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Impact analysis of meteorological variables on $PM_{2.5}$ pollution in the most polluted cities in China

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A R T I C L E I N F O

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A B S T R A C T

With the continuous promotion of urbanization in China, air pollution problems have become increasingly prominent in recent years. Various factors, such as emissions, meteorology, and physical and chemical reactions, jointly affect the severity of $PM_{2.5}$ pollution to a large extent. This study selected five meteorological variables (planetary boundary layer height (PBLH), wind speed (WS), temperature(T), water vapor mixing ratio(Q), and precipitation (PCP)) for perturbation, and 21 different scenarios were set up. In this study, the effects of changes in a single meteorological variable on the pollutants produced in the area were represented by subtracting the baseline scenario (i.e., without perturbation of meteorological variables) simulated in January 2017 separately from each post-disturbance scenario. The results showed that Handan (HD) has the highest annual mean $PM_{2.5}$ concentration of 85.75 $\mu g/m^3$ in 2017, while all cities in study area exceeded the secondary concentration limit of urban atmospheric particulate matter. The correlation coefficient (R) between the simulation values of models and the actual monitoring values ranges from 0.41 to 0.74, indicating good model performance and acceptable simulation errors. PBLH ($\pm$10%-$\pm$20%), WS($\pm$10%-$\pm$20%), and PCP($\pm$10%-$\pm$20%) all showed a single adverse effect among the five meteorological variables, meaning that a reduction in these three factors led to an increase in $PM_{2.5}$ concentrations. However, T ($\pm$1 K-$\pm$1.5 K) and Q ($\pm$10%-$\pm$20%) could indicate a positive impact under certain conditions. From the sensitivity calculations of single meteorological variables, it is clear that WS, PBLH, and PCP show a highly linear trend in all cities at the 0.01 level of significance. The hypothesis that T changes linearly in 10 cities in the study area is valid, while for Q, the hypothesis that Q changes linearly only occurs in Shijiazhuang and Baoding. When different meteorological variables are disturbed, there are significant spatial differences in the main affected areas of $PM_{2.5}$ concentrations. By discussing the impact of meteorological variable disturbance on air quality in critically polluted cities in China, this study identified the meteorological variables that can substantially affect $PM_{2.5}$ concentration. The more complex T and Q should be considered when formulating relevant emission measures.

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1. Introduction

A drastic air pollution problem has developed in China in recent decades due to rapid economic growth and urbanization, particularly particulate matter pollution [1,2]. As air pollution worsens, it poses a significant threat not only to human health [3–6] but also to industrial production, socioeconomics, and the sustainable development of society [7–10]. The Chinese government has enacted a series of control policies to alleviate the air pollution problem. For example, China officially launched the "Air Pollution Prevention and Control Action Plan" in 2013. Due to the strict implementation of relevant policies, the concentration of particulate matter in many areas of China has decreased significantly [11]. In most areas of China, although $PM_{2.5}$ concentrations have shown a decreasing trend, exceedance rates remain high [12,13].

The Ministry of Ecology and Environment of China stated in the 2017 China Ecological Environment Status Bulletin that among the 338 prefecture-level cities and above 70.7% of the cities exceeded ambient air quality in the country's standards [14]. Among them, $PM_{2.5}$ was the primary pollutant on 74.2% of polluted days in 2017 and PM_{10} was the primary pollutant on 20.4% of polluted days. The severity of $PM_{2.5}$ pollution is influenced mainly by a combination of emissions, meteorology, and physical and chemical reactions [15–20]. Within a particular period of time, if atmospheric pollutants particularly secondary aerosols are emitted and produced at roughly the same rate, then meteorological conditions will determine the level of air pollution [21,22]. Meteorological conditions play a critical role in the emission, transport, chemical transformation, and removal of atmospheric pollutants [23–26]. Gui et al. found that the change in variation due to changes in meteorological variables accounts for 48% of the change in $PM_{2.5}$ concentration in East China from 1998 to 2016 [19]. Liu et al. found a significant increase in the monthly mean $PM_{2.5}$ concentration in the Beijing-Tianjin-Hebei region in the winter of 2015 because of the influence of adverse meteorological conditions in the area [27].

Meteorological variables such as temperature, precipitation, temperature inversion, wind speed, relative humidity, and atmospheric pressure significantly affect $PM_{2.5}$ dispersion and accumulation [28]. Relevant studies have shown that $PM_{2.5}$ is affected differently by different meteorological variables. Li et al. analyzed the relationship between particulate matter and changes in meteorological parameters in 366 cities in China from 2015 to 2017, the results showed that there was a negative correlation between particulate matter concentrations and precipitation, relative humidity, air temperature, and wind speed, but a positive correlation with atmospheric pressure [29]. This means that studying the effects of changes in meteorological variables helps to analyze the changes in $PM_{2.5}$ concentrations better. Ma et al. also studied the influence paths of various meteorological variables on $PM_{2.5}$ and O_3, and found that temperature changes $PM_{2.5}$ concentration by affecting vertical diffusivity and relative humidity, the higher temperature leads to the increase of $PM_{2.5}$ [30]. The complex influence of meteorological variables on $PM_{2.5}$ is worth paying attention to. But previous studies have focused more on metropolises in northern China, which may have left out some important information. Based on previous research, the study area will be accurate to 14 northern China's most serious $PM_{2.5}$ pollution in this study, to explore the impact of meteorological interference on air quality in major polluted cities in China.

Therefore, this study selected 14 typical polluted cities located in North China as the study area and simulated them using the WRF-CMAQ model to explore the influence of changes in five meteorological variables (planetary boundary layer height, wind speed, temperature, water vapor mixing ratio, and precipitation) on $PM_{2.5}$ in polluted cities. The meteorological fields was predicted by the WRF model and the sensitivity of $PM_{2.5}$ associated with changes in meteorological variables was quantified using the CMAQ model. The changes in these meteorological variables due to climate change could potentially alter PM2.5 concentrations significantly, PM2.5 sensitivities to meteorological variables have spatial variations, and it should consider these effects when developing emission control strategies. There is consensus in atmospheric literature that emission reduction alone is not a viable solution and that a mix of policies is necessary, but it is imperative for policymakers to understand how the changes in meteorological conditions affect the effectiveness of emission control plans in reaching the designed air quality objectives.

