ENVIRONMENTAL STUDIES

Global disparities in indoor wildfire-$PM_{2.5}$ exposure and mitigation costs

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Wildfires have become more frequent and severe, and evidence showed that exposure to wildfire-caused $PM_{2.5}$ (fire-$PM_{2.5}$) is associated with adverse health effects. Fire-$PM_{2.5}$ exposure occurs mainly indoors, where people spend most of their time. As an effective and timely approach of mitigating indoor $PM_{2.5}$ pollution, air purifiers incur notable associated costs. However, the long-term global population exposure to indoor fire-$PM_{2.5}$ and the economic burden of using air purifiers remain unknown. Here, we estimated the indoor fire-$PM_{2.5}$ concentration and the cost of reducing indoor $PM_{2.5}$ exposure, along with the extra cost incurred because of fire-$PM_{2.5}$, at a resolution of 0.5° by 0.5° globally during 2003 to 2022. Our findings revealed 1009 million individuals exposed to at least one substantial indoor wildfire-air pollution day per year. We identified pronounced socioeconomic disparities in the costs of mitigating indoor $PM_{2.5}$ exposure, with low-income countries bearing a disproportionately higher economic burden, emphasizing the critical need for addressing these disparities.

INTRODUCTION

Given the context of climate change, extreme fire weather events have surged along with rising temperatures and decreasing relative humidity (*1*), leading to a higher risk of extreme and dangerous wildfires worldwide (*2*–*5*). Unlike direct exposure to the heat and flames of wildfires, the impact of exposure to wildfire smoke extends far beyond the immediate vicinity, potentially affecting populations hundreds to thousands of kilometers from the fire source because of its ability to travel long distances (*6*, *7*). Among the pollutants generated by wildfires, $PM_{2.5}$ (particulate matter with an aerodynamic diameter of 2.5 μm or less) is of great concern. Wildfire-caused $PM_{2.5}$ (fire-$PM_{2.5}$) tends to be more toxic compared with urban background particulate matter because of the smaller particulate size and higher concentrations of oxidative and pro-inflammatory components (*4*). Fire-$PM_{2.5}$ has been substantiated to exert substantial adverse effects on human health from contributing to premature mortality (*8*, *9*) and preterm birth (*10*), exacerbating respiratory (*11*–*13*) and cardiovascular disease (*14*). For example, a recent study (*15*) reported that ~0.62% of all-cause deaths in 749 cities worldwide were annually attributable to the short-term impacts of fire-$PM_{2.5}$. Thus, reducing exposure to fire-$PM_{2.5}$ is a crucial step in safeguarding human health.

To date, most of the studies focused on outdoor $PM_{2.5}$ levels resulting from wildfire. A previous study investigated global population exposure to landscape fire-$PM_{2.5}$ over a 20-year period, focusing on the effects of fires on outdoor $PM_{2.5}$ concentrations (*16*). However, modern people spend most of their time (more than 80%) indoors (*17*, *18*), and during wildfire smoke events, people are often advised and inclined to stay indoors to seek refuge from both the smoke and heat (*19*, *20*). Because fire-$PM_{2.5}$ can enter indoor spaces through continuous air exchange with the outdoors even when windows and doors are closed (*21*), indoor $PM_{2.5}$ pollution originating from wildfires plays a substantial role in determining individuals' exposure to fire-$PM_{2.5}$. Some early studies explored indoor $PM_{2.5}$ concentration during wildfire periods in North America (*21*–*23*), Southeast Asia (*24*), and Australia (*25*) and found sharp increases in indoor $PM_{2.5}$. However, despite these early efforts, there has been a lack of comprehensive investigation into the sustained, long-term effects of wildfires on indoor $PM_{2.5}$ exposures on a global scale. Because people spend most of time indoors, to better evaluate population exposure to fire-$PM_{2.5}$ and reduce relative adverse health impacts, it is critical to investigate the impact of wildfire on indoor $PM_{2.5}$ concentrations and to take measures to mitigate the exposure to fire-$PM_{2.5}$ indoors.

The deployment of air purifiers could effectively reduce indoor $PM_{2.5}$ concentrations during wildfire periods, thereby substantially improving human health (*26*–*29*). Nevertheless, the adoption of air purifiers entails associated costs (*30*). A study (*31*) modeled the reduction of hospital admissions and deaths by using portable air cleaners to reduce indoor $PM_{2.5}$ exposure during a 10-day wildfire period in Southern California and demonstrated its cost-effectiveness in terms of the health benefits. However, the cost of using air purifiers may impose economic burdens on low-income populations. The existing studies on the efficiency and cost of using air purifiers have been limited to specific wildfire events or specific regions. Furthermore, there is a lack of research on the long-term costs associated with using air purifiers to mitigate indoor $PM_{2.5}$ and fire-$PM_{2.5}$ pollution, especially on a global scale.

In this study, we used a comprehensive modeling approach integrated in a Monte Carlo simulation framework to explore the impact of wildfires on global indoor $PM_{2.5}$ levels (see Materials and Methods). We investigated three intervention scenarios where air purifiers were deployed globally among the population with the goal of reducing indoor $PM_{2.5}$ pollution to specified levels. The three scenarios, denoted as S1, S2, and S3, aimed to reduce indoor $PM_{2.5}$ to 25, 15, and 5 μg/m^3, respectively, aligning with the $PM_{2.5}$ guideline set forth by the World Health Organization (WHO) (*32*). For each scenario, we estimated the intervention cost and the extra cost

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incurred because of fire-$PM_{2.5}$ by using a cost assessment model in the Monte Carlo simulation framework. The analysis was conducted on a global scale with a spatial resolution of 0.5-by-0.5 longitude and latitude, spanning the period from 2003 to 2022.

The objectives of this study are threefold: first, to conduct a comprehensive assessment of the global population's exposure to indoor fire-$PM_{2.5}$; second, to evaluate the long-term global economic burden associated with mitigating indoor $PM_{2.5}$ and fire-$PM_{2.5}$ exposure through the use of air purifiers; and third, to explore socioeconomic disparities across different regions and income groups worldwide by integrating the results with global population distribution data and economic development indicators.

RESULTS

Global population exposure to indoor fire-$PM_{2.5}$

The exposure to indoor fire-$PM_{2.5}$ varied across different regions (Fig. 1, A and B). The greatest exposure was observed in Central Africa and South America, followed by North Asia, Southeast Asia, the west coast of North America, and Northwestern Australia. We incorporated population distribution data to calculate the annual population-weighted average indoor fire-$PM_{2.5}$ concentration from 2003 to 2022, aiming to investigate indoor exposure levels and disparities across the globe and continents. Globally, the annual population-weighted average indoor fire-$PM_{2.5}$ exposure concentration was 0.37 μg/m^3, which comprised 1.3% of indoor $PM_{2.5}$ exposure. The highest population-weighted average indoor fire-$PM_{2.5}$ concentration was recorded in Africa, reaching 0.83 μg/m^3. South America exhibited the highest proportion of population-weighted average fire-$PM_{2.5}$ to indoor all-source $PM_{2.5}$ at 5.0%, followed by Africa (3.4%), Oceania (3.2%), and North America (2.7%). Conversely, Asia and Europe exhibited comparatively lower contributions of wildfire to indoor $PM_{2.5}$, at 0.8 and 1.3%, respectively. Notably, the proportion of fire-related $PM_{2.5}$ in both indoor and outdoor environments followed a similar pattern, with indoor $PM_{2.5}$ concentrations consistently lower than outdoor concentrations, indicating the shelter effect of the building envelope (*19*, *20*).

To better quantify the population exposure to fire-$PM_{2.5}$, we defined a substantial indoor wildfire-air pollution (SIWAP) day as at least one of the following scenarios: (i) The daily average indoor $PM_{2.5}$ (all-source $PM_{2.5}$) exceeded the 2021 daily guideline value (15 μg/m^3) of the WHO (*32*), and indoor fire-$PM_{2.5}$ accounted for at least 50% of the daily indoor $PM_{2.5}$; (ii) daily indoor fire-$PM_{2.5}$ exceeded 15 μg/m^3. The findings indicated that an average of 1009 million individuals was exposed to at least one SIWAP day per year during the period between 2003 and 2022 on a global scale.

