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The air quality changes and related mortality benefits during the coronavirus disease 2019 pandemic in China: Results from a nationwide forecasting study

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\textbf{A B S T R A C T}

Air quality changes during the coronavirus disease 2019 (COVID-19) pandemic in China has attracted increasing attention. However, more details in the changes, future air quality trends, and related death benefits on a national scale are still unclear. In this study, a total of 352 Chinese cities were included. We collected air pollutants (including fine particulate matter [PM\textsubscript{2.5}], inhalable particulate matter [PM\textsubscript{10}], nitrogen dioxide [NO\textsubscript{2}], and ozone [O\textsubscript{3}]) data for each city from January 2015 to July 2020. Convolutional neural network-quantile regression (CNN-QR) forecasting model was used to predict pollutants concentrations from February 2020 to January 2021 and the changes in air pollutants were compared. The relationships between the socioeconomic factors and the changes and the avoided mortality due to the changes were further estimated. We found sharp declines in all air pollutants from February 2020 to January 2021. Specifically, PM\textsubscript{2.5}, PM\textsubscript{10}, NO\textsubscript{2}, and O\textsubscript{3} would drop by 3.86 \textmu g/m\textsuperscript{3} (10.81%), 4.84 \textmu g/m\textsuperscript{3} (7.65%), 0.55 \textmu g/m\textsuperscript{3} (2.18%), and 3.14 \textmu g/m\textsuperscript{3} (3.36%), respectively. The air quality changes were significantly related to many of the socioeconomic factors, including the size of built-up area, gross regional product, population density, gross regional product per capita, and secondary industry share. And the improved air quality would avoid a total of 7237 p.m\textsuperscript{2.5}-related deaths (95% confidence intervals [CI]: 4935, 9209), 9484 p.m\textsuperscript{10}-related deaths (95%CI: 3480, 9367), respectively. Our study shows that the interventions to control COVID-19 would improve air quality, which had significant relationships with some socioeconomic factors. Additionally, improved air quality would reduce the number of non-accidental deaths.

1. Introduction

The tragic coronavirus disease 2019 (COVID-19) pandemic, caused by severe acute respiratory syndrome coronavirus type 2, has generated unprecedented influence on human society (Zhou et al., 2020; Zhu et al., 2020). On August 31, 2020, the disease has resulted in 24854140 cases and 838924 death worldwide, and it is projected to cause 1.75 million deaths by the Spring of 2021 (World Health Organization, 2020a). To contain the rapid spread of the pandemic, a global response has been implemented, including centralized treatment of the disease, closures of business, and social distancing (United Nations, 2020; World Health Organization, 2020b). However, the consequent indirect effects of the response, especially on the atmospheric environment, are arising, which attracts increasing attention (Berman and Ebisu, 2020; Dutheil et al., 2020; Li et al., 2020; Zambrano-Monserrate et al., 2020).

China is the first country to report COVID-19 cases and is also one of the countries that have taken the strongest interventions to control the...
pandemic. On January 23, 2020, the government of China closed the traffic and travel in and out of Wuhan, the first city to report cases of China, and set up many quarantine points. Extra tough interventions such as home quarantine, travel restriction, and school and factory closure were also implemented in Wuhan and quickly enforced across the country (Hao et al., 2020; Pan et al., 2020; Qiu et al., 2021). These interventions subsequently reduced human and industrial activities, the major sources of air pollutants, to a minimum level nationwide. The National Aeronautics and Space Administration and European Space Agency (2020) pollution monitoring satellites detected a significant decrease in nitrogen dioxide (NO$_2$) over China in early 2020 compared to the same period in 2019. A study in China also found that the air quality index was reduced by 19.84 points and fine particulate matter (PM$_{2.5}$) was decreased by 14.07 μg/m$^3$ within nine weeks in the locked-down cities of China compared to the cities without formal lockdowns (He et al., 2020). Moreover, another study in China not only observed sharp drops with 12.9 μg/m$^3$ and 18.9 μg/m$^3$ in NO$_2$ and PM$_{2.5}$ due to stringent traffic restrictions and self-quarantine interventions but also found that the drops could avoid a total of 8911 NO$_2$-related deaths (95% confidence intervals [CI]: 6950, 10866) and 3214 p.m.3-related deaths (95%CI: 2340, 4087) (Chen et al., 2020). However, these studies did not provide more detailed information on air quality changes in the COVID-19 pandemic, because they only compared the air pollutants concentrations on the pandemic with the previous ones. Besides, the long-term impact of these interventions on air quality and mortality benefits is still unclear.

