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# Research on Carbon Emission Characteristics and Differentiated Carbon Reduction Pathways in the Yangtze River Delta Region Based on the STIRPAT Model

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**Abstract:** With the changes in the spatial structure of China's economic development, urban clusters have become the primary carriers of China's regional economy and green growth. We used annual data from 2010 to 2021 to study the carbon emission characteristics and carbon reduction pathways of 36 cities in the Yangtze River Delta region. Firstly, based on the decoupling elasticity coefficient and carbon intensity index, the researchers divided the cities in the Yangtze River Delta into six types of carbon emissions. Then, the STIRPAT model was used to regress the panel data of different carbon emission types for 11 years, analyze the driving factors of carbon emissions, and develop differentiated carbon emission reduction paths for cities with six carbon emission types. According to the results, the cities of Type I need to accelerate low-carbon technology innovation; the cities of Type II need to improve energy efficiency and strengthen low-carbon technology research and development; the cities of Type V need to suppress foreign investment in high-energy consumption and high-emission projects in the local area; the cities of Type VI need to accelerate the process of new urbanization and optimize industrial structure. However, the researchers found that the cities of Types III and IV have not yet received effective emission reduction pathways, and their emission reduction policies and measures need to be further studied.

**Keywords:** carbon peaking; carbon emission characteristics; carbon emission reduction path; STIRPAT model



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## 1. Introduction

Since entering the era of industrial civilization in the 19th century, human social production activities have consumed much fossil energy [1]. Excessive emissions of greenhouse gases such as carbon dioxide have led to the continuous acceleration of sea level rise, frequent extreme weather events, and natural disasters, posing a severe threat to human survival and development. China also faces severe environmental pollution problems, like many developed and developing countries. According to China's carbon emission data from the year 2005 to 2022, China's carbon emissions have shown an overall increasing trend, which began with 0.61 billion tons in 2005 and reached 1.8 billion tons in 2022 (adopted from Carbon Emission Accounts and Datasets, CEADs). In 2005, China surpassed the United States and became the world's largest carbon dioxide emitter. This distressing result is owing to a large amount of fossil energy consumption in China. China's dramatic economic growth has come mainly at the expense of the environment. If environmental pollution intensifies further, it will not only hinder the sustainable development of China's economy but also seriously affect residents' everyday lives. Under this background, China has actively proposed strengthening national independent contributions and the Double Carbon targets.

Scholars have applied different methods to study carbon emission characteristics in the past years and set differentiated carbon emission reduction pathways for the countries, provinces, and urban clusters. However, due to the vast territory of China, different regions have differentiated resource endowments, economic development levels, and significant differences in carbon emission characteristics; it is unrealistic and impractical to require all Chinese provinces to reduce carbon emissions with a uniform direction and pace. The researchers considered the Yangtze River Delta urban cluster's leading role in economic development and modernization and its severe ecological and environmental problems. Thus, we selected the 41 cities of the Yangtze River Delta urban cluster as the research objects. The Yangtze River Delta urban cluster includes Jiangsu Province (13 cities), Zhejiang Province (11 cities), Anhui Province (16 cities), and Shanghai Municipality (1 city). Observing the data over the past ten years, we noticed that the 41 cities in the Yangtze Delta urban cluster differ in several aspects. For example, there are significant differences in changing carbon emission trends, disparities in the decoupling situation between economic development and carbon emissions, and spatial differentiation between carbon sources and carbon sinks. From the aspect of the total amount of carbon emissions, Anhui Province increased by 43.3% from 2010 to 2019, Jiangsu Province increased by 20.8%, Zhejiang Province increased by 3.4%, and Shanghai Province decreased by 6.2% (adopted from Carbon Emissions Report in Yangtze River Delta Cities). In terms of the decoupling situation, nine cities, including Hangzhou and Shanghai, have achieved strong decoupling, five cities, including Nanjing, Ningbo, and Xuancheng, have achieved weak decoupling, 16 cities show weak coupling, and 11 cities still have strong coupling. From the aspect of carbon sources and carbon sinks, the Yangtze River and coastal areas are the main regions with high-carbon-source cities. In contrast, Anhui and southwestern Zhejiang mainly house the high-carbon-sink cities. These phenomena illustrate that 41 cities within the Yangtze River Delta have different carbon emission characteristics. Moreover, from previous studies, we can find that research on the carbon reduction pathways of the 41 cities is relatively insufficient, and the specificity of relevant emission reduction pathways and measures is inadequate. Therefore, it is necessary to conduct empirical research on 41 cities within the Yangtze River Delta urban cluster.

Referring to Cao's method [2], this paper analyzes the decoupling elasticity coefficient and carbon emission intensity of 41 cities within the Yangtze River Delta urban cluster. Then, it divides these cities into six carbon emission types according to the above two indicators. Furthermore, it uses the STIRPAT model to explore the driving factors of carbon emissions in different cities and set differentiated carbon emission reduction pathways for each type of city. Based on the study's results, the Chinese local government can focus on the essential factors that resulted in the growth of carbon emissions and thus draw up specific and differentiated carbon reduction pathways for the cities in the Yangtze River Delta urban cluster. The results can provide theoretical and realistic references for achieving carbon peaking in the Yangtze River Delta region.

The rest of the paper is structured as follows: Section 2 discusses the theories and models adopted, Section 3 describes the data and methodology employed, Section 4 presents and interprets the empirical results, and Section 5 concludes the study and gives some recommendations.

## 2. Literature Review

### *2.1. Decoupling Relationship between Carbon Emissions and Economic Growth*

The Organization for Economic Cooperation and Development (OECD) first proposed the "decoupling concept" in 1993, describing the relationship between economic driving factors and environmental pressure factors [3]. OECD classified decoupling in relative or absolute values. Classifications include relative decoupling, recession decoupling, expansion recoupling, and recession recoupling. Seeing the apparent shortcomings of the OECD decoupling model [4], Tapio proposed the concept of "decoupling elasticity" in 2005 [5], which can better reflect the sensitivity of carbon emission changes to economic growth. At the same time, the types of decoupling have also been expanded from four to eight. The relationship between carbon emissions and economic activities has achieved universal consensus since then.