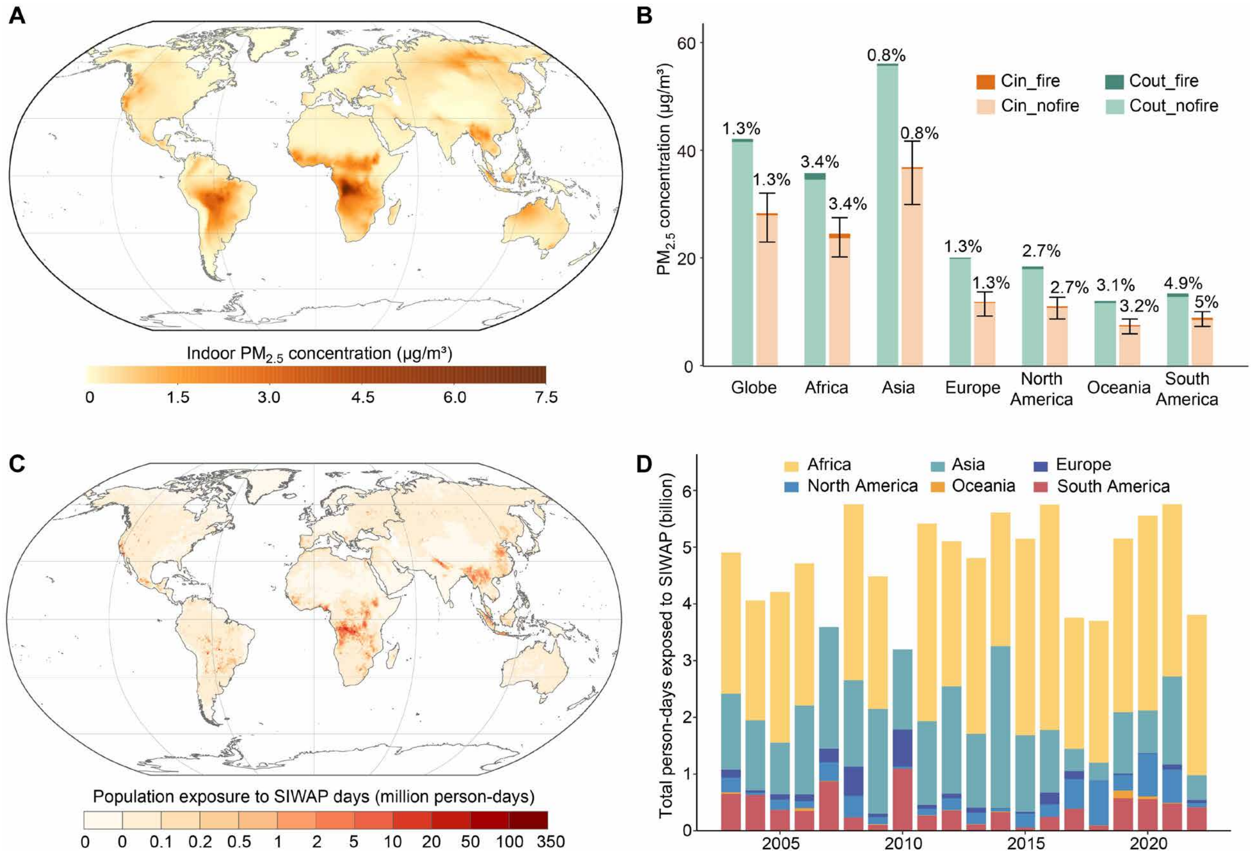

Fig. 1. Global maps of indoor fire-$PM_{2.5}$ concentration and population exposure to SIWAP days. (**A**) Map of annual indoor fire-$PM_{2.5}$ concentration of 2003 to 2022. (**B**) Population-weighted average indoor and outdoor fire-$PM_{2.5}$ contributions to total $PM_{2.5}$ concentration of different continents. The percentages represent the proportion of fire-$PM_{2.5}$ to all-source $PM_{2.5}$. The error bars represent the 95% confidence intervals of indoor all-source $PM_{2.5}$ concentrations. (**C**) Map of annual population exposure to SIWAP days of 2003 to 2022. (**D**) Total person-days exposed to SIWAP of six continents between 2003 and 2022.

There were notable differences in the population exposure to SIWAP days across different regions (Fig. 1, C and D). To provide a more comprehensive representation of the population exposure level, we used person-days, which represent the number of individuals exposed to one SIWAP day. Central Africa, Southeast Asia, and East Asia exhibited the highest population exposure levels, with numerous hotspots observed globally, including in Southern America and the western coast of North America. The global annual total person-days exposed to SIWAP were 5.0 billion, with the majority occurring in Africa (57.1%), followed by Asia (26.3%) and South America (8.1%).

Over the course of two decades, the population-weighted average SIWAP days demonstrated a downward trend globally (fig. S1), with a rate of −0.09 days per decade ($P = 0.076$ for the trend). This was also observed in Africa (−0.43 days per decade, $P = 0.022$), Asia (−0.13 days per decade, $P = 0.033$), Europe (−0.13 days per decade, $P = 0.194$), and South America (−0.38 days per decade, $P = 0.199$). Meanwhile, the trends in North America (0.30 days per decade, $P = 0.057$ for the trend) and Oceania (0.31 days per decade, $P = 0.518$ for the trend) were found to be increased. Notably, South America and Oceania experienced peaks in population-weighted average SIWAP days in 2010 and 2019, respectively. In most years, Africa consistently exhibited the highest count of population-weighted average SIWAP days, followed by South America. In contrast, Asia and Europe showed a relatively low overall count of population-weighted average SIWAP days.

Economic costs of using air purifiers to reduce indoor $PM_{2.5}$

The introduction of air purifiers as an intervention has the potential to reduce the annual average indoor $PM_{2.5}$ concentration to below the target levels (fig. S2A), yet this is accompanied by relative costs. In the intervention scenarios S1 to S3, the global annual total costs to purify indoor $PM_{2.5}$ were estimated to be 519 billion USD (95% confidence interval, 171 to 892), 1108 billion USD (374 to 1889), and 4242 billion USD (1488 to 7202), respectively. The costs varied across different regions worldwide (Fig. 2, A and C). In intervention scenario S3, ~78% of the Asian population had a per capita cost exceeding 200 USD, while 93% exceeded 100 USD. The population-weighted average annual per capita cost of Asia was 870 USD (298 to 1447). Similarly, Africa also reported substantial population-weighted average annual per capita cost of 433 USD (157 to 752). Also, the per capita costs of North America, Europe, and Oceania were 201 USD (84 to 425), 150 USD (68 to 303), and 149 USD (64 to 324) in scenario S3, respectively. South America exhibited a relatively low level, with a population-weighted average annual per capita cost of 84 USD (35 to 187).

In intervention scenarios S1 to S3, the annual total extra costs because of fire-$PM_{2.5}$ of the globe were estimated to be 8.9 billion USD (2.2 to 20.6), 18.9 billion USD (5.0 to 42.8), and 68.6 billion USD (19.4 to 148.6), respectively. There were also disparities across the world (Fig. 2, B and D). The western coast of North America and northern Asia (Siberia) bore the most substantial extra costs of reducing fire-$PM_{2.5}$, while South America, Central Africa, northern