Time-series forecasting methods are based on the historical information about things or phenomena and analyze their inherent trends and laws, to make reasonable estimates and/or speculation of future changes. Some models and their derived models, such as autoregressive integrated moving average (ARIMA), non-parametric time series (NPTS), exponential smoothing (ETS), and recurrent neural networks (RNNs), have been widely used in air quality prediction and achieved good results (Hajat et al., 2002; Mahajan et al., 2018; Ruchiraset and Tantrakarnap, 2018; Zhao et al., 2020). Recently, a new forecasting model, convolutional neural network-quantile regression (CNN-QR), has been developed by Amazon Co. (2020a). CNN-QR is a series-to-sequence probabilistic prediction model based on a convolutional neural network, which is used to test the effect of a prediction on the reconstruction of a decoded sequence of the condition of an encoded sequence. Compared with other models supported by Amazon (including ARIMA, NPTS, ETS, DeepAR+ [based on the RNNs model], and Prophet), CNN-QR is 30% more accurate and the training model is twice as fast (Namita et al., 2020).

Therefore, we conducted this nationwide time-series forecasting study in 352 Chinese cities based on the CNN-QR model to explore the impact of COVID-19 prevention and control on air quality in more detail and forecast future air quality trends. Then, we explored the relationships between the air quality changes and socioeconomic factors, including total population, size of built-up areas, gross regional product (GRP), GRP per capita, population density, secondary industry share, and greenery coverage rate. Finally, we estimated the mortality benefit of total non-accidental mortality and the cause-specific mortality for cardiovascular diseases (CVDs), hypertensive disease (HD), coronary heart disease (CHD), stroke, respiratory disease (RD), and chronic obstructive pulmonary disease (COPD) attributed to the air quality changes over China.

2. Methods

2.1. Study sites

To ensure the accuracy of the model, cities with less than 90% of records from January 1, 2015, to July 31, 2020, were excluded (n = 15), and missing data were replaced by the mean substitution method. Finally, a total of 352 Chinese cities located in 31 provincial administrative regions were included in the analysis (Fig. S1). According to geography, climate, and culture, these cities were classified into four regions: south (n = 180), north (n = 124), northwest (n = 32), and Qinghai-Tibet (n = 16).

2.2. Air pollutants concentrations data

We collected air pollutants (including PM$_{2.5}$, inhalable particulate matter [PM$_{10}$], NO$_2$, and ozone [O$_3$]) data for each city from January 1, 2015, to July 31, 2020, from the National Real-Time Air Quality Monitoring Stations maintained by China National Environmental Monitoring Center.

2.3. Socioeconomic data

Based on previous studies and data availability (Xu et al., 2019; Zhao et al., 2019), we selected five types of socioeconomic factors: 1) urban size (including total population, size of built-up areas, and GRP), representing the degree of urban development or energy consumption; 2) GRP per capita, representing the economic level of cities; 3) population density, representing the intensity of human activity or urban form; 4) secondary industry share, representing industrial activities; 5) greenery coverage rate, representing the degree of urban greening. Data on these factors were obtained from the Chinese city statistical yearbook in 2019 and the China urban construction statistical yearbook in 2017 (Table S1). Due to data limitations, we collected socioeconomic data for only 321 cities.