Since the signing of the Paris Agreement, scholars have studied the characteristics of carbon emissions in different countries and regions and mainly focused on the relationship between carbon emissions and economic growth [6]. Based on the Tapio Decoupling model, Chen (2018) analyzed the data of the Organization for Economic Cooperation and Development (OECD) from 2001 to 2015 and studied the decoupling between carbon emissions and the economic growth of OECD countries [7]. Li and Qin (2019) studied the decoupling relationship between China's carbon emissions and economic development by summarizing the historical development characteristics and predicting future action trends [8]. The Tapio Decoupling model is widely used in academic research to measure the decoupling relationship between economic growth and carbon emissions [2]. Still, some scholars simultaneously use the Tapio Decoupling model and the OECD Decoupling model. Grand and Mariana (2016) divided 21 countries into low-income countries, low and middle–income countries, high and middle–income countries, and high-income countries. They utilized the OECD Decoupling model and Tapio Decoupling model to analyze the dynamic changes in carbon emissions and the economic structure of the four types of countries [9]. Deutch (2017) used two decoupling models to conduct a quantitative study based on historical data and compared the differences in carbon emission and energy carbon intensity growth among China, the United States, and the world [10].

Academia has extensively studied countries', provinces', and urban clusters' decoupling relationship between economic growth and carbon emissions. The Tapio model has been widely used in the research due to its high accuracy, laying a solid foundation for conducting such studies. However, studies on cities' decoupling effects with regard to carbon emissions still need to be enriched and supplemented, especially in the cities within the Yangtze River Delta urban cluster.

### 2.2. The Application of the STIRPAT Model in Finding the Driving Factors of Carbon Emissions

In the past few years, scholars have conducted much research on carbon emission driving factors; there are two main types of methods for scholars to use:

First, scholars use the LMDI model [11], IPAT model [12], STIRPAT model [13], and CGE model [14] to analyze the impact of driving factors on historical pollutant changes. Second, to obtain the effect of driving factors on future carbon emissions, scholars determine the driving characteristics of carbon emissions [15] using the "scenario analysis combined with sensitivity analysis method".

York et al. (2003) proposed the STIRPAT model based on IPAT and ImPACT, overcoming the limitation of non-monotonic and varying proportions of influencing factors [16]. Shahbaz et al. (2016) used the STIRPAT model to study the impact of urbanization on carbon emissions in Malaysia [17]. Wang et al. (2016) empirically analyzed the main factors affecting the carbon intensity of countries and eight economic regions using the STRIPAT model, and the results showed that the level of economic activity and the secondary industry were the main factors influencing carbon intensity [18]. Liu et al. (2017) introduced spatiotemporal factors into the STRIPAT model, analyzed empirical data from 30 provinces in China, and concluded that population size, urbanization rate, energy intensity, industrial structure, energy consumption pattern, energy price, and openness are important driving factors of regional carbon emissions [19]. Dong et al. (2018) analyzed the driving factors of carbon emission intensity change in China using structural decomposition analysis and quantile regression. They found that energy structure, industrialization index, and final consumption rate positively impacted carbon emission intensity [20]. Chen et al. (2020) chose the eight economic regions of China as the research objects, used the StoNED model to measure energy efficiency, and built a geographical and time-weighted regression-STIRPAT model to analyze the influence of each driving factor of carbon emissions [21]. Liu et al. (2022) performed a statistical analysis of the scale development of six energy-intensive industries. They revealed the heterogeneity of the driving effects of 10 key factors, including economic level, urbanization level, industrial structure, technological innovation, and environmental regulation [22]. Liu et al. (2023) combined structural decomposition analysis and input–output subsystem analysis to build a decomposition model of influencing factors of carbon emissions in China. They concluded that the energy intensity effect is a significant influencing factor in curbing carbon dioxide emissions. Economic development is the main driving factor for increased carbon emissions [23].

In a word, scholars have identified the dominant factors of carbon emissions in different regions through the STIRPAT model, indicating its strong practicality. The STIRPAT model has many advantages. For example, it not only helps to disaggregate the factors influencing carbon emissions [24] but includes multiple indicator factors, such as technology, urbanization, and other indicators, in the equation simultaneously. It also considers the nonlinear impact of economic growth factors on carbon emissions. Thus, scholars extensively use the STIRPAT model to study the driving characteristics of carbon emissions [25].

### *2.3. Carbon Reduction Pathways of the Yangtze River Delta Urban Cluster*

Xu et al. (2016) estimated the carbon emissions at different spatial scales in the Yangtze River Delta region during 2008–2015. The results show that the pathway from urbanization to industrial structure significantly impacts carbon emissions [26]. Wu et al. (2021) used the LEAP model to analyze the energy demand and carbon emissions of the Yangtze River Delta region in China from 2020 to 2050 under different energy transition scenarios. Based on the empirical results, the author proposed a practical pathway for reducing carbon emissions in the Yangtze River Delta region: vigorously developing short- and long-term non-fossil energy [27]. Zhu et al. (2023) analyzed the situation of carbon emissions and summarized the pressure and potential of carbon emission reduction in the Yangtze River Delta region. By dialectically analyzing the characteristics of each emission reduction policy, the authors put forward suggestions from the perspective of implementing a carbon tax policy [28]. Zhou et al. (2023) used the Low Emissions Analysis Platform with five scenarios to construct a comprehensive assessment index system and evaluate the Yangtze River Delta region's pathways to carbon neutrality. The results show that the mixed policies of energy intensity reduction, energy structure reformation, and power technology innovation can promote the coordination of supply and demand, thus achieving the carbon neutrality target by accelerating energy transition in the Yangtze River Delta region [29].

In summary, scholars have conducted empirical studies on the carbon emission reduction pathways of the Yangtze River Delta urban cluster in recent years. They have proposed suggestions in terms of policy, clean energy, urbanization, and energy transformation, laying a solid foundation for this paper.

## 3. Research Methodology

### *3.1. Variable Selections and Data Sources*

The data come from the China Economic Data Network, the China Carbon Accounting Database, the National Bureau of Statistics websites, provincial statistical yearbooks, the National Anbang Database, and the Report on Implementing the National Economic and Social Development Plan. All data are annual data of 36 Yangtze River Delta region cities from 2010 to 2021.

Carbon dioxide emissions is an indicator commonly used for measuring environmental impact; thus carbon dioxide emissions was selected as the dependent variable.

In previous studies, scholars used the number of permanent residents (P) to represent the population, the GDP variable (GDP) to describe the economic level, and the number of green technologies (LCT) to represent the level of technological development. In the long run, there is a positive relationship between population, economic development level, and environmental pollution, while low-carbon technology has a negative relationship with these factors.

