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Effectiveness of Regional Collaborative Governance on Atmospheric Governance Performance Improvement

Juying Zeng*, David Sanz-Rivas, Jiaye Chen, Carlos Lassala

ABSTRACT

Addressing the trans-regional and dynamic transmission characteristics of air pollution is a considerable challenge for sustainable environmental management. Based on the sample data from 26 Yangtze River Delta (YRD) cities in the period of 2015-2022, this study employed a series of statistical and econometric methods, including spatial Markov chain, social cooperation network, weighted entropy method and spatial Durbin econometric model, to measure the dynamic inter-regional distribution shifts of air pollutants in YRD, the collaborative network involvement of the regional atmospheric collaborative governance and its effectiveness on atmospheric governance performance. It found a strong positive correlation among pollutants across different locations within YRD cities. The network structure of the collaborative regulation in YRD remains unstable with the cooperation density remaining at a low level despite a notable annual increase in collaborative intensity. The atmospheric governance performance has yielded substantially outstanding results. Furthermore, the effectiveness of regional atmospheric collaborative governance on atmospheric governance performance holds true, with the effects being more obvious in cities with more developed urbanisation and economy. Our research provides an important reference for the collaborative environmental regulation in other regions and China to achieve effective air pollution control and economic growth.

Keywords: *Air pollution, Atmospheric collaborative governance, Social cooperation network, Atmospheric governance performance, Spatial Durbin model*

JEL Classification: I38, Q53,O29

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1. INTRODUCTION

China's rapid economic growth has been accompanied by heightened concerns on environmental pollution, particularly atmospheric pollution. The trans-regional and dynamic transmission characteristics of atmospheric pollution are an important challenge for sustainable environmental management. Considering that air pollution is a widespread and trans-regional ecological challenge, no single region can effectively address it on its own (Liu et al., 2020). Data from the Ministry of Ecology and

Environment indicate that the average proportion of days with good air quality in 339 prefecture-level cities across China reached 85.8% and the average proportion of days with heavy and severe pollution decreased to 1.1% during the period of January 2024 to September 2024. The disparities in regional environmental regulations can lead to pollution transfer, and regional cooperation is necessary to mitigate pollution relocation and enhance the efficiency of government governance (Li et al., 2021).

Consequently, a 'regional joint prevention and control' strategy is proposed as the primary governance style in the country. Under this framework, the local government actively promotes green innovation among heavily polluting enterprises (Zuo & Lin, 2022) through various measures, including regulatory policies (Li & Shao, 2023) and government subsidies (Duan et al., 2022). The importance of atmospheric governance extends beyond mere air quality improvement; it is essential for transitioning China's economic growth from a rough and unsustainable path to a high-quality and sustainable one. However, the implementation of the regional collaborative environmental governance has revealed several weaknesses. Despite substantial investments in environmental governance and air quality improvement, the effectiveness of existing regulatory measures and cooperative frameworks has fallen short of expectations. This is mainly observed in two areas: First, the lack of policy coherence among cities leads to conflicts of interest, resulting in varied approaches to environmental planning, standards, assessments and oversight, which hampers collaboration in environmental governance. Second, the regional prevention and control mechanisms are insufficiently targeted, with weak connections among city clusters, key industries, critical regions and substantial issues, ultimately resulting in a lack of continuity and intrinsic motivation for joint prevention policies (Yan et al., 2021).

The Yangtze River Delta (YRD) is widely accepted as the pioneer region in China owing to its strong cooperation capabilities, rational industrial structure and rapid economic growth. Despite occupying only 2.3% of the nation's total area, YRD contributes nearly a quarter of China's Gross Domestic Product (GDP). However, due to the insufficient integration and utilisation of natural resources, YRD has suffered from long-term ecological damage and environmental pollution during the past decades (Zhou et al. 2022). With economic transformation and the strengthening of environmental regulations, the ecological environmental quality in the region has gradually improved; however, it still suffers from air pollution due to the non-optimised production structure of the enterprises. Along with the regional integration process in 2019, YRD cities have made efforts to accelerate the regional joint regulation on air pollution, making air quality management the top priority in the YRD region (Sun et al. 2023; Geng et al., 2024). The Outline of the Plan for the Integrated Development of YRD has set clear air quality targets, including generally meeting the standards for average $PM_{2.5}$ concentrations in cities and ensuring more than 80% of days with good air quality. Although the air quality in YRD has improved, the region still struggles with air pollution issues, particularly the ozone (O_3) levels not meeting the national Class I air quality standards. Moreover, during the summer, fall and winter months, the daily average concentrations of O_3 and $PM_{2.5}$ routinely exceed the acceptable limits, and the annual average concentrations of O_3 and carbon monoxide (CO) remain higher than the levels in the Guangdong–Hong Kong–Macao Greater Bay Area.

The singular air pollution regulation for one city could be confronted with the dilemma that the air pollutants and the pollutant emission of enterprises in its neighbouring areas will inevitably affect its air quality and the ineffectiveness of environmental regulation policies. To pursue sustainable environmental regulation effectiveness and economic optimisation, this study aimed to provide an accurate measurement of the effectiveness of inter-regional collaborative atmospheric pollution regulation on air quality improvement performances in YRD, with a sample data of 26 YRD cities during the period of 2015–2022. Specifically, the study aimed to answer the following questions concerning air quality improvement in YRD. First, what are the characteristics of the spatio-temporal distribution of atmospheric pollutants in YRD cities, and what are the dynamic shift features of the distribution of atmospheric pollutants within these cities? Second, the YRD region has proposed the Joint Prevention and Control System of Regional Air Pollution in 2019. What is the detailed extent of the collaborative atmospheric pollution regulation among YRD cities, and how has this collaborative regulation become involved and developed? Third, the air pollutants interact with each other, such as $PM_{2.5}$, NO_2 SO_2 and O_3. How can the comprehensive atmospheric governance performance with consideration of the dynamic change of multiple air pollutants be evaluated? Fourth, what are the detailed effects of the collaborative atmospheric pollution regulation in YRD on atmospheric governance performance?

To elucidate the above issues, based on the sample data from 26 YRD cities during the period of 2015–2022, the study first employed the spatial Markov chain to illustrate the spatial distribution and dynamic shift characteristics of air pollutants in YRD cities, which aims to provide evidences on the necessity of regional collaborative atmospheric pollution regulation among YRD cities. Second, the study employed the social cooperation network approach to innovatively establish the collaborative atmospheric regulation network based on the texts of joint prevention and control policy for multiple cities, which were collected from the official website of the ecological environment department of each YRD city. Third, the study used the weighted entropy method to estimate the atmospheric governance performance with consideration of the changing trend of various pollutants. Finally, the study established the spatial Durbin econometric model to evaluate the effects of collaborative atmospheric regulation on atmospheric governance performance in YRD.

The majority of research has focused on the theoretical aspects of the joint prevention and control regulation, whereas very few research have identified the accurate collaborative network and the effectiveness of the collaborative atmospheric regulation among YRD cities. The study innovatively established the collaborative atmospheric regulation network based on the text data of the joint prevention and control policy for multiple cities. Moreover, it employed multiple econometric approaches to realise an accurate evaluation of the effectiveness of collaborative atmospheric regulation on atmospheric governance performance in YRD, which provides an insight into the collaborative regulation involvement towards sustainable environmental improvement for YRD and other regions.

The remainder of this paper is organised as follows: Section 2 reviews the literature on air pollution, regional collaborative environmental regulation and collaborative governance network for atmospheric. Section 3 presents the research theoretical framework, research methodology and data illustration. Section 4 identifies the spatial distribution characteristics and regional collaborative network of atmospheric pollutants. Section 5 examines the detailed effects of collaborative environmental regulation on atmospheric governance performance in YRD. Section 6 concludes and provides closing remarks.

2. LITERATURE REVIEW

2.1 The spatial distribution identification of air pollution

Air pollution induces significant adverse impacts on human health, including respiratory and cardiovascular issues, environmental quality and sustainable development of cities (Dominski et al., 2021; Ren et al., 2023; Zeng et al., 2021; Azimi & Rahman, 2024). Based on a systematic mapping review of 3401 studies regarding the effects of air pollution, the majority of the studies were conducted by researchers from institutions in China, the USA, the UK and Italy (Dominski et al., 2021). Scholars believed that economic development is the root cause of air pollution (Magazzino et al., 2022). Jiang et al. (2022) found a U-shaped relationship between economic growth and air pollution. The economic development has substantial spatial agglomeration features; thus, urban air pollution is closely associated with the air conditions of neighbouring cities and exerts significant spatial spill-over effects (Ge et al., 2023). Zhou et al. (2024) held that air pollutants, such as $PM_{2.5}$ and PM_{10}, have the important features of spatio-temporal transmission variations along with the changes in emission characteristics, atmospheric oxidising capacity, meteorological conditions and even economic and financial features. To realise the effective mitigation of air pollution or waste emissions, the majority of research have made efforts to identify the spatio-temporal distribution of air pollution (Meng et al., 2023).

Scholars have investigated the spatial distribution from different range levels. For example, Wang et al. (2018) explored the spatial distribution of air pollution in major cities (ECN) in Eastern China in the winter of 2015 using the data of the Ministry of Environmental Protection’s hourly air quality index from the Ministry of Environmental Protection. Four typical types of spatial distribution of air pollution were identified and found that the spatial distribution of air pollution was mainly related to the lower horizontal axial winds. Only the persistence and strengthening of precipitation can be accompanied by more efficient wet removal and improved air quality. Ding et al. (2024) focused on the detection of air pollution in smaller areas. Air pollution is one of the serious environmental problems in the development of high-density cities, and the effective urban environmental monitoring technology helps predict and control the air pollution emitted by the transportation sector. Based on the limited data of the monitoring stations, they investigated the spatial and temporal patterns of air pollution and their correlation mechanism with urban elements, such as traffic. In addition, emerging monitoring technologies have been developed, such as mobile monitoring (Kousis et al., 2022), air quality monitoring using drones (Järvi et al., 2023) and low-cost sensor monitoring using artificial intelligence (Croce and Tondini, 2022). Furthermore, Liu et al. (2024) analysed the spatial distribution of air pollution from the perspective of a certain industry. They also analysed the driving mechanism of the space-related network of industrial air pollution.

