

# Identification of nonlinearity and spatial non-stationary effects of local drivers on the synergy between air quality management and carbon mitigation in the Yangtze River Delta urban agglomeration

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## Abstract

China is actively pursuing synergistic governance to address air pollution and carbon mitigation issues. This study, focusing on concentration as a key feature, assesses the synergy performance in the Yangtze River Delta Urban Agglomeration (YRDUA), revealing fluctuating trends with only seven cities showing improvement. To further understand the influences from local drivers, we employed an explainable spatial machine learning approach, integrating Geographical Weighted Regression (GWR), Random Forest (RF), and Shapley Additive Explanation (SHAP) to capture nonlinear, threshold, and interaction effects among explanatory variables. The analysis identifies longitude, SO<sub>2</sub> emissions from industrial sources, wind speed, latitude, and the proportion of GDP from tertiary sector as the top five influencing factors, emphasizing the importance of geographical position, local air pollution emission, and meteorological condition. Most drivers exhibit nonlinear impacts and interactions with clear thresholds. Such as, wind speeds, exceeding 9.3 m/s negatively impact synergy. Furthermore, spatial heterogeneity of drivers' influence is evident across cities and provinces. Specifically, cities along the eastern coast benefit from geographical advantages that enhance synergy in air quality improvement and carbon mitigation. Meteorological conditions, especially wind speed, significantly influence synergy, with notable differences between northern and southern coastal cities. These findings underscore the need for locally tailored governance strategies that leverage each city's unique geographical and socioeconomic attributes to enhance synergistic governance effectiveness. This research contributes to understanding the complex interplay of local drivers influencing synergistic governance in the YRDUA, providing valuable insights for policymakers aiming to improve air quality and promote sustainable development in rapidly urbanizing regions.

## 1. Introduction

Synergy governance, which refers to the cooperative interaction among entities to achieve a common goal, has been recognized as a critical strategy in the policy-making process, particularly in the realm of ecological governance (Kosow et al., 2022; Li et al., 2023a; Liu et al., 2024; Yi et al., 2023). As the world's top carbon emitter and coal consumer, China is actively implementing this strategy to address its national air quality issues and carbon mitigation (Chen et al., 2023; Liu et al., 2022; Zhu et al., 2023). Since 2013, China has launched a series of national anti-pollution campaigns, primarily focusing on controlling PM<sub>2.5</sub> levels (Shi et al., 2021). This effort has resulted in a significant reduction in PM<sub>2.5</sub> concentrations, with a 44% decrease from 65.7  $\mu\text{g}/\text{m}^3$  in 2013 to 36.8  $\mu\text{g}/\text{m}^3$  in 2019 (Zhong et al., 2021). Despite the slight impact of COVID-19 and subsequent economic recovery, air quality improvements have continued, with the average annual PM<sub>2.5</sub> concentration in 339 major Chinese cities dropping to 29  $\mu\text{g}/\text{m}^3$  in 2022 (Ministry of Ecology and Environment of China, 2023). Notable achievements have been made in improving air quality through cooperation among central governments, authorities, enterprises, and residents. But the current PM<sub>2.5</sub> concentration remains higher than international standards, falling short of the World Health Organization's (WHO) standard of 5  $\mu\text{g}/\text{m}^3$  (Shi et al., 2021; Zhao et al., 2024). Moreover, since 2018, the annual reduction in PM<sub>2.5</sub> levels has slowed, with a potential for an increase (Wang et al.,

2022). Another pressing concern is the rising O<sub>3</sub> concentration, which exacerbates respiratory conditions like asthma and chronic obstructive pulmonary disease and increases the risk of infections and cardiovascular diseases (Wang et al., 2024). The average ozone concentration at general monitoring stations has reached 59  $\mu\text{g}/\text{m}^3$  in 2022, representing a 4% increase from 2021 (AIRDUCATE, 2022).

In addition to air quality issues, China is also facing significant challenges in reducing its carbon emissions (Shi et al., 2021). The country's CO<sub>2</sub> emissions have been steadily increasing, reaching a total of 12.9 Gt in 2021 (Li et al., 2023b). The average annual CO<sub>2</sub> concentration in China has risen to 419.3 parts per million (ppm) in 2022, exceeding the global average (Ministry of Ecology and Environment of China, 2023). The Chinese government has set ambitious targets to peak CO<sub>2</sub> emissions before 2030 and achieve carbon neutrality by 2060 (Huang et al., 2023). In light of China's unique and pressing environmental issues, the priority of governance policies is shifting towards the synergistic management of air pollution and carbon mitigation (Guo et al., 2024). The Chinese government has demonstrated strong autonomy in policymaking and the ability to transmit pressures down to the lowest hierarchy levels to achieve air quality improvement and carbon mitigation. City level, as the basic administrative unit for spatial governance and planning, is the critical spatial unit for the synergistic governance (Shan et al., 2022).

Reviewing on the existing literature, synergistic governance performance has been evaluated across various spatial scales, including counties, cities, provinces in China (Guo et al., 2024; Wang and Di, 2024; Yi et al., 2023; Zha et al., 2023). Research in this field has primarily focused on verifying the existence of "co-benefit", identifying patterns of synergistic governance performance, and exploring future pathways for improvement (Lu et al., 2019; Yang et al., 2021). Most studies have concentrated on severe air pollutants, such as PM<sub>2.5</sub> and ozone as research objects, often neglecting other air pollutants in the context of synergistic governance (Guo et al., 2024; Liu et al., 2021; Yi et al., 2022). Additionally, some studies have combined the concepts of concentration and emissions within the evaluation system, complicating the exploration of synergies. However, there is a lack of studies that specifically examine the synergies between air pollution and carbon mitigation issues at the concentration level.

Furthermore, a review of research on driving factors affecting synergistic governance reveals that methodologies primarily focus on addressing spatial spillover effects and spatial non-stationary issues in relationship inference (Yi et al., 2023; Zhao et al., 2025). However, traditional linear models are limited in their ability to capture the complexity of local drivers, including socio-economic and meteorological factors, on synergistic governance performance. To address these limitations, the integration of traditional geostatistical models with machine learning approaches presents significant potential for revealing complex nonlinear relationships between drivers and synergistic governance performance (Li, 2022). Machine learning models, in particular, perform well in identifying nonlinear effects and turning points where effects change (Chen et al., 2024). By integrating advanced machine learning techniques with traditional geostatistical models, complex spatial patterns and relationships could be uncovered.

