Journal of Environmental Sciences 159 (2026) 471–479

Contents lists available at ScienceDirect

Journal of Environmental Sciences

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

JES JOURNAL OF ENVIRONMENTAL SCIENCES www.jesc.ac.cn

Research Article

Global health risk attributable to $PM_{2.5}$ pollution in relation to wealth inequality

Lulu Lian [a], Jianping Huang [a,b,*], Siyu Chen [a,b], Jianmin Ma [c], Xinbo Lian [a,d], Lihui Zhang [a], Shikang Du [a,d], Dan Zhao [a]

[a] College of Atmospheric Sciences, Lanzhou University, Lanzhou 730000, China
[b] Key Laboratory for Semi-Arid Climate Change of the Ministry of Education, Lanzhou University, Lanzhou 730000, China
[c] Laboratory for Earth Surface Processes, College of Urban and Environmental Sciences, Peking University, Beijing 100871, China
[d] College of Earth and Environmental Sciences, Lanzhou University, Lanzhou 730000, China

A R T I C L E I N F O

Keywords:
$PM_{2.5}$ pollution
Mortality
Health cost
Wealth inequality

A B S T R A C T

Ambient fine particulate matter ($PM_{2.5}$) pollution causes the largest environmental health risk globally, yet exposure levels and the resulting health risks vary across countries with different income levels. Global wealth inequality has intensified in recent years, yet the relationship between wealth inequality and health risks related to $PM_{2.5}$ pollution remains poorly understood. In this study, we evaluated the global mortality and health cost attributable to $PM_{2.5}$ exposure from 2017 to 2021, and analyzed the relationship between wealth inequality, $PM_{2.5}$ pollution, and the associated health risks across regions with varying economic levels. We found a consistent decline in mortalities and health costs attributable to $PM_{2.5}$ exposure from 2017 to 2020, followed by a rebound after 2020, driven primarily by the resurgence of $PM_{2.5}$ concentrations and a deceleration in the reduction of baseline mortality rates. We also found that the average $PM_{2.5}$ concentration and associated risks decrease as domestic wealth inequality decreases and national income level increases. However, regions with extremely high levels of wealth inequality consistently show lower national average $PM_{2.5}$ concentrations and health risks. These findings highlight the need to consider healthcare security during emergencies, as well as policy fairness across economic regions, in the formulation of global $PM_{2.5}$ pollution control measures to promote sustainable, more equitable economic growth and coordinated air pollution management.

1. Introduction

Data from the World Health Organization (WHO) indicates that almost everyone in the globe (99 %) breathes air that exceeds WHO's guideline thresholds, with the highest exposure levels found in low- and middle-income countries/regions (Huang et al., 2024; WHO, 2021a). According to the Global Burden of Disease, Injuries, and Risk Factors Study (GBD) 2021, particulate matter air pollution (including ambient and household particulate matter pollution) is the leading contributor to the global disease burden in 2021, ranking as the first largest risk factor for human health (Brauer et al., 2024). Especially, ambient fine particulate matter ($PM_{2.5}$) exposure increases the incidence and mortality rates of cardiovascular and respiratory diseases, as well as lung cancer (Bai et al., 2022; Li et al., 2018). Additionally, emerging evidence suggests that $PM_{2.5}$ pollution impacts other organ systems (Kang et al., 2024; Tong et al., 2023). Burden of disease assessments should comprehensively reflect all relevant exposure-response relationships and their effects on disease and mortality in target populations, which is critical for guiding population-based prevention efforts (Sigsgaard and Hoffmann, 2024). Meanwhile, the health burden caused by $PM_{2.5}$ pollution also imposes a significant economic burden (Yin et al., 2021, 2024). In many countries, the value of statistical life (VSL) is an important component of policy cost-benefit analysis (Miller, 2000).

In recent years, global air pollution and its associated health burden have shown a downward trend (Yu et al., 2024; Zhou et al., 2024). However, the global Corona Virus Disease 2019 (COVID-19) pandemic, which emerged at the end of 2019, has significantly impact the healthcare systems of most countries/regions, causing the world to deviate from the path of achieving the "Triple Billion" targets and the health-related Sustainable Development Goals (SDGs) (Organization, 2021b; Wei et al., 2023). COVID-19 has become an obstacle to health improvement in most regions globally, and its impact on $PM_{2.5}$ concentrations, mortality rates, and health costs varies across different regions (IHME, 2024; Sachs et al., 2022; Wang et al., 2022), further exacerbating existing inequalities (Antonia and Simion, 2023; Vonderschmitt et al., 2023).

* Corresponding author at: College of Atmospheric Sciences, Lanzhou University, Lanzhou 730000, China.
E-mail address: hjp@lzu.edu.cn (J. Huang).

https://doi.org/10.1016/j.jes.2025.03.045
Received 23 November 2024; Received in revised form 26 March 2025; Accepted 26 March 2025
Available online 27 March 2025

While reducing air pollution can undoubtedly yield substantial health and economic benefits (Lian et al., 2023), merely lowering atmospheric $PM_{2.5}$ concentrations may not necessarily alleviate the associated mortality burden and health costs (Zhao et al., 2024). In the framework of policy analysis, VSL is a key parameter for assessing the health benefits of environmental, transportation, and public health policies (Keller et al., 2021). Based on the VSL-derived $PM_{2.5}$ health loss model, a decomposition of driving factors (including $PM_{2.5}$ concentration, population size, age structure, and healthcare quality) allows for the exploration of significant differences in the health burden caused by $PM_{2.5}$ exposure across different countries/regions (Yue et al., 2024; Zhao et al., 2024). Understanding how these socioeconomic drivers influence the international disparities in air pollution-related mortality and health cost is critical for advancing global health and development.

In fact, many existing studies focus on the assessment of health risks and economic losses caused by air pollution (Kuźma et al., 2024; Liu et al., 2022; Pozzer et al., 2023). However, studies that associate global wealth inequality with $PM_{2.5}$-related health risks and economic costs, and discuss the relationship between them, remain scarce. Driven by long-term population and socio-economic factors, coupled with the frequent occurrence of major public health events and extreme climate events, air pollution remains an urgent global public health challenge. Thus, this study aims to reveal the spatiotemporal distribution of premature deaths and health costs caused by $PM_{2.5}$ pollution exposure globally from 2017 to 2021, and their relationship with regional wealth inequality. By integrating socio-economic data, this study analyzes the spatiotemporal variations in $PM_{2.5}$-related mortality rates and health costs across regions with varying income levels and wealth disparities, while identifying the key drivers underlying these patterns. Quantifying the impacts of these various risk factors on health will aid in formulating more effective national-level public health policies and prioritizing the allocation of scarce resources by identifying and addressing the most critical risk factors.

2. Methods

2.1. Integrated assessment framework

This study utilized a global high-resolution (1 km × 1 km) dataset of assimilated ambient $PM_{2.5}$ concentrations collected from 2017 to 2021 (Wei et al., 2023). To estimate the mortality burden and associated health costs attributed to $PM_{2.5}$ pollution exposure (MBAPP and HCAPP) from five specific causes (chronic obstructive pulmonary disease (COPD), ischemic heart disease (IHD), stroke (STR), lung cancer (LC), and lower respiratory infections (LRIs)) of death, we applied the Global Exposure Mortality Model (GEMM) and an age-adjusted Value of a Statistical Life Year (age-adjusted VSLY) approach, analyzing 20 age groups (in increments of 5 years, the age range spans from 0 years to 95 years and above). Furthermore, we quantified the impacts of five key driving factors-population growth, population aging, improved health care, $PM_{2.5}$ exposure, and GDP growth-on the health costs attributable to $PM_{2.5}$ pollution-related mortalities across four income-level regions: low income countries (LIC), lower middle income countries (LMIC), upper middle income countries (UMIC), and high income countries (HIC) (Hamadeh et al., 2023). To assess the influence of income inequality, we further categorized regions by Gini index into four groups: low Gini index (LGI, 0–25 %), lower-middle Gini index (LMGI, 25 %–50 %), upper-middle Gini index (UMGI, 50 %–75 %), and high Gini index (HGI, 75 %–100 %).