2.2. Research on regional collaborative governance network

Sun et al. (2015) found that air pollution in Chinese cities is not only the accumulation of air pollution in the region but also the convergence of air pollution transmission from neighbouring cities and other cities in the social network. Therefore, building a cross-regional cooperative governance network based on the spatial network characteristics of air pollution has become the key to solving the problem of regional air pollution.

Scholars have identified the spatial network structure of inter-regional air pollution spill-over and air governance using a gravitational model. Wu (2019) used the ‘pressure-state-response’ framework to assess urban air governance in China and the gravity model to map the spatial network of the governance performance of 31 provincial capitals, demonstrating an uncooperative urban network with inherent limitations. Liu et al. (2021) employs the gravity model to assess the inter-city connections using macroeconomic data, such as aggregate indicators, geographic distances and population sizes. However, this approach lacks micro-level data on actual inter-city ties, leading the gravity model to merely outline a hypothetical city cooperation network. This results in a discrepancy between the model’s representation and the genuine inter-city network ties. Consequently, many scholars have started exploring the construction of environmental collaborative regulation network using the social cooperation network approach. Zhou (2020) analysed the collaborative atmospheric governance network of the YRD cluster and found that Shanghai serves as the leading city, whereas Hangzhou and Nanjing are substantial cooperative partners. Contrarily, the province of Anhui, with the exception of Ma’anshan, shows poor integration into this network.

2.3 Impact of regional collaborative governance on air quality improvement

Li et al. (2021) pointed out that the differences between regional environmental regulations may lead to pollution transfer and regional cooperation to reduce the pollution relocation and improve the efficiency of government governance. Ideally, under the regional collaborative governance scene, the environmental benefits could be maximised through resource sharing and complementary advantages (Wang et al., 2022). Specifically, Jiang and Lyu (2021) found that regional collaborative governance could break down geographical administrative barriers, promote the flow of production factors and facilitate cooperation to expand technology spill-overs. Ge et al. (2023) used difference-in-differences (DID) model based on panel data from 285 Chinese cities in the period of 2023–2019 and found that the regional co-treatment substantially contributed to the reduction of air pollution in YRD. In addition, the efficiency and effectiveness of collaborative environmental governance in YRD have witnessed a significant increase along with the intensifying regional co-integration in YRD. Sun et al. (2023) investigated the impact of low-carbon policies on air pollution collaborative governance and found that the policy helps reduce these two types of air pollution, thereby producing a significant collaborative governance effect.

2.4 Literature review

The literature has substantially enhanced our understanding of the spatial distribution of atmospheric pollutants and the effects of the mitigation strategies on air pollution in China. However, there is a noticeable gap in research regarding the detailed collaborative network of the collaborative environmental regulation in YRD, the evaluation of atmospheric governance performance and the effect of collaborative environmental regulation on atmospheric governance performance in YRD.

First, it is clear that the spatial distribution of air pollutants has been extensively studied (Ding et al., 2024). Scholars have claimed that the air pollutants have witnessed significant spatial transmission among regions. Nonetheless, there is a noticeable gap in research concerning the spatial dynamics and transitional behaviours of these pollutants. The inter-regional spread of air pollution (Liu et al., 2020; Liu and Qiao, 2021) highlights an urgent need for coordinated regional efforts in pollution mitigation. The accurate measurement of dynamic transmission based on shift probability features is of crucial importance among YRD regions.

Second, even the cities have made efforts to implement the joint prevention and control policies to improve the air quality; however, the collaborative environmental regulation for atmospheric pollution in YRD and China is still in their infancy (Li et al., 2022). The majority of research has focused on the theoretical aspects of these collaborative mechanisms, with a notable lack of empirical studies providing quantitative insights (Wang et al., 2020). Accurate measurement of the development and involvement of the collaborative regulation state through the collaborative network of the joint policies among YRD cities could provide a new insight for the area.

Finally, there has even been fewer research on the comprehensive evaluation of atmospheric governance performance with multiple air pollutants and the effectiveness of collaborative atmospheric regulation on atmospheric governance performance in YRD. Normally, the existing literature take the overall Joint Prevention and Control Plan as the treatment policy for analysis, whereas no study has focused on how the intensifying collaborative network of the collaborative atmospheric regulation policies among YRD cities stimulates the air quality improvement. The more detailed investigation of the intensifying collaborative network on environmental sustainability could be of crucial importance for the sustainable collaborative atmospheric regulation and environmental improvement for other regions and China.

3. RESEARCH DESIGN

3.1 Research hypothesis development

Air pollution triggers the psychological (affective, cognitive, behavioural), economic and social effects of air pollution beyond its physiological and environmental effects (Lu, 2020). Air pollutants mainly stem from industrial pollution, vehicle exhaust emissions and coal combustion. Scholars have identified that numerous economic factors indirectly contribute to environmental pollution, including industrial structure, economic growth and urbanisation (Zheng and Shen, 2021). Consequently, air pollutants tend to be concentrated in densely populated metropolitan areas, particularly in the larger network of cities. In this sense, the dispersion of air pollutants must account for the spatial structural relationships between cities (Sekula et al., 2022). Besides, the severity of air pollution, geographical distance, urbanisation level and industrialisation level in neighbouring cities are all related factors that contribute to the flow and variation of air pollutants among regions (Afghan et al., 2022). Overall, air pollution is a public good with negative externalities; it is also likely to exhibit significant positive spatial correlation and presents profound regional clustering features (Shen et al., 2020). In this sense, the study proposes hypothesis 1 (H1) as follows:

H1: *Air pollutants in YRD cities exhibit a significant positive spatial agglomeration effect.*

Evidences are provided that the local governments cannot fundamentally solve the complex and severe regional air pollution problems by relying on singular common pollution control mechanisms, such as consultation, notification, early warning and linkage of air pollution information (Liu et al., 2022). YRD cities are always recognised as pioneers in economic development and environmental governance. With the regional integration process in YRD that began in 2019, multi-city cooperation in the areas of economy, technology and environmental governance has been strengthened and intensified. Realising the regional diffusion characteristics of air pollutants, the YRD region has implemented the Joint Prevention and Control Plan in 2019. In addition to the overall integration plan for YRD, the sub-level cities within the YRD, particularly the more developed ones, have taken the initiative to implement several integrated collaborative emission reduction policies to achieve more satisfactory environmental outcomes. In this sense, the study proposes H2 as follows:

H2: *There is intensifying collaborative network of the collaborative atmospheric regulation policies among YRD cities during the past years.*

Previous literature has investigated the overall Joint Prevention and Control Plan as the treatment policy for analysis and provided evidences that the regional collaborative pollution governance level will vigorously promote air quality improvement (Liu and Wang, 2020). Liu et al. (2022) reported that the emission reduction cost of regional cooperative governance is better than that of individual governance. In 2017, the cost of SO_2 cooperative governance in the YRD decreased by about 1.8% compared with that of individual governance. Ge et al. (2023) evaluated the impact of regional collaborative treatment on air pollution using a DID model, analysing panel data from 285 Chinese cities from 2003 to 2019. Their findings indicated that regional co-treatment significantly contributed to the reduction of air pollution.

The intensifying collaborative network of the collaborative atmospheric regulation policies among YRD cities could be more vigorous and brings about more effective role in realising environmental governance performance in the YRD. In this sense, the study proposes H3 as follows:

H3: *The inter-regional collaborative atmospheric regulation could bring about significant roles in enhancing environmental governance performances in the YRD.*

3.2 Data illustration and sample description

This study utilised the data of 26 cities in the YRD. The specific cities are listed in Table 1. The indicators for measuring regional cooperative governance were selected from the data regarding collaborative atmospheric governance among cities within the YRD. The data on collaborative atmospheric governance were collected from the policy texts on the official website of the ecological environment department of each province during the period of 2015–2022.

Tab.1. Cities included in the YRD. Source: Own research

Provinces	Cities
Shanghai	Shanghai
Jiangsu Province	Nanjing, Wuxi, Changzhou, Suzhou, Nantong, Yangzhou, Zhenjiang, Yancheng, Taizhou
Zhejiang Province	Hangzhou, Ningbo, Huzhou, Jiaxing, Shaoxing, Jinhua, Zhoushan, Taizhou
Anhui Province	Hefei, Wuhu, Maanshan, Tongling, Anqing, Chuzhou, Chizhou, Xuancheng

The study determined keywords by searching on crucial documents, including the ‘Three-Year Action Plan for Defending the Blue Sky’, the ‘YRD Comprehensive Control of Air Pollution in Autumn and Winter Action Plan’ and the ‘YRD Air Pollution Prevention and Control Mechanism’. By performing frequency analysis on these key documents pertaining to cooperative governance, this study finally determined eight keywords for data search: ‘cooperation’, ‘linkage’, ‘joint’, ‘joint control’, ‘synergy’, ‘common governance’, ‘collaboration’ and ‘hand in hand’.

Consequently, the study used the Python web crawler technology to gather all textual data containing the eight aforementioned keywords from the official websites of the ecological environment departments in the YRD. The study specifically filtered and included texts related to cross-regional agreements, policies, joint actions and working instructions concerning atmospheric governance among cities. The study collected a total of 561 cooperation texts. In line with the research objectives and the principles of social network analysis (SNA), non-eligible texts were excluded, resulting in the acquisition of 147 valid inter-governmental cross-regional cooperation documents.