2.4. Non-accidental mortality data

To estimate avoided mortality attributed to the air quality changes in China, we extracted the total non-accidental mortality and the cause-specific mortality data including CVD, HD, CHD, RD, and COPD from the China health and family planning statistical yearbook in 2019. The cause-specific coefficients (β) and 95%CI of the concentration-response functions (CRF) for the air pollutants were also obtained from previous studies (Chen et al., 2017, 2018, 2019; Yin et al., 2017) (Table 1).

Because the data used for this study were collected without any individual identifiers, this study was exempted from Institutional Review Board approval by the Ethics and Human Subject Committee of Tongji Medical College, Huazhong University of Science and Technology.

2.5. Statistical analysis

As described earlier, the Chinese government has implemented a series of interventions since late January 2020 to contain the spread of COVID-19 (Hao et al., 2020; Pan et al., 2020; Qiu et al., 2021). Therefore, we forecast the air pollutants concentrations (95%CI) after January
2020 by the CNN-QR model (for specific operational steps, see (Amazon Co, 2020a)) and split the process into two steps. First, we predicted pollutants concentrations without interventions. The concentrations of air pollutants for the six months after January 2020 (February 2020 to July 2020) were predicted according to air pollutants data from January 2015 to January 2021. Based on the predicted results, we further forecast air pollutants concentrations in the future six months (August 2020 to January 2021). Second, the concentrations after the interventions were also predicted. We forecast air pollutants concentrations from August 2020 to January 2021 based on the data from January 2015 to July 2020. At last, we calculated the changes and percent change between air pollutants concentrations without and with interventions from February 2020 to January 2021.

Then, we conducted ordinary least squares (OLS) multiple linear regression analysis by using air pollutants concentrations changes as response variables and socioeconomic factors as explanatory variables (Xu et al., 2019; Zhao et al., 2019). The total population, size of built-up areas, GRP, GRP per capita, and population density were log-transformed due to their right-skewed distribution. Stratified analyses were conducted to investigate whether different regions (south, north, northwest, and Qinghai-Tibet) modified the relationship.

Based on CRF and the mortality data, we estimated avoided mortality of total non-accidental and cause-specific diseases (including CVD, HD, CHD, RD, and COPD) attributed to the changes in air pollutants over China. The attributable fraction (AF) method was used to estimate the avoided mortality (Chen et al., 2020), which was calculated by formula 1. AF is then multiplied by the annual cause-specific death number to estimate the avoided death.

\[
AF = 1 - e^{-\beta \Delta c}
\]

where \( \beta \) is the cause-specific coefficient of the CRF and \( \Delta c \) is the air pollution change per time increment with and without interventions.

All analyses were performed using SAS version 9.4 (SAS Institute Inc., Cary, NC, USA). A two-sided \( P \) value < 0.05 indicates statistical significance.

2.6. Evaluation index

The CNN-QR model was trained three times to ensure the accuracy of the prediction results. Root mean square error (RMSE) (formula 2) and weighted quantile loss (wQL) (formula 3)/mean absolute percentage error (MAPE) (formula 4) were used as the evaluation indexes (Amazon Co., 2020b), as follows:

\[
RMSE = \sqrt{\frac{1}{nT} \sum_{i,t} \left( \hat{y}_{i,t} - y_{i,t} \right)^2}
\]

\[
wQL[\tau] = 2 \times \sum_{i,t} \left[ \tau \max \left( y_{i,t} - q_{i,t}^{(\tau)}; 0 \right) + (1 - \tau) \max \left( q_{i,t}^{(\tau)} - y_{i,t}; 0 \right) \right] / \sum_{i,t} |y_{i,t}|
\]

\[
MAPE = \frac{\sum_{i,t} \left| \hat{y}_{i,t} - y_{i,t} \right|}{\sum_{i,t} |y_{i,t}|}
\]

where \( nT \) is the number of data points in a testing set; \( i \) is the item index ranging from 1 to the total number of items (n); \( t \) is the time index of the time series ranging from 1 to the final time in the evaluation period (T); \( \hat{y}_{i,t} \) is the predicted value at point \( i,t \); \( y_{i,t} \) is the observed value at point \( i,t \). The CNN-QR model was trained three times to ensure the accuracy of the model prediction. The accuracy of the CNN-QR prediction model is shown in Table S2. The results of wQL/MAPE and RMSE for all pollutants were from 0.14 to 0.21 and from 6.37 to 22.96, respectively, which indicated that this model has good fitting accuracy in terms of data variation trend and data error.