To address the above gaps, this study aims to investigate the nonlinearity and spatial non-stationary effects of local drivers on synergistic governance performance between air quality management and carbon mitigation from the concentration perspective in the Yangtze River Delta Urban Agglomeration. The objectives of this study are: (1) to quantify the city-level synergy degree between air quality improvement and carbon mitigation; (2) to identify the global relative importance of each driver to the synergy governance performance; (3) to identify the non-linearity and threshold effect of drivers on local synergistic governance performance; and (4) to identify the spatial pattern of primary influencing factors at the local scale. By exploring these objectives, this study seeks to provide a local-tailored governance pattern for the cooperative governance of air quality improvement and carbon mitigation at the city level, as well as a methodology framework for policy making.

## 2. Study area and data

### 2.1 Study Area

In this study, we focus on the Yangtze River Delta Urban Agglomeration, which comprises the municipality of Shanghai and 26 core cities across the provinces of Anhui, Jiangsu, and Zhejiang (Figure 1). This region has experienced rapid economic growth, contributing 24.1% of China's total GDP in 2021 (Li and Wang, 2024). Population density has reached 16.6% of the national total (Li and Wang, 2024). However, the intense

anthropogenic activities in this area have led to significant challenges related to air pollution and carbon emissions. As a key demonstration area for Ecological and Green Integration Development, the Yangtze River Delta is supported by abundant high-quality capital, a skilled workforce, scientific expertise, and technological advancements.

### 2.2 Data sources

Air pollution concentration data (including CO, NO<sub>2</sub>, SO<sub>2</sub>, PM<sub>2.5</sub>, PM<sub>10</sub>, O<sub>3</sub>) were sourced from national ground-based station observations, providing hourly temporal resolution. CO<sub>2</sub> concentrations were obtained from a public dataset (DOI: <https://doi.org/10.57760/sciencedb.08258>). This dataset incorporates high-resolution spatiotemporal data from the Orbiting Carbon Observatory 2 (OCO-2), supplemented with various auxiliary datasets, to estimate full-coverage, monthly column-averaged carbon dioxide (XCO<sub>2</sub>) values across China from 2015 to 2022 at a spatial resolution of 0.05° using the deep forest model (Cai et al., 2024). This dataset has been validated against ground-based observations from the Total Carbon Column Observing Network (TCCON). For the HF (Hefei) station, located in our study area, the correlation coefficient between the estimated CO<sub>2</sub> concentration and observed data is  $R = 0.92$  ( $R^2 = 0.81$ ), with RMSE = 1.77 ppm and MAE = 1.44 ppm. Therefore, using XCO<sub>2</sub> to represent ground-level CO<sub>2</sub> in our study area is reasonable and reliable. In this study, all data were processed at the city-level spatial scale with an annual temporal resolution. Specifically, for air pollution, concentrations measured at all monitoring stations within each city were averaged to represent the city-level concentration. In contrast, gridded CO<sub>2</sub> concentration data were spatially aggregated to the city level to ensure consistency across datasets.

In addition to concentration data, we collected multi-source data on various drivers. First, the MOD13Q1 product was acquired and processed in Google Earth Engine (GEE) to derive the Normalized Difference Vegetation Index (NDVI) for the study area. Second, meteorological data, including temperature, wind speed, and precipitation, were collected from National Meteorological Stations. Third, we gathered socio-economic data, air pollutant-related data, greening-related data, and technological innovation capability data from city-level statistical yearbooks. The sources and descriptions of these drivers are summarized in Table A1 in the Appendix. To ensure consistency across datasets, these variables were aggregated to the city level at an annual temporal resolution.

## 3. Methodology

### 3.1 Quantification of synergistic governance performance

**3.1.1 Indicator evaluation system** In this study, we treated the synergy between air quality improvement (AP) and carbon mitigation (CM) as one system with the joint impact resulting from the intensity of interaction (coupling degree) and the extent of harmonious development (coordination degree) between AP and CM subsystems. The selected relative indicators were used to capture and represent the dynamic nature and interactions within each subsystem. The index evaluation system of AP-CM system is shown in Table 1. Due to the availability of ground-based station observations of air pollutant concentrations, the year 2015 was treated as the baseline for calculating the relative change in air pollutant concentrations. The approach of using relative change as the key feature eliminates the

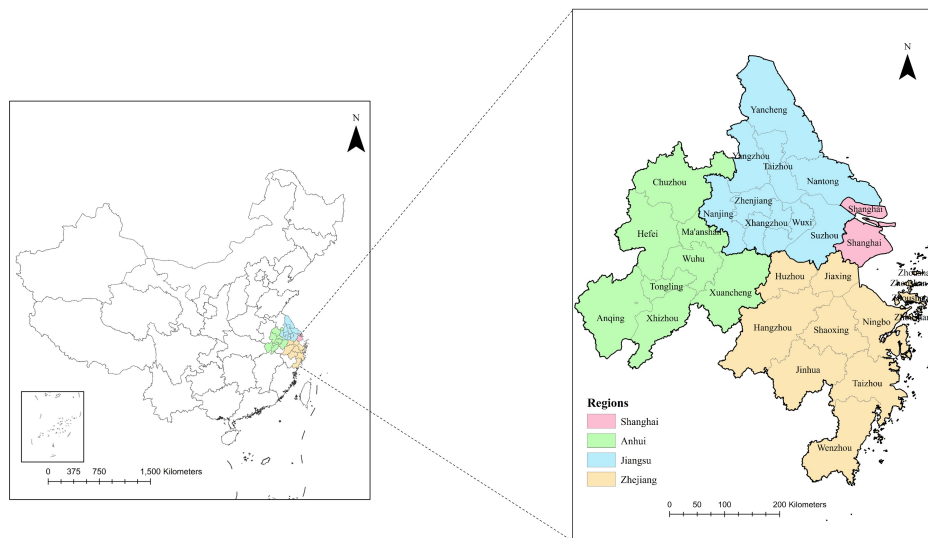


Figure 1. Geographical location of the Yangtze River Delta Urban Agglomeration.

influence of local emission capabilities, ensuring that all spatial units are evaluated at the same level.

