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Decrease in the chronic health effects from PM$_{2.5}$ during the 13$^{\text{th}}$ Five-Year Plan in China: Impacts of air pollution control policies

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A B S T R A C T

The Chinese government implemented a series of policies to improve air quality during the Thirteenth Five-Year Plan (13$^{\text{th}}$ FYP). However, the long-term health effects of the 13$^{\text{th}}$ FYP air pollution control policies have not been evaluated, and the outbreak of coronavirus disease 2019 (COVID-19) has brought great uncertainty regarding the evaluation of the effects. In this study, we selected 329 cities in mainland China to study the chronic health effects due to the decrease in fine particulate matter (PM$_{2.5}$) during the 13$^{\text{th}}$ FYP. The relative risk (RR) of PM$_{2.5}$ exposure was obtained from a previous study, and the total premature deaths were calculated. We also applied the grey prediction model to predict the PM$_{2.5}$ concentration in each city in 2020 to evaluate the impacts of COVID-19. The results showed that the annual PM$_{2.5}$ concentration was reduced from 49.7 µg/m$^3$ in 2015 to 33.2 µg/m$^3$ in 2020, and premature deaths were reduced from 1,186,201 (95% CI: 910,339–1,451,102) and 446,415 (in key regions, 95% CI: 343,426–544,813) in 2015 to 997,955 (95% CI: 762,167–1,226,652) and 368,786 (in key regions, 95% CI: 282,114–452,567) in 2020, respectively. A total of 188,246 (95% CI: 148,172–224,450) people avoided premature deaths due to the reduction in PM$_{2.5}$ concentrations from 2015 to 2020. Although the impacts of COVID-19 in 2020 brought a significant reduction of 35.3% in February (14.2 µg/m$^3$, $p < 0.0001$) and in March by 17.6% (5.8 µg/m$^3$, $p = 0.001$), we found that COVID-19 showed few obvious influences on China’s long-term air pollution control plans. The observed data and predicted data are very close in annual mean values and showed no statistical significance both in all cities ($p = 0.98$) and in key regions ($p = 0.56$) in 2020.

1. Introduction

Since the mid-20$^{\text{th}}$ century, the health effects of air pollution have been a global concern. Research has shown that air pollution causes serious harm to human health (Ortu et al., 2017). According to the World Health Organization (WHO) 2016 report, outdoor air pollution exposure has led to 4.2 million deaths a year (WHO, 2016). In China, with the continuous improvement of living standards and the development of a batch of central cities (Yang et al., 2019), people’s demand for a high-quality life is increasing constantly in the 21st century. However, behind vigorous economic development, China is facing extremely serious long-term fine particulate air pollution, which threatens the health of a large number of residents (Wu et al., 2020) in the urban areas. The Global Burden of Disease (GBD) report has shown that the mortality due to fine particulate matter (PM$_{2.5}$) pollution in China reached 1.1 million in 2015 alone, and the risk factor for death ranked first among the world’s leading countries (Cohen et al., 2017).

The research on the health effects of air pollution in developed countries started earlier in Western Europe (Kies, 2006) and the United States (Dominici et al., 2005). As to the PM$_{2.5}$, the earliest and the most essential research so far is the Harvard “Six Cities” study beginning in 1974 (Dockery et al., 1993) and a series of following studies (Daniel et al., 2005; Laden et al., 2006). Though this issue was paid attention later in China, the Chinese government has also recognized the enormous negative health effects from PM$_{2.5}$ and has taken positive measures to improve air quality across the country in recent years. In the earlier years, a series of air pollution control policies were implemented under the construction of phased national development plans (Jin et al., 2016).

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During China’s 12th Five-Year Plan (FYP), the State Council of China issued the “Action Plan of Air Pollution Prevention and Control” (APP-C-AP) in 2013, which included ten specific measures and set specific PM$_{2.5}$ reduction targets (State Council of China, 2013). Based on this, a past study used satellite data to evaluate the effects of this policy and pointed out dramatic decreases in PM$_{2.5}$ (2013 – 4.27 g/m$^2$/year for all China, $p < 0.001$) from 2013 to 2017 (Ma et al., 2019). During this period, several studies have estimated the health effects of air pollution control policies in China. However, most of these studies focused on acute effects without considering the long-term influences in the context policy effects (Chen et al., 2019; Peng et al., 2017) or simply limited to fewer large cities or regions (Li et al., 2013, 2017; Liu et al., 2018; Huang et al., 2018). For instance, some research conducted nationwide time-series analysis in 272 main Chinese cities, their focus is the acute health effects of PM$_{2.5}$ according to daily observed data instead of concentrating on the chronic effects in the long-run (Chen et al., 2019).

