Study of the Coupling Effect of CO_2 and $PM_{2.5}$ Emissions: A Case Study of Yangtze River Delta, China

【Abstract】

Many countries are confronted with the dual challenge of mitigating CO_2 emissions and controlling $PM_{2.5}$ pollution, attributed to the impacts of global climate change. This study explores the spatio-temporal pattern of the coupling effect between CO_2 emissions and $PM_{2.5}$ pollution by conducting a case study of the Yangtze River Delta (YRD) region of China and aims to identify the urban influencing factors that contribute to this coupling effect. Utilizing a coupled coordination model, this study conducted a spatio-temporal analysis of CO_2 emissions and $PM_{2.5}$ concentrations from 2008 to 2020.The model assessed the year-by-year coupling coordination degrees of CO_2 and $PM_{2.5}$ emissions in each of the five provinces in the YRD region.

This study's three main findings are the following: (1) The overall coupling coordination between CO_2 and $PM_{2.5}$ emissions exhibited a declining trend from 2013 to 2017, followed by a rebound in 2018. Most cities experienced their highest degree of coupling in 2020. (2) Of 41 cities in the YRD region, only 10 have achieved a state of coordinated development. This finding suggests that approximately 24% of the YRD region attained a positive degree of coordination. (3) The megacity Shanghai has achieved a stage characterized by high-quality coordination, emphasizing the city's significant role in mitigating CO_2 emissions and managing $PM_{2.5}$ pollution in the region. In addition, the analysis of urban influencing factors revealed a significant

correlation between several key urban factors, including land area, green space and water area, road network, technical development, and industrial structure.

This study recommends that cities aiming to reduce CO_2 emissions and control $PM_{2.5}$ pollution consider initiatives that address the coupling effect, such as optimizing industrial land use and prioritizing spatial planning strategies. The selection of the YRD region as the study area provides an exemplary model that offers implications not only for other regions in China but also for other countries that face similar issues.

【*Keywords:*】$PM_{2.5}$, CO_2, coupling effect, Yangtze River Delta, carbon mitigation, carbon neutrality

1. Introduction

The primary driver of climate change is the ever-increasing release of greenhouse gases, with carbon dioxide (CO_2) being the main culprit. As a result, CO_2 emission and particulate matter ($PM_{2.5}$) concentration have become a significant concern for nations that are working towards mitigating the negative impacts of air pollution and climate change. Developing countries' primary sources of greenhouse gases and air pollution are CO_2 and $PM_{2.5}$. These emissions are driven by the rapid growth of their economies, industrialization, and their continued reliance on conventional energy sources (World Health Organization, 2019). Air pollution has been further exacerbated by the rapid expansion of populations in these regions, leading to increased emissions in countries such as Indonesia, India, and China (Ghosh et al., 2024; Rahman et al., 2024; Zeng et al., 2019). The two nations with the highest emissions rates, China and India, have been making significant efforts to mitigate greenhouse gas emissions and manage air particulate matter, and their experiences have highlighted the major challenges faced by developing nations in addressing these global issues (Kumar et al., 2020; Wang & Azam, 2024).

A number of climate-related studies have found a coupling effect have demonstrated a coupling effect between $PM_{2.5}$ and CO_2, highlighting the interconnectedness of these two pollutants. For example, Dong et al. (Dong et al., 2019) found that the reduction of CO_2 emissions can lead to a substantial decline in $PM_{2.5}$ emissions. The Intergovernmental Panel on Climate Change (IPCC) found that there were co-benefits when CO_2 and $PM_{2.5}$ were viewed as homogeneous (Cai et al., 2021). Other studies proved that CO_2 and $PM_{2.5}$ were homogeneous and synchronous by testing both in a model and finding that efforts to reduce CO_2 significantly contributed to a decrease in $PM_{2.5}$ (Braspenning Radu et al., 2016; Guan et al., 2023; Jia et al., 2023). Furthermore, research has identified a significant synergistic effect between CO_2 and $PM_{2.5}$ from coal consumption: These studies found that coupling efforts to reduce $PM_{2.5}$ from coal consumption could have profound impacts on public health (Jia et al., 2023).

Past research that used spatial analysis identified a correlation between CO_2 and $PM_{2.5}$ emissions and shed light on the mechanism of carbon pollution homogeneity, investigations into the coordinated coupling of CO_2 and $PM_{2.5}$ at the spatial scale have been relatively scarce. This shortage of studies can be attributed primarily to inadequate data availability and quantifiability, and to the need for more research and application paradigms that are both standardized and reflective of local characteristics. These intertwined factors collectively cause a bottleneck in research efforts. Furthermore, past studies predominantly concentrated on the regional level and broader, with the highest resolution typically limited to administrative divisions at the county level. This limitation has made it challenging to fully understand the coupling dynamics between the two emissions in urban settings. To address these gaps, this study aims to analyze the spatial patterns of CO_2 and $PM_{2.5}$ emissions and identify the spatial driving factors that influence the coupling degree of CO_2 and $PM_{2.5}$ emissions in the YRD region.

2. Literature Review

2.1 Research progress in spatial on greenhouse gases (CO_2) and air pollution ($PM_{2.5}$)

The primary greenhouse gas that originates from human activities in the atmosphere is CO_2, which constitutes 70% of urban greenhouse gas emissions (U.S. Environmental Protection Agency, 2024.). Simultaneously, the predominant atmospheric pollutant, $PM_{2.5,}$ accounted for 45% of the total days when recommended levels were exceeded, surpassing other pollutants, such as O_3, PM_{10}, NO_2, and CO, which constituted 41.7%, 12.8%, 0.7%, and less than 0.1%, respectively (Ministry of Ecology and Environment of the Peoples Republic of China, 2021). The objective of the "The 14th Five-Year Plan of the People's Republic of China" is to synergistically reduce greenhouse gases and atmospheric pollutants to achieve high-quality development (Chen et al., 2020). Nevertheless, few research has focused on the theory of a synergy or coupling effect between CO_2 and $PM_{2.5}$.

Previous studies that focused on the synergistic reduction of CO_2 emissions and various atmospheric pollutants concentrated on two primary domains. First, several studies focused on the implementation of measures originating from different emission sources or sectors. These measures, such as technological advancements and industrial process enhancements, were aimed at concurrently curbing emissions of greenhouse gases and pollutants, thus promoting sustainable environmental protection and a climate change response (Li et al., 2022; Zeng & He, 2023). Research about emission sectors was relatively advanced and commonly employed the four sectors that had been identified by the IPCC to analyze carbon emissions associated with various economic activities, namely, energy, industry, agricultural land use, and waste (Eggleston, 2006).

Second, several studies concentrated on the synergy of emission reduction efforts in specific regions and spaces. This domain was characterized by a clear geographical or spatial scale perspective, and the research aim was to optimize emission reduction strategies by comprehensively considering emissions from different sources and their interactions to minimize impacts on the atmosphere (Alimujiang & Jiang, 2020; Li et al., 2019). The spatial scale was categorized as global, regional, local, and community, and studies revealed correlations between CO_2 and $PM_{2.5}$ in each category. The underlying cause of this correlation was attributed to the shared source of carbon pollution.

Both the above research domains have been instrumental in driving the development of emission reduction technologies and policies to address climate change and improve atmospheric quality. However, despite their significance, the advancement of spatial research in these areas has faced obstacles. Limited data granularity and the absence of standardized local research and application paradigms have hindered comprehensive investigations of the spatial dynamics of greenhouse gases and atmospheric pollutants. To meet the increasing global and domestic demands for carbon neutrality and clean air environments, urgent research on the spatial co-reduction of CO_2 and $PM_{2.5}$ is needed. Such research can provide a more precise understanding of the distribution patterns and interaction mechanisms of these emissions at different spatial scales, thus laying a solid foundation for the development of more scientifically sound and targeted emission reduction strategies.