**3.1.2 Ordering degree to evaluate the performance of AP and CM subsystem** To evaluate the performance of each subsystem, ordering degrees were calculated to assess the collaborative development level among indicators within each subsystem Mu et al. (2022). Therein, the entropy weight method, an objective weights assessment strategy was conducted to allocate weights for each indicator in the AP and CM subsystems, respectively. The calculation process followed the methodology described in the paper by Guo et al. (2023).

**3.1.3 Coupling coordination degree to evaluate the synergy degree in AP-CM system** For assessing the synergy degree of the system, the coupling coordination theory was employed to evaluate the coordination between the Air Pollution (AP) and Carbon Mitigation (CM) subsystems. Recognizing the equal importance of air quality improvement and carbon mitigation in China from 2013 to 2020, equal weights ( $\alpha = 0.5, \beta = 0.5$ ) were assigned to each subsystem (Yi et al., 2022). The comprehensive synergy degree of the AP-CM system was then obtained using the weighted averaging method. This step also followed the approach outlined in the study conducted by Guo et al. (2023) to calculate the coupling coordination degree for each city in each year.

### 3.2 GWR – Machine learning approach (GWR-ML)

In this study, we employed two traditional geostatistical models (OLS and GWR), two machine learning techniques (Random Forest and XGBoost), and two hybrid models (GWR-RF and GWR-XGBoost) to compare their explanatory power in characterizing the relationships between local drivers and synergistic performance. Compared with the spatial regression models (GWR), the traditional global models (e.g., OLS and machine learning techniques) assume spatial stationarity and independence of observations. Their direct application to geographic data ignores spatial autocorrelation and spatial heterogeneity issues. Conversely, while GWR addresses spatial non-stationarity by fitting localized models, it is fundamentally constrained by linear assumptions, which limit its ability to capture complex non-linear relationships and threshold effects. These

System	Subsystem	Indicators
AP-CM (Synergy system of air quality improvement and carbon mitigation)	CM (Carbon mitigation subsystem)	Relative change in CO <sub>2</sub> concentration (baseline–2015)
	AP (Air quality improvement subsystem)	Relative change in CO concentration (baseline–2015)
		Relative change in NO <sub>2</sub> concentration (baseline–2015)
		Relative change in SO <sub>2</sub> concentration (baseline–2015)
		Relative change in PM <sub>2.5</sub> concentration (baseline–2015)
		Relative change in PM <sub>10</sub> concentration (baseline–2015)
		Relative change in O <sub>3</sub> concentration (baseline–2015)

Table 1. Indicators system for AP-CM system

limitations provide the core rationale for exploring hybrid models that integrate a geostatistical spatial model with the non-linear modeling strengths of machine learning.

During the driving factor analysis, we first calculated the Variance Inflation Factor (VIF) of explanatory variables to check if the multilinearity exists. The result showed that all the VIFs are lower than 10, indicating there was no multilinearity among drivers. Then, we calculated the Moran's I to determine if the synergistic degrees were spatially associated. The result of Moran's I at the value of 0.534, indicates that the synergy performance were spatially autocorrelated with p-value below 0.05. This empirical evidence further justifies the application of GWR in this study.

In this study, we selected two widely used machine learning approaches to integrate with GWR, namely Random Forest and XGBoost(eXtreme Gradient Boosting). Random Forest is an ensemble learning method that combines multiple decision trees to enhance the accuracy and robustness of predictions. It operates as a global nonlinear model, where each sample is assigned equal weight in estimating the coefficients. In contrast,

XGBoost employs weights to adjust the importance of each sample when computing the gradient and Hessian, thereby influencing the direction and magnitude of updates made to the model during training. To address the issue of spatial non-stationarity in the machine learning approaches, we incorporated GWR with both methods. By applying GWR, we utilized a Spatial Weight Matrix  $W_i(w_{i1}, w_{i2}, w_{i3}, \dots, w_{in})$ , where  $w_{ij}$  represents the weight between city  $i$  and city  $j$ , to capture the importance of each neighbor during the training. In this study, we adopted the adaptive kernel and bi-square weighting kernel function to calculate the spatial weight matrix for each local regression model. The equation is presented in Equation 1. For each city, a specific spatial weight matrix was integrated into the local Random Forest training process.

$$w_{ij} = \begin{cases} \left[1 - \left(\frac{d_{ij}}{b}\right)^2\right] & \text{if } d_{ij} \leq b \\ 0 & \text{if } d_{ij} > b \end{cases} \quad (1)$$

Where  $d_{ij}$  represents the distance between city  $i$  and city  $j$ , and  $b$  denotes the specific bandwidth for each city. The data from neighbors with non-zero weights are selected for machine learning training. The spatial weight matrix (derived from the adaptive bandwidth for each specific location) is directly integrated into the machine learning algorithms by assigning specific training weights to surrounding observations. These weights, which correspond to the spatial weight matrix, ensure that neighboring points with higher spatial proximity exert a greater influence on the local model's splitting criteria and overall fitting. Hence, the GWR-ML regression equations, modified from RF and XGBoost, can be expressed as follows:

$$Y_i(u_i, v_i) = f(x^*, (u_i, v_i)) + \epsilon_i \quad (2)$$

Where  $(u_i, v_i)$  are the coordinates of spatial unit  $i$ ,  $f(x^*, (u_i, v_i))$  is the prediction of the ML model calibrated at position  $i$ .

During the training process, we employed Grid Search and 10-fold cross-validation to identify the optimal parameters for GWR-ML, which could reduce overfitting and address issues related to unbalanced data. The performance metrics for each model used in the comparison are presented in Table 2.

