Long-term health impact of $PM_{2.5}$ under whole-year COVID-19 lockdown in China[☆]

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ABSTRACT

The health impact of changes in particulate matter with an aerodynamic diameter <2.5 μm ($PM_{2.5}$) pollution associated with the COVID-19 lockdown has aroused great interest, but the estimation of the long-term health effects is difficult because of the lack of an annual mean air pollutant concentration under a whole-year lockdown scenario. We employed a time series decomposition method to predict the monthly $PM_{2.5}$ concentrations in urban cities under permanent lockdown in 2020. The premature mortality attributable to long-term exposure to ambient $PM_{2.5}$ was quantified by the risk factor model from the latest epidemiological studies. Under a whole-year lockdown scenario, annual mean $PM_{2.5}$ concentrations in cites ranged from 5.4 to 68.0 μg m^{-3}, and the national mean concentration was reduced by 32.2% compared to the 2015–2019 mean. The Global Exposure Mortality Model estimated that 837.3 (95% CI: 699.8–968.4) thousand people in Chinese cities would die prematurely from illnesses attributable to long-term exposure to ambient $PM_{2.5}$. Compared to 2015–2019 mean levels, 140.2 (95% CI: 122.2–156.0) thousand premature deaths (14.4% of the annual mean deaths from 2015 to 2019) attributable to long-term exposure to $PM_{2.5}$ were avoided. Because $PM_{2.5}$ concentrations were still high under the whole-year lockdown scenario, the health benefit is limited, indicating that continuous emission-cutting efforts are required to reduce the health risks of air pollution. Since a similar scenario may be achieved through promotion of electric vehicles and the innovation of industrial technology in the future, the estimated long-term health impact under the whole year lockdown scenario can establish an emission–air quality–health impact linkage and provide guidance for future emission control strategies from a health protection perspective.

1. Introduction

By March 2021, coronavirus disease 2019 (COVID-19) had swept across 223 countries and territories, becoming a global pandemic and causing more than 4.33 million deaths globally (https://www.who.int/emergencies/diseases/novel-coronavirus-2019, last access on 16 August 2021). Governments around the world have implemented prevention and control measures to reduce COVID-19 infections, such as the modification of consumption patterns, restrictions on large public gatherings, and even the lockdown of cities (Feng et al., 2020; Wu and McGoogan, 2020). Inadvertently, these drastic reductions in human activities caused unprecedented reductions in global emissions of greenhouse gas (Le Quéré et al., 2020) and air pollutants (Chauhan and Singh, 2020).

The effects of the lockdown on air pollution in China have been widely reported in previous studies. It was estimated that emissions of

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sulfur dioxide, nitrogen oxide, carbon monoxide, non-methane volatile organic compounds, and primary $PM_{2.5}$ (particulate matter with an aerodynamic diameter <2.5 μm) decreased by 24–36% in February 2020 compared to the same month in 2019, and industry and transportation were dominant contributors (Zheng et al., 2021). Satellite observation revealed an approximately 40% decrease in averaged nitrogen dioxide (NO_2) column over 16 Chinese cities (Bauwens et al., 2020), and the surface NO_2 concentration dropped dramatically by approximately 60% in northern China, with slightly lower reductions in carbon monoxide and sulfur dioxide (Shi and Brasseur, 2020). The surface $PM_{2.5}$ concentration decreased by approximately 35% in northern China during the lockdown relative to that in the same period in 2019 (Shi and Brasseur, 2020). The lockdown can be considered as an ideal experiment about the air pollution mitigation that can be achieved through cutting traffic and industrial emissions, and therefore, investigating the associated health impact is worthwhile.

Exposure to ambient $PM_{2.5}$, which partly contributes to the mortality rates from nonaccidental and cause-specific diseases, poses a serious public health hazard (Akhbarizadeh et al., 2021; Al-Hemoud et al., 2019; Cohen et al., 2017; Cooke et al., 2007; Faraji Ghasemi et al., 2020). Long-term exposure to ambient $PM_{2.5}$ is the fourth leading risk factor for mortality in the Chinese population (Yang et al., 2013) and led to 1255.4 thousand premature deaths in 2010 (Xie et al., 2016). The sudden reduction in $PM_{2.5}$ concentrations during the quarantine period between February 10 and March 14, 2020 prevented a total of 3214 premature deaths (95% CI: 2340–4087) in 367 Chinese cities (Chen et al., 2020). It is estimated that 24.2 (95% CI: 22.4–26.0) thousand

premature deaths were averted in China between February 1 and March 31 (Giani et al., 2020b). However, the reduced rate of mortality from long-term exposure to $PM_{2.5}$ caused by this unprecedented decline in its concentration was limited and challenged by the following: 1) the COVID-19 lockdown was a short-term emergency, which did not cover the whole year in China; and 2) emissions quickly rebounded to pre-pandemic levels in response to the fast economic recovery (Zheng et al., 2020).

This study aimed to investigate to possible extent of the long-term health impacts due to the unprecedented reduction in anthropogenic emissions during lockdown. We used observational data of $PM_{2.5}$ collected at more than 1500 monitoring sites from 2015 to 2020 and a time series decomposition approach to predict the annual mean $PM_{2.5}$ concentrations in 2020, assuming that the pandemic restrictions persisted throughout the whole of 2020. The premature mortality rates associated with long-term exposure to ambient $PM_{2.5}$ under this scenario were estimated. Our result could establish an emission–air quality–health impact linkage, providing guidance for future emission control strategies from a health protection perspective.