2.2. Mortality burden assessment

In this study, we assessed the five causes of mortality associated to ambient $PM_{2.5}$ pollution exposure applying the GEMM (Burnett et al., 2018). The GEMM parameters are shown in Table S1. Gridded baseline mortality data and population structure data were generated by mapping national data onto the grid cells of 0.1° × 0.1°. Then the grid (i), year (y), cause (c), and age group (a) mortality burden attributed to $PM_{2.5}$ pollution (MBAPP) was estimated with the following equation:

$$MBAPP_{i,y,c,a} = E0_{i,y,c,a} \times AF_{i,y,c,a} \times Pop_{i,y,a} \tag{1}$$

$$AF_{i,y,c,a} = \left(RR_{i,y,c,a} - 1\right)/RR_{i,y,c,a} \tag{2}$$

where, $E0_{i,y,c,a}$ represents the grid cell (i)-, year (y)-, age (a)-, and cause (c)-specific baseline mortality rate of the exposed population, obtained from the 2021 GBD study (Brauer et al., 2024); $AF_{i,y,c,a}$ is the attributable fraction of relative risks induced by $PM_{2.5}$ pollution, calculated using Eq. (2); $Pop_{i,y,a}$ is the exposure population at each grid, each year, and each age group. It is important to note that the gridded population data is only updated until 2020, here the 2021 gridded population data still relies on the 2020 data.

The relative risk (RR) refers to the risk of mortality from specific diseases due to exposure to $PM_{2.5}$ pollution. Here, $RR_{i,y,c,a}$ represents the risk for each grid cell (i), year (y), cause (c), and age group (a), which is calculated as follows:

$$RR_{i,y,c,a} = exp\left\{\theta_{c,a} lg\left(\frac{z_{i,y}}{\alpha_{c,a}+1}\left[\frac{1}{1+exp\left(-\frac{z_{i,y}-\mu_{c,a}}{\upsilon_{c,a}}\right)}\right]\right)\right\} \tag{3}$$

$$z_{i,y} = C_{i,y} - C_0 \tag{4}$$

where, $C_{i,y}$ is the ambient $PM_{2.5}$ concentration at grid cell (i) and year (y), and C_0 is the counterfactual $PM_{2.5}$ concentration below which no additional risk takes place. Here we used $C_0 = 5\ \mu g/m^3$, as recommended by the World Health Organization. $\theta_{c,a}$, $\alpha_{c,a}$, $\mu_{c,a}$, and $\upsilon_{c,a}$ are the parameters of Eq. (3) shown in the Appendix A **Table S1**.

The GBD and World Health Organization (WHO) treat mortality and YLL (years of life lost) as equally appropriate metrics for measuring the health burden of air pollution (Brauer et al., 2024; WHO, 2021). Furthermore, subsequent calculations for age-adjusted health costs are also based on YLL. The YLL of each cause c, at age a, at grid cell i, and in year y is given by Eq. (5):

$$YLL_{i,y,c,a} = MBAPP_{i,y,c,a} \times LE_{i,y,a} \tag{5}$$

where, $MBAPP_{i,y,c,a}$ is the number of mortalities, $LE_{i,y,a}$ is life expectancy.

2.3. Health cost assessment

Here, the health costs attributed to $PM_{2.5}$ pollution exposure (HCAPP) refers to the monetised estimate of the welfare loss due to mortality related to ambient $PM_{2.5}$ exposure (Yin et al., 2024). Using the age-VLSY method to estimate HCAPP, the calculation formula is as follows:

$$\mathrm{HCAPP}_{i,y,c,a} = \sum\left(VSLY_{i,y,c,a} \times YLL_{i,y,c,a}\right) \tag{6}$$

$$VSLY_{i,y,c,a} = \frac{VSL_{OECD} \times \left(\frac{GDP_{i,y}}{GDP_{OECD,y}}\right)^{e} \times \frac{LE_{i,y,a}}{LE_{i,y,mean}} \times \frac{w_a}{w_{mean}}}{\sum_a^T \left[P_a \times \left(1 + 1/(1+\gamma)^{T-a-1}\right)\right]} \tag{7}$$

where, $VSLY_{i,y,c,a}$ is the age-adjusted VSLY, the subscript i in VSLY denotes national-level data that is applied to each grid cell; $YLL_{i,y,c,a}$ is the years of life lost, calculated using Eq. (5); VSL_{OECD} is the base VSL from the Organisation for Economic Co-operation and Development (OECD) countries; $GDP_{i,y}$ is the gross domestic product (GDP) per capita; GDP_{OECD} is the average GDP per capita of OECD counties; e is the income elasticity of VSL in each country; LE is life expectancy; w is the wealth in each country; P_a represents the survival probability at age a in i region, γ denotes the discount rate, and T refers to the age of expected death at age a. Country-specific GDP per capita from 2017 to 2021 was collected from the World Bank database (https://data.worldbank.org/). The economic data are adjusted to purchasing-power-parity (PPP) dollars in 2021.

2.4. Health cost decomposition

To examine potential drivers that contribute to HCAPP, we decomposed the health costs into five factors, including (1) population growth, (2) population aging, (3) health care, (4) $PM_{2.5}$ exposure, and (5) GDP per capita growth. The contributions of each driver were estimated over two periods: 2017–2020, and 2020–2021. Further details are presented in Appendix A **Text S1**. A glossary of the abbreviations used in this study was listed in Appendix A **Table S2**.

2.5. Uncertainty analysis

In this study, we utilized gridded $PM_{2.5}$ concentration and population data, as well as national-/regional-level health benchmarks and population structure data. To address potential inconsistencies in data spatial resolution, we applied methods such as downscaling and data allocation to align datasets and resolve issues of scale mismatches. To quantify uncertainty in the estimates, we performed 10,000 Monte Carlo simulations using Crystal Ball software to estimate the 95 % confidence intervals (CI95) for mortality and health cost estimates. Key parameters, such as baseline mortality rates, survival probabilities, and life expectancy, were assumed to follow normal distributions, with standard deviations derived from historical data and literature. $PM_{2.5}$ concentrations were assumed to follow a uniform distribution to reflect variability across regions. Other parameters were treated as constants to isolate specific sources of uncertainty

3. Results

3.1. Mortality burden and health cost

Through concerted efforts by countries worldwide, significant progress has been made in mitigating air pollution in recent years (Li et al., 2023). However, the outbreak of COVID-19 at the end of 2019 led to a sharp decline in air pollution in some regions, followed by a subsequent rebound as restrictions were lifted. The decline in life expectancy during the COVID-19 pandemic and the impediment to health improvements have highlighted the health vulnerabilities faced by disadvantaged populations across different economic structures. Similar to the spatial distribution of $PM_{2.5}$ concentrations, premature deaths declined in most regions globally in 2020 compared to 2019, with increases observed in the United States, parts of South America, and central Africa (Appendix A **Fig. S1a**). By 2021, premature deaths rebounded in regions such as India and parts of Europe, with notable increases compared to 2020 in India, Europe, northern Africa, the Middle East, and parts of China (Appendix A **Fig. S1b** and **S1c**).

