



## OPEN ACCESS

## EDITED BY

Lingling Shen,  
Beijing Meteorological Information  
Center, China

## REVIEWED BY

Ying Zhou,  
Beijing University of Technology, China  
Duanyang Liu,  
Chinese Academy of Meteorological  
Sciences, China

## \*CORRESPONDENCE

Xiaoqin Rao,  
raoxq@cma.gov.cn  
Qiyang Chen,  
chenqy@cma.gov.cn

## SPECIALTY SECTION

This article was submitted to  
Geohazards and Georisks,  
a section of the journal  
Frontiers in Earth Science

RECEIVED 18 August 2022

ACCEPTED 01 November 2022

PUBLISHED 05 January 2023

## CITATION

Liu C, Rao X, Chen Q, Zhang B and  
Zhang B (2023), Objective identification  
and forecast method of PM<sub>2.5</sub> pollution  
based on medium- and long-term  
ensemble forecasts in Beijing-Tianjin-  
Hebei region and its surrounding areas.  
*Front. Earth Sci.* 10:1022565.  
doi: 10.3389/feart.2022.1022565

## COPYRIGHT

© 2023 Liu, Rao, Chen, Zhang and  
Zhang. This is an open-access article  
distributed under the terms of the  
[Creative Commons Attribution License  
\(CC BY\)](https://creativecommons.org/licenses/by/4.0/). The use, distribution or  
reproduction in other forums is  
permitted, provided the original  
author(s) and the copyright owner(s) are  
credited and that the original  
publication in this journal is cited, in  
accordance with accepted academic  
practice. No use, distribution or  
reproduction is permitted which does  
not comply with these terms.

# Objective identification and forecast method of PM<sub>2.5</sub> pollution based on medium- and long-term ensemble forecasts in Beijing-Tianjin-Hebei region and its surrounding areas

Chao Liu<sup>1</sup>, Xiaoqin Rao<sup>1\*</sup>, Qiyang Chen<sup>2\*</sup>, Bihui Zhang<sup>1</sup> and Bo Zhang<sup>1</sup>

<sup>1</sup>National Meteorological Centre, Beijing, China, <sup>2</sup>CMA Earth System Modeling and Prediction Centre, Beijing, China

Accurate long-term forecasts of PM<sub>2.5</sub> pollution are essential to mitigating health risks and formulating pollutant control strategies for decision-makers in China. In this study, an objective identification and forecast method for PM<sub>2.5</sub> pollution (OIF-PM<sub>2.5</sub>) is developed based on medium- and long-term ensemble forecasts of PM<sub>2.5</sub> in Beijing-Tianjin-Hebei region and its surrounding areas. The results show that the observed PM<sub>2.5</sub> pollution ratio increases with the aggravating PM<sub>2.5</sub> pollution. For example, the ratio of meteorological stations with heavy pollution is 4.4 times that of light pollution and 3.9 times that of moderate pollution. In addition, the correlation coefficients between observations and forecasts are above 0.60 for all forecast leading times. Statistical results show that the average accuracy for forecasts with the leading times of 1–3 days, 4–7 days, and 8–15 days are 74.1%, 81.3%, and 72.9% respectively, indicating that the OIF-PM<sub>2.5</sub> method has a high reliability in forecasts with the leading times of 1–15 days. The OIF-PM<sub>2.5</sub> method is further applied in a severe PM<sub>2.5</sub> pollution episode in the December of 2021, and the average forecast precision in forecasts with the leading times of 6–8 days reaches as high as 100%, showing a certain reference value for PM<sub>2.5</sub> forecasts.

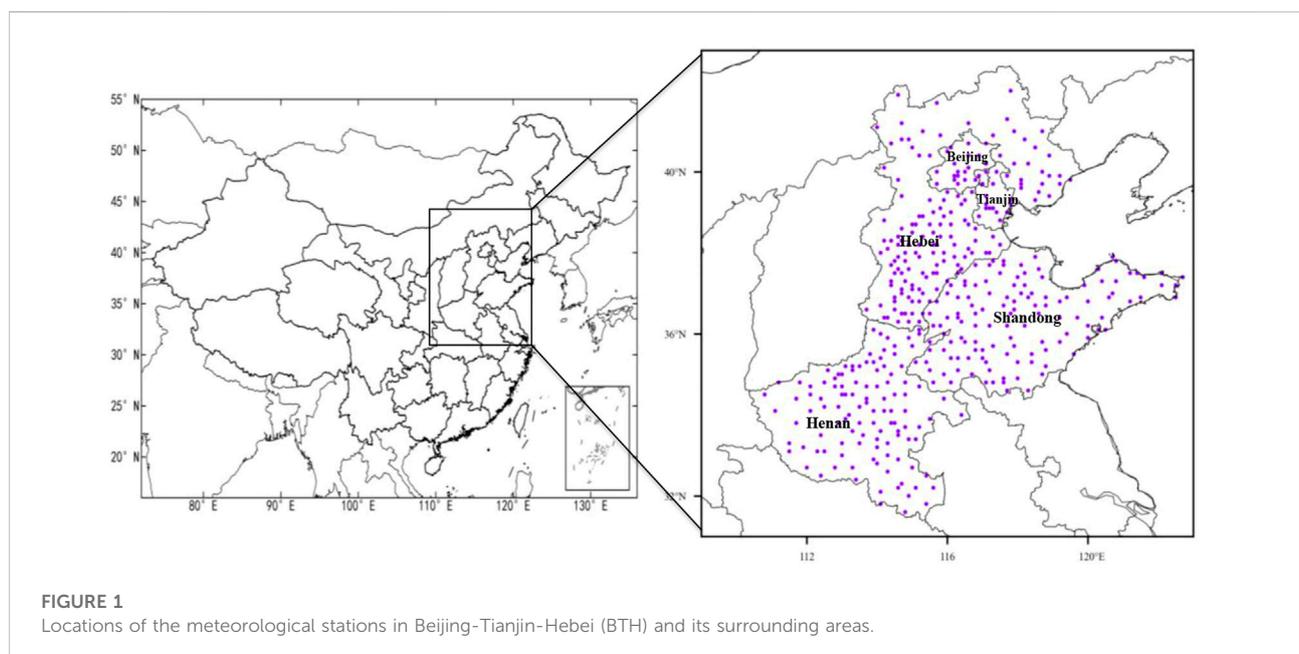
## KEYWORDS

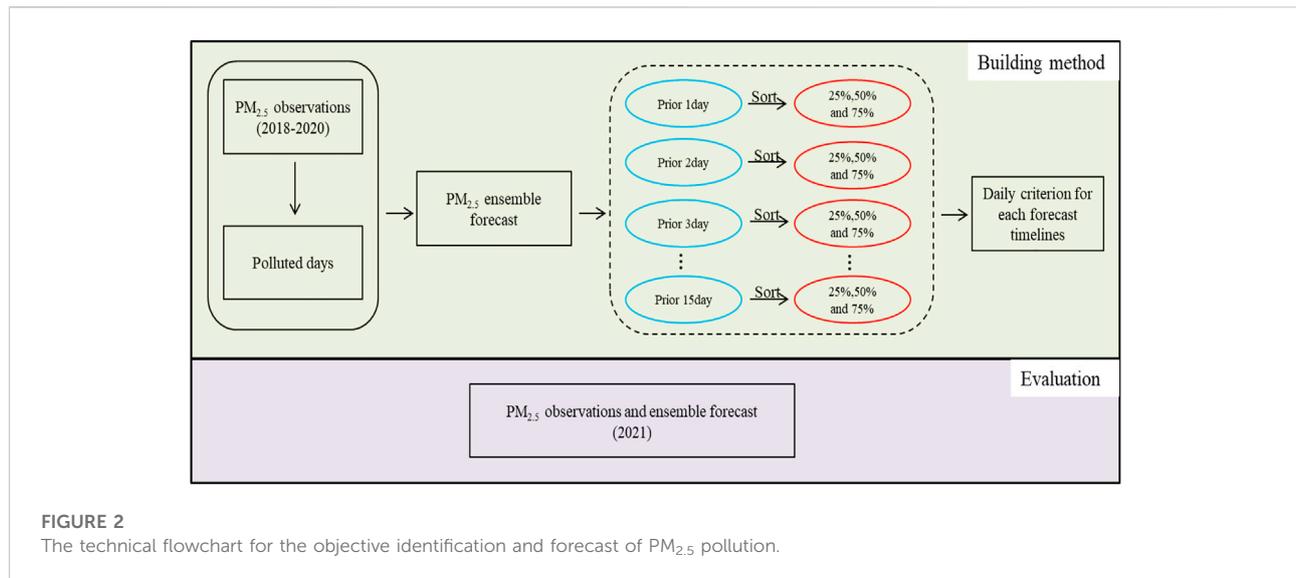
PM 2.5 pollution, ensemble forecast, forecast technology, objective identification and forecast method for PM<sub>2.5</sub> pollution, beijing-tianjin-hebei region and its surrounding areas

