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Original Research

The Influence of Technological Innovation on $PM_{2.5}$ Concentration in the Yangtze River Delta, China

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Abstract

$PM_{2.5}$ pollution seriously affects the environment, human health and socio-economic development, which has garnered wide-spread attention. Technological innovation plays a great role in $PM_{2.5}$ concentration. Thus, better understanding of the influence of technological innovation on $PM_{2.5}$ concentration is necessary. The Yangtze River Delta (YRD) was selected as the study area. This paper explored the spatial characteristic of $PM_{2.5}$ concentration and technological innovation. Then, bivariate Moran's *I* was applied to analyzed the spatial correlation between technological innovation and $PM_{2.5}$ concentration. The geographically and temporally weighted regression (GTWR) model was applied to explore the spatial heterogeneity of the influence of technological innovation on $PM_{2.5}$ concentration, and geographical detector model was applied to reveal the interactive influence between technological innovation and other factors. The main conclusions were as follows. (1) No city's $PM_{2.5}$ concentration fell below the standard which is considered harmless to human health. Cities in the northwest of the YRD had higher $PM_{2.5}$ concentration. (2) Cities in the core region of the YRD had relatively higher technological innovation. (3) There existed negative spatial correlation between technological innovation and $PM_{2.5}$ concentration, and three local spatial correlation types were found. (4) Technological innovation contributed to the decrease in $PM_{2.5}$ concentration. The interactive influence between technological innovation and natural factors was generally greater than that between technological factors and socio-economic factors. Comparing to other socio-economic factors, technological innovation and foreign investment had greater interactive influence on $PM_{2.5}$ concentration. Finally, some policy recommendations were drawn.

Keywords: $PM_{2.5}$ pollution, technological innovation, spatial heterogeneity, interactive influence, the YRD

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Introduction

Fine particulate pollutants have caused severe haze pollution in China, posing a significant threat to the environment, human health, and socio-economic development [1, 2]. $PM_{2.5}$ is the main cause of haze pollution in many Chinese cities [3]. Studies indicate that $PM_{2.5}$ can lead to respiratory diseases and cardiovascular diseases, weaken the human immune system and increase the mortality of exposed people [4]. Thus, the $PM_{2.5}$ issue has attracted widespread attention from the government and academia [5]. According to data released by China's Ministry of Ecology and Environment, the number of days with $PM_{2.5}$ as the primary pollutant failing to meet the air quality standards was the largest, accounting for 39.7% of the total. Thus, it is crucial to investigate the forces of $PM_{2.5}$ pollution and provide decision-making basis for $PM_{2.5}$ control.

Current studies of $PM_{2.5}$ mainly focused on chemical composition and sources [6], transmission and diffusion [7], impact on human health [8], temporal-spatial distribution [9], and influencing factors [10]. It is widely recognized that both natural conditions and social-economic factors influences on $PM_{2.5}$ concentration. Thus, many scholars have studied the influence of natural conditions such as temperature, rainfall and humidity [11-13], as well as social-economic factors such as economic development, population density, technological innovation [14-16] on $PM_{2.5}$ concentration. Technological innovation is also regarded as an important factor that influences $PM_{2.5}$ concentration [17]. Therefore, to clarify the influence of technological innovation on $PM_{2.5}$ concentration is conducive to the formulation of $PM_{2.5}$ control policies.

The studies on the relationship between technological innovation and $PM_{2.5}$ concentration focused on whether technological innovation can reduce $PM_{2.5}$ concentration. Firstly, technological innovation reduced $PM_{2.5}$ concentration. These who hold this view deemed that technological innovation reduced the environmental impact of industrial production by improving productivity and resource utilization while reducing factor input. In addition, the application of clean technologies effectively reduced pollution emissions. Therefore, technological innovation was regarded as an important means to reduce $PM_{2.5}$ concentration by many scholars [18-20]. Secondly, technological innovation increased $PM_{2.5}$ concentration. These who hold this view deemed that the original intention of technological innovation was to improve productivity, not to solve pollution problems. Productivity improvement promoted the reproduction of enterprises and expanded the production scale, and fossil energy consumption also increased. And technological innovation might also lead to new sources of pollution. Thus, technological innovation played a role in increasing $PM_{2.5}$ concentration [21, 22]. Thirdly, the influence of technological innovation on $PM_{2.5}$ concentration was uncertainty. Some scholars deemed that technological innovation had different impacts on $PM_{2.5}$ concentration [23], and there existed N-shaped, inverted U-shaped or other nonlinear relationship [24, 25].

However, the possible shortcomings were shown as follows. Firstly, while most studies analyzed the influence of multiple factors on $PM_{2.5}$ concentration, few have specifically examined the influence of technological innovation alone. As a result, a deeper analysis of the influence of technological innovation on $PM_{2.5}$ concentration was lacking. Secondly, the spatial heterogeneity of the influence of technological innovation on $PM_{2.5}$ concentration was insufficient. The geographically weighted regression (GWR) model is often utilized, but it has limitations as it employs cross-sectional data and cannot adequately address spatial-temporal nonstationarity, despite considering spatial effects and heterogeneity [26, 27]. The GTWR model can effectively solve this problem. Thus, this paper applied GTWR model to analyze the spatial heterogeneity of influence of technological innovation. Thirdly, studies, further exploring the interaction between technological innovation and other factors, were still scarce. $PM_{2.5}$ concentration is influenced by multiple factors which interact with each other. Thus, identifying the interactive influence between different factors made it clear which two factors could be combined to reduce $PM_{2.5}$ concentration.

