Research on the spatial effects of haze pollution on public health: spatial–temporal evidence from the Yangtze River Delta urban agglomerations, China

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Abstract

Haze pollution poses a serious threat to residents' health. In this study, a spatial econometric model of environmental health was established to investigate the direction, intensity, and spatial–temporal heterogeneity of the impact of haze pollution and its spillover effects on public health in 26 cities of the Yangtze River Delta urban agglomerations from 2005 to 2018. The study found that (1) PM_{2.5} pollution and public health level all show the characteristic of positive spatial correlation and spatial clustering. (2) Haze pollution is the main influencing factor of residents' public health level, with significant negative effects and obvious spillover effects. The urbanization rate, the number of health technicians, and the green area per capita have significant positive impacts on public health. (3) The spatial and temporal heterogeneity of the impact of haze pollution and other factors on public health is obvious. The negative correlation between PM_{2.5} pollution and public health in eastern cities is higher than that in other cities. Both urbanization rate and green area per capita have a greater positive impact on public health in the northeast of the Yangtze River Delta region. The improvement effect of the number of health technicians on the public health is stronger in the cities of Anhui Province. The research results of this paper provide certain support for the city governments to formulate targeted policies.

Keywords Haze pollution · Public health · Yangtze River Delta urban agglomerations · Spatial effects · Spatial correlation · Spatial and temporal heterogeneity

Introduction

For a long time, people have paid attention to economic growth but neglected the value of environmental resources, even at the expense of the environment to a certain extent,

resulting in increasingly prominent environmental pollution problems. In the last decade, the cost of environmental pollution control in China has reached 10% of GDP (Liu et al. 2017; Zeng et al. 2019b). As the largest developing country, the serious air pollution problem faced by China has become one of the major threats to the health status of the residents (Guan et al. 2016; Hunter, 2020). Global Burden of Diseases, Injuries, and Risk Factors Study reveals that PM_{2.5} ranks sixth among the level 4 of mortality risk factors (Murray et al. 2020). Despite the remarkable results of the implementation of China's "Air Pollution Prevention and Control Action Plan (2013–2017)," there are still 17 provinces where PM_{2.5} concentrations are not up to standard (Zheng and Xu, 2020). Numerous studies have confirmed that long-term exposure to PM_{2.5} pollution is associated with higher rates of COVID-19 transmission and mortality (Vasquez-Apestegui et al. 2021; Wu et al. 2020). Severe haze pollution is exposing people to major health risks. Moreover, the mobility of air makes the externality of pollution even more significant, and the regional pollution characteristics are obvious (Wang, 2014). It becomes very meaningful to consider the spatial

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relationship between the region and the surrounding areas when studying the environmental health effects. Therefore, the problem of air pollution in urban agglomerations is of great social relevance. It is necessary and urgent to deeply investigate the impact of PM_{2.5} pollution on public health in urban agglomerations.

As the most economically developed urban agglomerations in China, the Yangtze River Delta¹ (YRD) (Fig. 1) is one of the most severely polluted regions in China, and its air quality has always been a concern. With the booming economy of the region, severe haze pollution threatens public health as a by-product (Liu et al. 2020). PM_{2.5}, the primary air pollutant in the Yangtze River Delta region, decreased from an annual average concentration of 67 µg/m³ in 2013 to 46 µg/m³ in 2016, but it is still higher than the national standard, and the number of days exceeding the standard for PM_{2.5} in 2020 accounted for 50.7% of the total number of over-standard days (China, 2013; 2016; 2020). Long-term exposure to PM_{2.5} pollution caused 95,500 premature deaths per year in the Yangtze River Delta region from 2001 to 2017 (Lu et al. 2019). Therefore, severe haze pollution remains one of the urgent air pollution problems in the Yangtze River Delta urban agglomerations, and also one of the serious threats to the public health of residents. It is of great significance to study the impact of haze pollution on public health in the Yangtze River Delta urban agglomerations in China.

Research on the theme of environment and health has been paid more attention by the fields of medicine and environmental science. The economic loss caused by the impact of environmental pollution on health has also aroused the interest of policymakers and economists. The impact of the environment on health takes the health production function pioneered by Grossman (1972) as a starting point for research. Currently, studies are mainly carried out from the aspects of environmental health effects assessment, environmental health relationship, and environmental health differences. The assessment of environmental health effects includes two main aspects, namely the short-term (Chen et al. 2020b) and long-term (Lu et al., 2017) adverse health effects caused by air pollution and the economic losses caused by air pollution (Gao et al. 2015; Guan et al. 2019; Zheng et al. 2017). At the same time, a large number of scholars have focused on the relationship between the environment and health. Many studies have investigated the relationship between different air pollutants and related disease mortality using systematic review and meta-analysis (Fang

et al. 2016; Lu et al. 2015; Shah et al. 2015; Shang et al. 2013) and the Poisson distribution model (Liang et al. 2021; Shi et al. 2016), and found a significant positive correlation between the two (Jo et al. 2021; Peng et al. 2008; Pope, 1999). However, the Poisson regression.

model is not rigorous in calculating the health effects of air pollutants, and the endogenous problems of air pollution may cause certain errors (Knittel et al. 2016; Lleras-Muney, 2010). Scholars have thus used methods such as two-stage least squares or three-stage least squares to solve the endogenous problems (Knittel et al. 2016; Zhang et al. 2020). Moreover, air pollution is fluid (Cheng et al. 2017), and ignoring the spillover effects of air pollution will lead to serious deviations in the estimation results. Accordingly, scholars have analyzed the relationship between air pollution and health from the spatial perspective (Peng et al. 2021; Sun et al. 2021). Chen et al. (2017) and Zeng et al. (2019a) explored the direct and indirect effects of air pollution and its spillover effects on public health by constructing the spatial Durbin model. With the spread of COVID-19 around the world, some scholars have turned their attention to the study on the relationship between COVID-19, air pollution, and public health (Nakada and Urban, 2020; Nie et al. 2021). Benmarhnia (2020) and Travaglio et al. (2021) suggest that short-term and long-term exposure to air pollution, especially particulate matter pollution such as PM_{2.5}, may increase the risk of COVID-19 infection and mortality, and may increase vulnerability and have harmful effects on the prognosis of patients affected by COVID-19 infections (Ali and Islam, 2020). Iqbal et al. (2021) found that an average 1% increase in PM_{2.5} concentration resulted in an 11.67% increase in COVID-19 infections and an 18% increase in the number of COVID-19 deaths. In terms of research on regional differences in the health effects of air pollution, different scholars have conducted studies on different age groups, socio-economic factors, living environment, and other aspects, all of which found heterogeneity in the health performance of air pollution (Cakmak et al. 2016; Othman et al. 2014; Yang et al. 2021). Based on the Grossman health production function (Grossman, 1972), Feng et al. (2019) also found significant regional differences in the health effects of air pollution. Consequently, the heterogeneity of environmental health performance seems to revolve around individual differences (Moretti and Neidell, 2011), but in fact, it is closely related to factors such as economic development level and living environment.