In the collaborative atmospheric governance network, the 26 prefecture-level cities in the YRD serve as the ‘actors’ within the social network, and the collaborative atmospheric governance among these cities represents the ‘relationship bond’ of the social network, which is gauged by the quantity of atmospheric cooperation texts. For the effective cooperation texts after sorting and screening, if a text mentions the cooperation times of multiple specific cooperation cities, a value of 1 is assigned and summed up. However, if it pertains to regional cooperation within a single city, it is not regarded as cooperation information to be incorporated into the cooperation network, which means that the value of the main diagonal of the collaborative atmospheric governance matrix is 0. Eventually, we obtained the cooperation matrix of atmospheric governance. Based on this matrix, we used the UCINET software to analyse the overall structure of the cooperation network and the characteristics of each node. Subsequently, we used the Ucinet software to analyse the cooperation network, specifically focusing on its overall structure and the characteristics of each node.

In addition, the study collected air pollutant and other macroeconomic data from the China Air Quality Online Monitoring and Analysis Platform (CAQOMAP), the China Urban Statistical Yearbook, the statistical yearbooks of provinces and municipalities in the YRD and the statistical yearbooks of prefectural cities. The $PM_{2.5}$ concentration data were obtained from the CAQOMAP, and the annual $PM_{2.5}$ concentration values of the cities were calculated by weighting the monthly data. For certain missing data, the random forest method was employed to fill in the gaps.

3.3 Research methodology

(1) Global Moran’s I

Global spatial autocorrelation represents a research approach that delves into the overall spatial clustering characteristics of various entities. It reflects the average extent of spatial interconnection among events and is typically gauged by the Global Moran’s I index. In this study, the Global Moran’s I index was selected to depict the overall distribution of the $PM_{2.5}$ concentration, which serves as the principal indicator of air pollution in each city within the YRD. The value of the Global Moran’s I index ranges from −1 to 1. The closer the absolute value of this index is to 1, the more pronounced the degree of air pollution concentration in the YRD region. Conversely, when the absolute value is closer to 0, it implies that the air pollution in the YRD is randomly distributed in space. Equation (1) is presented as follows:

$$Global\ Moran's\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(\bar{y} - y_i)}{(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij})\sum_{i=1}^{n} w_{ij}(y_i - \bar{y})^2} \tag{1}$$

where n is the sample size of the city; y_i, the PM2.5 concentration of the city; and w_{ij}, the spatial neighbourhood weight matrix representing the relationship between the spatial location of the city. When there is a common boundary between the city i and city j, $w_{ij}=1$; otherwise, $w_{ij}=0$.

$$w_{ij}=\begin{cases}0, & \text{The i is not adjacent to j}\\ 1, & \text{The i is adjacent to j}\end{cases} \tag{2}$$

As the global index is only capable of reflecting the global spatial correlation characteristics of air pollution in the YRD and fails to disclose the local spatial correlation characteristics of air pollutants among different cities, the local spatial correlation index is introduced to measure the potentially significant regional spatial correlation. The formula is as follows:

$$Local\ Moran's\ I=\frac{n(y_i-\bar{y})\sum_{j=1}^{m}w_{ij}(y_i-\bar{y})}{\sum_{j=1}^{n}(y_i-\bar{y})^2} \tag{3}$$

If Local Moran's I is >0, the air pollution level of a city is spatially positively correlated with those of the neighbouring cities, with the air pollution showing a 'high–high' or 'low–low' agglomeration. If the Local Moran's I is <0, it means that there is a negative spatial correlation between the air pollution of a city and that of its neighbours, with the air pollution showing a 'low–high' or 'high–low' agglomeration.

(2) Markov chain

A Markov chain is a type of stochastic process where both the state and time are simultaneously depicted. The state-transition probability constitutes an important aspect of the Markov chain. This section analyses the state transfer characteristics of air pollutants in the YRD through the traditional Markov chain. Its calculation formula is as follows:

$$P_{ij}=\frac{n_{ij}}{n_i} \tag{4}$$

where n_i denotes the number of times that $x_t=i$ and n_{ij} denotes the number of times that the PM2.5 concentration x_t of each city in the YRD shifted from i to state j under x_{t+1} in the neighbouring time t and $t+1$. Based on this, the state-transition matrix is shown in Table 2 to simulate the evolution process of atmospheric pollutants in the YRD.

Tab. 2. Classical Markov chain state-transition matrix. Source: Own research

$X_t \backslash X_{t+1}$	1	2	3	4
1	P_{11}	P_{12}	P_{13}	P_{14}
2	P_{21}	P_{22}	P_{23}	P_{24}
3	P_{31}	P_{32}	P_{33}	P_{34}
4	P_{41}	P_{42}	P_{43}	P_{44}

To conduct a more in-depth analysis of the mutual influence among neighbouring regions, the study introduces a spatial lag term based on the classical Markov chain. By using the nearest-neighbour 0-1 matrix between cities as the weight matrix of the spatial lag term, this study constructed a spatial Markov chain. By measuring the spatial distribution regarding the transfer of air pollutants, the study explored the probability and direction of the transfer of atmospheric pollutant states in the YRD under the context of the spatial adjacency matrix. The study provides the calculated lag values of each YRD city as follows:

$$b_i = \sum_{j=1}^{n} \frac{w_{ij} \cdot \partial_j}{n} \tag{5}$$

where ∂_j denotes the value of air pollution status of neighbouring cities of city i; n, the number of neighbouring cities of city i; and ∂_j, the air pollution state value in the traditional Markov chain of ∂_i ($w_{ij} = 1$). n is the number of cities , w_{ij} is 1 when the city is fixed to i.

(3) Social network analysis

Acknowledging that the cooperation in atmospheric governance among cities in the YRD can be regarded as a social network, this study used SNA to conduct quantitative data associated with such cooperation. The principal indicators measured by SNA in this study were described as follows:

Network density measures the degree of connectivity between nodes in a network of nodes N and correlation lines L, which is expressed as follows:

$$d(G) = \frac{2L}{N(N-1)} \tag{6}$$

Degree centrality measures the number of connections a node has to other nodes in the network. A higher value indicates that the node is more influential and more closely associated with other nodes, which is expressed as follows (7):

$$C_{AD}(n_i) = \sum_{j-1}^{g} x_{ij} (i \neq j) \tag{7}$$

Betweenness centrality quantifies the ratio of the count of the shortest paths traversing a particular node to the overall count of the shortest paths in the network. A relatively higher value indicates a more prominent intermediary function of the node and a more substantial regulatory effect within the network. This association is mathematically expressed as follows (8):

$$C_{ABi} = \sum_{j}^{n} \sum_{k}^{n} \frac{g_{jk}(i)}{g_{jk}} (j \neq k \neq i, j < k) \tag{8}$$

Closeness centrality measures the sum of the shortest paths from all the other nodes to a specific node. The shorter the distance between this node and the others, the easier it is to share information within a cooperative network, which is listed as follows:

$$C^{-1}{}_{APi} = \sum_{j-1}^{n} d_{ij} \tag{9}$$

(4) Entropy weight method

This study employed the entropy weight method to calculate the weight of each indicator. It also used this method as the foundation for the comprehensive evaluation of the atmospheric governance performance of cities in the YRD.

First, the extreme difference method was employed to standardise each indicator x_{ij} in the YRD atmospheric governance performance indicator system to eliminate the inconsistency of different indicators in terms of scale and magnitude. For the positive indicators, the calculation formula is as follows:

$$Y_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})} \tag{10}$$

$$Y_{ij} = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \tag{11}$$

where i denotes the prefecture-level cities in the YRD; j, the measurement indicator; x_{ij} and y_{ij}, the original and normalised YRD atmospheric governance performance measurement indicator values, respectively; and x_{max} and x_{min}, the maximum and minimum values of x_{ij}.

Second, the weight of the i th indicator under the j th indicator in the YRD atmospheric governance performance indicator system is estimated.

Third, the information entropy of the j th indicator in the YRD atmospheric governance performance indicator system is calculated.

$$e_j = -k\sum_{i=1}^{26} p_{ij} \cdot \ln(p_{ij}) \tag{12}$$

where the information entropy satisfies $e_j \geq 0$

Fourth, the coefficient of variation g_j of the j th indicator in the YRD atmospheric governance performance indicator system is calculated.

$$w_j = \frac{g_j}{\sum_{j=1}^{12} g_j} \tag{13}$$

Fifth, the weighted comprehensive score of the air governance performance of each city in the YRD is calculated, which is expressed as follows:

$$s_j = \sum_{j=1}^{12} w_j \cdot p_{ij} \tag{14}$$

(5) Spatial Durbin Model

If there are n regions, the spatial weight W contains $n \times n$ elements and is expressed as follows:

$$W = \begin{bmatrix} w_{11} \cdots w_{1n} \\ \vdots \cdots\cdots\cdots \vdots \\ w_{n1} \cdots w_{nn} \end{bmatrix}$$

where w_{ij} denotes the ‘distance’ between region i and j, which means different ‘distance’ according to the research purpose. Because the main diagonal represents the ‘distance’ between region i and itself, the value of the element w_{ii} on the main diagonal is 0. According to the research content of this paper, the following spatial weight matrices are constructed:

When the collaborative atmospheric governance matrix is selected as the spatial weight matrix, the spatial weight matrix is determined as follows:

$$w_{ij}=\begin{cases} x_{ij}, & \text{There is a partnership between city i and city j} \\ 0, & \text{There is no cooperative relationship between city i and city j} \end{cases} \tag{15}$$

The spatial Durbin model is expressed as follows:

$$\begin{aligned} PM_{2.5} = \rho WPM_{2.5} + \beta_1 fdi + \beta_2 \ln GDP + \beta_3 (\ln GDP)^2 + \\ \beta_4 edu + \beta_5 urban + \beta_6 rain + \theta_1 Wfdi + \theta_2 W \ln GDP + \\ \theta_3 W (\ln GDP)^2 + \theta_4 Wedu + \theta_5 Wurban + \theta_6 Wrain + \varepsilon \end{aligned} \tag{16}$$

$$\begin{aligned} performance = \rho Wperformance + \beta_1 fdi + \beta_2 struct + \beta_3 urban + \beta_4 wet \\ + \theta_1 Wfdi + \theta_2 Wstruct + \theta_3 Wurban + \theta_4 Wwet + \varepsilon \end{aligned} \tag{17}$$

Among them, w denotes the weight matrix of collaborative atmospheric governance performance, $PM2.5$ is explained variable; $fdi, struct, urban, wet$ as the explanatory variables; β, the regression coefficient of the explanatory variable without considering the spatial effect; ρ, the spatial autoregression coefficient of the explained variable; θ, the spatial lag term coefficient of the explanatory variable; and ε, the random disturbance term and $\varepsilon \sim (0, \sigma^2 I_n)$.