2. Methods

2.1. p.m.2.5 observations and population data

The observational data for $PM_{2.5}$ from January 2015 to March 2020 were obtained from the Chinese Ministry of Ecology and Environment website (http://106.37.208.233:20035/). To ensure the continuity and
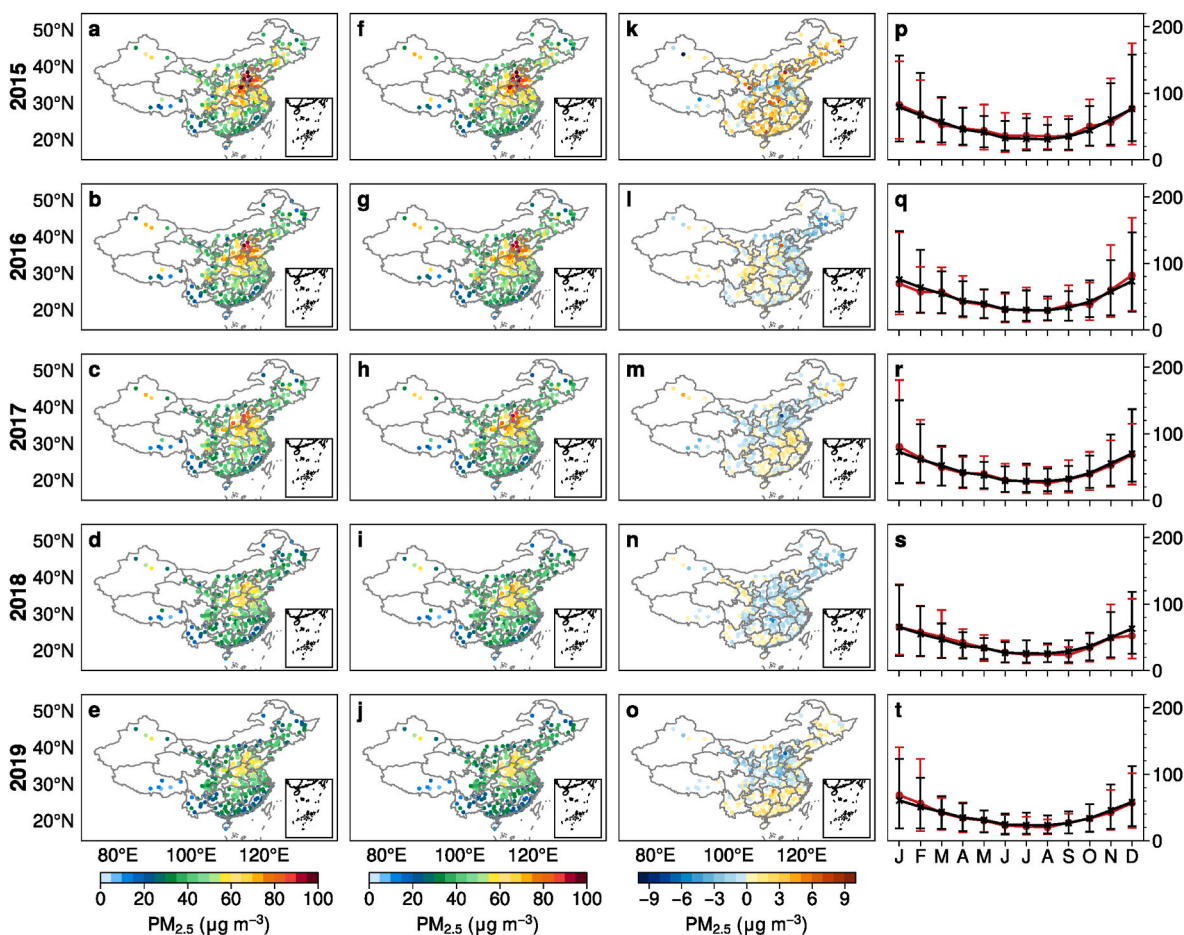

Fig. 1. Spatial distribution of observed surface $PM_{2.5}$ concentrations (leftmost column; unit: μg m^{-3}), reconstructed surface $PM_{2.5}$ concentrations (the second column; unit: μg m^{-3}), and differences between the observed data and reconstructed data (the third column; unit: μg m^{-3}) from 2015–2019. Rightmost column shows the seasonal variations in the urban $PM_{2.5}$ concentrations over China obtained from observed (red) and reconstructed (black) data; data points show the mean values for urban $PM_{2.5}$ concentrations, and error bars show the upper (2.5%) and lower (97.5%) quartiles.

availability of the data, the daily average $PM_{2.5}$ was preprocessed as described in a previous study (Li et al., 2019). The annual average urban population data for 2015–2018 were obtained from the China City Statistical Yearbook 2016–2019. Because of data availability, the urban populations during 2019–2020 were the same as those in 2018. The 295 prefecture-level cities with both $PM_{2.5}$ observations and populations are shown in Fig. 1a.