In addition, although some research evaluated the health effects after the implementation of APPC-AP during 12th FYP, the research area has not covered most cities in mainland China, one only focused on 31 provincial cities (Liu et al., 2018) and the other just selected 74 leading cities (Huang et al., 2018).

During the 13th FYP, although PM$_{2.5}$ pollution had been greatly reduced since 2013 (Wang et al., 2020a), it is still one of the main air pollution problems in China and is seriously threatening public health. Under this circumstance, the government of China constantly implemented a series of air pollution prevention and control policies. In the 13th FYP on Environmental Protection (2016–2020), it pointed out that we should advance the in-depth implementation of APPC-AP after the mid-term assessment (2015) to drastically reduce particulate matter emissions and achieve a significant reduction in the concentration of PM$_{2.5}$ in cities at prefecture-level across the country. In addition, the newly revised Law on the Prevention and Control of Atmospheric Pollution was put forward in 2016, giving regulations on the objectives, investments, responsibilities, assessments and etc. in order to prevent and control air pollution and safeguard public health. However, according to China’s Eco-Environment Bulletin, by 2018, there were still 217 cities where ambient air quality exceeded standards, which accounted for 64.2%. Among the days with severe pollution, the number of days with PM$_{2.5}$ as the primary pollutant accounted for 60.0%. Therefore, in 2018, the State Council of China further put forward the “Three-year Action Plan to Fight Air Pollution” (TAPPFAP) (State Council of China, 2018) according to the instruction of China’s 13th FYP. In this plan, 80 cities in China were chosen as key regions, and more specific air quality targets were set by taking the pollution levels in 2015 as baseline. This plan explicitly directed that the concentration of PM$_{2.5}$ should be significantly reduced by 18% compared with 2015 situation to significantly improve ambient air quality and brought huge health benefits to the public. As 2020 is the last year of this plan and the last year of China’s 13th FYP, it is necessary to evaluate the reduction of PM$_{2.5}$ concentrations nationally and its chronic health effects. Thus, it could provide a reference for policy-making regarding air pollution control plans at the beginning of China’s 14th FYP.

However, the outbreak of coronavirus disease 2019 (COVID-19), which was caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and first detected in Wuhan, China, in December 2019, is considered a disruptive viral event (Zhou et al., 2020a). To control the transmission of COVID-19, China implemented strict policies to lock down one-third of its cities and to curtail personal mobility and economic activities. Although it is undeniable that these effects of COVID-19 are devastating for the social economy, lockdown interventions resulted in an abrupt reduction in pollution emissions and led to the improvement of air quality in China according to satellite images (NASA, 2020) and empirical research (He et al., 2020). Moreover, this may lead to much uncertainty when evaluating the effects of China’s long-term air control policies in the 13th FYP. Several recent studies have managed to evaluate the short-term impacts of COVID-19 on China’s air quality improvement (Wang et al., 2020b) and its acute health effects during the lockdown period (He et al., 2020; Chen et al., 2020). Additionally, one previous study evaluated both short-term and long-term effects under different predicted scenarios of economic recovery and found that a positive number of long-term, premature fatalities were avoided due to reduced PM$_{2.5}$ concentrations, ranging from 76,400 (95% CI: 62,600–86,900) to 287,000 (95% CI: 233,700–328,300) in China (Giani et al., 2020). However, existing studies lack research under real situations and have not used total-year data to evaluate the long-term effects of COVID-19 in 2020. Thus, the influence of COVID-19 on China’s 13th FYP air pollution control policies is not clear.

Generally, this work focused on the two following research questions. One is how to systematically, comprehensively and accurately assess the health effects of decreasing PM$_{2.5}$ levels during the 13th FYP period and the other is how to identify the impact of the COVID-19 outbreak on the changes in PM$_{2.5}$ concentrations and the implementation of China’s long-term air pollution control policies? In this study, we selected 329 cities in mainland China as study settings to comprehensively estimate the chronic health effects of air pollution control of PM$_{2.5}$ from 2015 to 2020. By comparing empirical data with the predicted results, we also analyzed whether COVID-19 has had a large influence on China’s long-term air pollution control effectiveness. Since China is the largest developing country in the world today and is facing severe problems of particulate pollution, analyzing the effects of China’s air pollution control policies will not only assist the Chinese government in adjusting and implementing 14th FYP pollution prevention and control policies, but also inspire countries around the world facing serious pollution by PM$_{2.5}$, particularly those in development. Moreover, as China’s policy implements and control effectiveness in response to COVID-19 are unique in the world, there is a particular need to eliminate the impact of the sudden epidemic on changes in PM$_{2.5}$ concentrations.