The monthly change and percent changes of air pollutants concentrations from February 2020 to January 2021 are shown in Fig. 2. In the first month after the intervention, air pollutants concentrations without intervention were observed marked decreases from 2015 to 2019, among which PM2.5 and PM10 were the top two, with 26.35% and 22.96% decrease, respectively. The temporal variation of air pollutants during the study period is depicted in Fig. S2. Air pollutants concentrations fluctuated periodically and declined over time.

3.2. Predicted concentrations of air pollutants during the COVID-19 pandemic in China

The predicted concentrations of air pollutants from February 2020 to July 2020 in China are depicted in Fig. 1A. We found that the observed value of PM2.5, PM10, and NO2 was lower than the predicted value in February and March 2020, while this phenomenon was observed in June and July 2020 for O3. The air pollutants concentrations for the next six months (August 2020 to January 2021) after July 2020 are shown in Fig. 1B. From August 2020 to January 2021, both predicted values (with or without intervention) showed similar trends, and the changes between them were less than those from February 2020 to July 2020. The accuracy of the CNN-QR prediction model is shown in Table S2. The results of wQL/MAPE and RMSE for all pollutants were from 0.14 to 0.21 and from 6.37 to 22.96, respectively, which indicated that this model has good fitting accuracy in terms of data variation trend and data error.

The air quality change over one year in 352 cities are depicted in Fig. 3 and the national average change in these cities are shown in Fig. 4. We found that the observed concentrations of PM2.5, PM10, NO2, and O3 were 42.70 μg/m3, 76.64 μg/m3, 28.97 μg/m3, and 91.44 μg/m3, respectively. Air pollutants concentrations (except O3) were observed to decreased from 2015 to 2019, among which PM2.5 and PM10 were the top two, with 26.35% and 22.96% decrease, respectively. The temporal variation of air pollutants during the study period is depicted in Fig. S2. Air pollutants concentrations fluctuated periodically and declined over time.

3.3. Impact of socioeconomic factors on the changes in air pollutants concentrations in China

Air quality changes in February 2020 were used to explore their relationships with socioeconomic factors, which is shown in Table 3. The results show that the size of built-up area, GRP, population density, GRP per capita, and secondary industry share were significantly related to the changes in air pollutants concentrations. Specifically, the size of built-up areas (−7.54 [95%CI: −12.09, −3.00]), GRP (15.46 [95%CI: 5.47, 25.46]), population density (−6.85 [95%CI: −8.52, −5.18]), and GRP per capita (−13.77 [95%CI: −24.76, −2.78]) had significant relationships with the changes of PM2.5 concentrations; Population density (−6.05 [95%CI: −8.21, −3.88]) had negative relationships with the changes of PM10 concentrations; Size of built-up area (−3.28 [95%CI: −4.71, −1.85]), population density (−0.76 [95%CI: −1.28, −0.23]), and secondary industry share (−0.06 [95%CI: −0.11, −0.01]) had negative relationships with the changes of NO2 concentrations. Across different regions of China, the relationships show significant heterogeneity (Table 4). Generally, we found significant effects on air quality
Table 2  
Summary statistics of monthly air pollutants in China.