4. RESEARCH ON THE SPATIAL DISTRIBUTION CHARACTERISTICS AND GOVERNANCE COOPERATION NETWORK OF ATMOSPHERIC POLLUTANTS IN THE YRD

This study conducted spatial autocorrelation analysis and spatial state-transition analysis on the primary air pollutant $PM_{2.5}$ in the YRD with Global Moran's I and spatial Markov chain approaches.

4.1 Spatial aggregation characteristics of atmospheric pollutants

(1) Global spatial autocorrelation

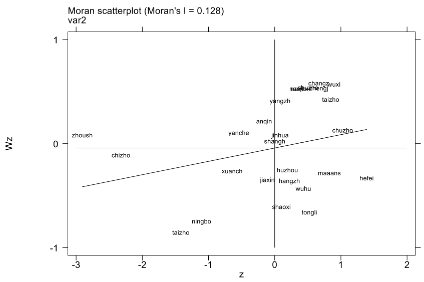
This section identifies the overall spatial agglomeration characteristics of atmospheric pollutants via global spatial autocorrelation. Table 3 lists the results of Global Moran's I. The results indicated that the Global Moran's I of YRD cities was significantly positive in the period of 2015–2022. Despite slightly decreasing in 2022, the global Moran's I exhibited an overall upwards tendency, indicating the prominent agglomeration phenomenon of the air pollution in the YRD. The $PM_{2.5}$ concentration has a significant positive correlation among adjacent cities, and this correlation gradually intensifies over time.

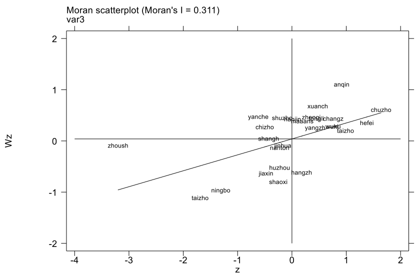
For cities with severe air pollution, as a result of the diffusion of air pollutants under the influence of air currents, these pollutants will be transmitted to neighbouring cities within a specific spatial range. Thus, this aggravates the air pollution situation in those neighbouring cities. The air quality of a city is not only contingent upon its own development but is also subject to the impact of the air quality of the surrounding cities, which implies that there exists a ‘positive feedback’ effect in the spatial dimension.

Tab.3. Global spatial autocorrelation value for PM2.5 concentration. Source: Own research

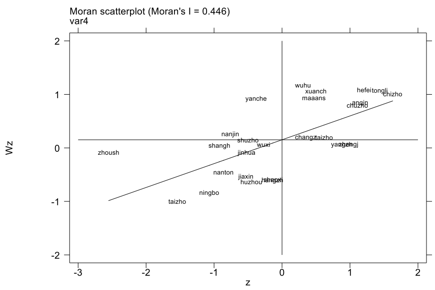
Year	I	E(I)	sd(I)	z	p-value*
2015	0.204	-0.040	0.111	2.198	0.028
2016	0.306	-0.040	0.109	3.173	0.002
2017	0.361	-0.040	0.116	3.466	0.001
2018	0.410	-0.040	0.114	3.955	0.000
2019	0.429	-0.040	0.114	4.122	0.000
2020	0.451	-0.040	0.113	4.329	0.000
2021	0.472	-0.040	0.104	4.935	0.000
2022	0.414	-0.040	0.102	4.427	0.000

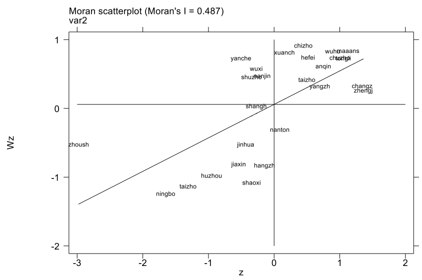
(2) Local autocorrelation analysis



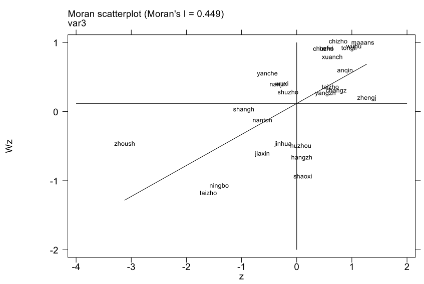


(2015) (2016)





(2017) (2021)



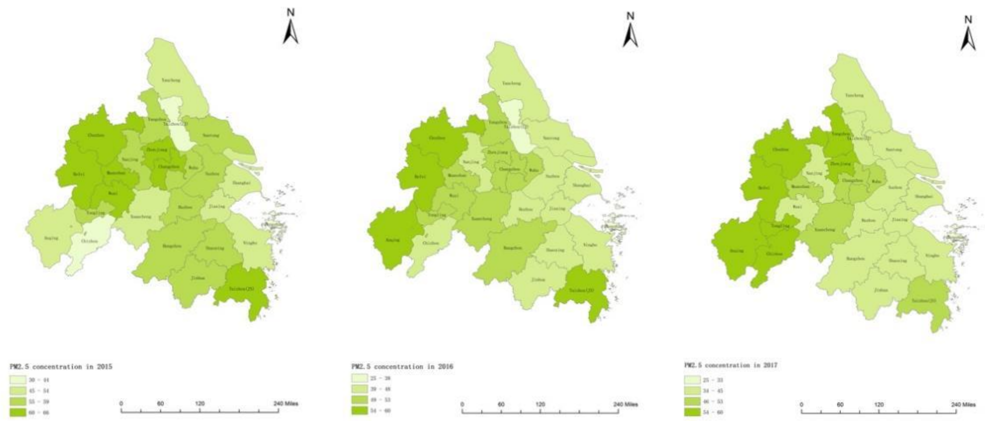
(2022)

Fig. 1. Spatial distribution of $PM_{2.5}$ for 26 YRD cities during the period of 2015–2022. Source: Own research

The majority of prefecture-level cities in the YRD exhibit either a ‘high–high’ or ‘low–low’ clustering pattern, which demonstrates a positive spatial correlation in the overall air pollution within the entire region. Furthermore, during the period of 2015–2022, the number of prefecture-level cities in the YRD categorised as ‘low–low’ has been continuously fewer than that of cities in a ‘high’ clustering state. This tendency might have stemmed from the inclination of numerous YRD cities to place a higher emphasis on economic growth rather than environmental well-being, giving rise to competition and emulation among neighbouring cities. Such approaches may impede the sustainable routes towards high-quality economic development.

Taking a geographical perspective, the prefecture-level cities in the YRD located within the ‘high–high’ and ‘low–low’ clustering areas roughly exhibit a significant difference between the southeast and the northwest regions. Jiaxing, Ningbo, Zhoushan, Taizhou, Jinhua and Shaoxing are essentially located in the ‘low–low’ clustering areas, which are all the cities on the southeast coast of Zhejiang Province. As the warm current of the Pacific Ocean can flow directly in, it can not only enhance the air quality to a certain extent but also prompt the surrounding cities to improve their air quality. However, Zhenjiang, Taizhou, Hefei, Anqing, Chuzhou, Chizhou, Tongling, Ma’anshan and Xuancheng, which are located in the northwest inland region, are basically situated in the ‘high–high’ gathering areas. Not only is their own air quality poor, but the air quality of the surrounding cities is also less than satisfactory.

Moreover, the Arcgis software was used to create a heat map of the average annual $PM_{2.5}$ concentration in the YRD from 2015 to 2022. As depicted in Figure 2, when combined with the analysis of the heat map and the Local Moran scatter plot, the $PM_{2.5}$ concentration in the YRD exhibits polarisation. Among them, the air pollution level in the southeast region is relatively low, whereas that in the northwest region is relatively high. The $PM_{2.5}$ concentration produces a significant clustering effect in space. This also validates the strong transmission of $PM_{2.5}$ within the YRD. Consequently, to address a series of ecological and environmental issues such as air pollution, it is evidently insufficient to rely on a single city to intensify its environmental governance efforts. This calls for regional cooperative governance among different regions.



