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Carbon Emissions and Innovation Cities: A SHAP-Model-Based Study on Decoupling Trends and Policy Implications in Coastal China

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Abstract: This study investigates the spatiotemporal distribution of carbon emissions and the decoupling relationship between emissions and innovation-driven urban development in six coastal provinces and municipalities in China from 2008 to 2022. The main questions of this paper are as follows: What are the spatial and temporal distribution characteristics of carbon emissions in the study area? What is the decoupling relationship between carbon emissions and innovation-driven urban development? What key variables contribute significantly to carbon emissions and urban development? Carbon emissions increased overall, with higher levels in northern regions such as Shandong, northern Jiangsu, and the Yangtze River Delta. Meanwhile, innovation levels rose but disparities widened, with northern cities leading and those in western Fujian and Guangdong lagging behind. The green economy and industrial transformation were key drivers of rapid development in some cities. To identify the driving factors, the SHAP (SHapley Additive exPlanations) model was employed to quantify the contributions of key variables, including energy structure, technological innovation, and industrial upgrading, to both carbon emissions and urban development. This study found that decoupling between carbon emissions and smart city development improved, transitioning from negative to strong decoupling, particularly in coastal cities. These insights can assist governments in formulating sustainable development strategies. High-emission cities should focus on integrating low-emission measures to mitigate their carbon footprint. High-carbon cities need to transition to low-carbon pathways, enhancing resource efficiency and reducing emissions. Low-emission cities should prioritize improving carbon sinks. Cities with weak economies but rich ecological resources should develop tertiary and ecological economies. Developed cities should optimize resource allocation, digitize industries, and pursue low-carbon growth. Additionally, adjustments in transportation and industry can further boost innovation and urbanization.

Keywords: Tapio decoupling model; spatiotemporal evolution; carbon emissions; innovation cities; interpretable machine learning

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1. Introduction

Global warming and carbon emissions are two closely intertwined issues that have garnered significant attention from both scientists and the general public in recent years. At the 75th session of the United Nations General Assembly in 2020, the Chinese government announced that it would commit to reaching peak carbon emissions by 2030 and to strive for carbon neutrality by 2060.

Carbon neutrality is widely regarded as a pivotal strategy in the battle against global warming. Numerous studies have aimed to explore the correlation between carbon emissions and socioeconomic development, seeking to understand how they interact and potentially balance each other. Understanding the relationship between carbon emissions and rising temperatures is critical and requires us to consider different emission pathways. At the same time, carbon trading schemes and emissions regulations have had a significant impact on inventory management and emission reduction investments [1]. Targeting specific sectors, such as China's coal-to-electricity energy chain, studies reveal the main drivers of CO_2 emissions, further highlighting the urgency and importance of reducing carbon emissions in key industries to mitigate environmental impacts [2,3]. To accelerate the process of carbon neutrality, it is necessary to comprehensively analyze the relationship between energy consumption, economic growth, and carbon emissions in China and quantify the key drivers [4]. At the same time, it is necessary to explore the harmonious coexistence of urbanization and carbon reduction and formulate policies that balance the economy and the environment. The improvement of the digital economy and industrial structure system plays an important role in promoting energy efficiency and emission reduction and is a key factor in promoting the achievement of carbon neutrality goals [5–9].

The construction of an innovative city should attach importance to the combination of local economic planning and innovation policy. Through industrial cooperation and innovation, we will promote the coordinated development of regional industries and pay attention to the promotion of talents for high-quality economic development [10,11]. Countries such as South Africa need to better integrate innovation policies with local planning [12]. At the same time, we should balance innovation with environmental sustainability, promote green technology innovation, and improve resource utilization efficiency [13,14]. In the era of the digital economy, scientific and technological innovation and the digital economy have become an important driving force for high-quality development [15,16], and industry–university–research cooperation is particularly critical in the construction of innovative cities, as shown in China's Chengdu–Chongqing economic Circle, which is crucial for building an innovative country and promoting economic growth [17]. This collaborative approach is crucial for building an innovative nation and driving economic growth.

In the process of building innovative cities, we have introduced the concept of an "urban innovation engine" [18], which aims to transform urban institutions into a core force driving innovation. This shift not only promotes in-depth research and exploration in the field of urban innovation, but also underscores the importance of sustainable partnerships and collaborative strategies among stakeholders, especially in the context of smart cities and the internet of the future [19]. As an effective method of urban innovation, crowdsourcing has shown its unique advantages through citizens' participation in the generation and selection of ICT innovation [20]. At the same time, studies on collaborative innovation in China's Yangtze River Delta and other regions measure the collaborative innovation ability of innovation subjects and cities by using the mutation series model and reveal the complexity of the regional innovation system and the interrelated innovation substages [21–23]. However, while pursuing economic growth and technological innovation, innovative cities also face severe challenges of carbon emissions. To address this challenge, we use the Tapio decoupling model to deeply analyze the relationship between urban carbon emissions and innovative cities and examine the decoupling of carbon emissions and economic growth in different regions [24–26]. A study found that improvements in technology and efficiency play a crucial role in promoting carbon decoupling [27]. In particular, in the case of the decoupling of urban economic growth and carbon emissions in China, the significant reduction in emissions intensity is mainly due to large improvements

in production and carbon efficiency [28]. Therefore, for innovative cities, decoupling carbon emissions from economic growth is the key to accelerating the process of carbon neutrality. By continuously optimizing the allocation of factor resources, promoting green technology innovation, and improving production and carbon efficiency, innovative cities can effectively reduce carbon emissions while maintaining economic growth, so as to achieve the strategic goal of carbon neutrality.

In this study, the coastal provinces and cities of China, which are also well-developed regions, have been selected as the study area to examine the decoupling relationship between carbon emissions and innovation at the prefecture level. The coastal areas are the growth poles of the Chinese economy, accounting for 43% of the country's GDP, and play a pivotal role in the economic development of China and the world. However, with the rapid economic growth, environmental and climate issues have become increasingly prominent and pose a major challenge that needs to be addressed. Therefore, these coastal cities play a crucial role in China's environmental protection and emission reduction efforts. Addressing this issue is of great significance for China to build innovative cities and achieve sustainable social and economic development of the "dual carbon" goal.

