

## Article

# Impact of Anthropogenic Emission Reduction during COVID-19 on Air Quality in Nanjing, China

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**Abstract:** To avoid the spread of COVID-19, China has implemented strict lockdown policies and control measures, resulting in a dramatic decrease in air pollution and improved air quality. In this study, the air quality model WRF-Chem and the latest MEIC2019 and MEIC2020 anthropogenic emission inventories were used to simulate the air quality during the COVID-19 lockdown in 2020 and the same period in 2019. By designing different emission scenarios, this study explored the impact of the COVID-19 lockdown on the concentration of air pollutants emitted by different sectors (industrial sector and transportation sector) in Nanjing for the first time. The results indicate that influenced by the COVID-19 lockdown policies, compared with the same period in 2019, the concentrations of PM<sub>2.5</sub>, PM<sub>10</sub>, and NO<sub>2</sub> in Nanjing decreased by 15%, 17.1%, and 20.3%, respectively, while the concentration of O<sub>3</sub> increased by 45.1% in comparison; the concentrations of PM<sub>2.5</sub>, PM<sub>10</sub> and NO<sub>2</sub> emitted by industrial sector decreased by 30.7%, 30.8% and 14.0% respectively; the concentrations of PM<sub>2.5</sub>, PM<sub>10</sub> and NO<sub>2</sub> emitted by transportation sector decreased by 15.6%, 15.7% and 26.2% respectively. The COVID-19 lockdown has a greater impact on the concentrations of PM<sub>2.5</sub> and PM<sub>10</sub> emitted by the industrial sector, while the impact on air pollutants emitted by the transportation sector is more reflected in the concentration of NO<sub>2</sub>. This study provides some theoretical basis for the treatment of air pollutants in different departments in Nanjing.

**Keywords:** WRF-Chem; anthropogenic emissions inventory; air pollutants; COVID-19



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## 1. Introduction

Air pollution is a global public health concern, particularly in developing countries such as China [1] and India [2]. According to the 2020 World Air Quality Report, air pollution remains one of the greatest health hazards that people face around the world [3]. Studies have shown that poor air quality increases the prevalence and mortality caused by novel coronavirus pneumonia [4,5].

In early 2020, the sudden outbreak of COVID-19 had a large impact on many aspects of China's society and economy. To avoid the spread of COVID-19, China has implemented strict lockdown policies and control measures. The widespread COVID-19 lockdown policies provided a rare opportunity to assess the impact of the reduction in anthropogenic air pollutant emissions on air quality, and the impact of COVID-19 on air pollutants has been described as “the largest controlled air quality experiment ever conducted” [6].

Many studies have shown that around the world, air quality has improved due to the implementation of lockdown policies [7,8]. In 366 urban areas across China, the concentrations of PM<sub>10</sub>, PM<sub>2.5</sub>, SO<sub>2</sub>, NO<sub>2</sub>, and CO were reduced, while O<sub>3</sub> showed increasing rates [9]. In the USA, a study using air quality data from 2017 to 2020 found that the concentrations of PM<sub>2.5</sub> and NO<sub>2</sub> decreased during the COVID-19 period [10]. Agarwal et al. [11] reported that nationwide lockdown and shutdown policies in India and China

resulted in a significant improvement in air quality status. The results demonstrated that in India and China, concentrations of PM<sub>2.5</sub> and NO<sub>2</sub> decreased by 65% and 66%, and 45% and 37%, respectively.

Most researchers use methods such as statistical analysis of ground observations, inversion of satellite data, machine learning, and modeling analysis to investigate the changes in air quality caused by the COVID-19 lockdown. Wong et al. [12] propose a novel research framework to investigate the observed and meteorological-normalized concentrations of nitrogen dioxide (NO<sub>2</sub>) and ozone (O<sub>3</sub>) across 62 cities in Taiwan. They found that throughout 2020, even in the absence of a lockdown, the daily mean meteorological-normalized NO<sub>2</sub> and O<sub>3</sub> levels across Taiwan decreased by 14.9% and 5.8%, respectively. Habibi et al. [13] obtained air quality data between January 2019 and April 2020 from the world air quality index project and showed that compared with the same period in 2019, the concentrations of NO<sub>2</sub>, CO, and PM<sub>2.5</sub> decreased and O<sub>3</sub> increased in most major cities around the world during February April 2020. Tang et al. [14] 2021 used ground air monitoring data and satellite data to investigate ozone changes caused by the COVID-19 lockdown in different parts of the world. The study found that, with significant reductions in NO<sub>x</sub>, O<sub>3</sub> concentrations showed an upward signal in East Asia and Europe, while those in North America showed a downward trend. Dai et al. [15] used a random forest algorithm to quantify the impact of meteorological elements on surface air quality in 31 major cities in China during the COVID-19 lockdown and showed that the impact of the epidemic lockdown on air quality was limited after removing the effect of the Chinese New Year holiday on air pollutants.

Other studies also used air quality models to study the effects of lockdowns on air quality. Feng et al. [16] 2021 used the WRF-CMAQ model to assess the emission reduction and related air quality impacts of the transportation and industrial sectors during the Wuhan lockdown. The results show that the contribution of the industrial shutdown to the emission reduction in pollutants is significantly greater than that of traffic restrictions. Ciarelli et al. [17] used the CAM<sub>x</sub> model to study potential changes in air quality and its chemical composition in northern Italy and Switzerland during the COVID-19 lockdown. The results showed that the lockdown measures reduced the NO<sub>2</sub> air concentration resolution in the Po River basin and the Swiss plateau by up to 46% and 25%, while the air concentration of fine particulate matter (PM<sub>2.5</sub>) only decreased by 10% and 6%. Wang et al. [18] used WRF-CMAQ to simulate the air quality changes in the Pearl River Delta before, during, and after the lockdown. Compared with before and after the lockdown, under the dual influence of anthropogenic emissions and meteorology, the air quality was significantly improved during the lockdown. PM<sub>2.5</sub>, NO<sub>2</sub>, and SO<sub>2</sub> decreased by 52%, 67%, and 25%, respectively, while O<sub>3</sub> did not change significantly.

At present, most studies basically adopt the anthropogenic emission inventory of MEIC<sub>2017</sub>. By adjusting the emissions of different emission sectors, the simulation results are more consistent with the situation of air pollutants during the COVID-19 lockdown. There are few studies on the impact of COVID-19 lockdowns on different emission sectors, and old emission inventories are not able to accurately quantify the impact of COVID-19 lockdowns on different emission sectors. Therefore, in this study, the WRF-Chem model and the latest emission inventories, MEIC<sub>2019</sub> and MEIC<sub>2020</sub>, were used to simulate air pollutants in Nanjing during the COVID-19 lockdown and the same period in 2019. They aim to more realistically reappear the temporal and spatial changes of air pollutants during the COVID-19 lockdown and the same period in 2019, as well as compare the levels of air pollutants during the two periods and assess the impact of anthropogenic emissions reduction caused by COVID-19 lockdown on air pollutants emitted by different emission sectors. We used the NP to represent the normal period (22 January 2019 to 25 February 2019) and the LP to represent the COVID-19 lockdown period (22 January 2020 to 25 February 2020). The COVID-19 lockdown provided an excellent opportunity to investigate the characteristics of Nanjing's air pollution and the distribution of pollution

sources. This study will provide an important basis for designing effective control strategies and further improving the air quality of Nanjing.

## 2. Data & Methods

### 2.1. Research Area

Located in eastern China, downstream of the Yangtze River and southwest of Jiangsu Province, Nanjing is an important node city where the eastern coastal economic belt and the Yangtze River economic belt meet strategically and is one of the largest cities in China. Due to urbanization and economic development, Nanjing has a growing population and a large industrial scale. As of 2021, the resident population of Nanjing reached 9.31 million, the number of motor vehicles reached 2.91 million, and the secondary industry accounted for 35.2% of the GDP. However, at the same time, air pollution in Nanjing also presents more obvious characteristics, such as regional complexity, and consequently brings about increasingly serious air pollution problems, causing serious impacts on resident health and air quality, making the air pollution in Nanjing a matter of great concern to scholars [19,20].

### 2.2. Air Quality Model

The WRF model is a fully compressible and non-hydrostatic model (with a run-time hydrostatic option). Arakawa C-grid is used in the horizontal direction of the WRF model. The WRF model uses Arakawa C-grid for the horizontal coordinate, and its vertical coordinate is a hybrid vertical coordinate (HVC) hydrostatic pressure coordinate. The model uses the Runge-Kutta 2nd and 3rd-order time integration schemes and 2nd to 6th-order advection schemes in both the horizontal and vertical. The dynamics conserve scalar variables. The dynamic frame adopts the completely compressible and non-static equilibrium Euler model.