The YRD is the densest, richest and most urbanized area in China, but it also faces the sharpest contradiction between economic development and eco-environment in China [28]. $PM_{2.5}$ pollution is also an issue in the YRD [29]. However, the YRD is the prior region for achieving China's strategic development with both economic and ecological goals [30]. Thus, it is necessary to take the YRD as the study area. In addition, the YRD is also a region with a relatively higher level of technological innovation in China, but there also exists imbalance among cities [31, 32]. Therefore, how to play the role of technological advantages in reducing $PM_{2.5}$ concentration according to local conditions is a topic worth discussing.

Overall, this study conducted the research using bivariate Moran's *I*, GTWR model, and geographical detector model. The findings highlighted spatial heterogeneity in how technological innovation impacts $PM_{2.5}$ concentration and offered policy recommendations based on these results.

Methodology

Data Resources

$PM_{2.5}$ data from Atmospheric Composition Analysis Group, using NASA satellites, ground-based monitoring, and regression models, commonly used. Other Relative data was collected from China City

Table 1. Index system of technological innovation.

First grade index	Second grade index	Explanations
Innovation input	Financial expenditure on science and technology	The proportion of science and technology expenditure in GDP
	Scientists	Number of staffs in universities and scientific research institutions
Innovation output	Patent for invention	The number of patents for innovation
	Design patent	The number of design patents
	Patent for utility models	The number of patents for utility models
Innovation environment	Universities	The number of Universities
	Books in libraries	The number of books in libraries

Table 2. Control variables and their explanations.

Control variables	Symbols	Explanations
Temperature	Temp	Average annual temperature
Rainfall	Rain	Average annual rainfall
Humidity	Humi	Average annual humidity
Vegetation coverage	Vege	Normalized Difference Vegetation Index (NDVI)
Economic development	PGDP	Per capital GDP
Industrial structure	Indu	Proportion of the secondary industry output value over the total GDP
Population density	Popu	Ratio of resident population to total area
Construction land	Cons	Ratio of urban built-up area to municipal area
Foreign investment	Fore	The proportion of actually utilized foreign capital in GDP

Statistical Yearbook, Shanghai Statistical Yearbook, Jiangsu Statistical Yearbook, Anhui Statistical Yearbook and statistical yearbook of each city. NDVI was collected from Resource and Environment Science and Data Center, Chinese Academy of Sciences. Economic data was converted in 2010 constant price.

This paper assessed technological innovation using input, output, and environment measures. A 3-level index system (3 first-grade indexes, 7 second-grade indexes) was used (Table 1). Entropy weighting determined indicator weights.

To identify the influence of technological innovation on $PM_{2.5}$ concentration, temperature, rainfall, humidity, vegetation coverage, economic development, industrial structure, population density, construction land and foreign investment was collected as control variables (Table 2).

Spatial Autocorrelation Analysis Method

Firstly, the univariate Moran's *I* index was used to explore the spatial distribution characteristics of technological innovation and $PM_{2.5}$ concentration, respectively. The univariate Moran's *I* index can be calculated as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{1}$$

Where I is the univariate Moran's I index; n is the number of cities; i, j represents the city i or j; x is the $PM_{2.5}$ concentration or technological innovation; $\bar{x}$ is the average value of x; W is the spatial weight matrix.

Secondly, bivariate Moran's I index was applied to explore the spatial correlation between $PM_{2.5}$ concentration and technological innovation. The bivariate Moran's I index can be calculated as follows:

$$II = \frac{n\sum_{i=1}^{n}\sum_{j\neq 1}^{n} W_{ij}(x_i - \bar{x})(y_j - \bar{y})}{\sum_{i=1}^{n}\sum_{j\neq 1}^{n} W_{ij}} \tag{2}$$

Where II is the bivariate Moran's I index; x is the $PM_{2.5}$ concentration; y is the technological innovation.

To identify the local spatial correlation between technological innovation and $PM_{2.5}$ concentration, bivariate local Moran's I index was also calculated as follows:

$$II_i = Z^a_i \sum\nolimits_{j=1}^{n} W_{ij} Z^b_j \quad (3)$$

Where, II_i is the bivariate local Moran's I index; Z_i^a is the standard variance of $PM_{2.5}$ concentration; Z_j^b is the standard variance of $PM_{2.5}$ concentration. For other details, please refer to Hu [33], Ge [34].

Geographically and Temporally Weighted Regression Model

By incorporating the temporal effect into the GWR model, the GTWR model can deal with both temporal and spatial non-stationarity [35]. Thus, Therefore, the GTWR model can capture the temporal-spatial heterogeneity by integrates temporal and spatial information in the spatial weighted matrix. The GTWR model is shown as follows:

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_k \beta_k(u_i, v_i, t_i) X_{ik} + \varepsilon_i \quad (4)$$

Where, Y_i is the $PM_{2.5}$ concentration; u_i, v_i is the dimension and longitude of the ith city; t_i is the year; (u_i, v_i, t_i) is the temporal-spatial coordinates of ith city; β_0 (u_i, v_i, t_i) is the regression constant; β_k (u_i, v_i, t_i) is the kth influencing factor's regression coefficient of ith city; X_{ik} is the value of the kth influencing factor in the ith city; ε_i is the residual.

Geographical Detector Model

Geographical detector model, proposed by Wang [36], can detect and explain the spatial heterogeneity of driving forces. It assumes that if an independent variable influences a dependent variable, their spatial distribution should be similar [37]. q value is used to measure the explanation of independent variable to dependent variable by geographic detector. By calculating and comparing the q value of each factor and the q value after the superposition of the two factors, the geographic detector can judge whether there is interaction between the two factors, as well as the strength, direction, linearity or nonlinearity of interaction. The q can be can be calculated as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} \sum_{i=1}^{N_h} (y_{h1} - \bar{y}_h)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} \quad (5)$$

Where, q is the power of determinate, which reflects the influence of X on the spatial heterogeneity of Y. The larger the q is, the larger the influence is. L is the number of strata; h is the h strata; N_h and N are the numbers of the units in the h strata and whole area, respectively; σ_h^2 and σ^2 are the variance of h strata and whole area, respectively.