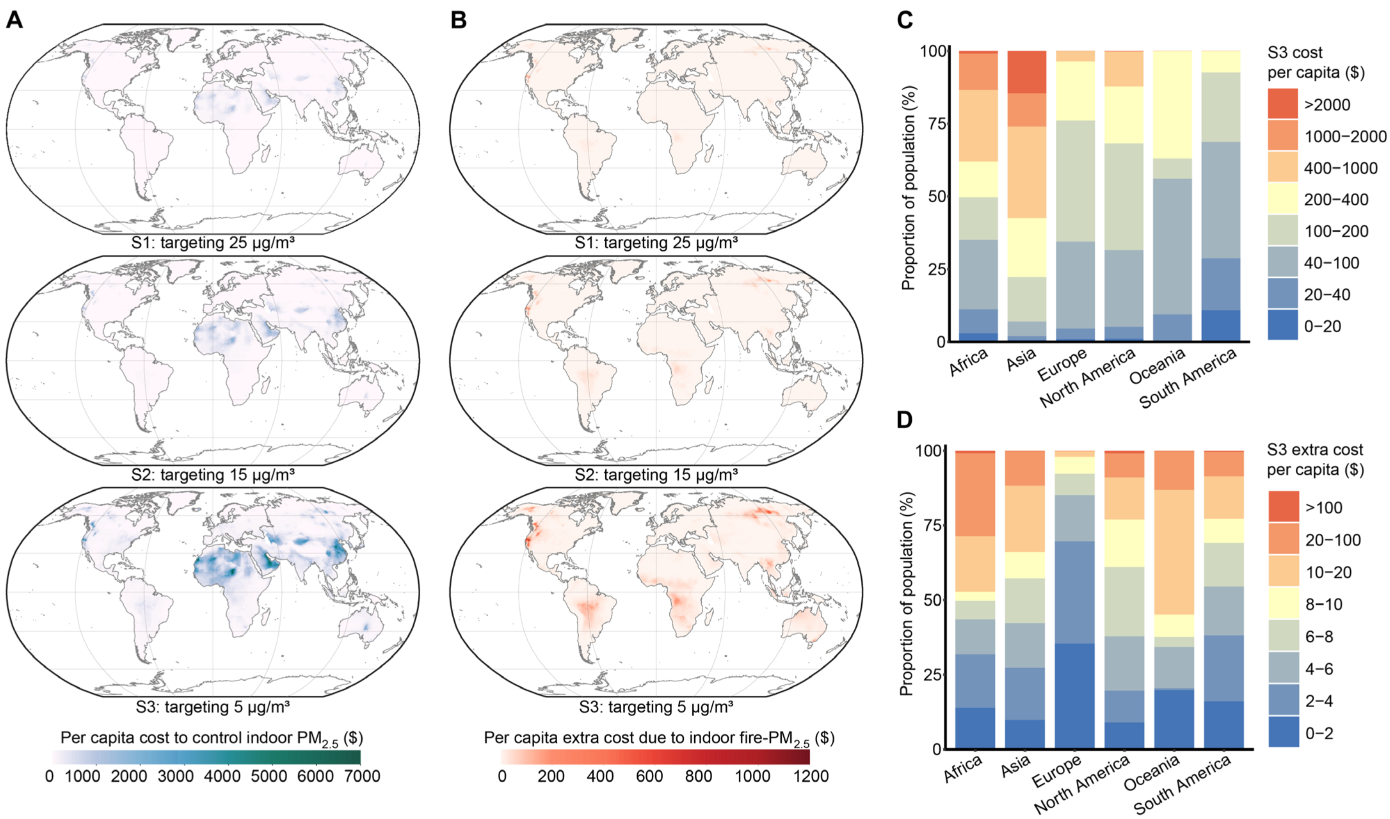

Fig. 2. Annual costs under the three intervention scenarios. (**A**) 2003 to 2022 annual cost per capita of controlling indoor $PM_{2.5}$ to target levels (S1: targeting 25 μg/m^3; S2: targeting 15 μg/m^3; S3: targeting 5 μg/m^3). (**B**) 2003 to 2022 annual extra cost per capita of controlling indoor fire-$PM_{2.5}$ under different scenarios (S1, S2, and S3). (**C** and **D**) Proportion of population of different continents for different cost (C) or extra cost (D).

Australia, and Southeast Asia also experienced high extra costs. The highest population-weighted average annual per capita extra cost was observed in Africa, with a value of 15.4 USD (5.1 to 30.8) in scenario S3. North America and Oceania also exhibited high per capita extra cost, with values of 11.6 (3.5 to 27.5) and 11.6 USD (3.8 to 28.3), respectively. The population-weighted average annual per capita extra costs in scenario S3 for Asia, South America, and Europe were 9.9 USD (2.5 to 21.3), 9.0 USD (3.2 to 21.0), and 3.5 USD (1.1 to 9.0), respectively.

In scenarios S1 to S3, the proportion of additional costs to total costs exhibited similar spatial patterns (fig. S2B). The regions of North America, South America, Australia, North Asia, and Sub-Saharan Africa showed the largest proportions, indicating that wildfires accounted for a substantial portion of the economic burden associated with controlling indoor $PM_{2.5}$. When the target concentration is set at 15 or 25 $\mu g/m^3$, a greater number of regions exhibit a proportion of 1, indicating that all costs are allocated to the control of fire-$PM_{2.5}$. This observation is particularly noteworthy in comparison to scenario S3 (target at 5 $\mu g/m^3$), suggesting that wildfires have a more pronounced impact on the situation of exceeding the target under higher-concentration control standards.

The trends of annual extra costs across the globe and six continents exhibited fluctuations (Fig. 3, A to C). During the period between 2003 and 2022, the population-weighted average per capita extra cost of North America in scenario S3 demonstrated an increasing trend, with a rate of 7.7 USD per decade ($P = 0.008$). However, the trends for other continents and the globe were not significant ($P > 0.05$). In the period spanning from 2013 to 2022, when compared to the preceding decade (2003 to 2012), North America and Oceania witnessed notable increases in population-weighted average per capita extra costs. Asia experienced a slight increase, while Africa, Europe, and South America exhibited slight decreases. The population-weighted average per capita extra costs of Oceania and North America reached their peaks in 2019 and 2020, respectively. This occurred concurrently with the occurrence of severe wildfires in those regions during the same years (*22*, *33*).

Considering seasonal differences in wildfire severity and building air exchange rates (*34*), we explored seasonal variations in extra costs globally and across six continents (Fig. 3D). The months of December to January and July to August were observed to be the peak months in Africa in terms of the population-weighted average per capita extra cost. In Asia, the peak months were March and July, while in Europe, the peak month was August. In North America, the peak months were from July to September; in Oceania, they were from November to February; and in South America, they were from August to October. The results were consistent with the wildfire seasons in these regions.

Socioeconomic disparities in the intervention cost

The financial burden of indoor air pollution mitigation on local residents cannot be fully elucidated by considering the costs alone. To investigate the socioeconomic disparities in controlling indoor $PM_{2.5}$ concentrations globally, we divided the population-weighted average annual cost and extra cost by the per capita gross national income (GNI) for each country (Fig. 4, A and D, and fig. S3).

West Africa, Central Africa, and South Asia exhibited a remarkable proportion of cost relative to per capita GNI. Niger exhibited the highest proportion, reaching up to 207.3%, followed by Chad at 141.8%. Although countries in the Middle East region incurred high costs in controlling indoor $PM_{2.5}$ (fig. S4A), their high GNI resulted in relatively low proportions. Conversely, Central African countries faced relatively lower costs, yet these costs accounted for notable proportions of their GNI. Sub-Saharan Africa exhibited the largest proportion of per capita extra cost relative to per capita GNI, followed by Southeast Asia. The Democratic Republic of Congo (DR Congo) had the highest proportion at 11.70%, followed by Central African Republic at 7.71%. Conversely, while the United States and Australia incurred high population-weighted average per capita extra costs (fig. S4B), the proportions relative to per capita GNI were low.

There were notable economic disparities in the burden of using purifiers to mitigate $PM_{2.5}$ exposure across different income groups (*35*) (fig. S5). In scenario S3, the upper-middle-income group had the largest population-weighted average annual cost at 1064 USD per capita, followed by the lower-middle-income group at 435 USD per capita. The low-income group exhibited the lowest population-weighted average per capita cost (258 USD) yet the highest proportion of cost to GNI (41.2%). Similarly, the upper-middle-income countries had the largest per capita extra cost (13.1 USD) in scenario S3, while high-income countries had the lowest per capita extra cost (7.2 USD). The low-income group also had the greatest proportion of extra cost to GNI at 2.72%, substantially higher than the proportion at 0.03% for the high-income group. Similar patterns were observed in scenarios S1 to S3.

