Effect of PM2.5 on the Incidence of Asthma in Children

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Abstract. As the global air pollution problem becomes increasingly serious, PM2.5 poses a significant threat to human health as a major pollutant, with children being susceptible to respiratory diseases such as asthma. This study aims to explore the effect of PM2.5 on the number of asthma incidences in children. We selected three countries with significant differences in air pollution levels between 2010 and 2019: Australia, China, and India. We analyzed the trends and correlations between the annual average PM2.5 concentrations and the number of asthma incidence and casualties among people under 20 years of age using the Global Burden of Disease (GBD) data. The results show that all three countries show a weak negative correlation (mean $R \approx -0.518$), contrary to theoretical expectations. Discussions suggest that this result may stem from data limitations, differences in health reporting systems between countries, and an underestimation of true exposure levels by aggregated data. This study sheds light on the complexities of conducting environmental health research on a global scale and highlights the importance of deciphering the socio-political context behind the data.

Keywords: PM2.5; Childhood Asthma; Global Burden of Disease (GBD); Correlation Analysis; Environmental Health.

1. Introduction

On average, with the increasing seriousness of environmental pollution, the global air quality index has been declining in recent years, and PM2.5 is the most important pollutant characteristic that endangers human health. Asthma, a significant air pollution disease, is gradually increasing among them. Among the affected groups, children are more likely to have asthma because their respiratory systems are not fully developed, their immune systems are weak, and they are more exposed to air pollution in terms of activity and metabolism, which affects the health of adolescents for a long time. It is estimated that around 358 million people worldwide had asthma in 2015, including about 14% of children worldwide. [1]

Although the adverse effects of PM2.5 on the respiratory system are widely recognized, there are still some obvious limitations and challenges in existing research. First, many studies focus on a single country or region, and there is a lack of systematic comparative analysis between different countries with large differences in pollution levels. This contrast is crucial because it reveals how environmental policies, socioeconomic levels, and medical conditions can regulate the relationship between pollution and health outcomes. Second, many studies rely on short-term or local data, which cannot reflect the profound effects of long-term, cumulative exposure to PM2.5 on children's health.

This paper focuses on comparing the effects of PM2.5 on the incidence of asthma in children across different countries. Three typical countries with large differences in air pollution levels were selected to systematically analyze and compare them to reveal the long-term effects of air pollution on children's health. It also reflects the differences between different environmental quality and socio-economic development levels on children's health. The study subjects were identified as children and adolescents under 20. The time span is from 2010 to 2019, covering the change trend of the past 10 years; Australia was selected as the control group with relatively good air quality, China as the middle level of moderate pollution level, and India as the high exposure group with high pollution level. Map the PM2.5 concentration data with the data on the incidence of asthma in children, find the relationship, and then compare the data from different countries to estimate the future.

2. Methods

2.1 Data Source

The two main data I studied were the average change in PM2.5 concentrations in Australia, China, and India from 2010 to 2019, and the number of asthma-related injuries or deaths in people younger than 20. The data on PM2.5 concentration and the number of asthma patients are derived from the Global Burden of Disease Study (GBD). Among them, the data on PM2.5 pollution levels are derived from the official Global Burden of Disease Study 2019 (GBD 2019) Air Pollution Exposure Estimates 1990-2019 database. The data on the number of asthma incidences are specifically derived from IHME GHDx. The GBD is selected to estimate the cause of death or injury, the amount of research is the incidence, the measurement is the total number, the cause is asthma, the age is less than 20 years old, the gender is the total, and then the time period and target location to be studied are selected. I will first use trend analysis to describe the trend of PM2.5 pollution concentration and asthma incidence in these three countries over time.

2.2 Data Analysis

Correlation analysis and regression analysis were carried out. The data on PM2.5 pollution concentration were used as the horizontal axis of the independent variable. The number of asthma incidences was used as the vertical axis of the dependent variable. The plot was drawn to discuss whether the pollution level of PM2.5 impacted the incidence of asthma in children. Finally, the fitted lines are tested for R-regression values, $r = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2} \cdot \sqrt{n\sum y_i^2 - (\sum y_i)^2}}$, conducting discussion and analysis. The correlation coefficient r value range is $-1 \leq r \leq 1$, where r=1 represents complete correlation, r=-1 represents complete negative correlation, and r=0 represents no correlation.

