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Effect of Evaluation of Various Emission Control Policies on $PM_{2.5}$ Reduction

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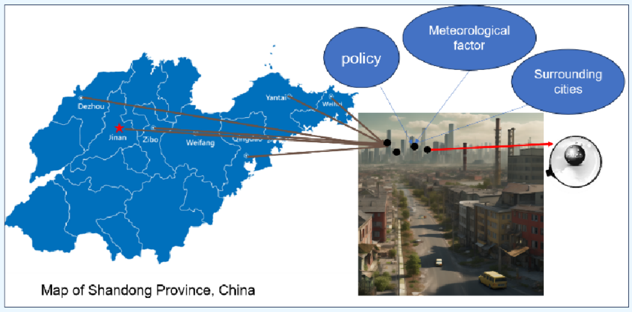

ABSTRACT: In previous work, a methodology was developed to discuss the influence of meteorological factors, policies, and surrounding cities on $PM_{2.5}$ concentrations in a city. Two models were constructed using Zibo City, Shandong Province, as the target city. Initially, we improved the established $PM_{2.5}$-Meteorological-Policy (PMP) model and applied it to six other target cities in Shandong Province. Concurrently, a novel model named the $PM_{2.5}$-Interregional (PI) model was further developed in each city to directly express the influence of surrounding cities on the target cities. The model construction period was from January 2014 to August 2022, with the extended prediction period until November 2022. The results confirmed that disparities in the spatial distribution in seasons became smaller after the implementation of environmental policies. Moreover, two models in each city revealed good interpretation with high adjusted R^2 values (>0.7) and lower MAPE and RMSE values (the lowest was 5.53% and 2.57), suggesting reasonable short-term prediction. Additionally, meteorological factors and the combined implementation of different policy types played crucial roles in reducing $PM_{2.5}$ concentrations in all cities. Specifically, the temperature and wind speed were negatively correlated with $PM_{2.5}$ concentrations in all models, with temperature having a stronger influence. The Law of the People's Republic of China on the Prevention and Control of Atmospheric Pollution (LAPAP), implemented in 2016, had a clear influence on reducing $PM_{2.5}$ concentrations, with the highest absolute fitted coefficient in most cities (−0.166 to −0.344). On the contrary, the influence of temperature seemed to be more significant compared to policies, due to the larger standardized coefficient in each city (−0.606 to −0.864).

1. INTRODUCTION

Fine particulate matter ($PM_{2.5}$) pollution has become a global environmental concern due to its adverse effects on the environment and human health.[1−3] The main sources of $PM_{2.5}$ emissions threaten air quality and atmospheric visibility.[2,4] Furthermore, the number of deaths attributable to $PM_{2.5}$ pollution in 2017 was nearly 3 million worldwide, which is three times the deaths caused by AIDS in that year.[5]

An increasing number of studies have demonstrated that atmospheric $PM_{2.5}$ concentrations are influenced by various factors, including emission control strategies, meteorological factors, and inter-regional atmospheric transport of pollutants,[6] as discussed in our previous research. Meteorological factors play an important role in the formation and dispersion of $PM_{2.5}$ concentrations.[7] However, results on the effects of meteorological factors on pollutants are still controversial, especially for temperature and relative humidity.[7−9] In Licheng Zhang's research, $PM_{2.5}$ concentrations were found to be negatively correlated with sunshine hours, wind speed, air pressure, and temperature and positively correlated with relative humidity.[10] Wind speed was found to be the most important factor influencing the distribution of $PM_{2.5}$, and traces of precipitation had essentially no effect on reducing $PM_{2.5}$ concentrations.[10] Some studies have found a significant negative correlation between atmospheric pressure and $PM_{2.5}$ concentrations.[10,11] As previously reported in our research, temperature and wind speed had clear reducing effects on $PM_{2.5}$ concentrations in Zibo city.[6] Similar results were found in Licheng Zhang's research for the same parameters.[10] However, $PM_{2.5}$ concentrations had clear negative correlations with precipitation in Zibo city in the research,[6] which differed from the result in Licheng Zhang's research.[10] Therefore, it is still necessary to conduct further in-depth analysis on the influence of meteorological factors in different cities.[10]

On the other hand, the Chinese government has implemented a set of policies and control measures to improve

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Figure 1. Location of the study area in Shandong Province.

Table 1. Basic Information of Each City in 2021

	Dezhou	Jinan	Zibo	Weifang	Qingdao	Yantai	Weihai
area (km^2)	10 356	10 233	5 965	16 167	11 293	13 864	5 799.8
GDP (billion yuan)	348.9	1 143.2	420	701.1	1 413.6	871.2	346.3
population (million)	5.6	9.2	4.7	9.4	10.2	7.10	2.9
GDP per capita (yuan)	62 303	124 261	89 362	74 585	138 588	122 704	119 414

air quality. In February 2012, the Environmental Protection Bureau revised China's "Ambient Air Quality Standard" (GB 3095-2012) (CAAQS), which included $PM_{2.5}$ in the routine monitoring indicators. In September 2013, China's most stringent clean air policy, the "Air Pollution Prevention and Control Action Plan" (the "Action Plan"), was implemented with the goal of reducing $PM_{2.5}$ emissions.[12] The $PM_{2.5}$ concentration reduction target was set for key regions in China.[13−15] The Action Plan promoted the implementation of a range of control measures. Meanwhile, a number of studies have emphasized that $PM_{2.5}$ concentrations can be influenced by environmental policies.[16,17] Strong policies not only significantly improve air quality, but also change the spatial distribution of air pollution. The disparities in air pollutant emissions between urban and rural areas led to the urban−rural disparity in $PM_{2.5}$ concentrations.[18] In addition, environmental policies play a crucial role in encouraging individual's $PM_{2.5}$ reduction behavior and reducing smog pollution.[19] Additionally, some research pointed out that clean air policies modified the relationship between $PM_{2.5}$ concentrations and gross domestic product (GDP) per capita, leading to lower $PM_{2.5}$ levels for the same GDP per capita after 2013. These findings can contribute to effective policy-making aimed at abating future $PM_{2.5}$ emissions from the perspective of policy proposals.[20−22]