In this study, WRF-Chem Version V3.9.1 was used, in which meteorological and chemical processes occur and interact simultaneously in the real atmosphere, and WRF-Chem enables the meteorological mode WRF [21] and chemical transport module Chem to be fully coupled online in terms of temporal and spatial resolution, and the same physical parameterization scheme is used in the subgrid transport [22]. The WRF-Chem model adopts classical three-dimensional Euler grid coordinates. The space-time evolution law of air pollutants conforms to the law of conservation of mass, and the equation is as follows:

$$\frac{\partial C_i}{\partial t} + \nabla \cdot (\vec{V} C_i) = \nabla \cdot (K \nabla C_i) + \left( \frac{\partial C_i}{\partial t} \right)_{conv} + \left( \frac{\partial C_i}{\partial t} \right)_{dep} + \left( \frac{\partial C_i}{\partial t} \right)_{chem} + \left( \frac{\partial C_i}{\partial t} \right)_{emis} \quad (1)$$

$C_i$  is the concentration of pollutant  $i$ ;  $\frac{\partial C_i}{\partial t}$  is the change of pollutant concentration in unit time step;  $\nabla \cdot (\vec{V} C_i)$  is the variation of pollutant concentration caused by advection transport; among them,  $\vec{V}$  is the wind speed,  $\nabla \cdot (K \nabla C_i)$  is the variation of pollution concentration caused by turbulent processes. Among them,  $K$  is the turbulence exchange coefficient;  $\left( \frac{\partial C_i}{\partial t} \right)_{conv}$ ,  $\left( \frac{\partial C_i}{\partial t} \right)_{dep}$ , and  $\left( \frac{\partial C_i}{\partial t} \right)_{emis}$  are the variations of convection, dry and wet deposition, chemical reaction, and emission intensity on pollutant concentration. Therefore, the variation of air pollutants concentration in the model is the result of careful consideration of multiple factors such as wind field transmission, turbulent diffusion, chemical transformation, dry and wet deposition, and pollutant emissions.

In this study, three layers of mode nesting were set; the third-layer nesting centers were 32.2° and 119.15°; the horizontal resolutions were 27 km × 27 km, 9 km × 9 km, and 3 km × 3 km; the number of nested grids in the third layer was 100 × 100, and the range of mode nesting is shown below. The model parameterization settings are shown in Table 1. Meteorological initial and boundary conditions were obtained from NCEP GDAS Final Analysis data with a spatial resolution of 0.25° × 0.25° for January–February 2019 and January–February 2020 [23]. Biogenic emission data used natural gas and aerosol

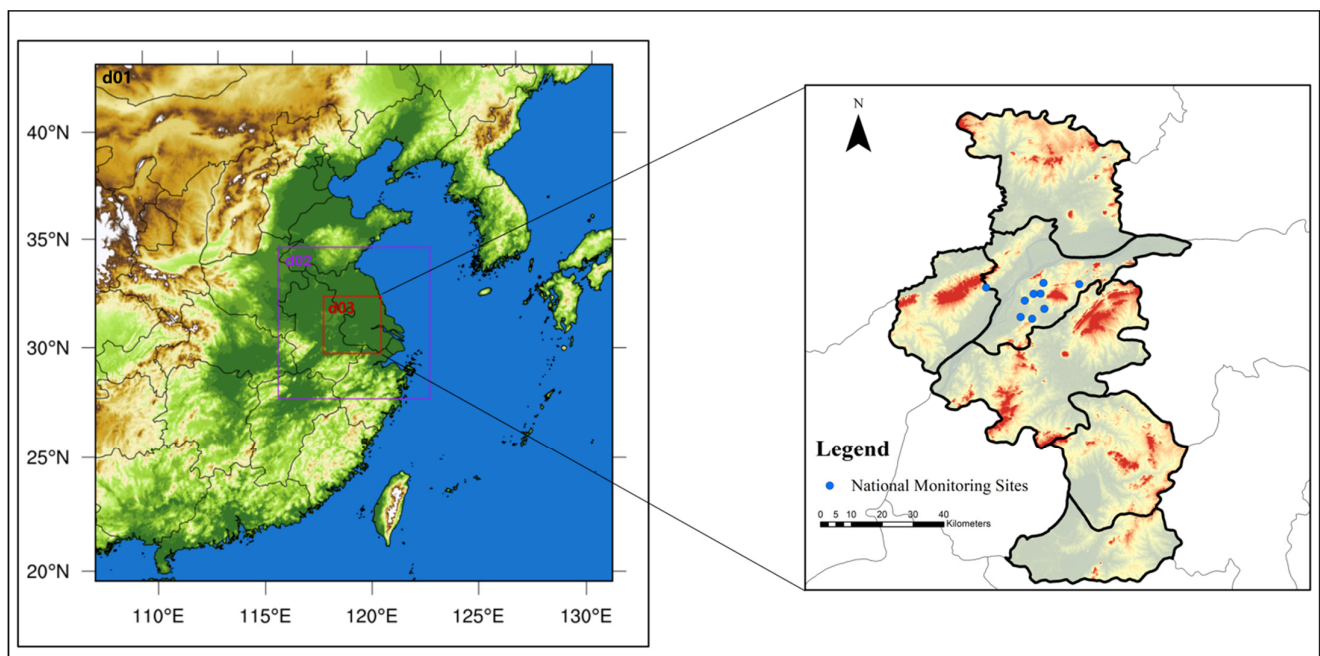
emission models (MEGANv2.1) [24]. CAM-Chem outputs were used as chemical initial boundary conditions for January and February 2019 and 2020 [24]. Each simulation time of the WRF-Chem model is two months, and each spin-up time for the model is 48 h.

**Table 1.** WRF-Chem parameterization settings.

|                                 |                            |
|---------------------------------|----------------------------|
| Microphysics Scheme             | Lin et al. scheme [25]     |
| Longwave Radiation Scheme       | RRTMG Scheme [26]          |
| Shortwave Radiation Scheme      | RRTMG Scheme [26]          |
| Surface Layer Scheme            | Eta similarity Scheme [27] |
| Planetary Boundary layer Scheme | MYJ Scheme [28]            |
| Land Surface Scheme             | Noah Scheme [29]           |
| Cumulus Parameterization Scheme | Grell-3D Scheme [30]       |
| Urban Surface Scheme            | BEP Scheme [31]            |
| Chemical Mechanism Scheme       | CBMZ Scheme [32]           |
| Aerosol Mechanism Scheme        | MOSAIC Scheme [33]         |

### 2.3. Observation Data

Hourly concentration data of four pollutants, including particulate matter  $\leq 10 \mu\text{m}$  in diameter ( $\text{PM}_{10}$ ), particulate matter  $\leq 2.5 \mu\text{m}$  in diameter ( $\text{PM}_{2.5}$ ), nitrogen dioxide ( $\text{NO}_2$ ), and ozone ( $\text{O}_3$ ), from nine Nanjing state-controlled ambient air quality testing stations (station locations are shown in Figure 1) were used in this paper for January and February 2019 and 2020 in Nanjing. Observational data were used to validate air pollutant results obtained from WRF-Chem model simulations.



**Figure 1.** Scope of the model nested areas: the three-nested domains consisting of the outer domain (d01), inner domain (d02), and innermost domain (d03) (horizontal resolutions of  $27 \text{ km} \times 27 \text{ km}$ ,  $9 \text{ km} \times 9 \text{ km}$ ,  $3 \text{ km} \times 3 \text{ km}$ , respectively) and the location of the national monitoring sites in Nanjing.

### 2.4. Anthropogenic Emissions Inventory Data

The emission inventory is indispensable data for air quality models. It contains information on emission rates of different species, such as  $\text{PM}_{2.5}$ ,  $\text{PM}_{10}$ ,  $\text{NO}_x$ ,  $\text{SO}_2$ , etc. In this



study, the anthropogenic emission data used the Multi-resolution Emission Inventory for China (MEIC) developed by Tsinghua University, which includes anthropogenic emissions from different sources, including power, industry, residential, transportation, and agriculture. We used MEIC's 2019 and 2020 emission inventories. MEIC<sub>2019</sub> and MEIC<sub>2020</sub> used the Multi-resolution Emission Inventory for China model to estimate China's emissions in 2018 and 2019 and then used 39 types of near-real-time activity data to update the emission estimates to 2020. MEIC<sub>2019</sub> and MEIC<sub>2020</sub>, for the first time, reported China's anthropogenic emissions from January to December 2019 and 2020 and provided the most up-to-date China's emissions input to chemical transport models and helped interpret the abrupt changes in pollutant concentrations during the COVID-19 lockdowns [34,35]. The temporal resolution of MEIC anthropogenic emission inventory is monthly scale. In this study, the total monthly emissions of the anthropogenic emission inventory are evenly distributed hourly and multiplied by the hourly emission coefficient to make the anthropogenic emissions more consistent with the actual daily situation.

### 2.5. Research Methods

In the early stage of COVID-19, in order to curb the spread of COVID-19, the Nanjing Municipal Government took up month-long lockdown measures. Since 23 January 2020, Nanjing has implemented measures such as home quarantine, suspension of public transport, and shutdown of factories and businesses. After 7 February 2020, some important national economy and livelihood-related enterprises in Nanjing began to resume work and production. After 24 February 2020, the daily life of residents gradually returned to normal, and all enterprises and factories resumed work and production. In this study, we use the WRF-Chem model to simulate the concentration of air pollutants, and the “zero-out” method is used to study the contribution of industrial and traffic emissions to air pollutants. The “zero-out” approach [36] means that the anthropogenic emissions of a sector in the anthropogenic emission inventory in the study area are removed and conduct sensitivity tests. On this basis, different emission scenarios were designed to study the impact on air quality of the reduction in anthropogenic emissions due to the COVID-19 lockdown and to quantify the impact of the COVID-19 lockdown on industrial emissions as well as on traffic emissions. Table 2 summarizes all emission scenarios.