By further studying this problem, scholars have found that some variables can also significantly impact environmental pollution. Cheng et al. (2018) analyzed the effect of industrial structures on carbon intensity [30] and found that upgrading and optimizing industrial structures are conducive to reducing carbon intensity. Chor et al. (2015) studied the relationship between carbon dioxide emissions and FDI (foreign direct investment) in Vietnam and found that FDI is the critical determinant of $CO_2$ emissions in Vietnam [31]. Rahman et al. (2022) found that energy intensity increases carbon intensity [32]. Yuan et al. (2015) successfully verified an inverse U-shaped curve relationship between urbanization and carbon emissions for OECD countries [33]. These research objects have similarities with China and can provide a reference for China's carbon emission reduction. Therefore, the study aims at finding the relationship between Industry Structure (IS), Foreign Direct Investment (FDI), Energy Intensity (EI), Urbanization (UR), and carbon emissions. The description of variables and the data sources are shown in Table 1.

**Table 1.** Variable selection and data sources.

| Variable Type | Variable Name | Abbrev. | Unit | Variable Description | Data Source |
|---|---|---|---|---|---|
| Explained Variable | Carbon dioxide emission | TC | 10,000 tons | The effectiveness of emission reduction | China Carbon Accounting Database |
| explanatory variable | Gross domestic product | GDP | 0.1 billion CNY | economic development level | provincial statistical yearbooks |
| | Population | P | 10,000 people | The number of permanent residents | provincial statistical yearbooks |
| | Low Carbon Technology | LCT | One item | The number of green technologies | CSMAR database |
| | Industry structure | IS | % | The ratio of industrial-added value to regional GDP | China Economic Data website |
| | Foreign Direct Investment | FDI | % | The ratio of foreign direct investment to regional GDP, the Exchange rate is 0.153 | China Economic Data website |
| | Energy Intensity | EI | % | The growth rate of energy consumption per unit of GDP | China Economic Data website, Provincial Report on the Implementation of the National Economic and Social Development Plan |
| | Urbanization | UR | % | The ratio of the urban population to the total population | China Economic Data website |

### 3.2. Sample Analysis and Data Processing

The Yangtze River Delta urban cluster consists of 41 prefecture-level cities. However, due to the lack of data on foreign direct investment, industrial structure, and regional GDP in individual years, researchers studied only 36 cities in the Yangtze River Delta region. The omitted cities include Huai'an, Taizhou, Bozhou, Chuzhou, and Huaibei.

Among them, foreign direct investment data for Jiaxing, Wenzhou, Ningbo, Changzhou, and Yancheng in 2020 and 2021 are missing, so the Linear Interpolation Method is used to estimate the missing values. In addition, the data on carbon emissions of 36 cities from 2020 to 2021 have not yet been disclosed, and the Linear Interpolation Method is also used for estimation.

$$X_t = 2 * X_{t-1} - X_{t-2} \tag{1}$$

where $X_t$ represents the carbon dioxide emissions in year $t$, and $t$ represents the year.

### 3.3. Model Construction

#### 3.3.1. Improved Tapio Decoupling Model

Considering that the population and economic development level vary greatly among cities, it is better to compare the situation of each region horizontally from the perspective of "per capita". Therefore, based on the improved Tapio model, the carbon emission characteristics of 36 cities in the Yangtze River Delta region were analyzed. The improved Tapio elastic coefficient calculation formula is as follows:

$$T_p = \frac{\frac{PCO_2^t - PCO_2^{t-1}}{PCO_2^{t-1}}}{\frac{PGDP^t - PGDP^{t-1}}{PGDP^{t-1}}} = \frac{\frac{\Delta PCO_2}{PCO_2}}{\frac{\Delta PGDP}{PGDP}} \quad (2)$$

where $t$ represents the current period; $t-1$ represents the previous period; $PCO_2$ represents per capita carbon emissions; PGDP represents per capita GDP.

The traditional Tapio model defines eight types of decoupling based on the value of the decoupling elasticity coefficient T and the positive or negative of $\Delta CO_2$ and $\Delta GDP$. Considering that China's GDP has a stable positive growth rate ($\Delta PGDP > 0$), according to the value of $T_P$ and the positive or negative of $\Delta PCO_2$ and $\Delta PGDP$, decoupling types are simplified into three classes in this article. The specific types of decoupling are shown in Table 2.

**Table 2.** Tapio decoupling types.

| Decoupling Types | Indicator | | |
|---|---|---|---|
| | $\Delta PCO_2$ | $\Delta PGDP$ | $T_P$ |
| Strong decoupling | <0 | >0 | $(-\infty, 0)$ |
| Weak decoupling | >0 | >0 | (0, 0.8) |
| Expansive negative decoupling | >0 | >0 | $(0.8, \infty)$ |

#### 3.3.2. STIRPAT Model

Dietz and Rosa (1994) improved the IPAT model in 1997 [34]. Then, they proposed the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model, which overcame the limitations of proportional changes in various driving factors in the IPAT model. The STIRPAT model is shown as follows:

$$I = \alpha P^a \times A^b \times T^c e \quad (3)$$

where $I$ represent environmental impact (emission level); $P$ represents population; $A$ represents economic level; $T$ represents technology; $a$, $b$, $c$, and $d$ represent the elastic coefficients; $\alpha$ is the coefficient; $e$ is the residual error. The parameters can be obtained through regression.

After taking the natural logarithm and adding the quadratic term, it can be transformed into the following form:

$$lnI = ln\alpha + alnP + blnA + c(lnA)^2 + dlnT + lne \quad (4)$$

Equation (4) expresses the nonlinear relationship among population $P$, wealthy level $A$, technological level $T$, and environmental pressure $I$.

This article selects carbon dioxide emissions as a representative of environmental pressure $I$ and also selects the factors that focus on carbon peaking and carbon neutrality—energy intensity, industrial structure, foreign trade level, urbanization level, and low-carbon technology level—to expand the STIRPAT model:

$$lnTC = \alpha + \beta lnP + \gamma lnPGDP + \delta lnLCT + \theta lnIS + \pi lnFDI + \rho lnUR + \varphi EI + D_1 + D_2 + \varepsilon \quad (5)$$

where $TC$ is the dependent variable, representing carbon dioxide emissions; $\alpha$ is a constant; $\beta$, $\gamma$, $\delta$, $\theta$, $\pi$, $\rho$, and $\varphi$ are the coefficients. The explanatory variables are as follows: $P$ represents population; $PGDP$ represents per capita GDP, measuring wealth level; $LCT$ is the number of green patents, measuring the level of low-carbon technology; $EI$ is the growth rate of energy consumption per unit of GDP, measuring energy intensity; $IS$ represents the ratio of industrial added value to regional GDP, representing the industrial structure; $FDI$ is the ratio of foreign direct investment to provincial GDP, meaning the level of foreign trade; $UR$ is the ratio of urban population to total population, representing the level of urbanization; $\varepsilon$ is the error term.