### Table 1

General characteristics of population, mortality rate and PM$_{2.5}$ concentrations of 329 cities.

|                | Mean | Min  | 25th | 50th | 75th | Max  |
|----------------|------|------|------|------|------|------|
| Population size ($10^7$) |      |      |      |      |      |      |
| 2015           | 4108.0 | 200.0 | 2157.0 | 3401.0 | 3127.0 | 30170.0 |
| 2016           | 4132.0 | 204.0 | 2162.0 | 3382.0 | 3535.0 | 30480.0 |
| 2017           | 4153.2 | 206.0 | 2172.0 | 3577.0 | 3527.0 | 36750.0 |
| 2018           | 4184.9 | 208.0 | 2172.0 | 3392.0 | 2597.0 | 31020.0 |
| 2019           | 4217.9 | 212.0 | 2180.0 | 3398.0 | 2578.0 | 31243.0 |
| 2020           | 4248.3 | 214.0 | 2200.0 | 3407.0 | 5401.0 | 31518.0 |
| Total mortality rate (%) |      |      |      |      |      |      |
| 2015           | 6.2 | 1.3 | 5.5 | 6.2 | 6.8 | 15.5 |
| 2016           | 6.0 | 1.3 | 5.2 | 6.0 | 6.7 | 15.9 |
| 2017           | 7.8 | 1.4 | 5.8 | 6.6 | 7.7 | 22.6 |
| 2018           | 6.2 | 0.4 | 5.4 | 6.3 | 7.0 | 11.8 |
| 2019           | 6.1 | 1.4 | 5.3 | 6.2 | 6.9 | 13.1 |
| 2020           | 6.5 | 1.4 | 5.7 | 6.4 | 7.1 | 12.1 |
| PM$_{2.5}$ (g/m$^2$) |      |      |      |      |      |      |
| 2015           | 49.7 | 12.9 | 36.8 | 48.3 | 59.2 | 112.3 |
| 2016           | 46.3 | 12.7 | 33.8 | 44.2 | 55.8 | 157.2 |
| 2017           | 42.2 | 10.1 | 31.8 | 41.7 | 51.5 | 154.9 |
| 2018           | 34.8 | 8.3 | 26.0 | 33.3 | 41.1 | 67.3 |
| 2019           | 36.8 | 6.6 | 27.2 | 35.1 | 45.4 | 88.6 |
| 2020           | 33.2 | 6.2 | 24.3 | 32.3 | 41.1 | 82.8 |

### 2. Data and methods

#### 2.1 Study settings

We selected 329 cities in mainland China as study settings because we could obtain data on both daily PM$_{2.5}$ concentrations from 2016 to 2020 and population sizes from 2016 to 2019 for the cities. We also collected data in 2015 as a reference before China’s 13th Five-Year Plan. In particular, we focused on 80 cities in the key regions included in
China’s latest TAPFAP.

2.2. Data

2.2.1. Ground PM_{2.5} data

The daily average concentrations of PM_{2.5} in all 329 cities in mainland China were collected from the China National Environmental Monitoring Center (http://www.cnemc.cn/) from 2015 to 2020. Then, the monthly and annual average concentrations of air pollutants in each city were calculated.

2.2.2. Population and mortality data

The annual average population size and mortality rate from 2015 to 2019 of each city were collected from the Statistical Yearbook or Statistical Bureau of each city, and a few missing values of mortality rate were replaced by the values of the province where the city is located. As there is a certain lag in statistical publicity, some population and mortality data were predicted in 2019 and 2020.

2.2.3. Basic characteristics of population, mortality and pollution data

Table 1 shows the basic characteristics of the studied cities. Except for a few cities lacking official data, more than 98% of cities in mainland China and a total of more than 99% of China’s population are included. The average population sizes of the 329 cities from 2015 to 2020 were 4108.0, 4132.0, 4159.2, 4184.9, 4217.9, and 4248.3 thousand, and the average total mortality rates were 6.2‰, 6.0‰, 7.8‰, 6.2‰, 6.1‰, and 6.5‰, respectively.