**Table 2.** Emission scenario design.

| Scenario       | Simulation Description                      | Emission Scenario                                                      |
|----------------|---------------------------------------------|------------------------------------------------------------------------|
| Scenario1-2019 | 2019 simulation with actual emissions       | Actual emissions(MEIC <sub>2019</sub> )                                |
| Scenario1-2020 | 2020 simulation with actual emissions       | Actual emissions(MEIC <sub>2020</sub> )                                |
| Scenario2-2019 | 2019 simulation with hypothetical emissions | Hypothetic emissions(MEIC <sub>2019</sub> without industrial emission) |
| Scenario2-2020 | 2020 simulation with hypothetical emissions | Hypothetic emissions(MEIC <sub>2020</sub> without industrial emission) |
| Scenario3-2019 | 2019 simulation with hypothetical emissions | Hypothetic emissions(MEIC <sub>2019</sub> without traffic emission)    |
| Scenario3-2020 | 2020 simulation with hypothetical emissions | Hypothetic emissions(MEIC <sub>2020</sub> without traffic emission)    |

Scenario 1 (urban activity as usual): using meteorological field data from January and February 2019 and 2020 and MEIC<sub>2019</sub> and MEIC<sub>2020</sub> anthropogenic emission inventory data, with no change in emissions from five sectors, industry, transportation, electricity, residential, and agriculture, in the MEIC emission inventory. Urban activities were business as usual. The WRF-Chem model is used to simulate the air pollutants in Nanjing in January and February 2020 and January and February 2019 during the same period.

Scenario 2 (removal of industrial emission scenario): Based on Scenario 1, using a “zero-out” approach, industrial emissions were removed from the MEIC emission inventory, i.e., no industrial emissions were assumed to occur in the simulation area, and emissions from four sectors, transportation, electricity, residential, and agriculture, remained unchanged, and the WRF-Chem model is used to simulate the air pollutants in Nanjing in January–February 2020 and January–February 2019 again.

Scenario 3 (removal of traffic emission scenario): Based on Scenario 1, using the “zero-out” approach, the traffic emission data in the MEIC emission inventory were removed, i.e., it was assumed that there were no industrial traffic emissions in the simulation area, and the emissions from four sectors, industry, electricity, residential, and agriculture, remained unchanged, and the WRF-Chem model is used to simulate the air pollutants in Nanjing in January and February 2020 and January and February 2019 again.

We first extract the simulation data of the NP and the LP from the simulation results. Then, by comparing the results obtained from the WRF-Chem model simulations in Scenario 1 for 2019 and 2020, the changes in air pollutant concentrations in Nanjing during the NP and LP can be obtained. The simulation results for 2019 and 2020 in Scenario 1 and Scenario 2 were correspondingly subtracted to obtain data on industrial emissions of air pollutants during the NP and LP. Similarly, the simulation results for 2019 and 2020 in Scenario 1 and Scenario 3 were correspondingly subtracted to obtain data on air pollutant emissions from transport during the NP and LP. By comparing the results of industrial and traffic emissions of air pollutants in 2019 and 2020, the impact of the COVID-19 lockdown on the concentration of industrial and traffic emissions of air pollutants in Nanjing is obtained.

Although atmospheric chemical processes are nonlinear in nature, the “zero-out” method does not provide very accurate results, and the method is more applicable to primary pollutants and has some uncertainties for highly nonlinear pollutants such as ozone, the “zero-out” method is still used in source analysis studies and quantitative assessments of transport contributions and has proven to be an effective method in a number of studies [37,38].

### 3. Results

#### 3.1. WRF-Chem Model Validation

The pollutant results simulated by the WRF-Chem model were extracted from the Nanjing state-controlled ambient air quality monitoring stations, and the observed data from the stations and the resultant data obtained from the WRF-Chem model simulation were averaged and tested for accuracy using the correlation coefficient ( $R$ ), normalized mean deviation (NMB), mean fractional deviation (MFB) and mean fractional error (MFE) as the criteria for the error test, and the specific formulae are shown in Table 3.

**Table 3.** Indices used to evaluate model performance.

| Index                           | Definition                                                                                                                                    |
|---------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------|
| Correlation Coefficient         | $R = \frac{\sum_{i=1}^n (C_m - \bar{C}_m)(C_o - \bar{C}_o)}{\sqrt{\sum_{i=1}^n (C_m - \bar{C}_m)^2} \sqrt{\sum_{i=1}^n (C_o - \bar{C}_o)^2}}$ |
| Normalized Mean Deviation (NMB) | $\text{NMB} = \frac{\sum_{i=1}^N (C_m - C_o)}{\sum_{i=1}^N C_o}$                                                                              |
| Mean Fractional Deviation (MFB) | $\text{MFB} = \frac{1}{N} \sum_{i=1}^N \frac{(C_m - C_o)}{(C_o + C_m/2)}$                                                                     |
| Mean Fractional Error (MFE)     | $\text{MFE} = \frac{1}{N} \sum_{i=1}^N \frac{ C_m - C_o }{(C_o + C_m/2)}$                                                                     |

Figures 2 and 3 show the hour-by-hour near-surface  $\text{NO}_2$ ,  $\text{O}_3$ ,  $\text{PM}_{2.5}$ , and  $\text{PM}_{10}$  concentration time series from ground-based observations and model simulations for January and February 2019 and 2020, and the model performance for  $\text{PM}_{10}$ ,  $\text{PM}_{2.5}$ ,  $\text{NO}_2$ , and  $\text{O}_3$  for 2019 and 2020 is given in Tables 4 and 5 and presented in Taylor diagrams (see Figures 4 and 5). Boylan and Russell [39] proposed the use of mean fractional deviation (MFB) and mean fractional error (MFE) as measures. If the MFB is within  $\pm 30\%$  and the MFE is less than 50%, the simulation performance is excellent; if the MFB is within  $\pm 60\%$  and the MFE is less than 75%, the model simulation capability is within acceptable limits.

**Table 4.** Statistical analysis of simulated and observed hourly near-surface NO<sub>2</sub>, O<sub>3</sub>, PM<sub>2.5</sub>, PM<sub>10</sub> concentrations (µg/m<sup>3</sup>) compared for the period 1 January 2019 to 28 February 2019.

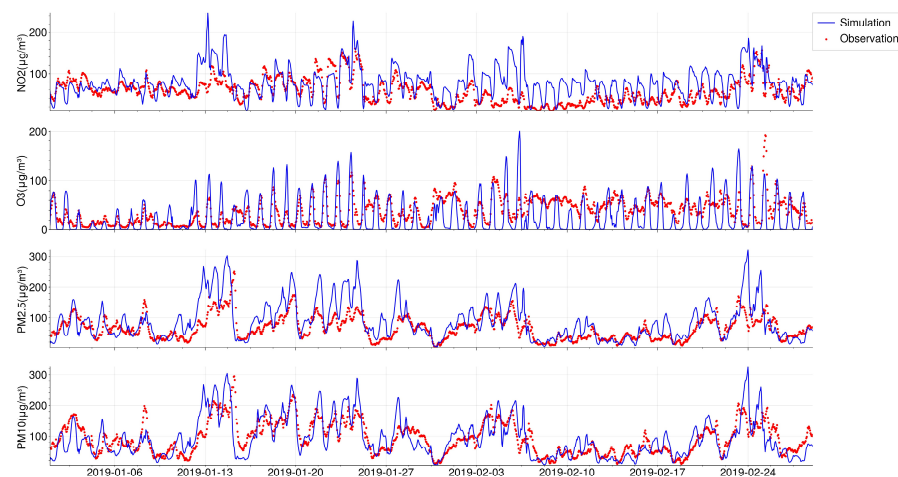
|                   | AVGM | AVGO | R       | NMB  | MFB   | MFE  |
|-------------------|------|------|---------|------|-------|------|
| NO <sub>2</sub>   | 77.6 | 58.2 | 0.48 ** | 33%  | 27%   | 36%  |
| O <sub>3</sub>    | 24.7 | 38.1 | 0.54 ** | −35% | −102% | 118% |
| PM <sub>2.5</sub> | 88.2 | 66.9 | 0.70 ** | 32%  | 10%   | 30%  |
| PM <sub>10</sub>  | 92.9 | 92.9 | 0.72 ** | 0%   | −7%   | 31%  |

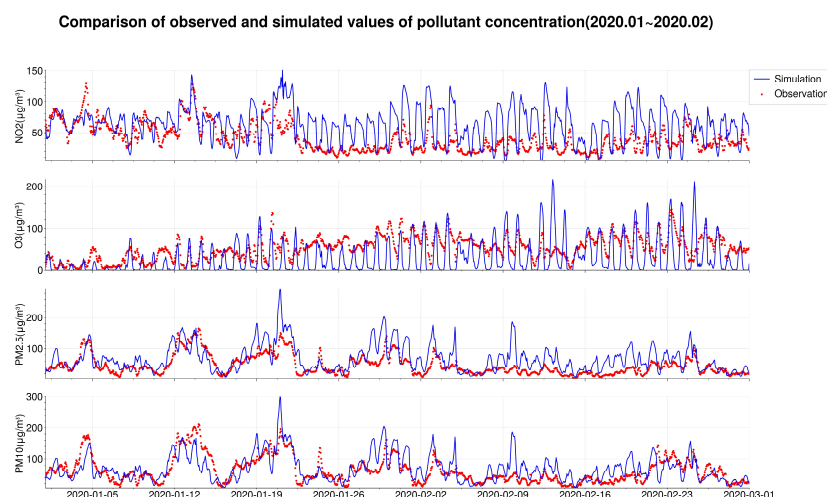
Note: AVGO and AVGM are the mean values of observations and model results at the observation sites, respectively; R is the correlation coefficient between observations and model results; NMB is the normalized mean deviation between observations and model results; MFB and MFE are the mean fractional deviation between observations and model results and the mean fractional error between observations and model results, respectively; \*\* indicates significant correlation at 0.01 level (bilateral).

