



## Understanding and revealing the intrinsic impacts of the COVID-19 lockdown on air quality and public health in North China using machine learning



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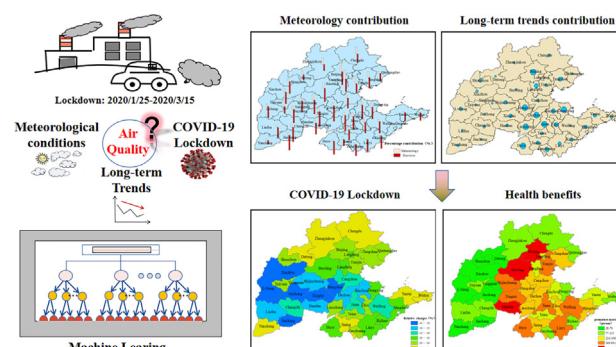
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### HIGHLIGHTS

- Meteorological conditions have a positive contribution of about 9.8 % to PM<sub>2.5</sub> in North China.
- The deweathered air pollutants concentration decreased significantly from 2015 to 2019, especially for SO<sub>2</sub>.
- Air pollutant changes during the lockdown could be overestimated 2-fold by using raw observation data.
- There is still much room for PM<sub>2.5</sub> pollution control in cities in Shanxi Province.
- The total avoided premature deaths would increase by 1146 if the meteorological condition remains unchanged.

### GRAPHICAL ABSTRACT



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### ABSTRACT

To avoid the spread of COVID-19, China implemented strict prevention and control measures, resulting in dramatic variations in urban and regional air quality. With the complex effect from long-term emission mitigation and meteorology variation, an accurate evaluation of the net effect from lockdown on air quality changes has not been fully quantified. Here, we combined machine learning algorithm and Theil-Sen regression technique to eliminate meteorological and long-term trends effects on air pollutant concentrations and precisely detect concentrations changes those ascribed to lockdown measures in North China. Our results showed that, compared to the same period in 2015–2019, the adverse meteorology during the lockdown period (January 25th to March 15th) in early 2020 increased PM<sub>2.5</sub> concentration in North China by 9.8 %, while the reduction of anthropogenic emissions led to a 32.2 % drop. Stagnant meteorological conditions have a more significant impact on the ground-level air quality in the Beijing-Tianjin-Hebei Region than that in Shanxi and Shandong provinces. After further stripping out the effect of long-term emission reduction trend, the lockdown-derived NO<sub>2</sub>, PM<sub>2.5</sub>, and O<sub>3</sub> shown variety change trend, and at -30.8 %, -27.6 %, and +10.0 %, respectively. Air pollutant changes during the lockdown could be overestimated up to 2-fold without accounting for the influences of meteorology and long-term trends. Further, with pollution reduction during the lockdown period, it would avoid 15,807 premature deaths in 40 cities. If with no deteriorate meteorological condition, the total avoided premature should increase by 1146.

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## 1. Introduction

In recent years, with the improvement of the level of industrialization and urbanization in China, the problem of air pollution has become increasingly prominent (Lelieveld et al., 2015; Zhang et al., 2018). In response, the Chinese government promulgated a series of measures (Chinese State Council, 2013; MEP, 2017; MEP, 2020) to reduce air pollution and achieved great results. However, due to extreme weather conditions, severe haze events still occur frequently, especially in northern China (Du et al., 2020; Gong et al., 2020). It is still an important task to continuously improve China's air quality with the goal of coordinated control of PM<sub>2.5</sub> and O<sub>3</sub>.

COVID-19 has spread rapidly and was declared as a global pandemic by the World Health Organization on March 11st 2020 (Le et al., 2020). Since the outbreak of COVID-19, countries around the world have taken strong containment measures (Tian et al., 2020), leading to a significant drop in anthropogenic emissions (Le et al., 2020; Li et al., 2020b; Wang et al., 2020a), providing a unique natural experiment to study the response of air quality under stronger emission reduction.

Previous studies evaluating the urban air quality during the COVID-19 lockdown by compared pre-lockdown air pollutant concentrations with those under lockdown, have documented significant reductions in air pollutants concentrations worldwide (Liu et al., 2020; Mahato et al., 2020; Bao and Zhang, 2020; Cameletti, 2020; Shehzad et al., 2020). However, the concentration variations in air pollutants are determined jointly by meteorological factors and emissions. Additionally, numerous actions have been implemented to alleviate atmospheric pollution over the past few years (Zhang et al., 2019). Therefore, the gap of pollution concentration between different time period cannot wholly present the effect from COVID-19 lockdown. In addition, the degree of air pollutants reduction may vary from city-to-city due to local factors diversity, such as the distribution of emission sources, meteorology and trends in pollutant emissions, which may complicate the precise quantification of COVID-19 lockdown-derived changes in air pollutants concentrations, and the associated public health benefits.

By training model with a set of features including meteorological data and other time variables, machine learning has been widely used to quantify changes in air quality caused by meteorology and emissions (Vu et al., 2019; Petetin et al., 2020; Cole et al., 2020; Lv et al., 2022). Here, we focus on the most polluted North China, and combined the de-weather method and Theil-Sen trend estimation techniques to strip out the influences of meteorology and long-term policies on air pollutant

concentrations, so as to precisely evaluate changes in their concentrations ascribed to COVID-19 lockdown (January 25th to March 15th 2020). Pollution concentration and various parameters from 258 official continuous air quality monitoring stations in North China during the lockdown and same period in 2015–2019 were used. Finally, we examined the potentially health impact due to the air quality changes during the lockdown.

## 2. Materials and methods

### 2.1. Study areas and data sources

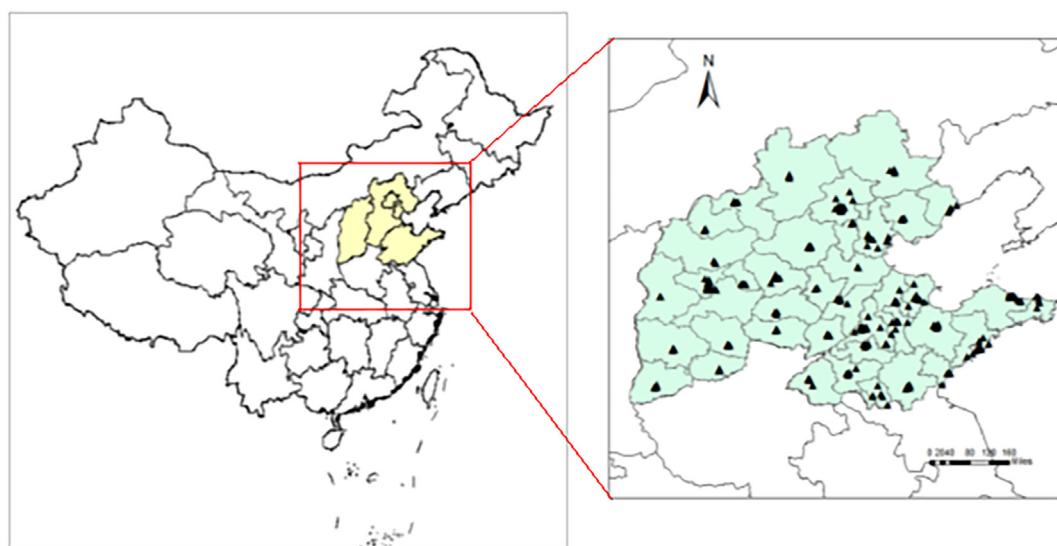
#### 2.1.1. Description of study areas

Our study area focused on the North China (see Fig. 1), including three province (Hebei, Shanxi and Shandong province) and two municipalities (Beijing and Tianjin), and totally constitute of 40 cities. The North China Plain is one of the most polluted regions in mainland China (Du et al., 2020; Gong et al., 2020), and has attracted worldwide attention.