3. Results

3.1 Raw Data and Trend Analysis

A. Australia

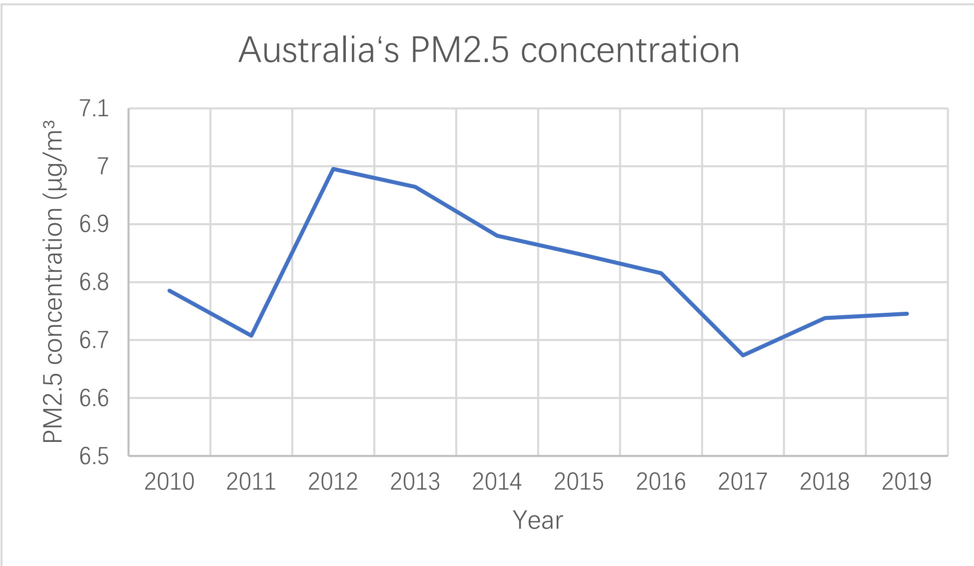

Figure 1. Trends in PM2.5 concentration (μg/m³) in Australia from 2010 to 2019.

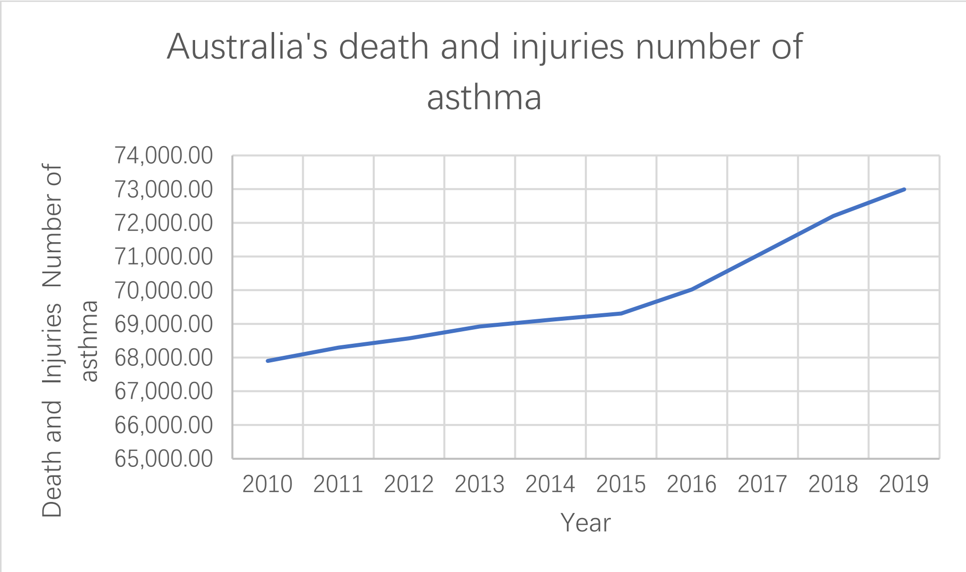

Figure 2. Trends in the number of deaths and injuries from asthma in Australia from 2010 to 2019.

Figure 1 presents the trend of the annual average concentration of PM2.5 in Australia, showing that in the past 10 years, the concentration of PM2.5 in Australia has shown a fluctuating trend, with the general trend rising first and then falling. The overall air quality in Australia is excellent. The overall air quality in Australia is excellent. According to the World Health Organization (WHO) guidance standards (an annual average of ≤5 μg/m³ is the best, ≤10 μg/m³ is good), Australia is at a "good" level throughout the process. [2]

Figure 2 shows the number of deaths or injuries caused by asthma, which describes the slow decline in the PM2.5 trend. Australia's asthma cases increased slightly and significantly between 2010 and 2019.