Disparities were also observed across countries with different Human Development Index (HDI) scores (Fig. 4, B and E) (*36*). The HDI measures average achievements in core dimensions of human development: a long and healthy life, being knowledgeable, and having a decent standard of living (*36*). Our results show that countries with high HDI scores exhibited the highest population-weighted average annual cost (1053 USD), whereas countries with low HDI scores had the highest cost proportion relative to GNI (41.3%). Moreover, low-HDI countries also had the highest population-weighted average extra cost (12.9 USD) and the highest proportion of extra cost to GNI (1.86%).

Inequality in the distribution of costs and economic burden across countries is quantified using the Gini index (Fig. 4, C and F), which ranges from 0 (representing perfect equality) to 1 (indicating maximum inequality). Here, the Gini index is calculated by ranking countries according to their costs and then computing twice the weighted difference between the Lorenz curve and the perfect equality line (*37*), with costs weighted by the population size of each country. The results show that the global Gini index for the cost of using air purifiers averaged 0.56, exhibiting a significant downward trend from 2003 to 2022 ($P = 0.008$). In contrast, the Gini index for the extra costs showed no significant upward trend over the same period ($P = 0.559$), with an average value of 0.47. In addition, we computed the Gini index for the proportion of costs relative to GNI. Both the proportions of total costs ($P = 0.047$) and extra costs ($P = 0.0002$) relative to GNI exhibited statistically significant increasing trends. Notably, the global Gini index for the proportion of extra costs to GNI was relatively high, averaging 0.72 over the two decades, highlighting a marked inequality in the economic burden associated with reducing fire-$PM_{2.5}$.

Top ranking countries in $PM_{2.5}$ concentration and mitigation cost

To better understand inequalities across countries, we identified the top 10 countries with the highest indoor $PM_{2.5}$ concentrations,

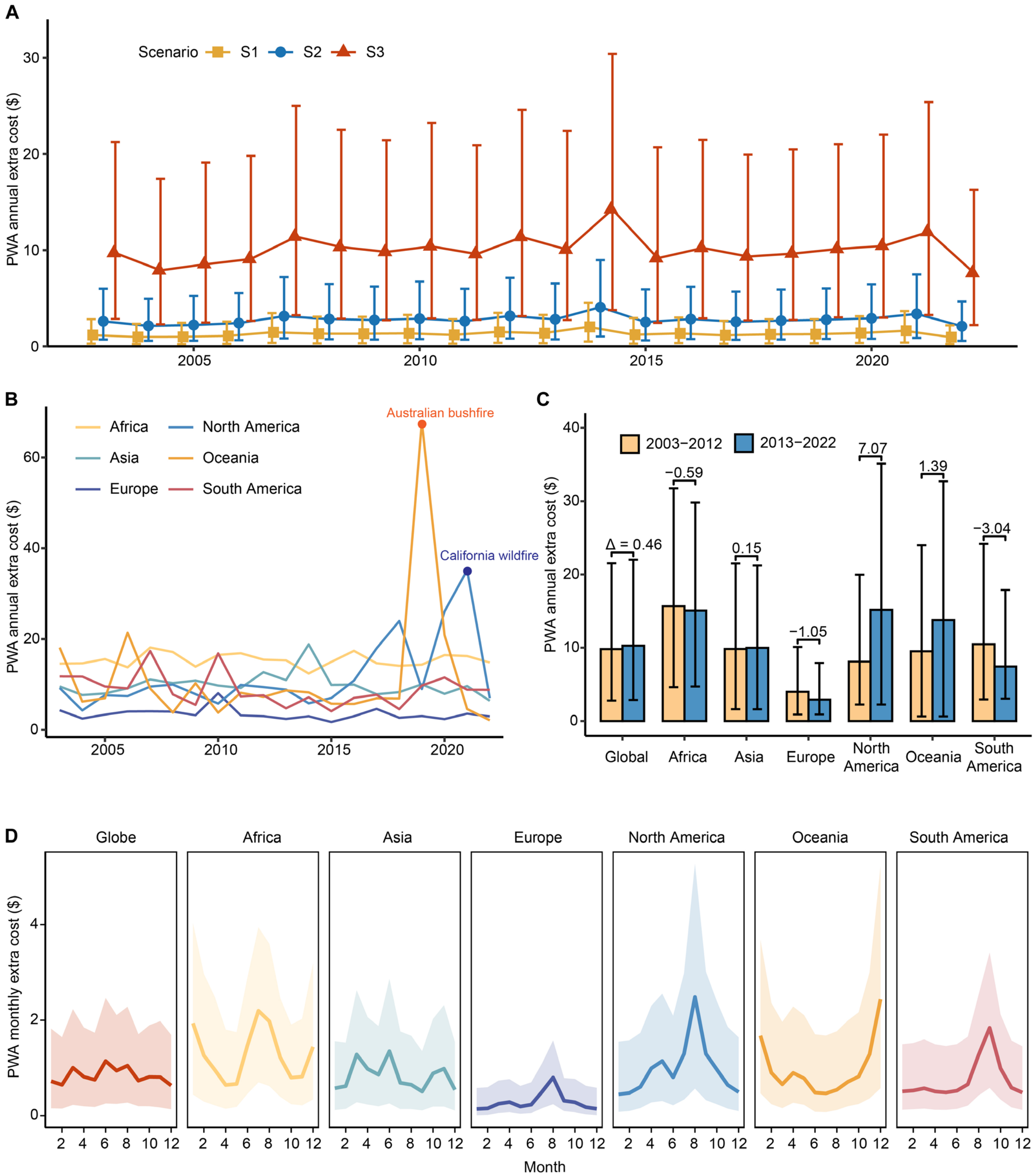

Fig. 3. Global and continental trends of extra cost and seasonal patterns. (**A**) Trends of population-weighted average (PWA) extra cost to control fire-$PM_{2.5}$ for the globe under different scenarios. (**B**) Trends of population-weighted average extra cost to control fire-$PM_{2.5}$ for different continents in scenario S3 (targeting 5 μg/m^3). (**C**) Population-weighted average annual per capita extra cost of 2003 to 2012 and 2013 to 2022 for the globe and six continents in scenario S3. The numerical values above each pair of bars denote the decadal change in annual extra cost. (**D**) Seasonal pattern of population-weighted average per capita extra costs for the globe and six continents in scenario S3. The error bars in (A) and (C) and the shaded areas in (D) represent the 95% confidence interval.