### 3.3 SHAP model

The SHAP model is a game-theoretical approach that reveals the contribution of each local sample of explanatory variables to the model output (Chen et al., 2024). SHAP values are additive, meaning that the aggregation of local explanations yields a global understanding of feature importance by calculating the mean Shapley value (Wang et al., 2023). The equation for the Shapley value is presented in Equation 3.

$$\phi_i = \sum_{s \in C_N(i)} \frac{|S|! \cdot (n - |s| - 1)!}{n!} [f(S \cup \{i\}) - f(s)] \quad (3)$$

Where  $\phi_i$  represents the contribution of the explanatory variable  $i$ ,  $N$  denotes the set of  $n$  explanatory variables,  $f(S \cup \{i\})$  and  $f(s)$  represents the model results with and without the explanatory variable  $i$ , respectively.

The interpretable model is then aggregated using an additive explanatory variable imputation approach, in which a linear function is defined as follows:

$$g(z') = \phi_0 + \sum_{i=1}^M \phi_i z' \quad (4)$$

Where  $z' \in \{0, 1\}^M$  indicates the observation status of an explanatory variable, with  $z' = 1$  when the variable is observed and  $z' = 0$  when it is unobserved.  $M$  represents the number of input features,  $\phi_0$  denotes the base value, and  $\phi_i$  is the Shapely value of explanatory variable  $i$ .

## 4. Results

### 4.1 Spatiotemporal pattern of synergistic governance performance

Figure 2 illustrates the spatial pattern of synergistic governance performance from 2016 to 2022, revealing significant differences across cities over time. Overall, the average synergy degree fluctuated during this period, with values recorded as follows: 0.77 in 2016, declining to 0.69 in 2017, followed by a gradual increase, peaking at 0.76 in 2019. Subsequently, a slight decrease occurred in 2020, bringing the value down to 0.70, before stabilizing at 0.75 in both 2021 and 2022.

With the exception of Shanghai, which experienced an increase of 0.06, the other three provinces exhibited a decline in overall synergistic governance performance throughout the period. The rankings in terms of performance changes were as follows: Anhui (-0.06) < Zhejiang (-0.03) < Jiangsu (-0.02).

From the perspective of city level, only seven cities demonstrated an upward trend in performance over time. These cities include Zhoushan (+0.072), Ningbo (+0.056), Shanghai (+0.054), Jiaxing (+0.023), Wuxi (+0.006), Zhenjiang (+0.002), and Nantong (+0.0001). Notably, the variance in synergy degree over time indicates that Jiangsu and Zhejiang provinces have shown a narrowing difference in their synergy degrees. This trend is particularly evident in Zhejiang Province, where the variance decreased from 0.003 to 0.0008.

### 4.2 Model performance comparison

As shown in Table 2, the performance of various models, including four traditional models (OLS, GWR, RF, XGBoost) and two GWR-ML models (GWR-RF, GWR-XGBoost) was evaluated using three metric (R-squared, MAE, RMSE). The results indicate that GWR-RF outperformed the other models, exhibiting a higher R-squared value and lower MAE and RMSE. Consequently, this study employed the GWR-RF model to explore the relationship between local drivers and synergistic governance performance.

Compared to GWR-XGBoost, GWR-RF demonstrates better adaptability to localized modeling in our study. Because GWR operates by fitting models on geographically restricted, distance-weighted sub-samples, the data available for each local model is limited and sensitive to noise. Random Forest's bagging mechanism mitigates this by reducing variance, naturally complementing GWR's localized approach. In contrast, XGBoost's boosting mechanism, which sequentially fits residuals to reduce bias, tends to exhibit a poor algorithmic match with GWR's local fitting principle, as it is significantly more prone to overfitting within these constrained spatial contexts.

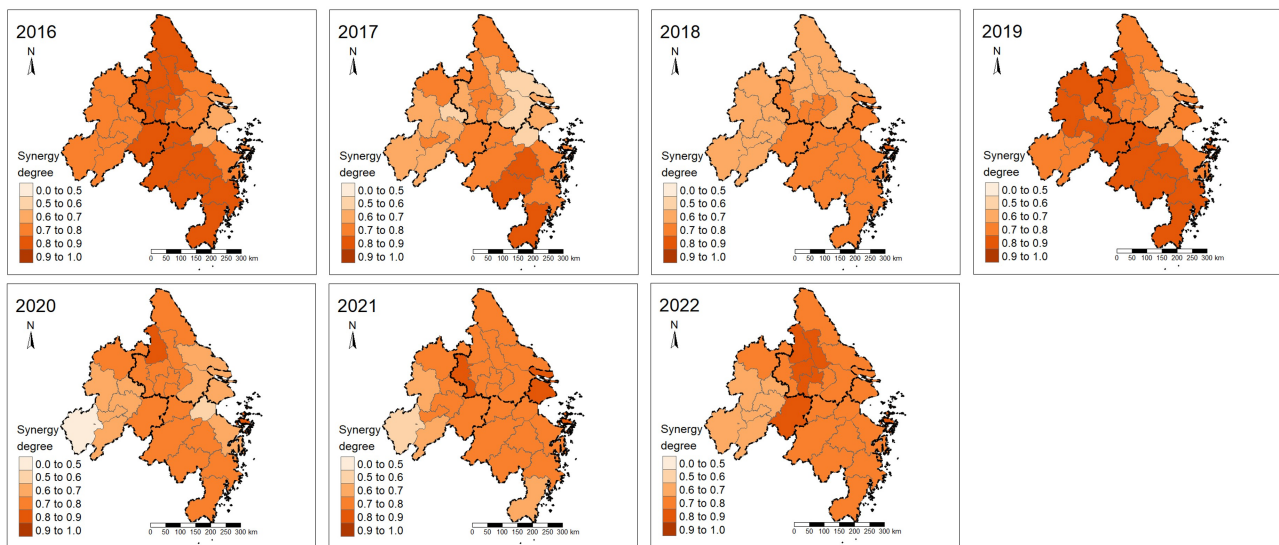


Figure 2. Spatial distribution of synergy degree at city level from 2016 to 2022.

Model	R <sup>2</sup>	MAE	RMSE
OLS	0.286	0.047	0.062
GWR	0.383	0.045	0.059
Random Forest	0.469	0.041	0.053
XGBoost	0.471	0.040	0.052
GWR + RF	0.557	0.040	0.051
GWR + XGBoost	4.10E-05	0.112	0.139

Table 2. Performance metric for each model.