Geographical detector model can detect whether different factors are independent in influencing the dependent variable, or evaluate whether the influence of one factor on the dependent variable is enhanced or weakened by another factor. Table 3 provides criteria for determining which type of interaction is involved.

Results and Discussion

The Spatial Evolution of $PM_{2.5}$ Concentration

This paper analyzed $PM_{2.5}$ concentration in 2003, 2011. In 2003, 36 cities exceeded the limit of 35 μg/m^3, with Huaibei and Xuzhou having higher levels. By 2011, 37 cities exceeded the limit, and Xuzhou, Huaibei, and Fuyang had highly polluted air. However, by 2019, only 25 cities exceeded the limit, with Xuzhou being the most polluted city. No city met the WHO's standard of an annual $PM_{2.5}$ concentration below 10μg/m^3. Cities in the northwest of the YRD had higher $PM_{2.5}$ concentrations compared to those in the southeast.

The Spatial Characteristics of Technological Innovation

To analyze the spatial evolution of technological innovation, the spatial distribution of technological innovation in 2003, 2011, and 2019 had also been mapped (Fig. 2). The Natural Breaks Classification method was applied to classify technological innovation. By comparing distribution of technological innovation from 2003 to 2019, it found that cities in the core region of the YRD, such as Shanghai, Nanjing, Hangzhou and Hefei, had relatively higher technological innovation,

Table 3. Interaction relationships.

Description	Interaction
PD(X1∩X2) < Min(PD(X1), PD(X2))	Weaken and nonlinear
Min(PD(X1), PD (X2))< PD (X1∩X2)<Max(PD (X1)), PD (X2))	Weaken and univariate
PD(*X1*∩ *X*2) > Max(*PD*(*X1*), *PD*(*X*2))	Enhance and bivariate
PD(*X1*∩ *X*2) = *PD*(*X1*)+ *PD*(*X*2)	Independent
PD(*X1*∩ *X*2) > *PD*(*X1*)+ *PD*(*X*2)	Enhance and nonlinear

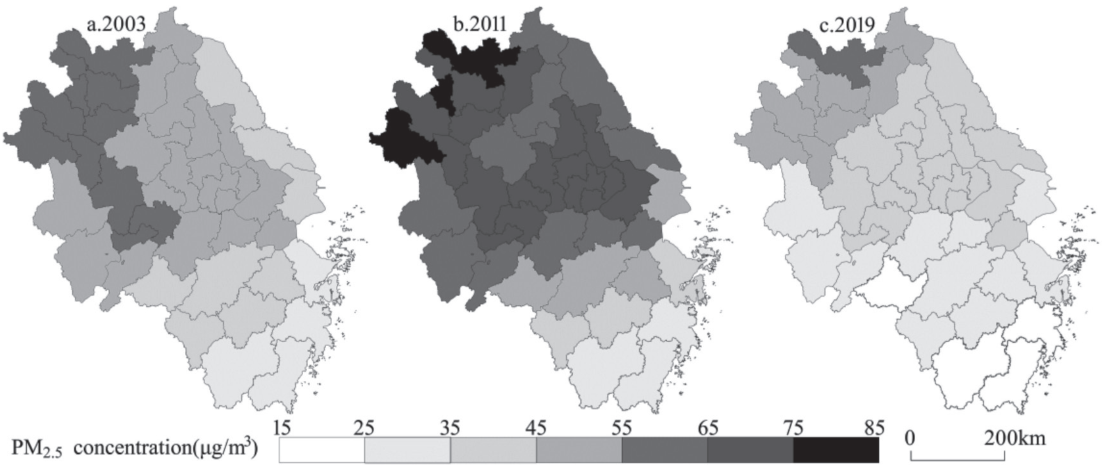

Fig. 1. Spatial distribution of $PM_{2.5}$ concentration in YRD.

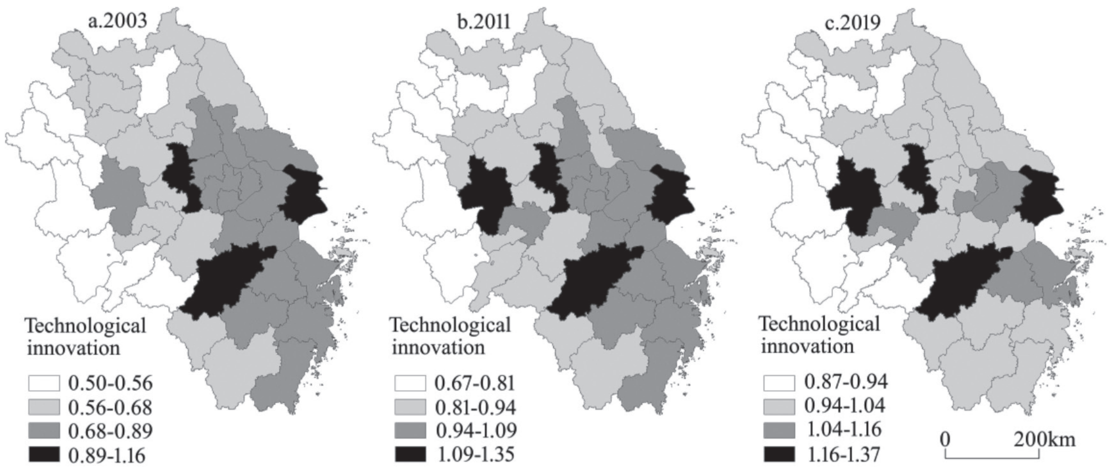

Fig. 2. Spatial distribution of technological innovation in YRD.

while cities in the peripheral regions, such as Suzhou and Bozhou, were relatively lower.