In previous research, a method was developed to quantitatively discuss the influence of meteorological factors, policies, and $PM_{2.5}$ levels of surrounding cities on a city's $PM_{2.5}$ concentrations. Two models were then constructed using Zibo City, Shandong Province, as the target city. One model was named the $PM_{2.5}$-Meteorological-Policy-Interregional (PMPI) model to explore the diversity of influences of all the above parameters; the other was named $PM_{2.5}$-Meteorological-Policy (PMP) model to consider the influences of meteorological factors and relevant air control policies. In these models, the absolute values of the coefficients of the independent variables were used to determine the magnitude of the effect of the influencing parameters. In addition, the quantitative analysis of control policies was achieved by introducing time series of dummy variables (DUM) into the modeling. Dummy variables (DUM), also known as nominal variables, are artificial variables used to reflect qualitative attributes. It is a quantized independent variable, usually taken as '0' or '1'. Specifically, if a policy was implemented in a certain year, the variable would be "1" starting from that year and "0" prior to that year.

Based on the above discussion and previous research, the aim here was to apply the established methodology to more cities in Shandong Province, such as Dezhou, Jinan, Weifang, Qingdao, Yantai, and Weihai. An attempt would be made to construct different models of $PM_{2.5}$ concentrations on the basis of different drivers. It was not only to conduct further in-depth analysis of the influence of meteorological factors on $PM_{2.5}$ concentrations, but also to quantitatively compare the influence of different policies on different cities.

2. METHODOLOGY

2.1. Study Area. Six cities in the eastern, central, and western parts of Shandong Province were selected for further research. The locations of these cities were shown in Figure 1, with Jinan as the capital of Shandong Province (marked by a red five-star). The city of Zibo, which was discussed in previous research, was also listed in the figure. The basic information on each city in 2021 is listed in Table 1. Here, population was the resident population, and GDP per capita was the ratio of a city's annual GDP to its resident population. The results showed that the GDP per capita in 2021 in Jinan, Qingdao, Yantai, and Weihai exceeded 10 000 yuan.

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ACS Omega 2024, 9, 330−340

Table 2. Involved Policies and Regulations in Each City

city	starting time	policy and regulations	parameter expression
Dezhou	January 2016	"Law of the People's Republic of China on the Prevention and Control of Atmospheric Pollution" (LPCAP)	DUM_{1601}
	September 2016	Regulations on the prevention and control of air pollution in Dezhou City (Dezhou Regulations)	DUM_{1609}
	April 2020	key points of air pollution control in Dezhou City in 2020	DUM_{2004}
Jinan	January 2016	LPCAP	DUM_{1601}
	May 2017	2017 Beijing-Tianjin-Hebei regional air pollution control implementation rules of Jinan City (Jinan Implementation Regulations)	DUM_{1705}
	December 2019	Action Plan for comprehensive air pollution control in autumn and winter 2019−2020 in Beijing−Tianjin−Hebei and surrounding areas	DUM_{1912}
Weifang	January 2016	LPCAP	DUM_{1601}
	May 2017	eight measures to prevent and control air pollution in Weifang City, including industrial and coal combustion control, dust control, vehicle oil and gas remediation, no burning and no discharging, heavy pollution weather warning, notification and responsibility, network-based monitoring, and inspection and control	DUM_{1705}
	November, 2020	Action Plan for comprehensive control of air pollution in autumn and winter 2020−2021 in Weifang city (Weifang Action Plan)	DUM_{2011}
Qingdao	January 2016	LPCAP	DUM_{1601}
	March 2019	Qingdao City Air Pollution Control Action Plan and 2013−2020 phase III of the Action Plan (2018−2020) (Qingdao Action Plan)	DUM_{1903}
	October 2020	work plan for the prevention and control of autumn and winter air pollution in Qingdao from 2020 to 2021 (Qingdao Work Plan)	DUM_{2010}
Yantai	January 2016	LPCAP	DUM_{1601}
	July 2018	Action Plan to combat air pollution in the Province of Shandong and phase III of the Action Plan for 2013−2020 (2018−2020) (The Shandong Province Action Plan)	DUM_{1807}
	November 2020	Action Plan for the comprehensive control of air pollution in the autumn and winter period from 2020 to 2021 in the Province of Shandong	DUM_{2011}
Weihai	January 2016	LPCAP	DUM_{1601}
	November 2016	decision to amend four local laws and regulations, including the Regulations of Shandong Province on the Prevention and Control of Air Pollution (the Amending Decision)	DUM_{1611}
	January 2020	implementation plan for comprehensive control of air pollution from industrial furnaces and kilns in Shandong Province	DUM_{2001}

2.2. Data Sources and Processing. Air pollutants have been routinely monitored in the six target cities since 2013. Specifically, the monitoring data have been published online by the Shandong Environmental Protection Bureau (http://sthj.shandong.gov.cn). Through the website, the daily $PM_{2.5}$ concentrations in the six cities and in their respective surrounding cities were collected from January 2014 to November 2022. Then, the monthly, seasonal, and annual concentrations were calculated based on the daily data. Meanwhile, data from each national monitoring station in Weifang City were also collected. Due to the maintenance behavior of the monitoring instruments, such as zero calibration, anomalous data appeared. To ensure accuracy and authenticity, these data were excluded from the study.

Meteorological data were obtained from the China Meteorological Administration and the World Weather Online website (https://www.worldweatheronline.com/), which included daily temperature (°C), relative humidity (%), air pressure (hPa), wind speed ($m \cdot s^{-1}$), and sunshine hours (h) during the same period. During the research, four seasons were classified as winter (December−February of the following year), spring (March−May), summer (June−August), and autumn (September−November), as in the previous research.[6] Relative air emission policies were discussed separately in Section 2.3.