**Table 5.** Statistical analysis of simulated and observed hourly near-surface NO<sub>2</sub>, O<sub>3</sub>, PM<sub>2.5</sub>, PM<sub>10</sub> concentrations (µg/m<sup>3</sup>) compared for the period 1 January 2020 to 28 February 2020.

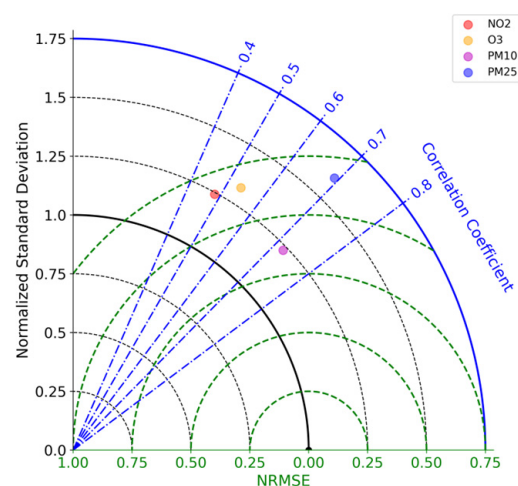
|                   | AVGM | AVGO | R       | NMB  | MFB   | MFE  |
|-------------------|------|------|---------|------|-------|------|
| NO <sub>2</sub>   | 63.4 | 41.1 | 0.42 ** | 54%  | 33%   | 42%  |
| O <sub>3</sub>    | 29.3 | 53.2 | 0.49 ** | −45% | −104% | 113% |
| PM <sub>2.5</sub> | 67.1 | 46.4 | 0.67 ** | 45%  | 20%   | 34%  |
| PM <sub>10</sub>  | 68.9 | 62.2 | 0.64 ** | 11%  | 5%    | 33%  |

Note: AVGO and AVGM are the mean values of observations and model results at the observation sites, respectively; R is the correlation coefficient between observations and model results; NMB is the normalized mean deviation between observations and model results; MFB and MFE are the mean fractional deviation between observations and model results and the mean fractional error between observations and model results, respectively; \*\* indicates significant correlation at 0.01 level (bilateral).

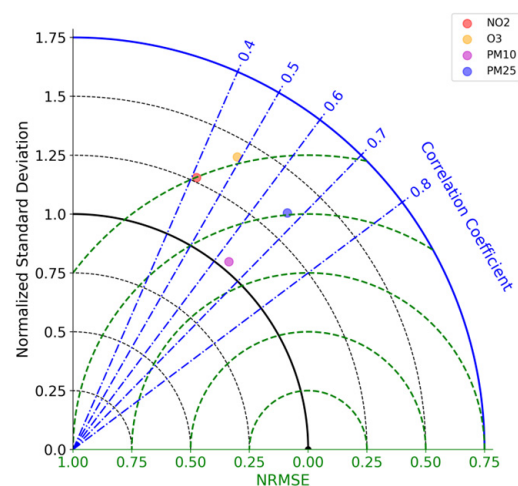
**Comparison of observed and simulated values of pollutant concentration(2019.01~2019.02)****Figure 2.** Hour-by-hour near-surface NO<sub>2</sub>, O<sub>3</sub>, PM<sub>2.5</sub>, and PM<sub>10</sub> (µg/m<sup>3</sup>) concentrations in Nanjing from 1 January to 28 February 2019, for observed (red dots) and simulated (blue line) values.



**Figure 3.** Hour-by-hour near-surface  $\text{NO}_2$ ,  $\text{O}_3$ ,  $\text{PM}_{2.5}$ , and  $\text{PM}_{10}$  ( $\mu\text{g}/\text{m}^3$ ) concentrations in Nanjing from 1 January to 29 February 2020 for observed (red dots) and simulated (blue line) values.



**Figure 4.** Taylor diagram on the left showing the statistical comparison between observed and model simulated values for Nanjing from 1 January to 28 February 2019.



**Figure 5.** Taylor diagram on the right shows the statistical comparison between observed and model simulated values for Nanjing from 1 January to 29 February 2020.



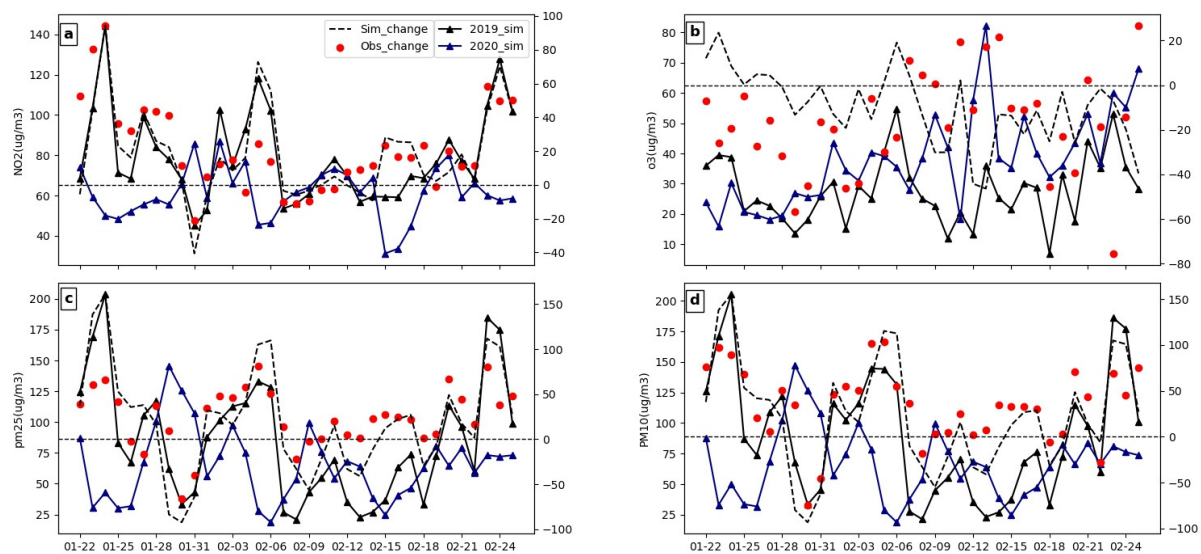
In terms of  $PM_{2.5}$ , the WRF-Chem model could reproduce well the trend of near-ground  $PM_{2.5}$  concentrations over time ( $R_{2019} = 0.70$ ,  $R_{2020} = 0.67$ ), but during the COVID-19 lockdown period, the model simulated significantly higher  $PM_{2.5}$  concentrations ( $NMB_{2019} = 32\%$ ,  $NMB_{2020} = 45\%$ ). For  $PM_{10}$ , the model was not only able to simulate the trend of  $PM_{10}$  concentration over time well ( $R_{2019} = 0.72$ ,  $R_{2020} = 0.64$ ) but could also simulate  $PM_{10}$  concentrations accurately ( $NMB_{2019} = 0\%$ ,  $NMB_{2020} = 10\%$ ). For  $NO_2$ , the correlation between the simulated values and the observed values was general ( $R_{2019} = 0.48$ ,  $R_{2020} = 0.42$ ), and the model could overestimate the concentration of  $NO_2$  ( $NMB_{2019} = 33\%$ ), and the simulated values of the concentration of  $NO_2$  during the COVID-19 lockdown period would be higher. ( $NMB_{2020} = 54\%$ ). For  $O_3$ , the correlation between the simulated values and the observed values of the model was also general ( $R_{2019} = 0.54$ ,  $R_{2020} = 0.49$ ), and the simulated values of the model showed obvious diurnal variation. The model could well reappear the situation when the concentration of  $O_3$  is high, but when the actual concentration of  $O_3$  is low, the simulation effect of the model is poor, and the simulated values were far lower than the observed values. From the perspective of MFE and MFB, the model performance of  $NO_2$ ,  $PM_{2.5}$ , and  $PM_{10}$  is excellent, except for  $O_3$ . From the perspective of NMB, the model overestimated the concentration of  $NO_2$  and  $PM_{2.5}$ , especially the concentration of  $NO_2$  and  $PM_{2.5}$  during the COVID-19 lockdown period in 2020, but the model underestimated the concentration of  $O_3$ .

Overall, the WRF-Chem model can better reappear the trends of pollutant concentrations over time, but it has some degree of error in the simulation of pollutant concentrations. The simulation effectiveness of the WRF Chem model in 2020 is decreasing compared to that in 2019, and the pollutant concentration results of the model simulation are higher during the 2020 COVID-19 lockdown period. The results of the patterns provide a research basis for discussing later the changes in air pollutants in Nanjing during the outbreak blockade period and the changes in pollutant concentrations from industrial emissions and traffic emissions.

