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# Quantitative evaluation of PM<sub>2.5</sub>-related health economic losses and analysis of their driving factors in Chinese cities

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## KEYWORDS

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## 1 Introduction

Globally, exposure to air pollution is estimated to cause millions of deaths annually as well as loss of healthy years of life (Li et al., 2021). PM<sub>2.5</sub> pollution has become a worldwide challenge, especially in developing countries such as China. PM<sub>2.5</sub> exposure not only affects the mortality rates of residents as well as outpatient and hospitalization rates for specific diseases but also increases cancer risk and death burden (Tan et al., 2018; Li et al., 2019). In addition, PM<sub>2.5</sub> pollution can cause economic losses by increasing health-related expenditures. Hence, evaluating the urban PM<sub>2.5</sub>-related health economic losses across China is of significance for environmentally sustainable and equitable decision-making developments.

Various scholars have studied PM<sub>2.5</sub>-related health economic losses in China for different spatial scales. The average PM<sub>2.5</sub>-related economic loss was 0.3% (amended human capital: AHC) to 1% (value of statistical life: VSL) of the total gross domestic product (GDP) of 190 Chinese cities from 2014 to 2016 (Yang et al., 2018). In the Beijing–Tianjin–Hebei (BTH) region of China, the PM<sub>2.5</sub> economic loss was 6,081 million USD in 2017 (Wang et al., 2020). Most of the previous studies on this topic were mainly targeted at limited and individual areas or cities, such as 190 major cities in China (Yang et al., 2018), the BTH region (Wang et al., 2020), and Shanghai (Wu et al., 2017). However, owing to the spatial spillover effects of PM<sub>2.5</sub> and regional joint management requirements, it is important to systematically analyze the urban PM<sub>2.5</sub>-related health economic losses from the national–regional perspectives.

Owing to regional differences in the economic, social, and environmental perspectives, the factors driving PM<sub>2.5</sub>-related health economic losses in different regions need to be analyzed further. The geographically weighted regression (GWR) is often used to identify such factors because of its flexibility in identifying relationships between different geospatial influences. Fu et al. (2014) used the GWR to analyze the factors influencing PM<sub>2.5</sub> health risks; the population, social, and economic factors accounted for about 45% of the PM<sub>2.5</sub> health risks. It is therefore helpful to identify

the factors driving urban PM<sub>2.5</sub>-related health economic losses for joint prevention and control at the regional level.

The major aims of this study were as follows: 1) to explore the spatiotemporal variations of PM<sub>2.5</sub> in 287 Chinese cities and to identify critical study regions by spatial autocorrelation analysis; 2) to evaluate PM<sub>2.5</sub>-related health losses in the studied cities based on the monitored data and health loss model; 3) to calculate the PM<sub>2.5</sub>-related health economic losses according to the VSL; 4) to identify the socioeconomic drivers of PM<sub>2.5</sub>-related health economic losses based on GWR and to formulate management strategies for key regions.

## 2 Materials and methods

### 2.1 Data sources

The daily mean PM<sub>2.5</sub> concentration data for 2015–2018 were collected from the website of the China National Environmental Monitoring Centre (CNEMC) (<http://www.cnemc.cn/sss/>). Based on the requirements of the ambient air quality standards (GB3095-2012), monitoring sites with valid PM<sub>2.5</sub> concentration data for less than 20 h a day, 27 days a month (25 days for February), or 324 days a year were eliminated. The missing data were identified from <https://www.aqistudy.cn/historydata/>. Because the monitoring data for Sansha and Taiwan were missing and because Lhasa, Urumqi, and Karamay were geographically far away from the other prefecture-level cities, a follow-up analysis of the prefecture-level cities in mainland China was conducted after excluding the abovementioned regions. Vector boundary data of the prefecture-level administrative divisions in China were obtained from the Center for Resources and Environmental Sciences of the Chinese Academy of Sciences (<http://www.resdc.cn/>). The population data, mortality data, as well as social and economic factors (population density, GDP, urbanization rate, proportion of secondary industry, green coverage rate of built-up areas, industrial sulfur dioxide emissions) were all obtained from the statistical yearbook.