#### 2.1.2. Data sources

We chose the continuous 50 days which starting from January 25th to March 15th 2020 as the study period (corresponding to the lockdown period to restrain COVID-19 spread), and at the same time chose the same period (January 25th to March 15th) in 2015–2019 as a reference period for comparison. The hourly monitoring concentration data of six criteria air pollutants (CAPs, which include NO<sub>2</sub>, PM<sub>2.5</sub>, O<sub>3</sub>, PM<sub>10</sub>, SO<sub>2</sub>, and CO) were acquired from China National Environmental Monitoring Center (CNEMC). The daily average concentration of every pollutant for each city was calculated by averaging the hourly concentration values measured at all available monitoring stations within the city. The geographical distribution of air quality monitoring stations was shown in Fig. 1, and 258 air quality monitoring stations were selected. Meanwhile, the ground-level hourly wind speed (WS), wind direction (WD), temperature (T), relative humidity (RH), and atmospheric pressure (Press) for cities in the study domain are obtained using the "worldmet" R software package from the nearest weather stations (<https://CRAN.R-project.org/package=worldmet>).

The annual all-cause mortality and population used to calculate the health burden in each city were obtained from the China City Statistical Yearbook 2019. The daily mortality was then calculated by annual mortality rate divided by the number of days per year.



**Fig. 1.** Map of the study area (The triangles point out the location of air quality monitoring stations).

## 2.2. Machine learning approach

### 2.2.1. De-weather model

Changes in the concentrations of atmospheric pollutants are jointly affected by emissions and meteorology. To evaluate the contribution of emissions to pollutant concentrations, the “normalweather” R package was utilized to eliminate the impact of meteorological factors (Grange and Carslaw, 2019; Shi et al., 2021; Lv et al., 2022).

Random forest (RF) is a statistical-based machine learning theory. The overall idea of the RF algorithm includes first predicting the concentration of pollutants based on a set of characteristic values (including meteorological data and other time variables) and training a reliable RF model. Then, the RF model can be used to predict the concentration of pollutants under a series of meteorological conditions, and the relevant average value is called the normalized time series of meteorology. In the algorithm, the concentration of a certain pollutant at a specific time point can be predicted by resampling meteorological data. This process was repeated 1000 times, and 1000 predicted concentrations were averaged to calculate the final weather standardized concentration for that particular hour, day, and year. In the process, only the weather data, not the time variable, was normalized and resampled from the entire study period. The flowchart of the machine learning-based RF algorithm can be observed in Supporting Information (SI) Fig. ST1.

This study performed RF models for each pollutant at each monitoring station for the corresponding period each year. The air pollutant concentration predicted by the RF model was normalized meteorological concentrations (called the “deweathered” concentrations). The weather normalization was carried out by the “rmweather” R package. Details of the models are described in the separate Supporting Information (SI) provided with this study.

By using a de-weather method, we obtained the air pollutants level under the average meteorological conditions in study period of 2015–2020. The differences between the deweathered pollutants concentrations for 2020 and 2015–2019 can be attributed to the real effect of reduction in anthropogenic emissions. Then the difference between the gap of deweathered pollutants concentrations and the actual decrease can further be attributed to change in meteorology. We used the following formulas to assess the contribution of emission reduction and meteorology to the changes in pollutants concentrations.

$$E_c = \frac{C_{2020}^p - C_{2015-2019}^p}{C_{2015-2019}^{ob}} \times 100\% \quad (1)$$

$$M_c = \frac{(C_{2015-2019}^p - C_{2020}^p) - (C_{2015-2019}^{ob} - C_{2020}^{ob})}{C_{2015-2019}^{ob}} \times 100\% \quad (2)$$

where  $E_c$  and  $M_c$  represent the contributions of emission reduction and meteorological conditions, respectively.  $C_{2020}^p$  and  $C_{2015-2019}^p$  represent the observed pollutants concentrations and de-weathered concentrations in 2020, respectively.  $C_{2015-2019}^{ob}$  and  $C_{2020}^{ob}$  represent the observed concentrations and de-weathered concentrations in 2015–2019, respectively.

### 2.2.2. Theil-Sen estimator

The Theil-Sen regression technique was performed on the concentrations of air pollutants after meteorological normalization to investigate the long-term trend of pollutants. The Theil-Sen approach, which computes the slopes of all possible pairs of pollutant concentrations and takes the median value, has been commonly used for long-term trend analysis over recent years. By selecting the median of the slopes, the Theil-Sen estimator tends to give us accurate confidence intervals even with non-normal data and non-constant error variance (Sen and Kumar, 1968). The Theil-Sen function is provided via the R’s “openair” package.

## 2.3. Health burden assessment

The estimated health burden owing to short-term exposure to air pollutants can be calculated by Eqs. (1)–(3):

$$M_i = AF_i \times BM \times POP \quad (3)$$

$$AF_i = \frac{RR_i - 1}{RR_i} \quad (4)$$

$$RR_i = \exp(\beta \times (C - C_0)) \quad (5)$$

where  $M_i$  denotes the total mortality due to exposure to air pollution,  $POP$  is the number of the exposed population,  $BM$  is the daily baseline mortality,  $AF_i$  is the daily attributable fraction associated with short-term exposure to air pollutant  $i$ . In Eq. (4),  $RR_i$  is the daily relative risk associated with short-term exposure to air pollutant  $i$ . In Eq. (5),  $\beta$  is the concentration-response coefficient for health endpoints exposure to air pollutants, which were obtained from recent epidemiological studies (Dong et al., 2016; Lai et al., 2013; Ma and Cui, 2016; Shang et al., 2013) (Table S1);  $C$  is the daily concentration of air pollutants, which is calculated from the average concentration of a city;  $C_0$  is the daily threshold concentration of air pollutants, which is assumed to be zero following previous studies (Chen et al., 2017; Yao et al., 2020).