2. Materials and methods

2.1. Study area and data source

According to data published in the China Ecological Environment Status Bulletin, 14 cities were in the bottom 20 of urban ambient air quality rankings for all three years during the 2018–2020 period. Furthermore, the number of cities with relatively poor ambient air quality announced in 2017 was only ten, and some cities were not counted among them. This research focuses on, Anyang (AY), Shijiazhuang (SJZ), Taiyuan (TY), Handan (HD), Linfen (LF), Xingtai (XT), Jiaozuo (JZ), Xinxiang (XX), Baoding (BD), Jincheng (JC), Yangquan (YQ), Hebi (HB), Jinzhong (JZH), and Changzhi (CZ) cities but some cities such as Tangshan, Zibo, Jinan, and Xianyang were excluded from this study due to their geographic distributions. These cities are the regions with the most challenging air pollution situation in China, as identified after the preliminary understanding of the air pollution situation in China during the 13th Five-Year Plan.

In this study, the hourly $PM_{2.5}$ concentration data of 80 air quality monitoring stations in 14 cities in January 2017 were collected from https://www.aqistudy.cn/historydata/. The monitoring method of $PM_{2.5}$ in the study area is automatic monitoring. Since all the stations used in this study are state-controlled air monitoring stations, the specific classification is based on the "Environmental air quality monitoring code" issued by the Ministry of Ecology and Environment of the People's Republic of China (https://www.mee.gov.cn/), it is up to the city governments to determine the specific locations, and the selected monitoring stations can objectively reflect the impact of environmental air pollution on the human living environment, based on the air quality status and its changing trend, the characteristics of industry and energy structure, population distribution, topography and meteorological conditions, the representativeness of monitoring data is fully considered. The city $PM_{2.5}$ concentration is represented by the mean of its air quality monitoring stations.The China Meteorological Data Network provided meteorological monitoring data (http://data.cma.cn). According to the Ambient Air Quality Standard (GB 3095-2012), data quality was ensured by screening all monitoring data for abnormal values. Both $PM_{2.5}$ concentration data and meteorological data were used for January 2017. Fig. 1 shows the locations of the air quality monitoring stations and meteorological monitoring stations.

2.2. The model configuration

This study used the Community Multiscale Air Quality (CMAQ) model version 5.3.2 and the Weather Research and Forecasting (WRF) version 3.9.1. Based on the National Centers for Environmental Prediction FNL analysis dataset, we have determined the meteorological initial and boundary conditions (http://rda.ucar.edu/datasets/ds083.2/) with a temporal resolution of 6 h and a horizontal resolution of $1^{\circ} \times 1^{\circ}$. The parameterization scheme used by WRF is shown in Table 1.

We set up two nested domains, as shown in Fig. 2. Among them, Region 2 mainly includes some cities in North China. The grid resolutions for each simulation domain are 18 and 6 km, respectively. The CMAQ model was configured using the AERO6 aerosol module and the CB06 gas-phase chemistry mechanism. Anthropogenic emissions were obtained using the 2017 China Multi-resolution Emissions Inventory (MEIC) inventory developed by Tsinghua University [31], with a spatial resolution of $0.25^{\circ} \times 0.25^{\circ}$, including emission information for five sectors: industry, agriculture, residental, transportation, and power. It has been widely used in China [31–33]. In this study, January 2017 was chosen as the simulation time, in agreement with the studies of Itahashi et al. [34]and Sun et al. [35], both of which took January to represent the winter season.The model was started five days in advance to reduce the effect of initial and boundary conditions.

2.3. Simulation scenarios

This study chose five meteorological variables for perturbation: planetary boundary layer height, wind speed, temperature, water vapor mixing ratio and precipitation. These meteorological variables were chosen to examine the impact of various meteorological conditions on $PM_{2.5}$ in polluted cities. In this case, Q is used to denote humidity [30] to eliminate the effect of temperature, pressure and other factors. The scope of the perturbation of meteorological variables refers to the study of Dawson et al. [36]. The emission inventory and other input criteria must remain constant during the CMAQ model's operation to guarantee that changes in one meteorological parameter result in all changes in the air quality in the research area. The model configuration remains the same for all simulations, with the only difference being a perturbation of a meteorological variable in each scenario. T is the absolute change, and the other meteorological variables are relative changes. Table 2 displays the setup of the specific parameters for the 21 scenarios.

To better judge the simulation performance of the model, this study compared the pollutant simulation values of the CMAQ model and the meteorological simulation values of the WRF model with the actual monitoring values in January 2017. At the same time, statistical indicators are used for evaluation to judge the reliability of the simulation results. Statistical indicators include correlation coefficient (R), mean bias (MB), root mean square error (RMSE), index of agreement (IOA), mean fractional bias (MFB) and mean fractional error (MFE). In order to validate the results of the CMAQ model, the scoring criteria adopted the MFB and MFE chemical species criteria proposed by Boylan and Russell [37]. If $-60\% \leq$ MFB$\leq 60\%$ and MFE$\leq 75\%$, then the model simulation results are