### 2.2 Health loss model

Some scholars have defined health loss as premature deaths or hospitalizations caused by PM<sub>2.5</sub> exposure (Li et al., 2020). PM<sub>2.5</sub> health economic loss refers to monetizing the PM<sub>2.5</sub> health loss via the willingness to pay (WTP), cost of illness (COI), or AHC method. Three steps were used to quantitatively assess the health impacts of PM<sub>2.5</sub>: 1) collecting and organizing PM<sub>2.5</sub>

concentration data from the study areas; 2) identifying the exposed population; 3) calculating the PM<sub>2.5</sub>-related health effects using the concentration-response coefficient obtained from epidemiological studies. The formula for calculating the health losses from the 287 cities exceeding Grade II standards (35 µg/m<sup>3</sup>) of the GB 3095-2012 is as follows (Xia, 2019):

$$\Delta Y = Y_0(1 - e^{-\beta \Delta PM_{2.5}}) * Pop \quad (1)$$

where  $\Delta Y$  (person) is the resulting premature deaths;  $Y_0$  (%) is the baseline rate of all-cause deaths;  $\beta$  is the coefficient between the PM<sub>2.5</sub> concentration and health effects (concentration-response coefficient);  $Pop$  (person) is the exposed population;  $\Delta PM_{2.5}$  (µg/m<sup>3</sup>) is the annual mean concentration (AM) change in PM<sub>2.5</sub>. All-cause deaths were identified as the endpoint of the health effects. In China, very few studies have investigated the concentration-response relationship between PM<sub>2.5</sub> exposure and all-cause mortality, and some of these were region-specific (Kan et al., 2007; Huang et al., 2012; Zhou et al., 2015; Qu et al., 2020). Since PM<sub>2.5</sub> was not monitored in China during the study cohort, Huang et al. (2012) converted PM<sub>10</sub> to PM<sub>2.5</sub> concentrations to analyze the concentration response between PM<sub>2.5</sub> exposure and health impact endpoints. Hoek et al. (2013) conducted a multiregional meta-analysis with well-defined health impact endpoints; the excess risk of all-cause mortality (ER) was 6% (95% CI: 4.8%) for every 10 µg/m<sup>3</sup> increase in PM<sub>2.5</sub> exposure. Therefore, the present study referred to the results of Hoek's study. The  $\beta$  value was 0.005827 and relative risk (RR) value was 1.06. Considering the GB 3095-2012 of PM<sub>2.5</sub> AM (35 µg/m<sup>3</sup>) as the control scenario, when  $\Delta PM_{2.5}$  is greater than 0, we consider  $\Delta Y$  as the PM<sub>2.5</sub>-related health loss.

### 2.3 Health economic loss model

The common methods used to assess the economic impacts of controlling air pollution include the COI, AHC, and WTP approaches. The COI mainly evaluates the medical expenses and other costs incurred by diseases, and it is suitable for assessing the economic impacts caused by air quality changes in small and highly polluted areas (Jo, 2014). The traditional human capital approach emphasizes the damage caused by air pollutants to workers' capital. The value of premature deaths of young, unemployed, and retired persons is very low, which has ethical and moral defects to a large extent (Qu et al., 2020). The WTP refers to the VSL of the samples calculated using the death risk intention survey value evaluation method. The advantage of the WTP approach is that it can be used to evaluate the use and non-use values of air pollution health losses (Yu et al., 2019). Compared with the three methods noted above, the VSL was selected owing to its

flexibility and operability. A model that monetizes the health effects of changes in PM<sub>2.5</sub> concentration is shown in the formula below (Ding et al., 2016):

$$HBE = \Delta Y \times VSL \quad (2)$$

where  $\Delta Y$  (person) is the resulting premature deaths,  $VSL$  (ten thousand RMB/person) is the unit economic value of the health endpoint, and  $HBE$  (billion RMB) is the health economic loss. The calculation of the  $VSL$  is shown in the [Supplementary Material](#).

## 2.4 Global autocorrelation

Global autocorrelation is a description of the spatial characteristics of properties throughout a region (Liu et al., 2018). Assuming that the entire study is divided into  $n$  units, where the value on the  $i$ th unit is  $x_i$  and mean observed value is  $\bar{x}$ , the Moran's I statistic can be expressed as follows:

$$I = \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^n \sum_{j=1}^n W_{ij}} \quad (3)$$

$$S^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 \quad (4)$$

where  $W$  is a spatial weight matrix, and  $W_{ij} (x_i - \bar{x})(x_j - \bar{x})$  represents the covariance.

## 2.5 Local autocorrelation

To study the relativity of the local regions within the entire region, the concept of local autocorrelation is introduced. For unit  $i$ , the corresponding local Moran's I can be defined as follows:

$$I_i = \frac{(x_i - \bar{x})}{s^2} \sum_{j=1, j \neq i}^n w_{ij} (x_j - \bar{x}) \quad (5)$$

where  $I_i$  represents the local Moran's I coefficient of position  $i$ .