## 3. Results and discussion

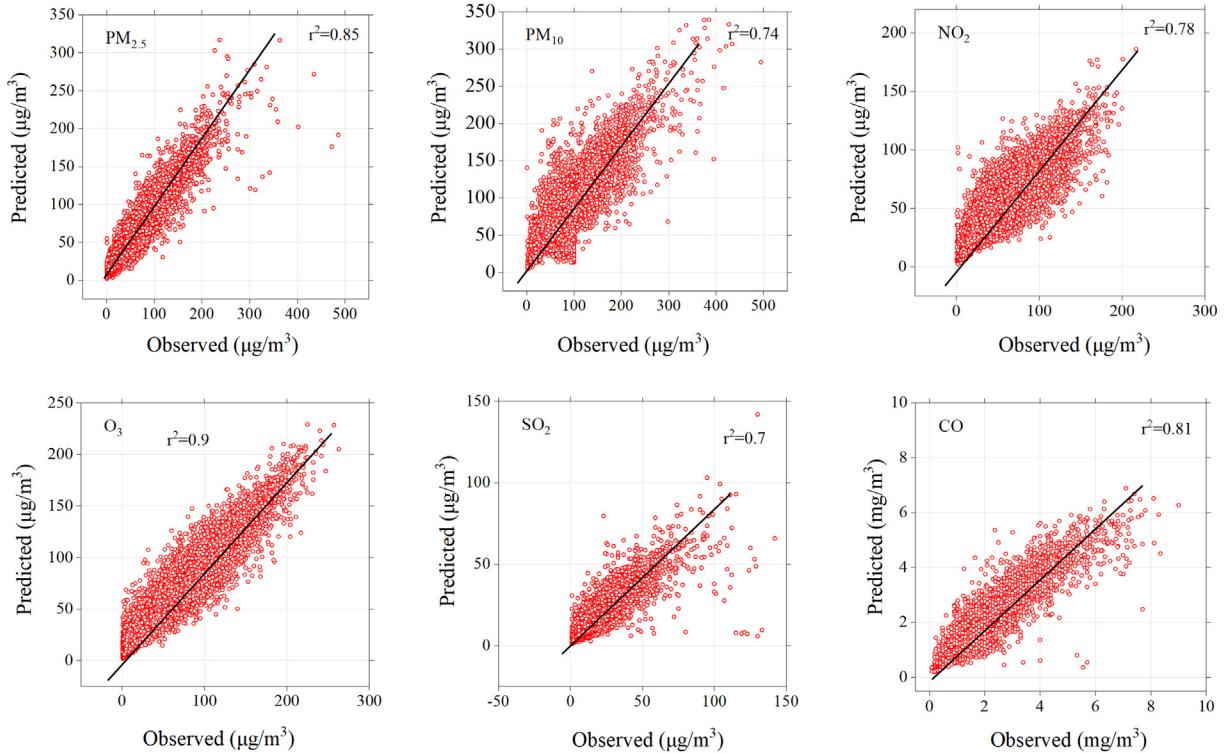
### 3.1. Model performance

**Table 1** and Fig. S1 show the ten statistical indices those were used to evaluate our model performance in different ways. The model evaluation metrics are shown in **Table 1** and Fig. S1. The high R values range from 0.78 to 0.96, indicating that the relation between the predicted and observed values is significant. The RF model performance is shown in **Fig. 2**. The  $R^2$  values are generally higher than 0.7. This indicates that the features of the established model are excellent. FAC2 (fraction of predictions with a factor of two) values were all greater than 0.9, which suggest that our model satisfies the condition for the fraction of predictions. MB (mean bias) value ranged within  $-0.03$ – $0.12$ , suggesting that the bias produced by our model is very small. Similarly, the lower values of NMB (normalized mean bias) and NMGE (normalized mean gross error) indicate that our

**Table 1**  
RF model performance for testing data set (in hourly time resolution).

Pollutants	RMSE	R	$R^2$	FAC2	MB	MGE	NMB	NMGE	COE	IOA
PM <sub>2.5</sub>	19.6	0.96	0.85	0.93	0.11	11.36	0.00	0.21	0.65	0.82
PM <sub>10</sub>	43.6	0.86	0.78	0.92	0.12	22.55	0.00	0.23	0.54	0.75
NO <sub>2</sub>	12.8	0.89	0.79	0.95	0.05	9.46	0.00	0.21	0.56	0.74
SO <sub>2</sub>	7.2	0.78	0.71	0.93	-0.03	2.87	-0.00	0.24	0.54	0.72
CO	0.4	0.89	0.78	0.98	0.002	0.23	0.01	0.16	0.60	0.80
O <sub>3</sub>	14.6	0.95	0.90	0.91	0.05	9.65	0.00	0.16	0.70	0.83

Note: FAC2 (fraction of predictions with a factor of two), MB (mean bias), MGE (mean gross error), NMB (normalized mean bias), NMGE (normalized mean gross error), COE (coefficient of Efficiency), and IOA (Index of Agreement).



**Fig. 2.** Model validation for testing data set of each criteria air pollutant (in hourly time resolution).

model performed well. Our model has sufficient prediction capability and performance, as indicated by all the above mentioned indices.

### 3.2. Air quality variations during the lockdown period

Fig. 3 shows the changed concentrations of 6 criteria air pollutants for 40 cities in North China during the lockdown when compared to the average for the same period during 2015–2019. As shown, almost all CAPs (except for  $\text{O}_3$ ) concentrations decreased significantly during lockdown period. In generally, the average concentrations of observed  $\text{PM}_{2.5}$ ,  $\text{NO}_2$  and  $\text{SO}_2$  in North China region declined by 22.4 %, 37.0 %, and 69.1 %, respectively, but with  $\text{O}_3$  increased by 21.5 %. Spatially,  $\text{PM}_{2.5}$ ,  $\text{PM}_{10}$ ,  $\text{NO}_2$ , and  $\text{SO}_2$  decrease most significantly in Shandong province, with a reduction of 37.1 %, 47.3 %, 43.7 % and 70.4 %, separately. Among all species, the drop of  $\text{SO}_2$  is particularly prominent, e.g., Beijing-Tianjin-Hebei region (BTH, 67.6 %), Shanxi province (69.1 %) and Shandong province (70.4 %) respectively, which can partly be attributed to the application of sulfur desulphurization technology and similar technologies in power and industry in recent years (Chen et al., 2019; Zhang et al., 2019).  $\text{O}_3$  concentrations show inverse effect compared with other species, with Shandong increased the highest (19.9 %), followed by BTH (18.1 %) and Shanxi (13.0 %).

### 3.3. Contribution of emissions and meteorology to the variation of $\text{PM}_{2.5}$ concentration

Fig. 4 used  $\text{PM}_{2.5}$  as an example to show city-specific pollution variation and the contribution rates ascribe to change in emissions and meteorology in North China. Compared to observed  $\text{PM}_{2.5}$  concentrations decrease ( $17.8 \mu\text{g}/\text{m}^3$ ; Fig. 4a), the de-weathered  $\text{PM}_{2.5}$  level shown more decrease ( $25.1 \mu\text{g}/\text{m}^3$ ; Fig. 4b), thus the meteorological conditions increased  $\text{PM}_{2.5}$  by about  $7.3 \mu\text{g}/\text{m}^3$ , indicate that the weather conditions during the lockdown period in 2020 are worse than the same period during 2015 to 2019. Spatially, change in meteorological conditions shows more adverse effect in BTH region ( $12.4 \mu\text{g}/\text{m}^3$ ) than Shanxi ( $6.4 \mu\text{g}/\text{m}^3$ ) and Shandong