2.1.1 Spatial research on CO_2 emission reduction

Previous research has elucidated the relationship between CO_2 emissions and various urban variables, demonstrating that population density, economic development, and industrial composition exert significant influences on carbon emissions. In South Korea, an inverted U-shaped relationship was observed between manufacturing agglomeration and carbon emissions. Specialized agglomeration was found to decrease both local and neighboring emissions, whereas diversified agglomeration primarily benefited local emissions in the short term but also contributed to long-term local emission reductions (Z. Wu et al., 2024). Specifically, population density and economic prosperity exhibited positive correlations with carbon emissions (Guan et al., 2023), while the impact of industrial structure and spatial factors varied across regions (Lu et al., 2019; Zhou et al., 2023). Policy implications drawn from these findings suggest that fostering an advanced industrial structure, optimizing land use, and modifying energy consumption patterns can effectively mitigate CO_2 emissions, with particular relevance for China.

Studies of economic factors revealed a significant negative correlation between GDP per capita and the interaction between urbanization, population, and CO_2 emissions. Some scholars also employed models such as the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model and Geographical and Temporal Weighted Regression (GTWR) model to investigate the spatiotemporal heterogeneity of driving factors, including low-carbon policies, air pollutant prevention and control policies, and industrial structure on the synergistic effects of pollution reduction and carbon reduction (Jiang et al., 2023; Shahbaz et al., 2016).

2.1.2 Spatial research on $PM_{2.5}$ reduction

China has made notable progress in curbing $PM_{2.5}$ pollution by implementing several concentration reduction and control measures. However, $PM_{2.5}$ concentration in urban areas remains an ongoing concern and subject of study. Researchers have identified certain key factors that impact urban $PM_{2.5}$, including the distribution of pollution sources throughout the city, traffic patterns, and the presence of green spaces (Long et al., 2021). Despite ongoing efforts, significant obstacles remain, largely due to the sparse distribution of environmental monitoring stations across the country, with a pronounced scarcity of such stations in smaller and medium-sized urban areas. Moreover, the temporal resolution of the monitoring data frequently suffer from a lack of precision. This imprecision has introduced inaccuracies into the scholarly discourse on the spatiotemporal dynamics of $PM_{2.5}$.

As cities increasingly pursued high-quality development and refined their air pollution control efforts, identifying spatial and temporal patterns in urban $PM_{2.5}$ concentration became imperative. Such identification is essential for reducing $PM_{2.5}$ levels through synergistic planning and management, thus facilitating comprehensive compliance with air quality standards in subsequent stages. Some studies emphasized the strong correlation between greenhouse gas emissions and atmospheric pollutants, which results in robust coupling effects between air quality and climate-related measures. This correlation highlights the potential for devising cost-effective air pollution policies through an integrated approach (Ang et al., 2015). Studies also underscored the significance of low-carbon policies, enhancing the public transportation infrastructure, and considering various socio-economic factors to achieve effective reductions in $PM_{2.5}$ and CO_2 emissions (Huang & Tsai, 2014; Wang et al., 2024). Some suggested that a comprehensive approach should be adopted to address the interconnected nature of environmental, economic, and social factors, ultimately working toward the attainment of sustainable and low-carbon urban development (Yi et al., 2022).

2.2 Coupling effect and driving factors

Coupling theory refers to the interaction between two or more systems or components, describing and analyzing the transmission and conversion of energy and information between systems, as well as the coordination and adjustment between systems (Boccaletti et al., 2006). When coupling theory is extended from physics to other fields, the analysis process involves the following steps: (1) identify and quantify the various systems involved in environmental problems (e.g., natural systems, social systems, economic systems) and the connections and impacts between them; (2) establish mathematical models and calculation methods to simulate and predict the dynamic change process and results of environmental problems and evaluate the effects and costs of different solutions; (3) find optimal solutions to achieve coordinated development of various systems and improve problem management efficiency and impact; (4) monitor and evaluate the implementation of solutions to maintain the stability and sustainability of each system (McCracken et al., 2024).

Both CO_2 and $PM_{2.5}$ exhibit relatively stable chemical characteristics, and their interactions in the air are not readily apparent. Their coupling characteristics primarily stem from similar emission sources and physical spatial diffusion. More recent studies of the coupling coordination of CO_2 and $PM_{2.5}$ have focused primarily on spatial disparities, policy impacts, and driving factor analysis (Fang et al., 2015; Wang et al., 2017; Wang et al., 2017). These studies aim to explore the emission characteristics of CO_2 and $PM_{2.5}$ at the provincial level, the influence of policy measures on emission reduction effects, and the key factors that cause change in emissions.

In recent years, applied research has gradually increased, with more studies focusing on the reduction of coupling coordination in atmospheric pollutants and greenhouse gases. Among such research, many foreign studies have predominantly employed modeling simulations to investigate the effectiveness and synergistic effects of various emission reduction strategies (Cai et al., 2021). This approach enables the simulation of emission scenarios and environmental impacts under different policy contexts, thus providing scientific evidence for policymakers. Concurrently, some studies have evaluated the cost-effectiveness and synergistic effects of China's air quality planning and greenhouse gas control measures from the perspective of input-output analysis (Yi et al., 2022). This perspective underscores the interaction between the economy and the environment and aims to identify policy scenarios that can achieve optimal synergistic benefits at minimal cost. Such considerations are particularly important for developing countries that have limited resources.

Studies of the factors that drive various forms of pollution have had varied findings. Considering the unique characteristics of China's economic development, existing research has identified several key factors that drive CO_2 emission. These factors include industrial structure, property rights structure, energy composition, level of urbanization, government regulations, and more (Fang et al., 2015).

However, regarding the driving factors that influence air pollutants, such as $PM_{2.5}$, relatively few studies have concentrated on the determinants of these pollutants' emission efficiency. Some research studies have identified factors that potentially affect $PM_{2.5}$ emission efficiency, including population density, economic development levels, environmental regulatory measures, and the degree of industrialization. In addition, studies have attempted to measure the impact of natural ecological factors, such as wind speed, precipitation, and urban green spaces, on measures to mitigate urban $PM_{2.5}$ emission (Wang et al., 2017). Some found ecological restoration projects prohibited $PM_{2.5}$ growth (Yang, Shi, et al., 2024). For a more comprehensive understanding, further in-depth research is necessary to explain the specific mechanisms by which these factors affect $PM_{2.5}$ emissions and their evolving trends in different regions and periods.

2.3 Multiple data sources and analysis

Many studies have focused on national, provincial, and urban agglomeration levels, leaving a research gap at the level of city and neighborhood. Some researchers believe that as China transitions towards a more localized approach to emissions issues, it is necessary to analyze large-scale data (e.g., measurements at the provincial level) to accurately reflect the actual state of CO_2 and $PM_{2.5}$ emissions across the country. Access to accurate air quality data at the county and municipal levels is crucial for developing effective emission reduction strategies. While national and provincial-level analyses provided macro-level insights into overall emission trends and policy implications, more robust analysis that accurately targets and assesses specific emission sources in different regions is required. Localized data allows for the formulation of customized regulations based on the varying nature and influencing factors of emissions in various cities and counties. Factors that play a role in these differences include industrial activities, traffic patterns, and geographical conditions.

The primary source of information about CO_2 and $PM_{2.5}$ levels has been satellite, statistical, and monitoring data. Such data has been used to extract meaningful information, including spatiotemporal distribution, trends, and source-sink analysis. Satellite remote sensing data has been of crucial importance to the observation of carbon emissions and $PM_{2.5}$ concentrations (Lin et al., 2018; Ma et al., 2016). Such data provides comprehensive coverage and flexibility in spatiotemporal resolution, offering multi-scale observations on a global level or the level of a specific area to reflect the spatiotemporal distribution characteristics of pollutants.