Spatial Correlation Analysis

Using GeoDa software, this paper calculated the univariate and bivariate Moran's *I* values and significance of technological innovation and $PM_{2.5}$ concentration. According to Table 4, univariate and bivariate Moran's *I* was statistically significant at least at 5% significance level. Technological innovation had positive spatial autocorrelation but decreasing differences in spatial distribution from 2003 to 2019, while $PM_{2.5}$ concentration had positive spatial autocorrelation with growing differences in spatial distribution during the same period. Bivariate Moran's I indicated negative spatial correlation between technological innovation and $PM_{2.5}$ concentration, meaning high technological innovation cities were adjacent to low $PM_{2.5}$ concentration cities or vice versa.

Table 4. Univariate and bivariate Moran's *I* values of technological innovation and $PM_{2.5}$ concentration.

Variable	Moran's *I* and P-value	2003	2011	2019
Technological innovation	Univariate Moran's *I*	0.3141	0.2998	0.1189
	P-value	0.001	0.002	0.040
$PM_{2.5}$ concentration	Univariate Moran's *I*	0.6543	0.7056	0.7147
	P-value	0.001	0.001	0.001
Technological innovation and $PM_{2.5}$ concentration	Bivariate Moran's *I*	-0.2329	-0.1773	-0.1879
	P-value	0.002	0.007	0.005

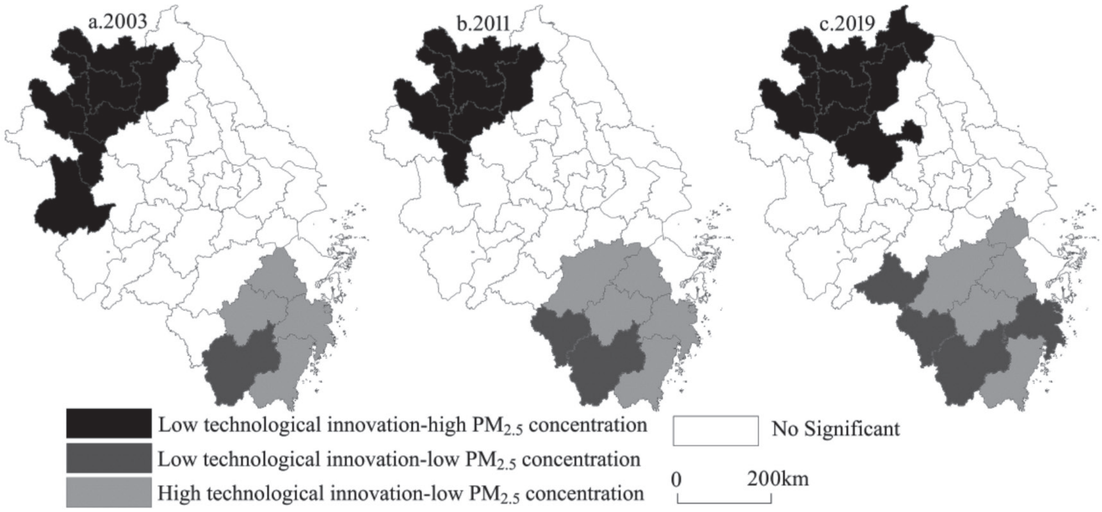

Fig. 3. Bivariate LISA cluster maps of technological innovation and $PM_{2.5}$ concentration in YRD.

To further examine the local spatial correlation between technological innovation and $PM_{2.5}$ concentration, the study created Bivariate LISA cluster maps. The maps showed three types of local spatial correlation: low technological innovation-high $PM_{2.5}$ concentration, high technological innovation-low $PM_{2.5}$ concentration, and low technological innovation-low $PM_{2.5}$ concentration, as shown in Fig. 3.

Cities with low technological innovation-high $PM_{2.5}$ concentration were mainly distributed in the northwest of the YRD. According to the previous analysis, the technological innovation of these cities was indeed low, while $PM_{2.5}$ concentration was high. It indicates poor technology transfer and diffusion effect along with ineffective optimization effects of low technological innovation on air pollution. Much work is needed to control $PM_{2.5}$ pollution in these cities. Cities with low technological innovation-low $PM_{2.5}$ concentration were mainly in the south of the YRD. For these cities, low technological innovation cannot effectively control increasing $PM_{2.5}$ concentration. Cities with high technological innovation-low $PM_{2.5}$ concentration were mainly in the southeast of the Yangtze River, indicating a potential to leverage technological advantages for cleaner production and better resource utilization.

Mechanism Analysis of the Influence of Technological Innovation on Air Pollution

Spatial Heterogeneity Analysis

This study examined the spatial heterogeneity of technological innovation's impact on air pollution while controlling for various factors such as temperature, rainfall, economic development, and population density. Collinearity tests were conducted, and the Variance Inflation Factor (VIF) values were all less than 10, indicating no collinearity. Diagnostic indexes of GTWR and GWR models were presented in Table 5, which indicated that the regression results of the GTWR model were more explanatory.

This paper focused solely on analyzing the impact of technological innovation on $PM_{2.5}$ concentration. Results showed that on average, technological innovation had contributed to reducing $PM_{2.5}$ concentration in 2003, 2011, and 2019, despite varying influence coefficients across cities (Fig. 9).

Cities with positive effects of technological innovation were mainly located in southern Anhui, southern Jiangsu, Shanghai, and northeastern Zhejiang. The number of such cities increased between 2003-2009, and compared to 2003, some cities including Shanghai and Suzhou had a positive effect on $PM_{2.5}$ concentration through technological innovation. Since the 1990s, the YRD had established high-tech industrial development zones, such as the Nanjing Economic-Technological Development Zone, and attracted foreign companies, leading to accelerated heavy and high-tech industry growth. The YRD had entered a period of accelerated development of heavy industry and high-tech industry. For these cities, technological innovation aimed at increasing production efficiency rather than addressing environmental concerns, which resulted in it contributing more to increasing $PM_{2.5}$ than inhibiting it. Although technological innovation helped decrease $PM_{2.5}$ levels, it could not fully address the increase caused by economic development.