It can be seen that a great deal of theoretical and empirical research has been done by predecessors, which has provided the basis and help for environmental governance in China and improvement of public health. However, there is still room for improvement and depth in the existing research. Previous multi-regional studies that have considered the mobility of air

¹ The Yangtze River Delta urban agglomerations include 26 cities: Shanghai, Nanjing, Wuxi, Changzhou, Suzhou, Nantong, Yancheng, Yangzhou, Zhenjiang, Taizhou, Hangzhou, Ningbo, Jiaxing, Huzhou, Shaoxing, Jinhua, Zhoushan, Taizhou*, Hefei, Wuhu, Maanshan, Tongling, Anqing, Chuzhou, Chizhou and Xuancheng. Among them, Taizhou in Jiangsu Province is denoted by Taizhou, and Taizhou in Zhejiang Province is denoted by Taizhou*.

Fig. 1 Study area

pollution have tended to focus on the provincial level, with fewer studies based on the urban scale. At the same time, the imbalance in economic development between regions and the huge differences between elements such as resource endowment, health care expenditure, air pollution, and policy systems make the issue of spatial and temporal heterogeneity of public health between regions impossible to ignore. In addition, existing studies tend to consider spatial dependence separately from spatial heterogeneity, and the research perspective is not yet comprehensive. Health is both the cornerstone of society and the result of social progress (Lancet, 2021). The impact of haze pollution on health deserves attention and discussion. Therefore, based on the fact that haze pollution has caused considerable damage to the health of the residents of the Yangtze River Delta urban agglomerations, the paper uses the macro health production function to comprehensively and systematically investigate the impact of haze pollution on public health in the Yangtze River Delta urban agglomerations from both the global and local perspectives. Moreover, through the construction of the spatial Durbin model and the panel spatiotemporal geographic weighted regression model, the paper analyzes the spillover effects of haze pollution in depth. In particular, the analysis of the temporal and spatial heterogeneity of environmental health between regions is not only a useful supplement to previous studies but also in line with the reality of the uneven distribution of regional economies and resources. The study found that haze pollution had a significant negative impact on the public health level of residents in the Yangtze River

Delta urban agglomerations, with significant spillover effects. It also found that the urbanization rate, the number of health technicians, and the green space per capita all had a significant positive effect on the level of public health. Moreover, the spatial and temporal heterogeneity of the impact of haze pollution, economic, social, medical and health care, and living factors on public health was obvious. On this basis, we put forward more scientific and targeted policy insights for different cities in the Yangtze River Delta urban agglomerations, to solve the outstanding environmental problems of haze pollution endangering public health and to contribute to the promotion of the strategy named “Health China 2030.”

Material and methods

Methods

Health production function

Grossman (1972) constructed a health production function based on the health micro-demand model to illustrate the relationship between health input and output. The model takes into account the impact of factors such as lifestyle, income level, public goods consumption, education, time investment, personal endowment, and environmental endowment on health. Since then, numerous scholars have devoted themselves to the study of factors affecting health. Cropper et al. (1981), Gerking and Stanley (1986) introduced

environmental pollution into the health production function and demonstrated the effect of pollution on the health depreciation rate. At the same time, considering China's national conditions, and referring to the studies of Wang and Chang (2007), Zhao and Hou (2005), and Qu and Yan (2015), from a macro perspective, it is determined that the factors affecting the health of Chinese residents are economic, social, health care, life, and environmental aspects. Therefore, the health production function of this paper is set as follows:

$$H = F(Eco, Soc, Hc, Life, Envi) \quad (1)$$

where H stands for public health level and Eco , Soc , Hc , $Life$, and $Envi$ represent economic, social, health care, life, and environmental factors respectively. Based on the selection of variable indicators, the following health production function expression is obtained in combination with Eq. (1).

$$\ln H = \ln \omega + \alpha_1 \ln PM_{2.5} + \alpha_2 \ln X_{control} \quad (2)$$

Among them, ω refers to the estimated value of the initial public health level, α_i is the elastic coefficient of each variable, $PM_{2.5}$ is the annual average concentration of environmental $PM_{2.5}$, and $X_{control}$ represents a series of control variables Eq. (2).

Global spatial econometric model

Considering that air pollution does not exist independently, the mutual flow of air pollution will pose a certain threat to the health of residents in neighboring cities. Traditional econometrics does not consider the spatial correlation between subjects, and the estimation results may be biased. Therefore, this paper uses the global spatial econometric model to consider the impact of haze pollution on public health at the macro level. Different spatial econometric models are set up with different spatial transmission mechanisms, and their indicators represent different economic meanings. To make the research process more scientific and reasonable, this paper starts with the spatial Durbin model (SDM), which is a nested form of the spatial error model (SEM) and the spatial lag model (SLM), and its expression is displayed as follows:

$$\ln H_{it} = \beta_0 + \theta W \ln H_{it} + \beta_1 \ln PM_{2.5it} + \beta_2 \ln X_{control} + \gamma_1 W \ln PM_{2.5it} + \gamma_2 W \ln X_{control} + a_i + \eta_t + \varepsilon_{it} \quad (3)$$

where H_{it} is the explanatory variable, indicating the public health level of the residents, and $X_{control}$ represents economic, social, health care, and life factor variables related to health level. $\beta_0\theta$, and ε_{it} denote the constant term, the spatial autoregressive coefficient, and the independent and identically distributed random error term, respectively. a_i and η_t indicate spatial and temporal fixed effect respectively, in the meantime, and γ_i correspond to the estimated coefficients of

spatial variables. W means the spatial weight, and this paper chooses the geographic Queen adjacency matrix for analysis.

Local spatial econometric model

The study of the impact of haze pollution on the public health of residents is still one-sided only from a global perspective. What cannot be ignored is the temporal and spatial non-stationarity of the data. Considering the issue of heterogeneity in the relationship between local point variables in public health level accounting, it is necessary to choose an empirical tool to describe the heterogeneity of time and space. Fan and Guo (2021) identified the inherent flaws in the traditional modeling process of the spatial-temporal geographic weighted regression model (GTWR) (Huang et al. 2010). By constructing an endogenous spatiotemporal weight matrix adapted to the local analysis of panel data spatial measurement, a holographic mapping-based spatiotemporal geographic weighted regression model capable of reflecting direct and indirect paths of influence effects between local points in space was established. As a result, this paper starts with the panel spatiotemporal geographic weighted regression model (PGTWR) to consider the spatiotemporal heterogeneity of the impact of haze pollution on the public health of residents, and its expression is applied as:

$$\ln H(u_j, v_j, t_j) = \rho_0(u_j, v_j, t_j) + \rho_1(u_j, v_j, t_j) \ln PM_{2.5} + \rho_2(u_j, v_j, t_j) \ln X_{control} + \mu(u_j, v_j, t_j) \quad (4)$$

Among them, H and $X_{control}$ have the same meaning as formula (3). (u_j, v_j, t_j) denotes a local point and u_j is the longitude of local point j , v_j is the latitude of local point j , and t_j is the time of local point j . $\rho_0(u_j, v_j, t_j)$, $\rho_1(u_j, v_j, t_j)$, and $\rho_2(u_j, v_j, t_j)$ are exogenous parameters at the specific spatial and temporal point (u_j, v_j, t_j) , $\rho_1(u_j, v_j, t_j)$ and $\rho_2(u_j, v_j, t_j)$ are the local effects of $PM_{2.5}$ concentration and related control variables on the public health level, respectively. $\mu(u_j, v_j, t_j)$ is the random disturbance term Eq. (4).