From a global perspective, global MBAPP and HCAPP decreased from 2017 to 2020 but increased after 2020. Our findings reveal that 1.04 million (95 % confidence interval [CI95]: 0.69–1.36 million) MBAPP globally in 2017, declining to 0.81 million (CI95: 0.54–1.06 million) by 2020 (Fig. 1**a**), before rebounding to 0.88 million (CI95: 0.58–1.15 million) in 2021. Similarly, HCAPP experienced a slight rebound post-2020, with the HCAPP amounting to 0.62 trillion US$ (CI95: 0.40–1.82 trillion US$) by 2021 Fig. 1**b**). In the context of increasing global ageing, the proportion of global MBAPP and HCAPP among the 65+ population has steadily increased, reaching 78.07 % and 35.95 % in 2021 (Appendix A **Fig. S2**), respectively.

From the perspective of regions with different income levels, middle income regions (including LMIC and UMIC) are the regions with the highest MBAPP and HCAPP, driving the global trend. All four income level regions experienced a decline before 2020, followed by an increase from 2020 to 2021, with the HIC regions showing the fastest rate (16.4 % and 16.1 %, respectively) of increase after 2020 (shown in Appendix A **Tables S3** and **S4**). Older populations, particularly those aged 65 and above, remain highly vulnerable to mortalities caused by $PM_{2.5}$ pollution exposure (Fig. 1**a** and **b**). However, in HIC regions, the proportion of MBAPP and HCAPP among the 65+ age group have shown fluctuating downward trend (the dashed lines in Fig. 1**c** and **d** represent the proportion of MBAPP and HCAPP among the 65+ age group in different economic level regions). Despite the ongoing intensification of population aging in HIC areas, this trend is primarily attributed to improvements in healthcare for the elderly population.

3.2. Mortalities and income inequality

The five countries with the highest five-year average MBAPP are China (48.79 10k, CI95: 32.40–63.89 10k), India (27.23 10k, CI95: 18.08–35.66 10k), Pakistan (2.72 10k, CI95: 1.81–3.56 10k), Egypt (2.12 10k, CI95: 1.41–2.77 10k), and Nigeria (1.33 10k, CI95: 0.88–1.74 10k), accounting for 88 % of the global total MBAPP (Fig. 2**a**). Among these countries, only China falls under UMIC, while the other four are classified as LMIC. The highest MBAPP are concentrated in regions with high average $PM_{2.5}$ concentrations and large populations in lower income regions. Meanwhile, China (452.14 billion US$, CI95: 293.17–597.50 billion US$), India (99.03 billion US$, CI95: 64.21–130.87 billion US$), Saudi Arabia (26.92 billion US$, CI95: 17.46–35.58 billion US$), Egypt (15.81 billion US$, CI95: 10.25–20.90 billion US$), and South Korea (10.74 billion US$, CI95: 6.97–14.20 billion US$) are the five countries with the highest five-year average HCAPP, accounting for 85.64 % of the global total HCAPP (Fig. 2**b**). Among these five countries, Saudi Arabia and South Korea are classified as HIC. Due to the calculation methods, we found that countries with higher HCAPP are predominantly located in UMIC and HIC regions. The details of the relationship between $PM_{2.5}$ concentration and wealth inequality shown in Appendix A **Text S2**.

Despite the fact that income levels have risen in most countries globally in recent years, nearly half of the countries/regions exhibited a trend of increasing wealth inequality between 2017 and 2021, particularly in UMIC and HIC regions (Appendix A **Figs. S3** and **S4**). In these two income level regions, 53.7 % and 61.5 % of the countries experienced an increase in their Gini index. So, what is the relationship between changes in income levels and wealth inequality and the mortality and health costs in different regions? Our study found that in the sample of 194 countries/regions with varying income levels (including 25 LIC, 53 LMIC, 48 UMIC, and 65 HIC regions), mortalities per million exposed increased with rising wealth inequality and decreased with higher per capita GDP. Specifically, MBAPP increased by 0.52 million for each 1 % rise in the Gini index (Fig. 2**c**), and decreased by 0.21 million for every 1000 US$ increase in GDP per capita (Fig. 2**e**). Similarly, HCAPP in countries/regions increased by 1.53 US$ for each 1 % rise in the Gini index (Fig. 2**d**), and decreased by 1.19 US$ for every 1000 US$ increase in GDP per capita (Fig. 2**f**). MBAPP is inversely correlated with GDP per capita, while HCAPP is positively correlated with GDP per capita. This phenomenon is mainly related to the different calculation methods of the two metrics. Although HCAPP increases with the rise in GDP per capita, after GDP per capita reaches a certain level and MBAPP decreases to a certain extent, HCAPP will start to decrease (Lian et al., 2023). Therefore, reducing wealth inequality and raising income levels across countries will effectively reduce MBAPP, thereby lowering HCAPP.

To further explore the relationship between income levels, wealth inequality, and MBAPP and HCAPP, we analyze the correlations of these metrics with countries grouped by income levels and wealth inequality. We found that regions with the highest mortality rates per million exposed are primarily located in LMIC or UMIC regions (Fig. 3**a**). In terms of wealth inequality, regions with the highest mortalities per million exposed are concentrated in LMGI and UMGI region (Fig. 3**b**). It can be observed that in lower income regions, mortality rates increase