2.3. Estimations of long-term health effects

To estimate the chronic health effects of air quality improvement, we applied a widely used function to compute annual premature deaths caused by PM_{2.5} exposure as follows (Chen et al., 2013; Liu et al., 2017):

\[
E_{it} = \left(1 - \frac{1}{RR_{it}}\right) \cdot E_{0it} \cdot Pop_{it} = AF_{it} \cdot E_{0it} \cdot Pop_{it}
\]

where \(i\) denotes each city and \(t\) denotes each year; \(E_{it}\) denotes the number of premature deaths; \(AF_{it}\) denotes the fraction of the disease burden attributed to PM_{2.5}; \(E_{0it}\) denotes the population’s all-age annual average mortality rate; \(Pop_{it}\) denotes the all-age total population size; and \(RR_{it}\) denotes the relative risk of premature mortality due to PM_{2.5} exposure, which is obtained from the previous Global Exposure Mortality Model (GEMM) (Chen et al., 2018) and closely related with PM_{2.5} exposure concentrations. We estimated RR as follows:

\[
RR = \exp \left\{ \theta \cdot \log \left( \frac{z}{a + 1} \right) \cdot \frac{1}{1 + \exp \left( \frac{-z}{\gamma} \right)} \right\}, \quad z = \max(0, PM_{2.5} - cf)
\]

where all parameters are obtained from the previous literature (Chen et al., 2018); \(\theta = 0.1430, \alpha = 1.6, \mu = 15.5, \gamma = 36.8, \) and \(cf = 2.4 \mu g/m^3\).

2.4. Estimation of COVID-19 impacts in 2020

To evaluate the real chronic effects of China’s long-term air pollution control plan, it is necessary to exclude COVID-19 effects in 2020. One possible solution is to predict the air pollutant concentration in each city in 2020 according to annual data in the past several years as a normal condition and then compare the difference between the data and real annual data in 2020. Considering the advantages of grey prediction theory in small sample prediction (Wu et al., 2013a, 2013b), it has been used to predict air quality indicators with limited original data and few samples (Zhou et al., 2020b; Wu et al., 2018; Chen and Pai, 2015). In this paper, the GM(1,1) model can be described as follows:

Step 1: Assume a nonnegative sequence \(X^{(0)} = (X^{(0)}(1), X^{(0)}(2) \ldots \ldots X^{(0)}(n))\), the one order accumulation sequence is

\[
X^{(1)}(k) = \sum_{i=1}^{k} X^{(0)}(i), \quad k = 1, 2, 3, \ldots n
\]

Step 2: Since the sum-of-squares of errors is minimized by least-square estimation, the parameters are obtained as follows:

\[
\left[ \frac{\hat{a}}{\hat{b}} \right] = (B^T B)^{-1} B^T Y
\]

where

\[
B = \begin{bmatrix}
-\frac{1}{2} X^{(1)}(1) + X^{(1)}(2) \\
-\frac{1}{2} X^{(1)}(2) + X^{(1)}(3) \\
\cdot \\
-\frac{1}{2} X^{(1)}(n) + X^{(1)}(n) \\
\end{bmatrix}, \quad Y = \begin{bmatrix}
X^{(1)}(2) \\
X^{(1)}(3) \\
\cdot \\
X^{(1)}(n) \\
\end{bmatrix}
\]

Step 3: Substitute \(\hat{a}\) and \(\hat{b}\) into the time-response function:

\[
X^{(1)}(k) = \left( X^{(0)}(1) - \frac{\hat{a}}{\hat{b}} \right) e^{-\frac{k-1}{\hat{b}}} + \frac{\hat{a}}{\hat{b}}
\]

Then, we obtain \(\hat{X}^{(1)}(1), \hat{X}^{(1)}(2)\ldots\)

Step 4: By using the one-order inverse accumulated generating operator in

\[
X^{(1)}(i) = \left\{ \hat{X}^{(1)}(1), \hat{X}^{(1)}(2) \ldots \hat{X}^{(1)}(n) \right\}
\]

We can then obtain the sequence

\[
d^{(i)}X^{(0)} = \left\{ d^{(i)}\hat{X}^{(0)}(1), d^{(i)}\hat{X}^{(0)}(2), \ldots d^{(i)}\hat{X}^{(0)}(n), d^{(i)}\hat{X}^{(0)}(n+1) \right\}
\]