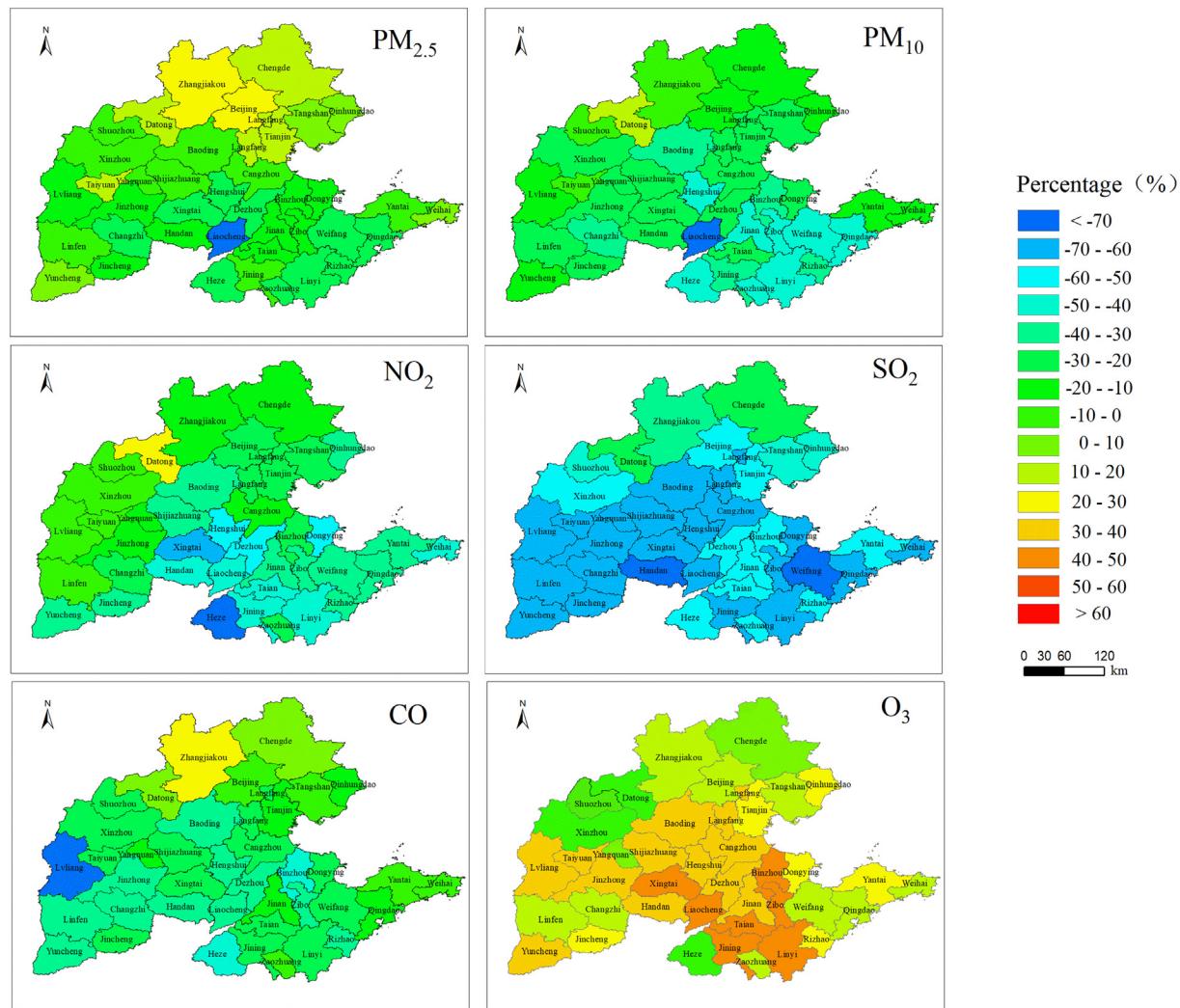
province ( $3.7 \mu\text{g}/\text{m}^3$ ) (Fig. 4b) (Huang et al., 2021). It is worth noting that the observed  $\text{PM}_{2.5}$  concentration during the lockdown period in Beijing in 2020 decreased by  $3.7 \mu\text{g}/\text{m}^3$  compared with the same period from 2015 to 2019, but the decrease can reach  $24.5 \mu\text{g}/\text{m}^3$  after excluding the influence of meteorological conditions, indicating that meteorological factors contributed to the increase of  $\text{PM}_{2.5}$  by  $20.8 \mu\text{g}/\text{m}^3$  in Beijing (Fig. 4c and Table S2).

Fig. 4d showed the relative contribution of changes in meteorology and anthropogenic emissions to the changes in  $\text{PM}_{2.5}$  concentration in 40 cities. Overall, the reduction of anthropogenic emissions has reduced  $\text{PM}_{2.5}$  concentration by about 32.2 % compared to the same period in 2015–2019, with a maximum drop for about 45.3 % in Hengshui (Table S3). On the contrary, the meteorological conditions deteriorated  $\text{PM}_{2.5}$  concentration during lockdown, particular for cities in BTH, such as Beijing, Langfang, Tianjin, Chengde, Zhangjiakou, Shijiazhuang, Tangshan, and Baoding, where the adverse meteorology increased the  $\text{PM}_{2.5}$  concentration by about 32.6 %, 27.1 %, 21.2 %, 19.7 %, 19.3 %, 18.0 %, 17.7 %, and 16.2 %, separately (Table S3). Spatially, the cities most affected by adverse meteorological conditions coincide with the typical pollution transmission channel cities around Beijing, indicating the importance to strengthen joint prevention and control between regions.

### 3.4. Changes in air quality attributable to long-term trends

#### 3.4.1. Air quality trends after de-weather during 2015–2019

Figs. 5 and S2 shown the relative decline trends for deweathered air pollutant concentrations during 2015–2019. After remove of meteorological effects, negative trends in air pollutants concentrations are widespread, with the largest reduction trends occurred in  $\text{SO}_2$ , particular for Shandong province (Fig. S2). The decline trend consisted with significant decrease trend of Shandong's  $\text{SO}_2$  emissions, estimated by the Multi-resolution Emission Inventory for China (Fig. S3). The annual average deweathered  $\text{SO}_2$  concentration reduction across all 40 cities is  $-20.4\%$  per year.



**Fig. 3.** Spatial distribution of relative changes of the air pollutants concentrations in North China during lockdown (January 25th to March 15th 2020) when compared to the same time period in 2015–2019.

Compared to  $\text{SO}_2$ , decline trends for deweathered  $\text{PM}_{2.5}$  concentrations were relatively small, its annual average reduction rates for BTH, Shandong, and Shanxi were only  $-8.8\%$ ,  $-9.6\%$ , and  $-5.8\%$  per year, respectively, but with significant reductions rates occurred in Beijing ( $-11.8\%$  per year) and several cities (e.g., Dezhou,  $-15.1\%$  per year, Liaocheng,  $-13.1\%$  per year, Jinan,  $-12.9\%$  per year) located in Shandong province (Figs. 5 and S2).

The deweathered  $\text{NO}_2$  concentrations decline rates are relatively small but shown diverse trends among regions and cities. Relative decline rate in the BTH, Shandong, and Shanxi were  $-4.5\%$  per year,  $-3.7\%$  per year, and  $-1.3\%$  per year, respectively. For several cities in Shanxi province, it even showed positive effects (e.g.,  $+6.6\%$  per year in Lvliang,  $+2.7\%$  per year in Datong,  $+1.2\%$  per year in Linfen) (Table S4), so strengthen the  $\text{NO}_2$  emission reduction would be of great urgent in North China, especially in Shanxi Province, in coming years.

Differ from other air pollutants, annual mean deweathered  $\text{O}_3$  shown a positive trend by  $+2.9\%$  per year in study areas during 2015–2019. And 82.5 % of the concerned 40 cities showed a rising trend, with particular higher rates for Binzhou (8.4 % per year), Handan (7.9 % per year), Tianjin (7.1 % per year) and Xingtai (7.0 % per year). This can partly be attributed to the lessened  $\text{NO}_x$  titration effect resulting from  $\text{NO}_x$  reduction, and finally promote the formation process of  $\text{O}_3$  (Jin and Holloway, 2015).

