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Nonlinear influence of winter meteorology and precursor on PM$_{2.5}$ based on mathematical and numerical models: A COVID-19 and Winter Olympics case study

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HIGHLIGHTS

• Nonlinear relationship was obtained between PM$_{2.5}$ and various factors.
• RH, NO$_2$ and O$_3$ played dominant roles on pollution formation in winter of Beijing.
• Pollution periods in 2020 was highly related to adverse weather conditions.
• Emission reduction of sources has opposite effect on PM$_{2.5}$ and O$_3$ concentration.
• Reasonable emission policy is key to improve air quality.

ARTICLE INFO

Keywords:
PM$_{2.5}$ and O$_3$
DLNM
Emission reduction
Formation of pollution
COVID-19 and winter olympics

ABSTRACT

Air pollution during the COVID-19 epidemic in Beijing and its surrounding regions has received substantial attention. We collected observational data, including air pollutant concentrations and meteorological parameters, during January and February from 2018 to 2021. A statistical and a numerical model were applied to identify the formation of air pollution and the impact of emission reduction on air quality. Relative humidity, wind speed, SO$_2$, NO$_2$, and O$_3$ had nonlinear effects on the PM$_{2.5}$ concentration in Beijing, among which the effects of relative humidity, NO$_2$, and O$_3$ were prominent. During the 2020 epidemic period, high pollution concentrations were closely related to adverse meteorological conditions, with different parameters having different effects on the three pollution processes. In general, the unexpected reduction of anthropogenic emissions reduced the PM$_{2.5}$ concentration, but led to an increase in the O$_3$ concentration. Multi-scenario simulation results showed that anthropogenic emission reduction could reduce the average PM$_{2.5}$ concentration after the Chinese Spring Festival, but improvement during days with heavy pollution was limited. Considering that O$_3$ enhances the PM$_{2.5}$ levels, to achieve the collaborative improvement of PM$_{2.5}$ and O$_3$ concentrations, further research should explore the collaborative emission reduction scheme with VOCs and NOx to achieve the collaborative improvement of PM$_{2.5}$ and O$_3$ concentrations. The conclusions of this study provide a basis for designing a plan that guarantees improved air quality for the 2022 Winter Olympics and other international major events in Beijing.

1. Introduction

Urban air quality in China is closely related to its emissions of various air pollutants and its weather conditions. Especially, in winter, coal-dominated energy consumption and periodic adverse meteorological conditions cause air pollution (Wang et al., 2021; Yang et al., 2021). China’s policies, including the “Action Plan for Air Pollution Prevention and Control” and the “three-year action plan to win the battle to protect our blue skies,” after the two stages of air pollution control, have remarkably improved the air quality in key regions (Li et al., 2020; Chen et al., 2019). The United Nations Environment Programme released two reports, one in 2016 and the other in 2019, highlighting the improvements in China’s air quality in response to its control strategies related to clean fuel, construction dust, traffic dust, and coal-fired boilers (Wang...
et al., 2018; Lang et al., 2018). Thus, China is a good example for other developing countries.

Beijing has hosted many international events; hence, its air quality has attracted international attention. According to the Beijing Municipal Ecology and Environment Bureau, the annual average PM$_{2.5}$ concentration in 2020 was 38 $\mu$g/m$^3$ substantially lower than that in 2013 (89.5 $\mu$g/m$^3$), and the frequency of heavily polluted days was reduced. However, pollution processes were observed in January and February of 2020 and 2021, during which anthropogenic emission reductions were reported because of the outbreak of COVID-19 and China’s Spring Festival (Dai et al., 2021; Zhao et al., 2020). The public has been concerned and confused about this phenomenon. Because of these international events, ensuring good air quality and materializing the “APEC blue” and “Parade blue” is of substantial significance to China’s reputation.