Thus, the fitting values are \(\hat{X}^{(0)}(1), \hat{X}^{(0)}(2), \ldots \hat{X}^{(0)}(n)\), and the predicting values are

\[
\hat{X}^{(0)}(n+1), \hat{X}^{(0)}(n+2), \ldots
\]

Step 5: As the sequence of residuals \(e^{(0)} = \left\{ e^{(0)}(1), \ldots \right\} = \left\{ X^{(0)}(1) - \hat{X}^{(0)}(1), \ldots \right\}\), we used capability index C and probability of small error P to estimate the prediction outcome:

\[
C = \frac{S_1}{S_2} \quad \text{and} \quad P = \text{Probability} \left( |e(k) - \bar{X}| < 0.6745S_1 \right)
\]

where, \(S_1^2 = \frac{1}{n} \sum_{k=1}^{n} (X^{(0)}(k) - \bar{X})^2\), \(S_2^2 = \frac{1}{n} \sum_{k=1}^{n} (e^{(0)}(k) - \bar{X})^2\).
In this paper, $X^{(0)}(i)$ denotes the annual population data and the concentration of PM$_{2.5}$ in each city in year $i$. $n$ equals 4 denoting the number of years from 2016 to 2019 when $X^{(0)}(n+1)$ is predicted denoting the predictable values of 2020, and $n$ equals 4 denoting the number of years from 2015 to 2018 when $X^{(0)}(n+1)$ is predicted denoting the predictable values of 2019 as a validation. Table 2 shows the annual GM(1,1) prediction results in all cities.

Generally, more than 99% of the results of the GM(1,1) prediction are qualified and we suppose the prediction effectiveness is fine. We then suppose these prediction data as the PM$_{2.5}$ concentrations in 2020 under the constant PM$_{2.5}$ declining trend in the 13th FYP, so that they could be compared with observed data in 2020. As to few unqualified prediction results, it showed that data fluctuated widely from 2016 to 2019 and showed no obvious trend, and we used the mean value from 2016 to 2019 as a substitution. Given that the number of unqualified prediction results is quite small, this would not have a big influence on the outcome.

![Fig. 1. Validation results for the grey prediction model using annual data from 2015 to 2018 and observed data in 2019 in all 329 cities (a) and 325 cities excluding four anomalous cities (b).](image1)

![Fig. 2. Annual average PM$_{2.5}$ concentrations in the 329 cities of China from 2015 to 2020. The shaded areas denote the lack of consistent PM$_{2.5}$ concentration data or population data from 2015 to 2020.](image2)
3. Results

3.1. Validation of GM predictions

We used annually observed data from 2015 to 2018 to predict data in 2019 and compared the outcome with observed data in 2019 in all 329 cities. The validation results are shown in Fig. 1. The predicted concentration has a clear correlation with the observed data. The adjusted $R^2$ value of all 329 cities is 0.65, and after deleting four anomalous cities in the Xinjiang autonomous region (with a large fluctuation in the last 5 years), the adjusted $R^2$ value of a total of 325 cities is 0.79. Overall, the annually predicted data showed good performance, and it is suitable to apply this approach to predict the assumed PM$_{2.5}$ concentrations in 2020.

3.2. The trend of PM$_{2.5}$ concentrations

The concentrations of ambient PM$_{2.5}$ decreased from 2015 to 2020 and reached a relatively lower level beginning in 2018 in most cities, though the decreasing trend since 2018 slowed down and even showed a slight fluctuation from 2018 to 2019 (Fig. 2 and Fig. 3). The annual published data in China’s Eco-Environment Bulletin also showed the same trend. Although the national average PM$_{2.5}$ concentration in 2018 and 2019 was the same (36 μg/m$^3$), the number of days when the PM$_{2.5}$ concentration exceeded the standard was 0.2% increasing in all 337 cities (Ministry of Ecological Environment, 2020). The difference between our calculated outcome and the ones in bulletins may be caused by missing data in a few cities and accidental error in the process of calculating mean values. After considering the 95% confidence interval, our calculated annual average data are consistent with the data published in China’s Eco-Environment Bulletin from 2015 to 2020. We further observed that the mean concentrations of PM$_{2.5}$ in the key regions were significantly higher than those in general. Furthermore, the decline in ambient PM$_{2.5}$ concentrations (average 22.4 vs 16.5 μg/m$^3$) in the key regions is very large (Fig. 3).