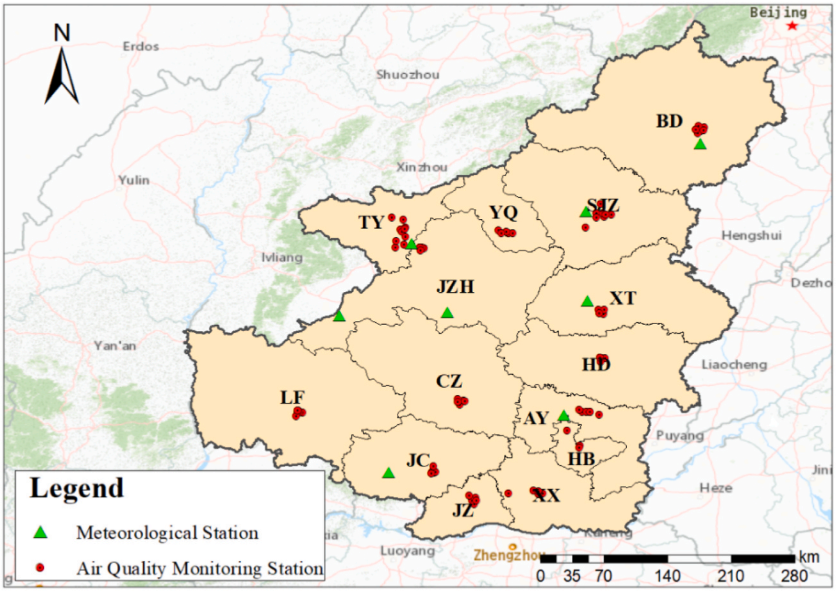

Fig. 1. Air quality monitoring stations and meteorological stations in major polluted cities.

Table 1
Configuration of physical and dynamics options in the WRF model.

Scheme	Configuration
Map projection	Lambert projection
Nested domain	2
Microphysics	Thompson graupel scheme
Cumulus Parameterization	Tiedtke scheme
Shortwave Radiation	RRTMG scheme
Longwave Radiation	RRTMG scheme
Planetary Boundary layer	Mellor-Yamada-Janjic (Eta) TKE scheme
Land Surface	unified Noah land-surface model

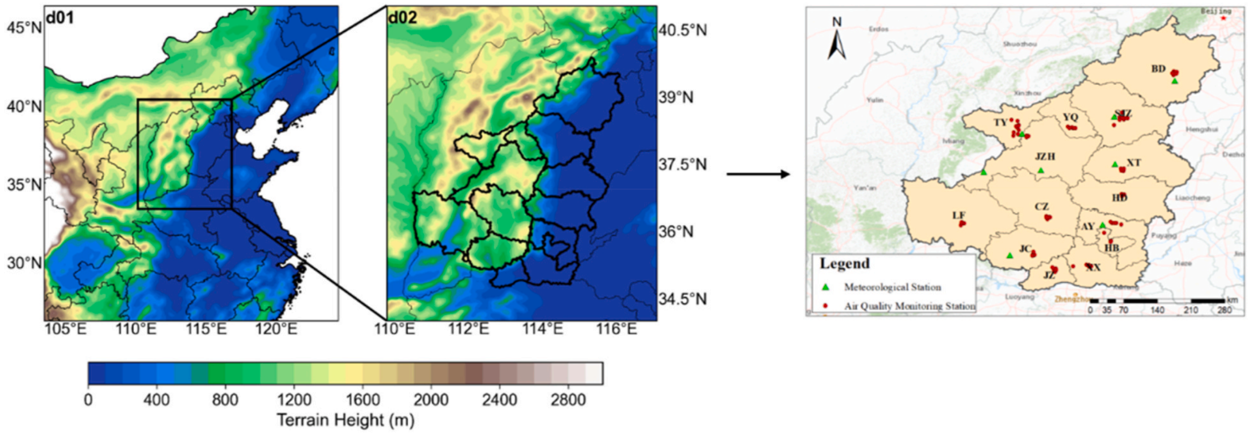

Fig. 2. Two nested modeling domains for model simulation and topographic distribution of 14 cities in the study area.

Table 2
Configuration of the simulation scenario.

Perturbed meteorolodical variables	Perturbed scheme (change)
Base	No perturbation
Temperature (T)	T1 (-1.5 K), T2 (-1K), T3 (+1 K), T4 (+1.5 K)
Wind speed (WS)	WS1(-20%), WS2(-10%), WS3(+10%), WS4(+20%)
Planetary boundary layer height (PBLH)	PBLH1 (-20%), PBLH2 (-10%), PBLH3 (+10%), PBLH4 (+20%)
Precipitation (PCP)	PCP1(-20%), PCP2(-10%), PCP3(+10%), PCP4(+20%)
Water vapor mixing ratio(Q)	Q1 (-20%), Q2 (-10%), Q3 (+10%), Q4 (+20%)

considered to be within the acceptable range [37,38]. If $-30\% \leq$ MFB$\leq 30\%$ and MFE$\leq 50\%$, then the model simulation results are considered excellent and within the ideal range. Because of the limited meteorological observation data, the meteorological variables for this evaluation were only the temperature at 2 m above the ground surface (T2) and the wind speed at 10 m above the ground surface (WS10).

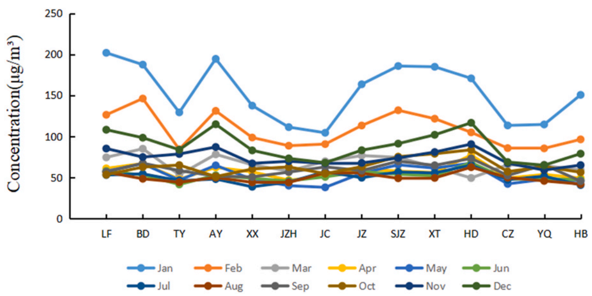

Fig. 3. The monthly contribution of $PM_{2.5}$ in the study area in 2017 according to experimental data.