Spatial autocorrelation test model

The spatial autocorrelation test is mainly divided into spatial correlation test and spatial heterogeneity test. The spatial correlation of air pollution and public health between regions is reflected in the mutual influence of the $PM_{2.5}$ concentration value and the number of deaths from respiratory diseases between adjacent regions. In addition, the spatial heterogeneity of air pollution and public health between regions is reflected in the lack of spatial homogeneity in $PM_{2.5}$ concentration and the number of deaths from respiratory diseases. Therefore, the global Moran's I and the local Moran's I are selected for the correlation test

in this paper. The global Moran's I is used to test whether there is a spatial autocorrelation effect in socio-economic phenomena. The formula is as follows:

$$\text{Moran's } I = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{s^2 \sum_{i=1}^n \sum_{j=1}^n W_{ij}} \quad (5)$$

where $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$, $s^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n}$. n denotes the number of spatial administrative districts investigating the economic phenomenon, and the corresponding regional feature value is represented by X_i . W_{ij} is a spatial weight to measure the spatial correlation of economic phenomena. If the value of Moran's I is in the range (0, 1), it means that the variable has a positive spatial correlation, and the more it converges to 1, the stronger the correlation is. Similarly, if Moran's I takes a value in the range (−1, 0), then the variable has a negative spatial correlation, and the closer to −1, the stronger the negative correlation. If the value of Moran's I is 0, it suggests that the variable is randomly distributed and there is no spatial effect.

The global spatial autocorrelation of socio-economic phenomena is measured by the global Moran's I index. Since economic phenomena tend to be spatially unbalanced (Xu and Lin, 2021), to reveal this imbalance, the use of local Moran's I is apt to show spatial heterogeneity (Anselin, 1995). The formula is as follows:

$$\text{Local Moran's } I = \frac{(x_i - \bar{x})}{s^2} \sum_{j=1}^n W_{ij} (x_j - \bar{x}) \quad (6)$$

Among them, the indicators are the same as formula (5). In this paper, the geographic Queen adjacency matrix is selected for correlation analysis Eq. (5) and Eq. (6).

Data

In this paper, data from a sample of 26 cities in the Yangtze River Delta region of China from 2005 to 2018 is selected to analyze the impact of environmental and other factors on public health. Therefore, the variables that define each factor are shown in Appendix Table 1.

Selection of explained variables

The selection of health indicators in the health production function is crucial. At present, a large amount of literature selects indicators such as mortality, respiratory disease mortality, lung cancer mortality, and perinatal infant mortality to characterize public health. Studies have shown that respiratory diseases caused by haze pollution are long-term chronic

diseases, and people with respiratory diseases are extremely susceptible to the effects of particulate matter (PM) (Manisalidis et al. 2020). $PM_{2.5}$ can cause serious damage to multiple systems in the body, with a significant increase in the incidence of respiratory symptoms (Guo and Wei, 2013). Consequently, this paper chooses the number of deaths from respiratory diseases that is more representative of $PM_{2.5}$ pollution as a proxy indicator of public health.

Selection of core explanatory variable

In this paper, the annual average $PM_{2.5}$ concentration is selected as a proxy indicator for environmental factors and at the same time as the core explanatory variable. The main reasons are as follows: firstly, compared with other environmental factors, the air environment is more exogenous and overflowing, which reduces the endogenous problem to a certain extent. Secondly, the probability of the national population as a whole being exposed to the air environment is higher than in other environmental factors, which to some extent compensates for the possible shortcomings of using macro data (Lu and Qi, 2013). Thirdly, a large number of epidemiological studies have confirmed that haze pollution is harmful to public health, and $PM_{2.5}$ is the primary pollutant in the frequent occurrence of atmospheric haze nationwide, showing typical regional characteristics (Zhou et al. 2017).

Selection of control variables

It is mainly considered from the four aspects of the economy, society, health care, and life. They are characterized by per capita disposable income of urban households (Miao, 2008), urbanization rate (Zhao, 2012), population density (Chen and Chen, 2014), number of health technicians per ten thousand people (Feng et al. 2019), per capita expenditure on health care in urban households (Sun et al. 2021), and green space per capita (Ruan et al. 2020).

Among them, the $PM_{2.5}$ concentration comes from the $PM_{2.5}$ concentration dataset obtained by the Atmospheric Composition Analysis Group of Dalhousie University in Canada (van Donkelaar et al. 2019). The remaining variables are obtained from "China Statistical Yearbook," "China City Statistical Yearbook," statistical yearbooks of various provinces and cities, statistical bulletins of national economic and social development of various cities, the official websites of statistical bureaus of various provinces and cities, "China Health Statistics Yearbook," Jiangsu provincial Center for Disease Control and Prevention (jscdc.cn), and EPS database. After that, the scale model of the exposure–response relationship and Poisson distribution is used to calculate the number of deaths from respiratory diseases in the exposed population (Zhou

et al., 2021). For indicator data that cannot be directly obtained, it is acquired by the conversion of the original data. Economic data have been adjusted with 2005 as the base period to eliminate the impact of price inflation. Also, all variables in this paper are taken as natural logarithms to control the influence of heteroscedasticity.

Results and discussion

Spatial autocorrelation test

Global spatial autocorrelation test

With the help of GeoDa software, the global Moran's I index was used to explore the clustering or correlation characteristic of the spatial distribution of respiratory disease deaths and PM_{2.5} pollution, and the results are shown in Fig. 2. The test results show that the Moran's I index of public health indicator is positive, and passes the 10% significance test. The Moran's I index over the years ranges from 0.110 to 0.236, indicating the spatial clustering of cities with a similar level of public health. On the other hand, the Moran's I index for PM_{2.5} pollution is positive from 2005 to 2018 and passes the 1% significance test. The Moran's I index fluctuated upwards between 0.585 and 0.763 from 2012 to 2018, implying that haze pollution presented the strong spatial clustering characteristic that continued to increase. That is, cities with more serious haze pollution tend to be spatially clustered, and cities with lighter haze pollution tend to be clustered in space, which is consistent with the research of Li et al. (2018). To sum up, the spatial correlation of haze

pollution and public health are both positive, and the spatial clustering of haze pollution is relatively stronger.

Local spatial autocorrelation test

To further detect the local clustering of respiratory disease deaths and PM_{2.5} pollution, the local Moran's I test was used. Using ArcGIS and GeoDa software, Fig. 3 demonstrates the concentration maps of 2005, 2011, and 2018. According to the local Moran's I scatter plots, the local clustering characteristic of both respiratory disease deaths and PM_{2.5} pollution are dominated by high–high clustering and low–low clustering. In terms of public health, high–high clustering cities are located in Nantong, Suzhou, and Shanghai, and the clustering trend has not changed significantly during the study period. High-high clustering cities with PM_{2.5} pollution are mainly distributed in the northwest part of YRD such as Wuhu, Hefei, Nanjing, and other cities. It may be due to the diffusion of air pollution caused by the development of heavy industry in the region, which in turn causes the intensification of haze pollution in neighboring regions. Meanwhile, low-low clustering cities show an upward trend in the time dimension, with 4, 4, and 6 cities in 2005, 2011, and 2018, respectively, mainly in part of the southeast of the YRD such as Shaoxing, Jinhua, Ningbo, and Taizhou. It may depend on the fact that industrial activity is less developed and polluting enterprises are few and scattered, which is conducive to the formation of low-level PM_{2.5} pollution clustering areas. Therefore, the public health level and PM_{2.5} pollution are not randomly distributed among cities in the Yangtze River Delta urban agglomerations but are characterized by spatial correlation and spatial clustering.