## 1 Introduction

In terms of economy, urbanization and population growth, the Beijing-Tianjin-Hebei region (BTH) and its surrounding areas are among the most developed regions in China. Meanwhile, severe and frequent  $PM_{2.5}$  (fine particulate matter with an aerodynamic diameter  $\leq 2.5 \mu m$ ) pollution in this region has attracted more and more attention in recent years due to its complex impacts on visibility, human health and ecological environment (Liu et al., 2019; Li et al., 2021a; Cheng et al., 2021; Sawlani et al., 2021; Zhang et al., 2021). The Chinese government launched the “Air Pollution Prevention and Control Action plan” in 2013 and “2017 Air Pollution Prevention and Management Plan for the Beijing-Tianjin-Hebei Region and its Surrounding Areas” to solve the severe  $PM_{2.5}$  pollution. A series of control measures have been implemented to reduce pollutant emissions, e.g., eliminating industries with high pollution and emission, optimizing industrial and energy structures and restricting vehicle use (Zhang et al., 2014; Chen et al., 2021; Liu et al., 2021). Nonetheless, heavy  $PM_{2.5}$  pollution episodes are still frequent in BTH and its surrounding areas, especially during autumn and winter due to unfavorable meteorological conditions (Zhang et al., 2018; Li et al., 2019; Bei et al., 2020). Accurate  $PM_{2.5}$  pollution forecasts can reduce the air pollutant exposure to sensitive groups and provide necessary reference for making pollution policies and starting control measures in advance, especially before some importance events such as the Asia-Pacific Economic Cooperation Summit 2014 and 70th anniversary of the founding of the People’s Republic of China. Therefore, medium- and long-term  $PM_{2.5}$  forecast is critically important.

Various methods have been used for air pollution forecasting. In general, the forecasting methods can be categorized into three groups: empirical method, statistical approaches and numerical simulations (Zhai and Chen, 2018; Liu and Chen, 2019). The empirical method, also known as a knowledge-based procedure, is based on previous observations, which requires a comprehensive understanding of the pollution dispersion/transport mechanisms and physical-chemical processes (Garner and Thompson, 2012; Yuval et al., 2012). Furthermore, the empirical method is highly dependent on pollution sources and meteorological factors, and previous studies (Zhou et al., 2019; Wu et al., 2020; Samal et al., 2021) have demonstrated that it performs poorly when compared with statistical approaches. Statistical approaches consist of multiple linear regression (Dimitriou and Kassomenos, 2014; Jeong et al., 2021; Liu et al., 2022), Kalman filtering, artificial neural network (Zhou et al., 2020; Bera et al., 2021), long short-term memory (Gao and Li, 2021), support vector machine (Wang et al., 2017) and other hybrid methods (Liu et al., 2020; Huang et al., 2021). It is found that they can successfully forecast the  $PM_{2.5}$  for their capacity of nonlinear mapping. In addition, the deep learning technology has sparked a lot of interest (Pak et al., 2020; Menares et al., 2021; Yang et al., 2021) and proven its superiority in several fields. Deep learning technology is proposed for analyzing the characteristics of historical data. However, all of these statistical approaches only focus on the historical data, which ignore the atmospheric dispersion and transport mechanisms. Furthermore, most of them could only provide short-term forecasts that usually range from 24 to





**FIGURE 2**  
The technical flowchart for the objective identification and forecast of  $PM_{2.5}$  pollution.

**TABLE 1** Accuracy index categories.

Polluted day	Forecasted $PM_{2.5}$ pollution ratio	
	$\geq 25$ th percentile	$< 25$ th percentile
Yes	NA	NC
NO	NB	ND

72 h (Jiang et al., 2021), while most planning and monitoring actions have a greater demand for long-term forecasts. Numerical simulations, such as the Community Multiscale Air Quality Modeling System and the Comprehensive Air quality Model with extensions, can simulate the chemical and physical processes of  $PM_{2.5}$  pollution (Cai et al., 2017; Liu et al., 2018) and thus provide a better understanding of the transformations and distributions of  $PM_{2.5}$ . Although numerical models can provide reliable medium-term forecasts, there may be some systematic errors in short-term forecasts. Such models tend to be sensitive to initial and boundary fields (Feng et al., 2020).

Over the past decades, ensemble forecast products have been a major contributor to improving weather forecasts (Yang et al., 2015; Zhao et al., 2022). These products take into account the uncertainty of initial states and process description in numerical weather forecasting models. Ensemble forecasts include several members, representing a set of possible atmospheric conditions in the future. In contrast to deterministic weather forecasts, ensemble forecasts increase the lead time of high-quality forecasts to more than several days. The Observing-system Research and Predictability Experiment (THORPEX) Interactive Grand

Global Ensemble (TIGGE) is a database of ensemble forecasts in medium and long ranges conducted by different forecasting centers established for scientific research (Tao et al., 2014). Among all TIGGE data, the European Centre for Medium-Range Weather Forecasts (ECMWF) have presented advantages in the number of ensemble members and spatial resolutions than other forecasting systems (Sagar et al., 2017), consisting of 51 members with a resolution of approximate  $0.5^\circ$  for the whole globe (Zhao et al., 2016). Regarding these advantages, the ECMWF ensemble forecasts are widely applied in forecasting precipitation (Cong et al., 2021), temperature (Verkade et al., 2013), tropical cyclone track (Nishimura and Yamaguchi, 2015) and water deficit depth (Zhao et al., 2016). Based on the ECMWF ensemble forecasts, Schumacher et al. (2011) studied a low-vortex induced rainstorm event in southern United States, and investigated the impact of disturbances in upstream weather systems on precipitation forecasts. Besides, Schauwecker et al. (2021) also conducted a research on the forecast performance of ECMWF Integrated Forecasting System ensemble median run in a heavy precipitation event over Switzerland. The uncertainty in atmospheric forecasts mainly arises from the parameters, initial states and model structure. In the past few years, researchers have proposed various techniques to tackle the uncertainties in ensemble forecasts from different aspects (Demeritt et al., 2007; Yu and Meng, 2016; Ali et al., 2018). For these uncertainties, the forecasting skill can be enhanced by post-processing through multiple-modeling, statistical methods and data assimilation (Li et al., 2021b; Whan et al., 2021; Zhao et al., 2022). However, there are few studies on ensemble forecasting post-processing techniques in the field of  $PM_{2.5}$  forecasting.

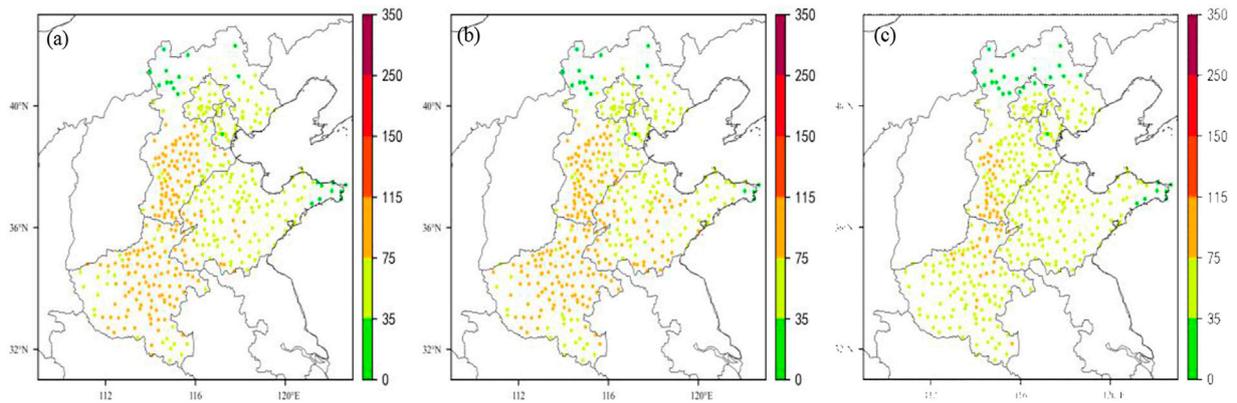


FIGURE 3

Observations of  $PM_{2.5}$  concentrations in BTH and its surrounding areas in (A) 2018, (B) 2019 and (C) 2020.

