were due to differences between countries in 2020. Put differently, even if $PM_{2.5}$ exposure was fully equalized within every country in the world, two thirds of global air quality inequality would remain.[5] Similar and even higher between-country contributions are shown by the other GE measures in Table 1.

Moreover, most of the increase in global air quality inequality is accounted for by rising exposure differences between countries. The between-country portion of the Global $PM_{2.5}$ Theil Index rose from 0.09 to 0.14 between 2000 and 2020, while the within-country portion grew only slightly from 0.05 to 0.06. Another way to see this is in Figure 3, which shows divergence in country-level $PM_{2.5}$ exposure between 2000 and 2020 (left panel). Many countries with high $PM_{2.5}$ levels in 2000 had even higher levels in 2020. This is visible for South Asian countries such as India, Pakistan and Bangladesh, but also for China, Saudi Arabia and others. Meanwhile, many of the less polluted countries in Europe and North America saw stagnating or even falling $PM_{2.5}$ levels. This reinforced a trend whereby $PM_{2.5}$ levels tend to be higher in low-income countries as shown in Figure 4. This confirms that air quality inequality likely compounds global economic inequality, as argued by previous work (Apte et al., 2021; Rentschler and Leonova, 2023).

On the other hand, within-country $PM_{2.5}$ inequality, measured by the Gini Index (right panel of Figure 3), increased in some countries but fell in others. Taken together, the analysis shows that global $PM_{2.5}$ inequality is largely and increasingly driven by differences between countries.

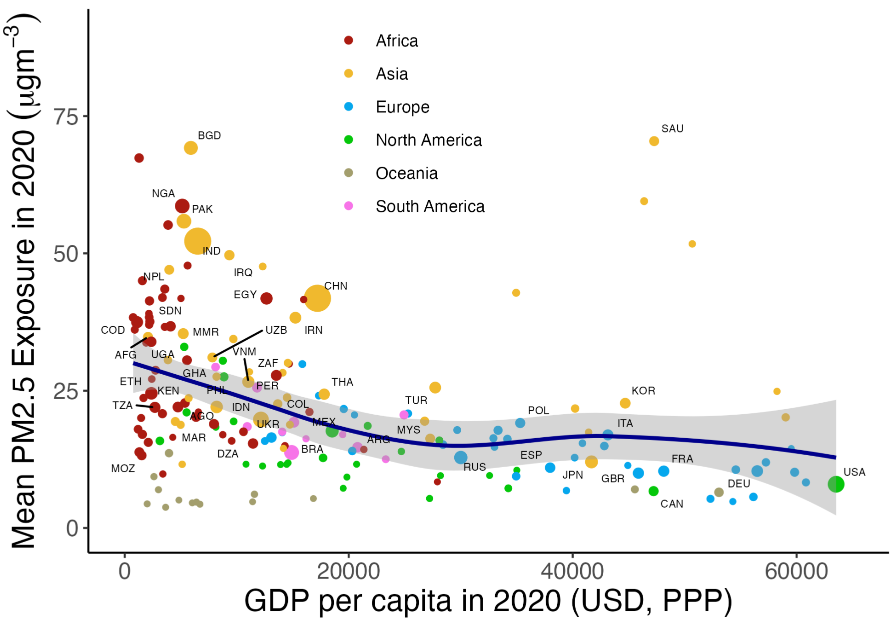
[5] These results are different from those for income, where much of global income inequality are due to within-country differences (68% in 2020 according to Chancel and Piketty (2021)). However, a similar share of global inequality in household carbon footprints is explained by differences between countries (64% in 2019 according to Chancel (2022)).

Figure 3: Country-level $PM_{2.5}$ exposure and inequality in 2000 and 2020.



Notes: Left panel: Country-level population-weighted mean $PM_{2.5}$ exposure ($\mu g m^{-3}$) in 2000 and 2020. Right panel: Country-level Gini Index for $PM_{2.5}$ exposure in 2000 and 2020. Circle size indicates population in 2020, color indicates continent. Diagonal line represents equal levels in 2000 and 2020. Population and pollution data from CIESIN (2018) and Van Donkelaar et al. (2021). Sample of N=50 countries/territories (out of 231 total) with largest 2020 population.

Figure 4: Country-level GDP per capita and mean $PM_{2.5}$ exposure in 2020.



Notes: Population and pollution data from CIESIN (2018); Van Donkelaar et al. (2021). Plot shows N=191 countries/territories (out of 231 total) with available GDP per capita in 2020 (current international dollars, PPP) from World Bank (2020). Circle size indicates population in 2020, color indicates continent. Line is fitted from a local polynomial regression with 95% confidence bands. Name labels limited to the 50 countries with largest 2020 population.