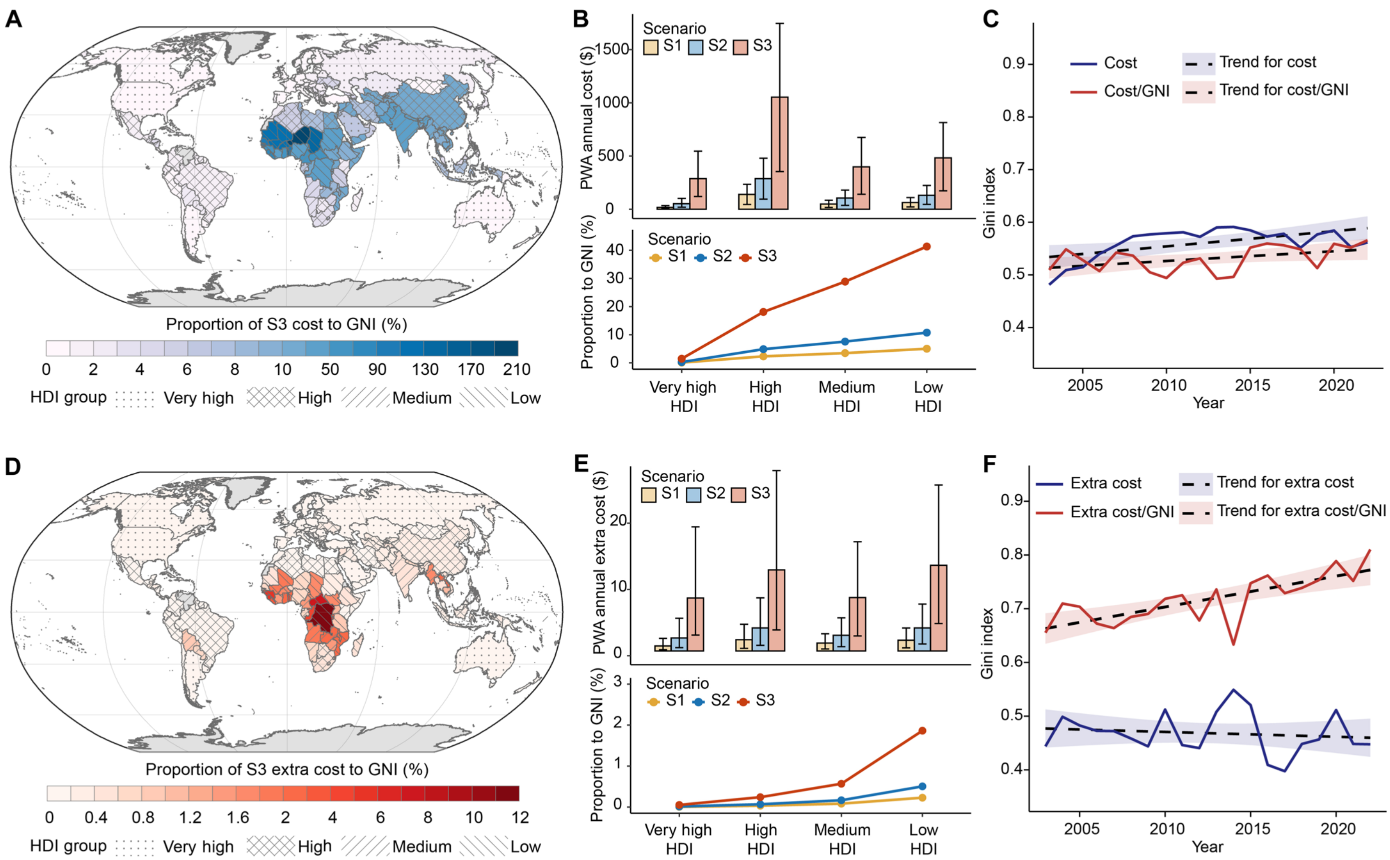

Fig. 4. Socioeconomic disparities in intervention cost between countries. (**A**) Proportion of population-weighted average annual cost to GNI in scenario S3. (**B**) Population-weighted average annual cost and proportions to GNI of different HDI groups. (**C**) Gini index of S3 cost and proportion of cost to GNI during 2003 to 2022. The shaded areas represent the 95% confidence interval for the trend. (**D**) Proportion of population-weighted average annual extra cost to GNI in scenario S3. (**E**) Population-weighted average annual extra cost and proportions to GNI of different HDI groups. (**F**) Gini index of S3 extra cost and proportion of extra cost to GNI during 2003 to 2022.

associated costs, and proportions of costs to GNI, as well as the highest indoor fire-$PM_{2.5}$ concentrations, associated extra costs, and proportions of extra costs to GNI. These findings are presented in Fig. 5.

Half of countries with the highest annual per capita costs were high-income countries (due in part to their large floor area). The population-weighted average annual per capita costs for all top-ranked countries exceeded 1000 USD, with Kuwait and Qatar ranking as the top two countries, reporting population-weighted average annual per capita costs of 6270 USD and 3500 USD, respectively. All top-ranked countries in proportion to GNI were low-income countries, with the exception of Mauritania, Benin, and Senegal, which are lower-middle-income countries. Notably, Mauritania and Senegal ranked high in all three dimensions: indoor $PM_{2.5}$ concentration, cost, and proportion to GNI.

The countries with the highest indoor fire-$PM_{2.5}$ concentration were predominantly low- and middle-income countries, while the top 10 countries of extra costs were from various income groups. The top-ranked countries in terms of extra cost's proportion to GNI were predominantly low-income countries, with exceptions including Congo (lower-middle-income) and Guinea (lower-middle-income). Notably, all of these countries were located in Africa. High-income or upper-middle-income countries like Kuwait, Gabon, and Botswana had relatively high extra cost but rather low proportions of extra cost to GNI. In contrast, low-income countries, such as Burundi, Liberia, and Rwanda, had low extra costs but high rankings in the proportion to GNI. Notably, Congo, the Democratic Republic of the Congo (DR Congo), Central African Republic, and Guinea ranked highly in all three dimensions (indoor fire-$PM_{2.5}$ concentration, extra cost, and proportion to GNI). For both costs and extra costs relative to their GNI, Togo and Guinea-Bissau exhibited the highest proportions, indicating a substantial economic burden from all-source $PM_{2.5}$ and fire-$PM_{2.5}$ in these countries.

DISCUSSION

We evaluated the global indoor fire-$PM_{2.5}$ concentration by using a Monte Carlo simulation approach in conjunction with a mass balance model. This approach addressed a critical gap in the assessment of population exposure to fire-$PM_{2.5}$ at a global scale. We then used a cost assessment model in the Monte Carlo simulation framework to estimate the global cost associated with reducing indoor $PM_{2.5}$ to three different levels using air purifiers, along with the additional costs incurred from indoor fire-$PM_{2.5}$. We found that the use of air purifiers can reduce indoor $PM_{2.5}$ concentrations to levels below our target values (fig. S2A), demonstrating that air purifiers are an effective measure for mitigating the impact of fire-sourced $PM_{2.5}$. We also conducted a quantitative analysis of the

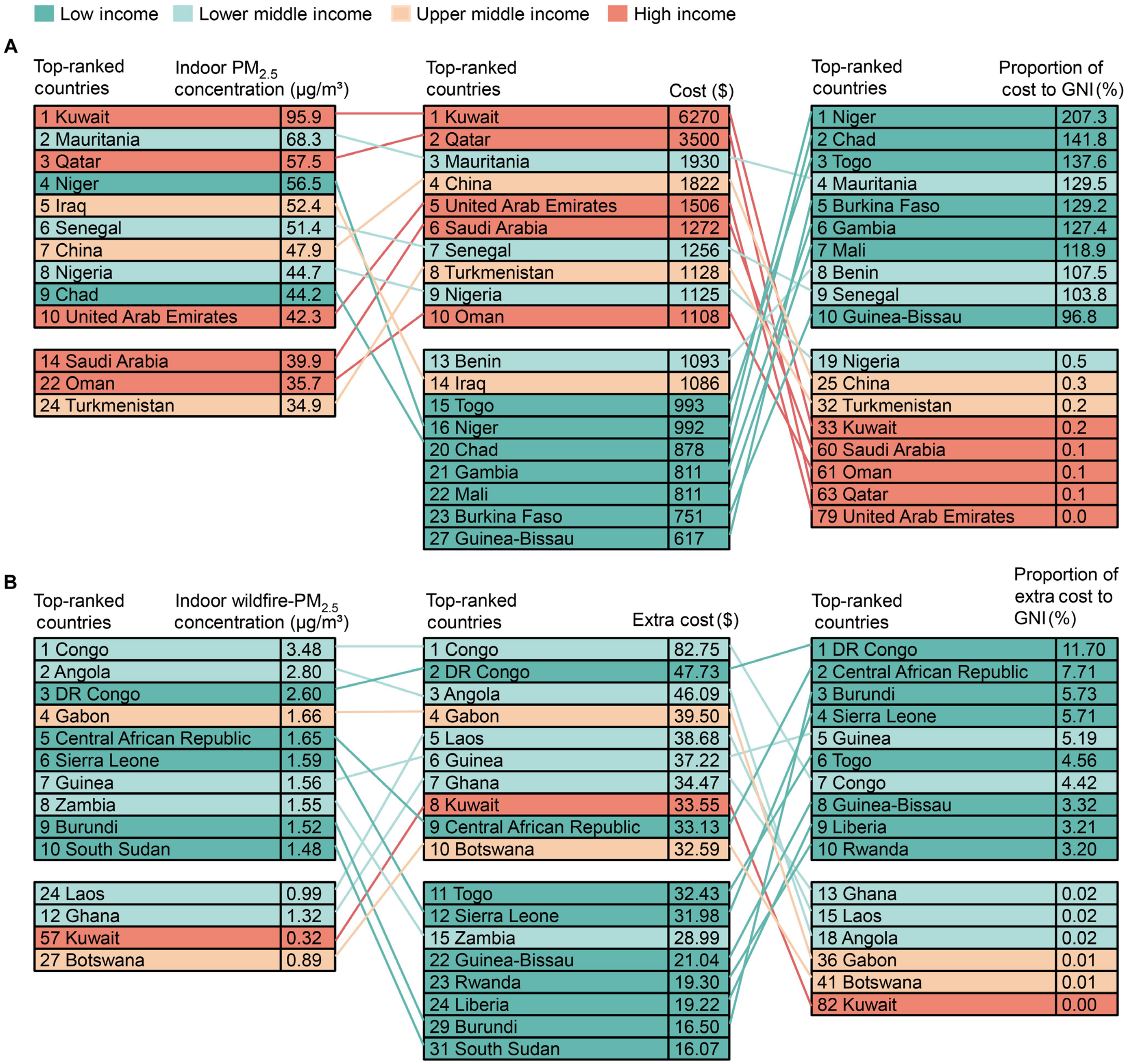

Fig. 5. Top-ranked countries with the greatest cost and extra cost in scenario S3. (**A**) Top 10 countries with the highest population-weighted average indoor $PM_{2.5}$ concentration, intervention cost, and proportion of cost to GNI. (**B**) Top 10 countries with the highest population-weighted average indoor fire-$PM_{2.5}$ concentration, extra intervention cost, and proportion of extra cost to GNI.

socioeconomic inequality in addressing wildfire-related air pollution among different regions globally.