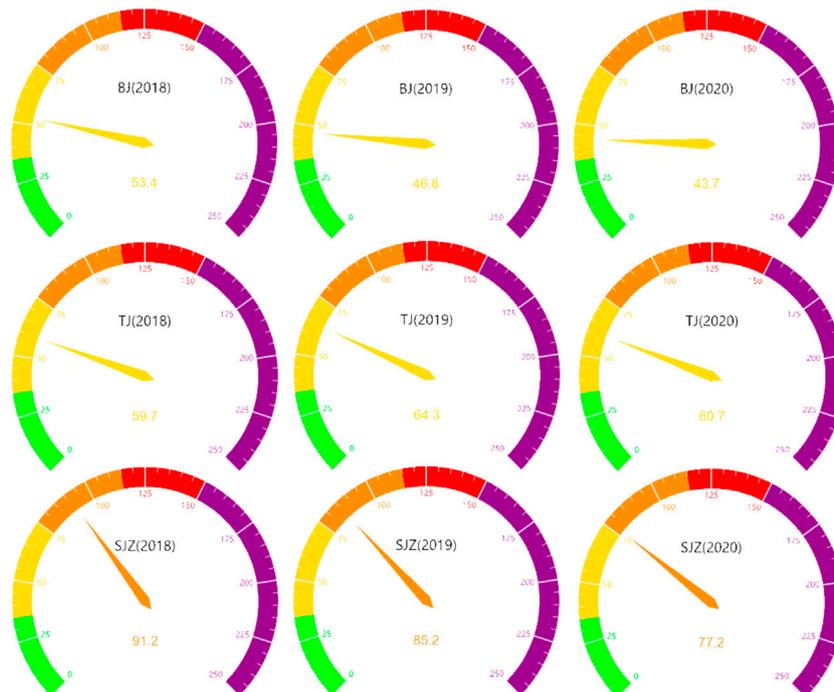


FIGURE 4

Observations of  $PM_{2.5}$  concentrations in Beijing, Tianjin and Shijiazhuang.

In this study, objective identification and forecast method of  $PM_{2.5}$  pollution (OIF- $PM_{2.5}$ ) is established based on the medium- and long-term ensemble forecasts with the leading times of 1–15 days. Besides, this method is evaluated by the forecast precision and its applicability is assessed in a  $PM_{2.5}$  pollution episode in BTH and its surrounding areas. The

remainder of this paper is organized as follows. Section 2 describes the study area, data and method. Section 3 presents the results and discussions, including the characteristics of  $PM_{2.5}$  pollution, the performance of  $PM_{2.5}$  ensemble forecast and the evaluation of OIF- $PM_{2.5}$  method. Finally, Section 4 gives the conclusions.

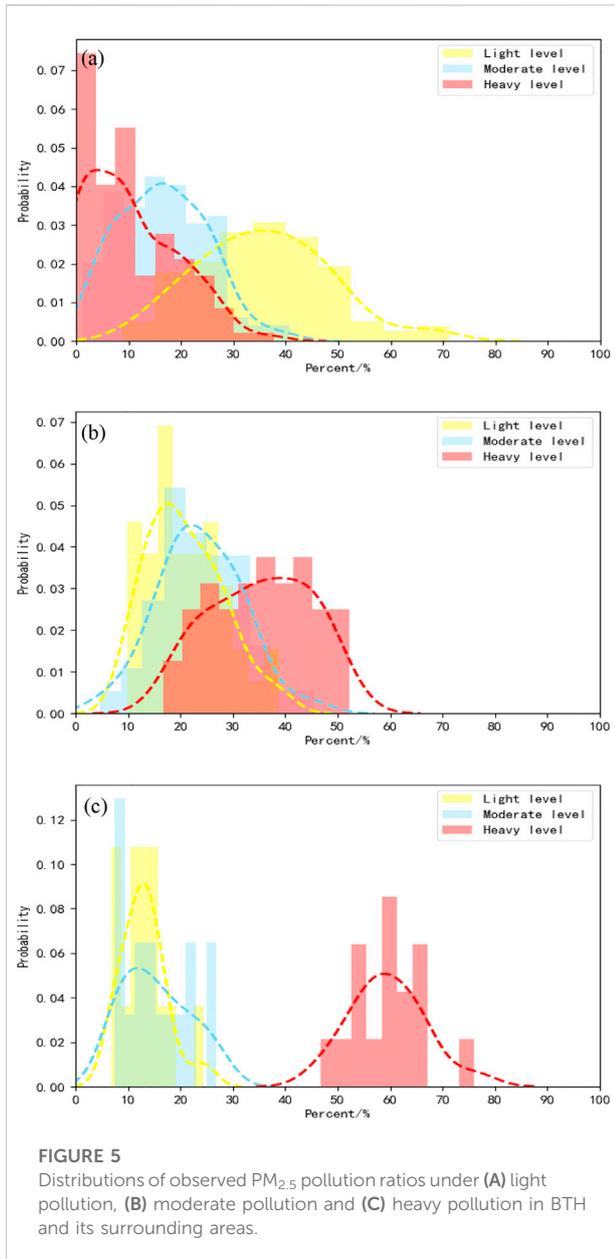
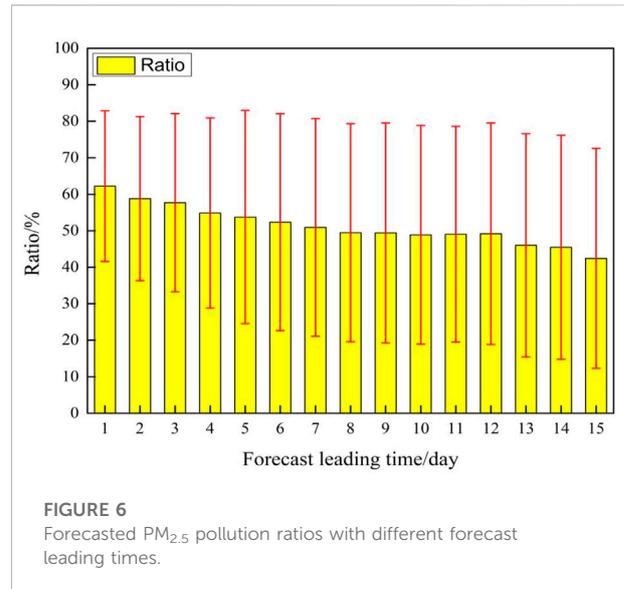


TABLE 2 Average PM<sub>2.5</sub> pollution ratios at different polluted levels in BTH and its surrounding areas.

Polluted level	PM <sub>2.5</sub> pollution ratio (unit: %)		
	Light	Moderate	Heavy
Light	35.8 ± 12.8	16.6 ± 8.4	10.4 ± 8.8
Moderate	20.9 ± 7.2	23.8 ± 8.2	35.3 ± 9.6
Heavy	13.1 ± 4.3	15.4 ± 6.4	59.5 ± 7.2



## 2 Data and methods

### 2.1 Study areas

The BTH and its surrounding areas include two municipalities (Beijing and Tianjin) as well as the provinces of Hebei, Henan and Shandong. This region is home to the majority of energy-intensive and polluting industries (Tong et al., 2019). In addition, the unfavorable geographical conditions with the Yanshan Mountains to its north and the Taihang Mountains to its west are conducive to the accumulation of pollutants (Bei et al., 2020).

### 2.2 PM<sub>2.5</sub> observations

The medium- and long-term ensemble forecasts of PM<sub>2.5</sub> are established based on ground observations from meteorological stations in China. The daily PM<sub>2.5</sub> observations are obtained through the neighboring-point interpolation algorithm conducted on data from 417 meteorological stations set up by the China National Environmental Monitoring Centre. All observed samples are divided into two groups of training dataset and testing dataset. The OIF-PM<sub>2.5</sub> is established by using the training dataset of the autumns and winters (January, February, March, October, November and December) from 2018 to 2020, and the testing dataset contains the data of the autumn and winter of 2021. The locations of meteorological stations in the study area is presented in Figure 1.