4 The unequal health burden of $PM_{2.5}$ exposure

The above analysis has focused on variation in $PM_{2.5}$ exposure across the world population. However, pollution exposure matters mainly due to the resulting adverse effects on health an well-being. With non-linear concentration-response functions, the resulting distribution of those damages may differ from the exposure distribution. In this section, I quantify inequality in resulting health burden based on the Global Burden of Disease (GBD) 2019 framework (described in Murray et al., 2020; Vos et al., 2020).

GBD 2019 quantifies the global health burden in 204 countries and territories, separately for 364 causes, 286 of them fatal, as well as 87 risk factors. $PM_{2.5}$ exposure is used as the main measure of the air pollution risk factor. It is linked to mortality from six causes separately by age group: ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD), lung chancer (LC), lower respiratory infections (LRI) and type II diabetes (DM). I translate $PM_{2.5}$ exposure into annual mortality rates using the concentration-response (CR) functions from GBD 2019 paired with country-level baseline mortality rates (using data and methods provided by McDuffie et al., 2021).[6] To capture within-country variation, I calculate mortality rates for each grid cell, assuming constant baselines within countries.

Global $PM_{2.5}$-related mortality risk is shown in Table 2. In my sample covering 85% of the world population, 3.3 million deaths per year are attributed to $PM_{2.5}$ exposure, for an average mortality rate of 507 per million.[7] The number for the 90th percentile was 991, 8.2 times higher than for the 10th percentile (121), as shown in Table 2. The Gini index of $PM_{2.5}$-related mortality was 0.36. The mortality burden is more unequal than $PM_{2.5}$ exposure itself. Again, decomposition analysis shows that the bulk of it (0.18 out of 0.21 for the Theil Index) stems from between-country differences. Separating the causes shows that $PM_{2.5}$-related mortality risk from Stroke, COPD and lung cancer is substantially more unequal than that from respiratory illness or diabetes.

[6] CR curves translate $PM_{2.5}$ exposure into relative risk of disease, which are then multiplied with baseline disease levels by country. If two locations have identical $PM_{2.5}$ levels, identical mortality shares are assigned to pollution, but the total can differ if baselines differ.

[7] McDuffie et al. (2021) attribute 4.1 million deaths in 204 countries/territories to $PM_{2.5}$ exposure in 2019. I replicate those numbers exactly with their pollution data but get a total of 3.8 million deaths when using country-level pollution from my data in 2020. Restricting this to the grid cells within my sample, which covers 85% of the world population, this falls to 3.3 million

Table 2: Global $PM_{2.5}$-related mortality inequality in 2020

	Mean	R9010	Gini	MLD	Theil	$0.5CV^2$
TOTAL	507	8.2	0.36	0.26	0.21	0.21
between				0.22	0.18	0.17
within/rest				0.04	0.03	0.04
IHD	174	8.7	0.37	0.31	0.23	0.24
between				0.27	0.21	0.21
within/rest				0.03	0.02	0.03
Stroke	151	14.9	0.45	0.41	0.34	0.37
between				0.37	0.30	0.32
within/rest				0.04	0.03	0.05
COPD	79	20.2	0.49	0.56	0.41	0.41
between				0.50	0.36	0.34
within/rest				0.05	0.04	0.07
Lung cancer	40	27.8	0.55	0.65	0.52	0.61
between				0.62	0.49	0.55
within/rest				0.04	0.03	0.06
LRI	34	6.5	0.36	0.25	0.22	0.25
between				0.19	0.17	0.19
within/rest				0.06	0.05	0.06
Type II diabetes	28	5.5	0.31	0.19	0.17	0.19
between				0.17	0.15	0.17
within/rest				0.02	0.02	0.03

Notes: Sample of N=80,021,591 grid cells in 204 countries/territories that could be matched to $PM_{2.5}$-attributable mortality following the Global Burden of Disease data and methodology outlined in McDuffie et al. (2021). Based on population data from CIESIN (2018) and $PM_{2.5}$ concentrations from Van Donkelaar et al. (2021). 'Mean' is population-weighted annual mean mortality due to $PM_{2.5}$ exposure (per million residents); 'R9010' is the ratio of the 90th to the 10th percentile; 'Gini' is the Gini Index; 'MLD' is the mean log deviation or GE(0); 'Theil' is the Theil Index or GE(1); $0.5CV^2$ is half of the squared coefficient of variation or GE(2).