In this research, the previous modeling approach was initially used to construct a PMP model of each target city, considering the influence of meteorological factors and air policies and measures on $PM_{2.5}$ concentrations in the target cities. Subsequently, a novel model named the $PM_{2.5}$-Interregional (PI) model was established in each city to explicitly examine the influence of the adjacent cities on the target city. The $PM_{2.5}$ concentrations of surrounding cities were employed as independent variables in the PI model. Concurrently, the ridge regression method was used to eliminate the high correlation between the independent variables. The model construction period was from January 2014 to August 2022, and the model prediction period was extended to November 2022.

Statistical tests including independent sample t test, adjusted R^2 (AR^2), and Sig F value were used to test the reliability of the models. The variance inflation factor (VIF) was used to characterize the degree of complex covariance between observations of the independent variables. In addition, the estimated and predicted series were compared with the actual series during the data processing periods by plotting the curves and calculating the values of the mean absolute percentage error (MAPE) and the root-mean-square error (RMSE). The MAPE and RMSE were calculated to assess the predictive accuracy of the models. In general, the model was reliable with an AR^2 above 0.6, a low p-value of each variable (t-tests), a reasonable VIF value (between 0 and 10), and lower MAPE and RMSE values. The detailed process of model construction and statistical testing can be found in the previous research.[6]

2.3. Emission Control Policies. Since 2006, the Chinese government has implemented various clean air policies to improve air quality. In conjunction with the 2013 Action Plan, a series of control measures have been promoted in each city. The relevant policies and strategies are summarized in Table 2. As emphasized in the previous research,[6] the quantitative analysis of control policies was achieved by introducing time series of dummy variables (DUM) into the model. In the model, it was introduced in the form of the DUM_t, where the subscript t, indicated the time of the policy implementation.

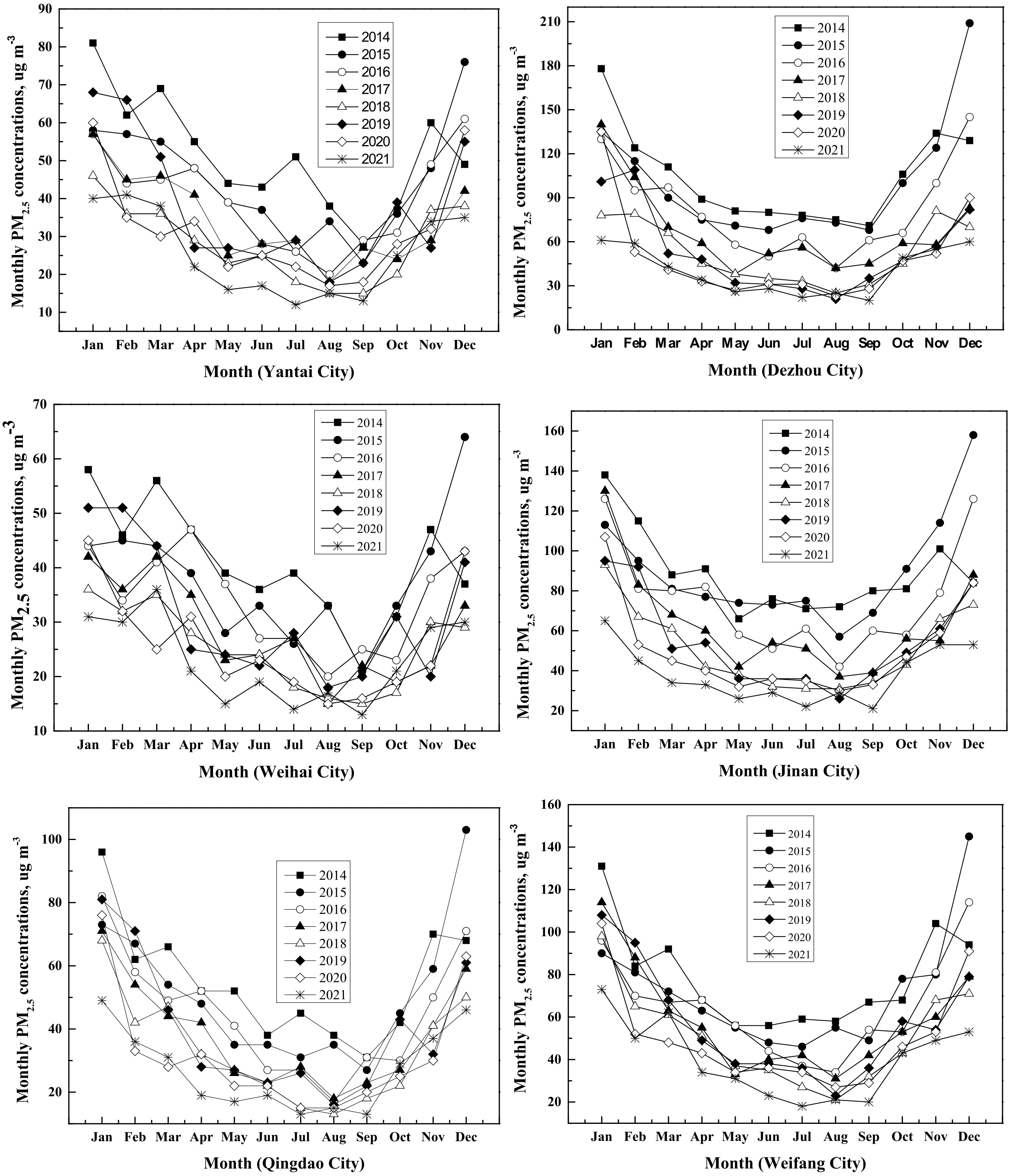

Figure 2. Temporal variation of the monthly mean $PM_{2.5}$ concentrations in each city.