After observing the above-mentioned research gaps, this paper presents three key issues: What are the spatial and temporal distribution characteristics of carbon emissions in the study area? What is the decoupling relationship between carbon emissions and innovation-driven urban development? What key variables contribute significantly to carbon emissions and urban development? The remainder of this paper is structured as follows: In Section 2, an indicator framework for evaluating the relationship between carbon emissions and innovative cities is proposed. Section 3 presents the study area, along with the relevant data and methods used in the analysis. Section 4 summarizes the results obtained from this study. Finally, Section 5 presents the conclusions and recommendations.

2. Indicator Framework

The decoupling process between innovation cities and carbon emissions constitutes a complex system, intricately weaving together society, economy, and environment aspects. This research delves into the mechanisms through which innovation cities impact carbon emissions, examining four key aspects: environment, population, society, and economy (Figure 1).

In the environment dimension, carbon emissions are influenced by innovation cities from three aspects. Liu et al. [11] explored the evolution of a green innovation city network in the Yellow River Basin cities, emphasizing the significance of regionalized spatial organization in addressing environmental challenges and promoting sustainable development within urban areas. Wang et al. [29] examined the impact of digital transformation on promoting green and low-carbon synergistic development in enterprises, particularly in heavily polluting industries in China, finding that digital transformation could improve pollution and carbon emissions reduction efficiency in the long run, emphasizing the potential of innovation cities in enhancing environmental sustainability. Bramwell [30] compared inclusive innovation programs in different cities, highlighting the need to rethink actor configurations in urban development priorities. Li et al. [31] used absorptive capacity theory to analyze the relationships between urban innovation processes and sustainable development, revealing complex configuration paths that affect sustainable urban development.

In the population dimension, carbon emissions are influenced by innovation cities from two aspects. Researchers highlight the importance of developing a predictive theory of urban organization and sustainable development as urbanization continues to be a global trend. They emphasize that the processes linking urbanization to economic development

and knowledge creation are shared by all cities within the same urban system, regardless of location or time. For population quality, researchers explore the institutional and socioeconomic context of Medellin as an 'innovative city', raising questions about the extent of urban innovation in the city.

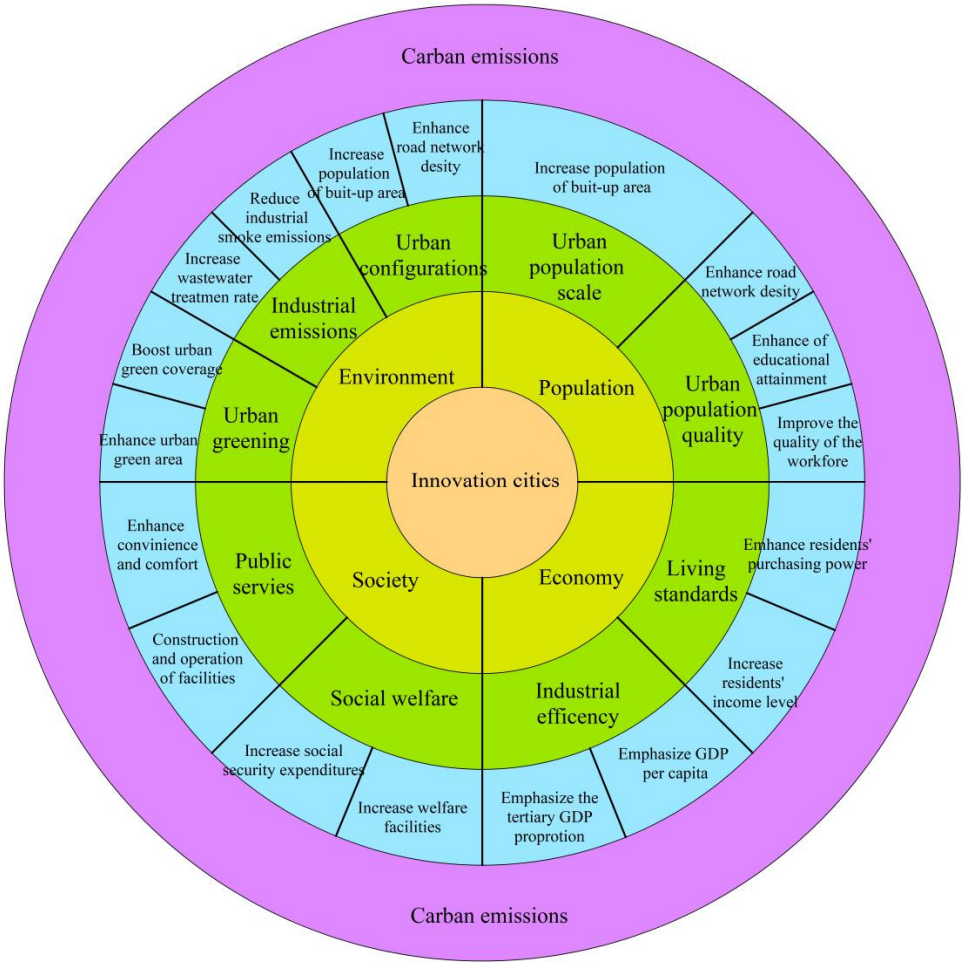

Figure 1. Conceptual process mechanism.

In the social dimension, carbon emissions are influenced by innovation cities from two aspects. Wu et al. [32] discussed the principles and methods of intelligent city evaluation systems, highlighting the importance of governance and public service in promoting smart, green, and low-carbon cities, and assessed the impact of Information Consumption City (ICC) policies on carbon emission efficiency in Chinese cities. Researchers propose a framework for analyzing social welfare innovations within the social innovation paradigm, emphasizing the interaction between organizations of social economy, local public institutions, and civil society. Although the increase in consumption patterns might lead to an augmentation of carbon emissions, the enhancement of welfare simultaneously encourages the utilization of communal facilities, which in turn diminishes individual energy consumption and subsequently reduces carbon emissions.