2.2. Time series decomposition

A time series can usually be split into four components (trends, cycles, seasonality, and remainder) to improve its predictive accuracy. We used a multiplicative decomposition because there is an obvious seasonal cycle in the $PM_{2.5}$ concentrations, which varies with the level of the time series. This was written as (Hyndman, 2018):

$$C_t = T_t \times CY_t \times S_t \times R_t \tag{1}$$

where C_t is the monthly $PM_{2.5}$ concentration data for one city; T_t is the trend component; CY_t is the cycle component; S_t is the seasonal component; and R_t is the remainder component. To obtain these components, a classical method of time series decomposition was used:

(i) The moving average of order m (MA_t) was calculated. In the first step, we used a moving average method to estimate the trend-cycle component ($T_t \times CY_t$), a moving average of order m (m = 12 for monthly data), which can be written as:

$$MA_t = \frac{1}{m} \sum_{j=-\frac{m}{2}}^{\frac{m}{2}} C_{t+j} \tag{2}$$

Using the average eliminates the seasonal variability and randomness in the data, leaving a smooth trend-cycle component.

(ii) In the second step, we estimated the seasonal component and remainder component ($S_t \times R_t$) for each month, as:

$$S_t \times R_t = \frac{C_t}{MA_t} \tag{3}$$

These values were then adjusted to ensure that the seasonal components of each summed to m (m = 12 for monthly data).

(iii) In the third step, we estimated a smooth seasonal component for each month. Because of the occasionality, randomness, and disturbance around the value 0 for the remainder component, $\widehat{S_t}$ can be calculated as the average of $S_t \times R_t$ in the same month.

(iv) We calculated the remainder component ($\widehat{R_t}$) as:

$$\widehat{R_t} = \frac{C_t}{\widehat{T_t} \times \widehat{S_t}} \tag{4}$$

In short-term predictions, this component and its effect on any prediction are negligible.

The T_t can represent emission trends, while the cycle component CY_t indicates multi-interannual variations in meteorology. The seasonality S_t includes both seasonal variations in meteorology and emissions. We considered the "anthropogenic" trends of emission reductions during COVID-19 lockdown and "natural" trends from meteorology. The seasonality, as a constant parameter, was learned from historical observations in the period of 2015–2019.

We decomposed MA_t for each month in 2015–2019 and $\widehat{S_t}$ for the 12 months of the year. Thus, the monthly surface $PM_{2.5}$ concentrations in a city were briefly determined as:

$$C_t^* = MA_t \times \widehat{S_t} \tag{5}$$

We found minimal changes in MA_t in the period 2015–2019. Therefore, the hindcast $PM_{2.5}$ concentration was briefly described as:

$$C_t^* = \overline{MA_t} \times \widehat{S_t} \tag{6}$$

where $\overline{MA_t}$ was the moving average of MA_t in one year. In February–March 2020, almost all the cities were under strict pandemic control. Using seasonal components, we inversely calculated the preventive MA in February and March 2020 and assumed that it was stable throughout the whole year. Then, the monthly $PM_{2.5}$ concentrations in cities were predicted using the preventive MA and $\widehat{S_t}$ during lockdown in 2020.

2.3. Premature mortality attributable to long-term exposure to ambient $PM_{2.5}$

The premature mortalities attributable to long-term exposure to ambient $PM_{2.5}$ were predicted with the following equation (Apte et al., 2015):

$$\Delta Mortality_{i,j} = y_{0j} \times \left(\frac{RR_j(C_i) - 1}{RR_j(C_i)} \right) \times Pop_i \tag{7}$$

where $\Delta Mortality_{i,j}$ is the premature mortality caused by exposure to $PM_{2.5}$ in city i for the endpoints of disease j; y_{0j} is the baseline mortality rate for disease j; Pop_i is the exposed population in city i; C_i is the annual mean ambient $PM_{2.5}$ ($\mu g\ m^{-3}$) concentration in city i; and RR_j (C_i) is the relative risk function for the disease j endpoints associated with the relative change in the $PM_{2.5}$ concentration C_i. $\Delta Mortality$ in one year was determined by summing it over all disease j endpoints for all cities i. The baseline mortality rate y_0 is the number of cause-specific and age-specific deaths divided by the country-level population (Table 1), based on the latest Global Health Estimates (2016) obtained from the World Health Organization (World Health Organization, 2018) and the population structure data of China (Population pyramid of China, 2015–2018 from the United Nations Department of Economic and Social Affairs, 2019).

We used two different $RR(C)$ models, including the integrated exposure-response model (IER; Burnett et al., 2014) and the Global Exposure Mortality Model (GEMM; Burnett et al., 2018). The $PM_{2.5}$-attributed IER was constructed for the disease j endpoint, including lower respiratory infections (LRI; for children <5 years), lung cancer (LC) and chronic obstructive pulmonary disease (COPD; for adults >25 years), and ischemic heart disease (IHD) and stroke (for adults >25 years and age-specifically). For disease j, the IER for ambient $PM_{2.5}$ concentrations above C_0 (range: 5.8–8.0 $\mu g\ m^{-3}$) was defined as:

$$RR_j(C_i) = 1 + \alpha \times [1 - exp(-\gamma \times (C_i - C_0)^\delta)] \tag{8}$$

Table 1
Age-specific baseline mortality rates (%) in China. COPD = chronic obstructive pulmonary disease; LC = lung cancer; LRI = lower respiratory infections; IHD = ischemic heart disease; NCD = noncommunicable disease.