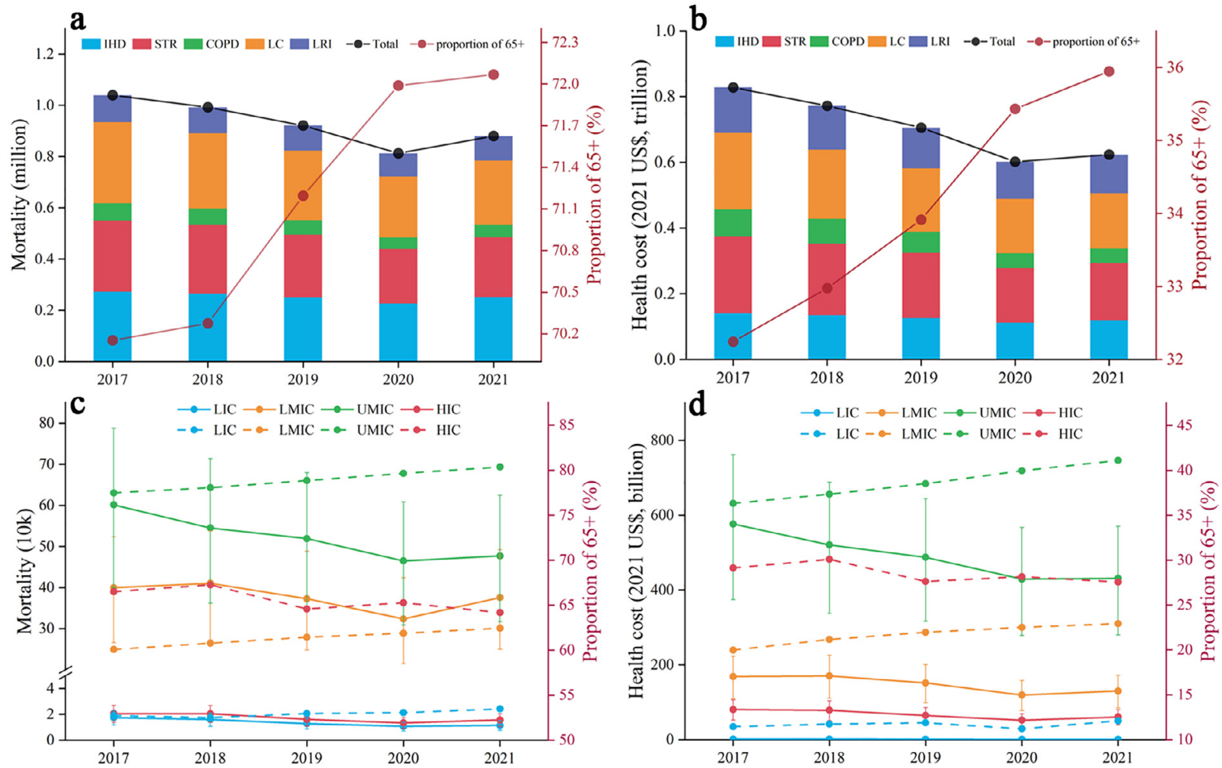

Fig. 1 – Mortalities (**a**, unit: million (left Y-axis)) and health costs (**b**, unit: 2021 US$, trillion (left Y-axis)) globally, along with the percentage change in population aged 65+ (right Y-axis, represented by red lines). Mortalities (**c**, unit: million (left Y-axis)) and health costs (**d**, unit: 2021 US$, trillion (left Y-axis)) across regions with four income levels, along with their respective percentage changes in the population aged 65+ (right Y-axis, represented by dashed lines). IHD: ischemic heart disease ; STR: stroke; COPD: chronic obstructive pulmonary disease; LC: lung cancer; LRI: lower respiratory infections; LIC: low income countries; LMIC: lower middle income countries; UMIC: upper middle income countries; HIC: high income countries.

with the rise in per capita GDP, indicating that economic development comes at the expense of public health. In contrast, only in HIC regions where the economy has reached a certain level, can economic growth occur without compromising air quality and public health (Fig. 3**c**). In regions with lower levels of wealth inequality (LGI and LMGI), mortality rates increase with rising Gini index. Conversely, in regions with higher levels of wealth inequality (UMGI and HGI), mortality rates decrease as the Gini index increases (Fig. 3**d**). In regions with lower Gini indices, an increase in wealth inequality may have a more pronounced negative impact on lower socio-economic classes, potentially leading to a deterioration in public health services and higher mortality rates. In contrast, regions with higher Gini indices are often more economically developed and have likely established mechanisms that mitigate the negative health impacts of inequality. In high Gini index regions, further increases in inequality may trigger greater wealth redistribution through tax policies or social welfare programs. Some highly unequal regions may benefit from cross-class income redistribution, which could reduce health risks associated with poverty, thereby even lowering mortality rates. In fact, due to the redistribution effect, mortality rates may decrease. The change in mortality rates with wealth inequality follows a pattern similar to the environmental Lorenz curve.

3.3. Driving factors of health cost

Global $PM_{2.5}$ concentrations continuously declined from 2017 to 2020, with an average decrease of 24.31 % in HIC regions. However, this trend reversed after 2020, with average $PM_{2.5}$ concentrations in HIC regions rising by 8.52 % (Fig. 4**a**). Population aging continued to increase across all regions globally, particularly in HIC areas, where the proportion of the 65+ population rose from 17.64 % to 18.90 % (Fig. 4**c**). The declining trend in mortality rates due to outdoor $PM_{2.5}$ exposure also vanished after 2020 (Fig. 4**d**), while per capita GDP rebounded in 2021 after declining in 2020 (Fig. 4**e**). These trends are likely influenced by the global COVID-19 pandemic that erupted at the end of 2019. The combined changes in these factors have led to shifts in premature mortality and health losses, which will be further analyzed in the following sections.

To further explore the impact of various driving factors on HCAPP, we decomposed the five key drivers. From a global perspective, HCAPP decreased by 226.00 billion US$ (27.3 %) from 827.70 billion US$ in 2017 to 601.70 billion US$ in 2020, with the reduction in $PM_{2.5}$ concentration (decreased by 639.20 billion US$) being the primary negative driving factor, followed by the health care (decreased by 490.67 billion US$) (Appendix A **Fig. S5**). However, after 2020, there was a rebound, with HCAPP increasing by 21.72 billion US$ (+3.61 %), primarily driven by a reversal in health care improvements (increased by 1.08 billion US$, +1.79 %) (Appendix A **Fig. S5**).

Specifically, in regions with different income levels, HCAPP decreased across all four income-level regions prior to 2020, driven by the negative contributions of health care and $PM_{2.5}$ concentration reductions (shown in Fig. 5). After 2020, however, HCAPP increased. In LIC regions, although GDP per capita continued to show a slow decline, the rebound in $PM_{2.5}$ concentration led to an increase in HCAPP (Fig. 5**a**). In all regions except LIC, health care became the largest positive driving factor, resulting in the rise in HCAPP (Fig. 5**b-d**). Additionally, $PM_{2.5}$ concentration rebounded in LMIC regions (Fig. 5**b**). This suggests that most countries and regions were unprepared to cope with the COVID-19 pandemic, which led to an increase in MBAPP and HCAPP.

In summary, global $PM_{2.5}$ concentrations have significantly declined in recent years. However, the outbreak of the COVID-19 pandemic has slowed this downward trend in most regions, and even led to signs of a rebound. Meanwhile, the pace of global population aging has not