3.3. Health effects of the PM$_{2.5}$ reduction from 2015 to 2020

The results showed that the annual PM$_{2.5}$ concentrations were reduced from 49.7 μg/m$^3$ in 2015 to 33.2 μg/m$^3$ in 2020, and premature
regions) in 2015 to 37 (12 in key regions) in 2020. In addition, the number of cities whose rate of annual average mortality caused by PM exposure that is less than 0.50 has decreased from 86 (31 in key regions) in 2015 to 61 (2 in key regions) in 2020. We observed obvious spatial variations in the mortality rates among all cities and a decreasing trend nationally. Although PM$_{2.5}$ concentrations are still above the guidelines and have led to huge mortality in China until 2020, the annual average concentrations of PM$_{2.5}$ in all cities were very close to the observed data and showed no statistical significance (t-value $= -0.02$, p-value $= 0.98$). In key regions, the predicted value is slightly higher than the real situation, though the difference is small and shows no statistical significance (t-value $= -0.58$, p-value $= 0.56$). Additionally, the predicted value is even slightly lower in other cities.

### 4. Discussion

In this study, we showed the changes in PM$_{2.5}$ concentrations from 2015 to 2020, and then we further assessed the mortality rates attributed to PM$_{2.5}$ pollution during the 13th FYP in 329 cities in China. To our knowledge, this is the first study comprehensively assessing the chronic health effects of PM$_{2.5}$ reduction based on empirical data at the city level across the 13th FYP period at the national level. We observed that the annual average concentrations of PM$_{2.5}$ showed a significant reduction in the 13th FYP. The reduction from 2015 to 2018 is obvious due to China’s APPC-AP, which is consistent with a previous study (Zhai et al., 2019). In particular, cities in the key regions showed greater reduction (Yu et al., 2020; Zhao and Xu, 2019) because the government adopted more stringent measures and greater capital investment both in APPC-AP from 2013 to 2017 and TAPFAP from 2018 to 2020.

We further assessed the accumulated mortality rates attributed to the air pollutant changes during the 13th FYP. Regarding the health benefits caused by the improvement of PM$_{2.5}$ pollution, previous studies have pointed out that a three-year (2013–2015) reduction in PM$_{2.5}$ concentration levels in 31 provincial capitals was expected to reduce deaths by approximately 120,000 people (Liu et al., 2018). By analyzing the relationship between levels of air pollutants and the causes of death in
74 key cities across the country, the Peking University team conducted a research study and found that this reduced the number of deaths by 47,000 in 2017 as air quality improved (Huang et al., 2018). Our study expanded the study area to a total of 329 cities in China and lengthened the study time from 2015 to 2020. This further illustrated the huge health benefits attributed to recent air pollution control plans implemented by the Chinese government in the 13th FYP. Under the guidance of constant implemented APPC-AP (2013–2017) and TAPFAP (2018–2020) and the targeted instruction of 13th FYP on Environmental Protection (2016–2020), 188,246 (95% CI: 148,172–224,450) people avoided premature deaths due to the reduction of PM$_{2.5}$ concentrations by 33.2% compared to 2015.

Furthermore, as our research covered almost all cities in China and all 80 cities within the key regions, it is clear to compare the spatial difference of accumulated health benefits from 2015 to 2020 and the difference between cities within and without key regions. It is obvious that the air pollutant concentration showed larger changes and had greater effects on the mortality rate in the 80 cities within the key regions. Fig. 2 shows the reduction of PM$_{2.5}$ concentrations in cities in the Beijing-Tianjin-Hebei Regions and nearby areas. The concentrations in the Yangtze River Delta and the Pearl River Delta have also decreased sharply since 2015, meeting the goal set by 13th FYP on Environmental Protection (2016–2020). Additionally, cities in the Fen-Wei Region still suffered serious pollution in 2018, which is why the Chinese government included these cities first in the TAPFAP in 2018. It is noticeable that the reduction of PM$_{2.5}$ concentrations in key regions is more significant (Fig. 3) and brought 77,629 (95% CI: 61,312–92,246) avoided premature deaths, accounting for more than 40% of the total. This all showed the effectiveness of China’s air pollution control policies implemented in the 13th FYP, especially the focus on key regions.