5 'Air quality poverty' and the 'Choking Billion'

High overall $PM_{2.5}$ exposure combined with pronounced inequality imply that a substantial portion of the world population faces excessive levels of air pollution. Continuing the analogy with economic inequality, we can designate a group of the most exposed people as suffering from 'air quality poverty'. To illustrate this, I focus on the 1 billion people in my sample that faced the highest $PM_{2.5}$ levels in 2020. I refer to this group as the 'Choking Billion'.[8] It was exposed to $PM_{2.5}$ levels of $59.5 \mu g m^{-3}$ or higher in 2020, twelve times higher than the WHO proposed limit of $5 \mu g m^{-3}$.

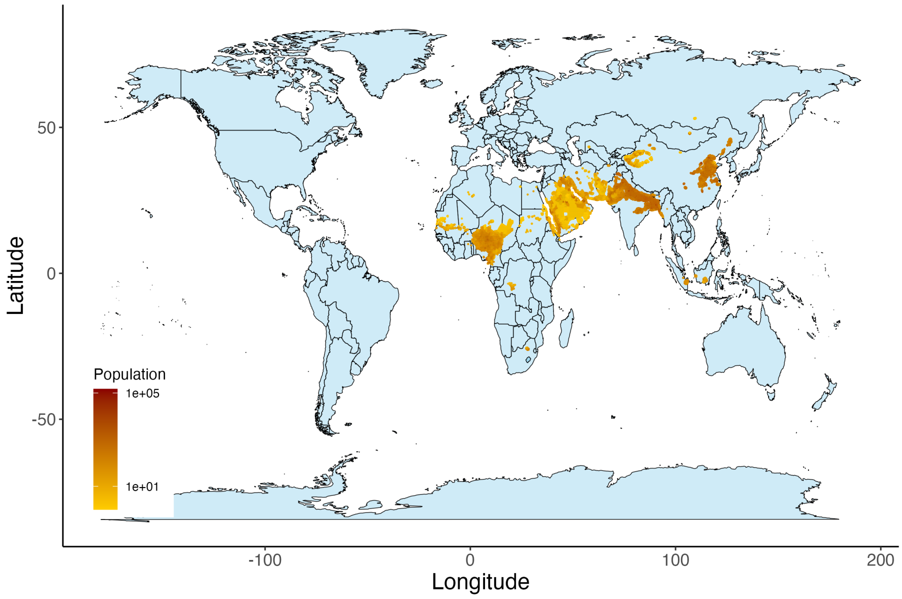
The map in Figure 5 shows that, while there are pockets of air poverty in many countries, a few geographic clusters accounted for most of the 'Choking Billion' in 2020. The biggest cluster spans Northern India, Bangladesh, Pakistan and Nepal, followed by other big clusters in and around Eastern China, Northern Nigeria, and the Arab peninsula. India alone was home to almost half (479 million) of the 'Choking Billion' in 2020, followed by China (184m), Bangladesh (128m) and Pakistan (85m), as shown in Table 3. Some smaller countries also had high rates of air quality poverty. For example, three quarters of the population of Saudi Arabia, half the population in Niger, and a third of people in Nigeria were part of the 'Choking Billion' in 2020, as were around [9]

The excessive $PM_{2.5}$ exposure levels faced by the 'Choking Billion' translate into high health burdens as well. Using again the GBD methodology discussed in Section 4, I find that the 'Choking Billion' on average face a 57% higher rate of $PM_{2.5}$-related mortality than the rest of the world population. While they represent 15% of the global population, they shoulder 22% of the $PM_{2.5}$-related mortality burden.

[8]The notion of the 'Choking Billion' to describe clusters of extreme air pollution exposure is inspired by the 'Bottom Billion' used to describe clusters of economic poverty (Collier, 2008).

[9]$PM_{2.5}$ estimates from Van Donkelaar et al. (2021) include mineral dust, which can represent a larger portion of the total count in regions close to deserts.

Figure 5: The 'Choking Billion'.



Notes: Location of 1 billion people facing annual $PM_{2.5}$ over 59.5 $\mu g m^{-3}$ in 2020 (sub-sample of N=4,143,990 grid cells out of 80,109,345). Shading indicates population density.

Table 3: The 'Choking Billion' by country

	'Choking' (million)	'Choking' (in %)	Coverage (in %)	Total Pop. (million)
India	478.7	38	91	1389
China	184.3	14	92	1403
Bangladesh	128.3	80	94	170
Pakistan	84.6	44	93	208
Nigeria	53.1	34	76	207
Saudi Arabia	22.6	77	85	34
Iraq	7.8	23	82	42
Nepal	7.8	27	95	30
Niger	7.8	53	61	24
Cameroon	6.9	41	64	26
Iran (Islamic Republic of)	4.8	7	82	83
South Africa	3.1	6	94	57
Yemen	2.3	12	64	30
Qatar	2.1	99	87	2
United Arab Emirates	1.9	22	86	10
Kuwait	1.8	51	83	4
Chad	1.4	14	62	16

Notes: N=17 countries/territories (out of 231) with over 1 million residents exposed to $PM_{2.5}$ over $59.5 \mu g m^{-3}$ in 2020 ('Choking'). % is share of country population in sample. 'Coverage' is sample share in total population ('Total Pop.') in CIESIN (2018).