Statistical data involves the use of economic, energy, industrial, and demographic information from a country’s census. Combined with the emission factor method, these statistics are used to calculate carbon emissions in specific regions. Monitoring data encompasses information obtained through on-site observation and measurement, including exhaust emission, meteorological, and air quality data. Such data can be used to directly measure emissions from carbon emission sources, such as industrial, transportation, and energy-production emissions. Monitoring data can also be utilized to evaluate greenhouse gas concentrations and air quality in the atmosphere, providing insights into environmental pollution. Due to the limitations of data, such as its difficulty to assess and often lower resolution, some studies have resorted to using satellite imagery, statistical analysis, and monitoring data to gain a more comprehensive and accurate understanding of carbon emissions, allowing for the analysis of emission trends, source and sink distributions, and environmental impacts. Numerous studies have explored synergistic emission reduction strategies concerning greenhouse gas emissions and various atmospheric pollutants, primarily focusing on provincial or metropolitan scales. Nevertheless, few, if any, have undertaken research at the city scale to specifically address the synergistic emission reduction of CO_2 and $PM_{2.5}$ in urban areas. Additionally, more exploration is needed of approaches to spatial planning that aim to achieve synergistic emission reduction in the pursuit of carbon neutrality goals. Therefore, the primary objective of this study is to investigate the spatial and temporal patterns and the coupling characteristics of CO_2 and $PM_{2.5}$ in urban environments. This research aims to clarify the influencing mechanisms through which key control factors influence synergistic emission reduction efforts at the city level.

3. Models and data sources

3.1 Study Area

The YRD (Figure 1) is one of the regions with the highest concentration of industry and the most rapid economic development in China. The YRD region has been designated a critical area for pollution reduction and carbon mitigation in terms of the Beautiful China initiative. Controlling fine particulate matter is a primary focus of this program, and vigorous efforts are directed at the coordinated reduction of multiple pollutants.

The YRD region is located between the longitudes of 114°54' and 123°10' east and latitudes of 27°02' and 35°20' north. YRD typically encompasses parts of China's

Shanghai, Jiangsu, Zhejiang, and Anhui provinces. Specifically, the YRD region includes the following cities: Shanghai; Jiangsu cities of Nanjing, Wuxi, Changzhou, Suzhou, Nantong, Yancheng, Yangzhou, Zhenjiang, and Taizhou; Zhejiang cities of Hangzhou, Ningbo, Jiaxing, Huzhou, Shaoxing, Jinhua, Zhoushan, and Taizhou; and the Anhui cities of Hefei, Wuhu, Ma'anshan, Tongling, Anqing, Chuzhou, Chizhou, and Xuancheng. According to data from the Seventh National Census Bulletin, by the end of 2020, the permanent resident population of the YRD had reached 235 million, accounting for 16.7% of the total population of China.

The YRD region is a cornerstone of China's economic prowess and plays a pivotal role in the nation's financial, technological, and trade sectors. Boasting major metropolitan areas like Shanghai and Hangzhou, the YRD has emerged as an innovation hub, driving technological advancement and contributing substantially to China's global competitiveness. However, the region's rapid urbanization and burgeoning population have created environmental challenges, necessitating robust policy making to control these issues.

According to the Air Pollution Prevention and Control Action Plan, issued by the State Council of China in 2013, $PM_{2.5}$ pollution has been effectively mitigated in the YRD region. However, further efforts are required to reduce emissions. The average $PM_{2.5}$ level in the YRD was 41 μg/m3 in 2019, surpassing the World Health Organization's standard of 10 μg/m3. Simultaneously, the Carbon Peaking and Carbon Neutrality Implementation Plan explicitly outlines China's strategic goal of reducing CO_2 emissions. The nation aims to achieve a peak in carbon emissions by 2030 and attain carbon neutrality by 2060.

China has implemented stringent environmental control measures in the YRD to tackle these challenges. These policies aim to address issues such as air and water pollution resulting from rapid industrialization and urbanization. Specific strategies include regulating industrial emissions, enhancing energy efficiency, and promoting the adoption of green technologies. The selection of the YRD region as the case study means that this study can potentially serve as a valuable reference for similar regions and provide insights that are applicable to developing countries.

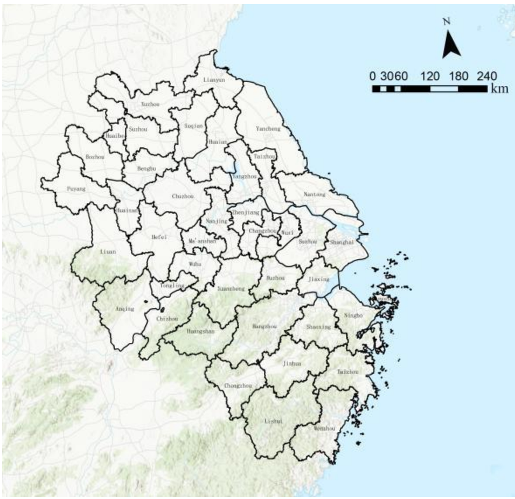


Figure 1: Map of Yangtze River Delta Megalopolis

3.2 Data Sources

The study employed CO_2 and $PM_{2.5}$ data from the Multi-scale Emission Inventory of China (MEIC model), a bottom-up model that estimates direct emissions across four critical sectors: transportation, industry, residential, and power. These emissions were directly released into the atmosphere without intermediary transformations. The same sectors were selected for the $PM_{2.5}$ data from MEIC v1.4, facilitating a comprehensive analysis in conjunction with CO_2 data to examine emission patterns, their socio-economic determinants, and the degree of coupling coordination between these emissions.

In order to assess the reliability of the MEIC data, the study compared MEIC carbon emissions with provincial data from the Carbon Emission Accounts & Datasets (CEADs). The deviation between datasets fell within an acceptable range, with a total deviation of 8.3% for MEIC data relative to actual figures. Larger discrepancies appeared in Zhejiang and Anhui provinces, while Shanghai and Jiangsu showed deviations around 5%, which were within expected error margins. Thus, deviations in Zhejiang and Anhui were considered during analysis. Given the challenges in accessing high-precision, sector-specific CO_2 emission data and historical $PM_{2.5}$ data, MEIC data proved to be a relatively reliable source for CO_2 and $PM_{2.5}$ emission accounting.

Additionally, the study incorporated road network data from OpenStreetMap's (OSM) History Dump (2024), providing crucial spatial information on road infrastructure. This data was essential for examining emissions relative to transportation networks and urban layouts. Socio-economic data from the China Statistical Yearbook (National Bureau of Statistics) included indicators such as GDP, population, industrial output, and energy use, which allowed for a comprehensive analysis of the socio-economic factors influencing CO2 and PM2.5 emissions across sectors. Detailed data sources were provided in Table 1.

Table 1: Data Source

Data Type	Source	Year	Description
CO_2 Emissions	MEIC v1.4: Multi-resolution Emission Inventory for China (Li et al., 2017; MEIC, 2023; Zheng et al., 2018)	2008 - 2020	MEIC offers comprehensive, high-resolution CO_2 emissions data for four sectors: transportation, industry, residential, and power. All data are Scope 1 direct emissions.
$PM_{2.5}$ Emissions	MEIC v1.4: Multi-resolution Emission Inventory for China (Li et al., 2017; MEIC, 2023; Zheng et al., 2018)	2008 - 2020	Contains sector-specific $PM_{2.5}$ emissions data (industry, residential, transportation) compatible with CO_2 data, facilitating analysis of emission synergies.
Road Network	OpenStreetMap (OSM) History Dump (OpenStreetMap, 2024)	2008 - 2020	Spatial data on road infrastructure, essential for studying emissions in relation to transportation networks and urban layout.