In the economic dimension, carbon emissions are influenced by innovation cities from two aspects. Apaydin et al. [33] introduced an efficient method for the controlled capture and release of carbon dioxide using an industrial organic pigment called quinacridone. This approach offers a nature-inspired, cheap, abundant, and non-toxic solution for limiting anthropogenic carbon dioxide emissions. In addition, Liu et al. [34] have deeply discussed the problem of greenhouse gas emissions in the economic development of eco-industrial parks, which provides a useful reference for the economic realization of carbon emission

reduction in the construction of innovative cities. Shi et al. [35] decomposed per capita urban carbon emissions in Chinese megacities to understand the specific drivers of carbon emissions, including urban growth and resident living standards. This new decomposition method provided insights into the sectors contributing to carbon emissions, such as manufacturing, transportation, and construction, highlighting the importance of addressing these specific drivers.

3. Data and Methods

This study examines six provinces and cities along China's eastern coast as case studies: Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, and Guangdong. The study area encompasses these municipalities and provinces, including one municipality directly under the central government, five provincial capitals, and 65 prefecture-level cities. It spans a land area of 680,500 square kilometers. In 2022, the study area accounted for 31.1% of China's population and contributed to a total GDP of CNY 51.5 trillion, representing approximately 43% of the nation's overall GDP despite occupying only 7.09% of China's total landmass. In recent decades, this area has emerged as a symbol of superior urban development, marked by advanced infrastructural facilities and flourishing high-technology sectors.

This paper is mainly based on prefecture-level coastal cities and provinces, currently totaling 71 cities (Figure 2). The collection and interpretation of data were conducted in accordance with the predefined administrative boundaries.

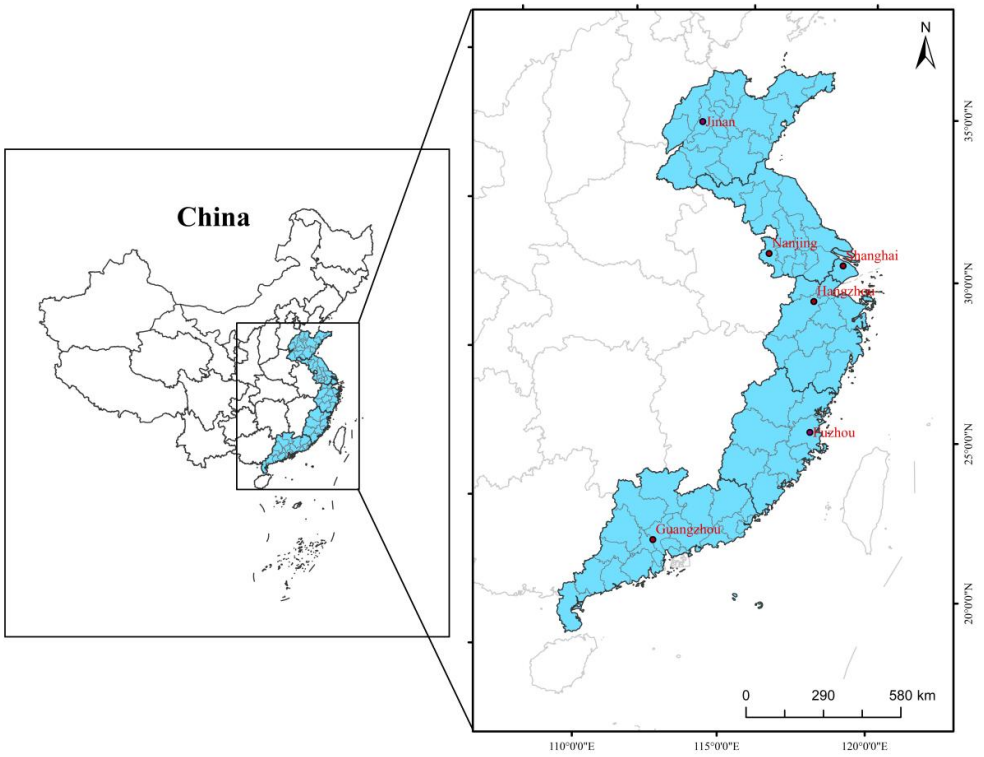

Figure 2. Study area and location. This figure is based on the standard map service website of the Ministry of Natural Resources with the number of GS(2024)0650.

3.1. Data Sources

The data utilized in this article for the innovation cities encompassed various sources, including regional socioeconomic attributes, government work reports, urban planning data, and urban carbon emission data. The socioeconomic attribute data were primarily sourced from the "China City Statistical Yearbook" and other provincial and municipal statistical yearbooks spanning the years 2008 to 2022. The urban carbon emission

data integrated information from the China Emission Accounts and Datasets (CEADs) (http://www.ceads.net) [36] and the China City Greenhouse Gas Working Group (CCG) (http://www.cityghg.com) [37], along with additional data from various prefecture-level cities. Notably, this dataset incorporated information gathered from relevant government departments, interviews with government officials, and field research (Figure 2 and Table 1).

Table 1. Innovation city evaluation indicators.