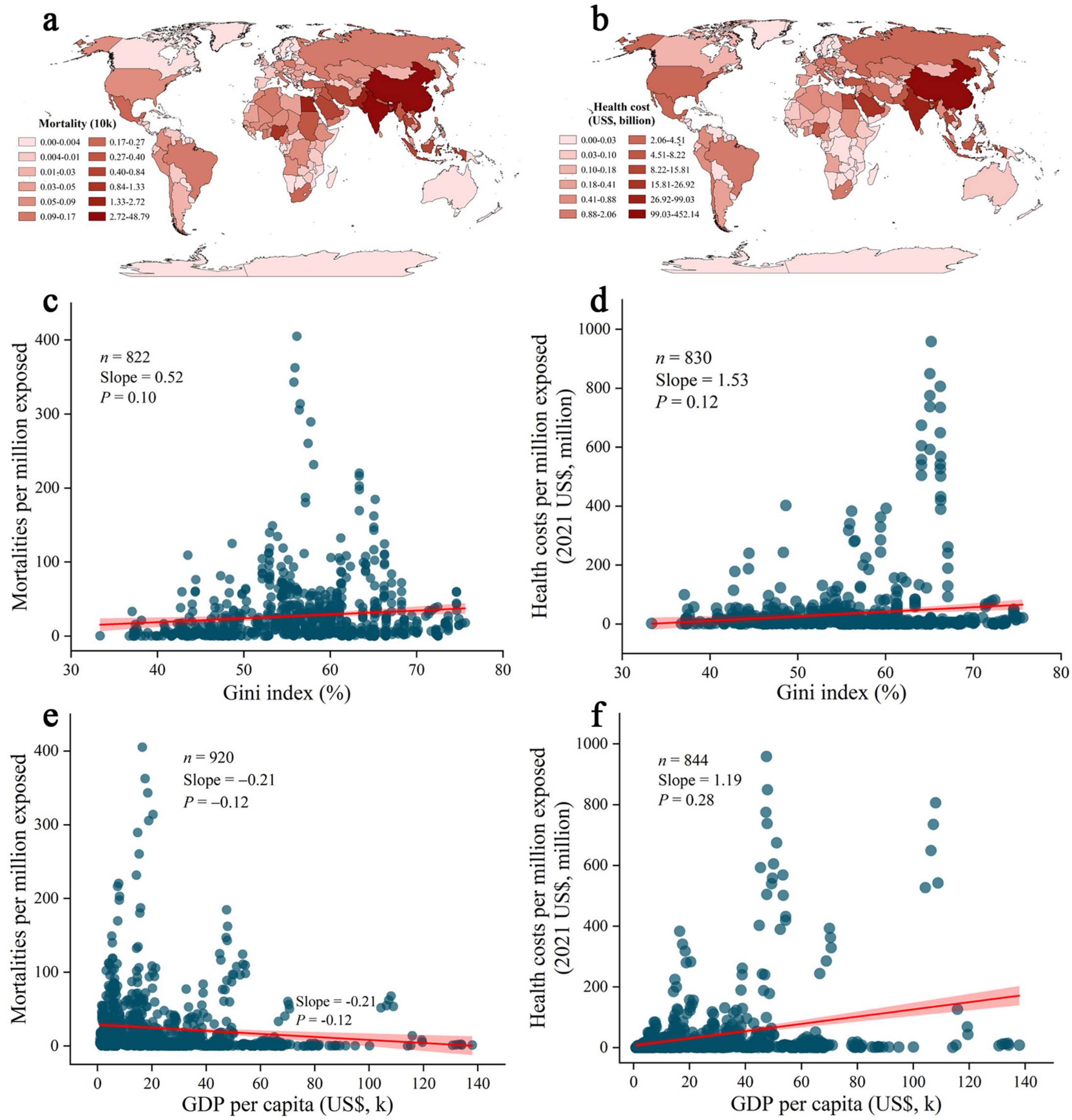

Fig. 2 – Spatial distribution of annual mortality burden attributed to $PM_{2.5}$ pollution (MBAPP) (**a**, unit: 10k) and health costs attributed to $PM_{2.5}$ pollution (HCAPP) (**b**, unit: US$, billion). Relationships between mortalities per million exposed and the Gini index (**c**), health costs per million exposed and Gini index (**d**), mortalities per million exposed and GDP per capita (**e**), and health costs per million exposed and GDP per capita (**f**). The red line represents the binomial fit model, with the shaded area indicating the 95 % confidence interval. *n* denotes the sample size, Slope represents the slope of the linear fit, and *P* indicates the Pearson correlation coefficient.

slowed, and the pandemic has exposed severe shortages in health care resources worldwide, exacerbating the burden of deaths attributable to $PM_{2.5}$ exposure. Mortalities and health costs have shown a significant upward trend.

4. Discussion

Strengthening global health care emergency response capabilities remain a critical priority for addressing health risks associated with $PM_{2.5}$ exposure. However, relying solely on improvements in healthcare systems cannot comprehensively tackle global environmental health challenges. Understanding the driving forces behind international disparities is crucial for addressing the unequal distribution of mortality burdens and promoting global development. Our findings reveal that mortality rates associated with $PM_{2.5}$ exposure increase with heightened wealth inequality between countries but decrease as per capita GDP rises. However, variations in mortality rates among countries within different income levels and wealth inequality brackets are inconsistent, highlighting the complex and dynamic relationship between economic development and environmental health.

Firstly, we found a positive correlation between domestic wealth inequality and the health risks associated with $PM_{2.5}$ exposure. Specifically, in countries within different wealth inequality brackets, in regions with lower levels of wealth inequality, greater wealth inequality is associated with higher mortality rates. However, in regions with higher wealth inequality, increased wealth inequality is associated with a decline in mortality rates. This can be interpreted as a distorted form of the environmental Lorenz curve. Further explanation suggests that in regions with lower wealth inequality, a rise in inequality is typically accompanied by rapid social and industrial development, which tends to weaken the resources and health conditions of lower socio-economic groups, leading to higher mortality rates. In contrast, in regions with higher wealth inequality, further exacerbation of inequality is often accompanied by the functioning of social adaptation mechanisms, economic growth, and improvements in the health of the affluent, resulting in a decline in overall mortality rates. This indicates that policymak-