6 Conclusion

The inequality indices calculated here document high and rising levels of global air quality inequality, as measured by annual ambient $PM_{2.5}$ exposure. Notably, levels of air quality inequality are similar in magnitude as levels of economic inequality. The associated health burden, measured by $PM_{2.5}$-related mortality rates, is even more unequally distributed. The bulk of this inequality comes from exposure differences between countries rather than variation within them. This contrasts with research efforts and public debates around environmental justice, which tend to focus on air quality differences within countries (Mohai et al., 2009; Banzhaf et al., 2019; Drupp et al., 2024). While a focus on within-country differences can be important, especially in national policy contexts, the global perspective taken here highlights another important dimension of global environmental inequality.

Underlying rising mean exposure and exposure inequality is an increase at the upper tails of the $PM_{2.5}$ distribution. The bulk of those exposed to the highest levels of ambient $PM_{2.5}$ live in just a few countries in Asia and Africa. Much like economic poverty, 'air quality poverty' is geographically concentrated, often in places that also face economic hardship (Apte et al., 2021; Rentschler and Leonova, 2023). The international community, which increasingly recognizes the importance of clean air for sustainable development (Sachs et al., 2019), might benefit from focusing on these pollution clusters.

The findings are subject to several limitations. Firstly, mismeasurement of either population counts or pollution levels may affect the results, which thus rely on the assumptions underlying the estimates in CIESIN (2018) and Van Donkelaar et al. (2021). Secondly, the spatial resolution of 30 arc-seconds (500-900 meters depending on latitude) used here necessarily overlooks variation at smaller scales. Finally, remotely-sensed measures of pollution concentrations only measure outdoor pollution and may not represent peoples combined exposure from outdoor and indoor sources (Jones, 1999).

Despite these limitations, the inequality indices calculated here offer a new, quantitative perspective on global air quality inequality. Similar indices may prove useful in describing other dimensions of environmental inequality. In particular, future research may test if air pollutants other than $PM_{2.5}$ are subject to similar inequality levels.

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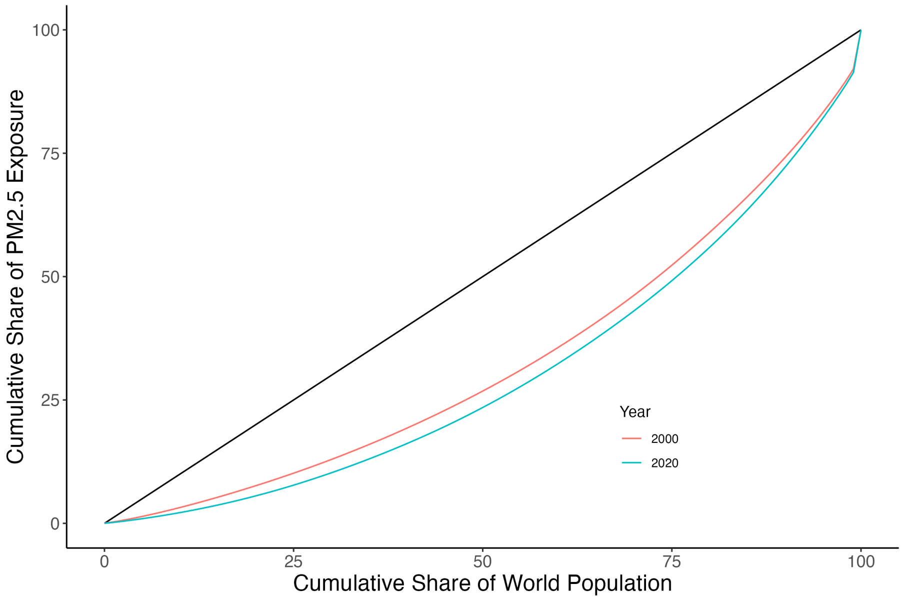
Appendix

Figure A1: Lorenz curves for global $PM_{2.5}$ exposure in 2000 and 2020.



Notes: Based on population data from CIESIN (2018) and $PM_{2.5}$ concentrations from Van Donkelaar et al. (2021). Population-weighted percentiles calculated from sample of N=80,109,345 grid cells in 231 countries/territories.