B. China

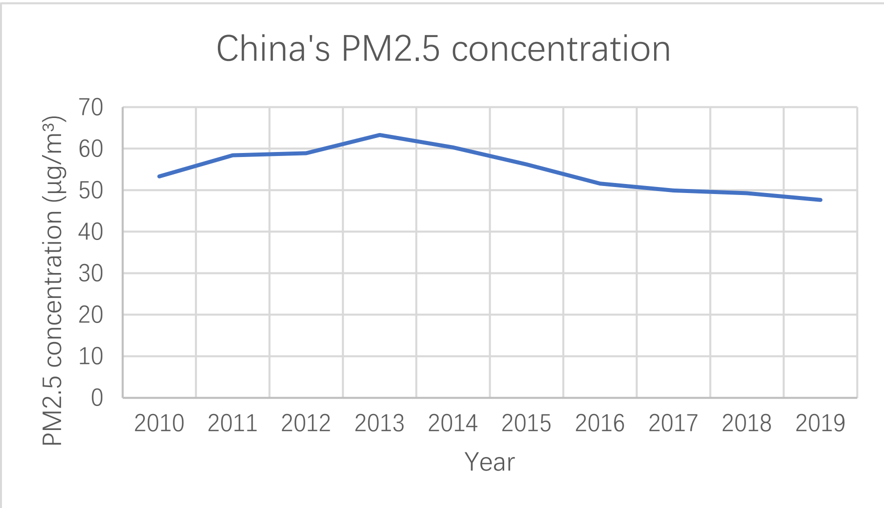

Figure 3. Trends in PM2.5 concentration (μg/m³) in China from 2010 to 2019.

Figure 3 shows that China's PM2.5 concentration was relatively stable in the past 10 years from 2010 to 2019, and there was a slow decline in the last 5 years. But even after the decline, the concentration level in 2019 (estimated at 28 μg/m³) was still well above the World Health Organization (WHO) recommended safe (annual average ≤5 μg/m³), but also significantly lower than the pre-2013 peak, indicating that air quality has improved significantly, but there is still room for improvement.

Figure 4 shows the number of deaths or injuries due to asthma in China. The number of asthma cases in China was relatively stable from 2010 to 2019 and increased slowly in the last five years.

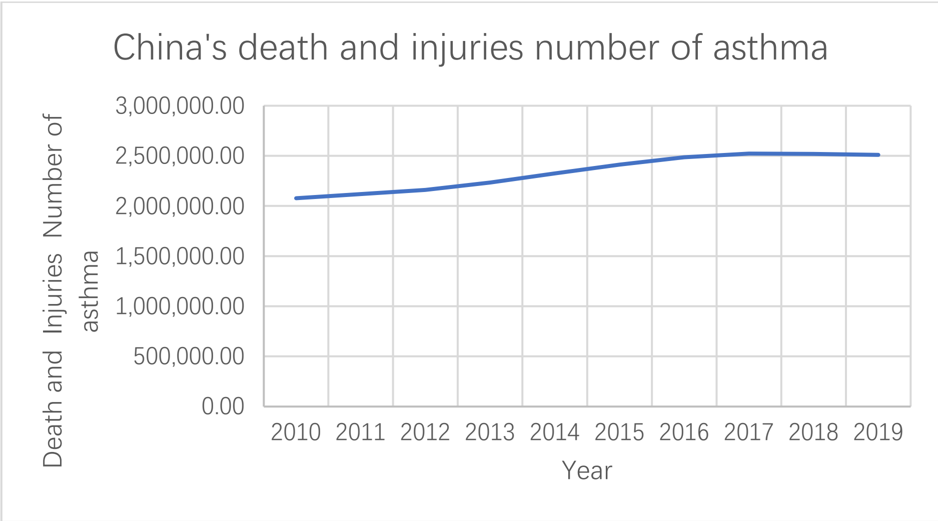

Figure 4. Trends in the number of deaths and injuries from asthma in China from 2010 to 2019.