Our findings revealed the large exposure of global population to indoor fire-$PM_{2.5}$ and highlighted the necessity of reducing indoor $PM_{2.5}$ concentrations during wildfire events. The considerable number of individuals exposed to SIWAP days indicated the contribution of wildfires to extreme indoor $PM_{2.5}$ pollution and drew attention to the public health concerns associated with indoor fire-$PM_{2.5}$. Our study also demonstrated that even when doors and windows were closed, individuals remaining indoors were still greatly affected by fire-$PM_{2.5}$. Consequently, there is a pressing need for more effective measures to reduce exposure to indoor fire-$PM_{2.5}$.

Our findings demonstrated the efficacy of air purifiers in mitigating global $PM_{2.5}$ exposure, thereby benefiting public health. Previous studies have demonstrated that air purifiers can lead to economic benefits considering the positive health outcomes (*31*, *38*). Given the substantial health economic losses associated with wildfire-related $PM_{2.5}$ exposure (*39*–*41*), utilization of air purifiers may result in net benefits. Johnston *et al.* (*42*) evaluated the health costs in Australia and found an unprecedented health cost of smoke-related $PM_{2.5}$ in the 2019–2020 wildfire season (October 2019 to March 2020), which is 1.95 billion AUD (~1.27 billion USD). This amount substantially exceeds the additional costs (0.42 billion USD) associated with fire-$PM_{2.5}$ in scenario S2, where the target indoor $PM_{2.5}$ concentration is 15 μg/m^3, in accordance with the WHO's daily guideline for $PM_{2.5}$ exposure (*32*), as estimated in our study. Wu *et al.* (*39*) estimated economic losses of 5.07 billion USD per year because of mortality attributable to wildfire-related $PM_{2.5}$ in Brazil from 2000 to 2016. In contrast, our study estimates the annual extra cost of fire-$PM_{2.5}$ in Brazil during 2002 to 2022 to be 1.95 billion USD under the most stringent intervention scenario (S3), which is substantially lower than the economic losses reported by Wu *et al.* Connolly *et al.* (*43*) estimated a total of 52,480 to 55,710 premature deaths attributable to wildland fire-$PM_{2.5}$ in California during 2008 to 2018, equating to an economic loss of 432 to 456 billion USD, which is much larger than the cost of using air purifiers. These results suggest that a modest investment in air purifiers can yield substantial economic and health benefits during wildfire episodes. However, it is crucial to recognize that the economic status and health impacts of fire-$PM_{2.5}$ vary across different regions worldwide. Consequently, the cost-effectiveness of purifier usage in different regions requires further investigation.

Our study revealed notable socioeconomic disparities in the costs of controlling indoor $PM_{2.5}$ and the additional costs associated with fire-$PM_{2.5}$. A previous study indicated that low- and middle-income countries were particularly vulnerable to fire-sourced pollution (*16*), and our results showed that the utilization of air purifiers can mitigate the inequality in $PM_{2.5}$ exposure concentrations (fig. S2A), yet this is accompanied by a large imbalance in the economic burden associated with the measure. Given that wildfires are becoming more frequent and severe as a consequence of climate change (*2*–*4*), our findings regarding the socioeconomic disparities in air purifier costs provide compelling evidence of climate injustice.

The unequal distribution of resources, resulting from socioeconomic disparities, has the potential to exacerbate global injustice by exposing those who cannot afford the cost of air purifiers to higher health risks. The unequal burden of costs or extra costs may also exacerbate social stratification, as affluent households can shield themselves from the adverse effects of air pollution, whereas impoverished families lack such resources. Therefore, government support is necessary to promote the popularization of purifiers and narrow the inequality. A previous study (*38*) evaluated the cost-effectiveness of a government-sponsored HEPA air filter rebate program aimed at improving asthma control and preventing exacerbations in British Columbia, Canada. The findings suggested that it would likely be cost effective for the government to subsidize a portion of the costs of air filters. The cost analysis for different intervention scenarios can help regions select appropriate control standards based on their current capacities. For example, in scenario S3, the cost of implementation in some countries exceeds their local per capita GNI, making this approach challenging to implement. In such regions, a more flexible approach could be adopted by increasing the indoor $PM_{2.5}$ concentration target, allowing for the selection of less stringent control standards, such as S2 or S1. While opting for the lowest-cost control standard, S1, may reduce expenses, the overall cost of air purifiers could still impose a substantial economic burden on certain regions such as some countries in Africa. To better reflect the financial burden on households and local governments, we have calculated costs at the subnational level (fig. S6). This enables local households to assess the costs of using air purifiers and choose a more appropriate indoor $PM_{2.5}$ control level based on their financial capacity. Moreover, subnational cost estimates provide regional governments with critical insights to tailor policies and air quality control standards that align with local income levels and economic conditions, facilitating the implementation of more context-appropriate and effective interventions. Moreover, the discrepancy in the financial burden called for the investigation in the development of more efficient and cost-effective air purification technologies from countries and companies. This innovation could facilitate advancements across the industry, ultimately leading to reduced costs and benefiting a larger population. In addition, the global inequality in costs also called upon countries to implement proactive policies and regulations aimed at mitigating wildfires and air pollution, thereby decreasing the reliance on air purifiers. Such measures may include improved fuel management practices, stricter emission standards, and initiatives to promote the use of clean energy sources and the development of public transportation infrastructure.

Compared with previous studies, we explored indoor wildfire-related $PM_{2.5}$ levels and associated exposure inequalities on a global scale over a 20-year period rather than focusing on specific wildfires or regions (*21*–*25*). In addition, we conducted a quantitative analysis of the economic costs associated with reducing wildfire-related air pollution, providing direct insights into the socioeconomic disparities exacerbated by wildfires. This comprehensive analysis offers a more robust understanding compared to previous studies that primarily focused on fire-$PM_{2.5}$ exposure concentration inequalities (*16*, *44*, *45*).

There are several limitations of our study. First, we used $PM_{2.5}$ concentrations from landscape fires to evaluate indoor fire-$PM_{2.5}$ exposure globally, ignoring some types of fires that could not be attributed to wildfires, such as prescribed fires and agricultural fires. Second, we did not consider the filtration effect of mechanical ventilation systems that some residences might use (although the input average air exchange rate for simulation accounts for mechanical ventilation). However, to facilitate a straightforward assessment of the cost associated with air purifiers, we adopted this baseline scenario to compare the reduction in exposure and cost burden from using air purifiers. Given the low global adoption rate of mechanical ventilation systems in residences (*46*–*48*), this simplification has a minimal impact on our findings. Third, in addition to the deployment of air purifiers, there are other measures that can be used to mitigate population exposure to wildfire-related air pollution. These include the relocation of high-risk individuals, enhancing building envelopes, wearing N95 or P100 face masks, and making people stay informed of the wildfire smoke (*3*, *4*, *49*). It is important to note that the cost-effectiveness of these various measures may vary across different regions and contexts, necessitating further exploration in future research endeavors. Last, our study primarily focused on the indoor $PM_{2.5}$ of outdoor origin; however, humans have exposure originating from both indoor and outdoor sources. Because outdoor sources contribute the most to indoor $PM_{2.5}$ levels (*50*), the indoor sources may not be as notable as outdoor sources, especially considering that the main objective of this study is focused on fire-$PM_{2.5}$. Our results highlight the need for further research on health impact assessments, which could help better understand the risks associated with fire-related pollution and explore the cost-effectiveness of air purifiers in mitigating exposure.