Table A1: Replication of Table 1 (sample restricted to nearest neighbor $PM_{2.5}$)

	Mean	R9010	Gini	MLD	Theil	$0.5CV^2$
2000	29.3	4.3	0.31	0.16	0.15	0.16
between				0.11	0.10	0.09
within				0.05	0.05	0.07
2020	32.3	6.7	0.35	0.22	0.19	0.21
between				0.17	0.14	0.14
within				0.05	0.05	0.07
2020 (2000 pop)	31.1	6.6	0.35	0.22	0.20	0.21
between				0.17	0.15	0.14
within				0.05	0.05	0.07

Notes: Replication of Extended Data Table 1, using restricted sample of N=44,493,936 grid cells in 231 countries/territories assigned non-missing $PM_{2.5}$ readings from only the single closest pollution grid cell (accounting for 47% of world population in 2020). Based on population data from CIESIN (2018) and $PM_{2.5}$ concentrations from Van Donkelaar et al. (2021). 'Mean' is population-weighted annual mean $PM_{2.5}$ exposure (in $\mu g m^{-3}$); 'R9010' is the ratio of the 90th to the 10th percentile; 'Gini' is the Gini Index; 'MLD' is the mean log deviation or GE(0); 'Theil' is the Theil Index or GE(1); $0.5CV^2$ is half of the squared coefficient of variation or GE(2). "2020 (2000 pop)" indicates that 2000 population weights are paired with 2020 $PM_{2.5}$ concentrations.

Table A2: Data coverage by country or territory.