Specifically, "DUM_{1601}" indicated that a particular type of air pollution control policy was implemented from January 2016, so time series variables of DUM were denoted by "1" in the model from January 2016. On the contrary, variables prior to January 2016 were denoted by "0". Similarly, "DUM_{2011}" indicated that the policy was implemented from November 2020, and the data from November 2020 were denoted by "1". The parameters of DUM_t in each model are also listed in Table 2.

3. RESULTS AND DISCUSSION

3.1. Temporal Distribution of $PM_{2.5}$ Concentrations in Different Cities. Based on the $PM_{2.5}$ concentration data during 2014−2021, this section analyzed the variation of monthly and annual $PM_{2.5}$ concentrations in different cities, as shown in Figure 2. In addition, the degree of change of the observed variables is listed in Table 3 by calculating the rate of increase of the annual concentration compared to the previous year. In the table, a positive rate of increase indicates that the

Table 3. Year-on-Year Growth Rate of $PM_{2.5}$ Concentrations in Each City, %

year	Yantai	Dezhou	Jinan	Qingdao	Weihai	Weifang
2015	−12.8	−4.2	1.4	−7.3	−7.4	−8.1
2016	−11.2	−18.2	−16.1	−12.5	−10.6	−10.2
2017	−13.8	−18.0	−15.5	−14.8	−16.3	−9.6
2018	−17.8	−22.3	−20.0	−12.9	−10.6	−12.9
2019	34.4	2.7	7.9	19.9	23.7	11.8
2020	−16.1	−8.0	−8.7	−19.9	−17.6	−12.3
2021	−19.2	−18.5	−24.6	−15.1	−10.9	−20.1

observed variables show an increasing trend over time, while a negative value indicates that the observed variables show a decreasing trend.

Some interesting conclusions were ascertained from Figure 2. (1) Within a certain period, the monthly $PM_{2.5}$ concentration series displayed a similar trend, consistent with the results in Zibo city[6] and in many Chinese cities.[8,13] In particular, the monthly variation of the $PM_{2.5}$ concentration presented a concave distribution. Levels were lower in summer, higher in winter, and moderate in spring and autumn. The maximum concentration in a year usually occurred in December and January, in agreement with the previous studies.[6] In winter in northern cities, the increased emission of pollutants from coal combustion and the weakened diffusion of pollutants caused serious $PM_{2.5}$ pollution.[20]

(2) From 2014 to 2021, a time series analysis illustrated that the annual $PM_{2.5}$ concentrations in each city gradually

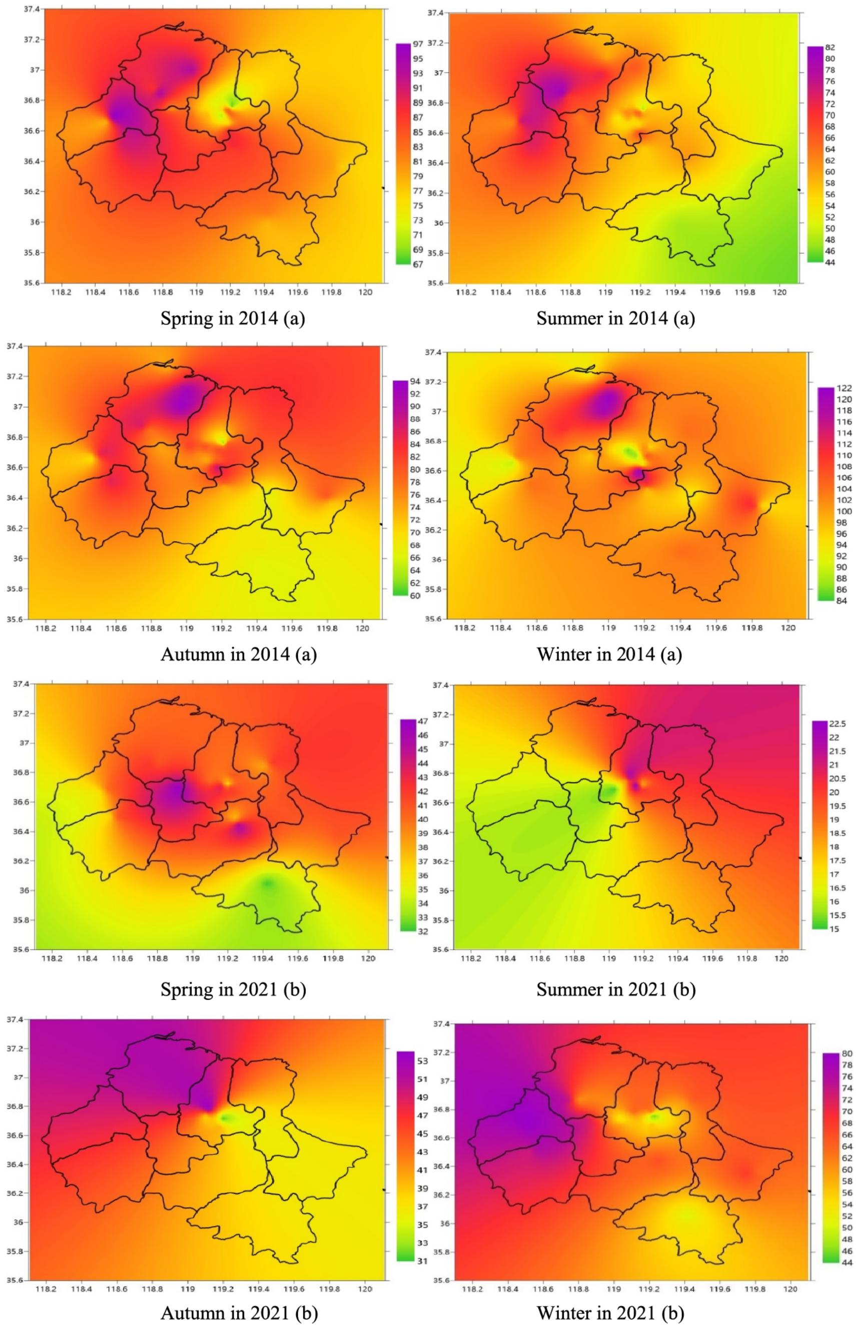

Figure 3. Spatial distribution of quarterly $PM_{2.5}$ concentrations in different years (a:2014; b:2021).

