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Global Air Quality Inequality over 2000-2020

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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 Sherif, 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

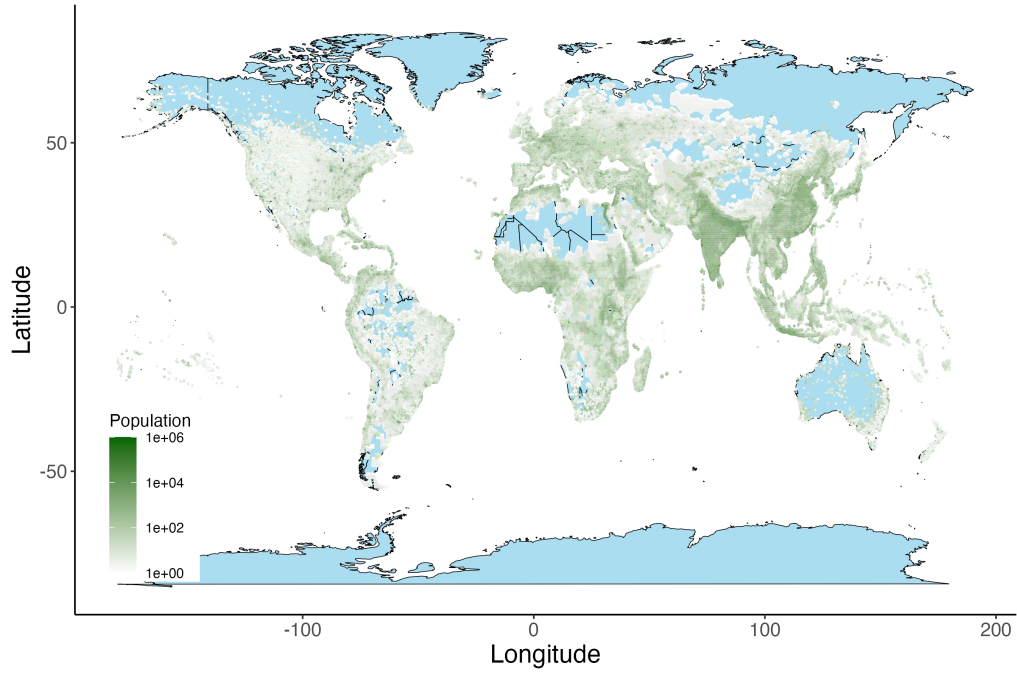
¹GPW v4.11 is available at <https://doi.org/10.7927/H4F47M65>. WUSTL ACAG Surface PM_{2.5} version V5.GL.04 is available at <https://sites.wustl.edu/acag/datasets/surface-pm2-5>.

²The 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.

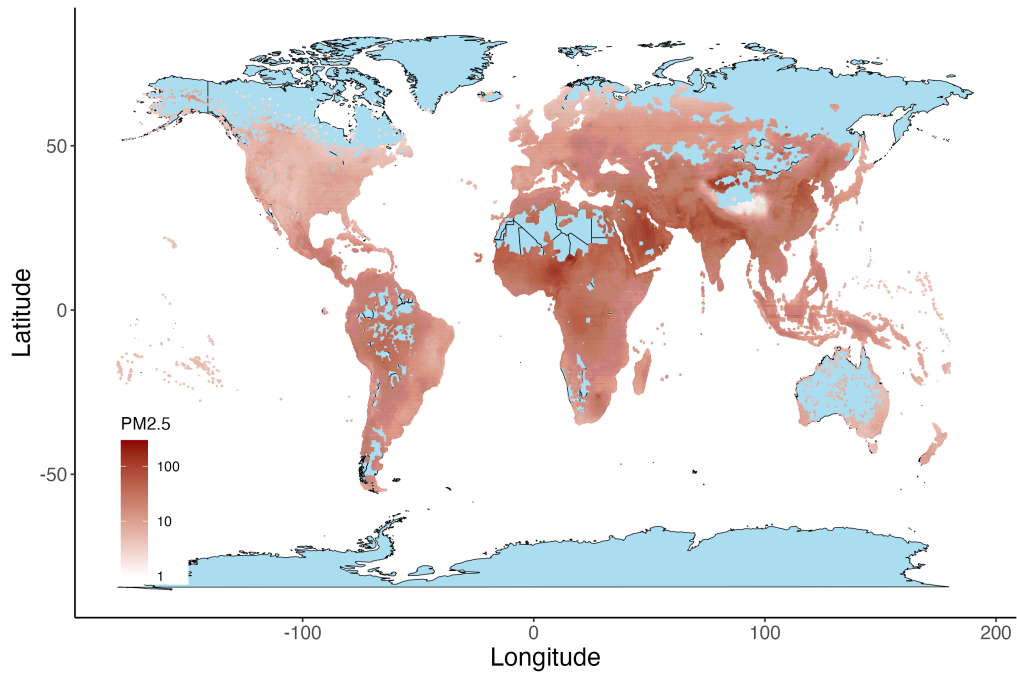
³GPW v4.11 contains a total population of 7,758,982,599 in 2020, of which I match 6,570,286,387 to PM_{2.5} levels. Countries and territories are based on the classification in [CIESIN \(2018\)](#) and population counts are UN WPP-adjusted versions from GWP v4.11. The full list of countries/territories 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 $\bar{P} = \frac{1}{N} \sum_i n_i P_i$ 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 $Gini = \frac{\sum_i n_i \sum_j n_j |P_i - P_j|}{2\bar{P}N^2}$. 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 $GE(0) = \frac{1}{N} \sum_i \left[n_i \log\left(\frac{\bar{P}}{P_i}\right) \right]$. When $\alpha = 1$, GE(1), also called the Theil Index, is defined as $GE(1) = \frac{1}{N} \sum_i \left[n_i \frac{P_i}{\bar{P}} \log\left(\frac{P_i}{\bar{P}}\right) \right]$. And when $\alpha = 2$, GE(2), equal to half the square of the coefficient of variation, is defined as $GE(2) = \frac{1}{2} \left(\left[\sum_i \frac{n_i P_i}{N \bar{P}} \right]^2 - 1 \right)$.