	ISO	Name of Country or Territory	Pop. in 2020 (thousands)	Coverage (%)	$PM_{2.5}$ in 2000 ($\mu g m^{-3}$)	$PM_{2.5}$ in 2020 ($\mu g m^{-3}$)
1	ABW	Aruba	105	46.3	10.3	10.5
2	AFG	Afghanistan	36452	89.0	29.3	34.8
3	AGO	Angola	29262	55.8	21.0	20.2
4	AIA	Anguilla	15	81.6	10.1	8.9
5	ALA	Åland Islands	30	91.4	6.6	4.9
6	ALB	Albania	2936	92.2	21.1	17.4
7	AND	Andorra	69	45.2	12.7	9.1
8	ARE	United Arab Emirates	9809	85.6	57.3	54.0
9	ARG	Argentina	45530	84.3	15.0	14.7
10	ARM	Armenia	3041	80.0	24.9	28.3
11	ASM	American Samoa	56	91.2	3.9	4.4
12	ATG	Antigua and Barbuda	96	79.8	10.3	9.3
13	AUS	Australia	25595	90.1	5.4	6.5
14	AUT	Austria	8660	71.7	16.4	12.0
15	AZE	Azerbaijan	10232	80.4	26.4	23.8
16	BDI	Burundi	13106	69.1	34.9	38.3
17	BEL	Belgium	11641	90.7	14.5	10.6
18	BEN	Benin	12355	77.9	40.2	42.0
19	BES	Bonaire Saint Eustatius and Saba	26	76.1	11.3	11.0
20	BFA	Burkina Faso	20865	60.5	45.5	41.3
21	BGD	Bangladesh	170397	94.1	51.2	69.2
22	BGR	Bulgaria	6909	89.7	28.2	20.8
23	BHR	Bahrain	1486	88.3	54.9	51.7
24	BHS	Bahamas	410	88.8	7.3	5.4
25	BIH	Bosnia and Herzegovina	3757	89.9	30.7	29.8
26	BLM	Saint-Barthelemy	12	74.4	10.8	9.3
27	BLR	Belarus	9362	90.2	17.3	14.0
28	BLZ	Belize	398	93.7	16.1	18.4
29	BMU	Bermuda	61	94.0	6.7	5.1
30	BOL	Bolivia (Plurinational State of)	11550	87.2	25.5	29.3
31	BRA	Brazil	215984	76.0	12.0	13.8
32	BRB	Barbados	288	59.9	12.0	11.9
33	BRN	Brunei Darussalam	450	76.9	5.8	8.4
34	BTN	Bhutan	834	94.2	21.7	28.4
35	BWA	Botswana	2458	87.2	15.1	15.0
36	CAF	Central African Republic	5399	79.2	37.7	36.1
37	CAN	Canada	37599	87.9	8.3	6.7
38	CHE	Switzerland	8653	74.2	15.1	10.3
39	CHL	Chile	18841	89.0	19.4	20.6
40	CHN	China	1402773	92.2	37.4	41.8
41	CIV	Côte d'Ivoire	25566	93.5	22.7	22.8
42	CMR	Cameroon	26350	64.0	56.2	55.2
43	COD	Democratic Republic of the Congo	90176	75.4	34.7	37.5
44	COG	Congo	5262	66.5	25.9	36.6
45	COK	Cook Islands	21	98.6	3.9	4.0
46	COL	Colombia	50230	73.2	16.7	19.3
47	COM	Comoros	883	66.0	9.1	9.8
48	CPV	Cape Verde	553	84.1	30.1	21.1
49	CRI	Costa Rica	5045	71.7	15.5	18.6
50	CUB	Cuba	11366	93.5	12.1	9.6
51	CUW	Curaçao	164	73.6	11.1	11.6
52	CYM	Cayman Islands	64	98.2	10.7	11.6
53	CYP	Cyprus	1218	80.3	19.5	17.4
54	CZE	Czech Republic	10576	73.0	21.0	14.9
55	DEU	Germany	80389	69.9	15.1	10.4
56	DJI	Djibouti	946	66.8	39.4	41.8
57	DMA	Dominica	74	61.5	11.9	11.6
58	DNK	Denmark	5776	61.0	13.4	8.3
59	DOM	Dominican Republic	11112	95.1	12.3	12.8
60	DZA	Algeria	43007	82.7	16.5	15.4
61	ECU	Ecuador	17340	70.3	14.6	18.5
62	EGY	Egypt	100524	94.0	41.5	41.8
63	ERI	Eritrea	5893	68.9	31.8	34.2
64	ESH	Western Sahara	634	70.2	34.5	29.5
65	ESP	Spain	46178	84.2	13.3	11.0
66	EST	Estonia	1293	88.7	8.9	6.8
67	ETH	Ethiopia	111983	65.3	18.6	24.5
68	FIN	Finland	5555	86.8	6.8	5.3
69	FJI	Fiji	915	98.9	6.5	6.1
70	FRA	France	65734	84.2	13.6	10.4
71	FRO	Faeroe Islands	49	90.0	4.9	4.8
72	FSM	Micronesia (Federated States of)	108	83.9	3.9	3.8
73	GAB	Gabon	1919	56.7	22.0	29.9
74	GBR	United Kingdom	66699	78.8	12.6	10.0
75	GEO	Georgia	3980	80.0	18.0	18.8
76	GGY	Guernsey	63	78.0	10.2	8.9
77	GHA	Ghana	30548	79.8	33.6	30.5
78	GIB	Gibraltar	34	84.0	12.0	12.0
79	GIN	Guinea	14354	50.9	30.7	28.7
80	GLP	Guadeloupe	419	81.5	11.8	10.9
81	GMB	Gambia	2319	63.0	45.2	39.0
82	GNB	Guinea-Bissau	2070	52.9	38.4	33.7
83	GNQ	Equatorial Guinea	970	53.5	35.1	41.6
84	GRC	Greece	10828	87.9	19.4	15.2
85	GRD	Grenada	109	64.6	12.1	11.5
86	GRL	Greenland	56	60.4	1.9	1.6
87	GTM	Guatemala	18015	71.6	28.9	27.5
88	GUF	French Guiana	305	63.8	14.3	14.8
89	GUM	Guam	180	64.7	3.0	3.8
90	GUY	Guyana	787	70.0	15.8	17.0