## 2.6 Geographically weighted regression

The GWR is a local statistical method that inserts the spatial locations of the data into the regression parameters to explore the spatial variations between the explained and explanatory variables; it can effectively solve spatial nonstationarity (Duan et al., 2018). The structure of the model is as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) X_{ik} + \varepsilon_i \quad i = 1, 2, \dots, n \quad (6)$$

where  $(u_i, v_i)$  is the spatial coordinate of the  $i$ th sample point;  $\beta_k(u_i, v_i)$  is the value of a continuous function  $\beta_k(u, v)$  at point  $i$ ;

$\beta_0$  represents the constant term of each location;  $X_{ik}$  is the  $i$ th observed value of the  $k$ th dependent variable;  $\varepsilon_i$  is the random residual.

## 3 Results and discussion

### 3.1 Spatiotemporal variation of PM<sub>2.5</sub> across China

The distribution of the PM<sub>2.5</sub> AM in 287 Chinese cities for 2015–2018 is shown in [Figure 1](#). From 2015 to 2018, the high concentration values were mainly observed in the BTH region and surrounding areas (BTHSA), Fenwei Plain (FWP), and middle reaches of the Yangtze River (MRYR). With the BTH region as the center, the distribution of PM<sub>2.5</sub> AM gradually decreased toward the surrounding areas. The areas with low concentrations were mainly observed in the southwest and south regions of China. The PM<sub>2.5</sub> AM in northeast China decreased each year, which was consistent with the general trend for the entire country. Overall, the air quality of the Pearl River Delta (PRD) was better than that of the Yangtze River Delta (YRD). The PM<sub>2.5</sub> AM in the PRD met the GB 3095-2012 standard (35  $\mu\text{g}/\text{m}^3$ ); however, from 2015 to 2017, Foshan and Zhaoqing exceeded the GB 3095-2012 value, whereas the value of Dongguan decreased first, increased next, and later decreased again. A few cities in the YRD met the GB 3095-2012 expectation, with three, four, four, and eight cities meeting the GB 3095-2012 from 2015 to 2018 in the YRD. Through the analysis of the spatiotemporal variations of the PM<sub>2.5</sub> concentrations, we concluded that the PM<sub>2.5</sub> pollution was gradually alleviated from 2015 to 2018 across China and that the number of areas with values below 35  $\mu\text{g}/\text{m}^3$  continued to increase. The lowest PM<sub>2.5</sub> AM was about 15  $\mu\text{g}/\text{m}^3$ . The area of high concentration decreased gradually, and the corresponding range of the PM<sub>2.5</sub> AM also decreased.

### 3.2 Evaluating health losses

The results of the PM<sub>2.5</sub> health loss assessment in China are shown in [Supplementary Table S1](#). From 2015 to 2018, the number of premature deaths in cities with PM<sub>2.5</sub> AM exceeding GB 3095-2012 decreased first, increased next, and decreased again, but the proportion of the total number of deaths decreased annually. The city with the maximum health loss for 2015–2018 was Beijing, the cities with the least health losses for 2015–2016 were Jinchang and Dingxi, and the city with the least health loss for 2017–2018 was Zhongwei.