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ACS Omega 2024, 9, 330−340

Table 4. Parameters and Statistical Testing of Each PMP Model

independent variables	implication	standardized coefficients					
		Dezhou[a]	Jinan[b]	Weifang[c]	Qingdao[d]	Yantai[e]	Weihai[f]
X_1	temperature	−0.606	−0.621	−0.752	−0.782	−0.864	−0.864
X_2	wind speed	−0.118	−0.119	−0.087	−0.049	−0.201	−0.248
Z_1	DUM_{1601}	−0.254	−0.21	−0.166	−0.27	−0.344	−0.257
Z_2	DUM_{1705}		−0.31	−0.135			
Z_3	DUM_{1807}					−0.048	
Z_4	DUM_{2011}			−0.194		−0.176	
Z_5	DUM_{1609}	−0.251					
Z_6	DUM_{2004}	−0.209					
Z_7	DUM_{1611}						−0.177
Z_8	DUM_{2001}						−0.183
Z_9	DUM_{1903}				−0.13		
Z_{10}	DUM_{2010}				−0.162		
Z_{11}	DUM_{1705}						
Z_{12}	DUM_{1912}		−0.179				

[a]Adjusted R^2 (AR^2) = 0.79, Sig F = 0.000, variance inflation factor (VIF) = 0−10. [b]AR^2 = 0.82, Sig F = 0.000, VIF = 0−10. [c]AR^2 = 0.80, Sig F = 0.000, VIF = 0−10. [d]AR^2 = 0.77, Sig F = 0.000, VIF = 0−10. [e]AR^2 = 0.74, Sig F = 0.000, VIF = 0−10. [f]AR^2 = 0.85, Sig F = 0.000, VIF = 0−10.

decreased. In 2014, the annual $PM_{2.5}$ concentrations in Yantai, Dezhou, Jinan, Qingdao, Weihai, and Weifang were 51.4, 104.7, 88.6, 50, 40.8, and 78.1 $\mu g \cdot m^{-3}$, respectively. The results demonstrated that all values were significantly higher than those of the Chinese Ambient Air Quality Standard (GB 3095-2012) (CAAQS) grade II (35 $\mu g \cdot m^{-3}$). The Dezhou value was the maximum and almost three times the standard. Fortunately, by 2021, the levels in each city had decreased to 25.7, 40.2, 37.8, 27.0, 23.0, and 39.8 $\mu g \cdot m^{-3}$, a decrease of 50%, 61.6%, 57.3%, 50.9%, 43.6%, and 49.3% respectively. Urban emissions in the target cities were significantly alleviated, and levels in Yantai, Qingdao, and Weihai had reached the grade II standard (CAAQS). $PM_{2.5}$ concentrations had been decreasing on an annual basis, demonstrating that air pollution control policies and reduction measures had begun to bear fruit.[3,10]

However, the $PM_{2.5}$ problem was still unsatisfactory in half of the target cities. The levels in Dezhou, Jinan, and Weifang were still higher than those of the grade II standard (CAAQS). In 2021, the percentage of days with good air quality was 63.8 in Dezhou, 62.7 in Jinan, and 79.2 in Weifang, indicating that further improvement in air quality was needed (http://sthj.shandong.gov.cn/zwgk/sqcspm/).

(3) As shown in Table 3, the result showed that almost all $PM_{2.5}$ concentrations in each city decreased gradually during the periods, although the degree of pollutant reduction in each year was different. The $PM_{2.5}$ concentrations dropped rapidly in 2018 and 2020. Moreover, the $PM_{2.5}$ problems in Dezhou and Jinan had improved the most, with a larger decrease rate. The sudden increase in $PM_{2.5}$ concentrations in all cities in 2019 might be due to adverse meteorological factors.

3.2. Spatial Distribution Analysis. The variation of the spatial distribution of $PM_{2.5}$ concentration before and after the implementation of the emission control policy was analyzed, using Weifang city as an example. Figure 3 depicts the spatial distribution isograms of the average $PM_{2.5}$ concentrations during four seasons in 2014 (a) and 2021 (b). The graph was based on data from the monitoring stations in Weifang city, including $PM_{2.5}$ concentration and the latitude and longitude coordinates of each monitoring station. For the 2014 figure, data from 37 stations were used for each season, while for the 2021 figure, the number of stations varied from season to season, with 27 stations used for spring and winter and 10 stations used for summer and autumn. Google Earth and Surfer 13.0 were used to obtain the spatial distribution map of $PM_{2.5}$ emissions. The detailed mapping method can be found in the previous research.[6] In the figure, the closer the color of the layer to dark purple, the higher the $PM_{2.5}$ concentration.

The results showed that the difference in $PM_{2.5}$ concentration in different seasons was obvious. $PM_{2.5}$ concentrations were high in spring and winter and low in summer and autumn in both 2014 and 2021. This was consistent with previous studies.[6,23] Meanwhile, the variation in $PM_{2.5}$ concentrations among national control monitoring stations was smaller in 2021 compared to 2014, as shown by the color of the figure.