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	ISO Code	Name of Country or Territory	Pop. in 2020 (thousands)	Coverage (%)	$PM_{2.5}$ in 2000 ($\mu g m^{-3}$)	$PM_{2.5}$ in 2020 ($\mu g m^{-3}$)
91	HKG	Hong Kong	7619	89.9	22.6	20.1
92	HND	Honduras	8656	68.9	28.7	33.0
93	HRV	Croatia	4164	80.5	21.6	17.8
94	HTI	Haiti	11373	93.9	13.9	15.9
95	HUN	Hungary	9684	89.6	23.2	16.2
96	IDN	Indonesia	271854	76.1	15.0	19.7
97	IMN	Isle of Man	91	78.5	8.4	7.8
98	IND	India	1388953	90.9	38.2	52.2
99	IRL	Ireland	4875	81.2	9.4	7.8
100	IRN	Iran (Islamic Republic of)	83401	82.1	38.7	38.3
101	IRQ	Iraq	41963	81.7	50.0	49.7
102	ISL	Iceland	342	81.3	4.6	4.8
103	ISR	Israel	8733	83.5	20.7	21.8
104	ITA	Italy	59743	66.3	20.7	17.0
105	JAM	Jamaica	2840	93.9	18.2	19.4
106	JEY	Jersey	105	88.9	10.4	9.1
107	JOR	Jordan	8167	83.9	29.3	34.4
108	JPN	Japan	125039	89.7	15.8	12.0
109	KAZ	Kazakhstan	18626	82.0	15.8	19.4
110	KEN	Kenya	52175	71.3	17.1	22.0
111	KGZ	Kyrgyzstan	6426	91.2	18.8	18.8
112	KHM	Cambodia	16809	67.4	17.3	19.4
113	KIR	Kiribati	122	39.8	4.1	4.4
114	KNA	Saint Kitts and Nevis	58	80.3	10.2	9.5
115	KOR	Republic of Korea	51252	89.6	23.3	22.7
116	KOS	Kosovo	2027	89.4	23.6	22.7
117	KWT	Kuwait	4314	83.0	59.3	59.5
118	LAO	Lao People’s Democratic Republic	7407	89.8	22.2	27.6
119	LBN	Lebanon	5897	84.4	28.6	30.1
120	LBR	Liberia	5093	69.3	17.4	20.0
121	LBY	Libya	6700	67.8	25.8	21.1
122	LCA	Saint Lucia	192	62.8	11.9	11.3
123	LIE	Liechtenstein	39	47.5	15.0	11.0
124	LKA	Sri Lanka	21157	76.7	19.8	22.6
125	LSO	Lesotho	2241	95.9	24.4	27.1
126	LTU	Lithuania	2795	89.2	15.6	12.8
127	LUX	Luxembourg	599	92.3	14.0	9.8
128	LVA	Latvia	1920	88.2	17.8	14.7
129	MAC	Macau	632	99.9	26.6	24.9
130	MAF	Saint-Martin (French part)	46	69.8	9.6	8.9
131	MAR	Morocco	36457	85.7	18.5	18.9
132	MCO	Monaco	26	75.9	16.4	12.5
133	MDA	Republic of Moldova	4015	91.1	18.4	15.8
134	MDG	Madagascar	27799	82.9	11.3	13.2
135	MDV	Maldives	393	56.8	14.3	14.5
136	MEX	Mexico	134787	93.7	18.7	17.7
137	MHL	Marshall Islands	53	78.0	4.3	4.6
138	MKD	Macedonia	2087	90.0	28.9	24.1
139	MLI	Mali	20458	65.2	43.5	37.6
140	MLT	Malta	423	64.2	12.7	11.4
141	MMR	Myanmar	56256	93.1	26.3	35.4
142	MNE	Montenegro	626	90.1	23.2	20.6
143	MNG	Mongolia	3180	68.9	30.5	47.6
144	MNP	Northern Mariana Islands	56	91.6	2.8	3.0
145	MOZ	Mozambique	32025	75.6	14.0	13.8
146	MRT	Mauritania	4569	63.1	55.9	47.8
147	MTQ	Martinique	395	62.9	15.2	15.3
148	MUS	Mauritius	1291	80.9	15.7	14.3
149	MWI	Malawi	19993	65.6	13.8	17.0
150	MYS	Malaysia	32374	68.0	14.8	16.3
151	MYT	Mayotte	273	62.7	11.0	11.3
152	NAM	Namibia	2722	77.4	14.8	15.9
153	NCL	New Caledonia	280	98.1	6.4	5.8
154	NER	Niger	24316	61.4	67.2	67.4
155	NGA	Nigeria	206824	76.4	59.3	58.6
156	NIC	Nicaragua	6416	70.5	18.9	21.0
157	NLD	Netherlands	17184	89.9	14.9	10.1
158	NOR	Norway	5490	65.2	8.2	5.6
159	NPL	Nepal	30197	95.1	35.8	47.0
160	NRU	Nauru	10	100.0	4.3	4.8
161	NZL	New Zealand	4730	88.8	6.4	7.0
162	OMN	Oman	4826	85.1	44.8	42.8
163	PAK	Pakistan	208366	92.9	47.9	55.9
164	PAN	Panama	4230	69.4	13.4	16.0
165	PER	Peru	33317	72.6	22.8	25.6
166	PHL	Philippines	108436	72.7	21.0	22.0
167	PLW	Palau	22	90.3	4.8	5.4
168	PNG	Papua New Guinea	8413	89.1	9.8	13.6
169	POL	Poland	38409	88.3	25.3	19.1
170	PRI	Puerto Rico	3675	94.8	8.2	7.2
171	PRK	Democratic People’s Republic of Korea	25760	89.8	22.6	25.7
172	PRT	Portugal	10163	67.1	11.9	9.4
173	PRY	Paraguay	7064	84.8	14.7	17.5
174	PSE	State of Palestine	5317	83.9	22.0	23.7
175	PYF	French Polynesia	296	97.0	4.5	4.5
176	QAT	Qatar	2452	87.1	85.3	101.0
177	REU	Réunion	892	83.4	6.7	6.3
178	ROU	Romania	18829	88.4	21.2	17.8
179	RUS	Russian Federation	142900	80.3	14.9	12.8
180	RWA	Rwanda	13013	53.9	36.6	38.4
181	SAU	Saudi Arabia	34371	85.1	62.8	70.4
182	SDN	Sudan	45307	70.2	34.8	36.7