| Air pollutants | 2015        | 2016        | 2017        | 2018        | 2019        | 2020        | Total        |
|----------------|-------------|-------------|-------------|-------------|-------------|-------------|--------------|
|                | Mean (SD)   | Median (IQR) | Mean (SD)   | Median (IQR) | Mean (SD)   | Median (IQR) | Mean (SD)   |
| PM$_{2.5}$, μg/m$^3$ | 50.61 (16.15) | 47.88 (16.58) | 46.69 (16.78) | 44.30 (16.58) | 39.13 (16.11) | 39.12 (16.07) | 37.27 (15.16) |
| PM$_{10}$, μg/m$^3$ | 87.43 (21.28) | 85.95 (23.40) | 82.42 (23.60) | 80.03 (23.20) | 75.89 (22.34) | 81.64 (23.34) | 76.36 (22.44) |
| NO$_2$, μg/m$^3$ | 30.18 (7.10) | 29.94 (7.78) | 30.47 (7.58) | 31.43 (7.58) | 28.74 (6.87) | 29.96 (6.87) | 27.68 (6.87) |
| O$_3$, μg/m$^3$ | 85.33 (22.15) | 88.11 (23.01) | 94.60 (22.63) | 93.85 (22.63) | 92.54 (22.54) | 92.54 (22.54) | 92.54 (22.54) |

Fig. 1. The predicted concentrations of air pollutants from February 2020 to January 2021. A. Concentrations (μg/m$^3$) from February 2020 to July 2020; B. Concentrations (μg/m$^3$) from August 2020 to January 2021. Note: dash line, 95% confidence intervals.

Fig. 2. Changes and percent changes between air pollutants concentrations from February 2020 to January 2021. A. Changes (μg/m$^3$) of air pollutants concentrations; B. Percent changes (%) of air pollutants concentrations.
The effects on air quality changes were more evident in the South and North regions. But there was no significant relationship between socioeconomic factors and air quality changes in the Qinghai-Tibet region. Only the relationship between population density and PM$_{2.5}$ was statistically significant in the Northwest region.

### 3.4. The mortality benefit during the COVID-19 pandemic in China

After one year since the interventions, the improved air quality in China would avoid a total of 7237 p.m.$_{2.5}$-related deaths (95%CI: 4935, 9209), 9484 p.m.$_{10}$-related deaths (95%CI: 5362, 13,604), 4249 NO$_2$-related deaths (95%CI: 3305, 5193), and 6424 O$_3$-related deaths (95%CI: 3480, 9367). Patients with CVDs (HD, CHD, stroke, and other CVDs) would have substantial health benefits related to the decreased concentrations of air pollutants, among which PM$_{2.5}$ and PM$_{10}$ brought the greatest (Fig. 4).

### 4. Discussion

In this study, we assessed the air quality changes during the COVID-19 pandemic based on the CNN-QR forecasting model. Sharp drops in the air pollutants levels during the pandemic were observed, particularly in February 2020, the first month since the strong interventions. We found that the air quality changes in February 2020 had significant relationships with some socioeconomic factors, including the size of built-up area, GRP, population density, GRP per capita, and secondary industry share.
Coefficients of the OLS regression models in four regions of China.