### 4.3 Global relative importance of features

As illustrated in Figure 3, the left side displays the global relative importance of features, calculated using the mean absolute SHAP ( $|SHAP|$ ) values for each explanatory variable, presented in descending order. The individual SHAP values are shown on the right side, where values greater than zero indicate a positive effect on the model output, while values less than zero indicate a negative effect.

The top five primary factors influencing the model output include longitude, SO<sub>2</sub> emissions from industrial sources, wind speed, latitude, and the proportion of GDP from the tertiary sector. In contrast, the proportion of GDP from the secondary industry and technology innovation capacities have a relatively lower impact on synergistic governance performance.

Regarding geographical location-related factors, longitude has the most significant contribution to the model output, with higher longitude values negatively impacting predictions. In terms of meteorological influences, both wind speed and temperature play crucial roles, as higher values for these variables adversely affect synergy predictions. Concerning socio-economic factors, the proportion of GDP from the tertiary sector has a more substantial impact on the model output, followed by population growth and overall GDP. A higher proportion of the tertiary industry negatively influences synergy predictions. Additionally, SO<sub>2</sub> emissions from local industrial sources are more critical than NO<sub>x</sub> emissions, with increased SO<sub>2</sub> emissions positively influencing synergy performance.

### 4.4 Nonlinear and threshold effects

Figure 4 presents the Local Dependence Plots (LDP) of the SHAP values for each explanatory variable, illustrating the nonlinear relationships between individual features and the synergy degree. The turning points indicate the thresholds at which specific variables transition from having a positive to a negative effect on the model output.

The geographical locations and relative positions of cities exhibit a nonlinear effect on the model output. Specifically, longitudes between 118.36 and 120.38 have a locally positive impact on the synergy degree, while latitudes below 30.39 also demonstrate a positive effect. In terms of relative locations, areas situated both within and at the boundaries of urban agglomerations positively influence the model output compared to the central points of these agglomerations.

The pattern of the Local Dependence Plot (LDP) for SO<sub>2</sub> emissions differs significantly from that of NO<sub>x</sub> emissions, with most values exceeding zero. The local effect of SO<sub>2</sub> emissions transitions from a negative to a positive effect at a threshold of  $5.21 \times 10^4$  tonnes. However, at the point of  $73.71 \times 10^4$  tonnes, the positive effect of SO<sub>2</sub> emissions begins to decline, indicating that as emissions increase, their impact diminishes. In contrast, the negative impact of NO<sub>x</sub> emissions becomes evident when levels exceed  $1.55 \times 10^4$  tonnes, suggesting that relatively high concentrations of NO<sub>x</sub> emissions can hinder synergy. Additionally, an increase in the number of industries (3132) positively contributes to synergy.

Meteorological factors also play a significant role in the transport and deposition of air pollutants. Among these factors, wind speed emerges as a critical variable influencing the model output, exhibiting a positive impact on synergy when speeds are below  $9.3 \text{ m s}^{-1}$ . Additionally, the effect of temperature transitions from negative to positive once it exceeds the threshold of  $18.31^\circ\text{C}$ . Lower levels of precipitation are associated with improved performance in synergistic governance. The findings highlight the importance of considering the local meteorological factors in the development of policies aimed at improving air quality and achieving carbon mitigation goals.

The local socio-economic status exhibits a complex interaction

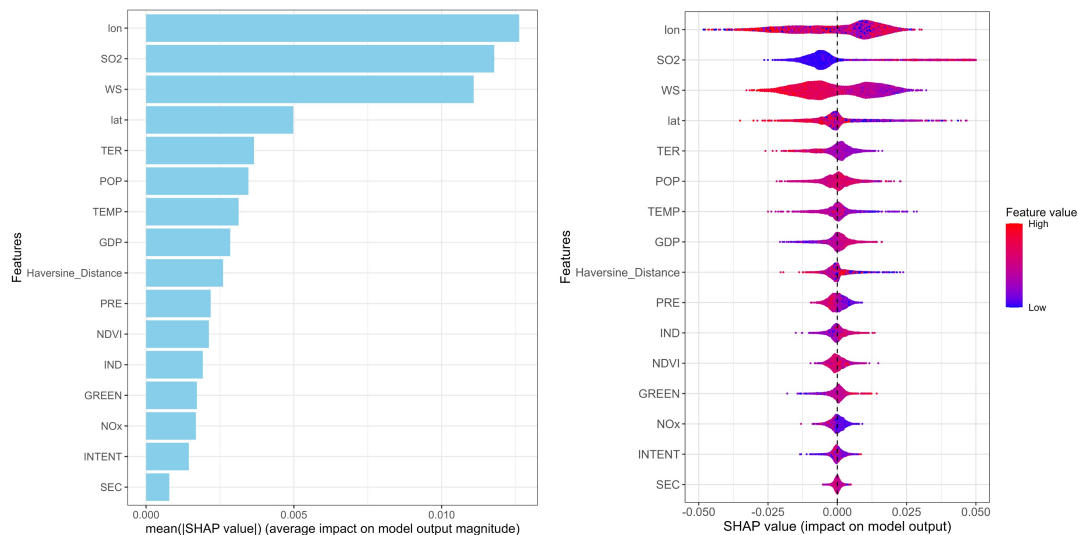


Figure 3. Relative importance by SHAP value for each variable.

with synergy performance. Gross Domestic Product (GDP) generally has a positive effect on synergy, with a threshold of 4812.85 (units: RMB 100 million). In terms of industry structure, when the proportion of secondary industry in GDP is lower than 40.87% or falls within the interval of 48.48% to 62.17%, it presents a positive effect on synergy. Conversely, for the tertiary sector, when the proportion is below 31% or above 54%, it negatively affects synergy. Similarly, both excessively high and low population levels can enhance synergy, with thresholds at 340.85 (units: 10,000 people) and 1758.39 (units: 10,000 people), respectively.

Moreover, a higher greening rate of built-up areas positively affects the prediction of synergy performance, while the Normalized Difference Vegetation Index (NDVI) shows a relatively slight and fluctuating positive effect on synergy when values are below 0.61. Finally, a higher degree of technological innovation contributes positively to local synergy performance.