In terms of spatial distribution in 2021, in spring, the concentrations at the monitoring stations were within a range of 40.1 ± 3.9 $\mu g \cdot m^{-3}$. $PM_{2.5}$ concentrations were higher in the central and northern regions than that in the southern regions due to the difficulty of dispersion of pollutants from a large number of industries. In addition, $PM_{2.5}$ pollution was the most severe in the Binhai Economic Development Zone in the northern part of Weifang City. That is because the Binhai district is a famous chemical industry park, which emits a large amount of pollutants.

In summer, the range of $PM_{2.5}$ concentrations was 19.1 ± 2.6 $\mu g \cdot m^{-3}$ in most areas. Levels in the northeastern plain area were significantly higher than those in the central and western hilly areas.

In autumn and winter, pollutants were higher in the northwest area than those in the southeast area. The concentration distribution in the winter was uniform, and the variation of the regional concentration was smaller than that in autumn. The range of $PM_{2.5}$ concentrations was 40.0 ± 7.2 $\mu g \cdot m^{-3}$ in autumn, which was lower than that in summer due to lower precipitation and temperature. The most severe $PM_{2.5}$ pollution occurred in winter, with the $PM_{2.5}$ concentration ranging within 62.3 ± 9.5 $\mu g \cdot m^{-3}$, caused by heating coal and the lowest atmospheric diffusion intensity.[3,17]

3.3. Estimation Result of $PM_{2.5}$ Concentrations using the PMP Model. To avoid collinearity between the independent variables, the ridge regression method was used to optimize the multiple regression model. Although it lost some information and was less accurate than the multiple

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ACS Omega 2024, 9, 330−340

linear regression method, it was more reasonable.[24] Table 4 lists the estimation results of the PMP model in each city, where the coefficient denoted the standardization coefficient in the model. X_i (i = 1,2,⋯,n) denoted the variable observations of each meteorological factor, and n is the number of factors. Z_j (j = 1,2,⋯,m) is the dummy variable reflecting the effect of policies, and m denoted the number of policies. Interpretation of each model revealed significance with high AR^2 values (>0.74), low p-values, Sig F, and appropriate variance inflation factor (VIF) values in the range of 0−10.

A closer look at the results revealed several notable findings. (1) From the results of all models, meteorological factors, including temperature (X_1) and wind speed (X_2), as well as various environmental policies had certain effects, on the change in $PM_{2.5}$ concentrations. Specifically, in terms of meteorological factors, temperature and wind speed were negatively correlated with $PM_{2.5}$ concentrations in all models. Among the meteorological factors, most studies showed that wind speed was negatively correlated with $PM_{2.5}$ concentrations,[25−27] and this was also found in this study. While sunshine duration, relative humidity, and precipitation had essentially no effect, which is consistent with the research by Zhang et al.[10] Therefore, the temperature and wind speed were selected as the significant meteorological factors in all models.

(2) In each city, the fitted coefficients of the variables represented the overall trend of variation of the observed variables within a given time period. The absolute values of the fitted coefficients were compared to reflect the influence of the observed variables. A larger absolute value means that the increasing or decreasing trend is more obvious. As seen from Table 4, the ranking order of each meteorological variable was similar in each city. The temperature factor had fitted coefficients higher than those of wind speed, indicating that it had a greater influence on the $PM_{2.5}$ concentrations in each city.

(3) The fitted coefficients of all policies were negative. It was highlighted that the joint implementation of different types of policies and measures played a critical role in reducing $PM_{2.5}$ concentrations in each city.[2,16,28] This could be because all policies activated the transformation of industrial structures, whether at low or high levels.[2] The parameter DUM_{1601} appeared in all models, signifying that the LAPAP law implemented in 2016 had a clear impact on the reduction of $PM_{2.5}$ concentrations in each city. Furthermore, among all of the policy parameters, the absolute fitted coefficient of DUM_{1601} was the maximum in most cities, indicating the most significant reduction effect on $PM_{2.5}$ concentrations. In Jinan city, the coefficient of DUM_{1705} was larger than that of DUM_{1601}, indicating that the "Jinan Implementation Regulations" issued later in 2017 had the most significant effect. In Yantai city, although the other two policies played some role in preventing and controlling air pollution, the influence was significantly weaker than that of DUM_{1601}. Therefore, of all of the relevant laws and regulations, the implementation of the LAPAP law has contributed significantly to the reduction of $PM_{2.5}$ emissions in all target cities. These findings can contribute to effective policy-making to reduce $PM_{2.5}$ pollution from the perspective of policy proposals.

(4) By comparing the coefficients of the different policies and meteorological factors, it was found that the coefficient of temperature was the largest and had the greatest influence on $PM_{2.5}$ concentrations of all of the parameters.

3.4. Estimation Result of $PM_{2.5}$ Concentrations using the PI Model.

Atmospheric pollution in surrounding cities has an impact on local $PM_{2.5}$ concentrations.[6] In this section, the PI model was run to account for the primary inter-regional influences on the target cities. The optimized modeling result of each city is tabulated in Tables 5, 6, 7, 8, 9, and 10, where β_i (i = 1,2⋯i) is the variable observation of the surrounding cities, and n is the number of factors.