Simulation techniques and various observation datasets have been widely used to identify the effects of emissions and weather conditions on air quality. Continuous monitoring of fine particles and their components throughout the past decade highlights the positive effect of control-measurement differences between industrial and mobile sources on improving air quality (Wang et al., 2019a, 2020; Zhang et al., 2019a; Shen et al., 2021). In Beijing, the SO$_4^{2-}$ concentration and proportion have decreased, and the NO$_3^-$ and NH$_4^+$ proportions within the total PM$_{2.5}$ concentration have increased, based on an offline monitoring project (Wang et al., 2019a, 2021). Remote sensing studies have also shown that emissions from combustion sources have been reduced (Xing et al., 2018; Zhou et al., 2021), contributing to the sharp decrease in PM$_{2.5}$ concentration in Beijing. Assessment of the emission reduction during international events held in Beijing showed that the strict control policies have resulted in the rapid improvement of air quality. During the APEC in 2014 and Parade in 2015, the PM$_{2.5}$ concentration and the concentrations of its major components were significantly lower than those before the emission reduction, and simulations indicated that implementing control measures could reduce the PM$_{2.5}$ concentration by approximately 30% during international events and heavily polluted periods in Beijing (Wang et al., 2017; Jia et al., 2017; Yang et al., 2017).

Additionally, changes in regional meteorological conditions have affected the diffusion and transformation of pollutants (Dang and Liao, 2019; Lv et al., 2020). A study indicated that such changes accounted for 3%–27% of the air quality improvement in the following regions: Beijing-Tianjin-Hebei (BTH), Yangtze River Delta, Pearl River Delta, and Sichuan Basin (Zhai et al., 2019).

Statistical methods have also been widely used in the field of air pollution. Based on observational datasets of high resolution and accuracy, multiple models were applied to investigate the regional transport, precursor conversion, and various other factors affecting the PM$_{2.5}$ and O$_3$ concentrations (Ge et al., 2018). The advantage of these methods is that the data source can represent the real atmospheric conditions better, providing a more objective conclusion. In addition, according to the research needs, various observational parameters can be selected for analysis; among these, the distributed lag nonlinear models (DLNMs) can represent the nonlinear effects of various factors on the concentrations of pollutants, including lag effects, pollution levels, and other dimensions (Duan et al., 2021; Yang et al., 2021). Thus, DLNMs are a reliable method for analyzing the nonlinear relationship between various factors and pollution formation. However, studies have mainly focused on extended regional-scale analyses while ignoring the differences among cities across regions.

In this study, we analyzed three key aspects based on numerical simulations and statistical models: (1) the pollution caused by PM$_{2.5}$ during the winter and Spring Festival periods in Beijing from 2018 to 2021; (2) the nonlinear relationship between various factors and PM$_{2.5}$; (3) the influence of meteorological conditions on the formation of air pollution in the past four years, especially during the COVID-19 outbreak in 2020. In the following sections, we select the most unfavorable year among the years 2018–2021, select the emission reduction scenarios, and discuss the air quality in Beijing. We also analyzed the air quality data during the Winter Olympic Games. The conclusions based on the results of this study support changing the winter-pollution characteristics in Beijing, influenced by a continuous emission reduction, as well as air quality assurance during international events.

2. Methodology

2.1. Data collection

We collected air pollutant and meteorological data for January and February from 2018 to 2021 in Beijing, as well as air pollutant concentrations during 2022. Surface meteorological data, including wind speed (WS), wind direction, air temperature (T), and relative humidity (RH), were obtained from the China Meteorological Administration observation network at hourly temporal resolution. The meteorological station (number 54511) is in Daxing District (39.8°N, 116.47°E). We obtained the information on the mass concentrations of air pollutants, including PM$_{2.5}$, SO$_2$, NO$_2$, and O$_3$ at national control sites from the Beijing Municipal Ecology and Environment Bureau at hourly temporal resolution. These data were the input for the meteorological and air quality models. The Final Operational Global Analyses data provided by the National Centers for Environmental Prediction’s Global Forecast System were used in the Weather Research and Forecasting (WRF) Model simulation.