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Table A2 – continued from previous page

	ISO Code	Name of Country or Territory	Pop. in 2020 (thousands)	Coverage (%)	$PM_{2.5}$ in 2000 ($\mu g m^{-3}$)	$PM_{2.5}$ in 2020 ($\mu g m^{-3}$)
183	SEN	Senegal	17493	59.8	47.5	43.5
184	SGP	Singapore	6007	44.8	17.1	16.4
185	SLB	Solomon Islands	640	78.1	5.9	9.3
186	SLE	Sierra Leone	7160	55.1	23.2	23.7
187	SLV	El Salvador	6227	70.1	28.4	30.5
188	SMR	San Marino	31	58.2	17.8	14.5
189	SOM	Somalia	12436	62.3	19.2	18.0
190	SRB	Serbia	6645	90.2	22.8	21.7
191	SSD	South Sudan	14116	71.9	23.0	23.7
192	STP	Sao Tome and Principe	211	97.5	17.9	16.5
193	SUR	Suriname	565	74.9	16.3	16.2
194	SVK	Slovakia	5434	89.3	22.3	16.4
195	SVN	Slovenia	2077	65.1	20.1	15.4
196	SWE	Sweden	10121	74.5	8.4	5.7
197	SWZ	Swaziland	1366	95.8	20.7	17.0
198	SXM	Sint Maarten (Dutch part)	42	83.1	10.0	9.6
199	SYC	Seychelles	99	67.6	9.2	8.4
200	SYR	Syrian Arab Republic	20987	81.2	30.2	32.6
201	TCA	Turks and Caicos Islands	37	94.0	9.7	7.2
202	TCD	Chad	16422	61.6	44.0	45.0
203	TGO	Togo	8273	63.5	40.0	37.0
204	THA	Thailand	68596	76.4	21.3	24.4
205	TJK	Tajikistan	9416	91.0	25.2	30.6
206	TKM	Turkmenistan	5702	80.0	33.5	28.3
207	TLS	Timor-Leste	1317	64.7	11.2	11.6
208	TON	Tonga	111	99.1	4.9	4.3
209	TTO	Trinidad and Tobago	1378	61.0	14.4	13.9
210	TUN	Tunisia	11836	62.2	22.0	17.5
211	TUR	Turkey	82262	86.1	24.8	25.6
212	TUV	Tuvalu	10	91.4	4.2	5.1
213	TWN	Taiwan	23402	93.5	23.5	18.6
214	TZA	United Republic of Tanzania	62280	65.4	17.2	22.0
215	UGA	Uganda	45836	73.8	30.1	33.9
216	UKR	Ukraine	43678	85.5	19.2	16.5
217	URY	Uruguay	3492	82.1	12.2	12.5
218	USA	United States of America	333422	90.3	12.9	8.0
219	UZB	Uzbekistan	31709	88.4	29.1	31.0
220	VCT	Saint Vincent and the Grenadines	111	76.2	11.6	11.6
221	VEN	Venezuela (Bolivarian Republic of)	33118	69.0	18.5	20.2
222	VGB	British Virgin Islands	33	94.6	7.4	6.7
223	VIR	United States Virgin Islands	107	91.8	7.1	6.8
224	VNM	Viet Nam	98139	80.5	21.6	26.6
225	VUT	Vanuatu	294	87.7	7.3	7.0
226	WLF	Wallis and Futuna Islands	13	77.8	4.4	4.9
227	WSM	Western Samoa	199	70.8	4.7	4.7
228	YEM	Yemen	30029	63.9	42.1	46.8
229	ZAF	South Africa	56689	93.9	24.8	27.8
230	ZMB	Zambia	18889	72.3	17.1	20.8
231	ZWE	Zimbabwe	17464	93.8	14.0	15.6

Notes: The N=231 countries or territories in the sample, sorted by 2020 population. Names and population estimates from CIESIN (2018). 'Coverage' shows the sample share in the total country population. '$PM_{2.5}$ in 2000/2020' are population-weighted mean exposure levels in 2000 and 2020 respectively, based on Van Donkelaar et al. (2021)