C. India

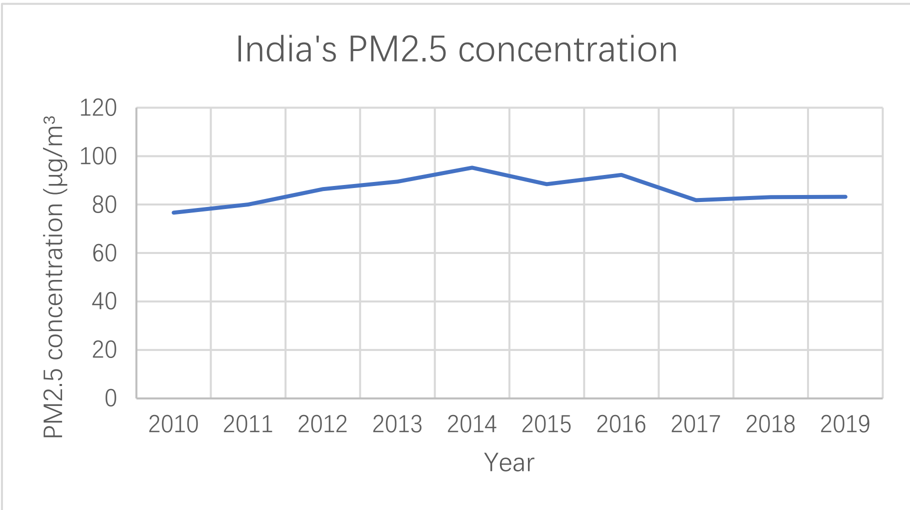

Figure 5. Trends in PM2.5 concentration (μg/m³) in India from 2010 to 2019.

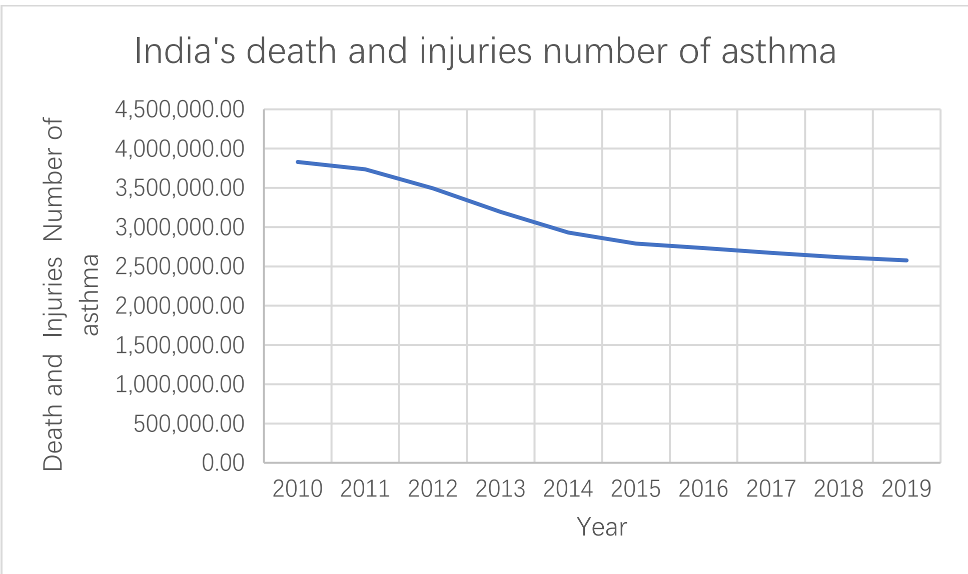

Figure 6. Trends in the number of deaths and injuries from asthma in India from 2010 to 2019.

Figure 5 shows that from 2010 to 2019, India's annual average PM2.5 concentration rose first and then decreased, remaining at a high level (about 80-100 μg/m³). This shows India's air pollution levels have exceeded the World Health Organization's recommended standards over the past decade.

Figure 6 shows that the number of deaths or injuries due to asthma in India showed a sharp decline between 2010 and 2019, dropping from about 4 million to about 2.5 million.