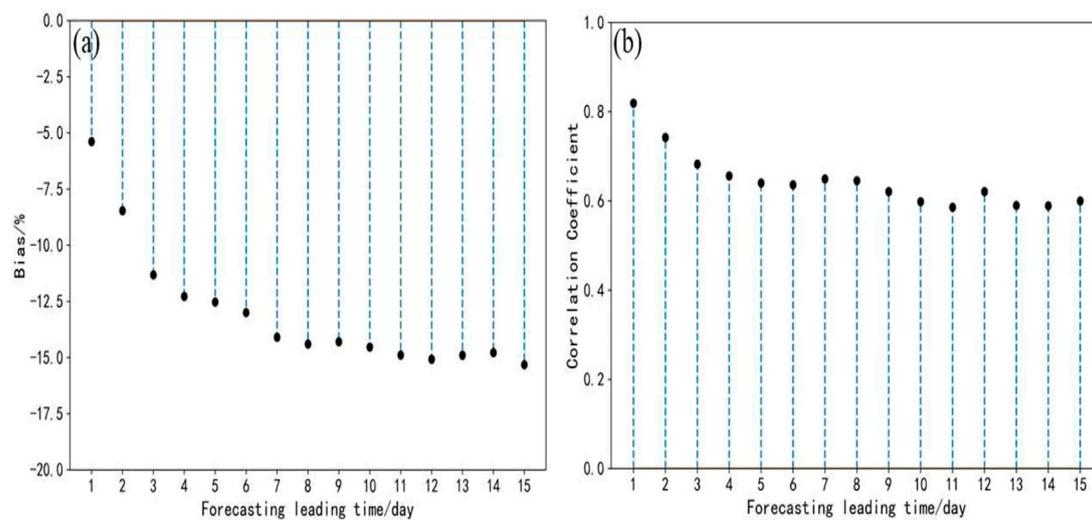


FIGURE 7

(A) Biases (forecast minus observation) of  $PM_{2.5}$  pollution ratios and (B) correlation coefficients between observations and forecasts with different forecast leading times.

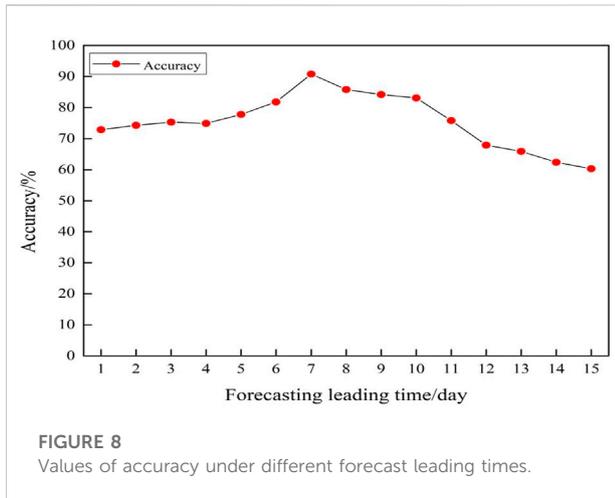
TABLE 3 The first, second and third quartiles of forecasted  $PM_{2.5}$  pollution ratios with different forecast leading times.

Forecast leading time (unit: day)	First quartile (unit: %)	Second quartile (unit: %)	Third quartile (unit: %)
1	47.6	69.4	79.9
2	42.2	66.2	78.6
3	37.5	64.7	77.1
4	35.7	63.8	75.9
5	32.8	60.4	76.2
6	31.5	58.2	75.4
7	28.3	58.3	74.9
8	26.8	57.1	73.6
9	24.1	55.8	75.0
10	21.8	55.1	73.7
11	22.3	53.3	72.0
12	19.2	54.6	72.6
13	19.4	51.2	71.4
14	18.6	49.3	70.1
15	17.8	48.8	69.8

## 2.3 $PM_{2.5}$ ensemble forecast

Based on regional pollution characteristics, topography and climate differences, the  $PM_{2.5}$  ensemble forecast products are made by using the ECMWF ensemble products. These products contain meteorological factors such as horizontal and vertical diffusion capacities and dry and wet deposition conditions.

Furthermore, the forecast equations of daily  $PM_{2.5}$  at each station is set up based on meteorological factors and pollution characteristics in different regions. Finally, the ensemble average forecast, control forecast and 51-members ensemble forecast products are obtained, forming 1–15-day forecast products. In this study, the ensemble average forecast is used to establish the OIF- $PM_{2.5}$ .



## 2.4 Methods

The OIF-PM<sub>2.5</sub> technical flowchart is presented in Figure 2. In this study, the performance of PM<sub>2.5</sub> ensemble forecast in varying forecasting time ranges is considered. The 25th, 50th and 75th percentiles of forecasted PM<sub>2.5</sub> pollution ratios are chosen as the identification thresholds for each forecasting time range corresponding to each polluted day (PM<sub>2.5</sub> ≥ 75 μg m<sup>-3</sup>) in the

training dataset. Here, the forecasted PM<sub>2.5</sub> pollution ratio is defined as the ratio of the number of stations with PM<sub>2.5</sub> ≥ 75 μg m<sup>-3</sup> in the ensemble forecast to the total number of stations in this region in each day.

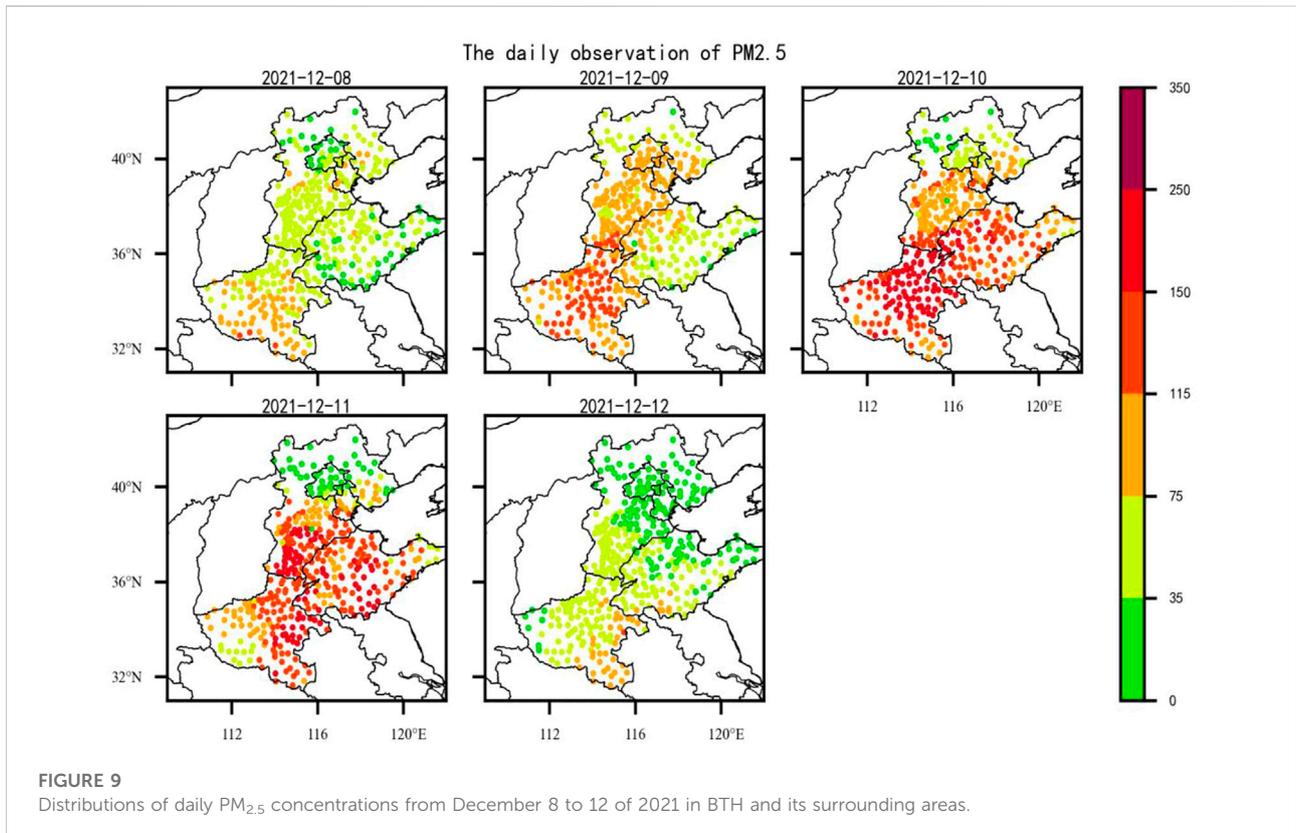
To evaluate the performance and precision of the OIF-PM<sub>2.5</sub> method, the 25th percentile is selected as the criterion, and the accuracy as the statistical index. The principle of the accuracy (AC, unit:%) index is listed in Table 1, where NA, NB, NC, and ND variables represent different categories. NA variable represents the forecasted PM<sub>2.5</sub> pollution ratio exceeds the 25th percentile on the polluted day, and NC variable means the forecasted PM<sub>2.5</sub> pollution ratio exceeds the 25th percentile on the polluted day is lower than the 25th percentile on the polluted day. Consequently, NB and ND variables represent the forecasted PM<sub>2.5</sub> pollution ratio are higher or lower than the 25th percentile on non-polluted day, respectively.