#### 4.5 Local influence of primary influencing factors

We calculated the mean of all local SHAP values for each local random forest model corresponding to each city. The average direction and degree of contribution of the top driver in each category (shown in Table A1 of the Appendix) were presented in Figure 5, illustrating their impact on the degree of synergy. Additionally, the statistical summary of each explanatory variable and its local SHAP values is presented in Figure A2 and Figure A1 of the Appendix.

Longitude emerged as a key factor within the geographical location category, directly influencing climate, ecology, and economic activities. Cities located along the eastern coast benefit from local geographical advantages (such as orientation, proximity to geographic features, and regional economic connections) which enhance synergy related to air pollution improvement and carbon mitigation. Notably, the longitude of Jiangsu province and Shanghai city exhibited a positive contribution to the model output. Meteorological conditions, especially wind speed, significantly influenced synergy predictions, with notable differences observed between northern and southern coastal cities. Among the provinces, Zhejiang province demonstrated the highest positive contribution of wind speed to the

model output. In terms of socio-economic factors, the proportion of GDP from the tertiary industry emerged as a prominent factor, particularly affecting cities like Wuhu (positive effect), Chizhou and Xuancheng (negative effect). When summarized across these provinces, only Jiangsu province showed a positive impact of GDP on synergy, although the differences in mean local SHAP values among the provinces were minimal.

Regarding industrial air pollution, SO<sub>2</sub> emissions were relatively higher in specific areas, particularly in Jiangsu and Anhui provinces, leading to significant disparities in their impact on synergy predictions across cities. Notably, local emissions in Chizhou and Wenzhou had a higher positive effect on synergy. At the provincial level, emissions in Jiangsu and Shanghai negatively affected the model output, indicating that lower local emissions enhance synergistic governance performance. NDVI, representing the greening rate, shows that provinces with better vegetation cover tend to have higher synergy, suggesting a positive relationship between green spaces and urban synergy, such as Zhejiang and Anhui provinces. Lastly, the influence of intent grants, indicative of technological innovation capabilities, varies across the provinces. Certain cities, such as Shanghai and Jiaying, benefited significantly from these grants.

Overall, the results underscore the complex interplay of these factors in shaping urban synergy, emphasizing the need for targeted strategies that consider these diverse influences.

## 5. Discussion

### 5.1 Spatiotemporal pattern of synergistic governance performance

In this study, an indicator evaluation system was used to quantify the degree of synergy between air pollution improvement and carbon mitigation performance. Unlike other research, we selected a specific year as the baseline for calculating relative changes, which serves as a key feature for each indicator within the air pollution (AP) and carbon mitigation (CM) subsystems. The observed fluctuations in synergy levels reflect the unstable nature of synergistic governance at the city level in the YRDUA (as shown in 2).

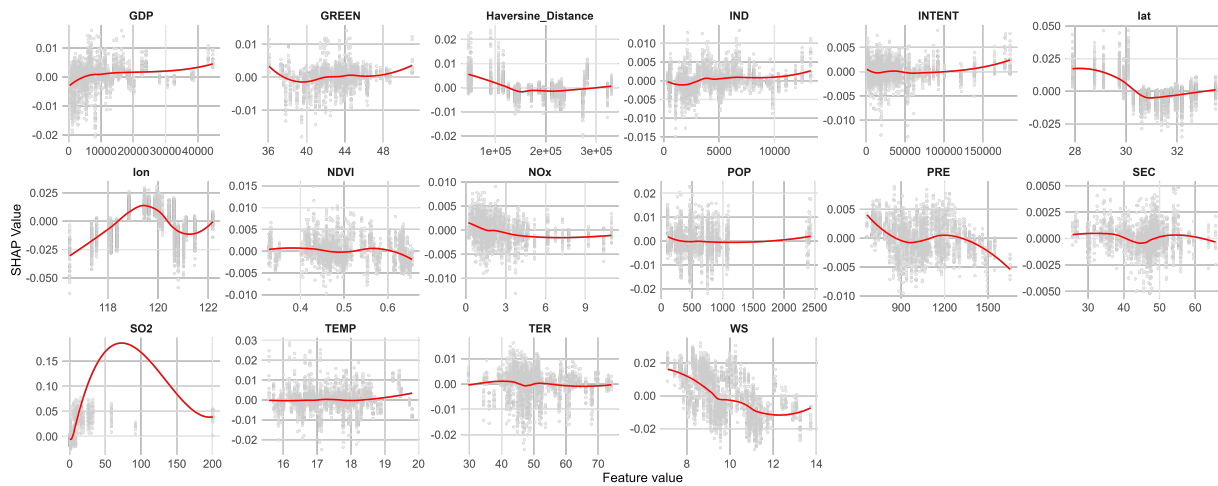


Figure 4. Local dependence plots for each explanatory variable.

However, improvements are evident at the provincial scale. While most provinces, except for Shanghai, experienced a decline in synergy degree, Jiangsu and Zhejiang exhibited minimal changes and a narrowing gap in their declining synergy within the province over the years. This finding highlights the importance of recognizing spatiotemporal patterns and the influence of various drivers in the context of policymaking. It is crucial to develop locally tailored governance strategies aimed at enhancing synergistic governance. Furthermore, establishing a robust and scientifically sound evaluation framework is essential for accurately assessing performance and guiding future policy interventions.

## 5.2 Nonlinear effect of local divers on synergistic governance performance

At the global scale, the longitude,  $\text{SO}_2$  emission from industrial source, wind speed, latitude, and the proportion of GDP from the tertiary industry exhibited higher contributions to the overall model output. Although the impact of other factors was limited, they remain informative for future synergistic governance. Detailed nonlinear relationships and threshold effects were identified through Local Dependence Plots for each explanatory variable.