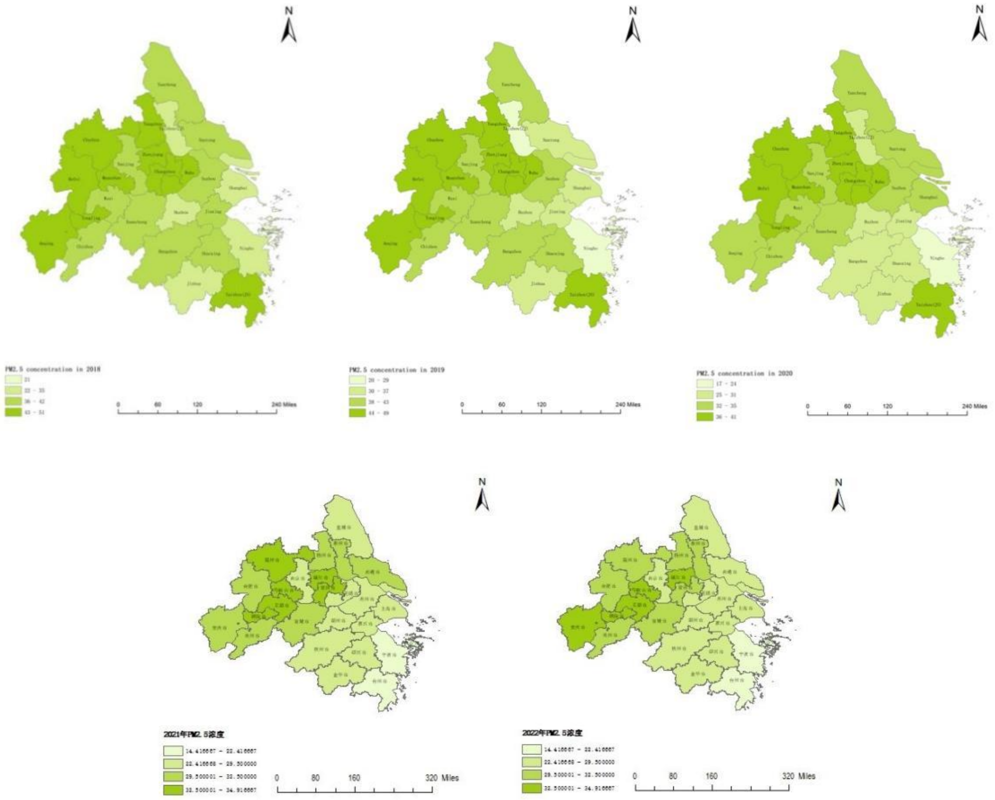


Fig. 2. Thermodynamic map of the $PM_{2.5}$ concentration in the YRD during the period of 2015–2022. Source: Own research

4.2 Analysis of the state transfer characteristics of air pollutants

(1) Identification results with classical Markov chain

This study employed the quartile method to categorise the $PM_{2.5}$ concentrations in the cities of the YRD into four states, namely, low concentration, lower concentration, higher concentration and high concentration. On this basis, the study computed the state transfer probabilities.

The classical Markov chain state-transition matrix for air pollution in the YRD is presented in Table 4. Notably, the values along the main diagonal are significantly greater than those on the non-main diagonal. In other words, the probability that the air quality state of each city in the YRD does not change in the subsequent year is substantially larger than the probability that the air quality state of each city in the YRD will change in the following year. The smallest value on the main diagonal is 0.400, which implies that the probability of a prefecture-level city in the YRD maintaining its original air quality condition in the next year is at least 40%.

Moreover, during the process of the state-transition of the four air quality states in the YRD, the values located on both sides of the main diagonal are significantly larger than those not adjacent to the main diagonal. In addition, the probabilities of transitioning from lower to higher concentrations, higher to lower concentrations and higher to lower concentrations are all zero. This suggests that the probability of the air quality of YRD prefecture-level cities transitioning to neighbouring states during the state-transition process is much larger than the probability of transitioning across different levels. Also, the greater the state span, the smaller the probability of such a state transition occurring.

Tab.4. Classical Markov chain transition state matrix during 2015–2023.Source: Own research

$X_t \backslash X_{t+1}$	Low concentration	Lower concentration	Higher concentration	High concentration
Low concentration	0.8542	0.1458	0.0000	0.0000
Lower concentration	0.3182	0.6364	0.0455	0.0000
Higher concentration	0.0508	0.3559	0.5593	0.0339
High concentration	0.0000	0.0175	0.4035	0.5789

(3) Identification results with spatial Markov chain

As the previous section showed that the air pollution status of cities in the YRD is not spatially independent, we found that the air pollution levels in neighbouring regions influence one another, resulting in a substantial spill-over effect. Consequently, we incorporated the spatial lag term into our analysis, building upon the traditional Markov chain approach.

The spatial lag order was first determined by calculating the mean PM2.5 concentrations in neighbouring cities within the YRD. The 26 prefecture-level cities in the YRD were then classified into four spatial lag states using the quantile method; the results are presented in Table 5.

The state-transition probability matrix on the spatial lag value is related to city i in the initial year, which is categorised as low concentration, lower concentration, higher concentration and high concentration. Then the study decomposes the traditional Markov chain's 4 × 4-state matrix into four conditional state-transition probability matrices of order 4 × 4, as presented in Table 6.

Tab.5. Type of spatial lag for YRD cities. Source: Own research

Cities	Spatial lag order	Cities	Spatial lag order
Anqing	1	Jiaxing	3
Jinhua	1	Maanshan	3
Ningbo	1	Shanghai	3
Shaoxing	1	Suzhou	3
Taizhou	1	Taizhou	3
Tongling	1	Wuxi	3
Zhoushan	1	Changzhou	4

Chizhou	2	Chuzhou	4
Hangzhou	2	Hefei	4
Huzhou	2	Nanjing	4
Nantong	2	Yancheng	4
Wuhu	2	Yangzhou	4
Xuancheng	2	Zhenjiang	4

Tab. 6. State transferring matrices for spatial Markov chain. Source: Own research

Spatial lag state	$X_t \backslash X_{t+1}$	1	2	3	4
1	1	$P_{11/1}$	$P_{12/1}$	$P_{13/1}$	$P_{14/1}$
	2	$P_{21/1}$	$P_{22/1}$	$P_{23/1}$	$P_{24/1}$
	3	$P_{31/1}$	$P_{32/1}$	$P_{33/1}$	$P_{34/1}$
	4	$P_{41/1}$	$P_{42/1}$	$P_{43/1}$	$P_{44/1}$
…	…	…	…	…	…
4	1	$P_{11/4}$	$P_{12/4}$	$P_{13/4}$	$P_{14/4}$
	2	$P_{21/4}$	$P_{22/4}$	$P_{23/4}$	$P_{24/4}$
	3	$P_{31/4}$	$P_{32/4}$	$P_{33/4}$	$P_{34/4}$
	4	$P_{41/4}$	$P_{42/4}$	$P_{43/4}$	$P_{44/4}$

By using these matrices, the study provides the classical Markov state-transition matrix for each spatial lag type and then obtains the spatial Markov chain state-transition matrix. Table 7 presents the results regarding the transferring matrix for air pollution in the YRD. Notably, substantial differences were observed in the state-transition probabilities of air quality among prefecture-level cities in the YRD under different spatial lag states. The cities in the low-, lower- and higher-concentration lag states have a high likelihood of downwards transition in the PM2.5 concentration and a low likelihood of upwards transition. Contrarily, the cities in the high-concentration lag state show a low probability of downwards transitions and a high probability of upwards transitions. This implies that the air quality conditions of neighbouring cities in the YRD affect the air quality transitions of individual cities.

Tab.7. Transferring matrix for air pollution in the YRD during 2015–2023.

Spatial lag state	$X_t \backslash X_{t+1}$	Low concentration	Lower concentration	Higher concentration	High concentration
Low concentratio	Low	0.8824	0.1176	0.0000	0.0000
	Lower	0.1250	0.7500	0.1250	0.0000
	Higher	0.0000	0.0000	0.0000	0.0000
	High	0.0000	0.0000	0.0000	0.0000
Lower concentration	Low	0.6250	0.3750	0.0000	0.0000
	Lower	0.3571	0.6429	0.0000	0.0000
	Higher	0.3000	0.5000	0.2000	0.0000

	High	0.0000	0.0000	0.0000	0.0000
Higher concentration	Low	1.0000	0.0000	0.0000	0.0000
	Lower	0.5000	0.5000	0.0000	0.0000
	Higher	0.0000	0.3590	0.6154	0.0256
	High	0.0000	0.1250	0.6250	0.2500
High concentration	Low	1.0000	0.0000	0.0000	0.0000
	Lower	0.2500	0.5000	0.2500	0.0000
	Higher	0.0000	0.2000	0.7000	0.1000
	High	0.0000	0.0000	0.3673	0.6327

Source: Own research

4.3 Collaborative atmospheric governance network in the YRD

(1) Measurement of overall indicators for collaborative atmospheric governance

Network density is a crucial indicator used to depict the overall structural pattern of social networks. The value range of network density lies between 0 and 1. The closer it gets to 1, the more seamless the information flow and the more frequent the cooperative actions among the nodes within the network. Conversely, the closer it gets to 0, the less smooth the information flow between the nodes in the network and the more estranged the cooperative relationship.

Tab. 8. Density of collaborative atmospheric governance in YRD during 2015-2022

Year	2015	2016	2017	2018	2019	2020	2021	2022
Network density	0.1477	0.2000	0.1877	0.2492	0.4185	0.4523	0.4769	0.4923

Source: own research

Table 8 shows the density of the atmospheric governance network in the YRD, indicating that with the exception of a slight decline in the density of collaborative atmospheric governance in 2017, the density of such cooperation in the YRD has exhibited on an upwards trend and the rate of increase has grown. The cooperation density in 2019 showed an 83.3% growth compared with that in 2015, indicating that the cross-border cooperation in atmospheric governance among cities is becoming increasingly closer. The density of collaborative atmospheric governance exhibited a steady upwards trend from 2020 to 2022. Although the current network structure is not yet stable enough and the cooperation density had not reached 0.5 by 2022, the overall trend is showing improvement.

By employing condensed subgroup analysis to map out the collaborative atmospheric governance network in the YRD, it becomes feasible to more distinctly identify the core and peripheral cities involved in collaborative atmospheric governance, along with the cooperation relationships and the degree of closeness between each city. Among them, the core degree of the urban cooperation status is represented by the size of a square. While the degree of cooperation is illustrated by the thickness of lines. The visualisation results are shown in Figure 3.