Age group (years)	Baseline mortality rates caused by specific diseases (%)					
	COPD	LC	LRI	IHD	Stroke	NCD + LRI
0–4	–	–	0.24	–	–	0.78
25–29	–	–	–	0.02	0.02	0.20
30–34	0.02	0.07	–	0.13	0.14	0.98
35–39	0.02	0.07	–	0.13	0.14	0.98
40–44	0.02	0.07	–	0.13	0.14	0.98
45–49	0.02	0.07	–	0.13	0.14	0.98
50–54	0.14	0.44	0.03	0.61	0.79	4.17
55–59	0.14	0.44	0.03	0.61	0.79	4.17
60–64	1.08	1.12	0.16	2.68	3.57	14.52
65–69	1.08	1.12	0.16	2.68	3.57	14.52
70–74	8.64	4.39	1.47	16.76	15.89	73.65
75–79	8.64	4.39	1.47	16.76	15.89	73.65
>80	8.64	4.39	1.47	16.76	15.89	73.65
>30	1.05	0.75	0.18	2.26	2.36	10.90
All ages	0.63	0.45	0.13	1.36	1.43	6.67

where parameters α, γ, and δ determine the shape and magnitude of the relative risk function RR. C_0 is a uniform random variable of the counterfactual concentration with lower bound at which it is assumed that there is no health risk (Burnett et al., 2018). One thousand groups of parameters for each disease and each age were obtained (Burnett et al., 2018) to estimate the uncertainty of the mortality.

The GEMM was constructed for adults >25 years, including the nonaccidental GEMM (noncommunicable diseases [NCD] and LRI; GEMM–NCD + LRI) and the GEMM for the five specific diseases LRI, LC, COPD, IHD, and stroke (GEMM5). The GEMM for NCD + LRI, IHD, and stroke were age-specific. For the endpoint of disease j, the GEMM for $PM_{2.5}$ concentrations $> C_0$ (2.4 µg m^{-3}) was defined as:

$$RR_j(C_i) = exp\left(\frac{\theta \times \log\left(\frac{C_i - C_0}{\alpha} + 1\right)}{1 + exp\left(-\frac{C_i - C_0 - \mu}{\nu}\right)}\right) \qquad (9)$$

where parameters θ, α, μ, and ν are from Burnett et al. (2018), with the inclusion of the Chinese Male Cohort. We calculated 1000 groups of parameters using Monte Carlo simulations by randomly sampling normal distributions to estimate the uncertainty of the mortality.

3. Results

3.1. Prediction of $PM_{2.5}$ under permanent lockdown in 2020

To verify the performance of the model, the $PM_{2.5}$ concentrations for 2015–2019 were hindcasted by the trained model and compared with the observed data (Fig. 1). Fig. 1a–e shows the spatial distributions of the observed annual mean $PM_{2.5}$ concentrations in Chinese cities from 2015 to 2019. The highest annual mean $PM_{2.5}$ concentrations, 60–106.1 µg m^{-3} in 2015, were observed on the North China Plain (NCP; Beijing, Tianjin, Hebei Province, and Shandong Province) and the Fenwei Plain (FWP; Shanxi Province, Shaanxi Province, and Henan Province), followed by the Yangtze River Delta, Sichuan Basin, Northeast China, and Xinjiang Province, with concentrations of 40–65 µg m^{-3}, and a few cities exceeded 70 µg m^{-3} in 2015. In the other cities, the urban $PM_{2.5}$ concentrations were <45 µg m^{-3}. With the implementation of the Clean Air Action Plan from 2013 to 2017, significant improvements in air quality were observed nationwide (Zhang et al., 2019). In 2019, the annual mean $PM_{2.5}$ concentrations in the NCP and FWP had declined to 20–69.6 µg m^{-3}; that in the Yangtze River Delta and Xinjiang Uygur Autonomous Region had declined to 20–55 µg m^{-3}; and that in the Sichuan Basin and Northeast China had declined to 15–45 µg m^{-3}. In the coastal areas of southern China and in southeastern Tibet, the $PM_{2.5}$ concentrations showed no substantial changes from 2015 to 2019. As shown in Fig. 1f–j, the hindcasted annual mean $PM_{2.5}$ concentrations in 2015–2019 reproduced the observed spatial patterns well (Fig. 1a–e), although there were some slight under- and over-estimations. The bias showed a heterogeneous distribution, with mean values ranging from 0.9 to 2.3 µg m^{-3} during 2015–2019 (Fig. 1k–o). The bias was <3 µg m^{-3} in 92.5–97.3% of cities in 2016–2019 and in 71.2% of cities in 2015. Large biases were spatially associated with high $PM_{2.5}$ concentrations, such as in the highly polluted cities of the NCP and FWP. Fig. 1p–t shows the seasonal variations in the observed and monthly hindcast $PM_{2.5}$ concentrations in 2015–2019. The $PM_{2.5}$ concentrations were higher in winter and lower in summer, which is attributed to variations in emissions and in meteorological factors. For example, northern cities emitted more pollutants from residential heating in winter, whereas most cities had good weather conditions in summer; e.g., more rainfalls and a higher boundary layer. The hindcast evaluations showed that the seasonal cycle of $PM_{2.5}$ could been well-captured, and the mean bias ranged between 2.5 and 3.2 µg m^{-3}. These evaluations gave us confidence to use the predictions for 2020 under the lockdown scenario to project the resultant health impact.