| Factors                      | PM$_{2.5}$ | PM$_{10}$ | NO$_2$ | O$_3$ |
|------------------------------|------------|-----------|--------|-------|
| South (Population)           | -22.76     | -16.94    | -1.88  | -0.67 |
|                             | (-43.22,   | (-43.86,  | (-8.51, | (-11.30,|
|                             | -2.31)     | -9.99)    | 4.74)  | 9.97)  |
| South (Built-up area)        | -6.62      | -2.77     | -2.23  | 1.18   |
|                             | (-7.70,    | (-12.09,  | (-3.17,| 4.86)  |
|                             | 6.46)      | 6.56)     | 1.41)  |        |
| South (ln(Gross regional)    | 23.67      | 21.17     | 1.67   | 0.07   |
|                             | (2.14,     | 17.11)    | 0.19   |        |
| South (ln(Gross product))    | 45.19**    |           |        |        |
|                             | (-11.23,   |           |        |        |
| South (ln(Population density)| -11.09     | -7.98     | 0.77   | -0.81  |
|                             | (-13.94,   | (-11.73,  | (-2.68,| 2.15)  |
|                             | -8.24)**   | -4.42)**  | -0.83) |        |
| North (Population)           | -23.13     | -15.16    | -2.28  | -0.47  |
| North (Built-up area)        | -45.78     | -44.97    | -9.61  | -12.24 |
| North (ln(Population density)| -1.49)     | 14.65)    | 5.06   | 11.30  |
| North (ln(Gross regional)    | -10.81     | -5.42     | -0.17  | 3.67   |
| North (ln(Gross product)     | -18.54     | -13.26    | -3.32  | 9.31   |
| North (ln(Built-up area)     | -3.08)**   | 2.42)     | 2.97   |        |
| North (ln(Population density)| -9.64      | -5.87     | -4.41  | -1.24  |
| North (ln(Gross regional)    | 11.98 (3.34)| 6.15 (2.62)| 1.24   | -2.12  |
| North (ln(Gross product)     | 20.62)**   | 14.91)    | -2.28  | -8.42  |
| North (ln(Population density)| -3.31      | -3.10     | -0.16  | 1.21   |
| North (ln(Gross regional)    | -5.58      | -5.41     | -1.09  | 2.87   |
| North (ln(Gross product)     | -1.03)**   | -0.79)**  | 0.77   |        |
| North (ln(Population density)| -19.13     | -13.16    | -0.89  | 4.01   |
| North (ln(Gross regional)    | -28.81     | -22.97    | -4.85  | 11.07  |
| North (ln(Gross product)     | -9.45)**   | -3.34)**  | 3.05)  |        |
| North (ln(Built-up area)     | 0.00       | 0.00 (-0.16)| 0.01   | 0.03   |
| North (ln(Population density)| -0.16      | -0.17     | -0.11  | -0.14  |
| North (ln(Gross regional)    | -0.04      | -0.19     | 0.07   | -0.03  |
| North (ln(Gross product)     | -0.29      | -0.44     | -0.03  | 0.30   |
| North (ln(Built-up area)     | 0.21       | 0.07      | 0.17   | 0.07   |
| North (ln(Population density)| 0.27       | 0.29      | 0.15   | 0.07   |

Note: ** and * indicate significance levels of 1% and 5%.

Industry share. Additionally, we found the air quality changes would avoid at least 27354 air pollutants-related deaths, 61.03% of which were from p.m.-related deaths.

The control of the COVID-19 pandemic has been accompanied by improvement in the air quality of the world. A study conducted in the U. S. found a 25% reduction (absolute decrease of 4.8 part per billion) in NO2 and an overall decline in PM$_{2.5}$ during the pandemic (Berman and Ebisu, 2020). Abdullah et al. (2020) found a sharp drop in PM$_{2.5}$ of up to 58.4% (absolute decrease of 24.1 µg/m³) after the Movement Control Order announced by the Malaysian government. Also, several studies in China found significant air quality improvement due to the coronavirus measures implemented by the Chinese government (Chen et al., 2020; Xu et al., 2020; Yuan et al., 2021). As mentioned above, these studies are based only on past data, which may mask the true impact of the pandemic on air quality. In our study, we used the CNN-QR forecasting model to explore the impact of interventions on the atmospheric environment across China and extended the period to January 2021. We found all air pollutants in China dropped in one year after the interventions, among which PM$_{2.5}$ had the highest percentage decline (~10.81%), followed by PM$_{10}$ (~7.65%), O$_3$ (~3.63%), and NO$_2$ (~2.18%), respectively. Given the reliability of the model, our study might shed light on the extent of air quality affected by extreme disruptions in human behaviors during the COVID-19 pandemic.