### 3.2. Changes in Air Pollutant Concentrations during the LP Compared to the NP

This section discusses the changes in air pollutant concentrations during the initial outbreak of the COVID-19 epidemic in Nanjing. Changes in atmospheric pollutant concentrations are influenced by a combination of meteorological conditions and anthropogenic emissions. It has been shown [40] that compared to February 2019, the average wind speed, relative humidity, and cumulative effective precipitation days were approximately the same during the same period in 2020 as during the COVID-19 lockdown period, with higher average temperatures and slightly higher cumulative precipitation, making meteorological conditions more favorable for the dispersion of pollutants. By comparing the simulation results in 2019 and 2020 in Scenario 1, the changes in air pollutants in Nanjing during the LP could be obtained. Figure 6 shows the time series of model-simulated daily mean near-surface  $NO_2$ ,  $O_3$ ,  $PM_{2.5}$ , and  $PM_{10}$  concentrations during the NP (2019\_sim) and LP (2020\_sim), with the differences between 2019 and 2020 observations and model-simulated  $NO_2$ ,  $O_3$ ,  $PM_{2.5}$ , and  $PM_{10}$  concentrations.

As shown in Figure 6 and Table 6, the simulated day-by-day average changes in  $NO_2$ ,  $O_3$ ,  $PM_{2.5}$ , and  $PM_{10}$  concentrations between the NP and LP agree well with the observed changes, indicating that the model could reproduce the daily  $NO_2$ ,  $PM_{2.5}$ , and  $PM_{10}$  changes between the NP and LP, with  $O_3$  not being too effective. From 24 January to 3 February, influenced by the COVID-19 lockdown policies and the 2020 Chinese New Year, the daily average  $NO_2$  concentrations in 2020 were much smaller than those in the same period in 2019, except for some days. Between 4 February and 12 February, influenced by the 2019 Chinese New Year, the difference in daily average  $NO_2$  concentrations gradually decreased, and the daily average  $NO_2$  concentrations in 2020 were the same as those in the same period in 2019. Between 4 February and 13 February, the difference in daily average  $NO_2$  concentrations gradually increased again.



**Figure 6.** Time series of daily mean near-surface  $\text{NO}_2$ ,  $\text{O}_3$ ,  $\text{PM}_{2.5}$ , and  $\text{PM}_{10}$  concentrations ( $\mu\text{g}/\text{m}^3$ ) simulated during the NP (black dashed line with triangles, 2019\_sim) and LP (blue dashed line with triangles, 2020\_sim), Differences in observed  $\text{NO}_2$ ,  $\text{O}_3$ ,  $\text{PM}_{2.5}$ , and  $\text{PM}_{10}$  concentrations ( $\mu\text{g}/\text{m}^3$ ) between the NP and LP (red dots, Obs\_change), Differences in model simulations between the NP and LP for  $\text{NO}_2$ ,  $\text{O}_3$ ,  $\text{PM}_{2.5}$ , and  $\text{PM}_{10}$  concentrations ( $\mu\text{g}/\text{m}^3$ ) (black dashed line, Sim\_change). (a) represents  $\text{NO}_2$ , (b) represents  $\text{O}_3$ , (c) represents  $\text{PM}_{2.5}$ , (d) represents  $\text{PM}_{10}$ .

**Table 6.** Statistics comparing the differences in observed and modeled daily mean concentrations ( $\mu\text{g}/\text{m}^3$ ) of  $\text{NO}_2$ ,  $\text{O}_3$ ,  $\text{PM}_{2.5}$  and  $\text{PM}_{10}$  during the NP and LP.

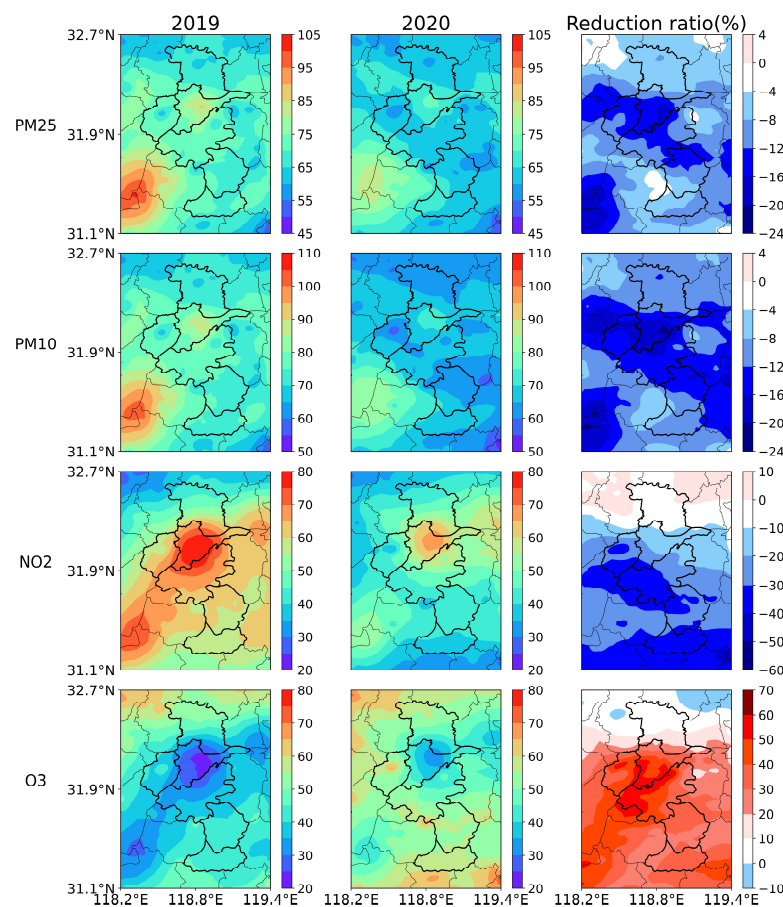
|                   | AVGM  | AVGO   | R      | RMSE  | NMB  |
|-------------------|-------|--------|--------|-------|------|
| $\text{NO}_2$     | 18.27 | 21.49  | 73% ** | 19.43 | 14%  |
| $\text{O}_3$      | −9.86 | −16.91 | −19%   | 31.02 | −41% |
| $\text{PM}_{2.5}$ | 20.28 | 24.56  | 79% ** | 38.78 | −17% |
| $\text{PM}_{10}$  | 22.16 | 34.28  | 79% ** | 38.82 | −35% |

Note: AVGO and AVGM are the mean values of the differences in observed and modeled daily mean concentrations; R is the correlation coefficient between the differences in observed and modeled daily mean concentrations; RMSE is the root mean square error between the differences in observed and modeled daily mean concentrations; NMB is the normalized mean deviation between the differences in observed and modeled daily mean concentrations; \*\* indicates significant correlation at 0.01 level (bilateral).

In terms of  $\text{PM}_{2.5}$  and  $\text{PM}_{10}$  daily mean concentration changes, the modeling results could reproduce well the observed daily mean concentration temporal trends and concentration trends. In addition to some days being affected by meteorological conditions such as rainfall, for example, between 24 January and 26 January, the weather conditions in 2020 were rainy and influenced by rainfall and the lockdown of the epidemic, and the concentrations of  $\text{PM}_{2.5}$  and  $\text{PM}_{10}$  in 2020 were much lower during this period than during the same period in 2019. Between 28 January and 30 January 2019, weather conditions were rainy, causing the 2019  $\text{PM}_{2.5}$  and  $\text{PM}_{10}$  concentrations to be lower than those during the 2020 COVID-19 lockdown. Between 4 February and 12 February, influenced by the 2019 Chinese New Year, the  $\text{PM}_{2.5}$  and  $\text{PM}_{10}$  daily average concentrations in 2019 decreased and were on par with the same period in 2020. After 13 February, the difference between the daily average  $\text{PM}_{2.5}$  and  $\text{PM}_{10}$  concentrations gradually increased again. Overall, the daily average concentrations of  $\text{PM}_{2.5}$  and  $\text{PM}_{10}$  showed an overall decreasing trend during the 2020 COVID-19 lockdown period due to strict lockdown policies. In contrast to the other three pollutants,  $\text{O}_3$  concentrations showed an increasing trend during the 2020 outbreak compared to the same period in 2019, except for some days, and although the model was

able to reproduce the trend in  $O_3$  concentrations, it still underestimated the increase in  $O_3$  concentrations.