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 $GE_W(\alpha) = \sum_k \left[\left(\frac{N_k}{N} \right) \left(\frac{\bar{P}_k}{\bar{P}} \right)^\alpha GE_k(\alpha) \right]$ 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

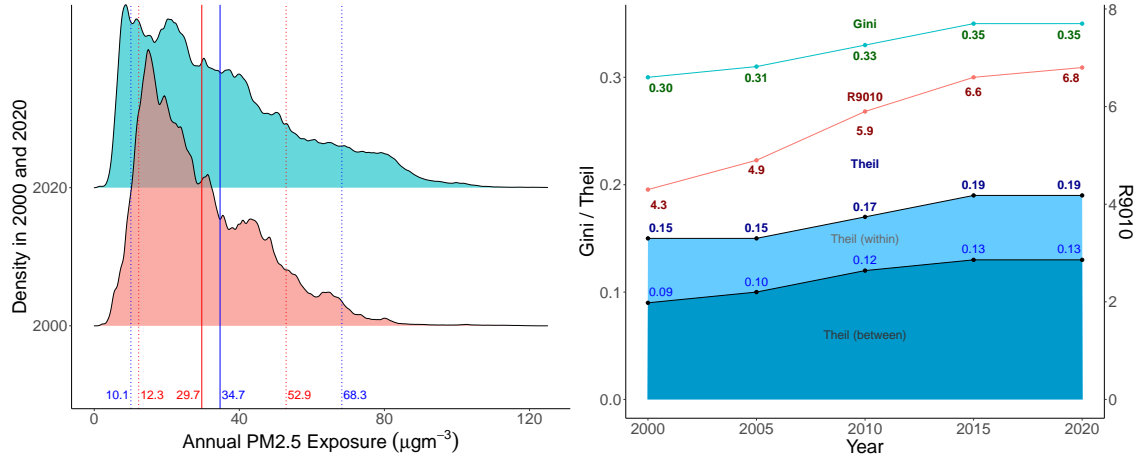
3.1 Global air quality inequality

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 ($33.6\mu g m^{-3}$) and nearly identical inequality indices (R9010=6.8, Gini=0.35, Theil=0.20).

⁴WHO 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 μgm^{-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); 0.5CV² 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