In this study, all air pollutants (except O$_3$) were observed sharp drops in the first month after the interventions (February 2020), among them the percentage decline in PM$_{2.5}$ and PM$_{10}$ were the top two. And the drops were significantly related to many of the socioeconomic factors. Previous studies have shown that the influence of socioeconomic factors is one of the important indicators for assessing urban air quality. For example, a study in China suggested that the total population, the size of built-up areas, gross domestic product (GDP), and population density were influential factors on PM$_{2.5}$ levels (Zhao et al., 2019). Also, Xu et al. (2019) considered that energy consumption and the secondary industry as a percentage of GDP can be linked to coal-burning and the emission of a wide range of pollutants. In our study, the results from the OLS multiple linear regressions showed that the associations between socioeconomic factors and the air quality changes were very different. We found that the changes in PM and NO$_2$ concentrations were negatively related to the size of built-up area, population density, GRP per capita, and secondary industry share. That is to say, the higher these factors of the city, the more decreases in pollutants concentrations during the COVID-19 pandemic. Besides, we found that GRP had a positive
relationship with the changes of PM$_{2.5}$ concentrations. This indicates that the economic development of the more developed cities may mainly depend on the tertiary industry (such as wholesale and retail, accommodation and catering, and finance). Besides, these cities may have experienced severe air pollution, which makes them pay more attention to and invest more resources to control air pollution in recent years (Zhao et al., 2019). Moreover, we found strong evidence for spatial heterogeneity in our study, which may be ascribed to climatic features and demographic characteristics. It means that governments of different regions should not only proceed from the geographical location of cities but also proceed from the social and economic development level of cities to effectively improve air quality.

According to a report by World Health Organization (2018), ambient air pollution results in 4.2 million deaths per year, 27% of which were in China. In this study, we found at least 27394 air pollutants-related deaths would be avoided from February 2020 to January 2021. This means the number of deaths averted by improved air quality has far exceeded COVID-19-related deaths in China (4634 as of August 31, 2020) (National Health Commission of the People’s Republic of China, 2020). Despite the huge economic losses and casualties in China during the COVID-19 pandemic, our findings suggest that the indirect effects of these interventions, namely improvements in air quality, can have some health benefits for society. But our results show that the effect of improvements on air quality would be offset in the short term as economic activity resumes in China, which means that these interventions are unsustainable in the long run. In the post-pandemic era, some sustainable approaches must be developed to tackle the root of environmental problems (Wang et al., 2016; Zhang et al., 2018, 2020).

There are several strengths in this study. First, we used the new forecasting model, CNN-QR, to predict concentrations of air pollutants during the COVID-19 pandemic, and its good prediction accuracy provided more detailed information than others; Second, to reduce potential spatial and temporal heterogeneity, our research area is geographically extensive, including 352 cities of 31 administrative regions in mainland China. Third, we assessed the mortality benefits due to the improvement of air quality during the pandemic, which provided a new idea for public health prevention. However, some limitations cannot be ignored. Firstly, there are many factors affecting air quality, such as short-term weather conditions and fuel combustion emissions, leading to a decline in prediction accuracy. Secondly, our estimates should be interpreted with caution, given the possible overlap between mortality rates associated with pollutants and the fact that most people stay indoors in the early stages of the pandemic.

5. Conclusion

Our study shows that the interventions to control COVID-19 would improve air quality, which had significant relationships with some socioeconomic factors. Additionally, improved air quality would avoid the number of non-accidental deaths. Our results provide background information for the air pollutants concentrations in China with or without the COVID-19 pandemic from February 2020 to January 2021. In future research, the direct and/or indirect benefits of air quality improvement for people’s health during the COVID-19 pandemic need to be further studied on a larger range and/or longer period; moreover, some specific measures that can fundamentally improve global air quality should not be ignored.

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CRediT authorship contribution statement

Weihong Qiu: Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Supervision, Project administration. Heng He: Formal analysis, Investigation, Resources, Data curation, Writing – review & editing. Tao Xu: Formal analysis, Data curation, Writing – review & editing. Chengyong Jia: Formal analysis, Data curation, Writing – review & editing. Wending Li: Formal analysis, Data curation, 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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Appendix A. Supplementary data

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