Socio-economic Data	China Statistical Yearbook (National Bureau of Statistics)	2008 - 2020	Includes key indicators (GDP, population, industrial output, energy use), enabling the analysis of socio-economic factors influencing CO_2 and $PM_{2.5}$ emissions patterns.

3.3 Models

This study designed a comprehensive methodological framework(Figure 2) to investigate the spatial factors influencing the coupling degree in the YRD region. By integrating diverse datasets, the framework provides an exhaustive understanding of the spatio-temporal patterns of CO_2 and $PM_{2.5}$ emissions, as well as socio-economic variables. Utilizing rigorous spatial autocorrelation, temporal trend analysis, and regression techniques, the model identifies key spatial factors that significantly impact the coupling degree within the YRD. The insights garnered from this framework are of utmost importance for informing the development of sustainable policies and fostering regional coordination in the YRD, thereby contributing to the advancement of environmental and socio-economic research in the region.

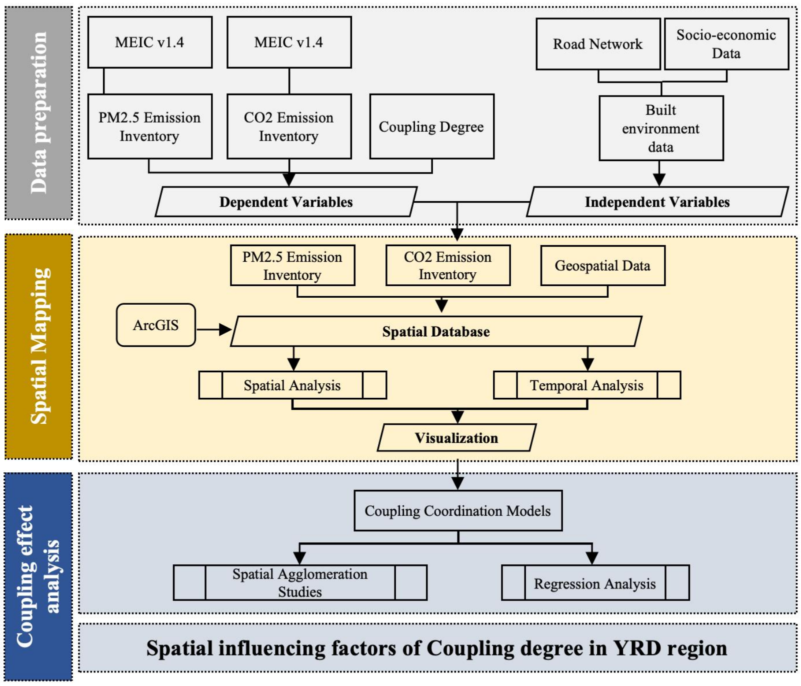


Figure 2: Methodological framework

3.3.1 Spatio-temporal visualization of CO_2 and $PM_{2.5}$ distribution

This study performed descriptive statistics and tests for the distribution of the CO_2 and $PM_{2.5}$ data. Outliers were removed, and ArcGIS was employed to conduct exploratory spatial data analysis (ESDA) on the emissions of CO_2 and $PM_{2.5}$ in the research area. The study simulated the spatial distribution patterns of CO_2 and $PM_{2.5}$ by using the ArcGIS software.

3.3.2 Coupling Coordination Model

In this study, a coupling coordination model was used to analyze the coupling between CO_2 emissions and $PM_{2.5}$ concentration. For each year, the annual coupling coordination values (D) for the Shanghai CO_2 emissions (U1) and $PM_{2.5}$ concentration (U2) systems were calculated. Both systems consisted of four subsystems: electricity, industry, residential, and transportation. D values fall within the range of $0 < D < 1$, where a higher D value indicates a higher degree of coupling coordination between the systems.

This step is primarily for data processing convenience, where the data is mapped within the range of 0 to 1. The formula for calculation is:

$$0.01 + (0.99 - 0.01) * (X - Min) / (Max - Min), \tag{1}$$

where Max and Min represent the maximum and minimum values of the data in the respective subsystem.

1) Calculate the coupling degree (C) and coordination index (T):

$$C=2\times\left[\frac{U1*U2}{(U1+U2)^2}\right]^{\frac{1}{2}}, \tag{2}$$

where U1 and U2 are the weighted sums of the interval values of each subsystem. The weights for each subsystem are determined using the SPSS-AU entropy method.

$$T=\beta1U1+\beta2U2, \tag{3}$$

where β1 and β2 represent the weights of the two systems within the current system. In this study, β1 = β2 = 0.5.

2) Calculate the coupling coordination value:

$$D=\sqrt{C * T}, \tag{4}$$

The classification of the coupling degree between CO_2 and $PM_{2.5}$ in the YRD based on the D value is presented in Table 2. The stages are: disordered coupling (D = 0), low coupling (D = 0 to 0.3), antagonistic (D = 0.3 to 0.5), integration (D = 0.5 to 0.8), and high coupling (D = 0.8 to 1). These stages reflect the correlation strength, ranging from lack of correlation to high correlation between CO_2 and $PM_{2.5}$. This classification helps clarify the environmental dynamics that are at work, thus facilitating effective policymaking in the YRD region.

Table 2: Classification and stage characteristics of coupling degree between CO_2 and $PM_{2.5}$ in YRD

Classification	Subclasses
Seriously unbalanced development	$0 < D \leq 0.2$
Moderately unbalanced development	$0.2 < D \leq 0.4$
Slightly unbalanced development	$0.4 < D \leq 0.5$
Barely balanced development	$0.5 < D \leq 0.6$
Favorably balanced development	$0.6 < D \leq 0.8$
Superiorly balanced development	$0.8 < D \leq 1$

3.3.3 Constructing the STIRPAT model

The IPAT model comprises the elements I (environmental impact), P (population size), A (affluence), and T (technology level). To improve on the limited scope of the IPAT model and examine more factors that affect environmental elements, Dietz and Rosa extended the IPAT model to create the STIRPAT model. The STIRPAT model is an expanded version of the IPAT model.

3.3.4 Geographically weighted regression

Geographically weighted regression (GWR) is a spatial statistical technique that extends traditional linear regression models by accounting for spatial variations in the relationships between dependent and independent variables. Unlike global regression models, which assume a constant relationship across the entire study area, GWR recognizes that the strength and nature of these relationships can vary spatially. This method is particularly useful in analyzing spatially heterogeneous data, where the relationship between variables may change across different locations.

4. Results

4.1 Spatial and temporal emissions of CO_2 and $PM_{2.5}$

This study compared the spatial and temporal emission data of CO_2 and $PM_{2.5}$ in the YRD region to the total emissions recorded from 2008 to 2020. The analysis revealed that the power, industry, residential, and transportation sectors accounted for a significant proportion of CO_2 emissions from various sectors in the administrative regions. Notably, the industry and power sectors were responsible for most of the CO_2 emissions in the YRD region. Regarding the provinces, Shanghai, Jiangsu, Zhejiang, and Anhui collectively contributed over 80% of the CO_2 emissions generated by the industrial and power sectors. Of these provinces, Shanghai's industrial sector made a higher contribution to emissions when compared to its power sector, while Anhui's residential sector had a higher impact than other provinces' residential sector This finding highlights that the industrial sector in Shanghai alone accounted for more than half of the total emissions in the region. Hence, it would be prudent for Shanghai to direct its efforts at industry and adopt a more rational approach to controlling industrial emissions to reduce CO_2 emissions effectively. Conversely, Anhui province should prioritize the residential sector and encourage the adoption of policies that promote reduced CO_2 emissions resulting from civilian use while considering the YRD region's synergistic policies.

The findings reveal the following three primary aspects of spatial distribution: (1) Cities with high population density and advanced economies, such as Shanghai and Suzhou, which are provincial capital cities and transportation hubs, have higher CO_2 emissions. (2) CO_2 emissions in the northern regions of the YRD area were notably higher than in the south due to the increased demand for residential heating in winter. (3) Except for the residential sector, CO_2 emissions generally decrease from the central region of Shanghai towards its periphery.