3. Results and discussion

3.1. Particulate matter distribution characteristics in polluted cities

Fig. 3 shows the monthly contribution of $PM_{2.5}$ concentrations in 14 cities in the study area in 2017. The figure illustrates that HD has the highest annual mean $PM_{2.5}$ concentration of 85.75 μg/m^3, while BD, AY, SJZ, LF, and XT are relatively high, with their concentrations exceeding 80 μg/m^3. However, most cities in the study area's western direction have lower annual mean $PM_{2.5}$ concentrations. As a matter of fact, all cities exceeded the secondary concentration limit of urban atmospheric particulate matter. The national population-weighted annual $PM_{2.5}$ average concentration annual in 2017, 2018 and 2019 were 43 μg/m^3,39 μg/m^3 and 36 μg/m^3 respectively.The fine particulate matter pollution in the region was worse in 2017, especially in January, when it is the worst and most widespread. Therefore, January 2017 was determined as the simulation time for this study.

The variation of the monthly mean $PM_{2.5}$ concentration in the study region in January 2017 is shown in Fig. 4, where the $PM_{2.5}$ concentrations of 14 cities in the region vary widely and show prominent spatial distribution characteristics. Like the monthly contribution of $PM_{2.5}$, $PM_{2.5}$ pollution still has the characteristic that the $PM_{2.5}$ pollution level in the east is significantly higher than that in the west. Because the daily mean $PM_{2.5}$ concentration in January is too dense, we use jitter plots to represent each data, and we can get the monthly mean concentration by processing the data (take the mean), among these citys, the maximum monthly mean $PM_{2.5}$ concentration in January occurred in LF with a concentration of 201.8 μg/m^3, which possibly due to its location in the core of the Fenwei Plain, where a large number of high-energy-consuming enterprises such as iron and steel enterprises gather, emitting a large number of air pollutants to the area. The high anthropogenic emissions in the area and the fact that mountains surround LF are not conducive to pollution and dispersion during periods of heavy pollution. The $PM_{2.5}$ concentrations in the study area peaked in January for the whole year of 2017, with a significant increase in anthropogenic emissions due to a heating period in winter, when coal-fired heating emits a large number of pollutants. Meanwhile, pollutants do not diffuse as easily in winter due to the lower temperature and more stable atmospheric structure. The study area covers parts of Hebei, Shanxi, and Henan provinces with developed heavy industries, high concentrations of iron and steel and power plants, and high pollution levels. In January, the winter's higher human emissions and adverse weather conditions contributed to higher particulate matter concentrations.

Fig. 5 shows the spatial distribution of the predicted monthly mean $PM_{2.5}$ concentrations in January 2017, with SJZ being the most polluted and $PM_{2.5}$ concentrations in some areas having exceeded 200 μg/m^3.The western part of TY and LF have lower $PM_{2.5}$ concentrations, with $PM_{2.5}$ concentrations less than 20 μg/m^3. On the whole, the pollutant load in the eastern part of the study area was significantly higher than that in the western part., and the $PM_{2.5}$ high pollution area is mainly located in the east of the study area.The model simulations correctly reproduced the variation of $PM_{2.5}$ in January. Since all the cities along the southwest-northeast line on the east side of Taihang Mountain, namely Handan, Xingtai, Shijiazhuang, Baoding, and Beijing, and the first four are located in this study area, the upstream cities have a significant contribution to the local $PM_{2.5}$ concentration [39,40]. Inter city regional transportation has contributed significantly to $PM_{2.5}$ in the research area [39].

3.2. Model performance evaluation

[37,37,38]The benchmark used in this study was the criterion proposed by Emery et al. [41]. For T2, the correlation coefficient R is 0.84, and IOA is 0.86, indicating that our simulation captures the signature of temperature variation. The MB value is 1.23, which exceeds the benchmark value, the RMSE value is 3.02, and the prediction of T2 is slightly overestimated. For WS10, except for the MB value of 0.52, the correlation coefficient was 0.48, the IOA value was 0.67, and the RMSE value was 1.55, which were all within the benchmark values, and the results were acceptable. Compared with other WRF-based meteorological models, the performance in this

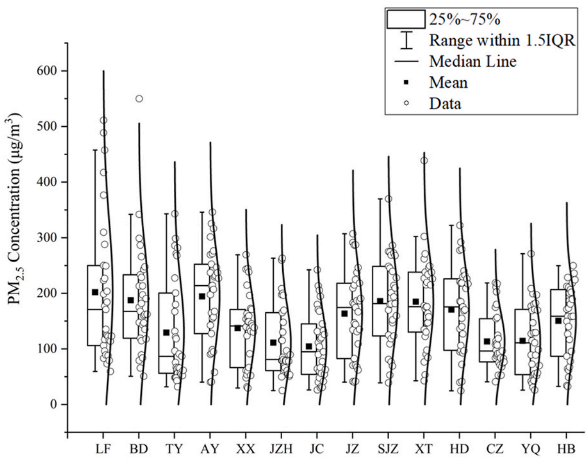

Fig. 4. The monthly mean concentration change of $PM_{2.5}$ in January 2017.

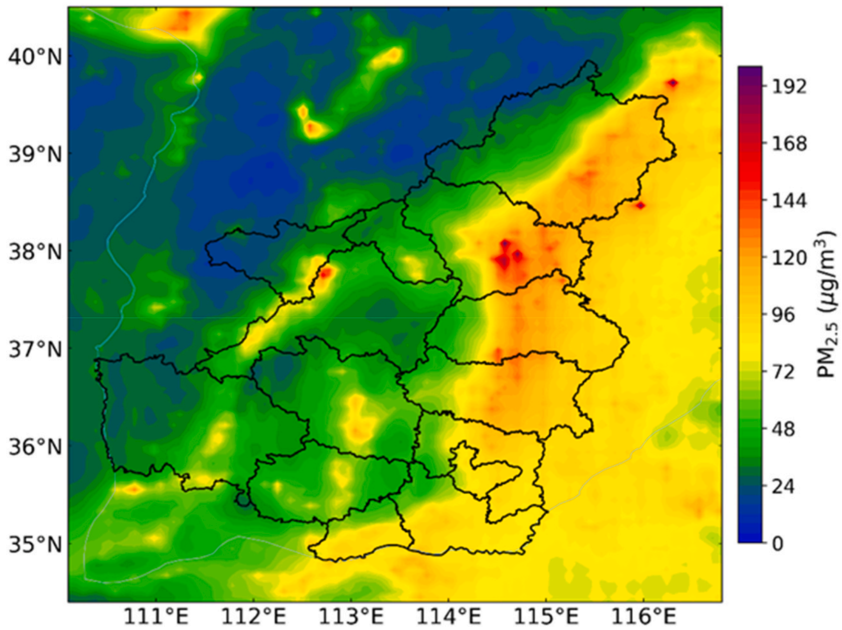

Fig. 5. Spatial distribution of simulated monthly mean $PM_{2.5}$ concentrations in January 2017.

study is acceptable [42–45].