During the COVID-19 outbreak, a large reduction in transportation emissions and a slight reduction in industrial emissions were observed in China in response to the preventive measures imposed (Wang et al., 2020). Fig. 2 shows the populations, the predicted $PM_{2.5}$ in cities, and its seasonal variability in 2020. Population is an important factor when quantifying the mortality attributable to long-term exposure to ambient $PM_{2.5}$ in cities. The total urban population is 343.6 million and accounts for 24.5% of the total population of China. In eastern China, the distribution of population density is consistent with the distribution of $PM_{2.5}$ (Fig. 2a). The spatial distributions of the $PM_{2.5}$ concentrations predicted for 2020 were similar to those from 2015–2019 (Fig. 2b). In response to the preventive measures taken during the pandemic, the annual mean $PM_{2.5}$ concentrations decreased to 5.4–68.0 µg m^{-3} in 2020, and the largest changes were observed in the NCP and FWP. The median of the concentrations fell from 43.3 µg m^{-3} in 2015–2019 to 29.3 µg m^{-3} in 2020, showing a 32.3% reduction. Even under this scenario, there were only three cities with annual mean $PM_{2.5}$ concentrations less than 10 µg m^{-3}, meeting the World Health Organization standard for avoiding the most common health effects of long-term $PM_{2.5}$ exposure (Pope Iii et al., 2002).

3.2. Premature mortality attributable to long-term exposure

The mortality caused by long-term exposure to ambient $PM_{2.5}$ varies substantially across China, depending on the concentrations of these pollutants and the population exposed. We considered several causes of death, including NCD, LRI, COPD, LC, IHD, and stroke caused by long-term $PM_{2.5}$ exposure. Fig. 3 shows the estimated premature mortality attributable to ambient $PM_{2.5}$ under the whole year lockdown scenario and the mortality rates. The IER model is a disease-specific model in which five causes of death were considered: LRI, COPD, LC, IHD, and stroke. According to the predictions of the IER model, long-term exposure to $PM_{2.5}$ contributed to 469.3 (95% CI: 245.5–676.7) thousand premature deaths and a mortality rate of 95.6‰ (Fig. 3d; 95% CI: 50.0–137.8‰). The numbers of deaths attributed to $PM_{2.5}$ from the five specific diseases (COPD, LC, LRI, IHD, and stroke) were 40.5, 35.9, 1.4, 182.1, and 209.4 thousand, respectively (Fig. 3a).

In the GEMM, many of the strong assumptions required by the IER model are relaxed and can better estimate the responses in highly polluted environments, such as in China. In the GEMM, the mortality attributable to long-term $PM_{2.5}$ exposure was considered for two conditions: for nonaccidental deaths due to noncommunicable diseases and LRI (GEMM-NCD + LRI), and for deaths from five specific causes (COPD, LC, LRI, IHD, and stroke) (GEMM-5 Total). According to the five-cause-specific GEMM, exposure to $PM_{2.5}$ caused an additional 609.4 (95% CI: 428.9–767.3) thousand deaths in the pandemic of 2020, including 81.7, 64.4, 26.7, 262.2, and 174.4 thousand deaths from COPD, LC, LRI, IHD, and stroke, respectively (Fig. 3b and c). The mortality rate was 124.1‰ (Fig. 3d; 95% CI: 87.4–156.3‰). According to the GEMM-NCD + LRI model, 837.3 (95% CI: 699.8–968.4) thousand deaths were attributable to long-term exposure to ambient $PM_{2.5}$ (Fig. 3c). The associated mortality rate during the pandemic in 2020 was estimated to be 170.5‰ (95% CI: 142.5–197.2‰) (Fig. 3d). We note that the GEMM was more sensitive to the $PM_{2.5}$ concentrations than the IER model, and the mortality estimated with the GEMM was higher than that estimated with the IER model. The mortality hazard ratios predicted with the GEMM were always larger than those predicted with the IER model under high-$PM_{2.5}$ concentration conditions (Burnett et al., 2018). Therefore, the $PM_{2.5}$ concentrations were still not low enough because of intensive emissions due to basic living needs in urban cities.

3.3. Discussion

Compared with the mean concentrations from 2015 to 2019, 99.3% of cities showed reductions in $PM_{2.5}$ concentrations (Fig. 4a). The national annual mean $PM_{2.5}$ concentrations dropped from 44.6 µg m^{-3}