The air pollutant emission inventory is an important basic dataset for numerical simulation research and substantially affects simulation results. To better reproduce the actual spatial and temporal distribution of air pollutant concentrations, the high-resolution air pollutant emissions in the BTH region were obtained by our research group. The details on the methodology and emission amount are available in our prior research (Zhou et al., 2012, 2015; Lang et al., 2018). The emissions in other areas across the domain were obtained from the MEIC emission inventory dataset (http://www.meicmodel.org/) and updated according to the policies released by the local government. The main pollutants included PM$_{2.5}$, PM$_{10}$, SO$_2$, NO$_x$, VOCs, CO, and NH$_3$.

2.2. DLNMs

DLNMs have been widely used in the fields of economics and environmental health considering the nonlinear exposure-lag-response association between dependent and independent variables. These models have been found to have a more accurate modeling ability than the multiple linear regression model (Duan et al., 2022; Guo et al., 2016; Chen et al., 2018). Due to time-intensive physical and chemical reactions, PM$_{2.5}$ concentration is closely related to its precursor and meteorological conditions in the current time and lagged dimensions. Therefore, a DLNM model can be used to study the characteristics of PM$_{2.5}$ and discuss the response relationship between meteorological conditions and concentrations, anthropogenic source emissions and concentrations, and the PM$_{2.5}$ characteristics of annual and seasonal variations.

In this study, a DLNM was applied to describe the influence of major precursors and meteorological factors on the PM$_{2.5}$ concentration in January and February from 2018 to 2021. The DLNM characterized the lagged and nonlinear response relationships between these factors and PM$_{2.5}$ concentration. To avoid overfitting and reducing collinearity, we used only WS, RH, SO$_2$, NO$_x$, and O$_3$ as independent variables in the DLNM because of the physical and chemical PM$_{2.5}$ reaction mechanisms. Due to the obvious hourly variation in O$_3$, the input data was the daily value. Because wind direction is an instantaneous variable, the average of the hourly wind direction could not accurately represent the actual
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C = \ln b_0 + b_0 \times \sum_{p=1}^{P} c_{bp} + \text{dow},

where C is the PM\(_{2.5}\) concentration; \(c_{bp}\) is the cross-basis of the \(p\)th influencing factor; \(\text{dow}\) is the dow category variable; and \(b_0\) and \(b_p\) denote the intercept and coefficient, respectively. The root-mean-square error built for the DLNM was 19.4 \(\mu\)g/m\(^2\), suggesting a relatively good fitness. Moreover, no collinearity was detected, because the GVIF\(^{2*}\)df of all independent variables was lower than 2.0.

Table 1

Comparison of observed and simulated results.

|       | Obs  | Sim | COR | NMB   |
|-------|------|-----|-----|-------|
| RH (%)| 52.7 | 43.0| 0.63| -18.5%|
| WS (m/s)|1.8  | 2.0 | 0.54| 10.3% |
| T (°C) | 0.11 | 0.14| 0.82| 32.6% |
| PM\(_{2.5}\) (\(\mu\)g/m\(^2\))| 69.2 | 58.0| 0.77| -16.2%|
| O\(_3\) (\(\mu\)g/m\(^2\))| 40.2 | 34.2| 0.68| -15.0%|

Fig. 1. Daily concentrations of air pollutants (i.e., PM\(_{2.5}\), O\(_3\), SO\(_2\), and NO\(_2\)) and meteorological parameters (i.e., T and RH).