Fig. 2 Recognition of spatial correlation between air pollution and public health. H stands for public health level. The 10%, 5%, and 1% significance levels are represented by the *, **, and ***, respectively

Regression results without considering spatial feature

Before the parameter estimation, first of all, this paper set up the ordinary panel model for regression analysis without considering spatial effect. Then, the *F* test was performed, along with the classic LM test proposed by Anselin and Griffith (1988) and the robust LM test proposed by Anselin and Smirnov (1996). By judging the spatial correlation of lag or residual terms, the SEM was deemed more appropriate. The joint significance of spatial and temporal fixed effect was also examined and it confirmed that model with time and space fixed effect should be expanded through the likelihood ratio test result. Based on the estimation results in Appendix Table 2, it is found that the core explanatory variable PM_{2.5} pollution had a significant positive effect on the number of deaths from respiratory diseases. And the coefficient is between 1.3478 and 1.6933, which is relatively stable. The results of the estimation of the control variables show that the majority of the estimates pass the significance test.

Among them, the number of health technicians per ten thousand people and the green space per capita both have significant positive effects on the deaths from respiratory diseases, with elasticity coefficients of -0.5455 and -0.0816 for dual fixed effect of time and space, respectively.

Spatial correlation study

Estimation and analysis of spatial Durbin model

The tests in “Regression results without considering spatial feature” section all point to SEM with dual fixed effect. However, according to LeSage and Pace (2009), even if the non-spatial model is rejected in favor of SLM or SEM based on the LM test, Wald and LR tests are still required and the SDM model is preferred. Thus, this paper used the SDM model under the dual fixed effect as a paradigm for Wald estimation and LR test to determine whether the SDM model can be degraded to a simple SEM model. The test results in Appendix Table 3 show that the null hypotheses of $\gamma = 0$ and $\gamma + \theta\beta = 0$ are rejected for both the Wald and LR statistics, indicating that the SDM is more reasonable. Afterwards, the SDM model was also subjected to the Hausman test and the null hypothesis was significantly rejected, so the SDM model under fixed effect was chosen for analysis. According to the results of the spatial Durbin model with different fixed effect in Appendix Table 3, it is found that the statistical properties of the model with dual fixed effect in time and space are optimal. To obtain more accurate parameter estimation, the spatial Durbin model with the dual fixed effect (including error correction) was chosen for the estimation analysis, taking into account that Lee and Yu (2010b), Lee and Yu (2010a), and Lee and Yu (2014) pointed out that the parameters in the fixed effect model may cause estimation errors.

The effect of the core explanatory variable on public health

The impact of $PM_{2.5}$ pollution on the number of deaths from respiratory diseases passed the 1% significance test and the elasticity coefficient was positive, indicating that the increase in haze pollution had a significant positive impact on the increase in the number of deaths from respiratory diseases among the population. The essential reason for this is still the serious air pollution problem in the region. For a long time, the coal-based energy structure in the Yangtze River Delta has not changed fundamentally, and the region's heavy industry accounts for a relatively large proportion, with the establishment of a large number of heavy industrial plants leading to a continuous decline in air quality (He et al., 2019). Coupled with the emission of vehicle exhaust, the aggravation of atmospheric pollution such as haze, acid rain, etc., poses a greater threat to the public health of residents, which greatly increases the risk of residents suffering from respiratory diseases (Chen et al. 2020a).

The effect of control variables on public health

The urbanization rate, the number of health technicians per ten thousand people, and the green space per capita all passed the 1% significance test, while other variables were not significant. In particular, the urbanization rate had a negative effect on the number of deaths from respiratory diseases, which is consistent with Wang and Chang (2007). The urban–rural gap has led to large differences in medical and health facilities between urban and rural areas, which in turn has a significant impact on the differences in public health between urban and rural residents. The increase in the number of health technicians per ten thousand people is conducive to the improvement of public health. The continuous improvement of medical equipment and the overall quality of health technicians have created a good treatment environment, thereby providing great convenience for patients to see and treat. Therefore, the increase of health technicians plays an important role in the improvement of public health. The effect of green space per capita on the number of deaths from respiratory diseases showed a significant negative effect, which is in line with the findings of Sun and Li (2017). Good environmental quality is not only favorable for purifying the air but also makes residents physically and mentally happy and helps to improve their health levels. The negative effect of per capita disposable income of urban households on the number of deaths from respiratory diseases was not significant. It may be on account of a series of unhealthy lifestyle habits caused by the growing economy and the rising standard of living, which has led to the decline in public health. Additionally, the positive effect of population density on the level of public health of the population was not significant. The agglomeration effect of population density was stronger than its scale effect, which facilitated local residents to make full use of health facilities and other services within the constraints of a certain health budget, thus exerting the positive externality effect of the agglomeration effect. In the meantime, per capita expenditure on health care in urban households had a negative but non-significant effect on the number of deaths from respiratory diseases. In the context of rapid economic development, despite increasing health care expenditure, the limited health care expenditure has made little improvement in health in the environment of scarce high-quality medical facilities and rising health care cost.

From the perspective of the spatial lag term, it characterized the impact of the explanatory variables of a certain city's neighboring cities on the level of public health in the region. According to the statistical results in Appendix Table 3, the coefficients of $PM_{2.5}$ pollution and green space per capita were significantly negative, and the coefficient of urbanization rate was significantly positive, while the spillover of other independent variables was not significant. It suggested that the interactive effect of pollution in urban agglomerations

(a)

(b)

(c)

(d)

(e)

(f)

Fig. 3 Local Moran's I index of **a** respiratory disease deaths in 2005; **b** PM_{2.5} concentration in 2005; **c** respiratory disease deaths in 2011; **d** PM_{2.5} concentration in 2011; **e** respiratory disease deaths in 2018; **f** PM_{2.5} concentration in 2018

was beneficial in reducing the number of deaths from respiratory diseases caused by haze pollution among residents. The increase in the green area in neighboring areas also had a beneficial impact on the health of residents, indicating that the planting of green plants not only beautifies the environment but also purifies the air for human beings and creates a pleasant living environment. In addition, the rising in the urbanization rate in neighboring regions increased the burden on the health level of the residents, which may be related to the continuous generation of pollutants such as exhaust gases and sewage in the process of urbanization.

Decomposition of spatial effect

Given the presence of spatial spillover effects, the impact of each factor on the number of deaths from respiratory diseases was further decomposed and its direct, indirect, and total effects are shown in Table 4.