Table 5. Parameters and Statistical Testing of the PI Model in Dezhou

independent variable	implication	coefficient	standardization coefficient	statistical testing
β_1	Jinan	0.003	0.002	AR^2 = 0.98, Sig F = 0.000
β_2	Liaocheng	0.526	0.483	
β_3	Binzhou	0.051	0.035	
β_4	Hengshui	0.447	0.449	
β_5	Cangzhou	0.043	0.032	
δ	constant	−6.301		

Table 6. Parameters and Statistical Testing of the PI Model in Jinan

independent variable	implication	coefficient	standardization coefficient	statistical testing
β_1	Liaocheng	0.475	0.556	AR^2 = 0.97, Sig F = 0.000
β_2	Binzhou	0.002	0.001	
β_3	Dezhou	0.022	0.028	
β_4	Zibo	0.421	0.406	
δ	constant	0.724		

Table 7. Parameters and Statistical Testing of the PI Model in Weifang

independent variable	implication	coefficient	standardization coefficient	statistical testing
β_1	Dongying	0.273	0.263	AR^2 = 0.96, Sig F = 0.000
β_2	Zibo	0.279	0.297	
β_3	Rizhao	0.107	0.092	
β_4	Qingdao	0.461	0.349	
δ	constant	0.573		

Table 8. Parameters and Statistical Testing of the PI Model in Qingdao

independent variable	implication	coefficient	standardization coefficient	statistical testing
β_1	Weifang	0.108	0.143	AR^2 = 0.98, Sig F = 0.000
β_2	Yantai	0.358	0.279	
β_3	Rizhao	0.509	0.586	
δ	constant	−3.512		

The interpretation of each PI model revealed significance with a high AR^2 value (>0.95) and each VIF value ranging

Table 9. Parameters and Statistical Testing of the PI Model in Yantai

independent variable	implication	coefficient	standardized coefficients	statistical testing
β_1	Weihai	0.88	0.635	AR^2 = 0.97, Sig F = 0.000
β_2	Qingdao	0.147	0.189	
β_3	Weifang	0.111	0.188	
δ	constant	−2.806		

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ACS Omega 2024, 9, 330−340

Table 10. Parameters and Statistical Testing of the PI Model in Weihai

independent variables	implication	coefficient	standardization coefficient	statistical testing
β_1	Yantai	0.701	0.973	AR^2 = 0.95, Sig F = 0.000
δ	constant	5.044		

from 0 to 10. It was also found that the concentrations of $PM_{2.5}$ in each surrounding city of the target city had different impacts on the target city. The ranking order of each surrounding city was determined by the standardization coefficient.

The model result in Dezhou is taken as an example. As shown in Table 5, the monthly mean $PM_{2.5}$ concentrations in the surrounding cities adjacent to Dezhou were positively correlated with the values in Dezhou. Liaocheng and Hengshui had more obvious impacts on Dezhou than other cities, with larger standardization coefficients. One of the reasons for this was that the average $PM_{2.5}$ concentration during the periods

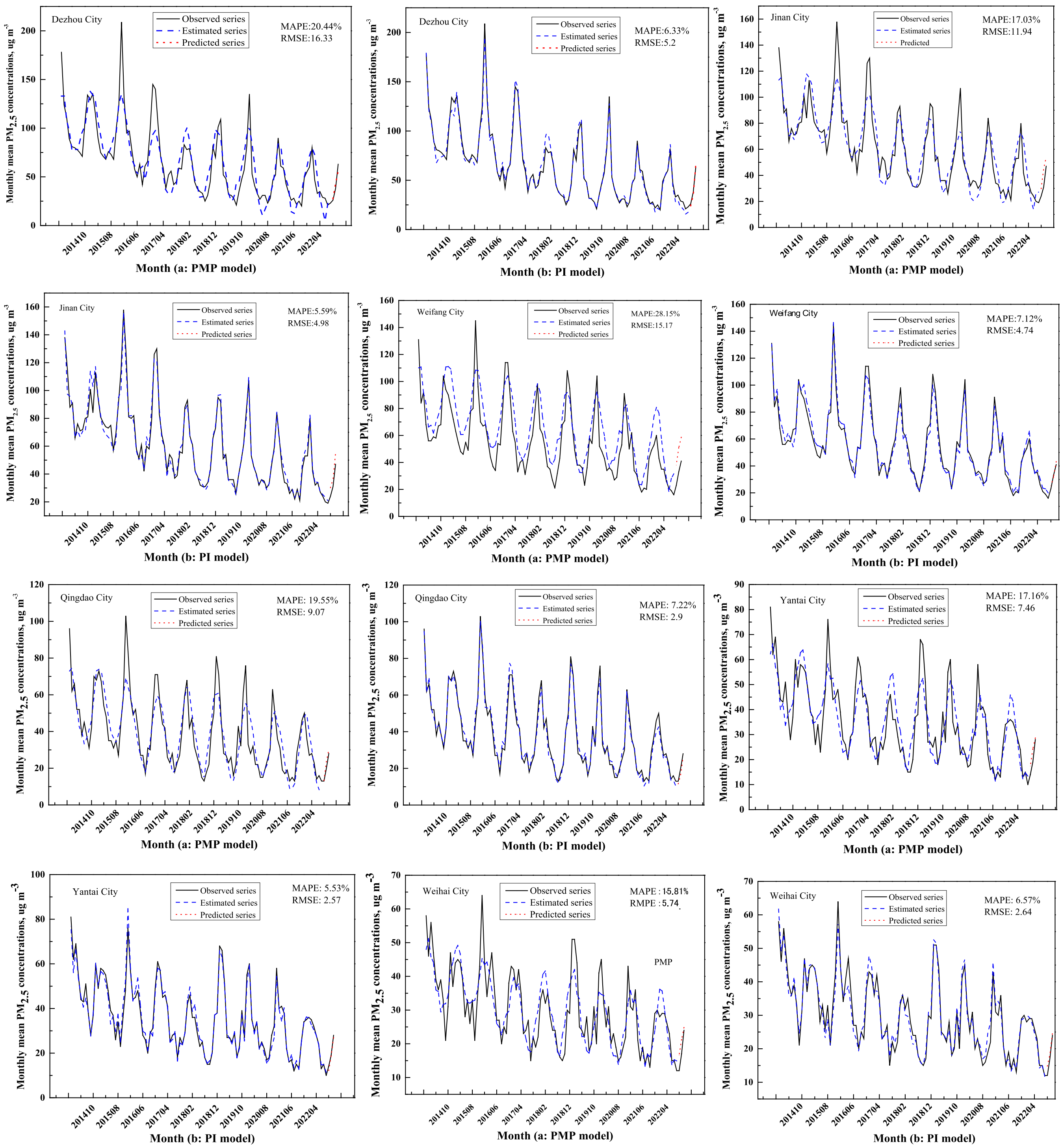

Figure 4. Monthly average $PM_{2.5}$ concentrations of actual, estimated, and predicted series in each city (a: PMP model and b: PI model).

was 67.3 $\mu g \cdot m^{-3}$ in Liaocheng and 68.6 $\mu g \cdot m^{-3}$ in Hengshui, which are higher than those in other cities. Higher levels of pollutants resulted in greater impacts on other cities.