Considering the impact of individual and time effects, adding dummy variables to the STIRPAT model is necessary to control the potential impact of factors that may cause changes in carbon emission. After adding the control variables, the model's accuracy is remarkably enhanced. $D_1$ and $D_2$ are dummy variables, respectively representing individual fixed effects and time fixed effects.

## 4. Research Findings

### *4.1. Classification of Carbon Emission Types Based on Tapio Elasticity Coefficient*

Firstly, based on the per capita GDP data and per capita carbon dioxide emissions data of 36 cities in the Yangtze River Delta region, calculate their decoupling elasticity coefficient, $T_P$.

Then, observe the calculated value of the decoupling elasticity coefficient, $T_P$, as well as the positive and negative of $\Delta PCO_2$ and $\Delta PGDP$. In 2019, the $\Delta PGDP$ of 36 cities was positive, of which 29 cities belonged to solid or weak decoupling types, and only seven cities, such as Zhoushan, belonged to the kind of expansive negative decoupling. The decoupling types of 36 cities are shown in Table 3.

**Table 3.** Decoupling types of cities in 2019.

| Decoupling Types | City |
|---|---|
| Strong decoupling | Huzhou, Lishui, Ningbo, Quzhou, Taizhou, Wenzhou, Nantong, Yancheng, Yangzhou, Anqing, Chizhou, Ma'anshan, Suzhou, Xuancheng, Tongling |
| Weak decoupling | Shanghai, Hangzhou, Jiaxing, Jinhua, Shaoxing, Changzhou, Lianyungang, Nanjing, Wuxi, Bengbu, Fuyang, Hefei, Huainan, Huangshan |
| Expansive negative decoupling | Zhoushan, Suzhou, Suqian, Xuzhou, Zhenjiang, Lu'an, Wuhu |

Next, calculate the carbon emission intensity (ES) of 36 cities in 2019 and divide them, taking ES = 1 as the boundary point. When 0 < ES < 1, it is defined as low carbon strength; when ES > 1, it is defined as high carbon intensity. Through calculation and induction, we found that 15 cities (including Ningbo) are high carbon intensity cities, with an average carbon intensity of 1.94 tons every CNY 10,000; Shanghai and 21 other cities are low carbon intensity cities, with an average carbon intensity of 0.63 tons every CNY 10,000. The carbon intensity types are shown in Table 4.

Finally, combining the Tapio decoupling coefficient and carbon intensity, 36 Yangtze River Delta region cities were classified by growth rate and absolute quantity. This article takes ES = 1, $T_P = 0$, and $T_P = 0.8$ as the critical value to divide 36 cities into six types of carbon emissions.

**Table 4.** Types of emission intensity of cities in 2019.

| Types of Carbon Emission Intensity | City |
|---|---|
| High carbon emission intensity (ES > 1) | Ningbo, Quzhou, Zhoushan, Nanjing, Suzhou, Xuzhou, Zhenjiang, Anqing, Chizhou, Huainan, Ma'anshan, Suzhou, Wuhu, Xuancheng, Tongling |
| Low carbon emission intensity (0 < ES < 1) | Shanghai, Hangzhou, Huzhou, Jiaxing, Lishui, Jinhua, Shaoxing, Taizhou, Wenzhou, Changzhou, Lianyungang, Nantong, Suqian, Wuxi, Yancheng, Yangzhou, Bengbu, Fuyang, Hefei, Huangshan, Lu'an |

We divided 36 cities into six carbon emission types (as shown in Table 5), namely carbon emission Type I (0 < ES < 1 and $T_P < 0$), Type II (0 < ES < 1 and $0 < T_P < 0.8$), Type III (0 < ES < 1 and $T_P > 0.8$), Type IV (ES > 1 and $T_P < 0$), Type V (ES > 1 and $0 < T_P < 0.8$), and Type VI (ES > 1 and $T_P > 0.8$). Carbon emission Type I includes seven cities: Wenzhou, Taizhou, Lishui, Nantong, Yancheng, Huzhou, and Yangzhou; Type II consists of 12 cities, including Shanghai, Hangzhou, Shaoxing, Jinhua, Jiaxing, Changzhou, Wuxi, Lianyungang, Fuyang, Bengbu, Hefei, and Huangshan; Type III includes two cities: Lu'an and Suqian; Type IV consists of 8 cities: Ningbo, Quzhou, Chizhou, Suzhou, Xuancheng, Anqing, Tongling, and Ma'anshan; Type V includes two cities: Nanjing and Huainan; Carbon emission Type VI consists of five cities: Zhoushan, Xuzhou, Suzhou, Wuhu, and Zhenjiang.

**Table 5.** Classification criteria.

| Indicators | Tapio Decoupling Coefficient | | |
|---|---|---|---|
| | $T_P < 0$ | $0 < T_P < 0.8$ | $T_P > 0.8$ |
| High carbon emission intensity (ES > 1) | Type IV (High-carbon, negative growth) | Type V (High-carbon, low growth) | Type VI (High-carbon, high growth) |
| Low carbon emission intensity (0 < ES < 1) | Type I (Low-carbon, negative growth) | Type II (Low-carbon, low growth) | Type III (Low-carbon, high growth) |

The classification results illustrate that the cities of Type I have achieved negative per capita carbon emission growth and low carbon intensity, making it a relatively ideal carbon emission type. The per capita carbon emission growth rate of cities of Type II is lower than the per capita GDP growth rate, and the carbon intensity is also at a relatively low level. Although the cities of Type III have low carbon intensity, their per capita carbon emission growth rate is greater than the per capita GDP growth rate, indicating that these cities are sacrificing the environment for economic development. The per capita carbon emission growth rate of the cities of Type IV shows a negative growth, but the carbon intensity is relatively high. The per capita carbon emission growth rate of the cities of Type V is lower than the per capita GDP growth rate, and their carbon intensity is higher; The per capita carbon emission growth rate of the cities of Type VI is higher than the per capita GDP growth rate, and the carbon intensity is relatively high, which is an unsatisfactory type of carbon emission.

### *4.2. Analysis of Regional Characteristics of Carbon Emissions Based on Decoupling Index*

The 2019 Tapio decoupling elasticity coefficient and carbon intensity distribution of 41 cities in the Yangtze River Delta region of China are shown in Figures 1 and 2, respectively. Next, we analyze the spatial distribution of the decoupling elasticity coefficient and carbon intensity in various cities for 2019.