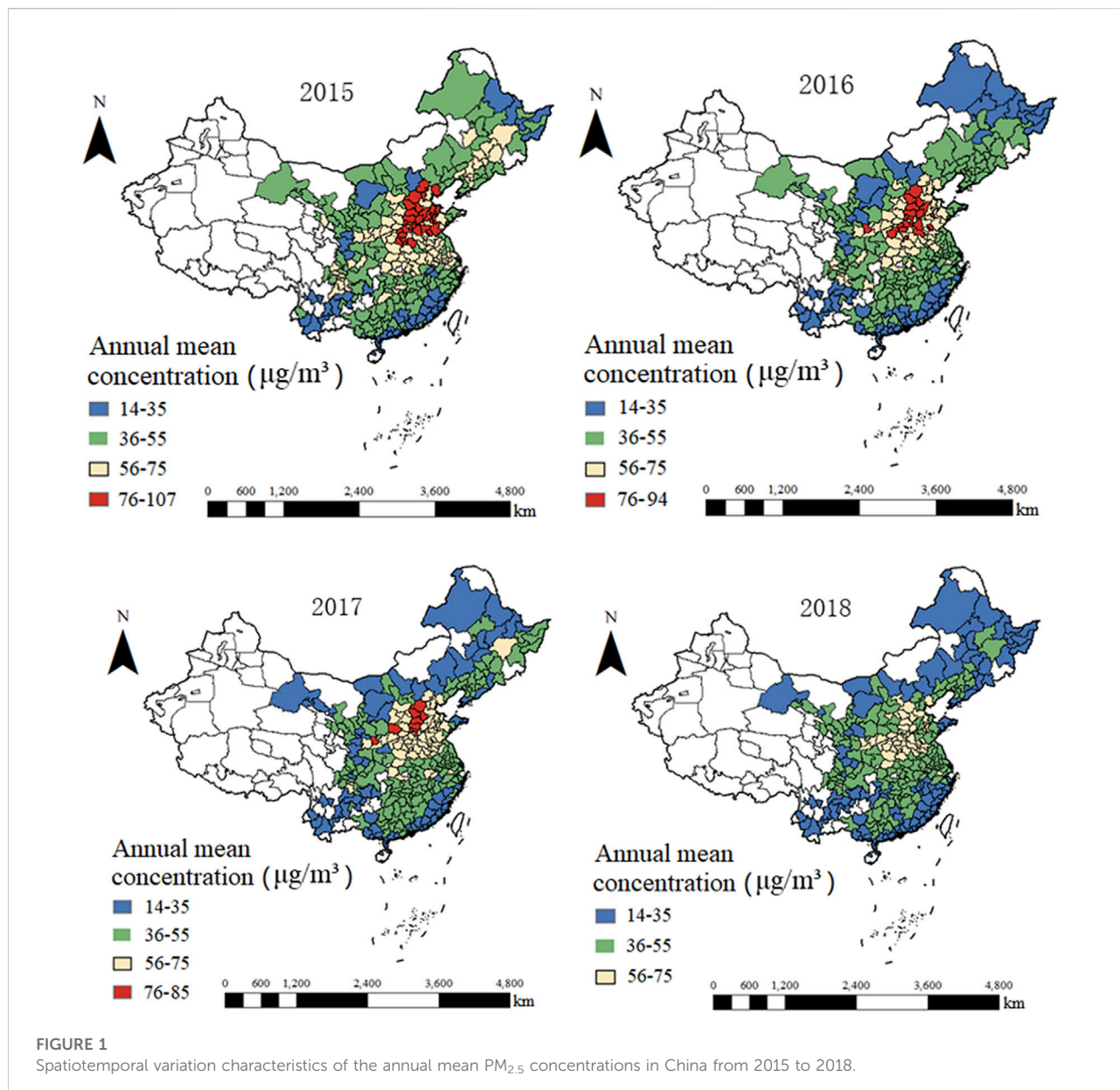


FIGURE 1 Spatiotemporal variation characteristics of the annual mean PM<sub>2.5</sub> concentrations in China from 2015 to 2018.

### 3.3 Evaluating health economic losses using VSL

By monetizing the health loss results based on the VSL, the health economic loss results for China from 2015 to 2018 were 1,410.626, 1,179.159, 1,295.754, and 772.668 billion RMB (1 RMB = 0.1485 USD as on 18 July 2022), respectively, which account for 1.98%, 1.54%, 1.56%, and 0.85% of the GDPs for the corresponding years for the 287 cities. The assessment results of the PM<sub>2.5</sub> health economic losses in key areas for air pollution prevention and control of the Blue Sky Protection Campaign are shown in Table 1. With the exception of the

TABLE 1 PM<sub>2.5</sub> health economic losses in key areas from 2015 to 2018 (unit: billion RMB).

Key areas	2015	2016	2017	2018
BTHSA	443.238	421.681	411.009	281.156
YRD	290.187	208.778	217.353	172.053
FWP	54.868	77.677	83.992	59.278
CC	108.578	114.173	89.676	45.484
MRYR	128.117	103.160	182.936	58.108
PRD	8.132	1.715	4.647	0.241

Chengdu-Chongqing (CC) region, the variation trend of the PM<sub>2.5</sub> health economic loss was similar to the health losses in other key areas, with inconsistencies in the variation range. The PM<sub>2.5</sub> health loss in the CC region decreased, but the health economic losses increased first and then decreased. Except for the PRD, the decline in PM<sub>2.5</sub> health economic losses in other key regions were highest from 2017 to 2018, which was consistent with the period of greatest decline in health losses. The PM<sub>2.5</sub> health economic losses in the PRD decreased sharply in 2015–2016 and 2017–2018 but increased by 1.7 times in 2017 compared with that in 2016. By comparing the evaluation results of the PM<sub>2.5</sub> health and health economic losses, the changes in the PM<sub>2.5</sub> health economic losses were influenced by not only the local PM<sub>2.5</sub> AM and exposed population but also other factors and mechanisms that remain to be explored.