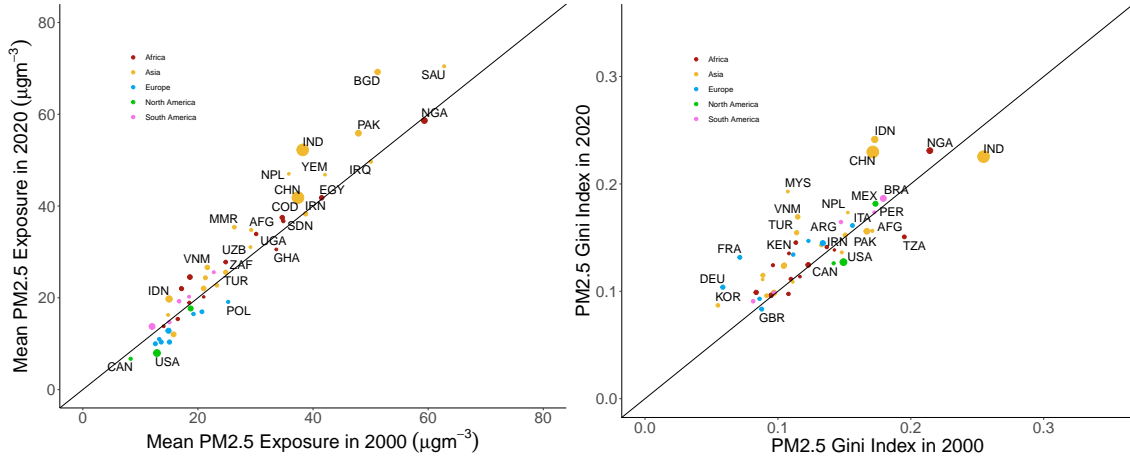
The bulk of global air quality inequality can be attributed to differences between countries rather than variation within them. Using the Theil Index, which is exactly decomposable ([Shorrocks, 1984](#)), in Figure 2 (right panel) we see that two thirds of global air quality inequality (0.14 out of 0.20) were due to differences between countries in 2020. Put differently, even if $\text{PM}_{2.5}$ 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 $\text{PM}_{2.5}$ 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 $\text{PM}_{2.5}$ exposure between 2000 and 2020 (left panel). Many countries with high $\text{PM}_{2.5}$ 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 $\text{PM}_{2.5}$ levels. This reinforced a trend whereby $\text{PM}_{2.5}$ 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 $\text{PM}_{2.5}$ 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 $\text{PM}_{2.5}$ inequality is largely and increasingly driven by differences between countries.

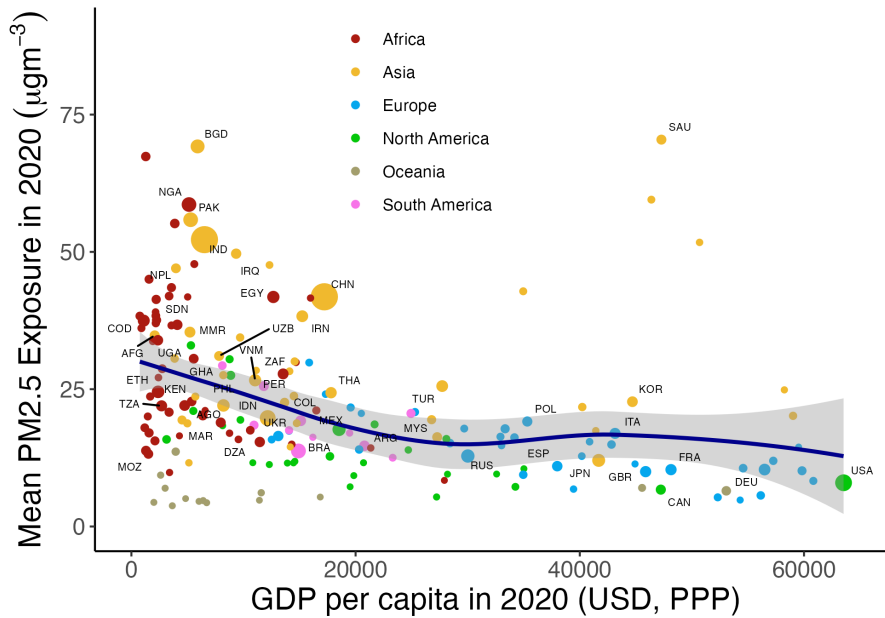
⁵These results are different from those for income, where much of global income inequality are due to within-country differences (68% in 2020 according to [Chancel and Piketty \(2021\)](#)). However, a similar share of global inequality in household carbon footprints is explained by differences between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

⁶CR 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); 0.5CV² 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 $5\mu g m^{-3}$.