According to the results of direct effect, the impact of PM_{2.5} pollution on the health level of the residents was still significantly negative. At the same time, the coefficient of 1.5057 under the direct effect is inconsistent with its estimated coefficient of 1.5740, because the direct effect takes into account both the impact of PM_{2.5} pollution in the neighboring area on the public health of the region and the feedback effect of the transmission of PM_{2.5} pollution in the region on the health effect in neighboring regions back to the region. The urbanization rate, the number of health technicians per ten thousand people, and the green space per capita all had a significant negative effect on the number of deaths from respiratory diseases, while the other variables were not significant. Of these, the number of health technicians had the greatest impact, indicating that the training of medical and health personnel should be taken into account even more in conjunction with vigorously advancing the process of urbanization.

As a result of the indirect effect, PM_{2.5} concentration had a significant positive effect on the public health level of residents in neighboring cities. It means that the PM_{2.5} pollution in a certain city was aggravated, and then the air pollution in its neighboring cities was relatively reduced, which had a beneficial impact on the health of residents in neighboring cities. The rise in the number of health technicians and the green space per capita was good for the public health of the neighboring cities. It shows that the improvement of medical services and green areas in the region had not only improved the quality of life of residents in neighboring cities, but also attracted neighboring residents to seek medical treatment in the region, in the case

of inadequate medical resources in neighboring cities, and ensured that people are treated for their illnesses. Additionally, the increase in the urbanization rate may inhibit the improvement in the health of residents in neighboring cities, while the effects of other factors were not significant. The reason for this may be that under the traditional urbanization development model, environmental problems such as heavy traffic and increased air pollution have adversely affected the health of residents in neighboring cities.

The results of the total effect show that the increase in PM_{2.5} concentration has a significant negative effect on public health. The number of health technicians per ten thousand people and the green space per capita both passed the 1% significance test for the positive impact of public health, while the effects of other factors were not significant.

Robustness test

In this study, the geographic Queen adjacency matrix was used to analyze the impact of PM_{2.5} pollution on the public health of residents. However, to avoid errors caused by the selection of the spatial weight matrix, a nested spatial weight matrix based on the Queen space nearest neighbor relations and economic scale was selected for analysis, taking into account economic factors and using GDP per capita as its proxy variable. The results of estimating the spatial spillover effects of variables such as PM_{2.5} concentration on the public health level of the residents under this spatial weight matrix with a dual fixed effect SDM model (including error correction) are further reported. It can be seen from Appendix Table 5 that the concentration of PM_{2.5} still presented a significant negative effect on public health. And yet the effect of per capita expenditure on health care in urban households was opposite to the above result, but its effect was not significant. Moreover, the other control variables only differ in the size of the overflow, the direction of the overflow does not change. On this ground, the robustness analysis results are consistent with the above results, indicating that the results are stable and reliable.

Spatial-temporal heterogeneity study

Estimation analysis of panel spatiotemporal geographic weighted regression model

To empirically demonstrate the temporal and spatial distribution of deaths from respiratory diseases under the influence of different environmental, economic, social, health care, and life factors, this paper constructed the PGTWR model to investigate the spatial and temporal heterogeneity of public health of cities in the Yangtze River Delta urban agglomerations. The variance inflation factor was also used to know that there was no multicollinearity in the indicators selected in this paper. Due to the weak diagnosis results of

the spatiotemporal geographic weighted regression model, this paper chose to incorporate OLS and GWR models for analysis and to compare the accuracy of the results. The annual average of each indicator from 2005 to 2018 is selected as the new cross-sectional data for GWR analysis, and we perform Gaussian, exponential, and tricube analyses according to the different choices of the kernel function. As shown in Appendix Table 6, the adjusted goodness of fit of the panel spatiotemporal geographic weighted regression model is higher, indicating that the PGTWR model is more suitable for the dataset in this paper.

The PGTWR model was used and the corresponding standardized program was run through MATLAB R2018a. Based on the AICc criterion, the GCV criterion, and the RSS criterion, the optimal spatial bandwidth for this dataset was determined to be 26 and the optimal temporal bandwidth to be 14. It reveals that in the estimation of the public health level of the residents in the Yangtze River Delta urban agglomerations, the number of deaths from respiratory diseases in a given city is not only affected by the health of the residents from other cities, but also by the number of deaths from respiratory diseases in that city in previous years, with an effective influence period time of 14 years. Given the above determination of the optimal spatial and temporal bandwidths, the overall statistical properties of the PGTWR model are shown in Appendix Table 7. It is worth pointing out that this paper discusses the impact of haze pollution on public health in the Yangtze River Delta urban agglomerations, which incorporates all spatial units, so the PGTWR model with random effect is not considered. According to the results of the overall statistical properties of the models with different effects, the model with spatial fixed effect embodied good statistical properties. The model under spatial effect has a significant ratio of 67.27% for the local coefficient estimates, the adjusted goodness of fit of 0.9902, and its estimated value of the variance of random disturbance term, CV criterion value, GCV criterion value, and AICc criterion value are smaller, and the F statistic passes the hypothesis test with a significance level of 1%. In consequence, the spatial fixed effect is more appropriate for the dataset in this paper, and the analysis is carried out according to its parameter results.

The calculation results of PGTWR with spatial fixed effect are shown in Appendix Table 8. Based on the absolute value of the mean of the regression coefficients of each indicator, it is found that PM_{2.5} pollution has the greatest impact on the level of public health, followed by per capita expenditure on health care in urban households, per capita disposable income of urban households, urbanization rate, and the number of health technicians per ten thousand people. By contrast, the green space per capita and population density have a less intense impact on public health.

Spatial and temporal differences in the impact of various factors on public health

The PGTWR model was used to study the spatial and temporal heterogeneity of the influence of environmental factors, economic factors, social factors, health care factors, and life factors on the level of public health. The revealed temporal and spatial differences are shown in Figs. 4 and 5.

Figure 4a presents PM_{2.5} pollution regression coefficients that are all positive, consistent with the results in the global analysis, indicating that the intensification in PM_{2.5} pollution has an inhibitory effect on the improvement of residents' health. Moreover, the public health level of residents from 2006 to 2009 was greatly affected by haze pollution. The average coefficient for each city was 1.274 in 2005, rising to 1.383 in 2018, manifesting that the impact of PM_{2.5} pollution on health level has increased in the time dimension. Fig. 5a plots the spatial distribution of the average coefficient of PM_{2.5} pollution and shows that there are significant regional differences in the impact of PM_{2.5} pollution on health. The cities with the highest correlation between PM_{2.5} pollution and public health level are mainly located in the eastern region of the YRD, including Taizhou* (1.5421), Ningbo (1.5104), Yancheng (1.4999), Taizhou (1.4779), and Shanghai (1.4764). It may be related to the distribution of PM_{2.5} pollution in the Yangtze River Delta urban agglomerations, with higher PM_{2.5} concentration in northwestern cities such as Hefei, Maanshan, Wuhu, Nanjing, and Yangzhou, and lower PM_{2.5} pollution level in eastern cities. Once air pollution intensifies, the public health of residents in eastern cities is at greater risk and will be more sensitive to change in PM_{2.5} pollution.