In the period 2011 to 2020, the growth rate of total CO_2 emissions has slowed down and even decreased, as can be seen in the time distribution. Anhui and Jiangsu provinces showed a decline in the transportation sector, while the power sector increased considerably. As for $PM_{2.5}$, the transportation sector in each region had the lowest growth rate. Encouragingly, the total amount of $PM_{2.5}$ has decreased over the past ten years, with industrial $PM_{2.5}$ declining significantly in 2013, marking a turning point. These positive changes suggest that the national $PM_{2.5}$ pollution control policy has had an impact. However, most cities in the YRD region were found to have experienced an increase in CO_2 emissions, and it was worth noting that megacities such as such as Shanghai and Jiaxing and Taizhou in Zhejiang province displayed a downward trend in CO_2 emissions. Despite this, the distribution of CO_2 emissions across the region remained largely unchanged over the past decade, with Shanghai and surrounding cities continuing to be identified as high-emission areas.

In 2020, as shown in Figure 3, Shanghai, Suzhou, and Hefei were the cities that recorded the highest total emissions of CO_2 and $PM_{2.5}$. Of the four sectors, industry was responsible for the highest rate of emissions, mainly in the cities of Shanghai, Suzhou, Hangzhou, and Hefei, which are the key economic pillars of their respective provinces. The residential sector followed, with the northwestern YRD exhibiting significant $PM_{2.5}$ while lower levels of CO_2 emission were observed in the southeastern portion. Emissions data for the power sector indicated that Ningbo and Zhenjiang had the highest emission rate in both CO_2 and $PM_{2.5}$. Finally, in the transportation sector, most of the coastal cities in the YRD had substantial levels of $PM_{2.5}$, with Shanghai having the highest rate of CO_2

emission.

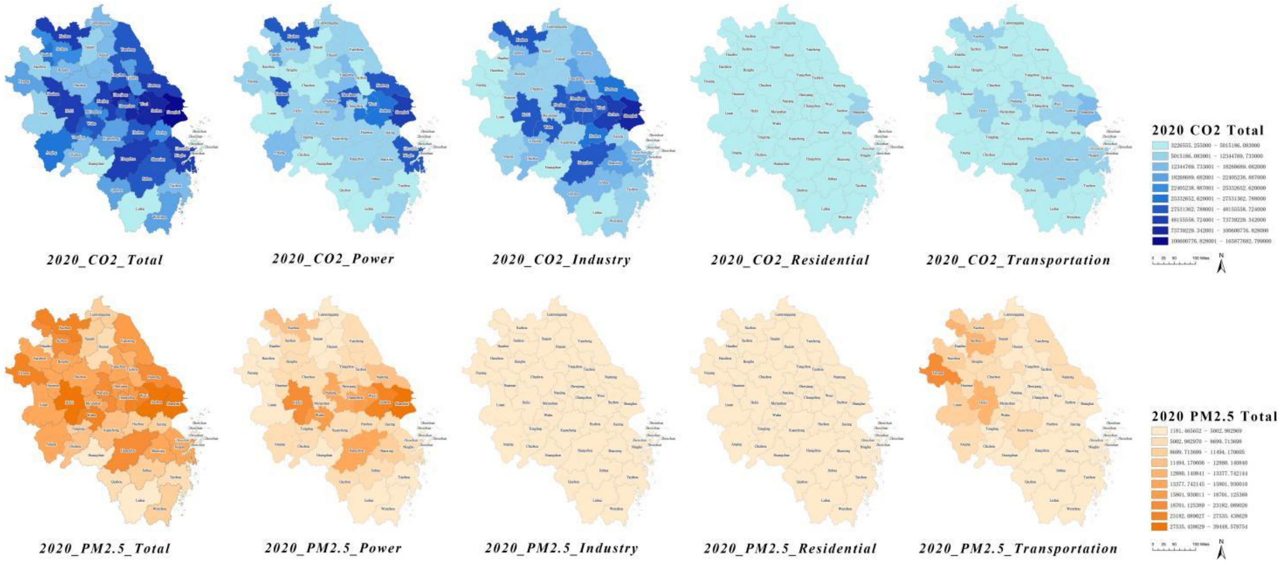


Figure 3: 2020 CO_2 and $PM_{2.5}$ emission in YRD region by factors: total, power, industry, residential, and transportation

The Moran's I analysis revealed that most emissions had positive values, indicating a certain level of positive spatial autocorrelation. However, the correlation was not strongly pronounced. The $PM_{2.5}$ emissions generated by the power sector displayed a negative Moran's I value close to zero, accompanied by a higher P-value, which indicated the absence of significant spatial autocorrelation in this category. Of the four sectors analyzed, industrial CO_2 and residential $PM_{2.5}$ showed significant spatial autocorrelation, while traffic CO_2 showed relatively significant spatial autocorrelation. In contrast, other emission categories and sectors did not show substantial spatial autocorrelation based on the analysis.

Furthermore, the study found that the primary areas with high CO_2 emissions were in and around Shanghai, indicating a clear spatial relationship in how emissions were distributed across various sectors. Additionally, Anhui province and western Zhejiang province showed significantly low levels of emissions. For residential CO_2 emissions, besides Shanghai, high concentrations of emissions were identified in the eastern and northern parts of Jiangsu province and northern Anhui province. However, there was a noticeable drop in emissions centered around Zhejiang province. While industrial CO_2 was linked to industrial agglomeration in the YRD region, transportation CO_2 did not demonstrate a distinct pattern. Furthermore, the distribution of hot and cold spots in power CO_2 displayed a step-like pattern extending from the southwest to the northeast of the YRD region.

While this study found that Shanghai and its surrounding cities were the primary hotspot areas for $PM_{2.5}$, other sectors showed variations in hotspot distribution. The concentration of industrial $PM_{2.5}$ was primarily in the central part of the YRD, and central Anhui province displayed a high-high pattern in industrial $PM_{2.5}$. This finding signals the importance of the Central Anhui as a critical area for targeted concentration control efforts. Residential $PM_{2.5}$ displayed a similar distribution to industrial $PM_{2.5}$, but with a larger proportion of cold spots. This distribution emphasized more pronounced spatial clustering, which was highly concentrated in central YRD. The distribution in the transportation sector was relatively modest, with most cities lacking significant high-high or low-low patterns. Primary hotspots persisted in Shanghai and surroundings, where key transportation hubs in the YRD are situated. The distribution in the power sector was more scattered, showcasing a multi-point and high pattern across the region.

4.2 Coupling coordination degree of CO_2 and $PM_{2.5}$

Between 2008 and 2013, the degree of coupling coordination increased consistently, reaching its peak in 2013 (Figure 4). Heightened synergy and improved coordination among the factors under consideration characterize this timeframe. However, from 2013 to 2016, the trend shifted, and the degree of coupling coordination declined. This finding suggests either a transitional phase or a change in the relationship between CO_2 and $PM_{2.5}$. Interestingly, a glimmer of recovery was observed in 2018, hinting at a potential stabilization or renewed alignment of the contributing factors that had been apparent since 2017. The trend observed from 2017 to 2018 is linked to the implementation of national policies aimed at addressing pollutants and environmental concerns. Remarkably, except for 2012 and 2017, the coupling coordination degree remained resilient, maintaining a relatively high level throughout the rest of the years under observation. The sustained level of coordination imply a consistent equilibrium or interdependence among the variables assessed, contributing to the system's overall stability. Nuanced temporal dynamics in the coupling coordination degree over these years reveal the intricate interplay of factors that influence the observed patterns and trends, highlighting the complexity of the system's behavior.