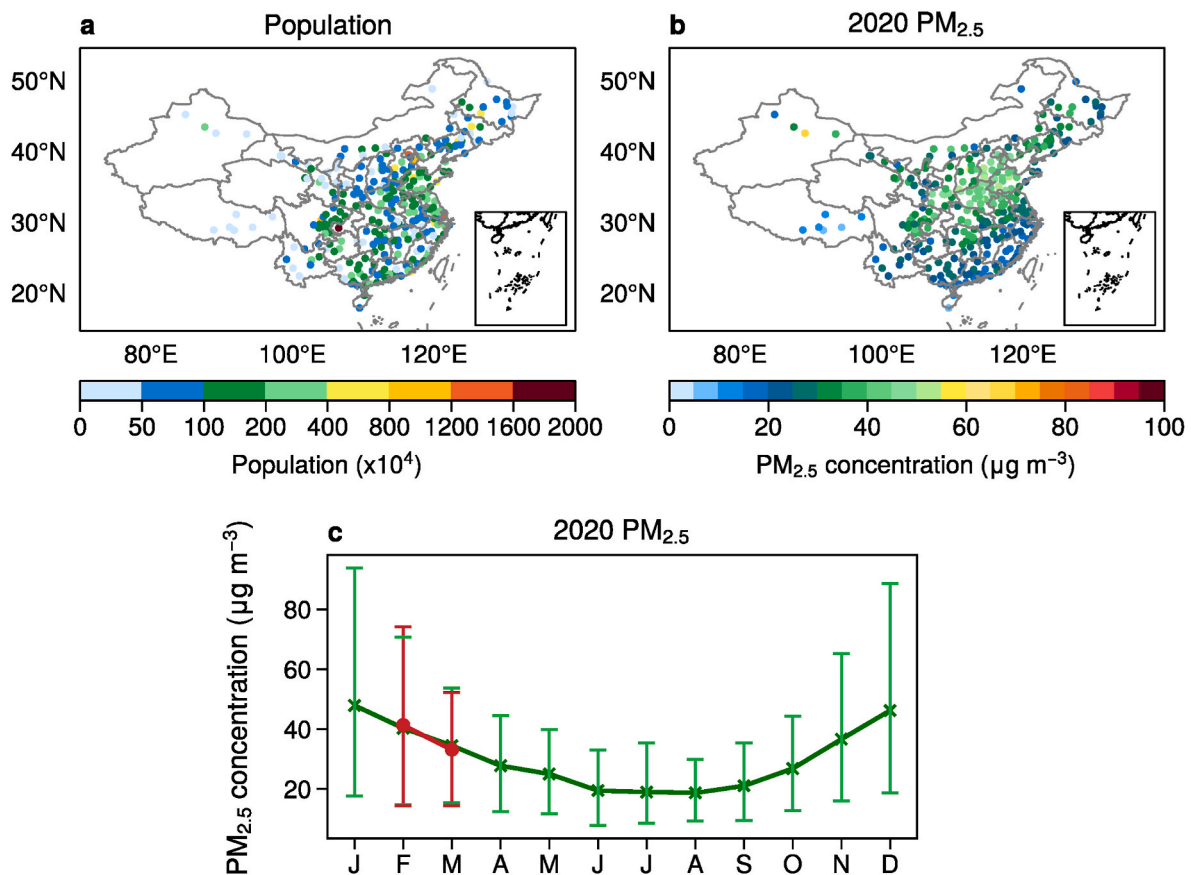**Fig. 2.** Spatial distribution of population (a; unit: $\times 10^4$), predicted annual mean PM$_{2.5}$ concentrations (b; unit: μg m^{-3}), and the seasonal variation in the predicted PM$_{2.5}$ concentrations (c; unit: μg m^{-3}) in cities in China under the pandemic 2020 scenario. Error bars in (d, e) indicate the upper (2.5%) and lower (97.5%) quantiles.

during 2015–2019 to 30.3 μg m^{-3} in the whole-year lockdown in 2020. The GEMM–NCD + LRI model estimated that 140.2 (95% CI: 122.2–156.0) thousand deaths (Fig. 4c) due to long-term exposure to PM$_{2.5}$ were avoided with respect to the average annual deaths from 2015 to 2019 (Fig. 4b). The estimated long-term health impacts in this study are lower than those reported by Giani et al. (2020b), which indicated that 28.7 (95% CI: 23.4–32.8) thousand premature fatalities were avoided in China under a permanent lockdown scenario in 2020. This underestimation is probably because we used PM$_{2.5}$ concentrations in urban cities instead of grid data covering the whole country.

Although anthropogenic emissions were sharply decreased, the 14.4% reduction in premature deaths is still low despite a 32.2% reduction of PM$_{2.5}$. Such limited health effects even with substantial air quality improvements were also recognized in previous studies (Giani et al., 2020a; Xue et al., 2019). The main reason is because PM$_{2.5}$ concentrations were still high in most cities, and even enhanced PM$_{2.5}$ was reported in some cities during short periods of full lockdown (Sokhi et al., 2021). Therefore, the associated changes in the premature death rates are less steep than those obtained under low-PM$_{2.5}$ conditions (Xue et al., 2019), China should adopt continuous emission control strategies to protect the population from air pollution.

We assumed a stringent lockdown throughout the whole of 2020, but such a pandemic scenario may not be 'too ideal'. According to previous studies, reductions in the industry and transport sectors contributed most strongly to the reductions in emissions during lockdown in China (Huang et al., 2020; Zheng et al., 2021). During lockdown, a 60–70% reduction in nitrogen oxide was detected in eastern China, and 70–80% of this reduction was attributed to the decline in road traffic (Huang et al., 2020). Similar emission reductions like those observed in the 2020 pandemic may be achieved in the future with the promotion of electric

vehicles (Liang et al., 2019) and innovation of industrial technology. The time series decomposition approach used here can be applied to any city with sufficient (at least two consecutive years) air pollutant observations (e.g., PM$_{2.5}$, ozone, and NO$_2$) to estimate the associated long-term health benefits from emission reductions due to COVID-19 lockdown.