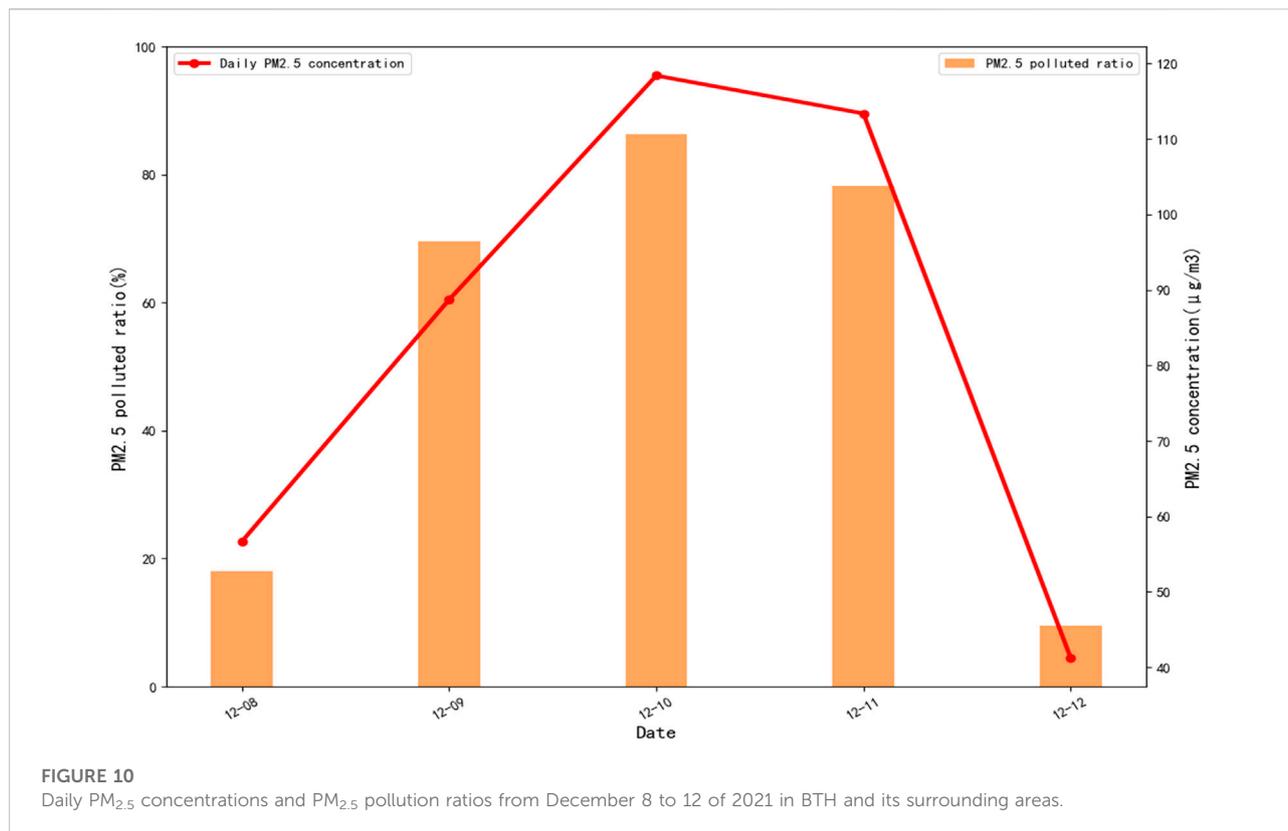
$$AC = \frac{NA + ND}{NA + NB + NC + ND} \times 100\%. \quad (1)$$

## 3 Results

### 3.1 Characteristics of PM<sub>2.5</sub> pollution

The spatial distributions of average PM<sub>2.5</sub> concentrations in BTH and its surrounding areas from 2018 to 2020 are shown in





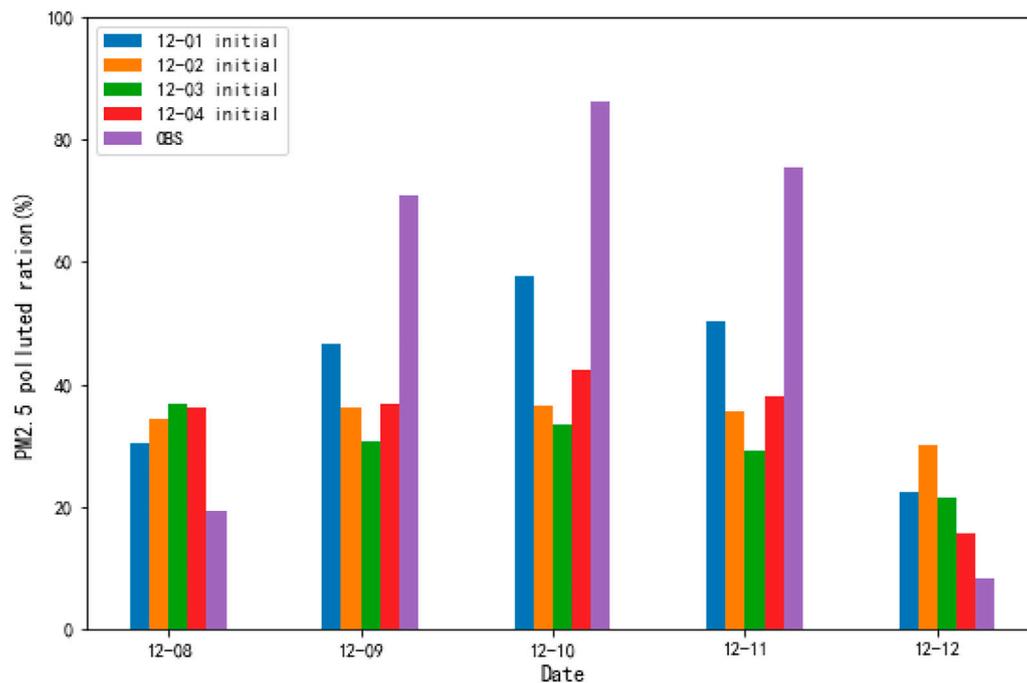
**Figure 3.** It is worth noting that the PM<sub>2.5</sub> concentrations in northern Hebei are below the threshold for the daily average of the China Ambient Air Quality Standard (GB 3095–2012) for PM<sub>2.5</sub> (Grade I: 35 µg m<sup>-3</sup>). However, the PM<sub>2.5</sub> pollution in 2018 and 2019 is heavy in the south and light in the north of the BTH and its surrounding areas, with the main pollution belts concentrated in southern Hebei, central-eastern Henan and western Shandong. In 2020, the PM<sub>2.5</sub> level is low in Beijing, Tianjin, Northern Hebei and Shandong, while slightly polluted in Southern Hebei and Northern Henan. In addition, Beijing, Tianjin and Shijiazhuang are selected for comparison (Figure 4). It can be seen that the PM<sub>2.5</sub> concentrations of Beijing decrease from 53.4 µg m<sup>-3</sup> in 2018 to 43.7 µg m<sup>-3</sup> in 2020, while those in Tianjin fluctuate between 59.7 µg m<sup>-3</sup> and 64.3 µg m<sup>-3</sup> within the same period. In other words, the PM<sub>2.5</sub> concentrations of 2020 are 1.2 times and 1.7 times the PM<sub>2.5</sub> Grade I in Beijing and Tianjin, respectively. What's more, the PM<sub>2.5</sub> concentrations in Shijiazhuang decrease from 91.2 µg m<sup>-3</sup> in 2018 to 77.2 µg m<sup>-3</sup> in 2020 by 15.3%, which is the largest decrease among the three cities. However, the magnitude of PM<sub>2.5</sub> concentrations in 2020 in Shijiazhuang is 2.2 times the PM<sub>2.5</sub> Grade I.