The $PM_{2.5}$ concentrations simulated in this CMAQ model were extracted from a grid of 80 air quality monitoring stations covering 14 cities. If multiple air quality monitoring stations in a city are located in different grids, the simulated $PM_{2.5}$ concentration of each city is represented separately by calculating the mean simulated $PM_{2.5}$ concentration of the grids, and the time series comparison is shown in Fig. S1. As shown in Table 3, the range of R for the 14 cities is 0.41–0.74, the MFB values are −36% to −8%, and the MFE values are 31%–45%. Except for LF, the model performance of all the cities reaches an excellent level, which can better capture the variation characteristics of $PM_{2.5}$. Furthermore, LF has a significant simulation error with low simulated values of fine particulate matter, which may be due to the presence of sandy and dusty weather effects as the city is located in the Loess Plateau region. The MFB values of $PM_{2.5}$ in all cities were negative, suggesting that the model underestimated $PM_{2.5}$ concentrations to some extent, which may be related to the choice of parameter schemes and the uncertainty of emission inventories. Overall, the simulation errors of the WRF and CMAQ models are acceptable, and the model results can be used for further analysis and discussion.

3.3. Impacts of variations in meteorological variables to $PM_{2.5}$ prediction

While anthropogenic emissions and natural sources are responsible for the total amount of pollutants released into the atmosphere, various meteorological conditions can impact how these pollutants disperse and accumulate. In this section, we further study the spatial distribution of $PM_{2.5}$ after the meteorological variables are disturbed.

When the PBLH is perturbed, the perturbation results are shown in Fig. 6a,b,c,d. The $PM_{2.5}$ concentration is greatly affected by the

Table 3
Statistics of hourly mean $PM_{2.5}$ concentration assessment by CMAQ model.

	SIM (μg/m^3)	OBS (μg/m^3)	R	MFB	MFE
SJZ	122.68	170.8	0.61	−0.14	0.33
HD	123.31	161.62	0.55	−0.08	0.34
BD	123.69	177.24	0.47	−0.12	0.31
XT	113.28	175.79	0.44	−0.18	0.33
TY	78.32	109.95	0.59	−0.08	0.36
CZ	90.98	101.29	0.41	−0.02	0.32
LF	69.5	155.21	0.65	−0.36	0.45
YQ	66.37	110.38	0.74	−0.21	0.35
AY	108.52	185.14	0.6	−0.24	0.34
JZ	85.96	153.15	0.57	−0.24	0.39
JC	70.48	97.74	0.7	−0.09	0.33
JZH	69.74	101.66	0.6	−0.13	0.35
HB	91.59	141.32	0.59	−0.19	0.33
XX	93.27	132.08	0.6	−0.12	0.33