According to Fig. 4b, the regression coefficients of per capita disposable income of urban households are all positive, which is in accordance with the results of the global analysis, demonstrating that there was a negative effect of per capita disposable income of urban households on public health. The impact of per capita disposable income of urban households on public health was greater in Chizhou, Anqing, Tongling, and Hefei from 2009 to 2018, and given that the average coefficient for each city was 0.632 in 2005, rising to 0.713 in 2018, the impact increased in the time dimension. Fig. 5b presents clear regional differences in the impact of per capita disposable income of urban households on public health. The cities with the highest correlation between the two are mainly located in western YRD cities such as Anqing (0.8937), Chizhou (0.8782), Hefei (0.8720), Tongling (0.8646), and Wuhu (0.8184).

Figure 4c indicates that the increase in the level of urbanization rate is conducive to the improvement of residents' health. In 2005, the average coefficient of each city was −0.406, and in 2018 it dropped to −0.383, reflecting the weakening of the impact of urbanization rate on health level in the time dimension. According to the spatial distribution

of the average coefficient of Fig. 5c, it is found that the cities with the higher correlation between urbanization rate and public health level are mainly located in the northeastern region of YRD, consisting of Yancheng (-0.5641), Taizhou (-0.4834), Yangzhou (-0.4650), Zhenjiang (-0.4478), Nantong (-0.4356), and other cities.

Figure 4d shows that the regression coefficients of population density are negative except for the coefficient of Ningbo, Zhoushan, and Shanghai in 2007, indicating that the increase of population density has a certain contribution to the improvement of public health. The average elasticity coefficient of population density to health level was -0.223 in 2005 and -0.068 in 2018, revealing that the intensity of the effect of population density on health level has weakened over time and that the intensity of the effect was greater in 2005 and 2006 during the study period. From Fig. 5d, it can be seen that the northern YRD cities of Yancheng (-0.1492), Chuzhou (-0.1353), Yangzhou (-0.1334), Nanjing (-0.1250), and Taizhou (-0.1243) are the regions with a high correlation between population density and public health level.

Figure 4e displays the regression coefficients of the number of health technicians per ten thousand people are all negative, in line with the results of the global analysis, which describe that the increase in the number of health technicians makes for the improvement of residents' health. It is worth noting that the average coefficient for each city in 2005 was -0.264 , and it decreased to -0.411 in 2018. The positive effect of the number of health technicians on the public health level is not only enhanced in the time dimension, but its enhancement reached 0.147 . Fig. 5e shows significant regional differences in the impact of the number of health technicians on the level of public health, with a trend of weakening from west to east. Moreover, the cities whose public health level is greatly affected by the number of health technicians are mainly located in the cities of Anhui Province, such as Anqing (-0.6774), Chizhou (-0.6419), Hefei (-0.6339), Tongling (-0.6151), and Wuhu (-0.5324).

It can be seen from Fig. 4f that the elasticity coefficients of per capita expenditure on health care in urban households are all negative, supporting the results of the global analysis. And the intensity of the impact of per capita health care expenditure on health levels was -0.118 in 2005, rising to -0.102 in 2018, with a weak change overall. According to Fig. 5f, it can be learned that the impact of per capita health care expenditure on public health has regional differences, and the major cities with a greater impact are mainly in Anhui Province, such as Anqing (-0.2588), Chizhou (-0.2399), Hefei (-0.2332), Tongling (-0.2257), and Wuhu (-0.1870).

Figure 4g details regression coefficients of green space per capita. The regression coefficients of green space per capita in the analysis by the PGTWR model are all negative except for Anqing in 2006 and 2007, revealing that good quality of the living environment is conducive to the improvement of

residents' public health. On the whole, the level of public health of residents in most cities was influenced to a greater extent by green space per capita from 2009 to 2018. The average coefficient for municipalities was -0.0523 in 2005 and decreased to -0.0860 in 2018. Fig. 5g shows the spatial distribution of the average coefficient of green area per capita. It is also found that the cities with the highest correlation between green space per capita and public health level were mainly distributed in the northeast region of YRD, consisting of Nantong (-0.0938), Suzhou (-0.0921), Wuxi (-0.0919), Shanghai (-0.0899), Changzhou (-0.0898), and so on.

Conclusions and policy implications

Based on the above empirical analyses, the main conclusions of this paper are as follows:

1. $PM_{2.5}$ pollution and public health level are not randomly distributed among cities in the Yangtze River Delta urban agglomerations but are characterized by spatial positive correlation and spatial clustering. And the local clustering of public health level is not significant. Relatively speaking, $PM_{2.5}$ pollution has the obvious characteristic of local clustering. The cities of Wuhu, Hefei, and Nanjing are high-high clustering areas for $PM_{2.5}$ pollution, while cities such as Shaoxing, Jinhua, Ningbo, and Taizhou are low-low clustering areas for $PM_{2.5}$ pollution.
2. Based on the results of SDM estimation, it is found from the global perspective of spatial econometrics that $PM_{2.5}$ pollution has a significant impact on the level of public health. Taking into account environmental, economic, social, health care, and life factors, $PM_{2.5}$ pollution is the main factor affecting the health level of residents, regardless of whether the spatial effect is included. Furthermore, the indirect effect coefficient of $PM_{2.5}$ pollution is significant at -0.8818 , indicating that the increase of $PM_{2.5}$ pollution in the city can have a beneficial effect on the public health of neighboring cities, and the spillover effects are significant. Among them, the urbanization rate, the number of health technicians per ten thousand people, and the green space per capita have a significant positive effect on the public health level, with each 1% increase being associated with 0.5680%, 0.4984%, and 0.0851% reduction in the number of deaths from respiratory diseases respectively. Besides, the effects of per capita disposable income of urban households, population density, and per capita expenditure on health care in urban households on public health were limited and not significant.

As a result, based on the above conclusions, this paper puts forward the following suggestions: (a) Pay attention to inter-city collaboration, improving the coordination mechanism of regional air pollution joint prevention and

(a)

(b)

(c)

(d)

(e)

(f)

(g)

Fig. 4 Coefficients for each region at different times. **a** Coefficients of $PM_{2.5}$ pollution ($PM_{2.5}$); **b** coefficients of per capita disposable income of urban households (PDI); **c** coefficients of urbanization rate (urban); **d** coefficients of population density (pd); **e** coefficients of number of health technicians per ten thousand people (num_tech); **f** coefficients of per capita expenditure on health care in urban households (hpe); **g** coefficients of green space per capita (green)

control, actively building cross-regional air pollution prevention and control command institutions, establishing the air pollution hotspot grid supervision system, and strengthening the whole process of collaborative supervision in order to reinforce the effective management of haze pollution. (b) Increase the investment in health care and actively train high-quality health technicians to improve the quality and efficiency of medical services, and improve and implement the diversified and comprehensive regulatory system for the health care industry to create a good medical environment for patients. (c) Strengthen the protection of the urban and rural ecological environment, strictly prohibit deforestation, actively expand the green area, while reinforcing the management of landscaping construction and improving the supervision of landscaping to create a good living environment for residents. (d) Lay stress on alleviating the trend of environmental pollution in the process of promoting urbanization and realizing environmental regulation of new-type urbanization to promote high-quality, healthy, and green development of urbanization.