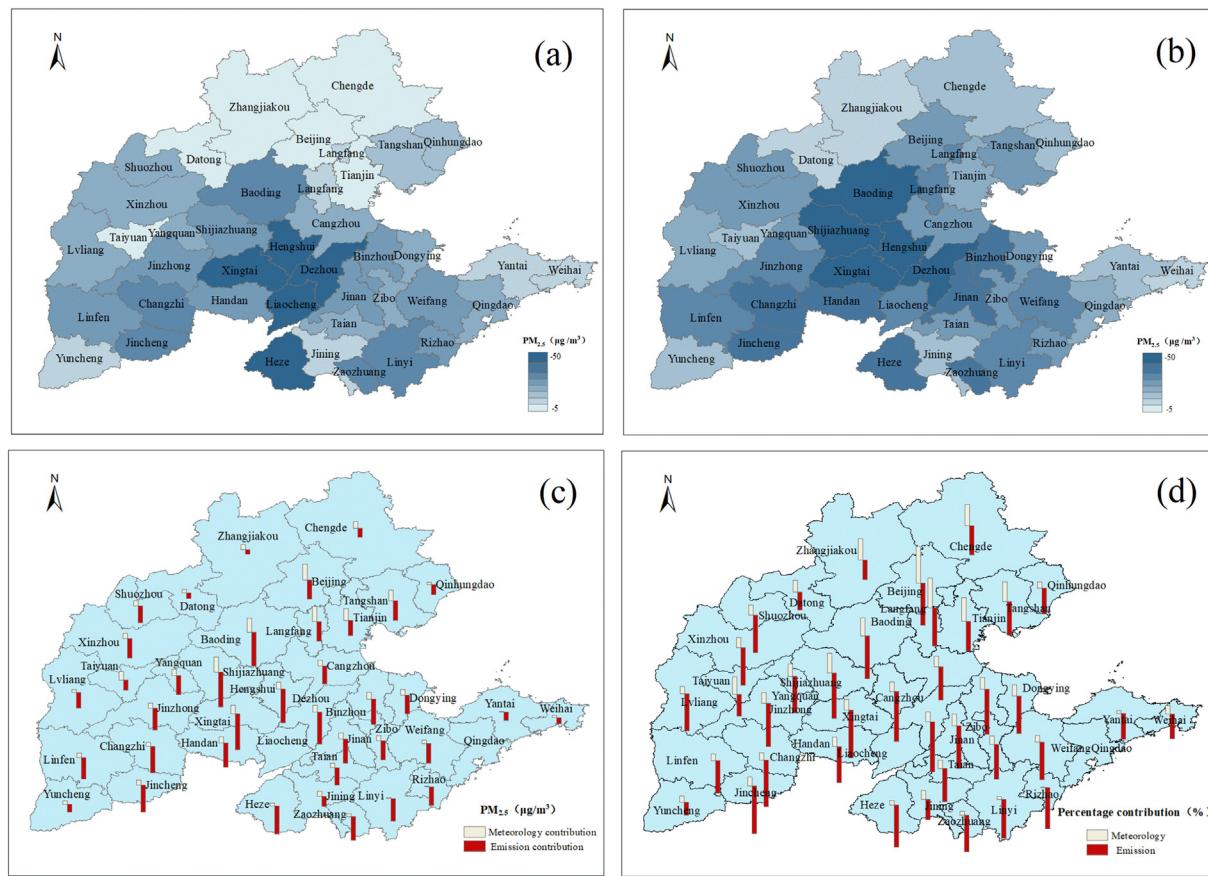
In general, BTH region shown more decline rate for deweathered  $\text{NO}_2$  concentration (4.9 % per year), revealing its effective  $\text{NO}_2$  emission control

in recent years (Zhang et al., 2020). While Shandong province shown more decline for deweathered  $\text{PM}_{2.5}$ ,  $\text{CO}$  and  $\text{SO}_2$  concentrations, with an average decrease rate of 9.6 % per year, 11.8 % per year and 25.3 % per year, respectively, reflecting the effectiveness of air pollution control relative emission sources in Shandong Province (Fan et al., 2020). Our results also showed that cities with the greatest improvement in air quality were typically located in the “2 + 26” region, proving the significant effects of enforced control measures in the BTH region and its surrounding areas in recent years, like the “2017 Air Pollution Prevention and Control Action Plan for the Beijing–Tianjin–Hebei region and its Surrounding Areas” (MEP, 2017) and the “Three-year Action Plan on Defending the Blue Sky” (MEP, 2020).

#### 3.4.2. Long-term trends during lockdown periods

To accurately reflect the true long-term pollution reduction trend during the lockdown time (from January 25th to March 15th), this study improves the time period estimated by Theil-Sen, and only selects the deweathered pollutant concentration input model from January 25th to March 15th for year from 2015 to 2019 to quantify the long-term trend change of this time period in recent years.

As shown in Table S5, the deweathered air pollutant concentration in North China during the lockdown period showed similar trends with the annual average rate, but with more variation degree. Some cities even reported an increase trend for deweathered  $\text{PM}_{2.5}$  concentration during the



**Fig. 4.** The change of PM<sub>2.5</sub> concentration during the lockdown period (January 25th to March 15th 2020) and the same time period from 2015 to 2019. (a) Apparently observed (b) de-weathered. Anthropogenic emissions and meteorological contributions to changes in PM<sub>2.5</sub> (c) absolute contribution (d) relative contribution.

study period, contrary to the previous reported annual declined trend since 2013 resulting from the implementation of “Action Plan for the Prevention and Control of Air Pollution” (Zhao et al., 2017). One possible reason may be that the monthly average PM<sub>2.5</sub> emissions is not continued to decline (Qu et al., 2020). Qu et al. (2020) used an improved regression tree method to remove meteorological effects and found that monthly PM<sub>2.5</sub> emissions in the Beijing-Tianjin-Hebei region fluctuated from 2016 to 2017.

### 3.5. Changes in air quality attributable to the lockdown measures

After removing the effects from meteorology and long-term decline trend, the PM<sub>2.5</sub> and NO<sub>2</sub> decline rates for North China ascribed to the lockdown measure occurred to be -27.6 % and -30.8 % (Fig. 6a), respectively, differing slightly from the observed values (-22.4 % and -37.1 %, respectively), but the effect on O<sub>3</sub> concentration is particularly significant, and the reduction rate ascribe to lockdown only occurred to be about half of that observed number (+10 % versus +21.5 %). These results suggested that the observed value overestimates the decrease of NO<sub>2</sub> concentrations and the increase of O<sub>3</sub> concentrations, but underestimates the reduction effect on PM<sub>2.5</sub> attributable to the lockdown. Our results address the importance to decouple the effects from meteorological variations and long-term decline trends in evaluating the real impact of lockdown measures on air quality.

Fig. 6b shows lockdown-derived PM<sub>2.5</sub>, NO<sub>2</sub>, and O<sub>3</sub> concentration decline in sub-areas. Compared to the slight decline rate for long-term reduction trend during 2015–2019, Shanxi province showed the largest reduction rates (30.5 %; -28.2 % and -25.2 % for BTH and Shandong, respectively) during the lockdown period, suggesting the effective of control measures on Shanxi's PM<sub>2.5</sub> pollution reduction. However, its decline rate for NO<sub>2</sub> (-23.0 %) was relative lower when compared to BTH (-36.1 %) and Shandong (-31.8 %), partly can be attributed to its vehicle

numbers (Fig. 6c). The higher reduction rate for BTH and Shandong also address the importance to control traffic activities to reduce NO<sub>2</sub> pollution.

To detect the interact effect between different pollutant species, we conducted a correlation analysis (Table S6), and results showed significant and strong negative correlation between NO<sub>2</sub> and O<sub>3</sub> concentrations, convinced the mechanism that the sharp decrease of NO<sub>2</sub> concentration during the epidemic led to the increase of O<sub>3</sub> concentration (Sicard et al., 2020). We also find a significant moderate negative correlation between PM<sub>2.5</sub> concentration and O<sub>3</sub> concentration (Table S6), consisting with the view that the decrease of PM<sub>2.5</sub> concentration during the epidemic promotes the increase of O<sub>3</sub> concentration (Liu et al., 2013; Murphy et al., 2007). Considering the nonlinear relationship between secondary pollutants and their gaseous precursors in the atmosphere, it would be of great importance to adopt collaborative emission reduction strategies to suppress VOC and NO<sub>x</sub> emissions at the same time, so as to slow down the increasing rates of secondary PM<sub>2.5</sub> and O<sub>3</sub> pollution (Rao et al., 2009).