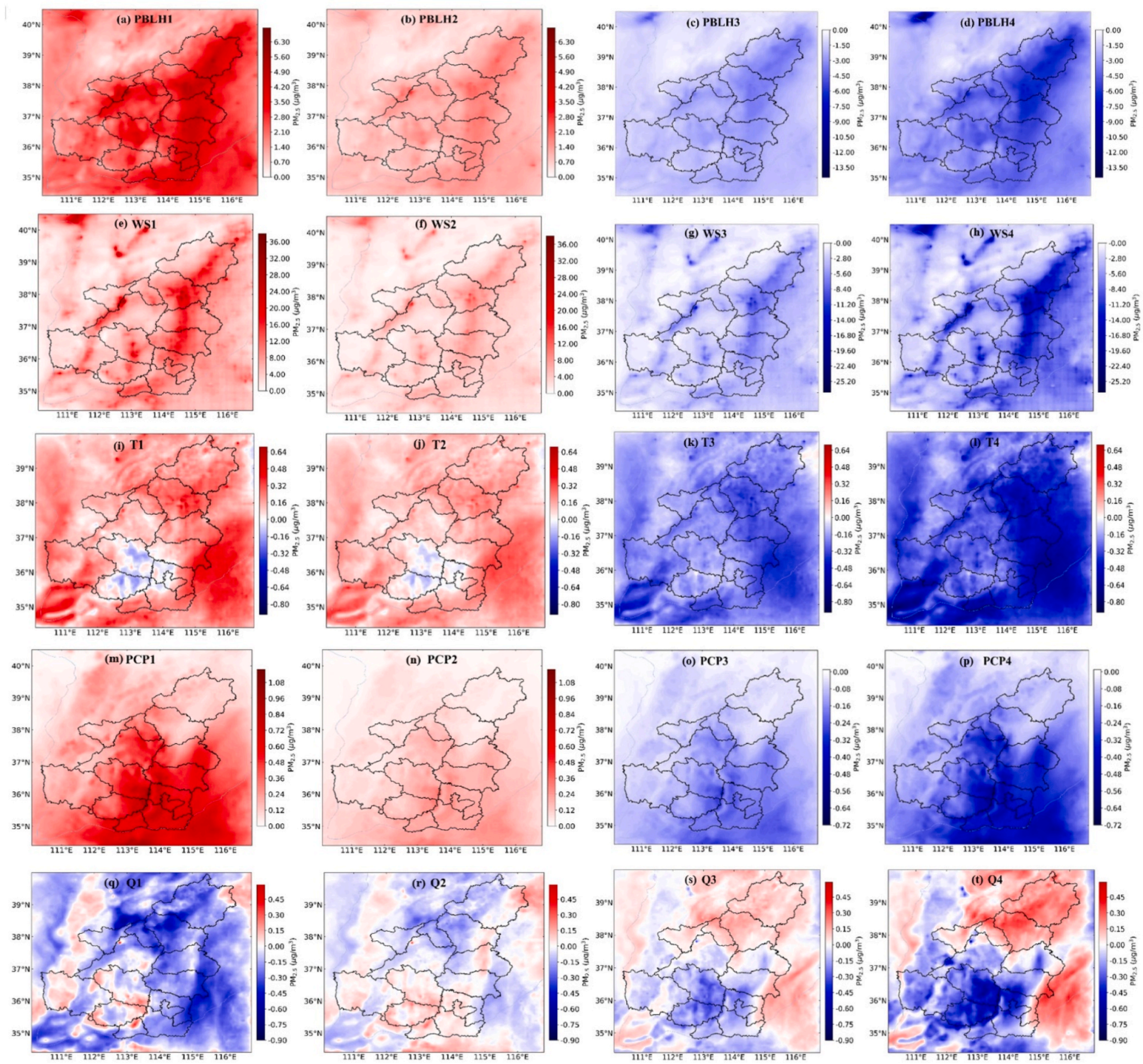

Fig. 6. Spatial distribution of monthly mean $PM_{2.5}$ differences in January caused by PBLH 、WS、T、PCP、Q perturbations, (a)PBLH -20%, (b) PBLH -10%, (c) PBLH +10%, (d) PBLH +20%; (e)WS -20%, (f) WS -10%, (g) WS +10%, (h) WS +20%; (i)T −1.5 K, (j) T −1 K, (k) T +1 K, (l) T +1.5 K; (m)PCP -20%, (n) PCP -10%, (o) PCP +10%, (p) PCP +20%; (q)Q −20%, (r) Q −10%, (s) Q +10%, (t) Q +20%.

PBLH, and an increase in PBLH can lead to a decrease in surface $PM_{2.5}$ concentration due to a mixing effect [46], with PBLH having a negative impact on $PM_{2.5}$ concentration. As shown in Fig. 6c and d, when the PBLH increases, it is favorable for the pollutants to undergo vertical dispersion, so a significant reduction in $PM_{2.5}$ concentration occurs. On the contrary, the concentration of pollutants increases.

Overall, in the PBLH1 scenario with a 20% reduction in PBLH, $PM_{2.5}$ concentrations increased by over 7.0 μg/m^3 in BD, SJZ, and some areas adjacent to TY and JZH. In the PBLH2 scenario, with a 10% reduction in PBLH, the growth of $PM_{2.5}$ concentration decreased, but the impact range remained largely unchanged. Moreover, the maximum reduction in $PM_{2.5}$ concentration was 14.37 μg/m^3 for the PBLH4 scenario (20% increase in PBLH). The impact range is relatively fixed in the different disturbance scenarios, which may be due to the developed heavy industries in these areas and the overall high anthropogenic emissions and more serious particulate matter pollution in the region. Simultaneously, we noticed a correlation between topography and areas that experienced notable alterations in $PM_{2.5}$ concentrations as a result of changes in PBLH (Fig. 2), especially in the basin areas within Shanxi Province, where the performance was more significant. When the PBLH is perturbed, the $PM_{2.5}$ concentration in these high emission areas produces a greater magnitude of change. It is important to note that the $PM_{2.5}$ concentration in scenarios with increasing PBLH (PBLH3, PBLH4) experiences a much more significant change than in scenarios with decreasing PBLH (PBLH1, PBLH2).

The spatial distribution of $PM_{2.5}$ concentrations following the disturbance of WS is illustrated in Fig. 6 e, f, g, and h. The results indicate that, as the WS increased, the stronger wind speed accelerated the horizontal dispersion of pollutants, ultimately resulting in a reduction of the $PM_{2.5}$ concentration [47]. Wind speed conditions play an essential role in the evaporation process of $PM_{2.5}$. As the wind speed picks up, the rate of evaporation for $PM_{2.5}$ particles accelerates, resulting in a notable reduction in their concentration levels [48]. The topographical barriers present in the Beijing-Tianjin-Hebei region, as illustrated in Fig. 2, significantly affect the surface winds, resulting in reduced wind speeds in the surrounding areas. Therefore, when the WS is disturbed, the area of $PM_{2.5}$ concentration change is still part of the cities in the North China Plain located on the eastern side of the Taihang Mountains, such as BD, SJZ, XT, HD, and AY. The Taihang Mountains act as a barrier, effectively blocking the transportation of pollutants from the North China Plain towards the northwest.

As shown in Fig. 6 e,f,g,h, $PM_{2.5}$ changes most significantly in the WS1 scenario. In the WS1 scenario (WS decreased by 20%), the maximum increase in $PM_{2.5}$ concentration was 38.3 μg/m^3, and the maximum increase in the WS2 scenario exceeded 18.2 μg/m^3. The WS4 scenario, which involved a 20% increase in wind speed, led to a noteworthy decrease of 27.1 μg/m^3 in $PM_{2.5}$ concentration. In the four scenarios where the WS perturbation occurs, the magnitude of $PM_{2.5}$ change is significantly greater than that of the previously introduced PBLH. However, it is noteworthy that the areas with significant $PM_{2.5}$ changes due to WS changes are similar to the four scenarios of PBLH perturbation, where the affected areas do not change significantly.

When the perturbation is performed on T, the perturbation results are shown in Fig. 6 i,j,k,l. The perturbation of T is carried out in all layers. Under specific conditions, T has a positive effect on $PM_{2.5}$ concentration, but it still shows a negative effect in general. When the temperature increases, the stability of the atmospheric stratification decreases, and the near-surface atmospheric convective activity is firm, which favors the vertical movement of the atmosphere [49] and thus contributes to the decrease in the concentration of pollutants in the near-surface layer.