3. Results and discussion

3.1. Air quality and meteorological conditions

Strict control strategies to control combustion sources in winter have been implemented in China, leading to an improvement in air quality (Wang et al., 2018, 2021; Lang et al., 2017). Fig. 1 shows the daily PM\(_{2.5}\), O\(_3\), SO\(_2\), and NO\(_2\) concentrations and the T and RH in January and February during the four target years. We found that the average SO\(_2\) concentration decreased from 2018 to 2021, and the annual values were 8.7 \(\mu\)g/m\(^3\), 7.3 \(\mu\)g/m\(^3\), 5.0 \(\mu\)g/m\(^3\), and 3.9 \(\mu\)g/m\(^3\), respectively. The highest average PM\(_{2.5}\) concentration was observed in 2020 (68.8 \(\mu\)g/m\(^3\)) and the lowest in 2018 (40.7 \(\mu\)g/m\(^3\)). Affected by the COVID-19 outbreak, emissions from traffic and industrial sources, as well as disorganized dust, decreased by varying degrees in 2020. By contrast, the number of days with PM\(_{2.5}\) concentrations higher than 150 \(\mu\)g/m\(^3\) (i.e., threshold value defining the heavily polluted days according to the National Ambient Air Quality Standard in China, GB 3096–2012) in 2020 was higher than those in the other three years. Accumulation and dissipation of the PM\(_{2.5}\) concentration were highly related to the meteorological conditions, which could affect the physical diffusion and chemical conversion of PM\(_{2.5}\) and its precursors. As illustrated in Fig. 1, from 2018 to 2021, the average RH was 32.2%, 33.5%, 52.7%, and 43.3%, and T was -1.9 °C, -0.9 °C, 0.1 °C, and 0.3 °C, respectively, and both were positively correlated with the average PM\(_{2.5}\) concentration.
The average WS values from 2018 to 2021 were 2.4 m/s, 2.1 m/s, 1.8 m/s, and 2.1 m/s, respectively, and thus show a negative correlation with PM$_{2.5}$ concentration.

Fig. 2 shows the backward trajectory results and distribution of the wind field coupled with PM$_{2.5}$ concentration from 2018 to 2021. Wintertime air mass transport in Beijing was directed mainly from the northwest and the nearby regions; however, the proportion of southern air mass varied (i.e., 22%, 35%, 53%, and 39% from 2018 to 2021, respectively), and they were mainly transported slowly by the surface layer to Beijing. Combining the wind field with the PM$_{2.5}$ concentration, the speed of the northern wind is generally higher than that of the southern wind, and polluted days are mainly related to southern and northeastern winds with speeds below 2 m/s. Beijing is surrounded by the Yan Mountains and Taihang Mountains in the north and west directions, respectively. Because of the high emission load related to the relatively larger proportion of secondary production in its southern cities, the PM$_{2.5}$ concentration is more likely to increase under weak southern wind conditions (Zhang et al., 2019b, 2021b). On the basis of the wind field-concentration analysis and backward trajectory results, the input of the polluted air masses transported along the weak southern wind with high frequency might be one of the predominant reasons leading to the heavy pollution in 2020. Studies have indicated that the regional transport of air mass from southern regions could promote the formation of air pollution in Beijing, due to the high emission load of its southern cities (Wang et al., 2018; Ji et al., 2014). The airflow could be blocked by mountains in the north of Beijing and continue accumulating, becoming severe pollution. Thus, the transport of southern air pollutants could be one of the main reasons for the air pollution in Beijing. This is consistent with that of this study.

Notably, three persistent pollution incidences occurred during the study period: (a) From January 26 to 28, 2020, (b) from February 10 to 13, 2020, and (c) from February 11 to 13, 2021. During these three incidences, the anthropological emission amount was relatively low because of the Spring Festival and the COVID-19 outbreak. The average SO$_2$ and NO$_2$ concentrations during the three incidences, namely, (a), (b), and (c), were 10.1 μg/m$^3$, 4.7 μg/m$^3$, and 7.5 μg/m$^3$, and 47.3 μg/m$^3$, 59.5 μg/m$^3$, and 37.2 μg/m$^3$, respectively. These values are not significantly larger than the two-month average concentrations of the precursors; however, the PM$_{2.5}$ concentrations were 2.8, 2.5, and 3.7 times the corresponding values. The historical pollution processes that occurred in Beijing in approximately 2010 have been reported to be closely related to the combustion emissions (Shao et al., 2018). The high concentration of the precursors SO$_2$ and NO$_2$ rapidly transformed into secondary components under adverse meteorological conditions, accompanied by primary particle accumulation, leading the daily PM$_{2.5}$ concentration to reach 400 μg/m$^3$ (Zhao et al., 2013; Zhang et al., 2013, 2014). The anthropogenic emissions during the study periods are obviously lower than those of the earlier years. The COVID-19 epidemic and the Spring Festival effect contributed to reducing emissions. The concentrations of precursors were much lower than those in the historical periods. However, the peak concentration of PM$_{2.5}$ could reach more than 200 μg/m$^3$, thereby meteorological conditions are important.