Figure 7 shows the spatial distribution of mean near-surface  $NO_2$ ,  $O_3$ ,  $PM_{2.5}$  and  $PM_{10}$  concentrations ( $\mu g/m^3$ ) and the proportional reduction in pollutants during the NP and LP for the Nanjing model simulation. The figure shows that most of the major  $PM_{2.5}$  reduction areas were near the main urban areas of Nanjing, with the average  $PM_{2.5}$  concentration falling from 72–90  $\mu g/m^3$  in 2019 to 60–80  $\mu g/m^3$  in 2020, a reduction in over 20%, and the  $PM_{10}$  situation was similar to that of  $PM_{2.5}$ . In addition, the change in the particulate matter also showed a clear urban-rural difference, with a greater reduction in particulate matter in the main urban areas of Nanjing than in the suburbs of Nanjing. The figure also shows that the average  $NO_2$  concentration decreased from 55–75  $\mu g/m^3$  in 2019 to 40–65  $\mu g/m^3$  in 2020, with a decrease of approximately 16–40% in the area covered by high  $NO_2$  concentrations, and it shows that there was a gradual increase from north to south. The average concentration of  $O_3$ , on the other hand, showed an opposite trend to the other three pollutants, with the average  $O_3$  concentration during the LP rising from 20–50  $\mu g/m^3$  to 30–65  $\mu g/m^3$  compared to the NP. The area of increase in the average  $O_3$  concentration was mainly near the main urban area of Nanjing, with an increase in more than 40%, and the average  $O_3$  concentration in the northern suburbs of Nanjing had a small decrease. Ozone chemistry was highly nonlinear, and its production was at  $NO_x$  saturation ( $NO_x = NO + NO_2$ ) during winter in urban China due to the relative lack of HOX radicals [41]. In addition, it can be seen from Table 7 that the decrease in  $NO_x$  significantly reduced  $O_3$  depletion ( $NO + O_3 = NO_2 + O_2$ ), which led to an increase in  $O_3$  concentration and eased ozone titration [42]. Thus, a decrease in  $NO_x$  led to an increase in ozone [43].



**Figure 7.** Spatial distribution of simulated mean near-surface  $NO_2$ ,  $O_3$ ,  $PM_{2.5}$ , and  $PM_{10}$  concentrations ( $\mu g/m^3$ ) and percentage reduction in Nanjing during the NP and LP.

**Table 7.** Average concentration and variation of pollutants during the NP and LP in Nanjing.

| Pollutants        | NP    | LP    | Variations | Variations (%) |
|-------------------|-------|-------|------------|----------------|
| NO <sub>2</sub>   | 78.27 | 60.84 | −17.43     | −22.3%         |
| NO                | 71.38 | 33.45 | −37.92     | −53.1%         |
| O <sub>3</sub>    | 27.24 | 37.91 | 10.67      | 39.2%          |
| PM <sub>2.5</sub> | 81.34 | 65.43 | −15.91     | −19.6%         |
| PM <sub>10</sub>  | 85.26 | 67.33 | −17.89     | −21.0%         |

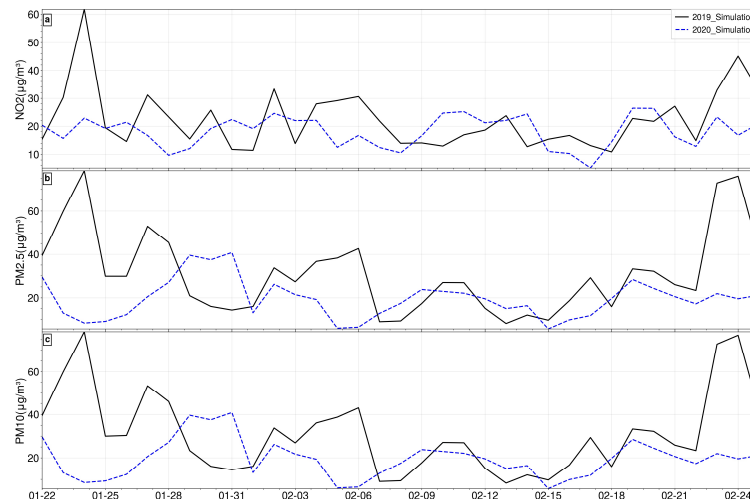
In conclusion, the reduction in mean NO<sub>2</sub>, PM<sub>2.5</sub>, and PM<sub>10</sub> concentrations and the increase in mean O<sub>3</sub> concentrations during the epidemic lockdown in Nanjing were comparable to previous results. The reduction in human mobility, traffic restrictions, and the shutdown of factories during the LP were the main reasons for the reduction in pollutant concentrations. In previous studies, Wang et al. [44] studied the nonlinear effects of four typical pollutants (PM<sub>2.5</sub>, NO<sub>2</sub>, SO<sub>2</sub>, and O<sub>3</sub>) in eight cities around the world (Wuhan, China; New York, USA; Milan, Italy; Madrid, Spain; Bandra, India; London, UK; Tokyo, Japan; and Mexico City, Mexico) and found that COVID-19 lockdown policies reduced only NO<sub>2</sub> and PM<sub>2.5</sub>, while O<sub>3</sub> concentrations increased somewhat. According to Chen et al. [9], strict COVID-19 lockdown policies significantly improved air quality in many provinces in mainland China, with national average concentrations of PM<sub>2.5</sub>, PM<sub>10</sub>, and NO<sub>2</sub> decreasing by 14%, 15%, and 16%, respectively, and O<sub>3</sub> concentrations increasing by 9% during January–April 2020 compared to 2019.

### 3.3. Changes in Pollutant Concentrations in Industrial Emissions during the LP Compared to the NP

The first priority for controlling air pollutant emissions is industrial emissions [45], which are the main source of PM<sub>2.5</sub>, PM<sub>10</sub>, and NO<sub>x</sub> emissions. The lockdown policies during the LP in 2020 had a significant impact on the industry, with factories and companies shutting down or reducing their operations, but we do not know from the observed data exactly how much industrial emissions were reduced. Therefore, we used MEIC's latest anthropogenic emission inventories for 2019 and 2020 [34] and designed experiments to quantify the changes in pollutant emissions from industry in Nanjing during the LP. By subtracting the simulation results of 2019 in Scenario 1 and Scenario 2, we obtained the industrial emission pollutant data during the NP, and by subtracting the simulation results of 2020 in Scenario 1 and Scenario 2, we obtained the industrial emission pollutant data during the LP, and the difference between the two was the change in industrial emission pollutants in Nanjing during the LP.

As shown in Figure 8, the impact of the lockdown policies at the beginning of the outbreak of COVID-19 in 2020 on the daily average concentrations of industrial emissions of NO<sub>2</sub> was limited. The daily average concentrations of industrial emissions of NO<sub>2</sub> during the entire LP were approximately 20 µg/m<sup>3</sup>, and the magnitude of change in the daily average concentrations of NO<sub>2</sub> was not too great except for some days. Compared to the NP, the overall average daily concentrations of industrial emissions of NO<sub>2</sub> for the LP were still somewhat lower, but the reduction was not too significant. Industrial emissions, specifically PM<sub>2.5</sub> and PM<sub>10</sub> daily average concentrations, changed with a similar trend. At the beginning of the outbreak in 2020, Nanjing implemented a shutdown of enterprises and factories. Between 22 January and 26 January, there was a clear downward trend in PM<sub>2.5</sub> and PM<sub>10</sub> daily average concentrations due to the lockdown policies and rainfall. Between 27 January and 31 January, as the weather gradually cleared and the atmosphere stabilized, forming stationary weather, the PM<sub>2.5</sub> and PM<sub>10</sub> daily average concentrations gradually increased. Between 1 February and 6 February, as the temperature increased, the PM<sub>2.5</sub> and PM<sub>10</sub> daily average concentrations decreased. During the period from 1 February to 6 February, the daily average concentrations of PM<sub>2.5</sub> and PM<sub>10</sub> gradually increased as the temperature increased. From 7 February to 15 February, some important livelihood enterprises in Nanjing started to resume work and production, and the daily average PM<sub>2.5</sub>

and  $PM_{10}$  concentrations gradually rose but were affected by rainfall and snowfall, and the daily average  $PM_{2.5}$  and  $PM_{10}$  concentrations still decreased to a certain extent after the rise. After 16 February, the daily average  $PM_{2.5}$  and  $PM_{10}$  concentrations gradually rose again and tended to stabilize. Overall, the industrial emissions, specifically  $PM_{2.5}$  and  $PM_{10}$  daily average concentrations, during the LP still decreased to a greater extent compared to the NP.

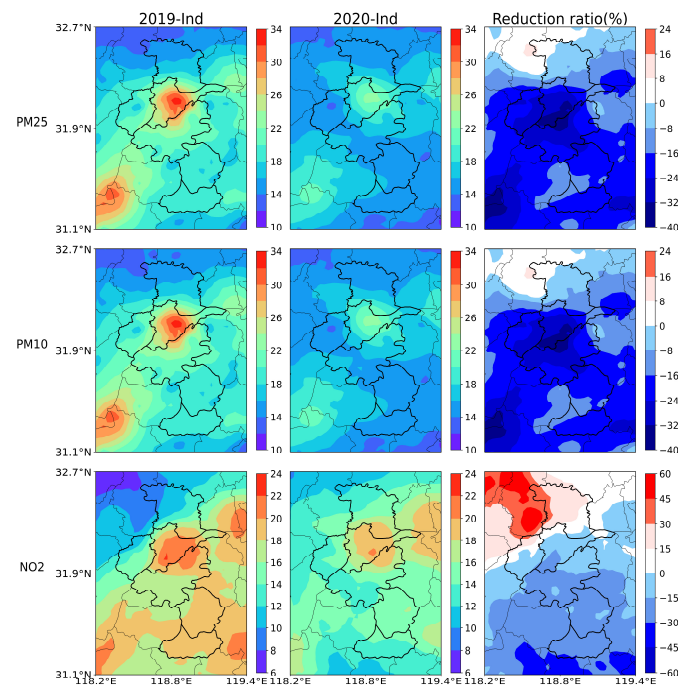


**Figure 8.** Daily average concentrations ( $\mu\text{g}/\text{m}^3$ ) of industrial emissions of  $\text{NO}_2$  (a),  $PM_{2.5}$  (b), and  $PM_{10}$  (c) in Nanjing during the NP and LP.