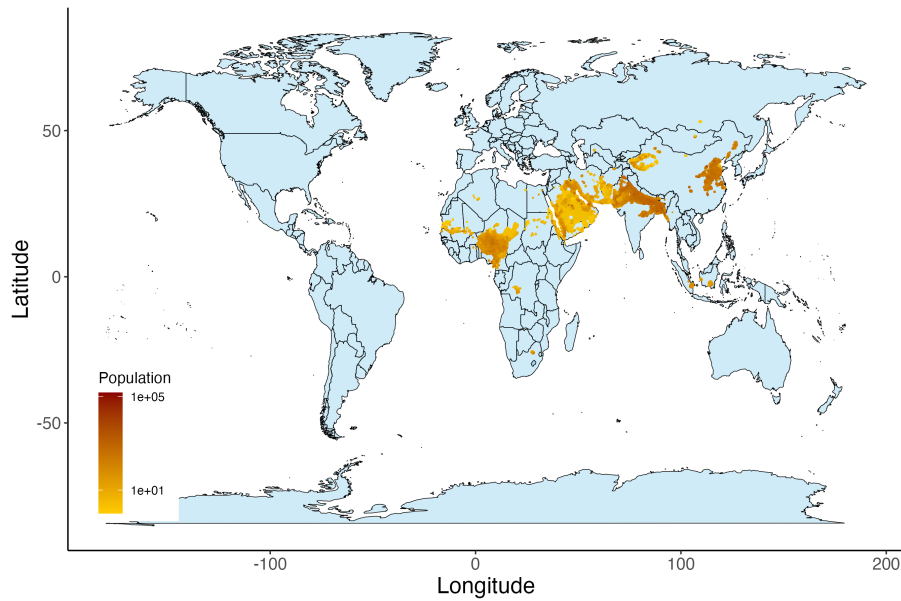
The map in Figure 5 shows that, while there are pockets of air poverty in many countries, a few geographic clusters accounted for most of the ‘Choking Billion’ in 2020. The biggest cluster spans Northern India, Bangladesh, Pakistan and Nepal, followed by other big clusters in and around Eastern China, 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.

⁸The 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).

⁹PM_{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 $\text{PM}_{2.5}$ over $59.5 \mu\text{gm}^{-3}$ 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 $\text{PM}_{2.5}$ over $59.5 \mu\text{gm}^{-3}$ 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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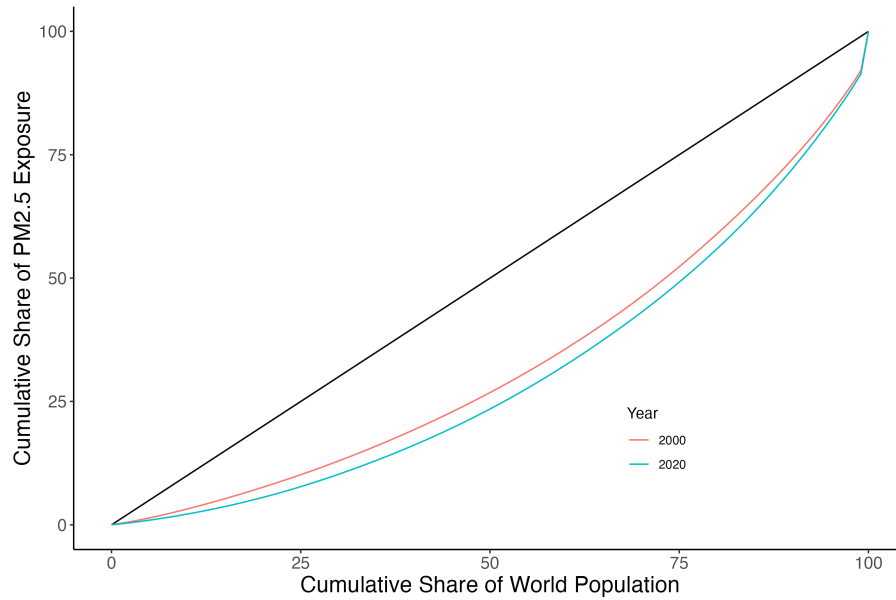
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Appendix

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); 0.5CV² 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 ($\mu\text{g m}^{-3}$) | PM _{2.5} in 2020 ($\mu\text{g m}^{-3}$) |
|----|-----|----------------------------------|-----------------------------|-----------------|---|---|
| 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 | PRO | 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 |

Continued on next page

Table A2 – continued from previous page

| | ISO Code | Name of Country or Territory | Pop. in 2020 (thousands) | Coverage (%) | PM _{2.5} in 2000 ($\mu\text{g m}^{-3}$) | PM _{2.5} in 2020 ($\mu\text{g m}^{-3}$) |
|-----|----------|---------------------------------------|-----------------------------|-----------------|---|---|
| 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 |

Continued on next page

Table A2 – continued from previous page

| | ISO Code | Name of Country or Territory | Pop. in 2020 (thousands) | Coverage (%) | PM _{2.5} in 2000 ($\mu\text{g m}^{-3}$) | PM _{2.5} in 2020 ($\mu\text{g m}^{-3}$) |
|-----|----------|------------------------------------|-----------------------------|-----------------|---|---|
| 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. \(2021\)](#)