The outbreak of COVID-19 may have influenced the evaluation of air control policies during China’s 13th FYP. Some previous studies have demonstrated the short-term health implications of improvements in air quality in China using measured PM$_{2.5}$ data (Chen et al., 2020) and comparing PM$_{2.5}$ concentrations between lockdown and non-lockdown cities (He et al., 2020), the 2020 situation and 2019 baselines (Wang et al., 2020c; Zheng et al., 2020). Here, we expanded this analysis based on 12 months of air quality data in 325 Chinese cities (excluding four anomalous cities with large fluctuations after data validation) and compared the chronic health effects under the COVID-19 situation and normal conditions. The comparison between the annual predicted data and observed data showed no significant difference, though the reduction reached approximately 9.8% and 13.5% in comparison with the annual average data in 2019, respectively.

One possible explanation is that COVID-19 influenced only limited sources of PM$_{2.5}$. Previous research has concluded that China’s primary PM$_{2.5}$ sources include vehicular exhaust, coal combustion, industry, road dust, and biomass burning (Zheng et al., 2017). The COVID-19 pandemic and lockdown policies curbed transportation, which reduced traffic sources (Chen et al., 2020). However, unfavorable meteorological conditions offset the benefits from the reduction of emissions in some areas, especially in northern China, and extreme particulate matter levels simultaneously occurred during COVID-19 (Le et al., 2020, Wang et al., 2020b). Generally, COVID-19 may have led to some obvious regional reduction; whereas the nationwide effect was not significant.

Another more important explanation is that our research focused on a longer time scale. To better explain this, we conducted monthly predictions based on monthly average data in 325 fine-predicted cities. Table 3 shows the predicted results in all 325 cities, and Fig. 7 shows the validation results in 2019. Although the predicted performance is slightly worse (adjusted R$^2$ equals 0.66) than the prediction conducted from annual data, it could still reflect the general situation in each month in China.

According to monthly data, Figs. 8 and 10 show a reduction of 14.2 μg/m$^3$ between the predicted data and real data in February (t-value = −15.87, p-value < 0.0001), which showed a consistent significant reduction during the COVID-19 lockdown in most cities in China (Giani et al., 2020; He et al., 2020, Wang et al., 2020a). However, the gap between the predicted data and observed data decreased in March (5.8 μg/m$^3$ decrease, t-value = −3.30, p-value = 0.0010) (Figs. 9 and 10), and since then, the differences in the following eight months were slight (Fig. 10) because the pandemic has been successfully controlled in China in the short term and the economy and people’s lives have quickly returned to normal (Zhang et al., 2020). Furthermore, it has been pointed out that around the world, including in New York, PM$_{2.5}$ levels dropped significantly during the pandemic lockdown and rose again.

| Variable       | January 2019 | February 2019 | March 2019 | April 2019 | May 2019 | June 2019 | July 2019 | August 2019 | September 2019 | October 2019 | November 2019 | December 2019 | January 2020 | February 2020 | March 2020 | April 2020 | May 2020 | June 2020 | July 2020 | August 2020 | September 2020 | October 2020 | November 2020 | December 2020 | Total Sample |
|----------------|-------------|--------------|-----------|------------|----------|-----------|-----------|-------------|----------------|-------------|--------------|--------------|-------------|-------------|-----------|-----------|----------|-----------|----------|--------------|--------------|--------------|--------------|-------------|
| January 2019   | 170         | 76           | 69        | 10         | 325      |
| February 2019  | 210         | 66           | 39        | 10         | 325      |
| March 2019     | 236         | 43           | 37        | 8          | 324      |
| April 2019     | 241         | 38           | 38        | 8          | 325      |
| May 2019       | 240         | 54           | 23        | 6          | 323      |
| June 2019      | 230         | 50           | 34        | 9          | 323      |
| July 2019      | 246         | 52           | 23        | 4          | 325      |
| August 2019    | 245         | 44           | 29        | 7          | 325      |
| September 2019 | 245         | 37           | 35        | 8          | 325      |
| October 2019   | 245         | 41           | 27        | 10         | 325      |
| November 2019  | 170         | 84           | 65        | 6          | 325      |
| December 2019  | 239         | 64           | 22        | 0          | 325      |
| Total          | 2717        | 649          | 71        | 8          | 3893     |

*Perfect means C<0.35 and P>0.95; fine means C<0.50 and P>0.80; qualified means C<0.65 and P>0.70; and unqualified means C<0.80 and P<0.60.*
Fig. 8. The comparison between the monthly predicted situation and the real situation in February 2020. The areas with shading denote the lack of consistent PM$_{2.5}$ concentration data or population data from 2015 to 2020 or with poor prediction outcomes.