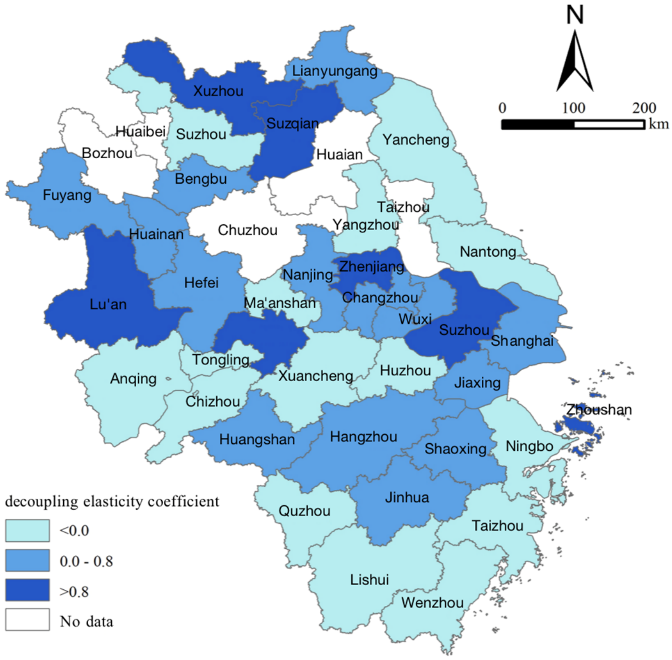


**Figure 1.** Spatial distribution of decoupling elasticity coefficient of cities in 2019.

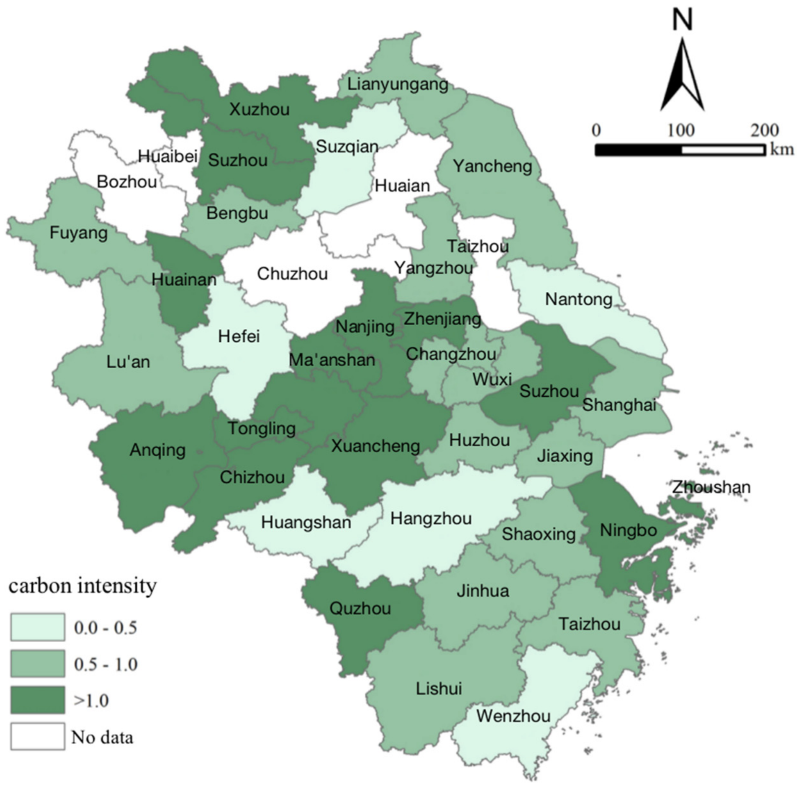


**Figure 2.** Spatial distribution of carbon intensity of cities in 2019.

Figure 1 shows the spatial distribution of decoupling elasticity coefficients for 41 cities in 2019. It can be observed that five central cities and two northern cities located in the Yangtze River Delta had high decoupling elasticity coefficients in 2019 (greater than 0.8), indicating that the economic development of these seven cities still relies on carbon emissions. At the same time, five southern cities, six central cities, and four northern cities have negative decoupling elasticity coefficients (all less than 0), indicating that the economic development and carbon emissions of these 15 cities have achieved decoupling, and carbon emissions have achieved negative growth. The growth rate of per capita carbon emissions in the remaining 14 cities is lower than the growth rate of per capita GDP.

In summary, less than 20% of cities have high per capita carbon emission growth, and over 80% have low or negative per capita carbon emission growth. Observing the spatial distribution, cities with negative per capita carbon emission growth are often located on the edge of the Yangtze River Delta region. In contrast, cities with positive per capita carbon emission growth occupy the interior of the Yangtze River Delta region in an "S" shape.

According to Figure 2, cities with high carbon intensity are primarily concentrated in Anhui Province (8 cities), followed by Jiangsu Province (4 cities) and Zhejiang Province takes (3 cities). About 40% of cities in the Yangtze River Delta region are still high carbon intensive, while less than 60% are low carbon intensive. Observing the distribution of carbon intensity in the Yangtze River Delta region, the picture shows a feature of "light at the ends and heavy in the middle".

According to the "classification criteria" for carbon emission types, a quadrant diagram for 36 cities in the Yangtze River Delta region 2019 can be established (Figure 3). The figure shows that 53% of cities belong to Type I and Type II. This indicates that at least half of the cities belong to the ideal carbon emission type. In addition, 5% of cities belong to Type III. Thus, technological innovation and upgrading are needed to reduce the growth rate of carbon emissions. About 28% of Type IV and Type V cities still have room for emission reductions. However, 14% of cities belong to Type VI, and both aggregate and growth rates of carbon emissions are high. Most cities in the Yangtze River Delta have good carbon emission characteristics.