3. In the light of the estimation results of the PGTWR model, a spatial-temporal analysis of the regression coefficients of each indicator is carried out. From the local spatial econometric perspective, it reveals that the impact of environmental, economic, social, health care, and life factors on public health level presents obvious temporal and spatial heterogeneity, leading to distinctly different public health problems in different cities. Among them, in terms of environmental factors, the public health level of cities such as Taizhou*, Ningbo, Yancheng, Taizhou, and Shanghai are greatly affected by $PM_{2.5}$ pollution. As for social factors, changes in the level of urbanization have a greater impact on the public health of cities such as Yancheng, Taizhou, Yangzhou, Zhenjiang, and Nantong. Additionally, concerning health care factors, cities where the number of health technicians has a greater impact on public health, include Anqing, Chizhou, Hefei, Tongling, and Wuhu. Referring to life factors, public health is strongly influenced by the green space per capita mainly in the cities of Nantong, Suzhou, Wuxi, Shanghai, and Changzhou. It is worth noting that the impact of $PM_{2.5}$ pollution, the number of health technicians, and the per capita green area on public health has increased over time. Of these, the strongest enhancement was in the number of health

technicians, whose impact intensity increased by 0.147, implying that more attention should be paid to the training of medical and health personnel.

Moreover, since the coefficients of various indicators show temporal and spatial heterogeneity, the differences in the degree of influence of different indicators should be considered when developing countermeasures against haze pollution. (a) Firstly, for cities such as Yancheng, Taizhou, Yangzhou, Zhenjiang, and Nantong, the city governments should actively promote new-type urbanization to take advantage of the population gathering and industrial agglomeration effects it brings. At the same time, the governments are supposed to promote the development of public services such as medical care and education to further improve the public health level of residents. (b) Secondly, in cities such as Anqing, Chizhou, Hefei, Tongling, and Wuhu, the city governments should strengthen the training of health care professionals and encourage the development of health care to gradually improve the level of medical and health services due to the imperfect medical facilities and services in the cities. (c) Thirdly, the city governments of Nantong, Suzhou, Wuxi, Shanghai, and Changzhou should step up environmental protection efforts, and pay attention to the improvement and effective implementation of air governance policies. At the same time, the governments are ought to strengthen the construction of urban and rural parks, and rationalize the arrangement of green space to form the park system with a reasonable layout. In addition, municipal governments should continuously improve urban resilience. The relevant functional departments should actively fulfill their regulatory responsibilities, strengthen the supervision of mobile source pollution control, and enhance their regulatory capacity by improving the legal standard system and increasing penalties.

This paper explores the spatial correlation and spatial-temporal heterogeneity of the impact of $PM_{2.5}$ pollution and other factors on residents' public health through the SDM and the PGTWR model, providing a scientific direction for 26 cities in the Yangtze River Delta urban agglomerations to cope with environmental health issues. Moreover, a comprehensive analysis of the impact of haze pollution on public health from both global and local perspectives makes up for the limitations of the existing literature, and the parameter estimation results are conducive to proposing targeted strategies for improving the public health level of different cities. Considering the spillover effects of haze pollution, each city government should take into account regional environmental governance and protection while implementing differentiated policies. Importantly, the government should pay attention to the realization of cross-regional environmental cooperation, effectively promote the joint prevention and control of regional air pollution, and timely evaluate the effect of collaborative regulation of air pollution prevention and control, to maximize the effect of collaborative governance.

Fig. 5 Results of PGTWR of factors in 16 cities in YRD. **a** Average coefficient of $PM_{2.5}$ pollution ($PM_{2.5}$). **b** Average coefficient of per capita disposable income of urban households (PDI). **c** Average coefficient of urbanization rate (urban). **d** Average coefficient of population density (pd). **e** Average coefficient of the number of health technicians per ten thousand people (num_tech). **f** Average coefficient of per capita expenditure on health care in urban households (hpe). **g** Average coefficient of green space per capita (green)

Appendix A

Table 1 Descriptive statistics of variables

Variable	Symbol	Description	Unit	Mean	Std.Dev	Min	Max
Explained variable	H	Number of deaths from respiratory diseases	person	227.1	189.7	11.76	1251
Core explanatory variables	PM _{2.5}	Annual average concentration of PM _{2.5}	µg/m ³	50.45	11.2	20.39	73.16
Economic indicator	PDI	Per capita disposable income of urban households	CNY	23,616	8829	7882	48,343
Social indicator	urban	The urbanization rate	%	60.9	12.18	30.7	89.6
	pd	The population density	person /km ²	762.1	624.4	189	3826
Health care indicator	num_tech	Number of health technicians per ten thousand people	person	53.16	16.08	19.59	119.7
	hpe	Per capita expenditure on health care in urban households	CNY	875.4	337.5	263.8	3414
Life indicator	green	Green area per capita	m ²	52.36	33.13	6.333	197.8

Table 2 Setting the panel data model without spatial effect

	OLS ^c	Spatial fixed effect	Temporal fixed effect	Spatial–temporal effect
constant	− 11.6363*** (− 8.9745) ^d			
lnPM _{2.5}	1.5813*** (10.9816)	1.3884*** (25.3935)	1.6933*** (9.8562)	1.3478*** (13.3265)
lnPDI	1.1150*** (7.2620)	0.7668*** (15.3645)	1.1954*** (5.4156)	0.2350 (1.4856)
lnurban	0.1841 (0.6336)	− 0.5868*** (− 5.0348)	0.1952 (0.6316)	− 0.5409*** (− 5.4803)
lnpd	0.6550*** (8.8063)	− 0.0284 (− 0.5571)	0.6396*** (7.9491)	− 0.0118 (− 0.2710)
lnnum_tech	− 1.0290*** (− 5.4121)	− 0.4691*** (− 6.2796)	− 1.0685*** (− 5.3220)	− 0.5455*** (− 8.4112)
lnhpe	− 0.0118 (− 0.1002)	0.0042 (0.1321)	− 0.0234 (− 0.1964)	0.0048 (0.1764)
lngreen	− 0.3646*** (− 5.7118)	− 0.0914*** (− 4.2632)	− 0.3681*** (− 5.6552)	− 0.0816*** (− 4.5373)
R ²	0.4955	0.7285	0.4822	0.5627
σ ²	0.3293	0.0134	0.3223	0.0092
D − W	1.7377	0.6290	1.7558	0.9736
Log − L	− 310.2726	271.5279	− 306.9022	339.7386
LM lag	0.8613	120.8406***	1.0218	34.9504***
LM error	7.0547***	149.1894***	10.2915***	46.0375***
Robust LM lag	6.1151**	1.7685	12.5481***	0.3988
Robust LM error	12.3085***	30.1173***	21.8179***	11.4858***

^c The 10%, 5%, and 1% significance levels are represented by the *, **, and ***, respectively