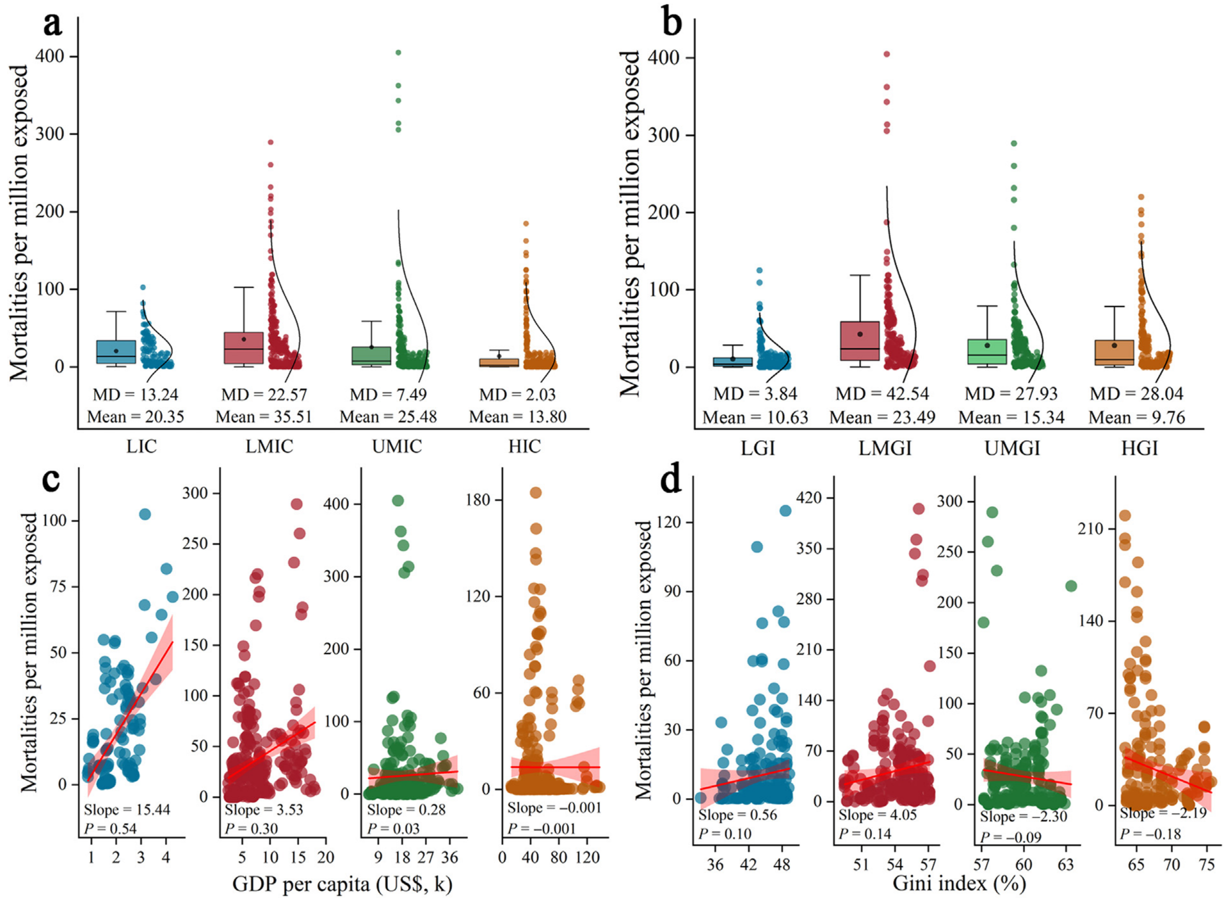

Fig. 3 – Mortality rates and wealth inequality. Scatter plot with boxplots of mortality rates for four income levels (**a**) and four Gini index levels (**b**), the lines in the boxplot represents the median, the black dots represent the mean value, and the colored scatter points represent the mortality rates for all countries/regions over the five years. The two bottom sub figures represent scatter plots of GDP per capita (**c**), Gini index (**d**) and mortality rates across four income levels and four Gini index levels, the blue scatter points correspond to LIC and LGI level, the red scatter points correspond to LMIC and LMGI levels, the green scatter points correspond to UMIC and UMGI levels, and the yellow scatter points correspond to HIC and HGI levels, the red lines represent binomial fit models, with the 95 % confidence interval indicated by the shaded area, Slope refers to the slope of the linear fit, and *P* denotes the Pearson correlation coefficient.

ers need to design targeted interventions based on different inequality brackets.

Overall, the increase in income levels is associated with a reduction in $PM_{2.5}$ exposure-related mortality rates. In fact, within different income brackets, income growth (usually accompanied by industrialization) is associated with an increase in $PM_{2.5}$ exposure-related mortality. Only when income levels reach the high-income bracket does economic development occur without a corresponding increase in health burdens. This suggests that economic development in low-income regions must be coupled with strict pollution control measures to prevent economic growth from becoming a cost to public health. By promoting effective environmental regulations and technological innovations, such as the industrial emission reduction policies of certain high-income countries, a win-win scenario can be achieved where both economic and health benefits are realized alongside economic growth.

Therefore, implementing stringent $PM_{2.5}$ emission reduction measures, increasing income levels, and reducing wealth inequality are effective strategies for lowering premature deaths and health costs due to $PM_{2.5}$ exposure. However, policies should still be tailored to regions with different levels of wealth inequality and income. Particularly for lower-middle-income regions, economic development must be combined with strict $PM_{2.5}$ emission controls, as reducing air pollution will lead to significant health benefits.

Vulnerable groups (including populations in low-income regions as well as the elderly) face the highest risks from the health impacts of air pollution, but they will also benefit the most from air pollution reduction policies (Rentschler and Leonova, 2023). Therefore, policymakers need to prioritize these groups to maximize the benefits of these policies. For example, through financial support and international aid, providing air pollution control technologies, funding, and medical equipment to lower-middle-income regions can effectively reduce the health burden from $PM_{2.5}$ exposure. This not only helps to improve global health inequalities but will also have a positive impact on global sustainable development.

Air pollution has a global impact on health, but some of the most polluted areas receive the least funding (Fund, 2024). There are significant regional disparities in funding for clean air projects, with low-income countries facing considerable resource shortages for clean air initiatives, even though these regions often require more urgent pollution control and health interventions (Zhang et al., 2024). These regional disparities need to be addressed through international cooperation, such as the establishment of a global pollution control fund to provide long-term support to high-pollution, high-risk areas.

At the same time, understanding the significant differences in the relative contributions of various driving factors is crucial for formulating fair and targeted policies. These policies need to take into account the specific balance of risk factors in countries at different stages of development. This is especially important when considering the pollution levels, changes in pollution sources, population structures, urbanization, and sudden major public health events across different regions. Indus-

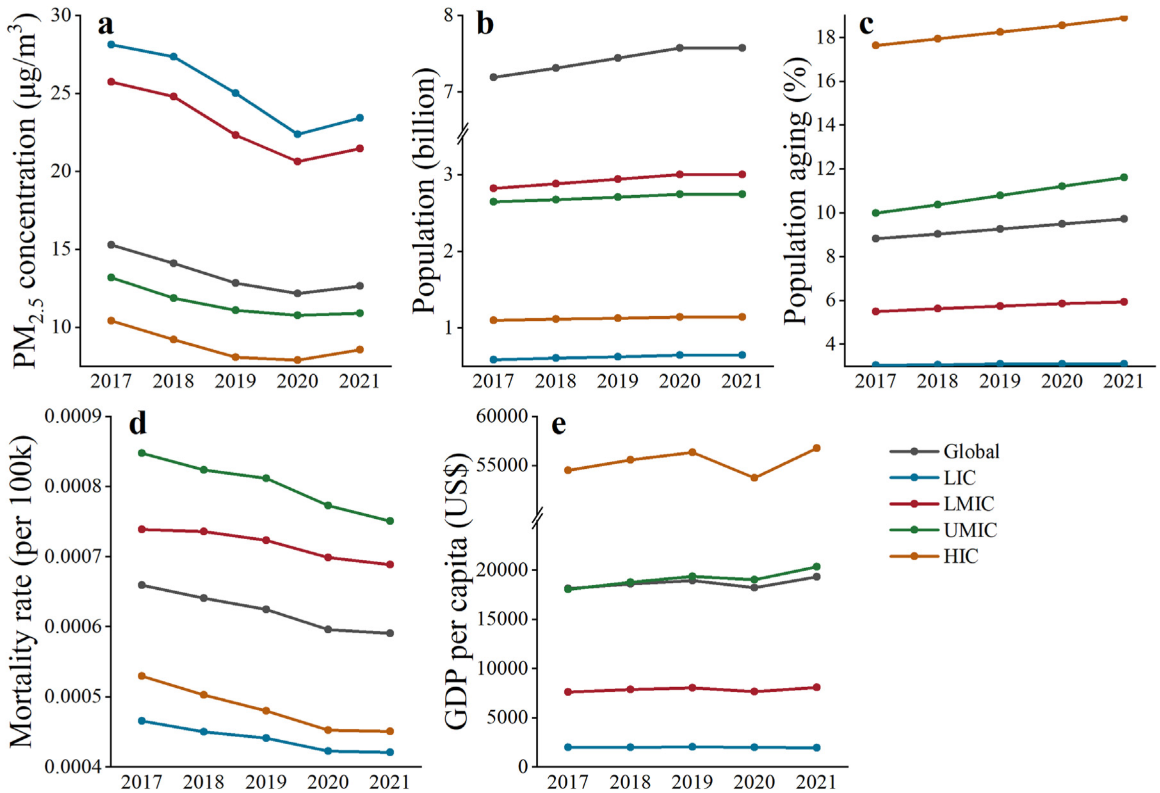

Fig. 4 – Driving factors affecting MBAPP and HCAPP. (**a**) The average $PM_{2.5}$ concentrations ($\mu g/m^3$), (**b**) population numbers (billion), (**c**) the proportion of the population aged 65+ relative to the total population, (**d**) baseline mortality rate (per 100k), and (e) GDP per capita (2021 US$) globally and across four income level regions from 2017 to 2021. The gray dotted line represents the global average, the blue dotted line represents LIC regions, the red dotted line represents LMIC regions, the green dotted line represents UMIC regions, and the yellow dotted line represents HIC regions.