The probability distributions and averages of observed PM<sub>2.5</sub> pollution ratios under different polluted levels in BTH and its

surrounding areas are given in Figure 5, Table 2, respectively. As can be seen, when the average PM<sub>2.5</sub> concentration reaches the light level, the ratio of the number of stations with light pollution is the highest within the range of 34%–40%, and the distribution curve follows the law of normal distribution. However, the average PM<sub>2.5</sub> pollution ratios for moderate pollution and heavy pollution are 16.6% and 10.4%, respectively. What's more, the highest ratio of the number of stations with heavy pollution rapidly increases to 35.3% under the level of moderate pollution, which is 1.7 times that of light pollution and 1.5 times that of moderate pollution. In addition, the number of stations with heavy pollution are more than half of the total in this region. Nevertheless, the heavy PM<sub>2.5</sub> pollution ratio is 4.4 times that of light pollution and 3.9 times that of moderate pollution. In general, the ratio of polluted meteorological stations is increasing as the PM<sub>2.5</sub> pollution aggravates in this region.

### 3.2 Performance of PM<sub>2.5</sub> ensemble forecasts

Some studies (Wang and Huang, 2006; Zhao et al., 2021) have revealed that the performance of forecasting products vary with the forecast leading times. The forecasted PM<sub>2.5</sub> pollution



**FIGURE 11**

PM<sub>2.5</sub> pollution ratios for forecasts under different forecast initial times and observations from December 8 to 12 of 2021 in BTH and its surrounding areas.

ratios with different forecast leading times are analyzed based on the training dataset (Figure 6). For PM<sub>2.5</sub> ensemble forecasts, the ratio of stations being polluted decreases with the increasing forecast leading times, which is consistent with other forecasting products. The averages of forecasted PM<sub>2.5</sub> pollution ratios with the forecast leading times of 1–3 days, 4–7 days and 8–15 days are 59.5%, 52.9% and 47.4%, respectively. That is, the PM<sub>2.5</sub> pollution processes at more than 50% meteorological stations in this region can be forecasted by 8 days in advance.

As illustrated in Figure 7A, the bias (forecast minus observation) of PM<sub>2.5</sub> pollution ratio increases with the increasing forecast leading time, and the biases are all negative, that is, the forecasted ratios are lower than the observed ones. The biases of PM<sub>2.5</sub> pollution ratio with the forecast leading times of 1–6 days are less than –13%; however, the bias remains between –14.1% and –15.4% when the forecast leading time is more than 7 days. Besides, the correlation coefficients of the ratios between the observations and forecasts are more than 0.68 with the forecast leading times being 1–3 days, while above 0.60 for other leading times (Figure 7B). In general, although the forecasted ratios are lower than the observed ones, the correlation between them remains high values, indicating a good performance of the PM<sub>2.5</sub> ensemble forecasts.

The forecasted PM<sub>2.5</sub> pollution ratios of the autumns and winters from 2018 to 2020 are calculated, and the corresponding 25th, 50th and 75th percentiles are given in Table 3. The 25th percentiles of the forecasted PM<sub>2.5</sub> pollution ratios are below 50% for all forecast leading times, which are below 20% for the leading times of 12–15 days. Besides, the 25th percentiles exceed 30% with the forecast leading times of 1–6 days, with the ratios being 47.6% and 42.2% for the leading times of 1 day and 2 days, respectively. The 50th percentiles are below 70% for all forecast leading times, which are over 60% with the forecast leading times of 1–5 days. Besides, the differences of the 50th percentiles among different forecast leading times are smaller than those of the 25th percentiles. The 75th percentiles of the forecasted PM<sub>2.5</sub> pollution ratios are above 70% for most of the forecast leading times, which exceed 75% with the leading times of 1–6 days. In addition, the differences of the 75th percentiles among different forecast leading times are further reduced when compared with those of the 50 percentiles, being only 10.1% between the 1-day and 15-day forecast leading times. In summary, the forecasts of PM<sub>2.5</sub> pollution ratio with different leading times are indicative of the occurrence of regional PM<sub>2.5</sub> pollution events to some extent.

### 3.3 Evaluation of the OIF-PM<sub>2.5</sub> method and its application

#### 3.3.1 Performance of the OIF-PM<sub>2.5</sub> method

In this study, the accuracy for forecasts in the autumn and winter of 2021 is examined. As illustrated in Figure 8, the accuracy of the OIF-PM<sub>2.5</sub> method show a trend of first increase and then decrease, being over 60% for different forecast leading times. The highest accuracy of 90.8% is achieved for the forecasts with the leading time of 7 days. In addition, the average accuracy for forecast leading times of 1–3 days, 4–7 days and 8–15 days are 74.1%, 81.3% and 72.9%, respectively. It is well documented that the ECMWF has better predictability for ensemble forecasts with the leading times of 4–7 days (Huang and Niu, 2017). The evolution of accuracy with different forecast leading times is consistent with that reported in Tao et al. (2017). It indicates that the OIF-PM<sub>2.5</sub> method has a high reliability in forecasts with the forecast leading times of 1–15 days.

#### 3.3.2 Application in a PM<sub>2.5</sub> pollution process

A regional PM<sub>2.5</sub> pollution event occurred in BTH and its surrounding areas from December 8 to 12, 2021 (Figures 9, 10). Most of the region was dominated by PM<sub>2.5</sub> pollution of light level on December 9, with the daily average PM<sub>2.5</sub> concentration being 88.7  $\mu\text{g m}^{-3}$  and the pollution ratio being 69.5%. In addition, the atmospheric dispersion conditions worsened in this region during December 10–11. The areas with high PM<sub>2.5</sub> concentrations were mainly located in southern Hebei, central and eastern Henan, and central and Western Shandong, with the regional averaged PM<sub>2.5</sub> concentrations reaching 118.3  $\mu\text{g m}^{-3}$  on December 10 and 113.4  $\mu\text{g m}^{-3}$  on December 11. In addition, the PM<sub>2.5</sub> pollution ratio increased to 86.3% on December 10 and 78.2% on December 11, indicating the significant expansion and enhancement of the PM<sub>2.5</sub> pollution. Eventually, the PM<sub>2.5</sub> concentrations decreased gradually from North to South due to the cold air on December 12, and the air quality reached the excellent and good level in most of the region.

Using different forecast initial times, the OIF-PM<sub>2.5</sub> method is applied to this pollution episode, and the forecast results are shown in Figure 11. It can be seen that the forecasted PM<sub>2.5</sub> pollution ratios for different initial times are consistent with the observations, which is of indicative significance for the evolution of pollution process. For the most polluted period of the pollution process, the pollution ratio of stations on December 10 is 57.7% with the forecast initial time being December 1, which even exceeds the 50th percentile (55.8%). In addition, the values of accuracy under different forecast leading times are also calculated. The results show that the average accuracy reaches 90% (100%) under the leading times of 4–11 days (6–8 days), indicating that the forecast stability of the OIF-PM<sub>2.5</sub> method is more stable and is of reference value for forecasts.

## 4 Conclusion and discussion

Based on the medium- and long-term ensemble forecasts of PM<sub>2.5</sub> concentrations, the OIF-PM<sub>2.5</sub> method is developed in this study. Specifically, different percentiles of forecasted PM<sub>2.5</sub> pollution ratios for each forecast leading time from 2018 to 2020 are determined and analyzed. The OIF-PM<sub>2.5</sub> method is further evaluated and applied in a PM<sub>2.5</sub> pollution episode in 2021. The main conclusions are as follows.

The observed PM<sub>2.5</sub> pollution ratio increases with the aggravation of PM<sub>2.5</sub> pollution in this region. For example, the heavy pollution ratio is 4.4 times the light pollution ratio and 3.9 times the moderate pollution ratio. Besides, the correlation coefficients between the observed ratios and forecasted ratios are above 0.60 for all forecast leading times in ensemble forecast products. Furthermore, the statistical results show that the average accuracy for forecasts with the leading times of 1–3 days, 4–7 days and 8–15 days in are 74.1%, 81.3% and 72.9%, respectively, indicating that the OIF-PM<sub>2.5</sub> method has a high reliability in forecasts with the leading times of 1–15 days. The OIF-PM<sub>2.5</sub> method is further applied in a severe PM<sub>2.5</sub> pollution episode in the December of 2021. It is revealed that the average accuracy for the forecasts with the leading times of 6–8 days reaches as high as 100%, showing a certain reference value.

The findings of this paper help to understand the PM<sub>2.5</sub> concentration forecasts with the forecast leading times of 1–15 days, which can help to minimize the adverse effects of high PM<sub>2.5</sub> pollution for society and public health. Moreover, it will help decision makers to formulate pollutant control strategies and take precautions.

## Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

## Author contributions

Conceptualization, XR; Methodology, BOZ; Data curation and formal analysis and writing—original draft preparation, CL; writing—review and editing, CL and QC; Visualization, BOZ; Funding acquisition: BHZ and QC. All authors have read and agreed to the published version of the manuscript.

## Funding

This study was supported by the National Key R & D Program Pilot Projects of China (2019YFC0214602), National Key R & D

Program Pilot Projects of China (2021YFC3000900) and National Meteorological Centre forecaster funding (Y202127).

## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## References

- Ali, M., Deo, R. C., Down, N. J., and Maraseni, T. (2018). An ensemble-ANFIS based uncertainty assessment model for forecasting multi-scalar standardized precipitation index. *Atmos. Res.* 207 (15), 155–180. doi:10.1016/j.atmosres.2018.02.024
- Bei, N. F., Li, X. P., Tie, X. X., Zhao, L. N., Wu, J. R., Li, X., et al. (2020). Impact of synoptic patterns and meteorological elements on the wintertime haze in the Beijing-Tianjin-Hebei region, China from 2013 to 2017. *Sci. Total Environ.* 772 (20), 135210. doi:10.1016/j.scitotenv.2019.135210
- Bera, B., Bhattacharjee, S., Sengupta, N., and Saha, S. (2021). PM<sub>2.5</sub> concentration prediction during COVID-19 lockdown over Kolkata metropolitan city, India using MLR and ANN models. *Environ. Challenges* 4, 100155. doi:10.1016/j.envc.2021.100155
- Cai, S. Y., Wang, Y. J., Zhao, B., Wang, S. X., Chang, X., and Hao, J. M. (2017). The impact of the “air pollution prevention and control action plan” on PM<sub>2.5</sub> concentrations in jing-jin-ji region during 2012–2020. *Sci. Total Environ.* 580 (15), 197–209. doi:10.1016/j.scitotenv.2016.11.188
- Chen, J. D., Gao, M., Li, D., Li, L., Song, M. L., and Xie, Q. J. (2021). Changes in PM<sub>2.5</sub> emissions in China: An extended chain and nested refined laspyres index decomposition analysis. *J. Clean. Prod.* 294 (20), 126248. doi:10.1016/j.jclepro.2021.126248
- Cheng, M. T., Tang, G. Q., Lv, B., Li, X. R., Wu, X. R., Wang, Y. M., et al. (2021). Source apportionment of PM<sub>2.5</sub> and visibility in Jinan, China. *J. Environ. Sci.* 102, 207–215. doi:10.1016/j.jes.2020.09.012
- Cong, J., Wu, Z. L., Ma, Y. X., Xu, S., Wang, Y., Sun, M. N., et al. (2021). Improving numerical forecast of the rainstorms induced by Mongolia cold vortex in North China with the frequency matching method. *Atmos. Res.* 262, 105791. doi:10.1016/j.atmosres.2021.105791
- Demeritt, D., Cloke, H., Pappenberger, F., Thielen, J., Bartholmes, J., and Ramos, M. H. (2007). Ensemble predictions and perceptions of risk, uncertainty, and error in flood forecasting. *Environ. Hazards* 7 (2), 115–127. doi:10.1016/j.envhaz.2007.05.001
- Dimitriou, K., and Kassomenos, P. (2014). A study on the reconstitution of daily PM<sub>10</sub> and PM<sub>2.5</sub> levels in Paris with a multivariate linear regression model. *Atmos. Environ.* 98, 648–654. doi:10.1016/j.atmosenv.2014.09.047
- Feng, L. W., Li, Y. Y., Wang, Y. M., and Du, Q. Y. (2020). Estimating hourly and continuous ground-level PM<sub>2.5</sub> concentrations using an ensemble learning algorithm: The ST-stacking model. *Atmos. Environ.* 223, 117242. doi:10.1016/j.atmosenv.2019.117242
- Gao, X., and Li, W. D. (2021). A graph-based LSTM model for PM<sub>2.5</sub> forecasting. *Atmos. Pollut. Res.* 12 (9), 101150. doi:10.1016/j.apr.2021.101150
- Garner, G. G., and Thompson, A. M. (2012). The value of air quality forecasting in the mid-atlantic region. *Weather, Clim. Soc.* 4 (1), 69–79. doi:10.1175/wcas-d-10-05010.1
- Huang, G. Y., Li, X. Y., Zhang, B., and Ren, J. D. (2021). PM<sub>2.5</sub> concentration forecasting at surface monitoring sites using GRU neural network based on empirical mode decomposition. *Sci. Total Environ.* 768 (10), 144516. doi:10.1016/j.scitotenv.2020.144516
- Huang, W., and Niu, R. Y. (2017). The medium-term multi-model integration forecast experimentation for heavy rain based on support vector machine. *Meteorol. Mon.* 43 (9), 1110–1116. (in Chinese).
- Jeong, J. L., Park, R. J. L., Yeh, S. W., and Roh, J. W. (2021). Statistical predictability of wintertime PM<sub>2.5</sub> concentrations over East Asia using simple linear regression. *Sci. Total Environ.* 776, 146059. doi:10.1016/j.scitotenv.2021.146059
- Jiang, S., Yu, Z. G., Anh, V. V., and Zhou, Y. (2021). Long- and short-term time series forecasting of air quality by a multi-scale framework. *Environ. Pollut.* 271, 116381. doi:10.1016/j.envpol.2020.116381
- Li, F., Yan, J. J., Wei, Y. C., Zeng, J. J., Wang, X. Y., Chen, X. Y., et al. (2021a). PM<sub>2.5</sub>-bound heavy metals from the major cities in China: Spatiotemporal distribution, fuzzy exposure assessment and health risk management. *J. Clean. Prod.* 286 (1), 124967. doi:10.1016/j.jclepro.2020.124967
- Li, W. T., Pan, B. X., Xia, J. J., and Duan, Q. Y. (2021b). Convolutional neural network-based statistical post-processing of ensemble precipitation forecasts. *J. Hydrology* 605, 127301. doi:10.1016/j.jhydrol.2021.127301
- Li, X., Gao, Z. Q., Li, Y. B., Gao, C. Y., Ren, J. Z., and Zhang, X. Y. (2019). Meteorological conditions for severe foggy haze episodes over north China in 2016–2017 winter. *Atmos. Environ.* 199 (15), 284–298. doi:10.1016/j.atmosenv.2018.11.042
- Liu, C., Hua, C., Zhang, H. D., Zhang, B. H., Wang, G., Zhu, W. H., et al. (2019). A severe fog-haze episode in Beijing-Tianjin-Hebei region: Characteristics, sources and impacts of boundary layer structure. *Atmos. Pollut. Res.* 10 (4), 1190–1202. doi:10.1016/j.apr.2019.02.002
- Liu, H., and Chen, C. (2019). Prediction of outdoor PM<sub>2.5</sub> concentrations based on a three-stage hybrid neural network model. *Atmos. Pollut. Res.* 11 (3), 469–481. doi:10.1016/j.apr.2019.11.019
- Liu, H., Long, Z. H., Duan, Z., and Shi, H. P. (2020). A new model using multiple feature clustering and neural networks for forecasting hourly PM<sub>2.5</sub> concentrations, and its applications in China. *Engineering* 6 (8), 944–956. doi:10.1016/j.eng.2020.05.009
- Liu, T., Lau, A. K. H., Sandbrink, K., and Fung, J. C. H. (2018). Time series forecasting of air quality based on regional numerical modeling in Hong Kong. *J. Geophys. Res.* 123, 4175–4196. doi:10.1002/2017jd028052
- Liu, Z. J., Szpiro, A. A., Workalemahu, T., Young, M. T., Kaufman, J. D., and Enquobahrie, D. A. (2022). Associations of perinatal exposure to PM<sub>2.5</sub> with gestational weight gain and offspring birth weight. *Environ. Res.* 204, 112087. doi:10.1016/j.envres.2021.112087
- Liu, Z. Y., Qi, Z. L., Ni, X. F., Dong, M. T., Ma, M. Y., Xue, W. B., et al. (2021). How to apply O3 and PM<sub>2.5</sub> collaborative control to practical management in China: A study based on meta-analysis and machine learning. *Sci. Total Environ.* 772, 145392. doi:10.1016/j.scitotenv.2021.145392
- Menares, C., Perez, P., Parraguez, S., and Fleming, Z. L. (2021). Forecasting PM<sub>2.5</sub> levels in Santiago de Chile using deep learning neural networks. *Urban Clim.* 38, 100906. doi:10.1016/j.uclim.2021.100906
- Nishimura, M., and Yamaguchi, M. (2015). Selective ensemble mean technique for tropical cyclone track forecasts using multi-model ensembles. *Trop. Cyclone Res. Rev.* 4 (2), 71–78.
- Pak, U., Ma, J., Ryu, U., Ryom, K., Juhyok, U., Pak, K., et al. (2020). Deep learning-based PM<sub>2.5</sub> prediction considering the spatiotemporal correlations: A case study of Beijing, China. *Sci. Total Environ.* 699 (10), 133561. doi:10.1016/j.scitotenv.2019.07.367
- Sagar, S. K., Rajeevan, M., Rao, S. V. B., and Mitra, A. K. (2017). Prediction skill of rainstorm events over India in the TIGGE weather prediction models. *Atmos. Res.* 198 (1), 194–204. doi:10.1016/j.atmosres.2017.08.017
- Samal, K. K. R., Panda, A. K., Babu, K. S., and Das, S. K. (2021). Multi-output TCN autoencoder for long-term pollution forecasting for multiple sites. *Urban Clim.* 39, 100943. doi:10.1016/j.uclim.2021.100943
- Sawani, R., Agnihotri, R., and Sharma, C. (2021). Chemical and isotopic characteristics of PM<sub>2.5</sub> over New Delhi from September 2014 to May 2015: Evidences for synergy between air-pollution and meteorological changes. *Sci. Total Environ.* 763, 142966. doi:10.1016/j.scitotenv.2020.142966
- Schauwecker, S., Schwarb, M., Rohrer, M., and Stoffel, M. (2021). Heavy precipitation forecasts over Switzerland – an evaluation of bias-corrected ECMWF predictions. *Weather Clim. Extrem.* 34, 100372. doi:10.1016/j.wace.2021.100372

## Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

- Schumacher, R. S. (2011). Ensemble-based analysis of factors leading to the development of a multiday warm-season heavy rain event. *Mon. Weather Rev.* 139 (9), 3016–3035. doi:10.1175/mwr-d-10-05022.1
- Tao, Y. M., Duan, Q. Y., Ye, A. Z., Gong, W., Di, Z. H., Xiao, M., et al. (2014). An evaluation of post-processed TIGGE multimodel ensemble precipitation forecast in the Huai river basin. *J. Hydrology* 519, 2890–2905. doi:10.1016/j.jhydrol.2014.04.040
- Tao, Y. W., Dai, K., and Dong, Q. (2017). Extreme analysis and ensemble prediction verification on cold wave process in January 2016. *Meteorol. Mon.* 43 (10), 1176–1185. (in Chinese). doi:10.7519/j.issn.1000-0526.2017.10.002
- Tong, D., Geng, G. N., Jiang, K. J., Cheng, J., Zheng, Y. X., Hong, C. P., et al. (2019). Energy and emission pathways towards PM<sub>2.5</sub> air quality attainment in the Beijing-Tianjin-Hebei region by 2030. *Sci. Total Environ.* 692, 361–370. doi:10.1016/j.scitotenv.2019.07.218
- Verkade, J. S., Brown, J. D., Reggiani, P., and Weerts, A. H. (2013). Post-processing ECMWF precipitation and temperature ensemble reforecasts for operational hydrologic forecasting at various spatial scales. *J. Hydrology* 501 (25), 73–91. doi:10.1016/j.jhydrol.2013.07.039
- Wang, P. F., and Huang, G. (2006). A study on the dependency of maximum prediction time on computation precision and time step size in numerical model. *Clim. Environ. Res.* 11 (3), 395–403. (in Chinese). doi:10.3878/j.issn.1006-9585.2006.03.17
- Wang, P., Zhang, H., Qin, Z. D., and Zhang, G. S. (2017). A novel hybrid-Garch model based on ARIMA and SVM for PM<sub>2.5</sub> concentrations forecasting. *Atmos. Pollut. Res.* 8 (5), 850–860. doi:10.1016/j.apr.2017.01.003
- Whan, K., Zscheischler, J., Jordan, A. I., and Ziegel, J. F. (2021). Novel multivariate quantile mapping methods for ensemble post-processing of medium-range forecasts. *Weather Clim. Extrem.* 32, 100310. doi:10.1016/j.wace.2021.100310
- Wu, H. P., Liu, H., and Duan, Z. (2020). PM<sub>2.5</sub> concentrations forecasting using a new multi-objective feature selection and ensemble framework. *Atmos. Pollut. Res.* 11 (7), 1187–1198. doi:10.1016/j.apr.2020.04.013
- Yang, J., Yan, R., Nong, M. Y., Liao, J. Q., Li, F. P., and Sun, W. (2021). PM<sub>2.5</sub> concentrations forecasting in Beijing through deep learning with different inputs, model structures and forecast time. *Atmos. Pollut. Res.* 12 (9), 101168. doi:10.1016/j.apr.2021.101168
- Yang, T. H., Yang, S. C., Ho, J. Y., Lin, G. F., Hwang, G. D., and Lee, C. S. (2015). Flash flood warnings using the ensemble precipitation forecasting technique: A case study on forecasting floods in taiwan caused by typhoons. *J. Hydrology* 520, 367–378. doi:10.1016/j.jhydrol.2014.11.028
- Yu, H. Z., and Meng, Z. Y. (2016). Key synoptic-scale features influencing the high-impact heavy rainfall in Beijing, China, on 21 July 2012. *Tellus A Dyn. Meteorology Oceanogr.* 68, 31045. doi:10.3402/tellusa.v68.31045
- Yuval, Broday, D. M., and Alpert, P. (2012). Exploring the applicability of future air quality predictions based on synoptic system forecasts. *Environ. Pollut.* 166, 65–74. doi:10.1016/j.envpol.2012.03.010
- Zhai, B. X., and Chen, J. G. (2018). Development of a stacked ensemble model for forecasting and analyzing daily average PM<sub>2.5</sub> concentrations in Beijing, China. *Sci. Total Environ.* 635, 644–658. doi:10.1016/j.scitotenv.2018.04.040
- Zhang, H., Xie, B., Zhao, S. Y., and Chen, Q. (2014). PM<sub>2.5</sub> and tropospheric O<sub>3</sub> in China and an analysis of the impact of pollutant emission control. *Adv. Clim. Change Res.* 5 (3), 136–141. doi:10.1016/j.accre.2014.11.005
- Zhang, Q. Q., Ma, Q., Zhao, B., Liu, X. Y., Wang, X. Y., Jia, B. X., et al. (2018). Winter haze over north China plain from 2009 to 2016: Influence of emission and meteorology. *Environ. Pollut.* 242, 1308–1318. Part B. doi:10.1016/j.envpol.2018.08.019
- Zhang, W. H., Hai, S. F., Zhao, Y. H., Sheng, L. F., Zhou, Y., Wang, W. C., et al. (2021). Numerical modeling of regional transport of PM<sub>2.5</sub> during a severe pollution event in the Beijing-Tianjin-Hebei region in November 2015. *Atmos. Environ.* 254, 118393. doi:10.1016/j.atmosenv.2021.118393
- Zhao, G. J., He, N., Hao, C., Li, J., and Li, S. (2021). Evaluation of models and objective methods for temperature in Beijing area. *Meteorological Sci. Technol.* 49 (6), 870–877. (in Chinese). doi:10.19517/j.1671-6345.20200409
- Zhao, J. F., Xu, J. W., Xie, X. M., and Lu, H. Q. (2016). Drought monitoring based on TIGGE and distributed hydrological model in Huaihe River Basin, China. *Sci. Total Environ.* 553 (15), 358–365. doi:10.1016/j.scitotenv.2016.02.115
- Zhao, P. C., Wang, Q. J., Wu, W. Y., and Yang, Q. C. (2022). Extending a joint probability modelling approach for post-processing ensemble precipitation forecasts from numerical weather prediction models. *J. Hydrology* 605, 127285. doi:10.1016/j.jhydrol.2021.127285
- Zhou, Y. L., Chang, F. J., Chang, L. C., Kao, I. F., Wang, Y. S., and Kang, C. C. (2019). Multi-output support vector machine for regional multi-step-ahead PM<sub>2.5</sub> forecasting. *Sci. Total Environ.* 651 (1), 230–240. doi:10.1016/j.scitotenv.2018.09.111
- Zhou, Y. L., Chang, F. J., Chen, H., and Li, H. (2020). Exploring copula-based bayesian model averaging with multiple ANNs for PM<sub>2.5</sub> ensemble forecasts. *J. Clean. Prod.* 263 (1), 121528. doi:10.1016/j.jclepro.2020.121528