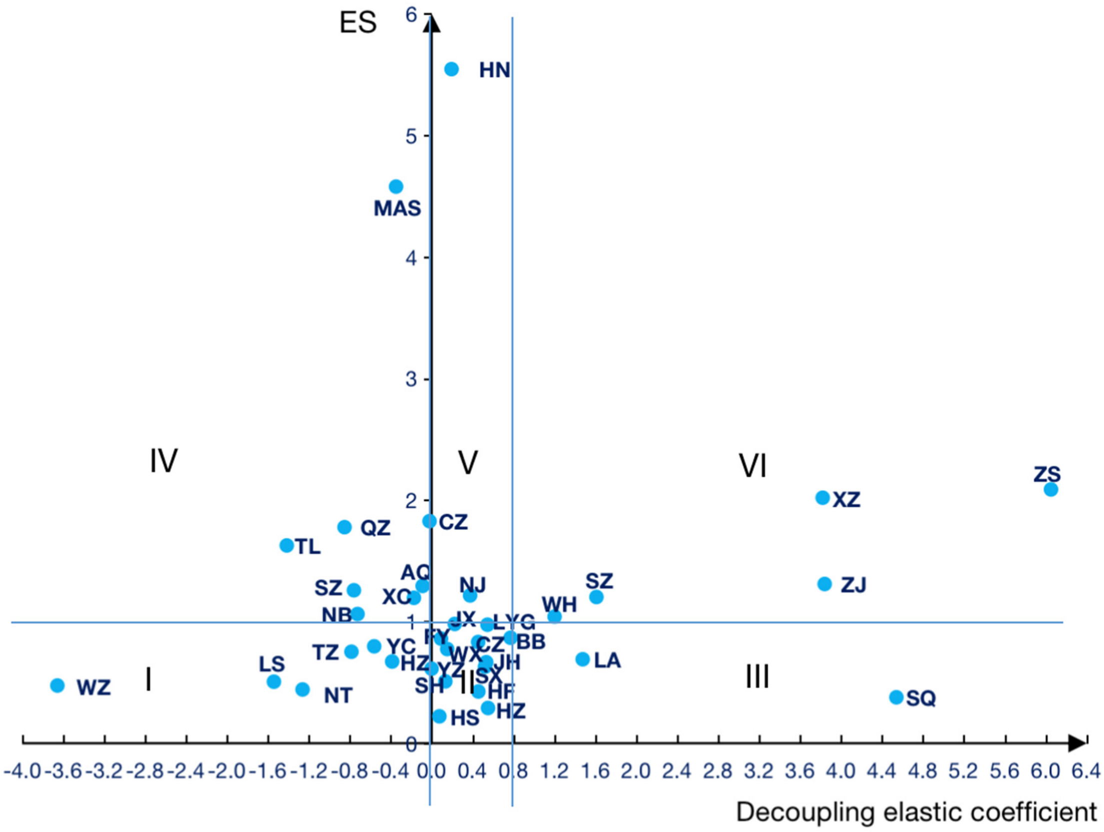


**Figure 3.** Quadrant diagram of carbon emission types for 36 cities in 2019.

### *4.3. Analysis of Carbon Emission Reduction Paths Based on the STIRPAT Model*

#### 4.3.1. Pre-Estimation Tests

Before OLS regression, the software Eviews10 was used to perform unit root tests and cointegration tests to avoid "pseudo regression" results.

Levin, Lin, and Chu's (LLC) method was used to test each variable's time series stationarity. The test results (as shown in Table 6) indicate that there are no unit roots in lnTC, lnP, lnPGDP, lnLCT, lnIS, lnFDI, lnUR, and EI, the sequences of each variable are stationary, and the sequences are integration of order zero.

**Table 6.** Results of unit root tests (LLC method).

| Variable | LLC Test | | Decision |
|---|---|---|---|
| | Statistic | *p*-Value | |
| DTC | −6.84324 | 0.0000 | I(0) |
| lnP | −33.8807 | 0.0000 | I(0) |
| lnPGDP | −10.9294 | 0.0000 | I(0) |
| lnLCT | −10.6621 | 0.0000 | I(0) |
| lnIS | −5.74237 | 0.0000 | I(0) |
| lnFDI | −6.18488 | 0.0000 | I(0) |
| lnUR | −5.22267 | 0.0000 | I(0) |
| EI | −11.0908 | 0.0000 | I(0) |

The researchers applied the Pedroni method to test for the cointegration of panel data (as shown in Table 7). According to the cointegration test results, the significance is 0.0000, indicating a long-term equilibrium relationship between variables.

**Table 7.** Results of cointegration test (Pedroni method).

| ADF | t-Statistic | Prob. |
|---|---|---|
| | **−7.370456** | **0.0000** |
| Residual variance | 0.071730 | |
| HAC variance | 0.052136 | |

Multicollinearity is the distortion or difficulty in accurately estimating the regression coefficient of explanatory variables in a linear regression model due to their high correlation. To eliminate the adverse effects of multicollinearity, we used the Variance Inflation Factor (VIF) value for judgment. The initial VIF test result (as shown in Table 8) shows the VIF value of $(\text{lnPGDP})^2$ and lnPGDP is much greater than 30, indicating a severe collinearity between these two explanatory variables. The result also shows no collinearity between other variables. After eliminating the variable $(\text{lnPGDP})^2$ from the equation, the VIF test result (as shown in Table 9) shows no collinearity between all variables.

#### 4.3.2. Estimation Techniques

We conducted a Hausman test on samples for each carbon emission type; the results of the Hausman test (shown in Table 10) illustrate that all types' *p*-values are significant ($0 < p < 0.1$), and the null hypothesis of the random effects model is rejected. Therefore, this paper chooses a fixed effects model for STIRPAT modeling.

**Table 8.** Results of the VIF test.

| Variable | Unstandardized Coefficient | | t | Sig. | VIF |
|---|---|---|---|---|---|
| | $\beta$ | Standard Error | | | |
| constant | 2.54 | 6.35 | 0.40 | 0.69 | |
| lnP | 0.67 | 0.05 | 12.58 | 0.00 | 3.83 |
| lnPGDP | −1.56 | 1.16 | −1.34 | 0.18 | 1166.12 |
| $(\text{lnPGDP})^2$ | 0.11 | 0.05 | 2.00 | 0.05 | 1132.99 |
| lnLCT | 0.14 | 0.04 | 3.35 | 0.00 | 10.92 |
| lnIS | 0.21 | 0.10 | 2.11 | 0.04 | 1.13 |
| lnFDI | 0.03 | 0.03 | 1.31 | 0.19 | 1.15 |
| lnUR | 0.75 | 0.21 | 3.64 | 0.00 | 5.39 |
| EI | 0.03 | 0.01 | 4.14 | 0.00 | 1.10 |

Explained variable: lnTC.

**Table 9.** Results of the VIF test after elimination.

| Variable | Unstandardized Coefficient | | t | Sig. | VIF |
|---|---|---|---|---|---|
| | $\beta$ | Standard Error | | | |
| constant | −9.98 | 1.02 | −9.83 | 0.00 | |
| lnP | 0.70 | 0.05 | 13.42 | 0.00 | 3.61 |
| lnPGDP | 0.76 | 0.10 | 7.81 | 0.00 | 8.03 |
| lnLCT | 0.14 | 0.04 | 3.19 | 0.00 | 10.85 |
| lnIS | 0.17 | 0.10 | 1.78 | 0.08 | 1.09 |
| lnFDI | 0.04 | 0.03 | 1.40 | 0.16 | 1.14 |
| lnUR | 0.70 | 0.21 | 3.38 | 0.00 | 5.28 |
| EI | 0.03 | 0.01 | 4.10 | 0.00 | 1.10 |

Explained variable: lnTC.