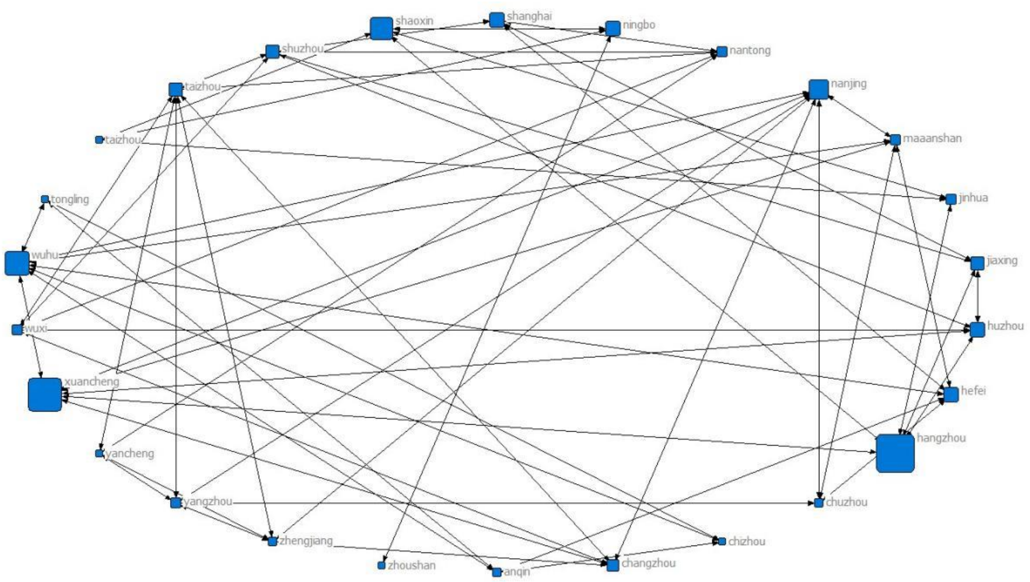


Fig. 3. Cooperation network for atmospheric governance in the YRD. Source: Own research

(2) Measurement of individual indicators for collaborative atmospheric governance

Degree centrality indicates the cooperation capacity of cities in the YRD within the collaborative atmospheric governance network. The greater the degree centrality of a city, the more closely it is associated with other cities in the collaborative atmospheric governance network and the more central the city's position is within the cooperation network. The measurement outcomes are shown in Table 9.

Based on the results, Suzhou, Jiaxing, Nanjing, Shanghai and Wuxi show the highest degree centrality, thus being identified as the core cities for cooperation. As provincial capitals and municipalities directly under the central government, Nanjing and Shanghai hold significant influence and allure. Furthermore, they are endowed with abundant human, material and financial resources, which empower them to effectively tackle environmental pollution. This robust resource foundation underpins their core positions in the collaborative atmospheric governance. It is also apparent that the cities surrounding Taihu Lake as well as those within the Nanjing Metropolitan Circle and the Hangzhou Metropolitan Circle maintain close cooperative ties. The geographical proximity among Shanghai, Jiaxing and Huzhou promotes frequent cross-border cooperation among these three cities. Contrarily, the overall cooperative ability of cities in Anhui Province is relatively weak. Ma'anshan exhibits the highest degree centrality within Anhui, yet with a score of only 39. This implies a peripheral overall position for Anhui Province within the atmospheric governance network.

Tab.9. Degree centrality of collaborative atmospheric governance during 2015–2022.

City	Degree centrality	City	Degree centrality
Suzhou	176	Wuhu	55
Jiaxing	147	Chuzhou	53
Nanjing	123	Nantong	51
Shanghai	118	Xuancheng	39
Wuxi	101	Jinhua	36
Hangzhou	94	Anqing	33
Changzhou	94	Ningbo	33
Huzhou	87	Hefei	32
Zhenjiang	77	Chizhou	31
Taizhou	74	Taizhou	23
Yangzhou	63	Tongling	23
Shaoxing	62	Yancheng	17
Maanshan	55	Zhoushan	9

Source: own research

Interestingly, Yancheng and Zhoushan in Zhejiang Province rank last in the YRD in terms of degree centrality, despite having some of the finest air quality in the region. This circumstance might arise from their favourable climate and geographical conditions, which lead to good air quality. Consequently, they may not have made substantial investments in collaborative atmospheric governance. Betweenness centrality emphasises the regulatory capacity among different cities within the YRD and other prefecture-level cities. A city's betweenness centrality is directly correlated with its level of control over cooperative resources in the atmospheric governance network. Most cities with higher betweenness centrality play a mediating role in the cooperation network, as shown in Table 9.

The outcomes suggest that among the 26 YRD cities, Hangzhou demonstrates the highest betweenness centrality. As the capital city of Zhejiang Province, Hangzhou holds a crucial position within the cooperation network. This position indicates a strong ability to manage cooperation resources and highlights its role as a connecting bridge in the atmospheric governance collaboration within the YRD. Xuancheng ranks second in terms of betweenness centrality and shares boundaries with Nanjing, Wuxi, Changzhou, Hangzhou, Huzhou, Wuhu, Ma'anshan and Chizhou. This geographical connectedness increases the probability of resource sharing via Xuancheng, leading to a relatively stronger capacity for resource control. However, Xuancheng does not hold an absolute core position in the collaborative atmospheric governance network, which indicates that its efficiency in resource utilisation needs to be improved. Shanghai, despite having a high degree of centrality, surprisingly shows a low resource control capability. This reflects that although it acts as a central element within the cooperative network, its effectiveness in handling cooperative resources is rather limited. Contrarily, Taizhou, Zhoushan, Tongling and Chizhou exhibit extremely low betweenness centrality, indicating their peripheral status within the cooperation network. As a result, these cities have restricted cooperation and control capabilities.

Closeness centrality measures the sum of the shortest distances between prefecture-level cities in the YRD and other prefecture-level cities. It reflects the capacity of each prefecture-level city in the YRD to be independent within the collaborative atmospheric governance network. The closer the prefecture-level cities are to other prefecture-level cities, the less they depend on them. Conversely, the farther they are from other central cities, the fewer cooperation benefits they obtain. Table 10 shows the measurement results of betweenness centrality.

Tab. 10. Betweenness centrality of collaborative atmospheric governance during 2015–2022.

City	Betweenness centrality	City	Betweenness centrality
Hangzhou	102.567	Yangzhou	11.515
Xuancheng	89.075	Jinhua	10.5
Wuhu	57.271	Nantong	9.941
Shaoxing	53.5	Wuxi	9.591
Nanjing	41.619	Maanshan	9.1
Huzhou	26.048	Zhenjiang	6.967
Hefei	25.145	Chuzhou	5.376
Shanghai	24.315	Anqing	4.667
Ningbo	24	Yancheng	2.25
Suzhou	19.741	Taizhou	1
Jiaxing	18.286	Tongling	0
Taizhou	18.215	Chizhou	0
Changzhou	17.31	Zhoushan	0

Source: own research

Tab. 11. Closeness centrality of collaborative atmospheric governance during 2015–2022.

City	Closeness Centrality	City	Closeness Centrality
Xuancheng	49.02	Zhenjiang	37.31
Nanjing	44.64	Taizhou	37.31
Hangzhou	43.86	Chuzhou	36.77
Huzhou	43.86	Nantong	35.71
Wuhu	43.10	Shaoxing	33.78
Maanshan	41.67	Anqing	33.78
Changzhou	41.67	Jinhua	32.89
Suzhou	40.32	Yancheng	31.65
Shanghai	40.32	Chizhou	31.25
Jaixing	39.68	Tongling	31.25
Wuxi	39.06	Taizhou	26.32
Hefei	37.88	Ningbo	26.32
Yangzhou	37.88	Zhoushan	21.01

Source: own research

According to the estimated results, Xuancheng, Nanjing, Hangzhou and Huzhou display higher closeness centrality. Notably, Nanjing and Hangzhou are the capital cities of Jiangsu Province and Zhejiang Province, respectively, whereas Xuancheng and Huzhou are located close to many cities in the YRD. These geographical locations endow them with advantages in information sharing, enabling them to reap greater benefits from the cooperation network. Contrarily, Anqing, Tongling and Chizhou in Anhui Province have lower closeness centrality. This can be attributed to their restricted control over cooperative resources and their relatively feeble capacity for collaborative atmospheric governance. Likewise, Ningbo, Taizhou and Zhoushan in Zhejiang Province exhibit lower closeness centrality, which might be affected by geographical factors. However, the air quality in these cities is generally good, leading to a lower demand for cooperative resources.

5. EFFECTIVENESS IDENTIFICATION OF COLLABORATIVE ENVIRONMENTAL REGULATION IN YRD

5.1. comprehensive evaluation of atmospheric governance performance

(1) Indicator illustration of atmospheric governance performance

According to the pressure state response (PSR) (Peng et al., 2020; Fu et al., 2022) and taking into account the rationality of indicators, data availability and the atmospheric governance process in the YRD, this study developed a three-level atmospheric governance performance indicator system. Table 12 lists the specific indicators of the evaluation index system for atmospheric governance performance.

Tab.12. Evaluation index system for atmospheric governance performance.