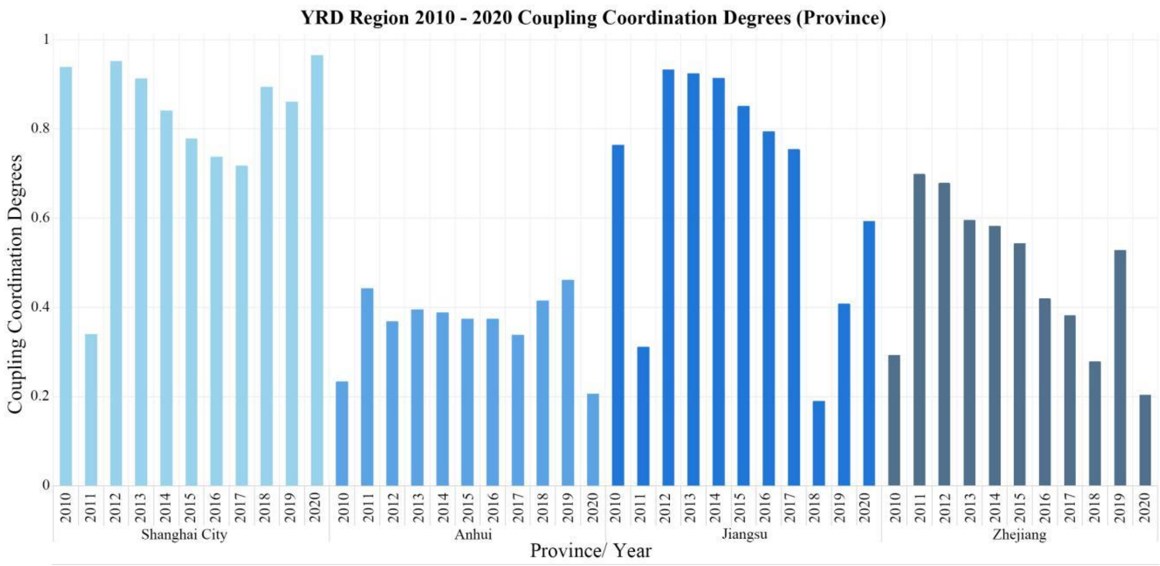
Between 2018 and 2020, Shanghai exhibited a consistent upward trend in coupling coordination, progressing from favorably balanced development to superiorly balanced development. This positive trend reflects sustained efforts towards enhanced synergy and harmonization among its various components and a positive coupling development trend in CO_2 and $PM_{2.5}$. Although cities such as Nanjing, Wuxi, Xuzhou, and Changzhou experienced minor fluctuations in coupling coordination, overall, they fell within the categories of slightly balanced development to barely balanced development of the coupling degree. This finding suggested a need for further improvement in emission control in these cities. Meanwhile, Suzhou observed a continuous enhancement in coupling coordination, progressing from barely balanced development to favorably balanced development. This steady upward trend in coupling development reflects Suzhou's sustained efforts towards achieving greater synergy and balance among its emissions. However, cities like Lianyungang, Huai'an, and Yancheng demonstrated coupling coordination levels classified as slightly unbalanced development. This finding indicates the need for greater effort to achieve balanced development and coordination. The analysis also revealed a spectrum of coupling development ranging from moderately unbalanced to slightly unbalanced in cities such as Zhoushan, Lishui, and Huangshan. This finding emphasizes the need for intensified policy support and coordinated development efforts in these places.

The findings reported above highlight significant regional disparities in coupling coordination among different cities. Various factors are at play, such as economic development levels, industrial structures, urban planning and management, and environmental protection. Notably, Shanghai, as an economically developed city, was the only city that experienced a gradual improvement in coupling coordination, which resulted in superiorly balanced development. This result suggests that Shanghai has stable control over CO_2 and $PM_{2.5}$. In contrast, cities in the central and western areas of the YRD, such as Huangshan and Xuancheng, demonstrated relatively lower coupling coordination. Some cities were even classified as severely disordered or moderately disordered, which could be attributed to insufficient environmental resources being committed to the control of CO_2 and $PM_{2.5}$ emissions.

According to the assessment of the CO_2 and $PM_{2.5}$ coupling coordination degree in 2020 (Table 3, Figure 5), only 10 of the 41 cities in the YRD region have achieved coordinated development. This observation suggests that roughly 24% of the cities have attained a certain degree of coordination, while the remaining 76% still need to reach such a status. Shanghai was the only urban center to have achieved a stage of high-quality coordination, underscoring its pivotal role in the region. Suzhou has demonstrated commendable progress by achieving a level of coordination indicative of favorably balanced development. In contrast, Wuxi has progressed to a state of barely balanced development.

Seven other cities (Nanjing, Xuzhou, Nantong, Zhenjiang, Hangzhou, Ningbo, and Hefei) have also made significant progress towards achieving coordination. However, it must be acknowledged that these cities still face challenges stemming from unbalanced development. It is therefore crucially important to continue making concerted efforts to enhance those cities' coordination levels, particularly when mitigating CO_2 emissions and $PM_{2.5}$ pollutants. If similar environmental mitigation strategies to those of Shanghai were implemented, these seven cities have the potential to greatly enhance the coupling effect of both emissions.

The cities that achieved a state of coupling coordination are primarily located in the provinces of Jiangsu (four cities), Zhejiang (three cities), and Shanghai (one). In Anhui province, Hefei was the only city to achieve a state of coordination. The cities that were found to be in a state of marginal coordination, nearing imbalance, or in a state of imbalance shared a common geographical feature, they are located on the periphery of their respective provinces, in another word, in rural areas. To promote synergistic emission reduction in these cities, it is imperative to enhance policy support, advocate for targeted emission reduction strategies, and advance initiatives for balanced regional development.



562 Figure 4: Coupling coordination degree, 2010–2020

563 Table 3: Coupling coordination degree in YRD cities, 2020

City	Coupling Coordination Degree	City	Coupling Coordination Degree	City	Coupling Coordination Degree
Shanghai	0.963	Ningbo	0.621	Huaibei	0.399
Nanjing	0.657	Wenzhou	0.392	Tongling	0.431
Wuxi	0.714	Jiaxing	0.415	Anqing	0.457
Xuzhou	0.694	Huzhou	0.479	Huangshan	0.166
Changzhou	0.573	Shaoxing	0.495	Chuzhou	0.411

Suzhou	0.824	Jinhua	0.458	Fuyang	0.493
Nantong	0.656	Quzhou	0.37	Suzhou	0.5
Lianyungang	0.364	Zhoushan	0.123	Lu'an	0.36
Huai'an	0.36	Taizhou	0.318	Bozhou	0.316
Yancheng	0.517	Lishui	0.186	Chizhou	0.396
Yangzhou	0.506	Hefei	0.696	Xuancheng	0.403
Zhenjiang	0.664	Wuhu	0.591		
Taizhou	0.415	Bengbu	0.402		
Sugqian	0.335	Huainan	0.568		
Hangzhou	0.627	Ma'anshan	0.442		