3.2 Correlation Analysis

A. Australia

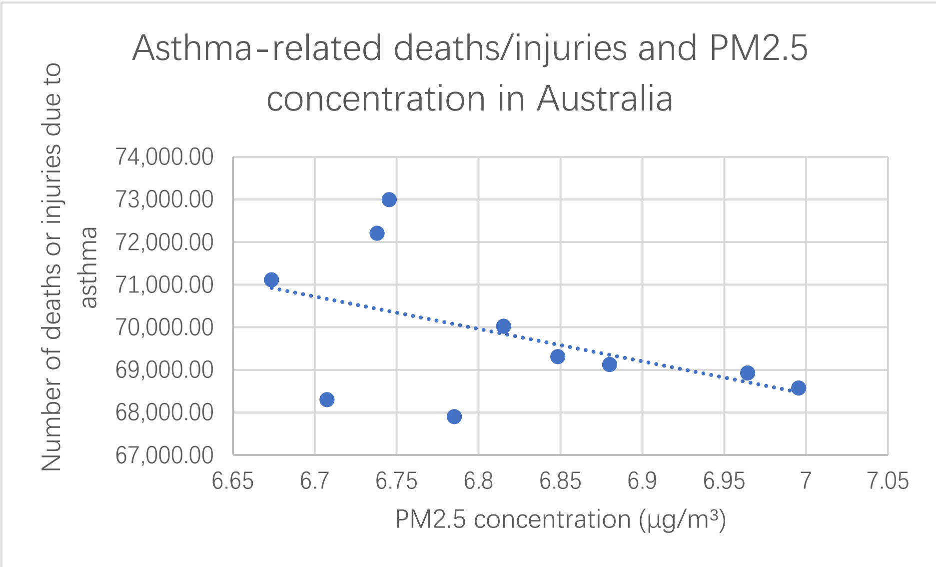

Figure 7. Trends in asthma-related deaths or injuries (left axis) and annual average PM2.5 concentration (right axis) in Australia from 2010 to 2019

The chart shows the correlation between the number of asthma cases and PM2.5 air pollution in Australia. Overall, the number of deaths or injuries from asthma in the first data set gradually decreased over time. The second set of data, PM2.5 air pollution concentration, gradually increased with time. From the perspective of the change direction of the data series, the change trend of the two data series is opposite. The two show a negative correlation in this data range, and the overall slope is negative. The calculated value according to the correlation formula of R is about -0.47498, indicating a negative correlation between the two, but the correlation is not strong.

B. China

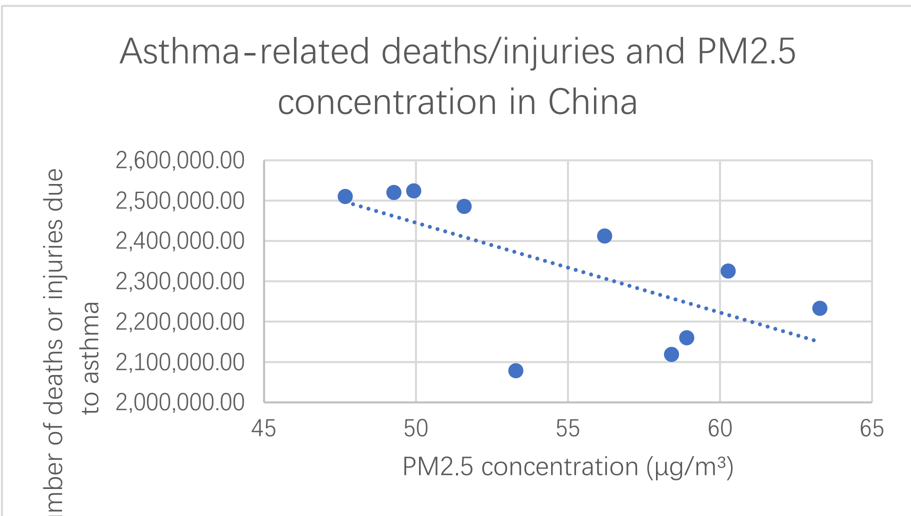

Figure 8. Trends in asthma-related deaths or injuries (left axis) and annual average PM2.5 concentration (right axis) in China from 2010 to 2019.

The chart shows the correlation between the number of asthma cases and PM2.5 air pollution concentrations in China. In terms of overall trends, the number of asthma-related deaths or injuries showed a downward trend during this period, while the average annual concentration of PM2.5 showed an upward trend. The two curves move in opposite directions, indicating a negative correlation between the two over the past 10 years. The correlation coefficient between the two is approximately -0.66325 based on the R-value, indicating a moderate negative correlation stronger than that observed in the Australian sample (R≈ -0.47498).