### 3.2. Nonlinear effect between various parameters and the PM$_{2.5}$ concentration

To identify nonlinear effects of meteorological parameters and air pollutants on PM$_{2.5}$ concentration, we applied DLNNs, and the three-dimensional results are shown in Fig. 3. In general, obvious nonlinear effects were identified for all five parameters. For the air pollutants, a larger effect was mainly detected at the 0-h and 1-h time lag in the high concentration stage; however, a difference was observed during the low concentration stage. For example, the SO$_2$ lag effect at the lowest concentration at the 6-h time lag was much more pronounced than at other moments. An explanation for this phenomenon might be that a low SO$_2$ concentration is insufficient for providing an adequate environment for secondary conversion; therefore, a certain accumulation process is required. Low WS had a positive effect on PM$_{2.5}$ accumulation at lag hours ranging from 0 to 6, leading to a concentration increase; high WS had the opposite effect. Regarding RH, an obvious effect was found at the 0-h time lag. This value was the highest value of all the conditions, demonstrating the important role of high RH during air pollution accumulation in winter. The comparison of the relationship between the five parameters and PM$_{2.5}$ concentration found that the RH and NO$_2$ concentration had more obvious effects on the PM$_{2.5}$ concentration, indicating that these two parameters are the main causes of winter haze in Beijing.

The cumulative effects over all the lag hours of the five parameters were further analyzed (Fig. 3). The values where the curves intersect the x-axis are the median of each parameter. WS variations exhibited a linear relationship with PM$_{2.5}$ concentration. As we mentioned in chapter 3.1, high PM$_{2.5}$ concentrations were mainly accompanied by WS lower than 2 m/s because of the weakening of the physical diffusion ability of the atmospheric environment. This response relationship has been confirmed (Duan et al., 2022; Wang et al., 2018). RH mainly had a positive effect on PM$_{2.5}$ concentration; and especially when it was larger than 50%, the increment of PM$_{2.5}$ concentration gradually increased, suggesting that high RH in winter promotes the chemical transformation of pollutants. The literature also reported that liquid and heterogeneous processes are dominant pathways for the transformation of SO$_2$ and NOx to secondary components and that high RH is a main factor promoting these processes (Li et al., 2022). In addition, the secondary SO$_2$ and NO$_2$ conversion intensity obviously, especially at RH values greater than 50% or 60%, on the basis of field observations and numerical simulations (Chen et al., 2016; Wang et al., 2019b). Both precursors, NO$_2$ and SO$_2$, promote the increase in PM$_{2.5}$ concentration. Notably, the effect of NO$_2$ on PM$_{2.5}$ concentration was greater, and the PM$_{2.5}$ increment increased more distinctly with the increasing NO$_2$ concentration than with the SO$_2$ concentration. On one hand, the “Action plan for Air Pollution Prevention and Control” from 2013 to 2017 and “A three-year action plan to win the battle to protect our blue skies” from 2018 to 2020 has led to a sharp decrease in combustion-source emissions. Therefore, the SO$_2$ concentrations have become a limiting factor in SO$_2$ production (Li et al., 2021). The other hand, environmental observations showed that the sulfur pollutants in the atmosphere decreased significantly more than those of NOx, especially during heavy pollution in autumn and winter in Beijing, and the SO$_2$ and NO$_2$ pollution processes decreased and increased, respectively. This is due to the more completed conversion of NO$_2$ to NO$_3$ than SO$_2$ to SO$_2$$^2$ (Zhang et al., 2021). O$_3$ is an important oxidant in atmospheric environments; polluted days with O$_3$ as the primary air pollutant appeared in spring and summer in Beijing. Following the PM$_{2.5}$ improvement, a high O$_3$ concentration was also evident in winter, which affected the liquid phase and heterogeneous transformation of precursors (Zhang et al., 2021). Additionally, for O$_3$, the low temperature in winter weakened its transformation to the gas phase, and the increased concentration of O$_3$ promotes the distribution of NO$_2$ into the particulate phase (Li et al., 2021). From the perspective of the cumulative O$_3$ impact, when the O$_3$ concentration is larger than 60 μg/m$^3$, its impact on PM$_{2.5}$ becomes more obvious, indicating the existence of coordinated pollution between PM$_{2.5}$ and O$_3$ in winter.
Fig. 2. Distribution of the wind field coupled with the PM$_{2.5}$ concentration during January and February in 2018–2021 and results of the backward trajectory analysis.
PM$_{2.5}$ concentration are clarified in this section. We used 2018 as the base year: WS from 2019 to 2021 was unfavorable for PM$_{2.5}$ improvement, and the worst conditions were in 2020. The RH during 2019–2021 was also unfavorable compared with that in 2018, and the maximum increment was in 2021, followed by 2020 and 2019. The largest effect of the sum of WS and RH was in 2020, demonstrating that the two coupled indicators are the most unfavorable. The effect of SO$_2$ in 2019 and 2021 was similar to that in 2018, and that in 2020 was much larger. The NO$_2$ effects in 2020 and 2021 were smaller than those in 2018 and 2019, which might be due to the COVID-19 outbreak in 2020, when a generalized lockdown was in effect, leading to higher emissions for heating and lower emissions from mobile sources than in the other years. The largest O$_3$ effect was in 2018, followed by 2021, 2020, and 2019. The study periods were divided into five groups according to the air quality standard: (1) 0–35 μg/m$^3$, excellent days (ED); (2) 35–75 μg/m$^3$, good days (GD); (3) 75–115 μg/m$^3$, lightly polluted days (LP); (4) 75–115 μg/m$^3$, moderately polluted days; and (5) >150 μg/m$^3$, heavily polluted days (HP). Statistical results showed that the effect of the five parameters on PM$_{2.5}$ concentration generally intensified with increased pollution, which also proved that they are closely related to PM$_{2.5}$ formation. In addition, the SO$_2$ and NO$_2$ effects during the Spring Festival and other periods were compared. The results indicated that the SO$_2$ effect during the Spring Festival was larger, and the NO$_2$ effect was smaller, which was mainly due to the different emission sources in the two periods.