**Table 10.** Results of the Hausman test.

| Type of city | Hausman Test | | |
|---|---|---|---|
| | Chi-Square Value | *p*-Value | Selection |
| Type I | $\chi^2(6) = 25.127$ | $p = 0.000$ *** | FE |
| Type II | $\chi^2(6) = 17.229$ | $p = 0.008$ *** | FE |
| Type III | $\chi^2(6) = 11.063$ | $p = 0.086$ * | FE |
| Type IV | $\chi^2(6) = 18.841$ | $p = 0.004$ *** | FE |
| Type V | $\chi^2(6) = 27.763$ | $p = 0.000$ *** | FE |
| Type VI | $\chi^2(6) = 13.768$ | $p = 0.032$ ** | FE |

Note: * represents $p < 0.1$, ** represents $p < 0.05$, and *** represents $p < 0.01$.

To determine the estimation techniques, we need to perform an inter-group heteroscedasticity test, intra-group autocorrelation test, and inter-group contemporaneous correlation test based on the extended panel data of each type of city. The results of the tests show no heteroscedasticity, autocorrelation, and contemporaneous correlation for the panel data. Thus, the OLS estimation and fixed effects models can be used for regression.

#### 4.3.3. Panel Estimation Results

We use the STIRPAT model to analyze the panel data of 36 cities with different carbon emission types from 2010 to 2021.

Table 11 shows the regression results of the STIRPAT model corresponding to the six carbon emission types. According to the regression coefficients and their significance, specific cities can be refined and assigned differentiated carbon emission reduction pathways. The analysis of particular regression results and the setting of effective emission reduction pathways are as follows:

**Table 11.** Panel regression results for different carbon emission types.

| Variable | lnTC | | | | | |
|---|---|---|---|---|---|---|
| | **Type I** | **Type II** | **Type III** | **Type IV** | **Type V** | **Type VI** |
| lnP | 0.538 ***<br>(0.102) | 0.942 ***<br>(0.109) | 2.544<br>(7.836) | 0.667 ***<br>(0.095) | 1.028<br>(0.638) | 0.894 ***<br>(0.088) |
| lnPGDP | 0.819 ***<br>(0.200) | 1.113 ***<br>(0.197) | 1.708<br>(1.027) | 1.318 ***<br>(0.383) | 1.380 ***<br>(0.460) | 0.516<br>(0.351) |
| lnLCT | 0.343 ***<br>(0.108) | 0.081 *<br>(0.190) | −0.175<br>(0.197) | 0.023<br>(0.084) | −0.472 **<br>(0.218) | 0.094<br>(0.071) |
| lnIS | 0.501<br>(0.351) | 0.152<br>(0.147) | −1.354<br>(2.262) | 0.316<br>(0.286) | −0.645<br>(0.882) | 0.645 ***<br>(0.175) |
| lnFDI | −0.037<br>(0.056) | 0.093 **<br>(0.046) | −0.040<br>(3.363) | −0.037<br>(0.054) | 0.811 ***<br>(0.276) | −0.210 ***<br>(0.063) |
| lnUR | 0.875<br>(0.872) | −0.452<br>(0.378) | 0.499<br>(2.765) | −0.049<br>(0.864) | −0.104<br>(1.663) | 1.135 *<br>(1.020) |
| EI | 0.048 ***<br>(0.013) | 0.027 ***<br>(0.012) | 0.042<br>(0.041) | 0.019<br>(0.017) | −0.039<br>(0.043) | 0.029 **<br>(0.015) |
| Constant | −13.113 ***<br>(3.861) | −10.889 *<br>(1.888) | −23.438<br>(40.709) | −12.626 ***<br>(2.185) | −9.120<br>(5.450) | −11.545 ***<br>(2.030) |
| FE | YES | YES | YES | YES | YES | YES |
| TE | YES | YES | YES | YES | YES | YES |
| N | 84 | 144 | 24 | 96 | 24 | 60 |
| $R^2$ | 0.868 | 0.924 | 0.910 | 0.861 | 0.965 | 0.959 |
| DW | 1.316 | 0.811 | 1.897 | 0.784 | 1.697 | 1.940 |

Note: * represents $p < 0.1$, ** represents $p < 0.05$, and *** represents $p < 0.01$. Standard errors are in the parentheses. N represents the number of cases.

By observing the first type of regression results, the researchers found that the total carbon emissions were significantly positively correlated with population, per capita GDP, low-carbon technology level, and energy intensity, with regression coefficients of 0.538, 0.819, 0.343, and 0.048, respectively. Since the first category mainly includes cities with population outflow and relatively stable economic development, reducing population and inhibiting economic growth are ineffective emission reduction measures. Therefore, it is necessary to start with continuous innovation of low-carbon technologies. At the same time, these cities can share low-carbon technologies and carbon reduction experiences with other cities.

Observing the regression results of Type II, carbon emissions have a significantly positive correlation with population, per capita GDP, low-carbon technology level, foreign trade level, and energy structure, with regression coefficients of 0.942, 1.113, 0.081, 0.093, and 0.027, respectively. The cities of this type have a large population inflow, relatively high economic level, and high levels of low-carbon technology and energy efficiency. Also, carbon emissions cannot be suppressed by sacrificing economic development. After comparing the regression coefficients, we found that the level of foreign trade is the main factor affecting carbon emissions. Thus, it is necessary to focus on adjusting foreign investment fields and product types while continuously improving energy efficiency and upgrading low-carbon technologies.

Observing the regression results of Type III, the regression coefficients of population, per capita GDP, and low-carbon technology level are insignificant, and all variables do not significantly impact such cities. Therefore, there are no effective emission reduction pathways for such types of cities; relevant policies must be taken based on their actual situation to suppress their carbon emission growth rate.

The regression results of Type IV show that cities' per capita carbon dioxide emissions have achieved negative growth. However, due to the rapid economic development in the past decade, the total amount of carbon emissions is large. The regression coefficients show a significant positive correlation between population, per capita GDP, and total carbon emissions, with regression coefficients of 0.667 and 1.318, respectively; other factors are not significant. Due to the large population inflow, rapid economic development, and high carbon emissions in these cities, it is necessary to strengthen their carbon sequestration capacity and reduce carbon emissions by enhancing residents' awareness of environmental protection and low-carbon lifestyles.

Observing the regression results of Type V, we found a significant positive correlation between per capita GDP, foreign trade level, and total carbon emissions, with regression coefficients of 1.380 and 0.811, respectively. There is a significant negative correlation between the level of low-carbon technology and the total carbon emissions, with a regression coefficient of −0.472. Therefore, emission reductions can be achieved by suppressing foreign investment in high-energy-consumption and high-emission projects and accelerating the improvement of low-carbon technology to reduce carbon emissions effectively.