C. India

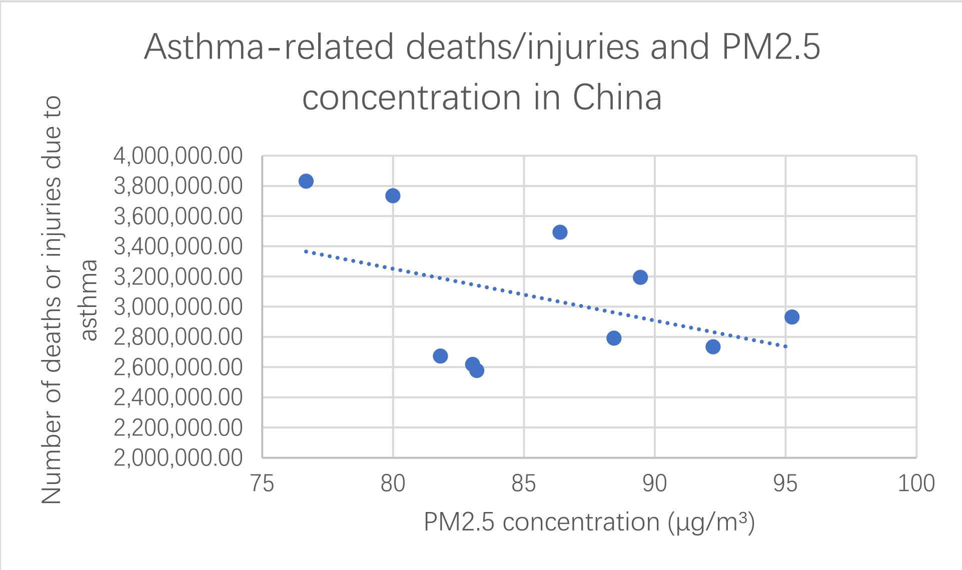

Figure 9. Trends in asthma-related deaths or injuries (left axis) and annual average PM2.5 concentration (right axis) in India from 2010 to 2019

According to the chart data, the number of asthma-related casualties in India showed an inverse relationship with PM2.5 concentration between 2010 and 2019. The number of asthma casualties continued to decline significantly. During the same period, PM2.5 concentrations continued to rise. From the perspective of numerical trends, the two curves are opposite: PM2.5 concentration is on the rise, while the number of asthma casualties is on a downward trend. This inverse change creates a negative correlation between the two. The R-value was -0.41544 by correlation calculation, confirming the existence of a negative correlation. Compared to the other two countries, India has the weakest negative correlation (R≈-0.47498 in Australia and R≈-0.66325 in China). This value indicates a statistically negative correlation between asthma casualties and PM2.5 concentrations in India during the observation period, but the strength of the association is relatively weak. [3]

4. Discussion

4.1 Error Analysis

The correlation analysis results of this study show that all three countries have a weak negative correlation (R≈ -0.518) and a significant deviation from theoretical expectations, indicating that there may be several systematic errors in the study. According to the result analysis part, it can be observed from the scatter plots of all three countries that there is a large deviation between the data points and the fitted regression line, indicating that simple linear models may not adequately capture the complex relationships between variables. This large deviation may stem from several aspects.

First, at the level of data collection, there are differences in asthma case statistics and air quality monitoring standards across countries. For example, the definition and recording standards of "asthma-related casualties" may be inconsistent in different countries, and there are also national differences in the distribution density and measurement methods of PM2.5 monitoring stations, which will introduce measurement errors and affect the comparability of data.

Second, regarding variable control, this study only investigated the binary relationship between PM2.5 and asthma incidence, but the factors affecting asthma incidence are multidimensional. In particular, the synergistic effects of other air pollutants (such as PM10, SO_2, NO_2, etc.) were not controlled, nor did they consider the regulatory effects of meteorological factors such as temperature and humidity and ignored the influence of socio-economic variables such as medical level, population age structure, and urban and rural distribution. These uncontrolled confounding variables can lead to biased analytical results.

Third, in terms of model setting, using linear regression models may oversimplify the real relationship between variables. Environmental health effects often have threshold effects, lag effects, and nonlinear features that cannot be captured by a simple linear model used in this study. For example, the health effects of PM2.5 may be significantly enhanced after a certain concentration threshold is exceeded, or there may be a lag of weeks or even months in its effects.