### 3.6. Short-term health effects attributable to changes in air quality

#### 3.6.1. Premature mortality attributable to air pollutants

By using the pollution exposure health risk models and average monitoring concentrations for six air pollutants during same period (from January 25th to March 15th) for 2015–2019 and 2020, the all-cause premature mortality by short-term exposure to air pollution in 40 cities in North China were calculated. The total premature deaths attributable to air pollution during the study period in 2015–2019 and 2020 were 43,871 (95 % CI: 33,291–53,037) and 28,064 (95 % CI: 21,474–34,057), respectively (Table 2). Both of which were dominated by NO<sub>2</sub> and CO pollution, far more than the effect from particulate matter (either PM<sub>2.5</sub> or PM<sub>10</sub>). It's worth noting that the relative contributions of SO<sub>2</sub> decreased from 15.0 % in 2015–2019 to 6.8 % in 2020, which may reveal the outstanding

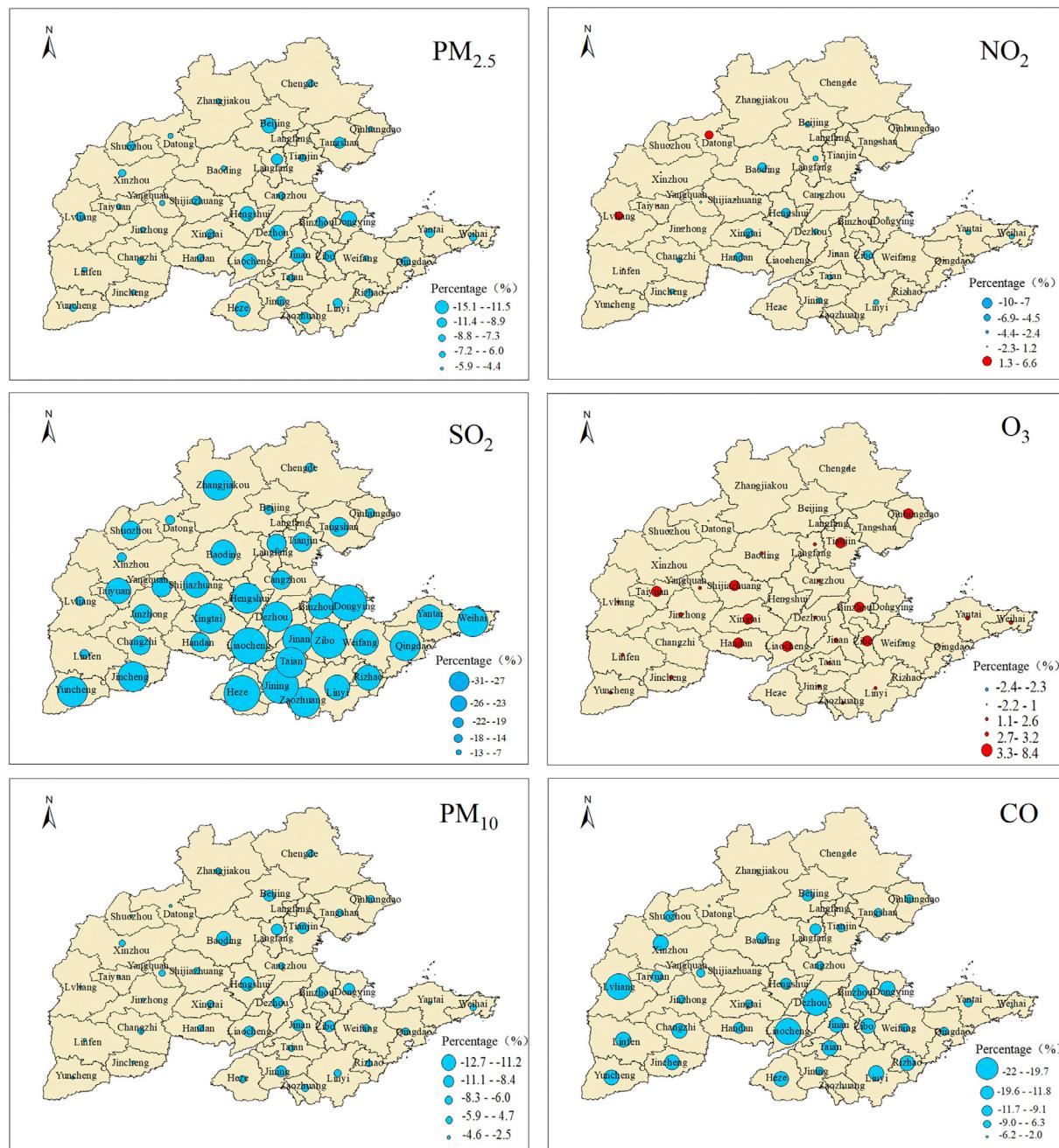


Fig. 5. Relative trends of deweathered criteria air pollutants from 2015 to 2019.

effect of implementing SO<sub>2</sub> control measures in recent years (Guo et al., 2019). Meanwhile, O<sub>3</sub> contribution increased substantially from 8.1 % in 2015–2019 to 14.9 % in 2020.

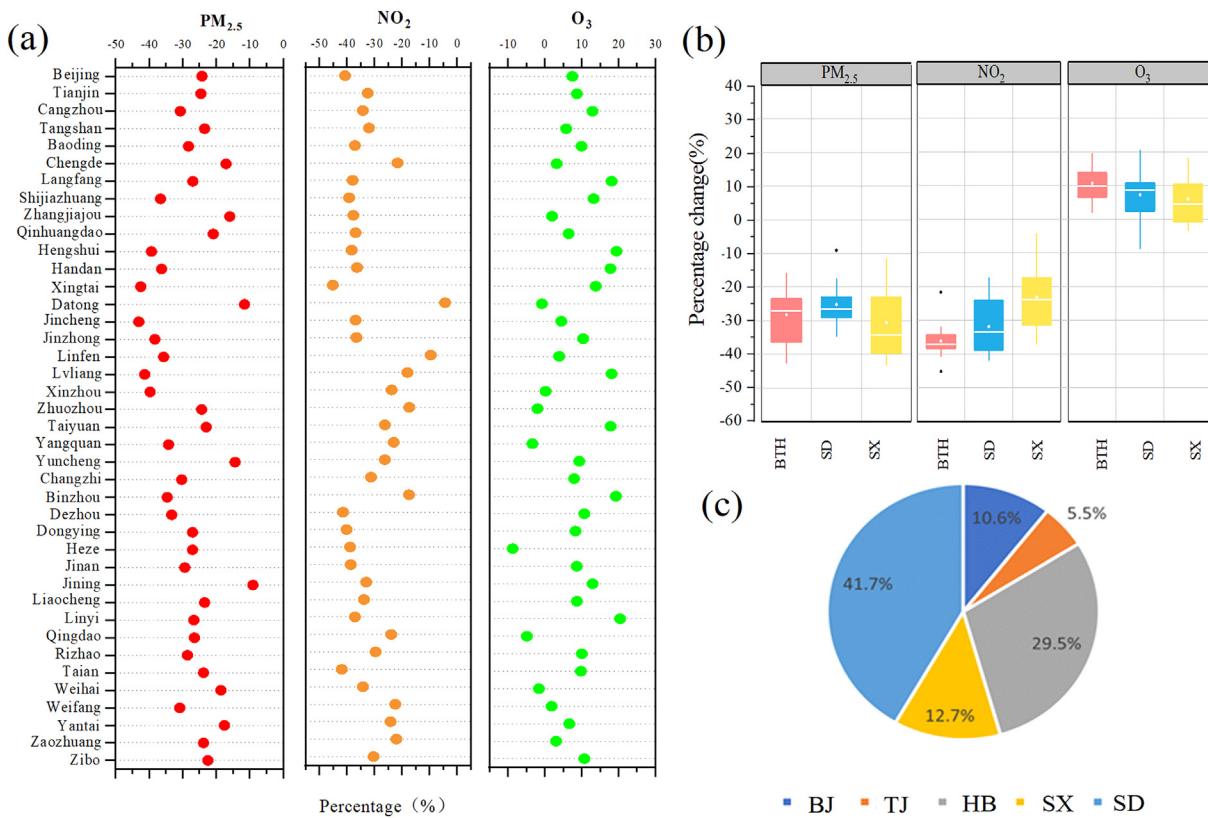
### 3.6.2. Avoided premature mortality due to air quality improvement during the COVID-19 lockdown