In conclusion, our results revealed the substantial impact of wildfires on indoor air quality and the large population exposure to indoor fire-$PM_{2.5}$. We highlighted that the utilization of air purifiers can reduce indoor $PM_{2.5}$ exposure and consequently mitigate the inequality in $PM_{2.5}$ exposure concentrations, yet this is accompanied by large disparities in the economic burden for different regions of the world. More measures need to be taken on mitigating wildfires, popularizing the air purifiers, and addressing the climate injustice incurred because of wildfires.

MATERIALS AND METHODS

Data description

Global daily $PM_{2.5}$ data

We used the Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2) (*51*) to calculate global daily surface $PM_{2.5}$ concentration from 2003 to 2022. MERRA-2 is one of the most widely used atmospheric reanalysis products (*52–54*), provided by National Aeronautics and Space Administration's Global Modeling and Assimilation Office. MERRA-2 contains five types of aerosol data (i.e., dust, black carbon, organic carbon, sea salt, and sulfate) since 1980, with a spatial resolution of 0.5° by 0.625°. We estimated surface-level $PM_{2.5}$ concentrations using the method of Ali *et al.* (*54*) and resampled the results to a 0.5° resolution.

Global daily fire-$PM_{2.5}$ data

Now, several approaches are used to estimate fire-$PM_{2.5}$ concentrations, including ground and satellite observations [e.g., burned area, fire radiative power (FRP), and true-color imagery] (*19*, *42*, *55*, *56*), as well as chemical transport models (*57–60*) and machine learning methods (*61*). Multiple datasets are available to evaluate fire emission (see table S1). For example, the Aerosol Robotic Network of the National Aeronautics and Space Administration can provide $PM_{2.5}$ data from biomass burning at ground sites located in regions exposed to fires. However, it lacks coverage in regions such as Northern Hemisphere South America and equatorial Asia during certain years, such as 2008 (*62*). In the United States, the National Oceanic and Atmospheric Administration's Hazard Mapping System generated fire smoke data based on visual classification of plumes using GOES-16 and GOES-18 ABI true-color imagery. Global fire-$PM_{2.5}$ emissions are also estimated by the Copernicus Atmosphere Monitoring Service and the Global Fire Emissions Database, which are based on FRP and burned area, respectively. While the Copernicus Atmosphere Monitoring Service offers higher-resolution data (0.1°), our model input requires concentration data.

Here, we used a fire-related $PM_{2.5}$ surface concentration dataset developed by the Finnish Meteorological Institute (*63*) to estimate long-tern fire-$PM_{2.5}$ exposure. This dataset has been previously used in studies on the health effects of wildfires (*8*, *64*, *65*) and exposure to wildfire-$PM_{2.5}$ (*66*). It provides global daily averages of fire-related $PM_{2.5}$ from 2003 to 2022 at a resolution of 0.5°, simulated by the System for Integrated Modelling of Atmospheric Composition chemistry transport model version 5.8. The model used FRP data from the MODIS instrument as input, covering various types of fires, including agricultural and wildfire. The required meteorological data were obtained from ERA5.

Population data

We used global population data from LandScan (*67*) to evaluate population-weighted costs in different regions. LandScan provides annual population distribution data at 30″ (~1 km) from 2000 to 2022 using global remote sensing data and a multivariable dasymetric modeling approach (*68*). To match the spatial resolution of the $PM_{2.5}$ data, we resampled the LandScan data to a 0.5° resolution using the "average" method from the R package "terra."

Models

Our calculation had two models, indoor $PM_{2.5}$ concentration assessment model and cost assessment model of air purifier, which are integrated in a Monte Carlo simulation framework (fig. S7). In this study, we used the parameters of residential buildings for all indoor environments, owing to the lack of reliable data for nonresidential settings, e.g., offices. This simplification has a negligible impact, as individuals spend ~80% of their indoor time in their residences (*17*, *18*).

Indoor $PM_{2.5}$ concentration assessment model

A mass balance model was used to estimate the indoor $PM_{2.5}$ concentration of outdoor origin (*50*, *69*, *70*). Ignoring the indoor source of $PM_{2.5}$, the indoor $PM_{2.5}$ concentration obeys the following mass balance principle

$$\frac{dC_{\text{in}}}{dt} = AER \times \left(P \times C_{\text{out}} - C_{\text{in}}\right) - K \times C_{\text{in}} \tag{1}$$

where C_{in} is the indoor $PM_{2.5}$ concentration (μg/m^3); C_{out} is the outdoor $PM_{2.5}$ concentration (μg/m^3); AER is the air exchange rate (hour^{-1}); P is the penetration factor of $PM_{2.5}$, which is the fraction of outdoor $PM_{2.5}$ that infiltrates the building envelope; and K is the indoor $PM_{2.5}$ deposition rate (hour^{-1}).

We obtained the distributions of the penetration factor and deposition rate from a study of 69 residences in Beijing by Ji and Zhao (*50*) and applied these data globally. We believe that this simplification is reasonable given the minimal fluctuation in P. When windows are open, P equals 1, and when windows are closed, P remains close to 1. In our study, we used a dataset with a mean value of 0.95, which aligns with results from a similar study conducted in the United States (*71*). In addition, the deposition rate is primarily influenced by indoor environmental factors, such as friction velocity over the indoor surfaces, wall roughness, and the spatial distribution of particles (*72*), which exhibit minimal variation because of the necessity for thermal comfort across indoor environments worldwide. To further validate the use of these data, we conducted sensitivity analyses for both P and K.

The AERs for different seasons were collected from 27 countries and 80 regions or cities (table S2). Because of limitations in data availability, we used a random forest model to predict AER values across various regions and seasons. This data-driven model incorporated key parameters, including seasonal average temperature, the SD of temperature across four seasons, seasonal ratio of temperature (average temperature of the season/annual temperature), latitude, longitude, and gross domestic product (GDP), all of which are key factors influencing building airtightness and ventilation modes. We evaluated the model performance using fivefold cross-validation, resulting in an R^2 value of 0.52 and a root mean square error of 0.3. In comparison, a similar study conducted in Europe reported an R^2 of 0.76 with a regression model (*73*). On the basis of the collected data, we assumed that the SD for a region had a linear relationship with the mean value, expressed as $\text{SD} = 0.88 \times \text{mean} - 0.07$, with an R^2 value of 0.72. Integrating the model results with the assumption, we derived the distribution of AER as input of Monte Carlo simulation, assuming that the AER in each region follows a lognormal distribution (*73–76*). The global AER data are shown in fig. S8.