For the city of Jinan, as shown in Table 6, Liaocheng, Binzhou, Dezhou, and Zibo had obvious positive impacts on the $PM_{2.5}$ concentration of Jinan, and the impacts of Liaocheng and Zibo were larger. However, Tai'an, a neighboring city to the south of Jinan, has a long border with Jinan, but the entire border is within the Taishan mountain range. The main peak of the Taishan, Yuhuangding, is 1532.7 m above sea level, blocking the mutual migration of pollutants. Therefore, the impact of pollution in Tai'an on pollution in Jinan was negligible and did not appear in the model.

In Yantai city, as shown in Table 9, the monthly mean $PM_{2.5}$ concentrations in the surrounding cities were positively correlated to those in Yantai. The annual $PM_{2.5}$ concentration in three surrounding cities in 2021 was 45.85 $\mu g \cdot m^{-3}$ in Weifang, 40.01 $\mu g \cdot m^{-3}$ in Qingdao, and 31.55 $\mu g \cdot m^{-3}$ in Weihai. According to the standardized coefficients, although Weihai had the lowest level of pollution, it had the most significant impact on the $PM_{2.5}$ concentrations of Yantai with the highest coefficient (0.635) due to its unique terrain advantages, temperate monsoon climate, and perennial stormy weather. Qingdao and Weifang had similar impacts on Yantai, and the coefficient of Qingdao city was slightly higher (0.189).

For the Weihai city, Yantai was the city with a significant impact, with a coefficient of 0.973.

Accordingly, in most cases, higher levels of pollutants resulted in greater impacts on other surrounding cities. Joint prevention and control between cities have become particularly important.

3.5. Extension Predictions. As mentioned above, the model construction period for each city was from January 2014 to August 2022. The prediction period of each model was extended to November 2022. The independent variables during the extended periods (September 2021−November 2022) were substituted in each model, and the predictions of the dependent variables of each city were obtained, called the extended prediction series. Subsequently, the series of observed, estimated, and extended predictions from the models were plotted in Figure 4 to examine the fitness of the predictions to the actual values. In each figure, black solid lines represented actual monthly $PM_{2.5}$ concentrations, "observed series", blue dashed lines represented "estimated series", and red dotted lines represented "extended predicted series". On the contrary, Figure 4 (a) in each city showed the result estimated from the PMP model and (b) was the result from the PI model. In addition, the MAPE and RMSE values of each model are shown in the figure to further assess the fitting accuracy of the models.

The inspection result was satisfactory. In each city, all of the model curves displayed good fitness with low MAPE and RMSE values, further confirming that the models were reasonable. The predicted values fit well with the observed values, suggesting a reasonable short-term prediction for each model. Furthermore, the results of the PI model of each city showed better fitness than the PMP model with lower MAPE and RMSE values. For example, in Yantai city, the MAPE and RMSE values of the PMP model were 17.16% and 7.46, respectively, while the corresponding values of the PI model were 5.53% and 2.57. The values decreased by 67.77% and 65.55%, respectively.

However, due to the increase in coal pollution during the heating season and unfavorable diffuse meteorological conditions, Shandong experienced heavy pollution weather in December 2015, resulting in large deviations in $PM_{2.5}$ concentrations in each city. The improvement in air quality in recent years was due to government efforts and improved meteorological conditions.[29] The sudden increase in the $PM_{2.5}$ concentration in January 2019 and 2020 may be related to the worse meteorological conditions. Therefore, the MAPE value was smaller, while the RMSE value was larger, showing a poorly fitting curve.

4. CONCLUSION

Based on the previous research, this paper conducted two models and applied them to six cities in Shandong Province. One model was called PMP to discuss the influence of meteorological factors and related environmental policies on $PM_{2.5}$ concentrations of target cities. The other model was PI to discuss the influence of surrounding cities on the target city. The main conclusions were the following:

(1) The monthly $PM_{2.5}$ concentration series displayed a similar trend in each city. The time-series analysis illustrated that the annual $PM_{2.5}$ concentrations gradually decreased in each city, although the respective degree of reduction in each year was different. The $PM_{2.5}$ problems in Dezhou and Jinan had improved the most with a larger reduction rate. However, the $PM_{2.5}$ problem in half of the target cities was still unsatisfactory, failing to meet the grade II standard (CAAQS).

(2) Meteorological factors, such as temperature, wind speed, and various environmental policies, had some influence on the change in $PM_{2.5}$ concentrations. Specifically, among the meteorological factors, temperature and wind speed were negatively correlated with $PM_{2.5}$ concentrations in all models, and the influence of temperature was greater. On the contrary, the joint implementation of different types of policies and measures played a crucial role in reducing $PM_{2.5}$ concentrations in each city. In all cities, the LAPAP law implemented in 2016 had a clear reducing influence on the $PM_{2.5}$ concentrations. However, of all the parameters, temperature had the greatest influence on $PM_{2.5}$ concentrations due to the largest standardization coefficient.

(3) $PM_{2.5}$ concentrations in cities surrounding the target city affected the target city differently. The predicted values fit well with the observed values with low MAPE and RMSE values, suggesting a reasonable short-term prediction for each model. Furthermore, the result of the PI model of each city showed better fitness than that of the PMP model.

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Notes

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