First-level index	Second-level index	Indicator illustration	Unit of measurement
Evaluation index system for atmospheric governance performance in the YRD	Pressure indicators Status indicators Response indicators Criterion layer	Industrial sulphur dioxide emissions per unit of GDP	Tons/million yuan
		Industrial nitrogen oxide emissions per unit of GDP	Tons/million yuan
		Industrial smoke (powder) dust emissions per unit of GDP	Tons/million yuan
		Industrial wastewater discharge per unit of GDP	10000 tons/million yuan
	Pressure indicators Status indicators Response indicators Criterion layer	Concentration of fine particulate matter ($PM_{2.5}$)	Micrograms/cubic metre
		Nitrogen dioxide concentration	Micrograms/cubic metre
		Sulphur dioxide concentration	Micrograms/cubic metre
		Inhalable particulate matter (PM_{10}) concentration	Micrograms/cubic metre
	Pressure indicators	Comprehensive utilisation rate of general industrial solid waste	%
		Centralised treatment rate of sewage treatment plant	%

	Harmless treatment rate of household waste	%
	Green coverage rate in built-up areas	%

Source: Own research

The PSR model is used to assess atmospheric governance performance by examining the pressure of pollutants on air quality, the state of the atmosphere and the response to air pollution. Industrial emissions such as sulphur dioxide and nitrogen oxide negatively impact air quality, with higher emissions per GDP indicating higher pressure. State indicators, such as PM2.5, PM10, nitrogen dioxide and sulphur dioxide levels, reflect air quality, with higher values indicating poorer conditions. Response indicators measure government and enterprise actions, including sewage treatment and waste management rates, with higher values indicating more effective governance. The model aligns with the process of atmospheric governance, making it a rational approach for evaluating performance in different cities within the YRD. The indexes are selected based on related literatures concerning atmospheric governance performance (Zhou et al., 2022;　Zhou et al., 2024；Sun et al, 2023).

(2) Evaluation of atmospheric governance performance

The measurement results of atmospheric governance performance are shown in Table 13. Overall, the atmospheric governance performance of the YRD is generally improving, with most cities demonstrating a fluctuating upwards trend between 2015 and 2022.

Tab. 13. Air governance performance evaluation for YRD during 2015- 2022.

City	2015	2016	2017	2018	2019	2020	2021	2022	Mean value
Shanghai	0.369	0.445	0.518	0.566	0.568	0.559	0.565	0.587	0.522
Nanjing	0.364	0.437	0.487	0.542	0.555	0.623	0.659	0.681	0.544
Wuxi	0.409	0.457	0.487	0.532	0.557	0.637	0.673	0.715	0.558
Changzhou	0.411	0.480	0.505	0.531	0.546	0.586	0.622	0.648	0.541
Suzhou	0.361	0.399	0.464	0.496	0.537	0.611	0.628	0.662	0.520
Nantong	0.490	0.536	0.576	0.616	0.634	0.672	0.686	0.704	0.614
yancheng	0.470	0.510	0.536	0.599	0.626	0.695	0.737	0.757	0.616
Yangzhou	0.462	0.512	0.491	0.555	0.586	0.637	0.653	0.673	0.571
Zhenjiang	0.456	0.478	0.497	0.584	0.581	0.640	0.650	0.668	0.569
Taizhou	0.382	0.444	0.508	0.571	0.593	0.661	0.687	0.721	0.571
Hangzhou	0.430	0.476	0.485	0.546	0.564	0.657	0.639	0.683	0.560
Ningbo	0.432	0.506	0.532	0.599	0.601	0.662	0.672	0.682	0.586
Jiaxing	0.507	0.574	0.513	0.559	0.583	0.639	0.613	0.636	0.578
Huzhou	0.599	0.635	0.634	0.671	0.680	0.710	0.693	0.696	0.665
Shaoxing	0.465	0.553	0.544	0.609	0.621	0.669	0.657	0.679	0.600
Jinhua	0.478	0.550	0.581	0.621	0.625	0.656	0.664	0.676	0.606
Zhoushan	0.572	0.626	0.663	0.690	0.695	0.778	0.777	0.795	0.699
Taizhou	0.604	0.635	0.751	0.698	0.715	0.724	0.711	0.744	0.698
Hefei	0.477	0.459	0.514	0.596	0.600	0.644	0.691	0.731	0.589
Wuhu	0.432	0.481	0.477	0.541	0.565	0.597	0.679	0.681	0.557
Maanshan	0.467	0.522	0.507	0.552	0.570	0.625	0.620	0.628	0.561

tongling	0.460	0.534	0.548	0.586	0.507	0.620	0.596	0.614	0.558
Anqing	0.530	0.538	0.554	0.591	0.588	0.571	0.673	0.676	0.590
Chuzhou	0.483	0.470	0.524	0.580	0.667	0.701	0.751	0.841	0.627
chizhou	0.570	0.543	0.534	0.622	0.646	0.709	0.706	0.738	0.634
Xuancheng	0.507	0.518	0.543	0.610	0.616	0.682	0.723	0.740	0.617

Source: Own research

YRD has shown high environmental governance performance, averaging over 0.5 for 8 years, supporting economic growth and ecological improvements. Shanghai and Zhejiang's close cooperation has led to substantial regional governance achievements, particularly in Zhoushan and Taizhou, which excel in atmospheric governance despite their low participation in collaborative networks.

Jiangsu and Anhui lag slightly behind Zhejiang in atmospheric governance. Jiangsu's Nantong and Yancheng have an average score of 0.6, whereas core YRD cities such as Nanjing, Suzhou and Yangzhou score around 0.5, indicating a need for these cities to balance local improvements with regional cooperation to prevent declines in atmospheric governance efficiency.

Anhui's Tongling and Wuhu also show low atmospheric governance performance, suggesting that Xuancheng needs to expedite the development of an efficient, high-quality environmentally friendly society. As a key city in the regional governance network, Xuancheng must enhance its cooperative governance efficiency and resource utilisation. Ma'anshan, the first in Anhui to implement digital environmental governance, has an average score of 0.561 over 5 years. Despite the rapid growth from 2019 to 2022, Ma'anshan's governance efficiency requires further enhancement, particularly with the rapid economic digitalisation, highlighting the importance of improving environmental governance efficiency.

5.2. Effectiveness identification of collaborative atmospheric regulation

(1) Variable illustration for the effectiveness identification

To measure the effectiveness of collaborative atmospheric regulation, Table 14 presents the explanatory variables and explained variables according to the impact features of collaborative atmospheric regulation, the influencing factors of air quality improvement and atmospheric governance performance improvement. The study not only focuses on the single air quality improvement through PM2.5 but also emphasises the comprehensive governance performance for analysis.

Tab. 14. List of explanatory variables and explained variables

Variable	Variable abbreviation	Variable illustration	Variable source
Air quality	$PM_{2.5}$	The annual average concentration of $PM_{2.5}$ in the YRD cities	China's air quality online monitoring and analysis platform

Atmospheric governance performance	Performance	The atmospheric governance performance of the YRD cities	China's air quality online monitoring and analysis platform
Foreign direct investment	fdi	The ratio of the amount of foreign direct investment and the number of foreign investment projects to represent the foreign capital	The Statistical Yearbook of Chinese Cities
Economic development level	lnGDP, $(\ln GDP)^2$	The logarithm of per capital GDP and its square to measure the level of economic development	The Statistical Yearbook of Chinese Cities
Industrial structure adjustment	struct	The ratio of the GDP of the secondary industry to the tertiary industry	The Statistical Yearbook of Chinese Cities
educational expenditure	educt	The proportion of education expenditure in local general public expenditure	The Statistical Yearbook of Chinese Cities
Urbanisation level	urban	The ratio of the urban population to the total population for the YRD city	The National Bureau of Statistics and the municipal Bureau of Statistics
Precipitation	rain	The rain volume	China surface climate data daily value data set
Humidity	wet	The air humidity	China surface climate data daily value data set

Source: Own research

(2) Identification of air quality improvement

Tab.15. Estimation results of factors influencing air quality improvement.

VARIABLES	(1) Spatial	(2) Main	(3) Wx	(4) Direct	(5) Indirect	(6) Total
ρ	0.595***					
	(0.00)					
lnGDP		61.220*	67.378	86.588**	228.066*	314.654**
		(0.09)	(0.30)	(0.03)	(0.08)	(0.03)
$lnGDP^2$		-2.871*	-3.063	-4.041**	-10.474*	-14.515**
		(0.09)	(0.30)	(0.02)	(0.07)	(0.02)
urban		-34.364***	-50.896**	-50.041***	-159.447***	-209.488***
		(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
edu		23.869	-75.710**	8.791	-142.167*	-133.376
		(0.24)	(0.05)	(0.70)	(0.09)	(0.18)
struct		5.520**	-8.503**	4.371*	-11.419	-7.048
		(0.01)	(0.04)	(0.07)	(0.21)	(0.51)

rain		-0.001	0.001	-0.000	0.001	0.000
		(0.73)	(0.73)	(0.80)	(0.87)	(0.96)
fdi		-17.129	-9.487	-21.253	-39.668	-60.922
		(0.49)	(0.80)	(0.43)	(0.61)	(0.49)
Observations	208	208	208	208	208	208
Number of cities	26	26	26	26	26	26

*** p<0.01, ** p<0.05, * p<0.1. Source: Own research.

Table 15 presents the estimation results of factors influencing air quality improvement in YRD cities. The LM test was employed to determine the suitability of the spatial error model or the spatial lag model for the empirical analysis in this study. However, it was deemed inappropriate for the selection between the spatial Durbin model, the spatial error model and the spatial lag model. The spatial Durbin model was selected as the reference, and its applicability, along with the other two models, was assessed using maximum likelihood estimation and the likelihood ratio test. Neither the spatial error model nor the spatial lag model's spatial terms passed the significance test. In this sense, the study adopted the spatial Durbin model for analysis.

The model's estimated results indicated a significant positive autocorrelation coefficient for air quality at 0.595, suggesting a strong positive correlation between the $PM_{2.5}$ concentrations in cities engaged in collaborative atmospheric governance. This implies that the air pollution in one YRD city exacerbates the pollution in others. The impact of economic development level on air quality followed an inverted U-shaped curve, aligning with the environmental Kuznets curve, indicating that economic growth can improve air pollution to some extent as the economy develops. Urbanisation had a significant negative impact on air quality, suggesting that the concentration of resources in urbanisation improves environmental governance efficiency and air quality. The spatial term of urbanisation also had a significant negative impact, indicating that urbanisation improvements in surrounding cooperative cities can substantially improve air quality.