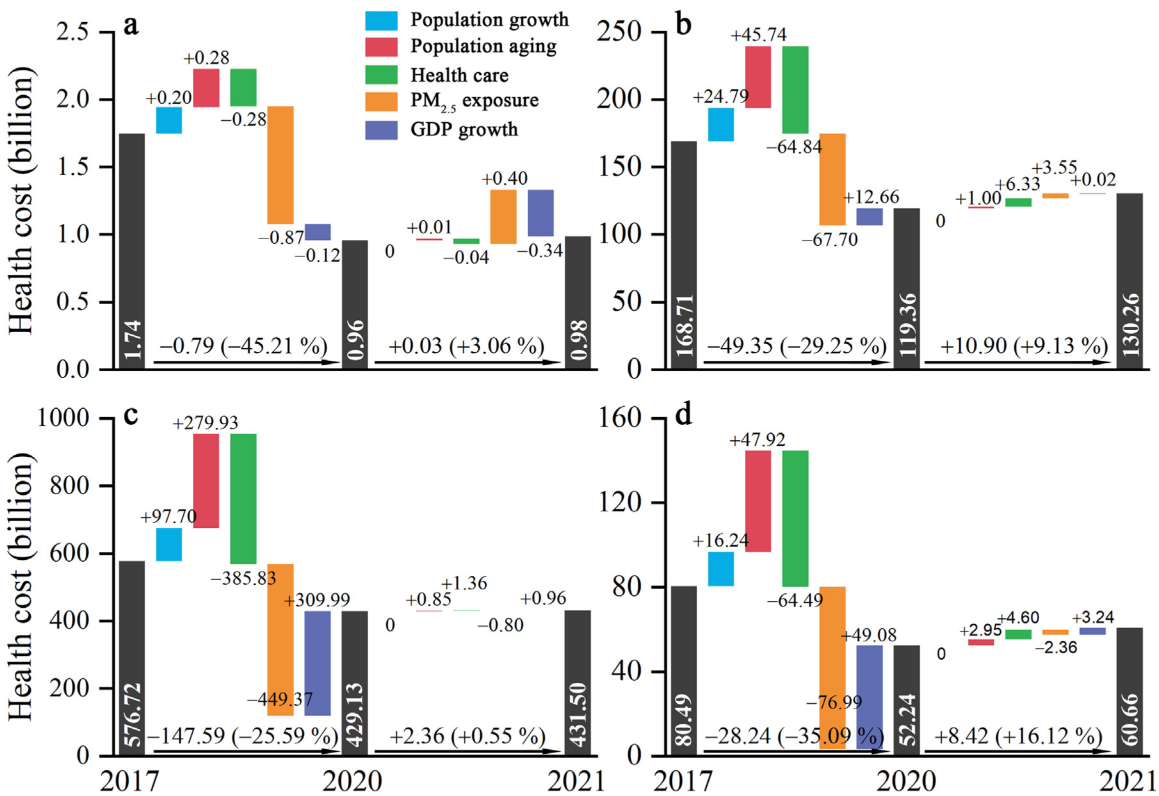

Fig. 5 – Variation of five drivers in HCAPP from 2017 to 2021. (**a**) LIC, (**b**) LMIC, (**c**) UMIC, and (**d**) HIC. The positive and negative values above the black arrow line indicate HCAPP (2021 US$, billion), and positive and negative value indicate the contribution (2021 US$, billion) of each $PM_{2.5}$-related driving factor, shown in the upper left corner of (**a**) to the HCAPP. Values shown in the dark bars are the total HCAPP attributed to $PM_{2.5}$ pollution (2021 US$, billion).

trialization and urbanization, along with population-intensive industrial activities, may lead to a significant increase in localized $PM_{2.5}$ exposure risks, and policies should focus on how to effectively disperse pollution sources and optimize urban planning.

However, this study is not without limitations. The datasets used in this research (e.g., health benchmarks and population data) may have limitations in resolution and coverage, which restrict the spatial and temporal precision of the results. Some analyses rely on linear correlations, which may underestimate the interactions between nonlinear and complex systems. Future research could benefit from incorporating higher-resolution health and population structure data, especially in low-income countries, which would significantly improve the accuracy of the models. Additionally, exploring more dimensions of driving factors (such as policy interventions, technological innovations, etc.) and their interactions, combined with regional case studies and macro analyses at the global scale, would help uncover the deeper causes of regional disparities.

5. Conclusions

Ambient fine particulate matter ($PM_{2.5}$) poses one of the most critical environmental health challenges globally, contributing to millions of premature deaths annually. While recent air pollution controls have successfully reduced $PM_{2.5}$ pollution and related health risks in many regions, a concerning rebound has occurred since 2020. However, the reduction in $PM_{2.5}$ pollution has not entirely eliminated its associated health risks. Additional driving factors contributing to increased health risks include healthcare quality, population structure, and other socioeconomic dynamics. This underscores the need to not only address $PM_{2.5}$ concentrations but also tackle disparities in healthcare infrastructure exacerbated by wealth inequality, as well as the challenges posed by population aging. And it is crucial to address the issue of medical resource shortages during emergency situations, such as public health crises and extreme weather events.

Our findings highlight the importance of integrating healthcare resilience and equitable policies into global $PM_{2.5}$ management strategies. By reducing wealth disparities and strengthening healthcare infrastructure, particularly in low- and middle-income regions and during emergencies, more equitable health outcomes can be achieved, safeguarding vulnerable populations. As nations strive for sustainable development, policies that balance economic growth with environmental health will be essential in mitigating health burden induced by $PM_{2.5}$ pollution and ensuring long-term global health security. These strategies will not only reduce current inequalities but also promote a healthier, more sustainable future for all.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Lulu Lian: Writing – original draft, Methodology, Investigation, Data curation. **Jianping Huang:** Writing – review & editing, Supervision. **Siyu Chen:** Methodology, Formal analysis. **Jianmin Ma:** Methodology, Formal analysis. **Xinbo Lian:** Writing – review & editing. **Lihui Zhang:** Writing – review & editing. **Shikang Du:** Data curation. **Dan Zhao:** Data curation.

Data availability

$PM_{2.5}$ concentration data can be accessed online at https://zenodo.org/record/4293239. Gridded population data are available from https://sedac.ciesin.columbia.edu/data/collection/gpw-v4/. The health benchmarks data (from the GBD) are available at https://vizhub.healthdata.org/gbd-results/. Country-specific GDP per capita and Gini index were collected from https://data.worldbank.org/.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (Nos. 42305089 and 42175106), the Self-supporting Program of Guangzhou Laboratory (No. SRPG22-007), the Youth Science and Technology Fund Project of Gansu (No. 22JR5RA512), and the Fundamental Research Funds for the Central Universities (No. lzujbky-2022-pd05).

Appendix A Supplementary data

Supplementary material associated with this article can be found in the online version at doi:10.1016/j.jes.2025.03.045.