The COVID-19 outbreak received substantial international attention. Air pollution processes around the 2020 Spring Festival also attracted considerable attention. Thus, we divided the two months into seven periods: three pollution periods (i.e., P1, P2, and P3) and four clean periods (i.e., C1, C2, C3, and C4) according to the daily PM$_{2.5}$ concentration. As shown in Fig. 4, WS and RH were pivotal for the formation of PM$_{2.5}$.
high PM$_{2.5}$ concentrations, especially when compared with clean periods. The effect of WS and RH was ranked in decreasing order: P2 > P3 > P1 and P1 > P3 > P2, respectively. The SO$_2$ effect ranked in decreasing order was P2 > P3 > P1, and that for NO$_2$ was P1 > P3 > P2. Because the three processes occurred before, during, and after the Spring Festival, the obtained effect could be related to the different emission sources among the three stages. The emissions of various pollutants were reported to decrease during the epidemic. NO$_x$ emissions, mainly from mobile sources, decreased sharply and subsequently increased after the Spring Festival; however, they were lower than those in 2019. Sun et al. also revealed that the NO$_3^-$ concentration in Beijing during the pollution process was higher after the Spring Festival compared with during the Spring Festival (Sun et al., 2020). SO$_2$ emissions did not decrease significantly compared with NO$_x$ emissions. This phenomenon occurred mainly because of the increased demand for heating and because heavy industry during the Spring Festival did not shut down; most emission reductions were in light industry (Yan et al., 2021; Zuo et al., 2022; Gu et al., 2022). Regarding O$_3$, statistics showed that its effect ranked in decreasing order was P3 > P2 > P1. Thus, the catalytic effects of O$_3$ on precursor conversion in P2 and P3 may have been stronger than those in P1, and this finding is supported by a finding based on online observations by Sun et al. (2020).