With a steady-state assumption (*70*), the mass balance equation (Eq. 1) can be solved

$$C_{in} = \left[\frac{AER \times P}{AER + K}\right] \times C_{out} \tag{2}$$

When there is a purifier in a room, the mass balance equation is

$$\frac{dC_{in}}{dt} = AER \times \left(P \times C_{out} - C_{in}\right) - K \times C_{in} - \frac{CADR}{V} \times C_{in} \tag{3}$$

where $CADR$ is the clean air delivery rate (m^3/hour), which is the equivalent volume of perfectly clean air (i.e., zero concentration of $PM_{2.5}$) that the device produces in an hour (*77*). V is the volume of the room; in this study, we use $A \times H$ to calculate the room space per capita, where H is the ceiling height of residences, which is set at 2.8 m (*78*). A is the per capita floor area. The steady-state C_{in} with air purifiers can be calculated using Eq. 4

$$C_{in_{purifier}} = \left[\frac{AER \times P}{AER + K + \frac{CADR}{A \times H}}\right] \times C_{out} \tag{4}$$

We collected data on per capita residential floor area (A) from various sources, including documents and websites, covering 66 countries (see table S3). To account for annual variations in floor area and limitations in data coverage, we applied a multiple linear regression model using the following parameters: GDP per capita (in USD) (*79*), population density (Pop_{den}, persons per square kilometer) (*80*), and per capita residential building volume ($BuVol$, m^3) (*81*). The multiple linear regression function is presented in Eq. 5, with an R^2 value of 0.82

$$A = 3.9 \times 10^{-4} \times GDP - 1.4 \times 10^{-3} \times Pop_{den} + 4.9 \times 10^{-2} \times BuVol + 4.9 \tag{5}$$

Cost assessment model of air purifiers

There are three parts of the cost of air purifiers, initial investment cost ($INVT$), which was spread in the service life of air purifiers; electricity cost for running the air purifier ($ELEC$); and the maintenance cost to replace filters in air purifiers ($FLTR$) (*69*)

$$Cost = INVT + ELEC + FLTR \tag{6}$$

C_{target} denotes the target indoor $PM_{2.5}$ concentration to be achieved through the use of air purifiers. We propose a system of automated monitoring and control, or notification-based control, for air purifiers, leveraging the availability of numerous cost-effective and reliable $PM_{2.5}$ sensors (*82–84*). These sensors enable the activation of air purifiers when indoor $PM_{2.5}$ concentrations exceed the target level. The required CADR in a given intervention scenario to achieve the indoor $PM_{2.5}$ level is

$$Required\ CADR = \left(\frac{AER_{win,c} \times P_{win,c}}{C_{target}} \times C_{out,t} - AER_{win,c} - K_{win,c}\right) \times A \times H \tag{7}$$

The needed cleaning capacity of air purifiers (device CADR, $CADR_d$) is set as the 95th percentile of distribution of the required CADR over the entire year in each scenario. For days when the required CADR is larger than $CADR_d$, the indoor $PM_{2.5}$ concentration is determined as $C_{capacity}$, which is the lowest $PM_{2.5}$ level the device can achieve

$$C_{capacity} = \left[\frac{AER \times P}{AER + K + \frac{CADR_d}{A \times H}}\right] \times C_{out} \tag{8}$$

The CADR of a certain day t can be determined by Eq. 9

$$CADR_t = \begin{cases} 0, \text{ if } C_{in} < C_{target} \\ Required\ CADR, \text{ if } C_{in} > C_{target} \text{ and } C_{capacity} < C_{target} \\ CADR_d, \text{ if } C_{in} > C_{target} \text{ and } C_{capacity} > C_{target} \end{cases} \tag{9}$$

To evaluate the purchase price and energy consumption of air purifiers, we collected data on best-selling air purifiers from three online appliance shopping websites (Amazon.com, JD.com, and Taobao.com). We estimated the price per CADR ($Price_0$, USD·hour/m^3) and power per CADR ($Power_0$, W·hour/m^3) as shown in table S4. These platforms offer a wide range of air purifier brands and are accessible for global purchases, making them representative of the global market. The data were log normally distributed, with $\ln(Price_0)$ following a normal distribution of $N(-0.198, 0.754)$ ($P = 0.064$ in Shapiro-Wilk test) and $\ln(Power_0)$ following a normal distribution of $N(-1.977, 0.384)$ ($P = 0.075$).

We assumed that the life of each purifier is 10 years, so the initial investment of purchasing a purifier was evenly divided into 10 years. The $INVT$ is

$$INVT = 10\% \times CADR_d \times Price_0 \tag{10}$$

We used the unit price of electricity (EP) [from Cable.co.uk (*85*); for regions where data were unavailable, we used the average EP from the website] and $Power_0$ to estimate the daily energy consumption for running the air purifier. We assumed that the operation time of an air purifier is 24 hours a day when the daily indoor $PM_{2.5}$ concentration was higher than the target. The running cost of air purifiers is

$$ELEC = \sum_{t=1}^{365} CADR_t \times Power_0 \times 24\ \text{hours} \times EP \tag{11}$$

In the case of a leap year, the number of days would be adjusted to 366 instead of 365. We collected price data for the best-selling purifier filters from shopping websites, most of which are HEPA filters, and presented it in table S4. A log-normal distribution of filter prices (FPs) was observed ($P = 0.056$), with $\ln(FP) \sim N(3.546, 0.901)$. The frequency of filter replacement was determined by summing the daily accumulated mass of particles over the course of a year, because the filter would be replaced when the accumulated mass reaches the filter's cumulative clean mass (CCM) (*69*). The CCM (mg) of a filter was calculated using a linear relationship between FP (USD) and $\ln(CCM)$, as derived from the data by Liu *et al.* (*69*). The relationship is described by the function $FP = 41.8 \times \ln(CCM) - 367.8$ ($R^2 = 0.72$). Therefore, the filter maintenance cost in a given intervention scenario would be

$$FLTR = \frac{\sum_{t=1}^{365}\left(C_{in} \times CADR_t \times 24\ \text{hours}\right)}{CCM} \times FP \tag{12}$$

Statistical analysis

We used Monte Carlo simulation to quantify the variations and uncertainties, and the simulation was performed in R (version 4.3.1). We performed 2000 iterations to capture the distribution of our results. We then reported the uncertainty intervals for these results as the 2.5th to 97.5th percentiles of their values in the 2000 uncertainty runs.

We estimated the Monte Carlo error (MCE) by repeating the same simulation 100 times to identify the number of Monte Carlo iterations sufficient to provide stable results. MCE is the SD of Monte Carlo means of a given target output across all simulations. The error ratio is defined as MCE over the Monte Carlo SD of the target output, which needs to be less than 5% (*86*). We used the minimum SD across the100 simulations as Monte Carlo SD in the denominator of error ratio (*87*). We calculated the error ratios for three target outputs: indoor $PM_{2.5}$ concentration, cost in using air purifiers, and extra cost incurred from fire-$PM_{2.5}$. Taking a grid from the Yunnan province in China as an example, all ratios were lower than 5%, and the results of the error ratios are listed in table S5.

Verification of the model

The validation process aims to assess both the accuracy of the physical model, which is supported by our experimental results, and the suitability of the input parameters for different regions, as demonstrated by the regional data included in the study. The verification of our model had three dimensions: validating the indoor-outdoor relationship during nonwildfire periods, confirming the indoor-outdoor relationship during wildfire events, and assessing the effectiveness of air purifiers. We collected and used available measuring data from published references to address the first two dimensions while conducting experiments in a real indoor environment to evaluate the efficacy of air purifiers in reducing indoor $PM_{2.5}$ levels (table S6). Results of our calculation corresponded well with the measured results from references and our experiment (fig. S9). All modeled results exhibited an absolute error ratio of less than 23%, ranging from 1.6 to 22.1%.

Sensitivity analysis

We performed a sensitivity analysis on four important factors including penetration factor, deposition rate, service life of air purifier, and *EP*. When the penetration factor P was set to 1, representing open windows, the indoor concentration increased by ~5%. The sensitivity analysis showed that for an AER of 1.70 (97.5th percentile globally), a 10% increase in K led to a 4.0% increase in indoor $PM_{2.5}$ concentration, while a 10.0% decrease resulted in a 3.7% reduction. For an AER of 0.53 (2.5th percentile globally), a 10% change in K led to a 1.7% change in indoor $PM_{2.5}$ concentration. When the *EP* was set at the minimum and maximum values (*85*), the global population-weighted average annual per capita cost in scenario S3 had a reduction of 25.5 USD (−4.1%) and an increase of 33.7 USD (5.4%), and the per capita extra cost had a reduction of 0.37 USD (−3.7%) and an increase of 0.43 USD (4.3%), respectively (fig. S10, A and B). We calculated the changes in the global annual total cost and extra cost when the service life is 8 or 12 years, instead of 10 years (fig. S10, C, and D). In scenario S3, the global annual per capita cost and extra cost increased by 6.2 and 6.0% if the service life is 8 years and decreased by 4.1 and 4.0% if the service life is 12 years, respectively. The sensitivity analysis did not alter our principal findings.

Supplementary Materials

The PDF file includes:
Figs. S1 to S10
Legends for tables S2 to S4
Tables S1, S5, and S6
References

Other Supplementary Material for this manuscript includes the following:
Tables S2 to S4

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