Primary Indicator	Sub-Indicator	Basic Indicator	Abbreviation	Unit
Environment	Environmental Friendliness	Urban green area per capita	ENU-UG	m^2/p
		Green coverage rate in built-up area	ENU-GC	%
		Domestic sewage treatment rate	ENU-DS	%
		Industrial smoke emissions	ENU-IS	tons
	Spatial optimization	Proportion of built-up area to total area	ENU-BA	%
		Length of roads per 10,000 people	ENU-RL	km/10,000 p
Population	Population size	Urbanization rate of resident population	POU-UR	%
		Resident population density	POU-PD	10,000 p/km^2
	Population quality	Ratio of employees in the tertiary sector	POU-TS	%
		Percentage of primary and secondary school attendance	POU-SA	%
Society	Public service	The number of books in the public library per 10,000 people	SOU-LB	n/10,000 p
		The number of beds in hospitals per 10,000 people	SOU-HB	n/10,000 p
	Social security	Public budget expenditure	SOU-FE	CNY 100,000,000
		The number of social welfare home beds per 10,000 people	SOU-WB	n/10,000 p
Economy	Industrial efficiency	Proportion of tertiary GDP	ECU-TG	%
		GDP per capita	ECU-PG	CNY/p
	Living standards	Disposable income per capita	ECU-DI	CNY/p
		Consumption expenditure per capita	ECU-CE	CNY/p
		The number of motor vehicles per capita	ECU-MV	n/p
		Sales of commercial properties per capita	ECU-CP	m^2/p

3.2. Methodology

3.2.1. Measurement of Innovation Cities

Drawing from previous studies, the study methodology employed in the paper delves into the mechanisms of the influence of innovation cities on carbon emissions. Subsequently, a comprehensive evaluation indicator system for innovation cities is established, encompassing four distinct dimensions: environmental, population, society, and economy. Table 1 outlines the indicator system for innovation cities.

To minimize subjectivity, this study adopts the entropy method, which determines the weight of each indicator based on the amount of information provided by its observed values. The entropy method is an objective weighting method, which is based on information entropy theory and determines the weight by evaluating the variation degree of each index. The benefit of this approach is that it avoids the impact of subjective judgment and is suitable for data-driven scenarios. The steps involved in this process are as follows:

(1) Data normalization

$$x_{ij} = \frac{x_{ij} - min(x_j)}{max(x_j) - min(x_j)} \quad (1)$$

$$x_{ij} = \frac{max(x_j) - x_{ij}}{max(x_j) - min(x_j)} \quad (2)$$

(2) Index normalization

$$w_{ij} = \frac{X_{ij}}{\sum_{i=1}^{n} X_{ij}} \quad (3)$$

$$E_j = -\frac{1}{lnn} \times \sum_{i=1}^{n} w_{ij} \times lnw_{ij} \quad (4)$$

(3) Weight calculation

$$\rho_j = 1 - E_j \quad (5)$$

$$\tau_j = \frac{\rho_j}{\sum_{j=1}^{n} \rho_j} \quad (6)$$

$$\alpha_i = \sum_{j=1}^{n} \tau_j \quad (7)$$

In Equations (1)–(7), X_{ij} refers to the normalized result of the j-th indicator for the i-th city, where $max(x)$ and $min(x)$ represent the maximum and the minimum initial value of the indicator across all areas, respectively. W_{ij} indicates the probability associated with the j-th indicator for the i-th city, E_j denotes the entropy value associated with j-th indicator, and ρ_j signifies the information utility for the same indicator. Additionally, τ_j represents the weight of the indicator, and α_i stands for the IC index.

3.2.2. Measurement of Carbon Emissions

XGBoost [38], an open-source machine learning model, is an optimized GBDT algorithm that boasts numerous advancements and notable achievements across various domains. It leverages second-order Taylor approximation of the objective function to enrich information retention and incorporates a regularization term to mitigate overfitting. XGBoost employs a forward distribution algorithm to sequentially train an additive model composed of k base learners.

$$\hat{y_i} = \sum_{t=1}^{k} f_i(x_i) \quad (8)$$

where $\hat{y_i}$ is carbon emission value of the i-th simulated sample x_i, and f_k is the k-th basic evaluator.

3.2.3. Tapio Decoupling Model

Decoupling can be used to describe the relationship between energy consumption or other relevant factors and economic development throughout the entire development process. In the early stages of economic growth, the extensive economic development model fuels economic expansion but also results in significant energy consumption and pollutant emissions. As a result, economic growth is closely tied to haze pollution during this period. However, as the economy shifts from an extensive model to a green development model, it continues to grow rapidly while the concentration of pollutants either remains stable

or decreases. This signifies the decoupling of economic growth from haze pollution, and achieving such a decoupled state is possible.

This paper adopts the Tapio decoupling model to analyze the correlative change during the process of decoupling of carbon emissions and innovation cities in coastal provinces and cities. The calculation for the decoupling index ε_{t-a}^{t} is as follows.

$$\varepsilon_{t-a}^{t} = \frac{\Delta CE_{t-a}^{t}}{\Delta IC_{t-a}^{t}} = \frac{(CE_t - CE_{t-a})/CE_{t-a}}{(IC_t - IC_{t-a})/IC_{t-a}} \tag{9}$$

where ΔCE_{t-a}^{t} denotes the variation in the carbon emission level between the year t and the year $t-a$, ΔIC_{t-a}^{t} signifies the corresponding change in the innovation city level across the same period. CE_t represents the carbon emission level. CE_{t-a} denotes the carbon emission level, IC_t represents the innovation city level, IC_{t-a} represents the innovation citie level, and a is the number of interval years.

Typically, there are eight types of decoupling. It is noteworthy that, with the exception of a very few cities, the innovation city index within the study area has been continuously increasing, resulting in only cases where $\Delta IC_{t-a}^{t} > 0$. Data indicate that the decoupling trends of innovation cities and carbon emissions within the study area are relatively similar. This suggests that the existing decoupling classification methods fail to demonstrate the disparities among cities. To highlight these differences, we adopt thresholds of $\varepsilon_{t-a}^{t} = 0.4$ and $\varepsilon_{t-a}^{t} = -0.4$. Consequently, weak decoupling is subdivided into types I and II, and strong decoupling is similarly divided into levels I and II. Therefore, strong decoupling II stands for the best state (Figure 3).