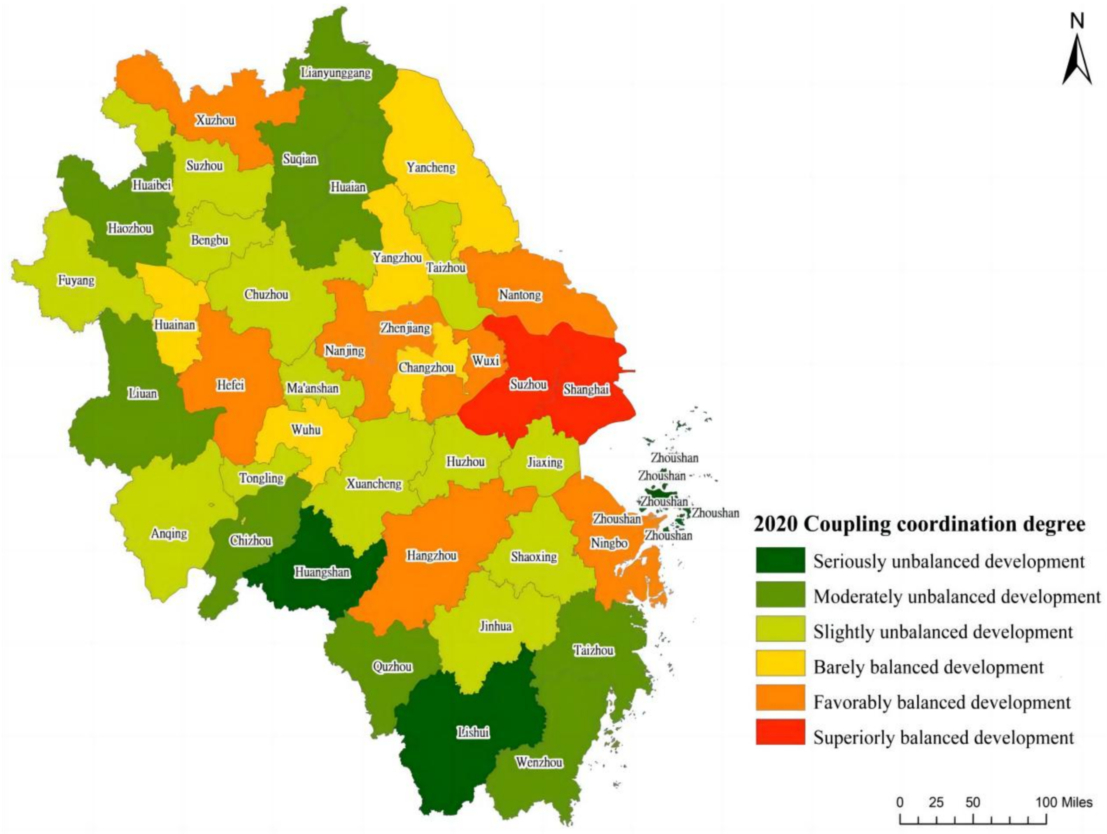


Figure 5: Coupling coordination degree, 2020

4.3 Spatial influencing factors

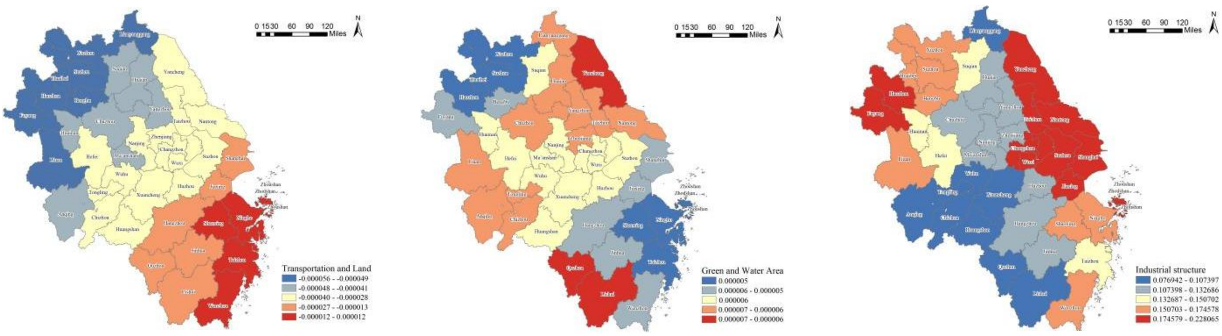
A total of 18 variables were included in the OLS regression model, covering socioeconomic factors, the built environment, level of urbanization, and traffic accessibility. To address concerns about potential multicollinearity, an evaluation was performed on factors that displayed a correlation coefficient exceeding 0.7. After the assessment, a refined set of five variables was identified and ultimately chosen for inclusion in the model, with the 2020 Coupling Coordination Degree serving as the dependent variable. The OLS result (Table 4) revealed that the independent variables Traffic_Land (Transportation and Land) and Industry_Structure (Industrial Structure) both exhibited a significant positive correlation with the dependent variable. In contrast, Tech_Lv (Technical Level) demonstrated a statistically significant negative correlation with the dependent variable. These findings suggest that neither Area nor GreenWater_Area (Green and Water Area) proved to be statistically significant predictors within this regression model. Overall, the model demonstrated a reasonable level of explanatory power, with an R^2 value of 0.499, while the adjusted R^2 value, accounting for the number of independent variables in the model, was 0.425.

Table 4: OLS regression result of coupling degree and independent variables

	Estimate	Std. Error	t-value	Pr(>|t|)	
(Intercept)	0.368	0.0532	6.92	<0.0001	***
Area	>-0.0001	<0.0001	-0.761	0.4517	
GreenWater_Area	<0.0001	<0.0001	1.443	0.1583	
Traffic_Land	<0.0001	<0.0001	2.489	0.0179	*
Tech_Lv	-0.862	0.419	-2.056	0.0475	*
Industry_Structure	0.111	0.0546	2.036	0.0496	*
R^2	0.499				
Adjusted R^2	0.425				

One of the objectives of this study was to examine the spatial relationship between coupling degree and independent variables across different regions, which is why a geographically weighted regression (GWR) model was adopted. The analysis found spatial heterogeneity in certain variables (Figure 6), specifically transportation and land (Figure 6(a)), as well as area (Figure 6(e)). For transportation and land, the results indicated a distinct spatial pattern in the YRD region, with positive correlations observed in the southeastern areas, such as Ningbo, Shaoxing, Wenzhou, and Taizhou, and negative correlations evident in the northern areas. Moreover, the analysis highlighted a positive correlation between area and coupling degree in two southwestern cities, Lishui and Quzhou. This finding indicates that increases in area correspond with increases in coupling degree in these localities.

Furthermore, both green areas and water areas (Figure 6(b)) and industrial structures (Figure 6(c)) exhibited positive correlations. However, significant spatial heterogeneity was observed across the YRD. The analysis revealed disparities between the northern and southern regions in terms of green and water areas, whereas industrial structure exhibited differences between the western and eastern areas. The only variable that displayed a negative correlation across the entire YRD region was the technical level (Figure 6(d)).



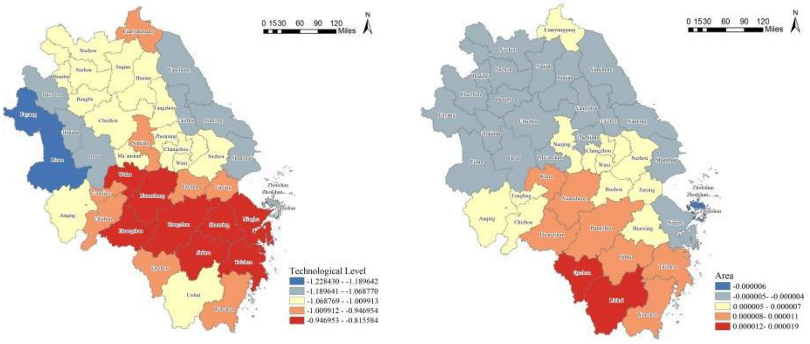


Figure 6: (a) Transportation and land; (b) Green and water area; (c) Industrial structure; (d) Technological level; (e) Area

5. Discussion

Spatial planning is crucial for achieving China's dual carbon goals and holds significant potential for improving air quality. Research has provided evidence that implementing land use planning strategies can facilitate the achievement of dual carbon objectives (Yang, Xie, et al., 2024). National regulations on spatial planning mandates rational spatial layout and land use control in land development. Such development must be guided by diverse regional, typological, and hierarchical functional orientations and developmental objectives (Chen et al., 2020). In addition, the needs of both socioeconomic advancement and ecological conservation must be met. On the one hand, such measures as optimizing urban-rural structures, regulating land use, and safeguarding ecosystems can effectively reduce the intensity and overall emission of greenhouse gases and atmospheric pollutants. On the other hand, national spatial planning can also drive innovative development in areas such as green transportation and clean energy. These goals can be accomplished through various strategies, such as optimizing transportation route planning, increasing clean energy infrastructure, and enhancing public transportation coverage, that align with the national goals of pollution reduction and emission mitigation (Chen et al., 2020).