### 3.3. Impact of emission reduction on air quality

Results from several major events and red alerts in the past ten years showed that the reduction in anthropogenic emissions can effectively decrease the PM$_{2.5}$ concentration. During the 2020 epidemic period, anthropogenic emissions also decreased significantly during and after the Spring Festival, owing to the impact of China’s home-quarantine policy. According to a report by the National Joint Center for Air Pollution Prevention and Control, emissions from anthropogenic sources decreased by approximately 30% during the 2020 epidemic period; hence, we simulated several scenarios as follows (see Table 2):

Table 2: Scenario design

| Scenario number | Description            | SO$_2$ | NO$_x$ | PM$_{2.5}$ | VOCs |
|-----------------|------------------------|--------|--------|------------|------|
| S0              | Base scenario with no emission reduction | 0      | 0      | 0          | 0    |
| S1              | Emission reduction from January 23 | 20%  | 30%   | 40%   | 30%  |
| S2              | Emission reduction through the simulation period | 35%  | 45%   | 40%   | 30%  |
| S3              | Emission reduction through the simulation period | 35%  | 45%   | 40%   | 45%  |
| S4              | Emission reduction through the simulation period | 35%  | 45%   | 40%   | 60%  |

As aforementioned, although O$_3$ pollution mainly occurred in sum- mer in northern China, it also promoted the liquid phase transition or heterogeneous reactions of PM$_{2.5}$ precursors in winter, leading to PM$_{2.5}$ pollution. Thus, next, we elaborate on the O$_3$ concentration variations. Our results indicated that the anthropogenic emission reduction during the COVID-19 outbreak increased O$_3$ concentrations by 19.0% since the Spring Festival, which differs from that of PM$_{2.5}$. The S2-S4 simulation scenarios further showed that under the 2020 meteorological field as a driver, the O$_3$ concentration of the three reduction scenarios after the Spring Festival was ranked in decreasing order as S2 > S3 > S4; the average concentration during the Spring Festival was higher than that of the base scenario. From the perspective of anthropogenic emissions, the reduction rates of NO$_x$ and VOCs in S1 were lower than those in S2-S4, indicating that the control of O$_3$ differs from that of PM$_{2.5}$. The enhanced reduction measures for NO$_x$ and VOCs might lead to an increase in O$_3$ concentration, and the S2-S4 scenarios indicated that the enhanced emission reduction of VOCs mitigates to some extent the O$_3$ pollution. A nonlinear relationship was observed between O$_3$ and its precursors, including NOx and VOCs. The formation mechanism of O$_3$ in clean and polluted atmospheres differs. The ratio of NO$_x$/VOCs could lead to a different sensitivity of O$_3$-NOx-VOCs (Liu and Shi, 2021). The literature has reported that NOx and NOx co-control is essential rather than NOx single-control strategy (Wei et al., 2022; Xiang et al., 2020). This result is similar to the results of the present study.

Notably, in the S2 scenario, although the emission reduction was implemented in advance and the SO$_2$ and NO$_x$ emission reductions were strengthened, the PM$_{2.5}$ concentration decreased significantly before the Spring Festival but increased slightly after. Next, we extracted the concentration of the PM$_{2.5}$ components. The findings demonstrated that the EC concentrations in the primary component in S1 and S2 were the same; however, in the S2 scenario, the NO$_3^-$ and OC concentrations increased. This cause of this difference might be that under the condition of advanced emission reduction, the O$_3$ concentration in S2 was higher than that in S1 before the Spring Festival, promoting the transformation of NO$_3^-$ and secondary organic aerosols, which is consistent with the aforementioned O$_3$-mediated enhancement of the PM$_{2.5}$ levels.