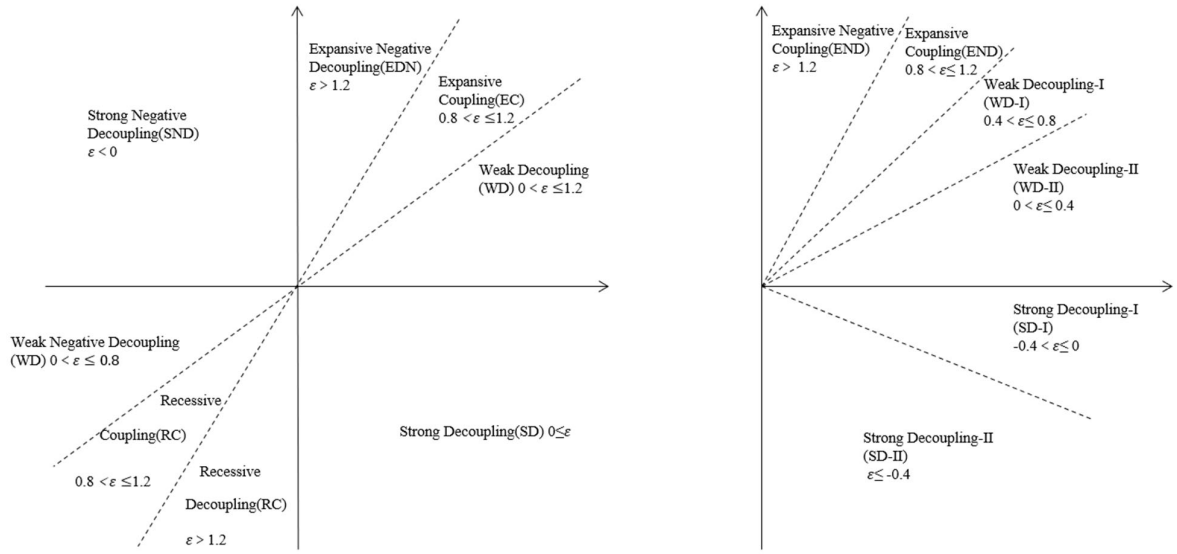

Figure 3. The Tapio decoupling model and reclassification.

3.2.4. Interpretability of Decoupling Index

In this paper, we aimed to interpret the influencing factors of the decoupling index from interpretable machine learning (IML). With the progress of artificial intelligence (AI), IML has become increasingly important. Approaches like Accumulated Local Effects (ALE) [39] and Local Interpretable Model-agnostic Explanations (LIME) [40] have been developed to address this need. The main goal of IML is to enhance the interpretability of the model performance, thereby promoting comprehension, reliance, and optimized control of complex machine learning systems.

As an approach to IML, the SHAP model is grounded in cooperative game theory and local explanation principles [41]. Shapley values were computed for every feature to assess their individual impact on the model's overall predictive capability [42]. The advantages of SHAP lie in its model independence, strong interpretability, applicability to high-dimensional datasets, and ability to reveal feature interaction effects, which are widely used in financial, medical, and other fields. However, its limitations include high computational complexity, unstable results that may be affected by feature order, and excessive interpretation should be avoided as SHAP values reflect the contribution of features to the model rather than causal effects. SHAP is particularly suitable for studies that need to explain complex model prediction processes, such as identifying risk factors or exploring the influence of variables, to enhance model transparency and decision reliability through visual tools. By applying the SHAP model in this study, the SHAP model can accurately quantify the contribution of key variables to carbon emissions and urban development, reveal the drivers of spatial–temporal heterogeneity, and help policy formulation. The formulae are as follows:

$$\omega(|s|) = \frac{(n-|s|)!(|s|-1)!}{n!} \tag{10}$$

$$\varphi_i(\nu) = \sum_{s \in S_i} \omega(|s|)[v(s) - \nu(s/\{i\})] \tag{11}$$

where n represents the entirety of variables, $\omega(|s|)$ represents the weight factor and s denotes the collection of all variables. $\varphi_i(\nu)$ stands for the Shapley value, while S_i refers to the collection of possible variable orderings, and $v(s)$ indicates the optimal value achieved by coalition s.

$$g(\acute{z}) = \phi_0 + \sum_{i=1}^{M} \phi_i \acute{z}_i \tag{12}$$

where ϕ_i is the contribution of each feature, $\acute{z}$ denotes observed or unobserved features, and M stands for the simplified input feature number.

4. Results

4.1. Spatiotemporal Distribution Characteristics of Innovation Cities and Carbon Emissions

The state has deeply affected carbon emissions in the coastal area through policies such as dual carbon emission control and carbon market construction, combined with low-carbon city pilot projects and major economic events. The dual control policy directly constrains Shandong, Jiangsu, and other industrial provinces, and the carbon market forces enterprises to reduce emissions. Regional quota allocation optimizes resources, benefiting Fujian, Zhejiang, and other low-carbon provinces. Low-carbon pilot cities such as Shanghai and Shenzhen use green infrastructure to reduce carbon. The financial crisis forced industrial upgrading, and the Paris Agreement accelerated the transformation of new energy. Policy and market coordination promotes the six provinces from extensive growth to structural carbon reduction and technology carbon reduction.

Figure 4 illustrates the total carbon emissions within the study area spanning from 2008 to 2022. Generally, the investigated region experienced a consistent rise in carbon emissions over this period. More specifically, emissions surged from approximately 2.6 billion tons in 2008 to roughly 4.3 billion tons in 2022. Prior to 2012, carbon emissions saw a sharp increase, climbing from around 2.6 billion tons to 3.3 billion tons. Between 2012 and 2016, emissions remained relatively stable at approximately 3.4 billion tons. This was because of economic restructuring and energy efficiency improvement, the promotion and application of clean energy, regional cooperation and collaborative governance, and the phased characteristics of total carbon emissions. The combined effect of these factors makes the coastal areas realize the effective control of total carbon emissions in the process of

economic development. Following 2016, carbon emissions resumed their upward trajectory, ultimately reaching 4.3 billion tons.