Figure 9 shows the average concentrations of industrial emissions of air pollutants in Nanjing during the LP, the NP, and the changes in industrial emissions of pollutants in Nanjing during the LP. The figure shows that the areas with the largest decrease in  $PM_{2.5}$  and  $PM_{10}$  concentrations from industrial emissions in Nanjing was located in the Yuhuatai, Jiangning, and Pukou districts of Nanjing, which is consistent with the actual locations of the major industrial zones in Nanjing. As a result of the COVID-19 lockdown policies, the average industrial emissions, specifically  $PM_{2.5}$  and  $PM_{10}$  concentrations, in Nanjing decreased by approximately  $3\sim 14 \mu\text{g}/\text{m}^3$ ; a decrease in approximately 24–40% compared to the NP. The decrease in the average concentration of industrial  $\text{NO}_2$  emissions was mainly located in the southern region of Nanjing (Jiangning District, Gaochun District, Lishui District, and Yuhuatai District), with a decrease in approximately 15–30%. The change in the concentration of industrial emissions of  $\text{NO}_2$  in the main urban area of Nanjing was not too great, while the average concentration of industrial emissions of  $\text{NO}_2$  in the northern area of Nanjing even showed a small increase, with a rise of approximately 15–30%.

Overall, the concentration of  $PM_{2.5}$  and  $PM_{10}$  from industrial emissions decreased by about 24–40% during the LP. In contrast, COVID-19 lockdown policies did not have as great an effect on the concentrations of  $\text{NO}_2$  from industrial emissions, which decreased by about 15% to 30%.  $PM_{2.5}$  and  $PM_{10}$  concentrations are more sensitive to primary particulate matter emissions [46], so the impact of COVID-19 lockdown policies on industrial emissions in 2020 is more reflected in  $PM_{2.5}$  and  $PM_{10}$ .





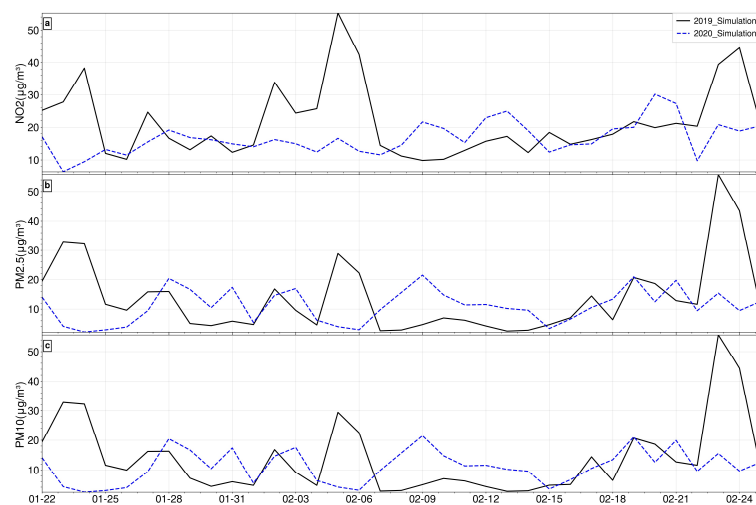
**Figure 9.** Spatial distribution of average  $\text{NO}_2$ ,  $\text{PM}_{2.5}$ , and  $\text{PM}_{10}$  concentrations ( $\mu\text{g}/\text{m}^3$ ) from near-surface industrial emissions and the percentage reduction during the NP and LP in the Nanjing City model simulation.

### 3.4. Changes in Pollutant Concentrations in Traffic Emissions during the LP Compared to the NP

In recent years, as the number of motor vehicles has increased year by year, the total amount of pollution emitted from motor vehicles has also increased dramatically. Anthropogenic emissions from the transport sector are also considered to be one of the main causes of air pollution, especially  $\text{NO}_x$  concentrations [47]. The impact of the COVID-19 lockdown policies, the implementation of very strict traffic controls at all levels of government from the end of January 2020, and the sharp reduction in motor vehicle road access, coupled with strict restrictions on residential travel, resulted in a significant reduction in traffic emissions. Feng et al. [48] used a regional data assimilation system and near-surface  $\text{NO}_2$  observations to extrapolate daily  $\text{NO}_x$  emissions and found that across China,  $\text{NO}_x$  emissions were reduced by 36% as a result of the COVID-19 lockdown, which was mainly due to a reduction in transport. Jeong et al. [49] found that in the Canadian city of Toronto during COVID-19, average traffic decreased by 58%, while  $\text{PM}_{2.5}$  decreased by only 4% relative to the baseline. Therefore, using the same approach as quantifying industrial emissions, the latest MEIC emission inventories for 2019 and 2020 were used to obtain traffic emission pollutant data for 2019 for the same period as COVID-19 lockdown by subtracting the simulation results for 2019 from Scenario 1 and Scenario 3 and subtracting the simulation results for 2020 from Scenario 1 and Scenario 3 to obtain traffic emission pollutant data for 2020 during the COVID-19 lockdown period, with the difference between the two being the change in traffic emission pollutant concentrations in Nanjing during the COVID-19 lockdown period.

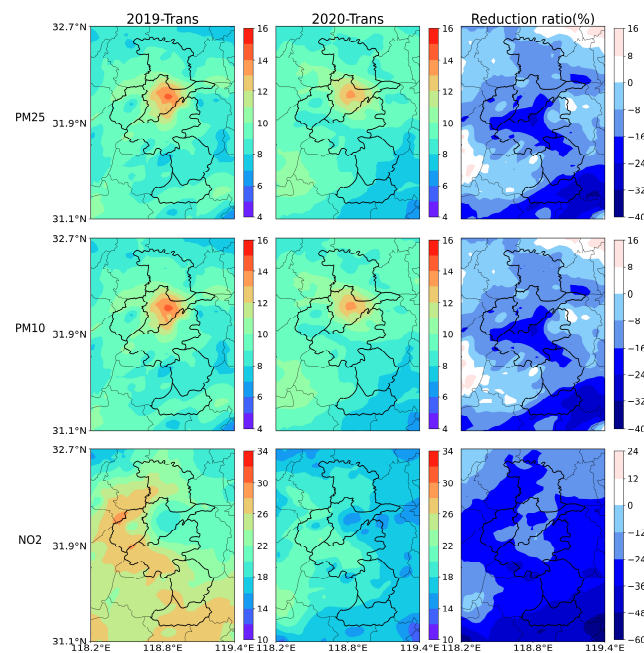
As shown in Figure 10, the average daily  $\text{NO}_2$  concentration from traffic emissions during the LP was approximately  $20 \mu\text{g}/\text{m}^3$ , which was not too different compared to the average daily  $\text{NO}_2$  concentration during the same period in 2019, except for some days. At the beginning of the LP, there was a significant decrease in the average daily  $\text{NO}_2$  concentration due to the COVID-19 lockdown measures and rainfall, after which the average daily  $\text{NO}_2$  average concentrations gradually increased, with concentrations remaining at approximately  $16 \mu\text{g}/\text{m}^3$ . From 7 February to 10 February 2020, there was a clear upward trend in the daily average  $\text{NO}_2$  concentration as enterprises gradually resumed work and production, residents were gradually able to go out, the gathering of

people increased, and public transport gradually resumed operation. 12 February to 15 February 2020 was affected by rainfall, and the daily average  $\text{NO}_2$  concentration started to decrease and gradually increased after 16 February. From 1 February 2019 to 5 February, influenced by the 2019 Chinese New Year, there was a peak in  $\text{NO}_2$  concentrations from traffic emissions and a significant downward trend in the daily average  $\text{NO}_2$  concentrations in 2019 from 6 February to 14 February, influenced by prolonged rainfall. Overall, except for some days, the overall traffic emission,  $\text{NO}_2$  daily average concentration was still somewhat lower in the LP compared to the NP. Traffic emissions, specifically  $\text{PM}_{2.5}$  and  $\text{PM}_{10}$  daily average concentrations, in 2020 changed in a similar trend to that of  $\text{NO}_2$ . At the beginning of the LP, there was a significant decrease in the daily average  $\text{PM}_{2.5}$  and  $\text{PM}_{10}$  concentrations, with a significant increase after 7 February. From 9 February to 15 February, there was a downward trend in the daily average  $\text{PM}_{2.5}$ , and  $\text{PM}_{10}$  concentrations as the temperature rose, and rainfall occurred.



**Figure 10.** Daily average concentrations ( $\mu\text{g}/\text{m}^3$ ) of traffic emissions of  $\text{NO}_2$  (a),  $\text{PM}_{2.5}$  (b), and  $\text{PM}_{10}$  (c) in Nanjing during the NP and LP.