3.4. Study limitations

Inevitably, there are a few uncertainties in the long-term health impact estimation. Firstly, although the risk factor models for long-term exposure to ambient PM$_{2.5}$ from the latest epidemiological studies (Burnett et al., 2018; Burnett et al., 2014) were used, uncertainties remained in the parameters, such as baseline mortality rates, the concentration-response coefficient, and the counterfactual concentration. These parameters were available on a country-level scale without consideration of the particle size and composition (Akhbarizadeh et al., 2021; Faraji Ghasemi et al., 2020), which may vary by city. Additionally, city-level populations were used to calculate population exposure to average PM$_{2.5}$ concentration in the city, and the spatial heterogeneity of ambient PM$_{2.5}$ concentrations was ignored. Furthermore, there was still some bias in specific start time and end time of lockdown for each city. For example, cities in Hubei province recovered more slowly because of stringent measures implemented until April 2020. Therefore, overestimation or underestimation in predicted annual mean PM$_{2.5}$ concentrations existed under the whole-year lockdown scenario, but it is acceptable to use PM$_{2.5}$ concentrations from February–March to predict the annual mean concentrations because both China's emission and PM$_{2.5}$ concentrations were substantially reduced from February to March 2020 (Shi et al., 2021; Zheng et al., 2021). Finally, we only
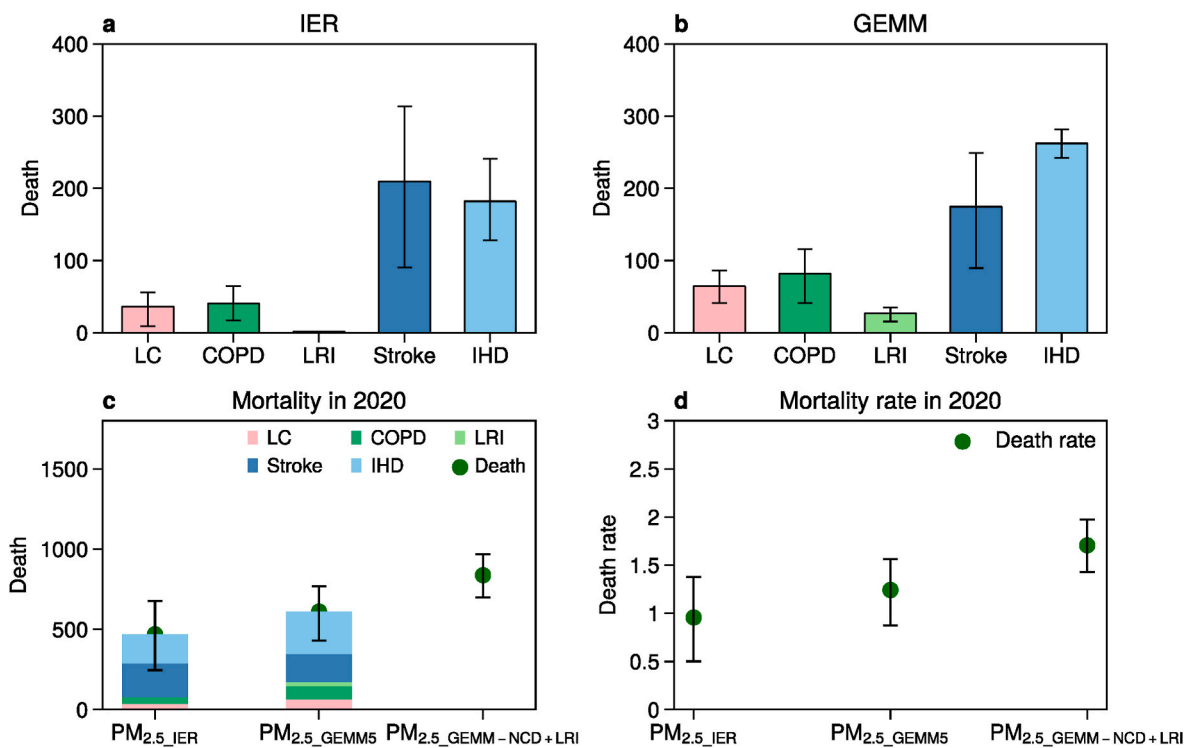
Fig. 3. Annual deaths ($\times 10^3$) and death rates caused by long-term exposure to ambient $PM_{2.5}$ in urban China under the pandemic 2020 scenario, estimated with the IER model and GEMM. Each specific cause of death attributable to ambient $PM_{2.5}$ in IER (a) and GEMM (b) are presented. Total deaths and death rates estimated with the IER model, GEMM five-causes model, and GEMM–NCD + LRI are shown in (c) and (d). Data points show the mean numbers of deaths, and the error bars indicate the 95% confidence intervals (CI).
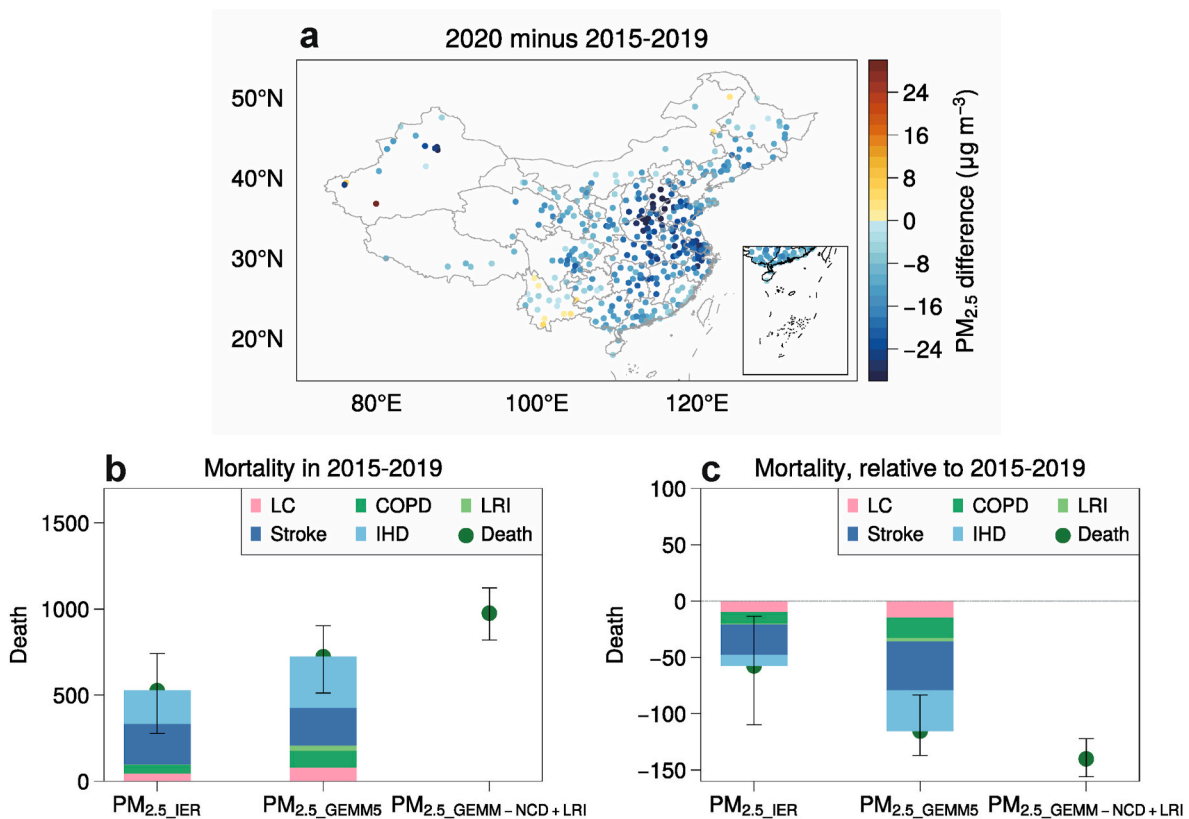