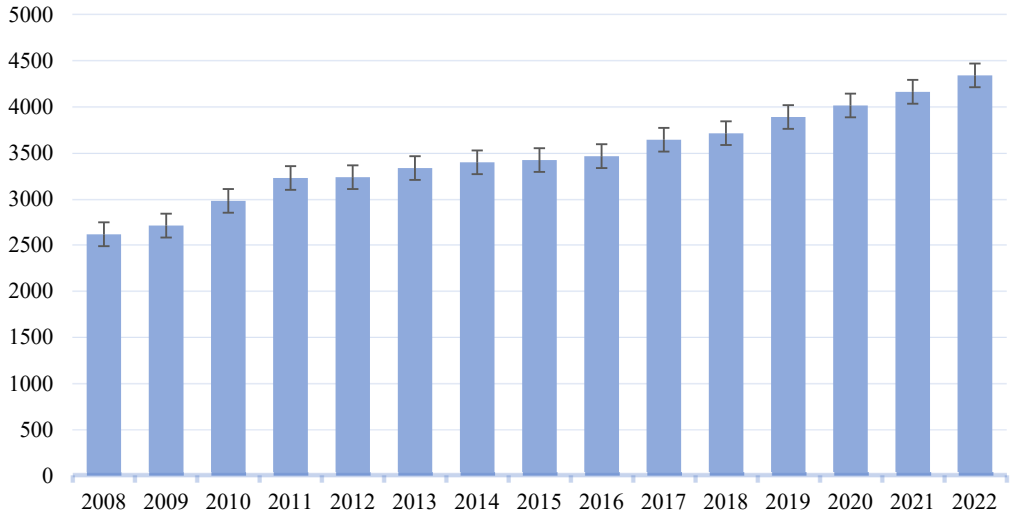

Figure 4. Total carbon emission change in coastal provinces and cities from 2008 to 2022.

Figure 5 depicts the spatiotemporal distribution of carbon emissions in the study area from 2008 to 2022. When compared to southern regions, the northern areas exhibit notably higher levels of carbon emissions. In particular, several locations in central Shandong (such as Jinan, Weifang, Zibo, and Qingdao) and southwestern Shandong (including Jining, Zaozhuang, and Heze) show higher carbon emissions. Furthermore, the Yangtze River Delta region, which encompasses Shanghai, Suzhou, Wuxi, Changzhou, Zhenjiang, and Zhoushan, also demonstrates significant carbon emission levels, along with Guangzhou and Fuzhou.

Notably, carbon emissions in Shandong Province have been consistently increasing, with Qingdao and Binzhou being the exceptions. As of 2022, the entire territory of Shandong Province showed high levels of carbon emissions. In comparison to 2008, the central and southern regions of Jiangsu Province (including Yancheng, Yangzhou, Taizhou, and Suqian) experienced a significant rise in carbon emissions in 2022, with urban areas emitting more carbon than rural ones. Shanghai has maintained consistently high emission levels from 2008 to 2022. The northeastern region of Zhejiang Province exhibits significantly higher carbon emissions than other areas, showing a pattern of decreasing emissions from the northeast towards the southwest. The eastern coastal areas of Fujian Province (such as Fuzhou, Quanzhou, and Zhangzhou) have also seen notable increases in carbon emissions. In the central regions of Guangdong Province (specifically Guangzhou and Dongguan), high carbon emissions are evident, and within this area, Shaoguan and Zhanjiang have shown rapid growth in their carbon emissions. In the north, especially in Shandong, the Yangtze River Delta, and parts of Guangdong, carbon emissions are high and growing. It is suggested that policy makers focus on these hot spots, formulate targeted emission reduction strategies, strengthen urban carbon emission supervision, promote industrial green transformation, and promote low-carbon sustainable development.

According to Table 2, when comparing different years, the carbon emissions of prefecture-level cities exhibited substantial increases. Throughout the period of investigation, the ranking of carbon emissions among the surveyed cities remained relatively stable, with Suzhou, Nanjing, and Shanghai consistently occupying the top positions. Notably, due to its industrial green transformation and digital economic development, Shanghai exhibited a relatively small increase in carbon emissions during the investigation period, resulting in a gradual decline in its ranking. Between 2018 and 2022, Laiwu was

incorporated into Jinan. As a resource-based city with abundant coal production and high resource consumption, Laiwu contributed to a sharp rise in Jinan's carbon emissions, propelling it to the top spot.