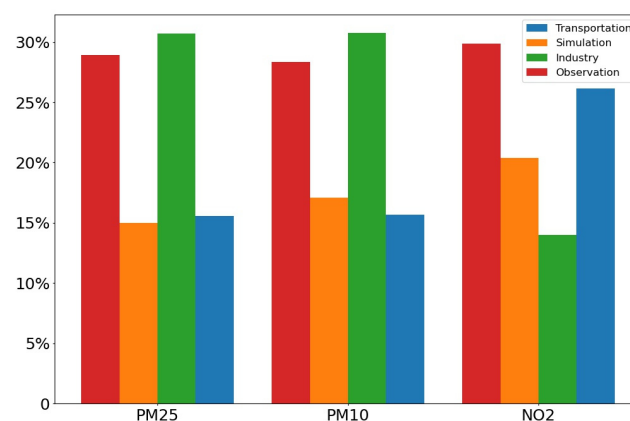
Figure 11 shows the average concentrations of air pollutants emitted from traffic in Nanjing during the LP, NP, and the reduction rate of pollutants emitted from traffic in Nanjing during LP. The graph shows that the  $\text{PM}_{2.5}$  and  $\text{PM}_{10}$  concentrations from traffic emissions in Nanjing in 2019 were approximately  $8\text{--}15 \mu\text{g}/\text{m}^3$ , while in the same period in 2020, there was a small decrease with overall concentrations in a range of  $7\text{--}12 \mu\text{g}/\text{m}^3$ ; an overall decrease in approximately 18–24%, with  $\text{PM}_{2.5}$  and  $\text{PM}_{10}$  reduction areas mainly in Jiangning District, Nanjing, which is an important transportation and logistics hub and airport hub in Nanjing; therefore, the results obtained from the simulation are consistent with the actual situation. While the concentration of traffic  $\text{NO}_2$  emissions was smaller in the main urban area of Nanjing, it was larger around Nanjing. The 2019 Nanjing traffic emission  $\text{NO}_2$  concentration was approximately  $18\text{--}30 \mu\text{g}/\text{m}^3$ . In 2020, during LP, the traffic emission  $\text{NO}_2$  concentration decreased significantly, and in 2020, the Nanjing traffic emission  $\text{NO}_2$  concentration decreased to  $15\text{--}22 \mu\text{g}/\text{m}^3$ , with an overall reduction in approximately 20–40%, representing a large reduction. Overall, the impact of the 2020 COVID-19 lockdown policies on traffic emission pollutants was reflected more in the impact on  $\text{NO}_2$  concentrations, while for  $\text{PM}_{2.5}$  and  $\text{PM}_{10}$ , the changes during the COVID-19 lockdown period were not as significant as the changes in  $\text{NO}_2$  concentrations.



**Figure 11.** Spatial distribution of average  $\text{NO}_2$ ,  $\text{PM}_{2.5}$ , and  $\text{PM}_{10}$  concentrations ( $\mu\text{g}/\text{m}^3$ ) and reduction ratio of near-surface traffic emissions during the NP and LP in the Nanjing City model simulation.

#### 4. Discussion

In this study, the changes in air pollutant concentrations during the LP in Nanjing compared to the NP were obtained, as well as the changes in pollutant emissions from industry and transportation. As shown in Figure 12, the observed  $\text{PM}_{2.5}$ ,  $\text{PM}_{10}$ , and  $\text{NO}_2$  concentrations during the LP in Nanjing were 28.9%, 28.3%, and 29.8% lower, respectively, compared to the NP. Due to the different time periods selected for the COVID-19 lockdown, the observed pollutant reduction concentrations obtained in this study were slightly lower than those in the study by Chu et al. [40]. The model-simulated  $\text{PM}_{2.5}$ ,  $\text{PM}_{10}$ , and  $\text{NO}_2$  concentrations were reduced by 15%, 17.1%, and 20.3%, respectively, and similar results were obtained by Cai et al. [50] using an assimilation system. The results of the study showed that the reduction in anthropogenic emissions resulting from the strict lockdown policies, such as traffic restrictions and factory shutdown implemented in Nanjing during the LP, was effective in reducing  $\text{PM}_{2.5}$ ,  $\text{PM}_{10}$ , and  $\text{NO}_2$  concentrations. Previous studies have shown that other cities implemented strict lockdown policies to reduce air pollutant concentrations [51] and that  $\text{PM}_{2.5}$  and  $\text{NO}_2$  were more sensitive to anthropogenic emission reductions [52].



**Figure 12.** Proportional reduction in model-simulated pollutants observed pollutants, traffic emissions, and industrial emissions of pollutants concentrations during the LP.

Since the COVID-19 lockdown policies had a significant impact on the reduction in emissions from the transport and industrial sectors, this study used a “zero-out” approach to quantify the changes in industrial and transport emissions during the LP by designing different scenarios. The results showed that both industrial and transport emissions decreased to a certain extent in the LP compared to the NP. The concentration of industrial emissions of PM<sub>2.5</sub>, PM<sub>10</sub>, and NO<sub>2</sub> decreased by 30.7%, 30.8%, and 14%, respectively, and the impact of the lockdown policies on industrial emissions was greater on PM<sub>2.5</sub> and PM<sub>10</sub>. At the same time, the impact on transport emissions was 15.6%, 15.7%, and 26.2%, respectively. The impact of the COVID-19 lockdown policies on traffic emissions was greater on the NO<sub>2</sub> concentration [48]. In other studies, Jia et al. [53] concluded that automobile exhaust emissions and petrochemical industry emissions were the main contributors to VOCs in the atmospheric environment. Ciarelli et al. [17] highlights the importance of other emission categories other than traffic for the total PM<sub>2.5</sub> levels. Feng et al. [16] showed that industrial shutdowns contributed much more to pollutant reductions than transport restrictions, and Liu et al. [54] showed that significant reductions in vehicle emissions were effective in reducing urban NO<sub>x</sub> concentrations. Wong et al. [55] found that reduced public transportation use had a more significant impact than meteorology on air quality improvement in Taiwan, while Wang et al. [56] highlights that large emissions reduction in transportation and a slight reduction in industrial would not help avoid severe air pollution in China, especially when meteorology is unfavorable.

## 5. Conclusions

In this paper, we studied the changes in air pollutant concentrations in Nanjing during the LP and the NP by using the WRF-Chem model and the latest anthropogenic emission inventory of Tsinghua University MEIC for 2019 and 2020 to simulate the air pollutants during the LP and NP. Based on the “zero-out” method, different emission scenarios were designed to quantify the impact of the lockdown policies on the industrial and transportation air pollutants in Nanjing. The WRF-Chem model can better capture the spatio-temporal characteristics of the four air pollutants, but it overestimated the concentration of air pollutants during the COVID-19 lockdown, which may be due to the uncertainty of the anthropogenic emission inventory. The study found that affected by the COVID-19 lockdown, the concentration of PM<sub>2.5</sub> and PM<sub>10</sub> in Nanjing decreased by 10–20%, and the concentration of NO<sub>2</sub> decreased by 16–40% compared with the same period in 2019, while the concentration of O<sub>3</sub> showed the opposite trend, rising by about 10–40%. The results showed that strict lockdown policies implemented during the COVID-19 lockdown, such as home quarantine, closing factories, and reducing public transport operations, reduced anthropogenic emissions and reduced air pollutant concentrations. The decrease in atmospheric pollutant concentration was mainly concentrated in the main urban area and main industrial area of Nanjing. The strict lockdown policies implemented during the COVID-19 lockdown had a greater impact on the concentrations of PM<sub>2.5</sub> and PM<sub>10z</sub> emitted by industry and NO<sub>2</sub> emitted by traffic in Nanjing.

However, the study had some limitations. Since the data given in the MEIC anthropogenic emissions inventory is the total monthly emissions, and hourly data are required for model input, we divided the MEIC emissions inventory equally among the hours. Since the COVID-19 lockdown began in late January and ended in late February, there may be some errors between the input anthropogenic emission data and the actual situation, which may overestimate the concentration of air pollutants during the COVID-19 lockdown. Due to the nonlinear nature of the atmospheric chemical reaction process, although the “zero-out” method can preliminarily quantify the impact of the COVID-19 lockdown policies on pollutant emissions from industry and traffic in Nanjing, there may still have been some discrepancies with the actual situation. This paper prioritizes the impact of lockdown measures on emissions from the industrial and transport sectors, as COVID-19 lockdown policies have had the greatest impact on these sectors. In future studies, we may discuss the impact of COVID-19 lockdowns on the two remaining emitting sectors (the power sector

and the residential sector). In addition, the study did not discuss in detail the impact of changes in meteorological conditions on air pollutants during the COVID-19 lockdown. Despite some limitations, the results of this study can still provide a theoretical basis for the future treatment of PM<sub>2.5</sub> and NO<sub>2</sub> pollution in Nanjing.

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**Conflicts of Interest:** The authors declare no conflict of interest.

## Abbreviations

|        |                                                         |
|--------|---------------------------------------------------------|
| LP     | Lockdown Period                                         |
| NP     | Normal Period                                           |
| MEIC   | Multi-resolution Emission Inventory for China           |
| RRTMG  | A new version of Rapid Radiative Transfer Model         |
| MYJ    | Mellor-Yamada-Janjic                                    |
| BEP    | Building Environment Parameterization                   |
| CBMZ   | Carbon-Bond Mechanism version Z                         |
| MOSAIC | Model for Simulating Aerosol Interactions and Chemistry |

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