Compared to 2015–2019, the total avoided premature deaths in study areas during the COVID-19 pandemic due to air quality improvement was 15,807 (95 % CI: 11,817–18,980) (Table 2). Particularly attributed to the reduction of NO<sub>2</sub> (29.7 % of total), followed by SO<sub>2</sub> (29.4 %), CO (20.7 %), PM<sub>10</sub> (16.5 %) and PM<sub>2.5</sub> (7.6 %), respectively. As expected, O<sub>3</sub> increased premature deaths by 3.9 %, indicating the complexity and importance of synergistic control of PM<sub>2.5</sub> and O<sub>3</sub> in the future.

Fig. 7a and b shows the spatial distribution and ranking of the avoided premature deaths due to air pollutants reduction during the COVID-19 lockdown in 40 cities, respectively. Due to significant diversity existing for

factors such as population, baseline mortality rate, and air pollutants reduction, the short-term avoided premature death varies significantly among cities. Baoding, Beijing, and Handan benefit the most, avoiding about 1181, 1038 and 1005 premature deaths, respectively. However, their reduction rate contributed by each species differ significant. In Beijing, the reduction of NO<sub>2</sub> concentration (47.0 %) contributed the most to the reduction of premature deaths, followed by SO<sub>2</sub> (18.9 %), CO (17.7 %) and PM<sub>10</sub> (17.0 %). While for Handan, SO<sub>2</sub> (30.1 %) contributed the most, followed by NO<sub>2</sub> (26.0 %), CO (23.4 %), PM<sub>10</sub> (14.5 %) and PM<sub>2.5</sub> (6.9 %). It suggests the notable differences/heterogeneity in the industrial/energy structure and the response to lockdown control measures among cities in North China Plain.

As it is hard to split the objective effect from anthropogenic emissions and meteorological factors on health impacts during the lockdown, here we simply use their contribution rates to the concentration change as proxies to attribute their contribution to avoided premature deaths (Fig. 7c).



**Fig. 6.** Percentage changes in meteorologically normalized NO<sub>2</sub>, PM<sub>2.5</sub>, and O<sub>3</sub> attributable to additional lockdown effects in 2020 among (a) 40 cities and (b) three regions. (c) Distribution of number of vehicles of five provinces and cities in North China in 2019. (Shandong-SD; Shanxi-SX; Hebei-HB; Tianjin-TJ; Beijing-BJ).

Compared to the average impact during 2015–2019, pollution reduction during the lockdown period in 2020 would avoid premature death in North China by 15,807 (95 % CI: 11,817–18,980), and this avoided value would increase by 1146 if the meteorological condition during the lockdown period remains the same as the average situation in 2015–2019 for the same period. The meteorological conditions during 2015–2019 would be promote the reduction of PM<sub>2.5</sub> and CO concentrations, which can avoid 635 (55.4 % of the total) and 523 premature deaths (45.6 %), separately. Regionally, if the meteorological conditions remained as those of 2015–2019, the health burden would further reduce by 1362 in the BTH region (478 in Beijing, 153 in Tianjin and 731 in Hebei) and 48 in Shanxi province, but increased in Shandong province during the lockdown period in 2020.

### 3.6.3. Uncertainties and limitations

Similar to previous studies (Liu et al., 2016; Wang et al., 2020b), some uncertainty in the estimation of health effects were observed in our study due to the uncertainty of the model and the existence of relevant assumptions. Firstly, the parameters of the exposure-response function (such as concentration-response coefficient and threshold concentration) are uncertain. In order to ensure the rationality of the estimation, the parameter

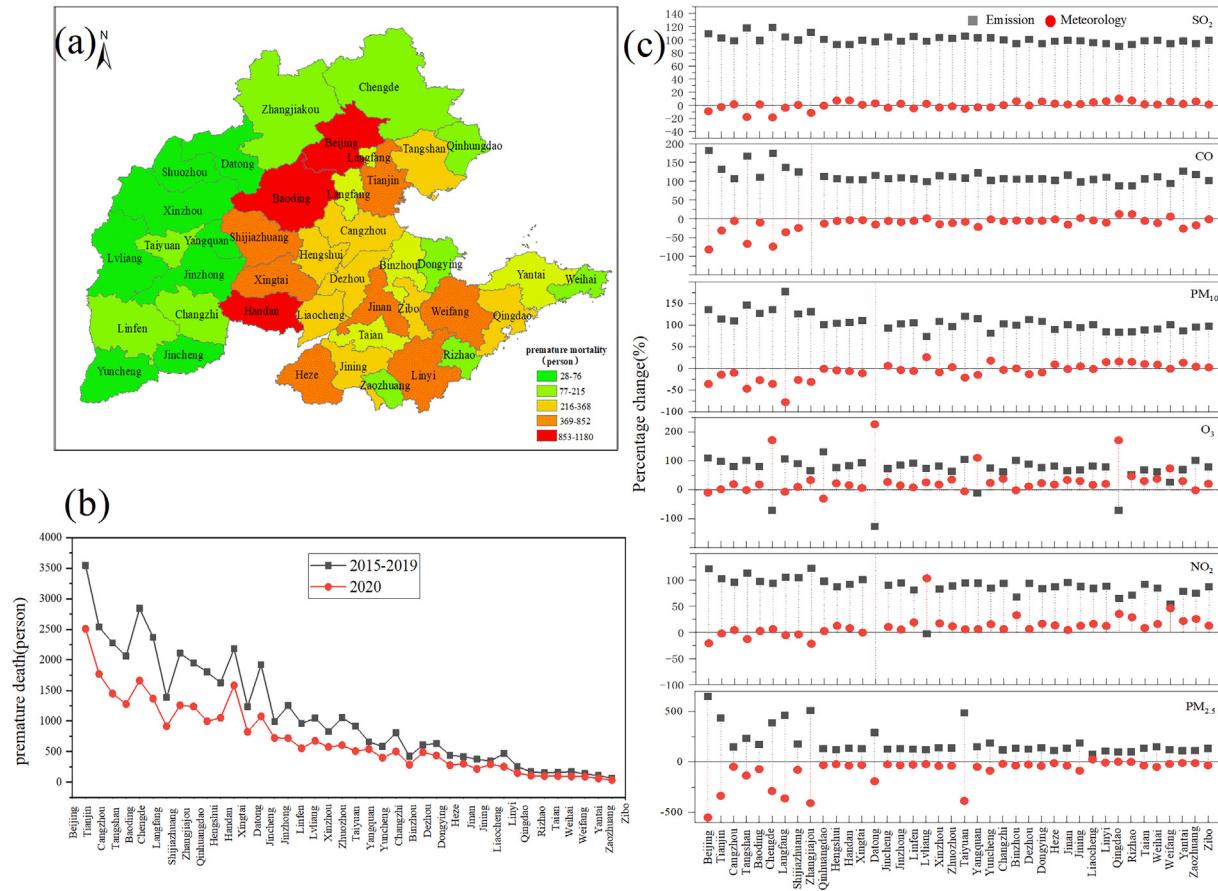
model provided in the recent epidemiological study (Dong et al., 2016; Lai et al., 2013; Ma and Cui, 2016; Shang et al., 2013) was used in this study to reduce the uncertainty of the exposure-response coefficient. However, due to the limitations of the model, other uncertainty simple assumptions were observed including that the exposure-response coefficient does not change with age, and that the average daily mortality rate were calculated from the average annual mortality rate. When characterizing the exposure concentration of urban population, the average value of air pollutant concentration observed at all monitoring sites in the city were used as the exposure concentration, ignoring the spatial heterogeneity of air pollutant concentration in urban and rural environments. This results in an underestimate when more monitoring sites are located in rural and less populated areas, and an overestimate when more monitoring sites are more likely to be located in urban and densely populated areas of a city. Methods to further improve the spatial accuracy of health impact assessments include the use of high spatial resolution population distributions and interpolation concentrations based on low-cost sensor networks (Cavaliere et al., 2018; Holstius et al., 2014) or satellite-based data (Li et al., 2020a).