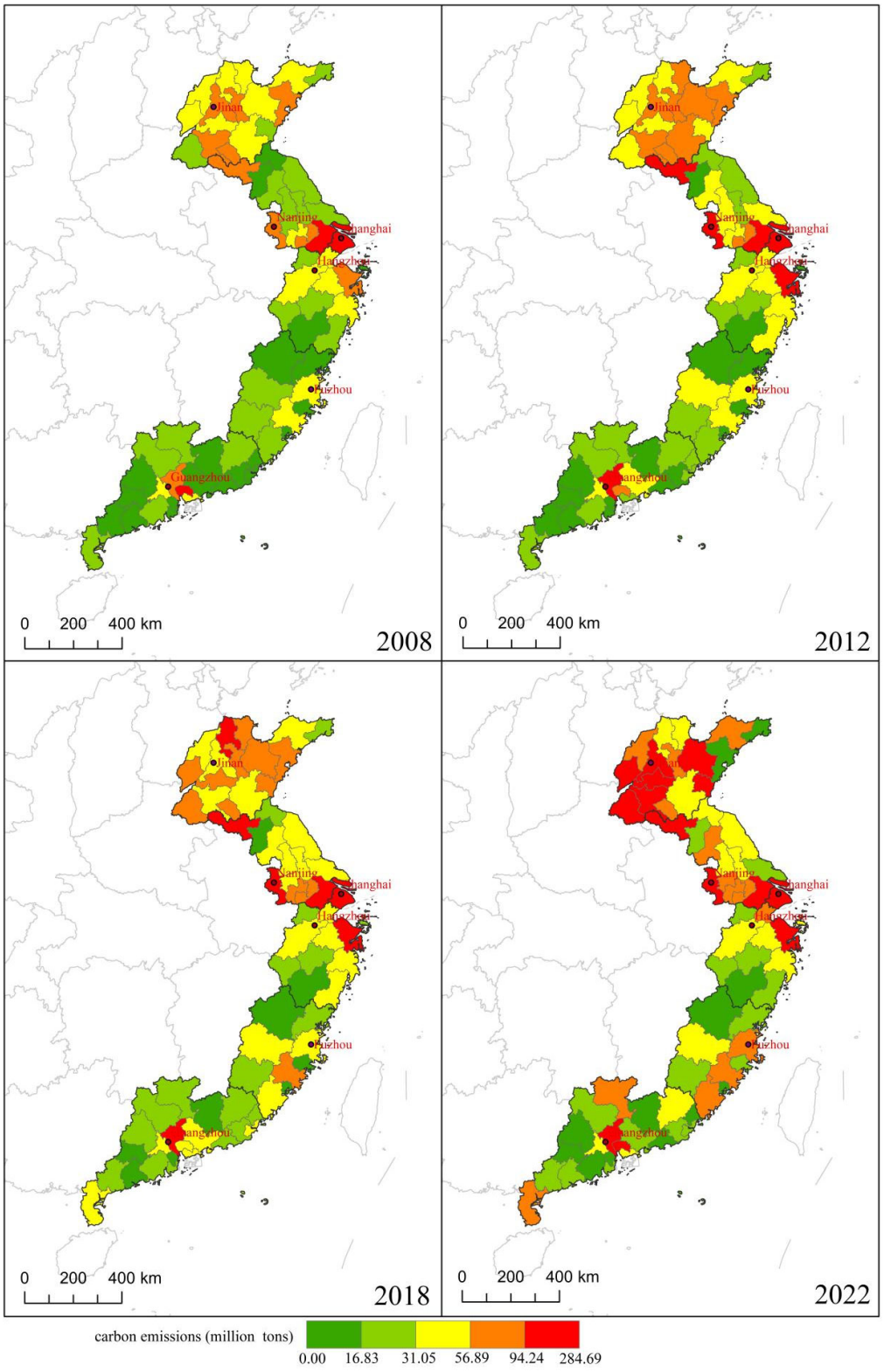

Figure 5. Spatiotemporal distribution of carbon emissions in the coastal area from 2008 to 2022.

Table 2. The specific values of carbon emissions.

	CE (2008)	CE (2012)	CE (2018)	CE (2022)
1	Suzhou, 150.06	Suzhou, 207.79	Suzhou, 213.41	Jinan *, 284.69
2	Shanghai, 144.42	Shanghai, 168.52	Binzhou, 185.55	Suzhou, 284.53
3	Dongguan, 115.32	Nanjing, 139.47	Nanjing, 164.91	Xuzhou, 257.27
4	Nanjing, 94.24	Ningbo, 120.16	Xuzhou, 154.50	Najing, 186.85
5	Ningbo, 87.36	Xuzhou, 100.07	Shanghai, 151.47	Shanghi, 167.96
6	Guangzhou, 87.35	Guangzhou, 97.27	Ningbo, 130.05	Jining, 142.47
...	...	...	...	...
66	Shanwei, 6.70	Zhongshan, 11.73	Xianmen, 14.75	Qingdao, 8.38
67	Suqian, 5.62	Lishui, 8.25	Heyuan, 10.60	Zhongshan, 8.32
68	Zhoushan, 5.37	Putian, 8.25	Zhongshan, 9.90	Jiangmen, 8.14
69	Putian, 4.79	Heyuan, 7.66	Suqian, 8.53	Lishui, 5.65
70	Yangjiang, 4.41	Suqian, 7.38	Lishui, 8.06	Weihai, 3.34
71	Heyuan, 4.15	Nanping, 6.85	Nanping, 5.63	Shanwei, 1.28

* The incorporation of Laiwu into Jinan in 2019 led to a sudden rise in Jinan's carbon emissions.

As illustrated in Figure 6 and Table 3, From 2008 to 2022, the innovation city index values of the cities that have consistently ranked at the top (Xiamen, Shenzhen, Shanghai, Suzhou, Nanjing) have nearly doubled. This indicates a significant improvement in residents' living standards, continuous enhancement in environmental conditions, and the ongoing refinement of public facilities, social welfare, and educational and cultural systems.

Table 3. The specific values of innovation cities.

	IC (2008)	IC (2012)	IC (2018)	IC (2022)
1	Xiamen, 0.45	Xiamen, 0.59	Xiamen, 0.72	Shanghai, 0.84
2	Shenzhen, 0.40	Shenzhen, 0.55	Hangzhou, 0.70	Hangzhou, 0.77
3	Nanjing, 0.39	Hangzhou, 0.50	Shanghai, 0.66	Suzhou, 0.72
4	Suzhou, 0.38	Suzhou, 0.49	Shenzhen, 0.63	Xiamen, 0.72
5	Fuzhou, 0.37	Nanjing, 0.46	Suzhou, 0.62	Nanjing, 0.72
6	Hangzhou, 0.33	Wuxi, 0.41	Nanjing, 0.57	Ningbo, 0.70
...	...	...	...	...
66	Jiangmen, 0.08	Ningde, 0.09	Shanwei, 0.09	Heyuan, 0.13
67	Shanwei, 0.06	Shanwei, 0.08	Heyuan, 0.09	Shanwei, 0.12
68	Heyuan, 0.06	Heyuan, 0.07	Meizhou, 0.09	Zhanjiang, 0.12
69	Yangjiang, 0.05	Qingyuan, 0.06	Yangjiang, 0.09	Zhaoqing, 0.12
70	Qiangyuan, 0.05	Yangjiang, 0.06	Qingyuan, 0.08	Meizhou, 0.11
71	Yunfu, 0.04	Yunfu, 0.06	Yunfu, 0.06	Yunfu, 0.07

Within the study period, significant spatial heterogeneity was observed in the level of innovation city development across cities within the study area. Generally, the northern regions exhibited higher levels of innovation city development compared to the southern regions. Since 2008, cities in Jiangsu Province have continuously enhanced their innovation city capabilities, attributed to the province's emphasis on economic development, comprehensive infrastructure construction, and improvements in living conditions. By 2022, all 13 prefecture-level cities in Jiangsu Province had attained high-level innovation city status. Between 2018 and 2022, several cities in Shandong Province, including Yantai, Weifang, Dongying, Linyi, Jining, and Heze, experienced rapid growth in smart city development, reflecting industrial upgrading, logistics development, and the introduction of talent and capital. The coastal cities of Fujian and regions in Guangdong, including Guangzhou, Dongguan, and Shenzhen, have seen significant enhancements in their level of innovation city development. This is due to the impact of coastal economic development,

the digital economy, and the increased proportion of the tertiary industry on innovation city development.