Educational expenditure had a significant negative coefficient of −75.71 at significant level of 5%, indicating that increased educational spending can slow down air pollution in related cities through environmental governance cooperation, potentially enhancing environmental awareness and air quality. In summary, the spatial Durbin model was found to be the most suitable for analysis, and factors such as economic development, urbanisation and educational expenditure considerably influence air quality in the YRD, with urbanisation and educational expenditure showing potential for air quality improvement through cooperative governance.

Furthermore, analysis of the spatial Durbin model revealed that the total effect on air quality is decomposed into direct and indirect (spatial spill-over) effects. Direct effects, which are the local impacts of air quality factors, such as industrial structure, economic development and urbanisation, indicate that economic development has the most significant influence, with a coefficient of 86.588, highlighting its crucial role in air environment improvement. The indirect effects demonstrate that factors in cooperating cities, such as economic development, urbanisation and educational expenditure, substantially influence a city's air pollutant concentrations. The combined total effect of economic development is 314.654, significant at the 5% level, whereas the total effect of urbanisation is significantly negative at the 1% level, indicating that the acceleration of urbanisation contributes to better air quality in the YRD.

Table 16 provides the analysis results for YRD provinces. It shows distinct dynamics in air quality and its determinants. In Zhejiang, the spatial lag term coefficient of the $PM_{2.5}$ concentration is 0.52, suggesting that Zhejiang's air quality is influenced by cooperative cities. Zhejiang's economic development level has a significantly negative spatial lag term coefficient, indicating a transition to high-quality development where economic growth improves air quality rather than exacerbating ecological deterioration. Urbanisation in Zhejiang also has a significantly negative impact, implying that urbanisation improvements can enhance air quality, and the same is true for surrounding cooperative cities.

In Jiangsu, educational expenditure has a positive coefficient of 63.102, potentially worsening air pollution, but the negative spatial lag term coefficient of −229.139 indicates that increased educational spending in cooperating cities can alleviate the city's environmental pollution. Urbanisation in Jiangsu also has a significantly negative spatial lag term, suggesting that urbanisation improvements in neighbouring cooperative cities can reduce a city's environmental pollution.

Tab.16. Estimation results of factors influencing air quality improvements in three provinces.

	Zhejiang	Jiangsu	Anhui
ρ	0.502***	0.242*	0.369***
	(0.00)	(0.06)	(0.00)
fdi	-18.618	-13.640	-88.844
	(0.73)	(0.89)	(0.14)
$lnGDP$	-162.724*	284.173**	171.066*
	(0.09)	(0.03)	(0.09)
$(\ln GDP)^2$	7.012*	-12.823**	-8.335*
	(0.09)	(0.02)	(0.08)
edu	58.447**	63.102**	-18.103
	(0.03)	(0.02)	(0.73)
$urban$	-73.962***	18.131	-92.278**
	(0.00)	(0.19)	(0.01)
$rain$	-0.004*	0.000	-0.006
	(0.10)	(0.83)	(0.33)
$W \cdot fdi$	-162.647*	-117.218	64.746
	(0.06)	(0.54)	(0.39)
$W \cdot lnGDP$	-675.513**	-104.042	38.336

	(0.01)	(0.68)	(0.82)
$W\cdot(\ln GDP)^2$	29.142**	3.742	-1.930
	(0.01)	(0.73)	(0.80)
$W \cdot edu$	6.374	-229.139***	-69.471
	(0.89)	(0.00)	(0.46)
$W \cdot urban$	-76.510***	-132.885***	26.597
	(0.01)	(0.00)	(0.62)
$W \cdot rain$	0.002	-0.004	0.006
	(0.41)	(0.24)	(0.46)
Observations	64	72	64
Number of cities	8	9	8

*** p<0.01, ** p<0.05, * p<0.1. Source: Own research.

Anhui presents a different picture with urbanisation, where the coefficient is significantly negative but the spatial lag term is significantly positive. This indicates that while urbanisation improvements in Anhui enhance air quality, similar improvements in surrounding cooperative cities increase the city's air pollution, reflecting an irrational urbanisation structure. Anhui's economic development level coefficient is 171.066, with a quadratic term coefficient of −8.335, indicating that economic development initially worsens air pollution but that attention to the ecological environment strengthens over time, leading to environmental protection becoming a priority in economic development.

(3) Identification of atmospheric governance performance

(4)

Tab.17– Estimation results of atmospheric governance performance improvement.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Spatial	Main	Wx	Direct	Indirect	Total
ρ	0.395***					
	(0.00)					
fdi		-0.427	0.576	-0.365	0.616	0.251
		(0.15)	(0.20)	(0.22)	(0.31)	(0.71)
urban		0.354**	1.149***	0.512***	1.987***	2.499***
		(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
struct		0.009	0.078**	0.022	0.125**	0.147**
		(0.70)	(0.04)	(0.32)	(0.02)	(0.01)
wet		0.000	-0.000***(0.00)	0.000	-0.000***	-0.000***(0.00)
		(0.31)		(0.58)	(0.00)	

Observations	208	208	208	208	208	208
Number of city	26	26	26	26	26	26

*** p<0.01, ** p<0.05, * p<0.1. Source: Own research.

Table 17 presents the identification results of enhancing atmospheric governance performance through regional cooperative governance with the spatial Durbin model. The model's estimated results, as shown in Model (1), indicate a significant positive correlation between atmospheric governance cooperation and performance, with a spatial lag coefficient of 0.395 at the 1% significance level. This suggests that improvements in a city's atmospheric governance can substantially influence and improve the performance of surrounding cooperative cities. The spatial lag term of the industrial structure is 0.078, significant at the 5% level, indicating that industrial cooperation among surrounding cities enhances a city's atmospheric governance performance. Its urbanisation and spatial lag terms have significantly positive estimated coefficients, implying that urbanisation in local and surrounding cities contributes to better atmospheric governance performance. In addition, the study found that the introduction of foreign capital into cities exacerbates air pollution, suggesting that it is detrimental to atmospheric governance. This calls for strategies to either reduce foreign capital inflow or increase environmental standards to raise the entry bar for foreign enterprises, thereby improving the overall atmospheric governance performance.

6 . CONCLUSIONS AND SUGGESTIONS

6.1. Conclusions

Based on the sample data from 26 YRD cities during the period of 2015 – 2022, this study employed a series of statistical and econometric methods, including spatial Markov chain, social cooperation network, weighted entropy method and spatial Durbin econometric model, to measure the dynamic inter-regional distribution shifts of air pollutants in the YRD, the collaborative network involvement of the regional atmospheric collaborative governance and the effectiveness of regional atmospheric collaborative governance on atmospheric governance performance. The conclusions of this study are as follows:

The spatial Markov chain identification validates a strong positive correlation and cross-border diffusion features among air pollutants across different locations within the YRD cities. Southeastern coastal cities have better air quality and positively influence their surroundings, whereas northwestern inland cities suffer from poor air quality owing to natural conditions and negatively affect neighbours.

The collaborative network structure of the collaborative regulation in the YRD remains unstable, with the cooperation density staying at a low level despite a notable annual increasing trend in the collaborative intensity during the period of 2015 – 2022. The collaborative network structure shows Shanghai, Zhejiang and Jiangsu located at the centrality in the collaborative network and Anhui on the margin with weaker collaboration in the collaborative environmental regulation.

The air quality and atmospheric governance performance in the YRD exert significant positive spill-over effects. In addition, the air quality and the atmospheric governance performance have greatly improved, and the effectiveness of regional atmospheric collaborative governance on atmospheric governance performance holds true, with the effects being more obvious in cities with more developed urbanisation and economy.

Overall, our study highlights the importance of regional cooperation in atmospheric governance and identifies the key factors influencing air quality and governance performance in the YRD, which provides an important reference for the collaborative environmental regulation in other regions and overall China to achieve effective air pollution control and economic growth.

6.2. Policy suggestions

The study proposes the following suggestions to enhance regional atmospheric governance based on our main findings:

First, given the strong positive correlation and cross-border diffusion of air pollutants, there is a need for a more robust and stable collaborative network. Furthermore, the cooperation density needs to be increased and all provinces, including Anhui, should be involved more centrally in the network to balance regional efforts.

Second, recognising the differences in air quality between southeastern coastal and northwestern inland cities, it is imperative to implement tailored strategies for different regions. The YRD cities should develop region-specific strategies that address the unique challenges posed by natural conditions and existing infrastructure.

Third, as urbanisation and economic development have significant positive spill-over effects on air quality and governance performance, policies should be designed to leverage these factors. Furthermore, the YRD cities should be encouraged to implement urban planning that considers environmental impact and supports sustainable economic practices

Fourth, it is important to increase public awareness about air pollution and encourage participation in environmental protection. This can help in garnering support for environmental policies and in implementing community-level solutions. The governments should also constantly invest in clean technology and innovation to reduce emissions, which could fundamentally provide the solution of collaborative environmental regulation.

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Contact information

Prof. Juying Zeng, Ph.D.
Department of Statistics and Data Science, Hangzhou City University
Hangzhou, China
E-mail: riverzjy@163.com
ORCID: 0000-0002-7166-7270

Prof. David Sanz-Rivas
Facultad de Humanidades y CC Sociales, Universidad Tecnológica Atlántico – Mediterráneo UTAMED
Málaga, Spain,
E-mail: david.sanz@utamed.es
ORCID: 0000-0002-2577-4198

Jiaye Chen
Wenzhou Branch of Zhejiang Mobile Communications Group Co.,Ltd,
WenZhou, China
E-mail: 1532470628@qq.com

Prof. Carlos Lassala
University of Valencia,
Valencia, Spain
Email: carlos.lassala@uv.es
ORCID: /0000-0001-8217-4968