As shown in Fig. 6k, l, the maximum decrease in $PM_{2.5}$ concentration is about 0.5 μg/m^3 when the temperature increases by 1 K. The maximum decrease in $PM_{2.5}$ concentration of about 0.9 μg/m^3 when the temperature increases by 1.5 K still occurs in the northeastern part of the North China Plain, and the remaining cities in the western part of the study area show relatively small changes in $PM_{2.5}$ concentration, except for the central part of LF and the border areas of TY and JZH. When the surface temperature increases, it will strengthen the atmospheric convection and increase the evaporation loss of $PM_{2.5}$ [49,50]. Fig. 6i and j demonstrate that the T1 scenario (T-1.5 K) and the T2 scenario (T-1 K) exhibited an overall increase in $PM_{2.5}$ concentration across the study area, with the exception of CZ, JC, and AY, which experienced a decrease. Notably, JC experienced the most substantial decrease in $PM_{2.5}$ concentration, with a reduction of approximately 0.5 μg/m^3.This phenomenon may occur with low winter temperatures in these areas. As the temperature rises, the cold air weakens and creates a stable temperature inversion structure [51], which constitutes unfavorable meteorological conditions and causes the accumulation of pollutants, thus making the $PM_{2.5}$ concentration increase.

When the PCP is perturbed, the perturbation results are shown in Fig. 6 m,n,o,p. PCP was negatively correlated with $PM_{2.5}$ concentration.This is because precipitation dilutes pollutants in the air, causing them to have a sedimentation effect [52]. When precipitation increases, the scavenging effect of precipitation becomes more robust, making $PM_{2.5}$ concentrations decrease.

As shown in Fig. 6 m,n,o,p, the maximum increase in $PM_{2.5}$ concentration is about 1.1 μg/m^3 in the PCP1 scenario (20% reduction in PCP). It is noteworthy that, in comparison to previous meteorological disturbance scenarios, the primary area impacted by $PM_{2.5}$ concentration has shifted significantly towards the central and southern regions of the study area. There is a correlation between the spatial distribution of $PM_{2.5}$ changes due to PCP changes and the distribution of precipitation in the study area in January 2017 (Fig. S2). In areas with low precipitation, the variation of $PM_{2.5}$ is minimal, such as in BD and TY; in areas with high precipitation, the variation of $PM_{2.5}$ is relatively high, such as in most of the south-central part of the study area It is noteworthy that when the precipitation in LF is at the mean level, the variation of $PM_{2.5}$ is low, which is caused by its low initial $PM_{2.5}$ concentration simulation.

When Q is perturbed, as shown in Fig. 6 q,r,s,t. Q shows mainly positive effects with surface $PM_{2.5}$ concentrations, but under certain conditions, it also shows adverse effects.

As shown in Fig. 6s and t, Q positively affects $PM_{2.5}$ concentrations in the northern part of the study area in the Q3 scenario (10% increase in Q) and the Q4 scenario (20% increase in Q). Q makes $PM_{2.5}$ attach more vapors [53,54], which will induce the growth of $PM_{2.5}$ fraction adsorption [55] and intensify the level of particulate pollution, causing $PM_{2.5}$ concentrations to increase instead of decrease, in agreement with the findings of studies by Zhou et al. Cheng [56]et al. and Qiu et al. [57]. The central and southern regions of the study area exhibit significant adverse effects, which align with the high precipitation areas in the perturbed PCP scenario.When the humidity exceeds a certain threshold, the higher Q at this time dilutes the pollutants in the air, causing the pollutants to settle and thus the $PM_{2.5}$ concentration to decrease. Fig. 6q and r demonstrate that when Q declines, all the cities' $PM_{2.5}$ concentrations move downward except for a few areas in the study area's southwest.

3.4. Quantitative analysis of the sensitivity of $PM_{2.5}$ to five meteorological variables

This study aimed to investigate the impact of a specific meteorological variable on the $PM_{2.5}$ concentration in various polluted cities. To achieve this, linear regression was used to analyze the monthly mean $PM_{2.5}$ concentration under different scenarios, with five meteorological parameters being perturbed. The sensitivity value was determined using R (n-2, 0.01) = 0.9587, with a significance level of 0.01 when n is 5. The linear fitting results are exhibited in Table S1.

Out of the five meteorological parameters, WS appears to have the greatest sensitivity. Specifically, it has been observed that WS has a notable negative impact on $PM_{2.5}$ concentrations, and the hypothesis of a linear variation of WS in all 14 cities passed at a significance level of 0.01. The $PM_{2.5}$ concentration showed a linear trend of gradual decrease with the increase of WS, and the effect on different cities varied significantly, with the sensitivity variation ranging from −0.7615 μg/m^3/% to −0.3997 μg/m^3/%. Among them, the cities of SJZ, HD, and XT, which are located on the eastern side of the Taihang Mountain, show particularly notable changes, with SJZ being the most affected by WS with a sensitivity of -0.7615 μg/m^3/%.