The cities with negative influence of technological innovation were mainly distributed in central and northern Jiangsu province, central and northern Anhui

Table 5. Diagnostic indexes of GTWR model and GWR model.

Model	AICc	R^2 Adjusted	RSS	Sigma
GWR	781.280	0.938	1475.940	3.464
GTWR	820.980	0.957	1022.220	2.883

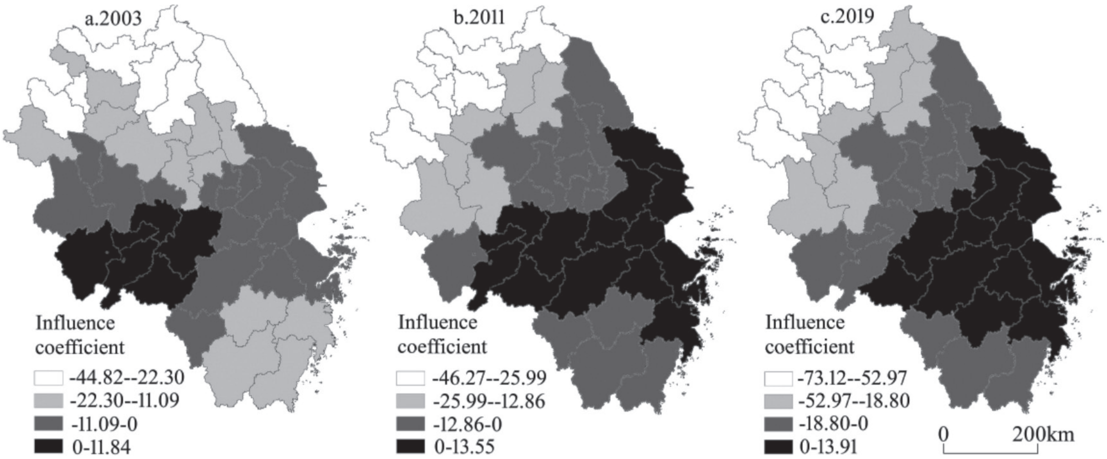

Fig. 4. Spatial distribution of regression coefficient of technological innovation.

Province, and southwestern Zhejiang Province. While the number of such cities decreased from 2003-2009, mean negative effect increased from –13.45 to –21.44, indicating that technological innovation had gradually enhanced its inhibitory effect on $PM_{2.5}$ concentration. Local governments paid more attention to haze control, leading to the formulation of relevant policies such as Xuzhou's measures for air pollution prevention and control. Technological innovation became an important means for local governments to solve environmental problems. Additionally, better natural environments, such as those found in cities like Lishui and Wenzhou with low $PM_{2.5}$ concentrations and strong environmental self-purification abilities, made it easier for technological innovation to decrease $PM_{2.5}$ concentrations.

Interaction Detections

The GTWR model is limited to analyzing the independent effect of technological innovation, with other factors acting as control variables. Since $PM_{2.5}$ concentration is influenced by various factors, this study used a geographical detector model to analyze their interactive influence. Technological innovation and other factors were classified into five categories using the Natural Breaks Classification method, and the results are presented in Table 6.

There were two types of interactive influence between technological innovation and other factors on $PM_{2.5}$ concentration, which were nonlinear enhancement and bivariate enhancement. It indicated that the interactive influence between technological innovation and other factors was greater than the influence of technological innovation itself. The spatial heterogeneity of $PM_{2.5}$ concentration was more influenced by the interaction between technological innovation and other factors. As shown in Table 4, the interactive influence between technological innovation and natural factors was generally greater than that between technological

Table 6. Results of the interaction detections between technological innovation and other factors.

	2003		2011		2019	
	q	Types	*q*	Types	*q*	Types
Tech ∩ Temp	0.689	EN	0.726	EB	0.762	EN
Tech ∩ Rain	0.580	EB	0.575	EN	0.686	EN
Tech ∩ Humi	0.415	EN	0.835	EN	0.673	EB
Tech ∩ Vege	0.399	EB	0.634	EN	0.495	EN
Tech ∩ PGDP	0.433	EN	0.325	EB	0.262	EN
Tech ∩ Indu	0.420	EN	0.429	EB	0.420	EN
Tech ∩ Popu	0.503	EN	0.353	EN	0.547	EN
Tech ∩ Cons	0.395	EN	0.475	EN	0.492	EN
Tech ∩ Fore	0.541	EN	0.806	EN	0.528	EN

Notes: EN denotes enhance and nonlinear; EB denotes bivariate enhance and bivariate factors and socio-economic factors. Therefore, a good ecological environment was conducive to the improvement of $PM_{2.5}$ concentration by technological innovation. Compared to other socio-economic factors, technological innovation and foreign investment had greater interactive influence on $PM_{2.5}$ concentration. While attracting foreign investment, strengthening management and environmental regulations was conducive to the improvement of technological innovation on $PM_{2.5}$ concentration.

The study found two types of interactive influence between technological innovation and other factors, namely nonlinear enhancement and bivariate enhancement. These interactions were greater than the influence of technological innovation alone, suggesting that $PM_{2.5}$ concentration was heavily influenced by their interaction. Ecological factors had a stronger effect on $PM_{2.5}$ concentration than socio-economic factors, with technological innovation and foreign investment showing the greatest influence. Strengthening management and environmental regulations during foreign investment could improve the effects of technological innovation on $PM_{2.5}$ concentration.