^d T statistical value is indicated in brackets

Table 3 SDM estimation results

	Spatial fixed effect ^e	Temporal fixed effect	Spatial–temporal effect	Spatial–temporal effect (including error correction)
lnPM _{2.5}	1.4652*** (8.0472) ^f	0.4337 (1.3567)	1.566*** (8.9708)	1.5740*** (8.5925)
lnPDI	0.1368 (0.9195)	0.6157** (1.9707)	0.1690 (1.1635)	0.1591 (1.0444)
lnurban	−0.5875*** (−6.3777)	−0.6904** (−2.1327)	−0.5588*** (−6.4016)	−0.5680*** (−6.2042)
lnpd	−0.0009 (−0.0228)	0.7602*** (9.2556)	−0.0097 (−0.2503)	−0.0084 (−0.2067)
lnnum_tech	−0.4808*** (−8.0345)	−0.6426*** (−3.5224)	−0.5034*** (−8.8503)	−0.4984*** (−8.3539)
lnhpe	−0.0064 (−0.2547)	0.1087 (1.0096)	−0.0102 (−0.4225)	−0.0100 (−0.3963)
lngreen	−0.0740*** (−4.2540)	−0.2123*** (−3.4612)	−0.0885*** (−5.2444)	−0.0851*** (−4.8165)
W*lnPM _{2.5}	−0.9225*** (−4.6064)	3.0008*** (5.8998)	−1.1133*** (94.5157)	−1.2050*** (−4.7057)
W*lnPDI	0.2112 (1.2254)	2.5741*** (4.5949)	0.2348 (0.9091)	0.2002 (0.7394)
W*lnurban	0.7857*** (3.7287)	−4.5107*** (−5.6058)	0.7887*** (3.8202)	0.8160*** (3.7718)
W*lnpd	−0.1277 (−1.5336)	0.3605** (2.0425)	−0.1007 (−1.1676)	−0.0971 (−1.0735)
W*lnnum_tech	0.1947* (1.8579)	1.0964*** (2.7640)	−0.0128 (−0.1160)	0.0348 (0.3035)
W*lnhpe	0.0095 (0.2101)	0.4576** (2.1389)	0.0247 (0.5302)	0.0246 (0.5045)
W*lngreen	−0.1513*** (−3.2440)	−0.1731 (−1.1222)	−0.2168*** (−4.5172)	−0.2048*** (−4.0786)
σ ²	0.0079	0.2308	0.0068	0.0075
R ²	0.9885	0.6524	0.9893	0.9894
Adjusted R ²	0.763	0.6159	0.6243	0.6243
Log-L	358.7278	−248.0857	383.4405	383.4405
Wald_lag	59.2761***			
LR_lag	54.4850***			
Wald_error	43.0194***			
LR_error	40.5219***			

^e The 10%, 5%, and 1% significance levels are represented by the *, **, and ***, respectively

^f T statistical value is indicated in brackets

Table 4 Direct, indirect, and total effect of the SDM model with dual fixed effect

	Direct effect ^g	Indirect effect	Total effect
lnPM _{2.5}	1.5057*** (9.0037) ^h	−0.8118** (−2.6410)	0.6939*** (2.8340)
lnPDI	0.1945 (1.3106)	0.5018 (1.0850)	0.6962 (1.3268)
lnurban	−0.4882*** (−4.5051)	0.9523** (2.4026)	0.4641 (0.9905)
lnpd	−0.0226 (−0.5361)	−0.1761 (−1.1409)	−0.1987 (−1.1625)
lnnum_tech	−0.5279*** (−8.1287)	−0.3389* (−1.8247)	−0.8668*** (−3.9707)
lnhpe	−0.0067 (−0.2426)	0.0349 (0.3976)	0.0282 (0.2721)
lngreen	−0.1199*** (−5.5068)	−0.4243*** (−4.4507)	−0.5442*** (−4.8981)

^g The 10%, 5%, and 1% significance levels are represented by the *, **, and ***, respectively

^h T statistical value is indicated in brackets

Table 5 Robustness test results

	Direct effect ⁱ	Indirect effect	Total effect
lnPM _{2.5}	1.5544*** (9.1464) ^j	−0.6521** (−2.3237)	0.9023*** (4.0567)
lnPDI	0.1905 (1.2483)	0.4032 (0.9237)	0.5937 (1.1909)
lnurban	−0.5258*** (−4.8013)	0.6055* (1.7378)	0.0796 (0.1899)
lnpd	−0.0187 (−0.4321)	−0.1197 (−0.7980)	−0.1384 (−0.8382)
lnnum_tech	−0.5264*** (−7.8752)	−0.2915 (−1.6666)	−0.8179*** (−3.9134)
lnhpe	0.0023 (0.0794)	−0.0437 (−0.5417)	−0.0414 (−0.4271)
lngreen	−0.0925*** (−4.5002)	−0.1856*** (−2.9457)	−0.2782*** (−3.6039)

ⁱ The 10%, 5%, and 1% significance levels are represented by the *, **, and ***, respectively

^jT statistical value is indicated in brackets

Table 6 Comparison of accuracy under different models

	Weight decay type	Adjusted R ²	Bandwidth	Observations
OLS	–	0.4856	–	364
GWR	Gaussian	0.7609	1.1035	26
	Exponential	0.6968	2.2925	26
	Tricube	0.7058	–	26
PGTWR	–	0.9902	–	364

Table 7 Estimates of the overall statistical properties of the model with the four effects

	Mixed effect	Spatial fixed effect	Temporal fixed effect	Spatial–temporal effect
Significant ratio of local coefficient estimates	0.6466	0.6727	0.5436	0.6432
Observations	364	364	364	364
Degree of freedom	106	106	106	107
Estimated value of variance of random disturbance term	4.6108	0.2426	1.9302	5.5862
CV	488.742	25.7151	204.6038	597.7257
GCV	0.0039	0.0002	0.0016	0.0047
AICc	1610.3	537.1661	1291.3	1679.1
Adjusted R ²	0.9992	0.9902	−11.5822	1
F	105,280	127,320	39.2604	1,068,000,000
Probability of F statistic value	3.0049E-195	5.3519E-142	8.7249E-20	1.1722E-318
Log-L	−794.6616	−258.7158	−636.1834	−829.5888

Table 8 Description statistics of PGTWR parameter estimation

	Min	LQ	Mean	UQ	Max	Std.Dev
Local_lnPM _{2.5}	1.1301	1.3492	1.4458	1.5227	1.8140	0.1564
Local_lnPDI	0.4239	0.6146	0.6964	0.7919	0.9453	0.1252
Local_lnurban	−0.6155	−0.4227	−0.3703	−0.3084	−0.1484	0.0857
Local_lnpd	−0.2721	−0.1128	−0.0897	−0.0539	0.0246	0.0520
Local_lnnum_tech	−0.7553	−0.4866	−0.3763	−0.2454	−0.0857	0.1637
Local_lnhpe	−0.3292	−0.1671	−0.1236	−0.0792	−0.0085	0.0689
Local_lngreen	−0.1018	−0.0917	−0.0756	−0.0647	0.0064	0.0216

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Data availability The datasets generated and/or analyzed during the current study are available on:

- 1.<http://data-cnki-net-s.webvpn.cug.edu.cn:8118/yearbook/Single/N2020100004>
- 2.<http://data-cnki-net-s.webvpn.cug.edu.cn:8118/yearbook/Single/N2021050059>
- 3.<http://data-cnki-net-s.webvpn.cug.edu.cn:8118/yearbook/Single/N2021020144>
- 4.<http://www-epsnet-com-cn-s.webvpn.cug.edu.cn:8118/index.html#/Index>
- 5.<http://www.jscdc.cn/>
- 6.http://fizz.phys.dal.ca/~atmos/martin/?page_id=140#V4.CH.03

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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