This study provides a reasonable estimate of the avoided premature deaths associated with air pollution due to COVID-19 lockdown for nearly

**Table 2**

The premature mortality attributable to short-term exposure to air pollutants in 2015–2019 and 2020.

Pollutants	2015–2019		2020		2020–(2015–2019)	
	Premature death (person)	Contribution (%)	Premature death (person)	Contribution (%)	Premature death (person)	Contribution (%)
PM <sub>2.5</sub>	5429 (4441–6410)	12.4	4227 (3456–4994)	15.1	1202 (985–1416)	7.6
PM <sub>10</sub>	7277 (5196–9560)	16.6	4667 (3325–6146)	16.6	2610 (1871–3414)	16.5
SO <sub>2</sub>	6559 (4403–7979)	15	1906 (1273–2326)	6.8	4653 (3130–5653)	29.4
NO <sub>2</sub>	11,473 (9077–13,051)	26.1	6784 (5353–7732)	24.2	4689 (3724–5319)	29.7
CO	9562 (7489–11,585)	21.8	6297 (4921–7645)	22.4	3265 (2568–3940)	20.7
O <sub>3</sub>	3571 (2685–4452)	8.1	4183 (3146–5214)	14.9	-612 (-461–762)	-3.9
Total	43,871 (33,291–53,037)	100	28,064 (21,474–34,057)	100	15,807 (11,817–18,980)	100



**Fig. 7.** (a) Spatial distribution of avoided total premature death. (b) Premature deaths of 40 prefecture-level cities in North China during the study period 2015–2019 and 2020. (c) Meteorological and anthropogenic contributions to changes in pollutant concentrations.

two months from January 25th to March 15th in early 2020, demonstrating the importance of improving air quality. However, this work does not in any way support the positive impact of COVID-19 on human society. In fact, the potential health and economic benefits of improved air quality during the COVID-19 pandemic are far less than the huge socio-economic and other costs paid during the pandemic.

#### 4. Conclusions

The nationwide lockdown during the COVID-19 pandemic provided a precious opportunity to demonstrate the potential improvement in air quality that anthropogenic emissions could bring. In this study, we combined machine learning algorithm and Theil-Sen estimator to strip out the effects of meteorology and long-term trends, and try to estimate the true effect of lockdown measures on air quality improvement during the COVID-19 pandemic (January 25th to March 15th 2020) in North China (consisted by 40 cities). By using widely used exposure response functions, we further evaluate the associated health benefit resulting from changes in air pollutant concentrations in North China during the COVID-19 lockdown period.

Our results show that the meteorology during the lockdown period in 2020 are more conducive to the increase of PM<sub>2.5</sub> concentration compared to the same period in 2015–2019, and increased the PM<sub>2.5</sub> concentration in North China by about 9.8 %, while the reduction of anthropogenic emissions led to a 32.2 % drop in PM<sub>2.5</sub> concentration. Adverse meteorological conditions have a greater impact on the BTH region than on Shanxi and Shandong provinces. The regions bear the more adverse effects from meteorology change coincided with the BTH air pollution transmission channel, indicating the important contribution of the regional transport of pollutants during COVID-19 outbreak has offset the effect from anthropogenic

emissions reduction to some extent, addressing the importance to joint control among these regions or cities. Meanwhile, the significant role of meteorology in this variation of PM<sub>2.5</sub> underscores the importance of taking meteorological factors into account when short-term stringent emission controls are planned.

After decoupling the meteorological and long-term trend impacts, we found that the observed pollutant concentration overestimated or underestimated quality improvement attributable to the lockdown measures for specific species. The average change in deweathered NO<sub>2</sub>, PM<sub>2.5</sub>, and O<sub>3</sub> attributable to the lockdown were -30.8 %, -27.6 %, and +10.0 %, respectively. Our results address the importance to decouple the effects from meteorological variations and long-term decline trends in evaluating the real impact of lockdown measures on air quality.

Furthermore, relative to the same period in 2015–2019, we found an overall improvement of air quality, and such improvement could avoid premature deaths by 15,807 (95 % CI: 11,817–18,980), with dominant contribution from anthropogenic emission reduction. However, if the lockdown period meteorological conditions remained the same as this of 2015–2019 for the same period, the total avoided premature would increase by 1146 in whole 40 cities, with significant increase occurred in BTH regions. It suggests that, in addition to persist continuously strengthening the primary air pollutants emission reduction from various anthropogenic activities, the non-negligible influences from meteorology should be given sufficient attention in the future regional air quality management in order to better protect public health, especially during the winter season in North China. Overall, our study comprehensively spans the entire chain from air pollution to health benefits, as well as the positive contribution of meteorological effects, and this information is beneficial for future air pollution remediation. In addition, the specific contribution of each

meteorological factor is still unclear and needs further study. In the future work, it is necessary to quantitatively decompose meteorological factors and quantify the importance of different variables.

### CRediT authorship contribution statement

**Yunqian Lv:** Conceptualization, Methodology, Modelling, Software, Investigation, Writing-Original Draft preparation.

**Hezhong Tian:** Conceptualization, Data curation, Formal analysis, Writing-Review & Editing, and Supervision.

**Lining Luo:** Validation, Formal analysis, Visualization.

**Shuhan Liu:** Validation, Formal analysis, Visualization.

**Xiaoxuan Bai:** Validation, Formal analysis, Visualization.

**Hongyan Zhao:** Formal analysis, Writing-Review and Editing.

**Kai Zhang:** Formal analysis, Writing-Review and Editing.

**Shumin Lin:** Formal analysis, Visualization.

**Shuang Zhao:** Formal analysis, Visualization.

**Zhihui Guo:** Validation, Formal analysis.

**Yifei Xiao:** Validation, Formal analysis.

**Junqi Yang:** Validation, Formal analysis.

All authors contributed to interpretation of the data and provided comments on the manuscript.

### Data availability

Data will be made available on request.

### 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

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2022.159339>.

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