Based on the above findings, this study offers several planning proposals to address environmental concerns. Considering the complex interplay between CO_2 and $PM_{2.5}$, a thoughtful and nuanced approach is essential. Therefore, it is essential to carefully select an indicator system at the regional level that considers per capita emissions, per area emissions, and total emissions. This multifaceted approach enables the accurate assessment and monitoring of CO_2 and $PM_{2.5}$ emissions, laying a strong foundation for the development of effective mitigation strategies. Regarding urban planning strategies, it is essential to move beyond mere expansion and development and prioritize the control of city size and growth rates. Moreover, some studies have suggested that individual cities require their own, uniquely targeted urban expansion and environmental protection strategies to achieve the goal of controlling both CO_2 and $PM_{2.5}$ (Cai et al., 2018; Liu et al., 2023; Xia et al., 2022).

Based on the findings of the GWR analysis, a zoning strategy can be instrumental in effectively reducing emissions and improving air quality. By dividing regions at the provincial level based on spatial autocorrelation results, targeted emission reduction strategies can be developed to address each area's unique challenges and opportunities. On the one hand, regions with a high coupling coordination degree in CO_2 and $PM_{2.5}$ emissions tended to adopt more effective and efficient governance strategies that worked in synergy. Implementing such measures effectively reduced pollutant emissions, especially in regions with high coupling coordination. On the other hand, regions with a low coupling coordination degree may have faced challenges from alternative sources of pollution and emission factors. Tailored governance strategies must therefore be developed to address these challenges. It is important to understand that in regions with a low coupling coordination degree, synergistic governance strategies should not be enforced indiscriminately.

In addition, when pollution control measures are being devised, it is crucial to consider the correlation between CO_2 and $PM_{2.5}$ emissions. Each region's coupling coordination degree had its own nuanced characteristics, which highlights the need for tailored governance approaches based on specific contextual attributes. A tailored approach to governance would ensure specifically targeted interventions that promote synergy and collaboration between, on the one hand, efforts to reduce diverse types of emissions and pollution and, on the other hand, sustainable urban development. The findings of this study indicate that if these concerns are prioritized in urbanization plans, natural resources can be safeguarded and the risks posed by emissions and pollution mitigated. Ultimately, the result will be healthier and more livable urban environments.

Furthermore, a previous study found that high-density, compact urban land-use patterns reduce CO_2 emissions because this approach enhances energy consumption efficiency by developing public transportation and compact urban structures (Xia et al., 2022). This study found that the industrial sector emerged as a predominant contributor to CO_2 and $PM_{2.5}$ emissions within the city, and policy interventions targeting this sector could yield substantial environmental benefits. Industrial land use has significantly impacted CO_2 and $PM_{2.5}$, suggesting that urban planning strategies should prioritize the mitigation of emissions from industrial activities (Ben-Ahmed & Ben-Salha, 2024; L. Li et al., 2022; S. Wang & Li, 2023; Zhang et al., 2021). Optimizing industrial structure allocation and promoting the adoption of clean energy and low-carbon technologies are critical steps toward achieving sustainable development goals (Ben-Ahmed & Ben-Salha, 2024; Li et al., 2022; Wang & Li, 2023; Zhang et al., 2021). Consequently, urban planners should explore such measures as promoting cleaner production technologies, implementing emission control regulations, and fostering the adoption of renewable energy sources in industrial zones to effectively curb emissions and improve air quality in urban areas.

This study encountered significant challenges to the collection of accurate and comprehensive data on carbon emissions and greenhouse gases. Despite the researcher's diligent effort, many obstacles stood in the way of accessing official data that precisely captured the intricate dynamics of emissions at the regional level. This hampered the comprehensiveness of this study's analysis and limited the insights that could be gained from the complex interplay of factors that drive emissions in specific administrative regions. It is imperative that future investigation should consider high-resolution data on CO_2 and $PM_{2.5}$ at the county level. To overcome all these limitations, this study used a time-space multi-sector model. This approach enabled the quantitative identification and analysis of the underlying reasons for synergistic emissions.

Given the inherent uncertainties and challenges in acquiring reliable data for specific emission categories—especially carbon emissions from transportation—this study have excluded these from the analysis. This exclusion is essential for aligning with the IPCC framework, which provides a consistent methodology for carbon accounting, and ensures transparency regarding the study's scope and limitations. Also, there is a significant source of uncertainty arises from the MEIC data, particularly in sectors such as coating, printing, and dyeing, where the extensive use of solvents introduces higher variability in emission factors and activity data (N. Wu et al., 2024). These uncertainties may lead to potential overestimations of emissions, which is why these sectors were not included in the current study. The imprecision in emission factors is largely due to the lack of precise data on solvent consumption and the varying efficiency of emission control technologies across regions. In addition, we acknowledge the uncertainties introduced during the data processing phase, specifically when converting MEIC raster data into county-level estimates. This transformation process, which involves data aggregation and interpolation, introduces spatial uncertainties that can lead to either over- or underestimations of emissions in specific regions.

6. Conclusion

The findings of this study suggest that the coupling coordination degree was a good indication of the success of pollution governance methods. This research highlighted the importance of the synchronized management of CO_2 and $PM_{2.5}$ emissions in regions with high coordination degrees by demonstrating its role in the reduction of environmental pollution. This study therefore underscores the importance of proactive and integrated policies that align with economic and urban development at the regional level, given that they can have a substantial impact on environmental quality overall.

The study aimed to examine the relationship between coupling degree and independent variables using a GWR model, with a focus on spatial analysis. The findings revealed spatial heterogeneity in certain variables, particularly transportation and land, as well as area. Positive correlations were found in the southeastern areas (including Ningbo, Shaoxing, Wenzhou, and Taizhou) of the YRD region, while negative correlations were observed in the northern areas for transportation and land. In addition, this study emphasizes the importance of caution in regions with low degrees of coupling coordination and highlights the complexity of pollution dynamics. It is crucial to tailor governance strategies to these regions and to consider the diverse influences from alternative pollution sources and emission factors. In other words, flexibility and adaptability in environmental policies are a necessity. There should be a move away from a one-size-fits-all approach toward nuanced, region-specific interventions.

This study was limited by the difficulty experienced in obtaining high-resolution data for CO_2 and $PM_{2.5}$, which necessitated a focus on the regional scale. The challenges related to the accuracy and quantification of CO_2 and $PM_{2.5}$ data impeded the examination of their coupling effects at the city or community scales. These obstacles underscore the urgent need for future research to improve data quality, strengthen synergistic management, and explore multidimensional integrated approaches. As we look toward the future, there is a growing need for more detailed investigations at the micro level, which presents a promising avenue for future research endeavors. Such thorough analyses at the local level can uncover the nuanced factors that influence emissions, providing a solid foundation for specific, focused spatial planning recommendations. Investigations at the micro level can enhance our academic understanding of environmental dynamics and offer environmental dynamics and offers practical insights for policymakers and urban planners working towards synergistic emission reduction goals.

The choice of the YRD region as the study area provided an outstanding model, yielding important insights for other regions in China and for the global community. This is particularly the case for developing countries, such as Indonesia, India, and Africa, that are dealing with comparable issues.

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CRediT authorship contribution statement

Weng In, Chung: Writing – original draft, review & editing, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Visualization. **Chao, Liu**: Conceptualization, Resources, Supervision, Project administration, Funding acquisition

Data availability statement

The research data collected for this study is referenced in the article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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