Fourth, each country contains only about 10 data points, and such a limited sample size makes the analysis results abnormally sensitive to extreme values, reducing the statistical power of finding true effects. Besides, only three countries were selected for analysis: Australia, China, and India. Although these three countries are representative regarding economic development and pollution levels, the small sample size seriously limits the generality of the research conclusions, making the results vulnerable to the national conditions of specific countries.

Fifth, the data used in this study are large and span years, which may be too crude to capture the effect of short-term fluctuations in PM2.5 on asthma incidence, and annual data also mask the impact of seasonal changes and short-term pollution events. From the perspective of time, the study period (2010-2019) coincided with the rapid development of global public health. Aggressive interventions that have generally strengthened respiratory disease prevention and control systems and promoted standardized treatment options for asthma may have offset some of the health risks posed by increased pollution, leading to patterns of correlation that do not match theoretical expectations.

4.2 Data Quality

In addition, there are certain limitations in terms of data quality. In some countries, surveillance data may be missing or less reliable in early years, and asthma incidence data are affected by diagnostic levels, reporting systems, and access to care, all of which can interfere with analytical results. [4]

In addition, there are huge differences in the accuracy and consistency of health data reporting across countries. Underrepresentation of exposure data: Annual average PM2.5 concentration data may originate from limited ground-based monitoring sites, and for countries with extremely uneven geographical, climatic, and demographic distributions, such as China and India, a national annual average cannot capture the spatial heterogeneity of population exposures and short-term high-concentration exposure events. For example, China's healthcare system has undergone dramatic changes over the past few decades, with diagnostic criteria for asthma and the integrity of death registries changing over time, introducing measurement errors that are difficult to quantify. In India and some developing countries, inadequate primary care coverage can lead to a large number of asthma cases being undiagnosed or misclassified (e.g., attributed to "pneumonia" or "chronic bronchitis"), resulting in systematic misclassification of health outcomes that distort the true association with PM2.5. Besides, developed countries like Australia have well-established medical reporting systems but face specific data challenges. For example, mild asthma cases may not be counted, and trends in population aging can change the distribution of asthma disease burden. Together, these factors lead to significant differences in the quality of health data across countries, making cross-border comparisons particularly cautious. Using this highly aggregated data can lead to an individual's true exposure level being misestimated, often diluting the true effect, causing the correlation to decay towards zero.

Moreover, the chemical composition and sources of PM2.5 are also significantly different in different countries and periods. The health effects of PM2.5 from industrial emissions, coal combustion, motor vehicle exhaust, or dust storms may vary, and the mass concentration indicators used in this study do not reflect these important differences, further limiting the explanatory power of the results.

Finally, from the perspective of theoretical mechanisms, the inherent limitations of ecological research design are particularly obvious in this study, and the results of weak negative correlation suggest that we need to re-examine the research hypothesis. Since the analysis unit is aggregated data at the national level, it is impossible to control confounding factors at the individual level, which is prone to ecological fallacies. The weak negative correlation pattern in all three countries suggests that unobserved country-level variables (e.g., health input, environmental policy, population flows, etc.) may simultaneously affect pollution levels and health outcomes, obscuring the true biological effects. This may mean that the effects of PM2.5 on asthma are heterogeneous in different populations and environmental contexts, or that the mechanism of action is more complex than expected and needs to be interpreted through more refined study designs.

5. Conclusion

This study examined the ecological correlation between PM2.5 concentrations and asthma-related health burdens in Australia, China, and India. Interestingly, the results revealed weak and negative correlations, contrary to expectations. Rather than representing the true exposure–response relationship, these findings highlight the methodological challenges and complexities inherent in conducting environmental health research on a global scale.

Although the data did not confirm the anticipated associations, the process offered important insights. Unexpected results compelled deeper reflection on broader determinants—such as healthcare disparities, policy interventions, and differences in reporting systems—that shape health outcomes beyond measured exposures. This underscores the reality that public health research rarely occurs under idealized laboratory conditions; instead, it must grapple with the institutional, cultural, and historical contexts that influence disease patterns.

From a decision-making perspective, the study cautions against relying solely on simple correlation analyses with macro-level data, which may yield misleading conclusions. Effective environmental health policy requires integration of multi-level and multi-source evidence, including individual cohort studies, mechanistic toxicological research, and community-based interventions. Policies can only be scientifically sound and responsive to the real-world complexity of global public health challenges through such comprehensive approaches.

References

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