From a geographical perspective within the Yangtze River Delta Urban Agglomeration, lower latitudes and mid-level longitudes, particularly in areas both within and at the boundaries of urban agglomerations, are beneficial for enhancing local synergistic governance performance. Cities located in the eastern part of the region, where longitudes are relative higher, experience distinctive climate conditions due to their proximity to the East China Sea. As a result, this area tends to have higher wind speeds. For Ningbo and Shanghai cities, which are closer to the sea, wind speed exhibits an opposite effect on the synergistic performance. This divergence may be related to differences in cities' spatial ventilation patterns. In contrast, for Hangzhou, wind speed exerts a negative impact on synergy. Although higher wind speeds can disperse pollutants more effectively, thereby reducing their accumulation and influencing the interactions between air pollutants and  $\text{CO}_2$  concentrations, urban spatial design can substantially modify these effects. In particular, whether effective ventilation corridors align with prevailing wind directions may determine how pollutants and  $\text{CO}_2$  accumulate or disperse. Therefore, eastern cities should adopt

tailored environmental governance strategies that account for both meteorological conditions and local spatial planning to optimize their environmental governance outcomes.

Additionally, the negative influence of a higher proportion of tertiary GDP in coastal areas (with higher longitude) on synergy performance indicates that a sound industrial structure is essential for local synergistic governance in the context of sustainable development. Coastal areas in the Yangtze River Delta (YRD) are hubs of high-quality capital, human resources, and technological innovation, making them critical to China's economic landscape. However, the pursuit of a high proportion of tertiary (service-oriented) industries alone, while seemingly beneficial due to their lower pollution levels, does not necessarily lead to effective synergistic governance for air quality improvement and carbon mitigation. A balanced and diversified industrial base can enhance resilience against economic fluctuations and environmental challenges. Moreover, integrating advanced technologies can lead to cleaner production processes and effective pollution control. This is further supported by the finding that a higher degree of technological innovation positively influences synergy predictions. Therefore, the optimization of industrial structures in these coastal cities must be considered within the framework of synergistic governance. This approach will not only enhance the effectiveness of governance strategies but also ensure that the YRD can leverage its rich socio-economic and technological resources to achieve long-term sustainability.

Distinct patterns in the effects of local emissions from industrial sources on synergistic governance performance were observed. The local effect of  $\text{SO}_2$  emissions transitions from negative to positive at a relatively lower value, indicating a complex relationship where initial increases in  $\text{SO}_2$  emissions may be associated with enhanced governance performance. However, this positive effect diminishes beyond a threshold of 737,100 tonnes, suggesting that excessive  $\text{SO}_2$  emissions can overwhelm governance efforts, leading to diminishing returns in synergy. In contrast, the negative impact of  $\text{NO}_x$  emissions becomes apparent when levels exceed 15,500 tonnes, indicating that high concentrations of  $\text{NO}_x$  emissions can significantly hinder synergistic governance. Furthermore,  $\text{NO}_x$  is a precursor to ground-level ozone formation, which can elevate  $\text{O}_3$  concentrations and reduce overall air quality. Wind speed, as a significant factor interacting with other explanatory variables, is associated with lower  $\text{NO}_x$  emissions, contributing positively

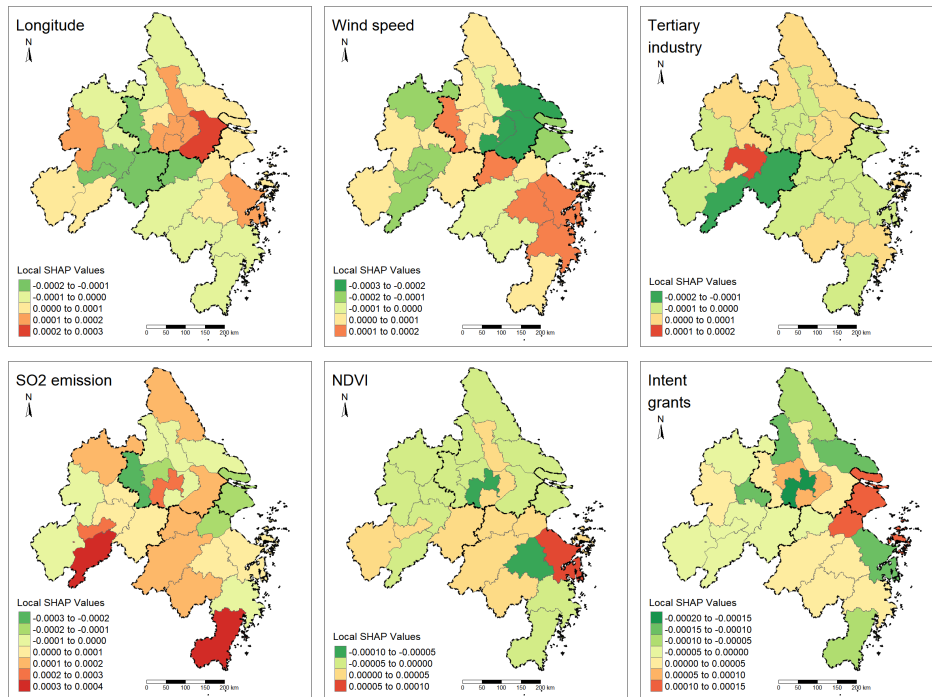


Figure 5. The spatial pattern of mean local SHAP values.

to synergy. Therefore, it is crucial to maintain emissions within optimal ranges to ensure effective synergistic governance outcomes, considering the interactions with local meteorological conditions.

### 5.3 Spatial non-stationarity effects of local divers on synergistic governance performance

At the local scale, we investigated the spatial non-stationarity of each driver's impact on synergy performance. Although the underlying modeling was conducted at the city level, the discussion is organized by administrative region, specifically the provinces of Anhui, Jiangsu, and Zhejiang, alongside the municipality of Shanghai, to facilitate interpretation.