Observing the regression results of Type VI, it was found that there is a significant positive correlation between urbanization, population, industrial structure, energy intensity, and total carbon emissions. The regression coefficients are 1.135, 0.894, 0.645, and 0.029, in descending order. There is a significant negative correlation between the level of foreign trade and the total carbon emissions, with a regression coefficient of −0.210. The cities of this type have a high level of urbanization, with population inflow. Thus, these two variables cannot effectively suppress carbon emissions. However, carbon emissions can be reduced by optimizing the industrial structure and achieving the transformation from production industries to service industries as soon as possible. At the same time, improving energy efficiency can reduce energy intensity and carbon emissions in the production process. It is also possible to increase foreign trade in order to transfer carbon emissions.

## 5. Conclusions and Recommendations

### *5.1. Conclusions*

Based on the empirical results, the researchers draw the following conclusions:

First, the 36 cities in the Yangtze River Delta urban cluster can be divided into six types of carbon emissions based on the two characteristic indicators of decoupling elastic coefficient and carbon emission intensity, namely carbon emission Type I, Type II, Type III, Type IV, Type V, and Type VI. Based on the panel data of cities in the Yangtze River Delta from 2010 to 2021, a STIRPAT model was constructed. According to the regression results, we can conclude that cities with different carbon emission types have various carbon emission driving factors. Factors that significantly affect the carbon emissions of cities in the Yangtze River Delta urban cluster include population size, per capita GDP, low-carbon technology level, industrial structure, foreign trade level, urbanization level, and energy intensity. It is noteworthy that population size and per capita GDP have a significant positive driving effect on a particular type of city; at the same time, per capita GDP has a more substantial driving effect than population size. The impact of low-carbon technology level, industrial structure, foreign trade level, urbanization level, and energy intensity on carbon emissions vary in trend and size among the different carbon emission types of cities. Thus, it is necessary to develop differentiated carbon emission reduction paths tailored to local conditions for cities with different carbon emission types.

Then, based on panel data from 2010 to 2021, a STIRPAT model was constructed to explore the dominant driving factors for carbon emission reduction in each type of city and to develop differentiated carbon emission reduction pathways for them. According to empirical results, the carbon emission reduction path can be arranged as follows (shown in Table 12): the cities of carbon emission Type I should strengthen innovation in low-carbon technologies, improve energy efficiency, and reduce their energy intensity. For the cities of Type II, various methods are not very effective in suppressing carbon emissions. Therefore, consideration should be given to innovation in low-carbon technologies, adjustment of foreign trade product types, and improvement of energy efficiency. The cities of Type V should limit foreign investment in high-energy-consumption and high-emission projects in the region, applying low-carbon technologies on a large scale. The cities of Type VI should accelerate the new urbanization process, adjust and optimize the industrial structure, and improve the level of foreign trade and energy efficiency. The cities of Types III and IV do not have effective emission reduction pathways. For these two types of cities, further research should explore other effective emission reduction pathways, such as adopting carbon tax policies and other related policies in specific cities or industries and taking carbon reduction steps from the perspective of a "carbon sink".

**Table 12.** Carbon reduction pathways for each type of city.

| Type of City | Carbon Emission Reduction Pathways |
| --- | --- |
| Type I | strengthen innovation in low-carbon technologies;<br>improve energy efficiency and reduce energy intensity |
| Type II | develop low-carbon technologies;<br>adjust foreign trade product types;<br>improve energy efficiency |
| Type III | conduct further research |
| Type IV | conduct further research |
| Type V | limit foreign investment in high-energy-consumption and high-emission projects;<br>apply low-carbon technologies on a large scale |
| Type VI | accelerate the process of new urbanization;<br>adjust and optimize the industrial structure;<br>improve the level of foreign trade and energy efficiency |

*5.2. Recommendations*

(1) Achieve carbon peaking in the Yangtze River Delta region in batches (known as "cascade peaking"). Under the background of achieving the "carbon peaking" target before 2030, it is necessary to consider the differences in economic development and industrial structure among cities in the Yangtze River Delta and pay attention to the priority order of carbon peaking among cities in the Yangtze River Delta. Priority should be given to achieving carbon reduction in cities with high carbon emission levels and high carbon emission growth rates, and then systematically achieve "carbon peaking" in other cities.

(2) Strengthen cooperation among cities within the Yangtze River Delta urban cluster to achieve carbon peaking through the Collaborative Emission Reduction Mechanism. There is a spatial spillover effect between adjacent cities, and the development of collaborative emission reduction mechanisms cannot be ignored in achieving a carbon peak in the Yangtze River Delta region. Each city can impart its "comparative advantages" to others and provide carbon reduction experience and low-carbon technologies for other cities.

(3) Improve carbon market rules and enhance the economic value of carbon reduction by relying on the construction of the Shanghai carbon trading market, strengthening the binding force of the carbon market on the trading entities, and promoting market management through issuing laws and regulations. Restart the registration and review of CCER projects as soon as possible, promote the certification of new energy utilization through CCER, and conduct carbon trading on the platform with the issued emission reduction quotas. At the same time, actively promote the establishment of a Carbon Inclusive Mechanism and enhance residents' participation in the carbon reduction activity.

In summary, the deadline for achieving "carbon peaking" before 2030 is approaching; meanwhile, the carbon reduction task is heavy. As one of China's fastest-growing urban clusters, the Yangtze River Delta region needs to actively implement carbon emission reduction activities and set an excellent example for other urban clusters. Seeing the significant differences within the Yangtze River Delta Urban Cluster, the different types of cities should adopt differentiated and diversified carbon reduction measures and provide successful carbon reduction experiences for other urban clusters. Other urban clusters should consider factors such as geographical location and economic level and explore unique carbon reduction pathways that are suitable for their needs.

### 5.3. Study Limitations

(1) The study's main limitation is the absence and distortion of data. In China, the total carbon emission amount is estimated by indirect methods, such as the emission coefficient method. It is not detected by modern information technologies (such as big data technology) and monitoring technologies (such as satellite remote sensing high-precision continuous measurement technology). Therefore, there may be some differences between the actual and estimated values of carbon emission, causing the empirical results to differ from the real situation.

(2) The second limitation of the study is the lack of comparison between different urban clusters. The paper only considered the carbon emission characteristics and reduction pathways in the Yangtze River Delta region and selected cities within the Yangtze River Delta as the research objects. However, the study overlooked the carbon emission situation of some underdeveloped cities. It did not compare the Yangtze River Delta urban cluster with other Chinese urban clusters regarding low-carbon technology levels and the related situation of carbon market development.

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