Fig. 4. (a) Differences in annual mean $PM_{2.5}$ concentrations between 2020 and 2015–2019. (b) Annual mean deaths ($\times 10^3$) caused by long-term exposure to ambient $PM_{2.5}$ in urban China in 2015–2019 and (c) those under the pandemic 2020 scenario relative to the 2015–2019 mean levels estimated with the IER model and GEMM, respectively.

focused on premature mortality attributable to ambient $PM_{2.5}$ exposure. However, side effects from COVID-19, such as increased risks of indoor air pollution exposure (Du et al., 2021), mental health effects (Marazziti et al., 2021), and changes in dietary habits (Batlle-Bayer et al., 2020) may also impact human health. Hence, more investigations should be performed in the future.

4. Conclusions

Based on the $PM_{2.5}$ concentrations observed from 2015 to 2019, we used time series decomposition to divide the $PM_{2.5}$ concentrations into their trend, cyclic, seasonal, and remainder components. The hindcast evaluations showed that the annual hindcast results satisfactorily reproduced the spatial distribution of the observed annual mean $PM_{2.5}$ concentrations for the period of 2015–2019, generally with a small bias of <3 μg m^{-3}, respectively. Based on the observed $PM_{2.5}$ data for February–March 2020, we used the decomposed seasonal component to inversely calculate the other components in 2020 and then predicted the monthly $PM_{2.5}$ concentrations for 2020. The predicted annual mean $PM_{2.5}$ concentrations in urban China declined to 5.4–68.0 μg m^{-3} in 2020, and the largest changes were detected in the NCP and FWP. Even under the lowest emissions scenario, the annual mean $PM_{2.5}$ concentrations in urban cities were not low and had adverse health effects. Under lockdown in 2020, 469.3 (95% CI: 245.5–676.7), 609.4 (95% CI: 428.9–767.3), and 837.3 (95% CI: 699.8–968.4) thousand people died prematurely from illnesses attributable to long-term exposure to ambient $PM_{2.5}$ in Chinese cities, when estimated with the IER model, GEMM5, and GEMM–NCD + LRI, respectively. Our findings affirm the significant improvements in air quality under the whole year lockdown scenario when stringent control measures are taken to reduce emissions from industrial and traffic sectors. We suggest that future mitigation policies, such as promotion of electric vehicles and the innovation of industrial technology, should remain in place, and more stringent measures should be implemented on other emission sources (e.g., from power plants and residential sectors) to achieve substantial health benefits.

Credit author statement

Xin Hao: Conceptualization, Methodology, Investigation, Data curation, Visualization, Writing – original draft. **Jiandong Li**: Methodology, Investigation, Visualization, Writing – original draft. **Huijun Wang**: Writing – review & editing, Supervision, Funding acquisition. **Hong Liao**: Writing – review & editing, Supervision, Funding acquisition. **Zhicong Yin**: Writing – review & editing, Supervision. **Jianlin Hu**: Writing – review & editing, Supervision. **Ying Wei**: Data curation. **Ruijun Dang**: Methodology

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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