Discussion

Haze pollution is a significant environmental and development obstacle that must be addressed for sustainable development [38, 39]. However, $PM_{2.5}$ pollution in the Yangtze River Delta remains serious. Solving haze pollution in the Yangtze River Delta is not only essential for the area but also to the entire country, given its role as a model for China's social-economic development. Based on our findings, technological innovation is conducive to the reduction of $PM_{2.5}$ concentration in YRD. Therefore, enough attention should be paid to the role of technological innovation in the reduction of $PM_{2.5}$ concentration.

The role of technological innovation in $PM_{2.5}$ pollution control should be brought into play in light of local conditions. Technological innovation can reduce $PM_{2.5}$ concentration by promoting clean technologies and energy efficiency but may also increase it through productivity improvements. Therefore, it's crucial to assess the impact of technological innovation on $PM_{2.5}$ concentration in different cities. According to our findings, the influence of technological innovation on $PM_{2.5}$ is spatially heterogeneous in the YRD. In some cities with high level of technological innovation, such as Shanghai, technological innovation promoted the increase of $PM_{2.5}$ concentration. Compared with other cities in the YRD, these cities were characterized by relatively lower $PM_{2.5}$ concentration and higher level of technological innovation (In sub-section 3.3, the local spatial correlation of these cities was not significant, because we calculated it apply Geodata software, and it only detected a significant level of 5%). Many of these cities fall under China's major function zoning as optimized or key development zones aimed at promoting industrialization and urbanization. As a result, technological innovation is mainly geared towards improving productivity rather than addressing environmental concerns. To effectively reduce $PM_{2.5}$ concentration, it's necessary for these cities to implement additional measures alongside technological innovation.

The loss of self-purification function of natural ecosystems is one of the major causes of haze pollution. When the functions of natural ecosystems are perfect, a large number of air pollutants are absorbed by various water bodies and forest systems. Urbanization and industrialization have seriously damaged natural ecosystems. This paper found that technological innovation had a stronger interaction with natural factors than with socio-economic factors. Therefore, protecting natural ecosystems can enhance the effectiveness of technological innovation in controlling haze pollution. However, many natural factors are inelastic, such as average annual temperature and precipitation, which are hard to change greatly. Although the interaction between socio-economic factors and technological innovation is smaller, it is more operational. Furthermore, this paper also finds that socio-economic factors can also increase the influence of technological innovation on $PM_{2.5}$ concentration. To maximize the effectiveness of technological innovation in controlling $PM_{2.5}$ pollution, it's essential to consider natural and socio-economic factors comprehensively.

Compared to other socio-economic factors, this paper found that the interactive influence between technological innovation and foreign investment was greater. Some scholars believe that foreign investment will bring high-polluting enterprises, and open trade policies will make developing countries produce more pollution [40, 41]. Some scholars hold the point that foreign investment brings advanced production technology and management experience, which helps to improve the environment [42, 43]. The impact of foreign investment on environmental pollution is uncertain. But, we found that foreign investment increased the influence of technological innovation on $PM_{2.5}$ concentration. Therefore, when introducing foreign investment, it is necessary to increase the threshold of environmental access and reject the introduction of enterprises with low efficiency, high consumption and high pollution. Instead, it should strengthen the influence of technological innovation on $PM_{2.5}$ concentration by introducing green, clean and energy-saving enterprises.

Conclusions and Recommendations

Some conclusions were drawn as follows.

(1) No city's $PM_{2.5}$ concentration fell below the standard which is considered harmless to human health. By comparing distribution of $PM_{2.5}$ concentration in different years, it found that cities with higher $PM_{2.5}$

concentration were mainly located in the northwest of the YRD, while cities with lower $PM_{2.5}$ concentration were located in the southeast.

(2) Cities in the core region of the YRD, such as Shanghai, Nanjing, Hangzhou and Hefei, had relatively higher technological innovation, while cities in the peripheral regions, such as Suzhou and Bozhou, were relatively lower.

(3) Technological innovation showed positive spatial autocorrelation, but the differences in spatial distribution were decreasing. $PM_{2.5}$ concentration also exhibited positive spatial autocorrelation, and its differences in spatial distribution were growing. there existed negative spatial correlation, that is, cities with high technological innovation were adjacent to low $PM_{2.5}$ concentration, or vice versa. There were three local spatial correlation types, including low technological innovation-high $PM_{2.5}$ concentration, high technological innovation-low $PM_{2.5}$ concentration and low technological innovation-low $PM_{2.5}$ concentration.

(4) Technological innovation had been contributing to the decline in $PM_{2.5}$ concentration. The influence coefficient of technological innovation presented obvious spatial differentiation characteristics. There were two types of interactive influence between techno-logical innovation and other factors on $PM_{2.5}$ concentration, which were nonlinear enhancement and bivariate enhancement. The interactive influence between technological innovation and natural factors was generally greater than that between technological factors and socio-economic factors. Comparing to other socio-economic factors, technological innovation and foreign investment had greater interactive influence on $PM_{2.5}$ concentration.

Some policy recommendations were drawn.

Firstly, promoting the development of green technology is necessary. Green technology is an environment-friendly technology with the characteristics of recycling, low energy consumption and cleanliness. This paper also found that technological innovation in some cities with higher technological innovation increased the $PM_{2.5}$ concentration. For these cities, the technological level is relatively higher, but clean innovation is still needed in products, production processes and other links.

Secondly, in view of the spatial heterogeneity of influence of technological innovation on $PM_{2.5}$ concentration, formulating the $PM_{2.5}$ pollution control plan according to local conditions is necessary. Fully understanding the conditions of different cities can ensure that technological innovation controls $PM_{2.5}$ pollution without compromising steady socio-economic development. Lower technological innovation in cities like Xuzhou has led to a reduction in $PM_{2.5}$ concentration. Incentive policies for technological innovation and source control should be given priority. While end-of-pipe treatment is an option, it's expensive, incomplete, and produces waste residue. Therefore, future technological innovation in Xuzhou should focus on source control to improve resource utilization and reduce waste.