The negative effect of PBLH and PCP on $PM_{2.5}$ concentration sensitivity was also observed. At the significance level of 0.01, the hypothesis that PBLH and PCP of the 14 cities showed linear changes were valid. The sensitivity ranges of PBLH and PCP in 14 cities were -0.3064 μg/m^3/% to -0.1404 μg/m^3/% and -0.0282 μg/m^3/% to -0.0039 μg/m^3/%, respectively. The $PM_{2.5}$ concentration exhibits a clear linear trend of decreasing as the PBLH increases. The areas that demonstrate stronger sensitivity are primarily located in cities within the North China Plain, specifically on the eastern side of the Taihang Mountains, such as BD, SJZ, XT, and HD. Compared with several other meteorological variables, the sensitivity of $PM_{2.5}$ to PCP is relatively low, and the maximum sensitivity of PCP is -0.0282 μg/m^3/%, which occurs in CZ. The impact of meteorological variables on $PM_{2.5}$ concentrations varied significantly in terms of sensitivity. Among the meteorological variables studied, WS, PBLH, and PCP showed highly linear trends, whereas T and Q exhibited different variation characteristics. Similar to the previous meteorological variables, the sensitivity of $PM_{2.5}$ concentration to T also shows a negative influence. Notably, the hypothesis that T varies linearly in 10 cities in the study area passes at the 0.01 significance level, while the hypothesis that T varies linearly in CZ, JC, AY, and HB cities does not pass. In the cities studied, it was observed that T had a non-linear negative impact on $PM_{2.5}$ concentrations. This phenomenon could be attributed to the low temperatures prevalent during winter months, as well as the inversion structure that occurs when the temperature rises and the cold air weakens. This results in higher $PM_{2.5}$ concentration.

The water vapor mixing ratio (Q) on $PM_{2.5}$ concentration shows a non-linear influence characteristic overall, and there are significant differences between the fitting results of 14 cities. The hypothesis that Q changes linearly at the significance level of 0.01 is valid only for SJZ and BD, and the effect is positive. The $PM_{2.5}$ concentration in these two cities exhibited a gradual increase in correlation with Q. However, SJZ and BD presented different characteristics compared to other cities, which could be attributed to the minimal precipitation during this period. As a result, the humidity levels did not surpass the threshold. The hypothesis that Q changes linearly in other cities does not hold at the significance level of 0.01, which mainly shows positive effects, but also shows negative effects under certain conditions. As the Q value increases, the $PM_{2.5}$ concentrations in most metropolis increase slightly and then decrease. This may be due to the existence of the water vapor mixing ratio threshold, when the increase of the Q value exceeds this value, the higher Q dilutes the pollutants in the air and causes wet deposition of the pollutants, while before that, their concentration increases due to the adsorption growth of the $PM_{2.5}$ component.

By discussing the sensitivities of the five meteorological variables in the study area, we found that $PM_{2.5}$ concentrations in the 14 cities were consistent for the five meteorological variables as a whole, but the performance varied among cities for a single element. WS remains the primary meteorological variable that affects $PM_{2.5}$ concentrations, so the construction of ventilation corridors to mitigate serious air pollution problems can be considered in conjunction with local conditions. At the same time, it is also essential to consider the influence of PCP on $PM_{2.5}$ concentration and take measures such as artificial rainfall and setting up sprinkler systems for high-rise buildings to reduce pollution on time.

4. Conclusions

In this study, our findings are as follows, among the five meteorological variables, PBLH, WS, and PCP all show a single adverse effect, while T and Q can show a positive impact under certain conditions. When the PCP is reduced by 20%, the maximum increase in $PM_{2.5}$ concentration is about 1.1 μg/m^3, and the main affected areas are the central and southern component of the research area. When PBLH increases by 20%, the reduction in $PM_{2.5}$ concentration exceeds 14.37 μg/m^3. The higher PBLH benefits pollutants for vertical dispersion and reduces surface $PM_{2.5}$ concentration through the mixing effect. When WS was increased by 20%, $PM_{2.5}$ concentration was significantly reduced by 27.1 μg/m^3. As T decreases, the $PM_{2.5}$ concentration experiences the most significant decrease in JC and CZ, located in the southern region of the study area, as the maximum increase in $PM_{2.5}$ concentration is observed in SJZ. When Q decreases, $PM_{2.5}$ concentrations show a decreasing trend in all cities except for some areas located southwest of the study area. When Q increases, however, the $PM_{2.5}$ concentration in the central and southern parts of the study area show a decreasing trend, corresponding to the high precipitation areas of the perturbed PCP scenario.

It is important to recognize that regions with elevated levels of $PM_{2.5}$ are particularly responsive to meteorological variables. This can result in more significant fluctuations in $PM_{2.5}$ levels when there are disturbances in the local weather patterns. In this study, the calculation of individual meteorological variable sensitivities revealed that WS, PBLH, and PCP showed a highly linear trend in all cities at the 0.01 level of significance. The hypothesis that the T varies linearly in 10 cities in the study area passes, while the hypothesis that T varies linearly in CZ, JC, AY, and HB cities does not hold. For Q, the hypothesis of linear change in Q in Shijiazhuang and Baoding is only valid, while the hypothesis of linear change in Q in other cities is not valid at the significance level of 0.01.

This study aims to identify the meteorological variables that have a significant impact on $PM_{2.5}$ concentrations. It does so by examining the effects of perturbations in meteorological variables on air quality in cities in China that are critically polluted. The results help policymakers to propose better countermeasures for key polluted cities so that more targeted meteorological tools such as artificial precipitation and wind corridors can be used to reduce$PM_{2.5}$ concentrations in the future. Artificial rainfall is to increase precipitation by man-made means, so as to purify the particulate matter in the air. This can be achieved by cloud atomization, which is the spraying of cloud atomizers to induce the condensation of water vapor in the cloud into droplets, thereby promoting precipitation. A wind tunnel is a facility that changes the direction and velocity of the wind through a building or other structure. For example, in urban planning, green belts and park layouts can be used to guide air currents and create better ventilation conditions that help to dilute and release pollutants far from populated areas.

Author contribution statement

Ju Wang: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.
Jiatong Han: Performed the experiments; Analyzed and interpreted the data; Wrote the paper.
Tongnan Li: Performed the experiments; Analyzed and interpreted the data; Wrote the paper.
Tong Wu: Contributed reagents, materials, analysis tools or data; Chunsheng Fang: Contributed reagents, materials, analysis tools or data;

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Informed consent statement

Informed consent was obtained from all subjects involved in the study.

Data availability statement

Not applicable

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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