**Socio-economic development** Compared to the other three provinces, Anhui exhibits relatively lower GDP, population, and proportion of GDP from the tertiary industry. Given the significant contributions of these three drivers to synergy, Anhui's synergy degree experiences an average negative effect from them. This indicates a deviation between socio-economic development and local synergistic governance concerning air quality improvement and carbon mitigation. Similarly, for Zhejiang, the local development and relatively higher proportion of GDP from the tertiary industry appear to hinder synergy. At the city level, this negative effect is also observed in key cities, such as Hangzhou and Ningbo, where tertiary industry development exerts negative impacts on synergy. Therefore, it is essential to optimize their industrial structure, fostering a collective approach that promotes both local economic development and environmental sustainability. In contrast, Jiangsu's economic development and relatively high proportion of GDP from the tertiary industry have positively influenced synergistic effects. The balanced development of its industrial structure and economy has facilitated coordinated environmental progress. However, it is important to note that the high population density in Jiangsu may constrain the overall synergy, suggesting that population management strategies could be beneficial

in enhancing governance outcomes. Additionally, Shanghai's economic growth and population dynamics contribute significantly to synergistic governance aimed at pollution reduction and carbon mitigation. However, the high proportion of the tertiary industry in its economic structure has not yielded a positive effect on synergy. This indicates a need for further optimization of the industrial structure to enhance the effectiveness of synergistic governance efforts.

**Local air pollution emission from industrial source** Compared from the influence from  $\text{NO}_x$  emissions,  $\text{SO}_2$  emissions demonstrates a strong impact on the synergy degree prediction. In Jiangsu and Zhejiang provinces, effective control of  $\text{NO}_x$  emissions contributes positively to synergy. However, the situation is different for  $\text{SO}_2$  emissions. In Jiangsu, where emissions are relatively high, the impact on synergy is negative. Conversely, in Anhui, which also has high  $\text{SO}_2$  emissions, the effect is relatively positive. Lastly, Zhejiang and Shanghai, with relative lower  $\text{SO}_2$  emissions, exhibit positive and negative influences on synergy, respectively. Given that Shanghai has a higher number of industries, there is a need to focus on green factory management to mitigate the impact of  $\text{SO}_2$  emissions on synergy. Similarly, while Zhejiang has a significant number of factories that promote synergy, attention must also be paid to the effects of  $\text{NO}_x$  emissions. Overall, from the perspective of local emissions, Anhui presents an overall favourable effect on synergy due to its relatively lower emissions. In contrast, Jiangsu's moderate emission levels negatively impact synergy. Therefore, it is crucial to enhance the development of green industrial enterprises while also considering the seasonal relationships between emission sources and local meteorological conditions to design effective spatial strategies, especially the benefits from lower wind speed, higher temperature and more precipitation.

**Technological innovation capabilities and Greening rate** Shanghai's level of technological development significantly enhances synergistic governance outcomes. The integration of ad-

vanced technologies can lead to more effective pollution control and carbon mitigation strategies. Additionally, Shanghai, with its relatively low level of urban greening, negatively impacts the final model output. Therefore, it is essential for Shanghai to strengthen its greening efforts and increase vegetation coverage. Similarly, the greening rate in build-up areas in Zhejiang also has a negative effect on synergy, as does the vegetation coverage in Jiangsu. Both provinces exhibit lower greening values compared to other provinces. Thus, enhancing greening initiatives is beneficial for improving synergistic effects across these areas. However, at the city level, Ningbo city, characterized by a higher greening rate, shows a clear positive effect on synergistic performance, illustrating how green-city development can improve environmental quality.

#### 5.4 Limitations

Despite these inspiring findings, several limitations were identified in this study. Firstly, the quantification of synergy degree is influenced by the selection of features or variables, which can lead to varying results. In this research, we focused on assessing overall air pollution concentrations as a representation of air quality levels. However, future studies could benefit from incorporating additional important factors, such as per capita emissions or emissions per unit of GDP, as components for evaluating synergy. Secondly, the selection of local drivers was constrained by the availability of city-level statistical data. While we identified key drivers, other significant factors may interact and exert synergistic effects on air quality improvement and carbon mitigation. Thirdly, the spatial resolution of the analysis could be improved. The use of finer spatial units may provide a more detailed understanding of local variations and interactions.

#### 6. Conclusion

This research quantifies the synergistic governance performance of air quality improvement and carbon mitigation at the city level within the Yangtze River Delta urban agglomeration. By integrating Geographically Weighted Regression (GWR), Random Forest (RF), and SHAP (SHapley Additive exPlanations), we identified the nonlinear relationships with local drivers and their spatial heterogeneity in local influence. Our analysis revealed fluctuations in synergistic governance performance over the years, highlighting significant spatial heterogeneity in the primary drivers, as well as the direction and magnitude of their impacts across different cities and provinces.

Global results showed that longitude, SO<sub>2</sub> emissions from industrial source, wind speed were the primary contributors to the model output, followed by latitude and the proportion of GDP from the tertiary industry. Higher longitude negatively impacted synergy. In terms of meteorological factors, increased wind speed and temperature adversely affected synergy predictions. The analysis also uncovered clear threshold effects for each explanatory variable. Among these factors, wind speed emerged as a critical variable influencing the model output, demonstrating a positive impact on synergy when speeds were below 9.3 m/s.

Local results regarding the spatial patterns of the primary influencing factors indicated that longitude, SO<sub>2</sub> emissions and wind speed significantly contributed to the model output. However, other socio-economic and meteorological variables, such as GDP, population, and temperature, were also identified as

key drivers across provinces. From a spatial distribution perspective, cities located along the eastern coast benefited from geographical advantages that enhanced synergy. Meteorological conditions, particularly wind speed, significantly influenced synergy predictions, with notable differences observed between northern and southern coastal cities.

This study presents a flexible spatial scale analytical framework in which modeling was conducted at the city level, while the results were interpreted within a provincial context. These findings highlight the complex interplay and spatial non-stationarity of various factors in shaping urban synergy, emphasizing the necessity for targeted strategies that consider these diverse influences. By integrating advanced machine learning techniques with traditional geostatistical models, this research provides valuable insights for policymakers aiming to improve air quality and promote sustainable development in rapidly urbanizing regions. Additionally, the methodological integration aligns closely with the themes of ISPRS 2026, contributing to the domain of GeoAI by demonstrating how artificial intelligence can be leveraged to address spatial heterogeneity and reveal nonlinear relationships, offering innovative approaches to tackling pressing environmental and urban challenges.

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## Appendix

All supplementary materials supporting the findings of this study are organized in a Figshare repository, which can be accessed at <https://doi.org/10.6084/m9.figshare.31868782>.