### 3.4 Spatial agglomeration effects

The PM<sub>2.5</sub> AM, PM<sub>2.5</sub>-related health losses, and health economic losses in cities exceeding the standard of 35 µg/m<sup>3</sup> showed spatial agglomeration effects in China from 2015 to 2018. The Moran's I index values for the PM<sub>2.5</sub> AM, health losses, and health economic losses all showed the increasing–decreasing–increasing trend. ArcGIS was used to test the local autocorrelation. The hotspots of PM<sub>2.5</sub> AM from 2015 to 2018 were concentrated mainly in the BTHSA and FWP. In addition, Wuhan, Xiangyang, Jingmen, Xiaogan, and Suizhou of Hubei province showed high–high agglomerations in 2015. The cold spots of PM<sub>2.5</sub> AM were concentrated mainly in southwest and south China, with low–low agglomerations in Zhaoqing, Liuzhou, Guilin, Wuzhou, Guigang, and Baiyin for 2015–2018. These cities had relatively lower PM<sub>2.5</sub> AM and light pollution.

Areas with high PM<sub>2.5</sub> health losses for 2015–2018 were concentrated mainly in the north of the Yangtze River. Although the number of cities with PM<sub>2.5</sub> AM exceeding 35 µg/m<sup>3</sup> decreased annually, the number of cities with high concentrations did not decrease significantly. The difference between the spatiotemporal variation of the PM<sub>2.5</sub> health loss and PM<sub>2.5</sub> AM may be related to the difference in the exposed population and baseline mortality rate. Areas with high PM<sub>2.5</sub> health economic losses for 2015–2018 were concentrated mainly in the north of the Yangtze River, i.e., most cities in Hebei, Henan, and Shandong provinces. The differences among the spatiotemporal variations of the health economic losses, PM<sub>2.5</sub> AM, and health losses may be relevant to the differences in the levels of economic development in these research units.

### 3.5 Analysis of factors driving health economic losses

As the number of cities with PM<sub>2.5</sub> AM values exceeding 35 µg/m<sup>3</sup> decreased gradually, the number of cities included from 2015 to 2018 decreased as 235, 214, 204, and 178, respectively. The missing

values were mainly replaced with the mean values of the corresponding provinces under which the city is included. The stepwise regression method was used to eliminate linear correlations between variables (Yang et al., 2016). The independent variables included in this study were population density (Den\_Pop), GDP, urbanization rate (Urban), proportion of secondary industry (Sec), and industrial sulfur dioxide emissions (SO<sub>2</sub>). Their VIF values were less than 10. Statistical descriptions of the variables used in this study are shown in Supplementary Tables S2–S5. The results of the GWR model are shown in Supplementary Table S6. Supplementary Figures S2–S4 show the distributions of the influences of various driving factors on health economic losses. The spatial distribution of the regression residuals is shown in Supplementary Figure S1; these residuals are randomly distributed in space, which indicates that the residuals follow a normal distribution. There are spatial differences in the impact degrees of each of the variables on PM<sub>2.5</sub>-related health economic losses. Because the regression coefficients of the GDP and SO<sub>2</sub> were too small, empirical results only show the influences of Den\_Pop, Urban, and Sec.

#### 3.5.1 Proportion of secondary industry

Supplementary Figure S2 shows the spatial pattern of the influence of Sec on PM<sub>2.5</sub>-related health economic loss. The Sec values for BTHSA, YRD, and FWP were inversely proportional to the PM<sub>2.5</sub>-related health economic losses. The Sec value for PRD is directly proportional to the PM<sub>2.5</sub>-related health economic loss. For the remaining regions (CC and YRMR), the coefficient directions vary for each year. Thus, the empirical results of the dynamic changes in the different regions serve as a reminder to researchers and decision-makers to further explore the mechanisms of the impact of industrial structure on air pollution, population health, and economy.