Fig. 9. The comparison between the monthly predicted situation and the real situation in March 2020. The areas with shading denote the lack of consistent PM$_{2.5}$ concentration data or population data from 2015 to 2020, or with poor prediction outcomes.

Fig. 10. The comparison of pollutant concentrations between the real situation in 2019 and 2020 and the monthly predicted situation in 2020.
When a sense of normalcy resumed (Jackson, 2020). Additionally, several past studies have shown that the pollution level and emissions rebounded after COVID-19 (Zheng et al., 2020); thus, the reduction level may not be as large as expected because of the restart of economic activities (Liu et al., 2020). This could explain why the real concentrations in some months are even slightly higher than the predicted concentrations since April, offsetting the reduction in February and March during lockdown. Therefore, the influence of COVID-19 is not large enough in China’s long-term PM$_{2.5}$ pollution control. However, regardless of the predicted situation or real situation, the reduction in PM$_{2.5}$ concentrations between 2019 and 2020 is obvious (Fig. 10), indicating the effectiveness of TAPFAP in the 13th FYP.

Regarding key regions, Figs. 8 and 9 show that the real data are lower than the predicted data, indicating that the COVID-19 pandemic contributed more to the PM$_{2.5}$ improvement in key regions than in other cities in China. Fig. 11 shows that the reduction in key regions in February and March were extremely significant ($30.2 \mu g/m^3$ and $9.6 \mu g/m^3$ respectively). Some previous studies have also proved that. For instance, one study found that the total number of avoided premature deaths associated with PM$_{2.5}$ reduction during the lockdown was estimated to be 42.4 thousand over the Yangtze-River-Delta region, with Shanghai, Wenzhou, Suzhou, Nanjing, and Nantong being the top five cities with the largest health benefits (Huang et al., 2020).

One limitation of this study is that some mortality data were estimated according to provincial data because few cities have not published them, which may cause some overestimation or underestimation when calculating the deaths and mortality rate. Second, the RR values in the GEMM model were usually age 25 years and over (Chen et al., 2018). However, as the long-term detailed population structure in China is not available, we used the aggregated all-age data instead. Though this may lead to some bias, it is acceptable because these baseline mortalities mostly occurred in adults according to the National Health and Family Planning Commission of China (NHFPCC). Additionally, due to fluctuations in PM$_{2.5}$ concentrations, the predicted values in some cities are not significant enough, which may cause uncertainty in the final analysis. Last, our prediction outcomes were not able to explain the influence of meteorological factors on PM$_{2.5}$ concentrations in different years, which may enlarge or shrink the effects of policies.

5. Conclusions

The present study provides evidence that PM$_{2.5}$ pollution in China is still causing serious health effects for the people in China, on the basis, this paper expanded the study area to 329 cities in China and calculated the most recent mortality benefits between 2015 and 2020 according to GEMM method. Due to the effective national control policies, the significant reduction during the 13th FYP in China may have led to substantial mortality benefits to the public, and these impacts are particularly obvious in 80 cities in key regions. In reference to most studies which focusing on short-term effects of COVID-19 in 2020, this paper applied GM(1,1) model to assess its impacts in the long-run in the context of China’s long-term PM$_{2.5}$ reduction trend. We found that COVID-19 generally showed no significant influence on China’s air pollution control, while it brought a significant reduction in PM$_{2.5}$ concentrations in the short term, and these effects were more obvious in the cities within the key regions. Generally, China’s constant air pollution control policies made great contributions on the reduction of PM$_{2.5}$ concentrations and the outbreak of COVID-19 showed no significant impacts on this trend. After the epidemic and normalized 14th FYP period, Chinese government should consistently set up specific air pollution control targets and make positive measures to continually improve air quality to better safeguard public health and achieve new long-run “Clean China” goals in 2035 under the guidance of phased Five-year National Environmental Protection plans.

CRediT authorship contribution statement

Wangjinyu Shi: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Visualization. Jun Bi: Methodology, Writing – review & editing, Project administration, Funding acquisition. Riyang Liu: Data curation, Validation. Miaomiao Liu: Supervision, Methodology, Writing – review & editing. Zongwei Ma: Supervision, Conceptualization, Methodology, Writing – review & editing.

Declaration of competing interest

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

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