The impact of pollutant emission reduction on PM$_{2.5}$ and O$_3$ concentrations in the BTH region followed the same trend as that in Beijing: PM$_{2.5}$ concentrations decreased, and O$_3$ concentrations increased in S1 compared with S0. In general, the coordinated control of multiple pollutants in winter could alleviate PM$_{2.5}$-induced pollution in urban cities; the implementation of control measurements before the HP periods and strengthening the control of VOCs could further reduce the PM$_{2.5}$ concentration. However, these measures had limited effects on the improvement of air quality during HP days. Regarding O$_3$, due to the nonlinear relationship between precursors and O$_3$, the coordinated control of NO$_x$ and VOCs in equal proportions in this study cannot achieve pollution alleviation. Based on the fixed NO$_x$ emission reduction rate, increasing the emission reduction of VOCs plays a role in reducing the O$_3$ concentration. Previous literature has reported that in winter, O$_3$ is less sensitive to VOCs and NO$_x$ than PM$_{2.5}$, which is consistent with the results in this study. Because of the PM$_{2.5}$ pollution in winter and the O$_3$-mediated enhancement of the secondary reactions, the coordinated control of PM$_{2.5}$ and O$_3$ levels in winter should be considered an important goal in the BTH region.

Overall, the emission reduction of pollution sources has played a positive role in the improvement in air quality in Beijing and the surrounding areas. Notably, under the meteorological conditions in 2020 and various emission reduction schemes, occurrences of air pollution will be observed during the study periods. We also collected the air pollutant concentrations and meteorological data during the 2022 Winter Olympics. The average concentrations of SO$_2$, NO$_x$, and PM$_{2.5}$ in Beijing in February 2022 were 2.5 μg/m$^3$, 18.6 μg/m$^3$, and 21.5 μg/m$^3$, respectively, the lowest values since 2018. The highest daily concentration of PM$_{2.5}$ was only 61.6 μg/m$^3$. From the perspective of meteorological conditions, the average values of RH and WS were 36.9% and...
Fig. 5. Distribution of PM$_{2.5}$ and O$_3$ concentrations in five scenarios.
2.0 m/s, respectively, and there was no long-term precipitation. Although we did not obtain the emission reduction plan for regional pollution sources, according to the observation data, under relatively favorable meteorological conditions, the implemented emission reduction plan has better guaranteed the air quality during the winter Olympics. However, on the basis of the scenario analysis of the 2020 meteorological conditions, for satisfactory air quality during major international events, the control of key emissions, such as VOCs and NOx, must be strengthened to achieve the synergistic improvement of PM$_{2.5}$ and O$_3$.

4. Conclusions

In this study, the research periods were January and February (from 2018 to 2021) in Beijing; further, nonlinear relationships between various parameters and PM$_{2.5}$ concentration were studied using DLNMs. We discussed in detail the annual variations in the influence of various parameters on the PM$_{2.5}$ concentration, as well as the causes of high PM$_{2.5}$-induced pollution during the 2020 epidemic period. Next, a multiple-scenario simulation was designed to analyze the improvement in air quality under emission reduction scenarios. The conclusions could provide references for air quality assurance during major international events.

The results indicated that meteorological conditions and pollutant concentrations have nonlinear effects on the PM$_{2.5}$ concentration. The effects of NO$_x$ on PM$_{2.5}$ concentration are more prominent than those of SO$_2$, indicating the relative importance of mobile sources with regard to pollution formation. The meteorological conditions in 2020 are more likely to cause air pollution than those in 2018, indicating unfavorable weather during the 2020 epidemic period. In addition, there were significant differences in the causes of the three PM$_{2.5}$ pollution processes during the 2020 epidemic period, which were related to the changes in the levels of manmade emissions.

The altered anthropogenic emissions during the epidemic period contributed to the PM$_{2.5}$ concentration reduction in Beijing and the surrounding areas but also promoted the increase in O$_3$ concentrations; the multi-scenario simulation demonstrated that the enhanced emission reduction of NO$_x$ and VOCs had marked effects on the PM$_{2.5}$ concentration, but the effect on O$_3$ concentration was different. Further enhancing the emission reduction of NO$_x$ has a certain effect on the reduction of O$_3$ concentration. Combined with data analysis during the 2022 Winter Olympics, in order to ensure air quality under different meteorological conditions, the relevant parties should perform emission reduction in advance. In further research, the control of VOCs should be explored to achieve the synergistic improvement of PM$_{2.5}$ and O$_3$ concentrations.

Credit author statement

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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.

Acknowledgment

This work was supported by the National Natural Science Foundation of China (No. 52000005, 52022005, 51638001, and 51678007).
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