#### 3.5.2 Population density

Supplementary Figure S3 shows the spatial pattern of the impact of Den\_pop on PM<sub>2.5</sub>-related health economic loss. From 2015 to 2018, the coefficients of Den\_Pop for BTHSA, FWP, and CC were all positive, indicating that the increase in Den\_Pop contributed to increase in PM<sub>2.5</sub>-related health economic losses. In the YRD, only Wenzhou, Quzhou, Chizhou, Jinhua, Anqing, and Hangzhou had negative coefficients for Den\_Pop in 2017.

#### 3.5.3 Urbanization rate

Supplementary Figure S4 shows the spatial pattern of the influence of Urban on PM<sub>2.5</sub>-related health economic loss. From 2015 to 2018, the coefficients of Urban for BTHSA and MRYR were negative. In the YRD, except for Shaoxing, Hangzhou, and Jiaying, the coefficients for Urban were positive in 2018 and negative for the other years. In the FWP, the coefficient of Urban was negative for all years except in Xi'an, which was positive in 2017 and 2018. In 2015 and 2016, the coefficients of Urban for cities exceeding the 35 µg/m<sup>3</sup> standard in CC were negative. The coefficient changes of Urban for the PRD were strongly similar to those of Den\_Pop.

The following two anomalies were observed in this study and should be discussed further. First, the increase in the proportion of the secondary industry will reduce PM<sub>2.5</sub>-related health economic losses. Some studies have shown that the proportion of the secondary industry had a significant positive impact on the PM<sub>2.5</sub>-related health losses (Fu et al., 2014); this means that the increase in the proportion of the secondary industry will increase the PM<sub>2.5</sub>-related health economic losses, which is contrary to the results of this study. Therefore, the mechanisms of the impact of the industrial structure on air pollution and health economic loss need to be discussed further. Second, the strategy of “increasing the green coverage rates of built-up areas” has no direct impact on improving the PM<sub>2.5</sub> health economic losses. Tong et al. (2015) showed that increasing the green coverage will reduce PM<sub>2.5</sub> concentration and improve health benefits. However, in this study, the green coverage rates of the built-up areas did not directly affect the PM<sub>2.5</sub>-related health economic losses. Hence, it is necessary to conduct in-depth analysis of the influence of the green coverage rates of built-up areas on the health economic levels of the residents in the future.

## 4 Policies

According to the results of this study, the status quo of PM<sub>2.5</sub> control and air pollution control policies in China were combined to propose PM<sub>2.5</sub> control suggestions for different regions. In addition to improving the PM<sub>2.5</sub> health economic loss assessment system, the following key control areas were screened out according to the geographical environment, economic development level, and other factors. Some of the specific governance suggestions are as follows: For the BTHSA and Fenwei Plain, the urbanization rate can be improved to reduce the health economic losses. The YRD region requires attention on the construction of a regional joint prevention and control system. The CC region needs a balanced relationship between population density and urbanization rate, with additional attention in terms of the impacts of economic development, industrial structure, and human resources on local air quality. Subsequent developments to the MRYR region should be focused on finding a balance between economic development and environmental quality. The PRD region requires attention in terms of maintaining air quality.

## 5 Conclusion

The PM<sub>2.5</sub> AM has gradually decreased from 2015 to 2018, and areas with concentrations below 35 µg/m<sup>3</sup> continue to increase; however, the pollution levels still vary in different regions. The Beijing–Tianjin–Hebei and surrounding areas,

Yangtze River Delta, Chengdu–Chongqing region, Middle Reaches of the Yangtze River, and Pearl River Delta are some of the key areas for air pollution prevention and control. The number of PM<sub>2.5</sub>-related premature deaths in 287 cities where exceeded Grade II standards (35 µg/m<sup>3</sup>) were 872035, 702948, 731110 and 414141, respectively, based on the VSL measure. The population distribution, industrial structure, and economic and social development levels accounted for 83%, 83%, 66%, and 74% of the PM<sub>2.5</sub>-related health economic losses over 2015 to 2018, respectively, based on the GWR. Therefore, policy makers should consider the impacts of population distribution, industrial structure, and economic and social development levels on health economic losses when formulating air pollution control policies in the future.

## Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/Supplementary Material.

## Author contributions

JG and XW structured and wrote the manuscript draft. JY, YZ, and SK analyzed the data and conducted descriptive analyses. FL and ZQ reviewed and polished the manuscript. All authors contributed to manuscript revision, reading, and approval of the submitted version.

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## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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## Supplementary material

The Supplementary Material for this article can be found online at <https://www.frontiersin.org/articles/10.3389/fenvs.2022.951505/full#supplementary-material>