Thirdly, attention must be paid to the interaction of other factors and technological innovation on $PM_{2.5}$ concentration. Natural factors played a significant role in exerting the influence of technological innovation on $PM_{2.5}$ concentration. It is necessary to improve the eco-environment to play its self-purification function. Meanwhile, adaptive strategies need to be developed, such as reasonable design of urban air duct, industrial location optimization, reasonable layout of green belt. However, the formulation of socio-economic countermeasures is more operable. Some regulatory policies, such as the adjustment of industrial structure and the relief of overloaded population, need to be formulated.

Fourthly, cities should strengthen technical cooperation and jointly control $PM_{2.5}$ pollution. Technological innovation can be supported through taxation and other means to improve resource utilization and reduce pollutant emissions. The YRD also should promote cooperation among cities in technical personnel exchanges, joint laboratory construction and technology transfer. Besides, the spatial correlation of $PM_{2.5}$ pollution is strong. Cities can share $PM_{2.5}$ detection data and establish joint prevention and control mechanisms.

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Conflict of Interest

The authors declare no conflict of interest.

References

1. HAN X., LI H., LIU Q., LIU F., ARIF A. Analysis of influential factors on air quality from global and local perspectives in China. Environmental Pollution. **248**, 965, **2019**.
2. YANCHAO F., XIAOHONG W., ZHOU L. How does environmental information disclosure affect economic development and haze pollution in Chinese cities? The mediating role of green technology innovation. Science of The Total Environment. **775**, 145811, **2021**.
3. LOPES T.D.B.M., GROTH E.E., VERAS M., FURUYA T.K., COSTA N.D.S.X., JÚNIOR G.R., LOPES F.D., ALMEIDA F.M.D., CARDOSO W.V., SALDIVA P.H.N.,

CHAMMAS R., MAUAD T. Pre- and postnatal exposure of mice to concentrated urban $PM_{2.5}$ decreases the number of alveoli and leads to altered lung function at an early stage of life. Environmental Pollution. **241**, 511, **2018**.
4. ZHANG L., LUO G., HU X., QIU R. Quantifying public health benefits of $PM_{2.5}$ reduction and spatial distribution analysis in China. Science of The Total Environment. **719**, 137445, **2020**.
5. ZHANG Y., CHEN J. An empirical study of the efficiency of haze pollution governance in Chinese cities based on streaming data. Science of The Total Environment. **739**, 139571, **2020**.
6. ZHANG Y., LANG J., CHENG S., LI S., ZHOU Y., CHEN D., ZHANG H., WANG H. Chemical composition and sources of PM 1 and $PM_{2.5}$ in Beijing in autumn. Science of The Total Environment. **630**, 72, **2018**.
7. XIE Z., LI Y., QIN Y. Allocation of control targets for $PM_{2.5}$ concentration: An empirical study from cities of atmospheric pollution transmission channel in the Beijing-Tianjin-Hebei district Journal of Cleaner Production. **270**, 122545, **2020**.
8. CHUNG C., WU C., HWANG B., WU C., HUANG P., HO C., HSU H. Effects of ambient $PM_{2.5}$ and particle-bound metals on the healthy residents living near an electric arc furnace: A community- based study. Science of The Total Environment. **728**, 138799, **2020**.
9. LIU Y., SHI G., ZHAN Y., ZHOU L., YANG F. Characteristics of $PM_{2.5}$ spatial distribution and influencing meteorological conditions in Sichuan Basin, southwestern China. Atmospheric Environment. **253**, 118364, **2021**.
10. LI G., FANG C., WANG S., SUN S. The Effect of Economic Growth, Urbanization, and Industrialization on Fine Particulate Matter ($PM_{2.5}$) Concentrations in China. Environmental Science Technology. **50** (21), 11452, **2016**.
11. MA S., SHAO M., ZHANG Y., DAI Q., XIE M. Sensitivity of $PM_{2.5}$ and O_3 pollution episodes to meteorological factors over the North China Plain. Science of The Total Environment. **792**, 148474, **2021**.
12. YANG Z., YANG J., LI M., CHEN J., OU C. Nonlinear and lagged meteorological effects on daily levels of ambient $PM_{2.5}$ and O_3: Evidence from 284 Chinese cities. Journal of Cleaner Production. **278** (4), 123931, **2020**.
13. XIONG H., CHEN J., MA X., FANG M. Estimating the $PM_{2.5}$ concentration over Anhui Province, China, using the Himawari-8 AOD and a GAM/BME model. Atmospheric Pollution Research (20), 101110, **2021**.
14. WANG P., FENG H., BI X., FU Y., HE X., ZHANG G., NIU J. Phase objectives analysis for $PM_{2.5}$ reduction using dynamics forecasting approach under different scenarios of PGDP decline. Ecological Indicators. **129** (5), 108003, **2021**.
15. YAN D., KONG Y., JIANG P., HUANG R., YE B. How do socioeconomic factors influence urban $PM_{2.5}$ pollution in China? Empirical analysis from the perspective of spatiotemporal disequilibrium. Science of The Total Environment. **761**, 143266, **2020**.
16. FANG D., YU B. Driving mechanism and decoupling effect of $PM_{2.5}$ emissions: Empirical evidence from China's industrial sector. Energy Policy. **149**, 112017, **2021**.
17. YI M., WANG Y., SHENG M., SHARP B., ZHANG Y. Effects of heterogeneous technological progress on haze pollution: Evidence from China. Ecological Economics. **169**, 106533, **2020**
18. XUE W., ZHANG J., ZHONG C., JI D., HUANG W. Satellite-derived spatiotemporal $PM_{2.5}$ concentrations and variations from 2006 to 2017 in China. Science of The Total Environment. **712**, 134577, **2019**.
19. GAN T., LIANG W., YANG H., LIAO X. The effect of Economic Development on haze pollution ($PM_{2.5}$) based on a spatial perspective: Urbanization as a mediating variable. Journal of Cleaner Production. **266** (1), 121880, **2020**.
20. ZHANG Y., CHEN X., MAO Y., SHUAI C., JIAO L., WU Y. Analysis of resource allocation and $PM_{2.5}$ pollution control efficiency: Evidence from 112 Chinese cities. Ecological Indicators. **127**, 107705, **2021**.
21. ZHANG M., LIU X., DING Y., WANG W. How does environmental regulation affect haze pollution governance? – An empirical test based on Chinese provincial panel data. The Science of the Total Environment. **695**, 133905, **2019**.
22. DONG F., YU B., PAN Y. Examining the synergistic effect of CO_2 emissions on $PM_{2.5}$ emissions reduction: Evidence from China. Journal of Cleaner Production. **223**, 759, **2019**.
23. CHEN J., WANG S., ZHOU C., LI M. Does the path of technological progress matter in mitigating China's $PM_{2.5}$ concentrations? Evidence from three urban agglomerations in China. Environmental Pollution. **254**, 113012, **2019**.
24. JIA R., FAN M., SHAO S., YU Y. Urbanization and haze-governance performance: Evidence from China's 248 cities. J Environ Manage. **288**, 112436, **2021**.
25. XU B., LUO L., LIN B. A dynamic analysis of air pollution emissions in China: Evidence from nonparametric additive regression models. Ecological Indicators. **63**, 346, **2016**.
26. SONG W., JIA H., HUANG J., ZHANG Y. A satellite-based geographically weighted regression model for regional $PM_{2.5}$ estimation over the Pearl River Delta region in China. Remote Sensing of Environment. **154**, 1, **2014**.
27. WU C., REN F., HU W., DU Q. Multiscale geographically and temporally weighted regression: exploring the spatiotemporal determinants of housing prices. International Journal of Geographical Information Science. **33** (3), 1, **2018**.
28. ZHANG X. Estimation of eco-efficiency and identification of its influencing factors in China's Yangtze River Delta urban agglomerations. Growth and Change. **51** (2), 792, **2020**.
29. SHE Q., CAO S., ZHANG S., ZHANG J., ZHU H., BAO J., MENG X., LIU M., LIU Y. The impacts of comprehensive urbanization on $PM_{2.5}$ concentrations in the Yangtze River Delta, China. Ecological Indicators. **132**, 108337, **2021**.
30. SUN C., CHEN L., TIAN Y. Study on the urban state carrying capacity for unbalanced sustainable development regions: Evidence from the Yangtze River Economic Belt. Ecological Indicators. **89**, 150,**2018**.
31. WANG J., YANG L. Does factor endowment allocation improve technological innovation performance? An empirical study on the Yangtze River Delta region. Science of The Total Environment. **716**, 137107, **2020**.
32. CAO Y., WAN N., ZHANG H., ZHANG X., ZHOU Q. Linking environmental regulation and economic growth through technological innovation and resource consumption: Analysis of spatial interaction patterns of urban agglomerations. Ecological Indicators. **112** (5), 106062, **2020**.
33. HU B., SHAO S., NI H., FU Z., HUANG M., CHEN Q., SHI Z. Assessment of potentially toxic element pollution in soils and related health risks in 271 cities across China. Environmental Pollution. **270**, 116196, **2020**.
34. GE Y., DOU W., WANG X., CHEN Y., ZHANG Z. Identifying urban-rural differences in social vulnerability