References

Antonia, M., Simion, L., 2023. The evolution of economic disparities in Romania during the COVID-19 pandemic: a comparative analysis of pre-existing and emerging challenges. Proc. Int. Conf. Bus. Excell. 17 (1), 352–363.
Bai, L., Benmarhnia, T., Chen, C., Kwong, J.C., Burnett, R.T., van Donkelaar, A., et al., 2022. Chronic exposure to fine particulate matter increases mortality through pathways of metabolic and cardiovascular disease: insights from a large mediation analysis. J. Am. Heart Assoc. 11 (22), e026660.
Brauer, M., Roth, G.A., Aravkin, A.Y., Zheng, P., Abate, K.H., Abate, Y.H., et al., 2024. Global burden and strength of evidence for 88 risk factors in 204 countries and 811 subnational locations, 1990–2021: a systematic analysis for the global burden of disease study 2021. Lancet 403 (10440), 2162–2203.
Burnett, R., Chen, H., Szyszkowicz, M., Fann, N., Hubbell, B., Pope, C.A., et al., 2018. Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter. P. Natl. Acad. Sci. U.S.A. 115 (38), 9592–9597.
Clean Air Fund, 2024. Philanthropic foundation funding for clean air: advancing climate action, health and social justice. Available at: https://www.cleanairfund.org/resource/philanthropic-funding/.
Hamadeh, N., Rompaey, C.V., Metreau, E., 2023. World bank group country classifications by income level for FY24 (July 1, 2023- June 30, 2024). Data Blog. Available at: https://blogs.worldbank.org/en/opendata/new-world-bank-group-country-classifications-income-level-fy24.
Huang, W., Xu, H., Wu, J., Ren, M., Ke, Y., Qiao, J., 2024. Toward cleaner air and better health: current state, challenges, and priorities. Science 385 (6707), 386–390.
Institute for Health Metrics and Evaluation, 2024. Global Burden of Disease 2021: Findings from the GBD 2021 Study. IHME, WA.
Kang, N., Wang, R., Lu, H., Onyai, F., Tang, M., Tong, M., et al., 2024. Burden of child anemia attributable to fine particulate matters brought by sand dusts in low- and middle-income countries. Environ. Sci. Technol. 58 (29), 12954–12965.
Keller, E., Newman, J.E., Ortmann, A., Jorm, L.R., Chambers, G.M., 2021. How much is a human life worth? A systematic review. Value Health 24 (10), 1531–1541.
Kuźma, Ł., Dąbrowski, E.J., Kurasz, A., Święczkowski, M., Jemielita, P., Kowalewski, M., et al., 2024. Effect of air pollution exposure on risk of acute coronary syndromes in Poland: a nationwide population-based study (EP-PARTICLES study). Lancet Reg. Health – Eur. 41, 100910.
Li, C., van Donkelaar, A., Hammer, M.S., McDuffie, E.E., Burnett, R.T., Spadaro, J.V., et al., 2023. Reversal of trends in global fine particulate matter air pollution. Nat. Commun. 14 (1), 5349.
Li, T., Hu, R., Chen, Z., Li, Q., Huang, S., Zhu, Z., Zhou, L.-F., 2018. Fine particulate matter (PM2.5): the culprit for chronic lung diseases in China. Chronic Dis. Transl. Med. 4 (3), 176–186.
Lian, L., Chen, S., Ma, J., Li, T., Yang, Y., Huang, T., Wang, Y., Li, J., 2023. Population aging driven slowdown in the reduction of economic cost-attributed to $PM_{2.5}$ pollution after 2013 in China. Environ. Sci. Technol. 57 (3), 1237–1245.
Liu, Y., Tong, D., Cheng, J., Davis, S.J., Yu, S., Yarlagadda, B., et al., 2022. Role of climate goals and clean-air policies on reducing future air pollution deaths in China: a modelling study. Lancet Planet. Health 6 (2), e92–e99.
Miller, T.R., 2000. Variations between countries in values of statistical life. J. Transp. Econ. Policy 34 (2), 169–188.
Pozzer, A., Anenberg, S.C., Dey, S., Haines, A., Lelieveld, J., Chowdhury, S., 2023. Mortality attributable to ambient air pollution: a review of global estimates. GeoHealth 7 (1), e2022GH000711.
Rentschler, J., Leonova, N., 2023. Global air pollution exposure and poverty. Nat. Commun. 14 (1), 4432.
Sachs, J.D., Karim, S.S.A., Aknin, L., Allen, J., Brosbøl, K., Colombo, F., et al., 2022. The *Lancet* Commission on lessons for the future from the COVID-19 pandemic. Lancet 400 (10359), 1224–1280.
Sigsgaard, T., Hoffmann, B., 2024. Assessing the health burden from air pollution. Science 384 (6691), 33–34.

Tong, M., Lin, W., Liu, H., Gong, J., Zhang, J., Xue, T., 2023. Gestational age modifies the association between exposure to fine particles and fetal death: findings from a nationwide epidemiological study in the contiguous United States. Environ. Health 22 (1), 65.
Vonderschmitt, J., Wöhlke, S., Schicktanz, S., 2023. Scarce resources, public health and professional care: the COVID-19 pandemic exacerbating bioethical conflicts — findings from global qualitative expert interviews. BMC Publ. Health 23 (1), 2492.
Wang, Y., Wu, R., Liu, L., Yuan, Y., Liu, C., Hang Ho, S.S., et al., 2022. Differential health and economic impacts from the COVID-19 lockdown between the developed and developing countries: perspective on air pollution. Environ. Pollut. 293, 118544.
Wei, J., Li, Z., Lyapustin, A., Wang, J., Dubovik, O., Schwartz, J., et al., 2023. First close insight into global daily gapless 1 km $PM_{2.5}$ pollution, variability, and health impact. Nat. Commun. 14 (1), 8349.
World Health Organization, 2021a. COVID-19 continues to disrupt essential health services in 90% of countries. Available at: https://www.who.int/news/item/23-04-2021-covid-19-continues-to-disrupt-essentialhealth-services-in-90-of-countries.
World Health Organization, 2021b. WHO global air quality guidelines: particulate matter ($PM_{2.5}$ and PM_{10}), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide: executive summary. Available at: https://www.who.int/publications/i/item/9789240034228/.
Yin, H., Brauer, M., Zhang, J., Cai, W., Navrud, S., Burnett, R., et al., 2021. Population ageing and deaths attributable to ambient PM2.5 pollution: a global analysis of economic cost. Lancet Planet. Health 5 (6), e356–e367.
Yin, H., McDuffie, E.E., Martin, R.V., Brauer, M., 2024. Global health costs of ambient PM2.5 from combustion sources: a modelling study supporting air pollution control strategies. Lancet Planet. Health 8 (7), e476–e488.
Yu, W., Xu, R., Ye, T., Abramson, M.J., Morawska, L., Jalaludin, B., et al., 2024. Estimates of global mortality burden associated with short-term exposure to fine particulate matter ($PM_{2.5}$). Lancet Planet. Health 8 (3), e146–e155.
Yue, H., He, C., Huang, Q., Zhang, D., Shi, P., Moallemi, E.A., et al., 2024. Substantially reducing global $PM_{2.5}$-related deaths under SDG3.9 requires better air pollution control and healthcare. Nat. Commun. 15 (1), 2729.
Zhang, B., Wang, S., Slater, L., 2024. Anthropogenic climate change doubled the frequency of compound drought and heatwaves in low-income regions. Commun. Earth Environ. 5 (1), 715.
Zhao, X., Wu, T., Zhou, W., Han, L., Neophytou, A.M., 2024. Reducing air pollution does not necessarily reduce related adults' mortality burden: variations in 177 countries with different economic levels. Sci. Total Environ. 933, 173037.
Zhou, R.X., Liao, H.J., Hu, J.J., Xiong, H., Cai, X.Y., Ye, D.W., 2024. Global burden of lung cancer attributable to household fine particulate matter pollution in 204 countries and territories, 1990 to 2019. J. Thorac. Oncol. 19 (6), 883–897.