to natural hazards: a case study of China. Natural Hazards. **108**, 2629, **2021**.
35. HUANG B., WU B., BARRY M. Geographically and temporally weighted regression for modeling spatio-temporal variation in house prices. International Journal of Geographical Information Science. **24** (3), 383, **2010**.
36. WANG J.F., LI X.H., CHRISTAKOS G., LIAO Y.L., ZHANG T., GU X., ZHENG X.Y. Geographical Detectors – Based Health Risk Assessment and its Application in the Neural Tube Defects Study of the Heshun Region, China. International Journal of Geographical Information Science. **24** (1), 107, **2010**.
37. ZHANG X., ZHAO Y. Identification of the driving factors' influences on regional energy-related carbon emissions in China based on geographical detector method. Environmental Science and Pollution Research. **25** (10), 9626, **2018**.
38. ZHANG M., LIU X., DING Y., WANG W. How does environmental regulation affect haze pollution governance? – An empirical test based on Chinese provincial panel data. Science of The Total Environment. **695**, 133905, **2019**.
39. LIU Y., DONG F. Haze pollution and corruption: A perspective of mediating and moderating roles. Journal of Cleaner Production. **279**, 123550, **2021**.
40. LI W., QIAO Y., LI X., WANG Y. Energy consumption, pollution haven hypothesis, and Environmental Kuznets Curve: Examining the environment-economy link in belt and road initiative countries. Energy. **239**, 122559, **2022**.
41. XU C., ZHAO W., ZHANG M., CHENG B. Pollution haven or halo? The role of the energy transition in the impact of FDI on SO_2 emissions. Science of The Total Environment. **763** (2), 143002, **2020**.
42. ZHANG X., ZHAO Y., WANG C., WANG F., QIU F. Decoupling effect and sectoral attribution analysis of industrial energy-related carbon emissions in Xinjiang, China. Ecological Indicators. **97**, 1, **2019**.
43. WANG C., WANG F., ZHANG X., YANG Y., SU Y., YE Y., ZHANG H. Examining the driving factors of energy related carbon emissions using the extended STIRPAT model based on IPAT identity in Xinjiang. Renewable and Sustainable Energy Reviews. **67**, 51, **2017**.