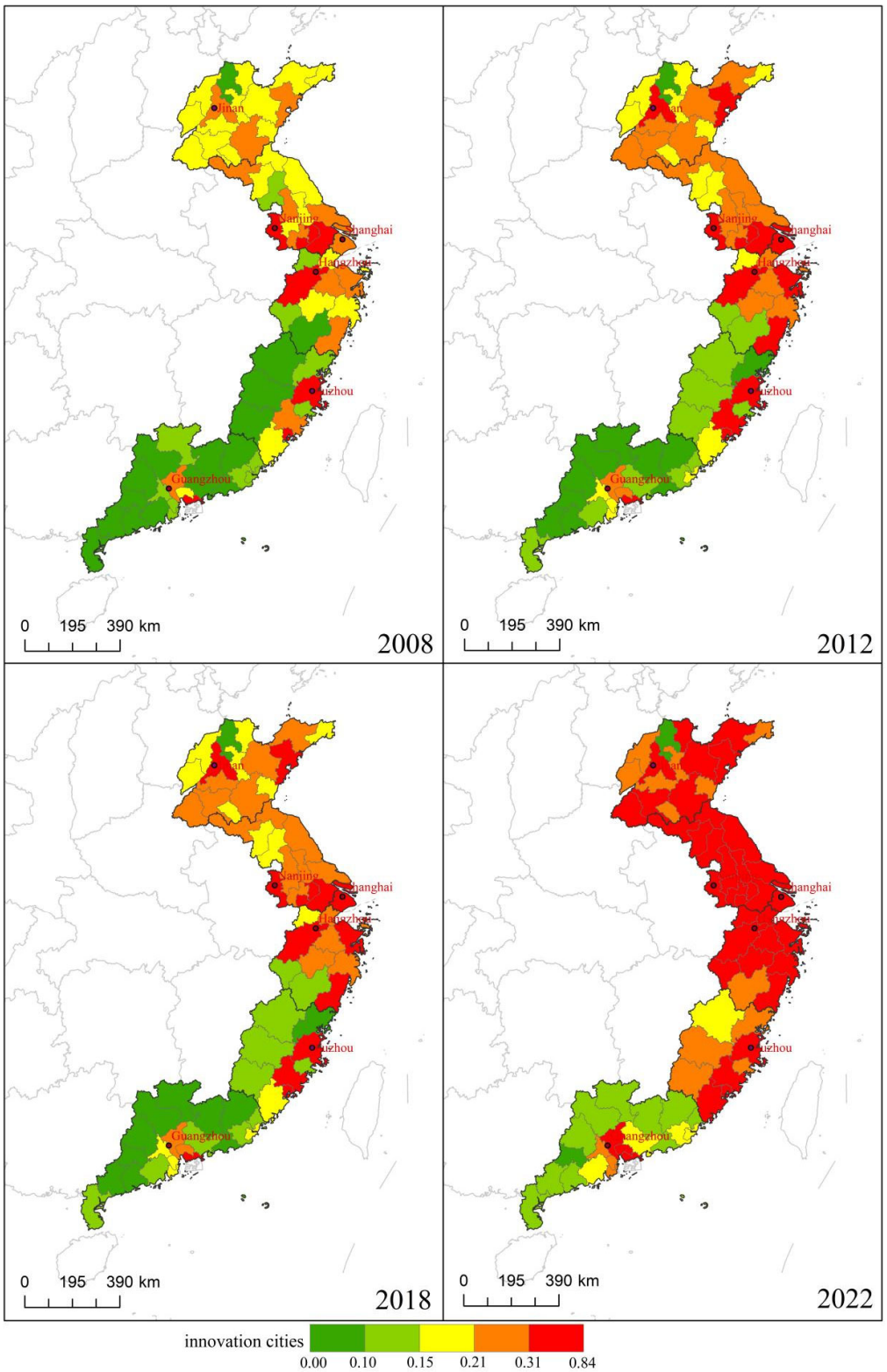

Figure 6. Spatiotemporal distribution of innovation cities in the coastal area from 2008 to 2022.

4.2. Evolving Decoupling Relationship of Carbon Emissions and Innovation Cities and Influencing Factors

Table 4 illustrates that within the study area, from 2008 to 2013, the decoupling status of prefecture-level cities was predominantly characterized by expansive negative decoupling, which accounted for as much as 43.7% of the total. As observed in Figure 7, expansive negative decoupling was predominantly distributed in cities within Jiangsu and southern Shandong. The results indicate that during this period, some cities failed to make progress in innovation city development while also failing to effectively curb carbon emissions. This suggests that many cities still adopted a high-emission, energy-intensive development model. The number of cities with expansive strong decoupling type 2 was identical to those showing strong decoupling type 1, both accounting for 14.1% of the total. This reflects the support these cities have given to the tertiary industries and their characteristic of not relying on heavy industries. It is noteworthy that cities exhibiting weak decoupling type 2 and weak decoupling type 1 account for 11.3% and 12.7%, respectively, and are mostly concentrated in Zhejiang and Shanghai. This indicates that these cities have made some progress in innovation city development.

Table 4. Proportions of different decoupling types within the study period.

Time	SD-II	SD-I	WD-II	WD-I	EC	END
2008–2013	14.1%	14.1%	11.3%	12.7%	4.2%	43.7%
2013–2018	19.7%	18.3%	15.5%	8.5%	12.7%	25.4%
2018–2022	31%	7.1%	14.1%	8.5%	4.2%	35.2%

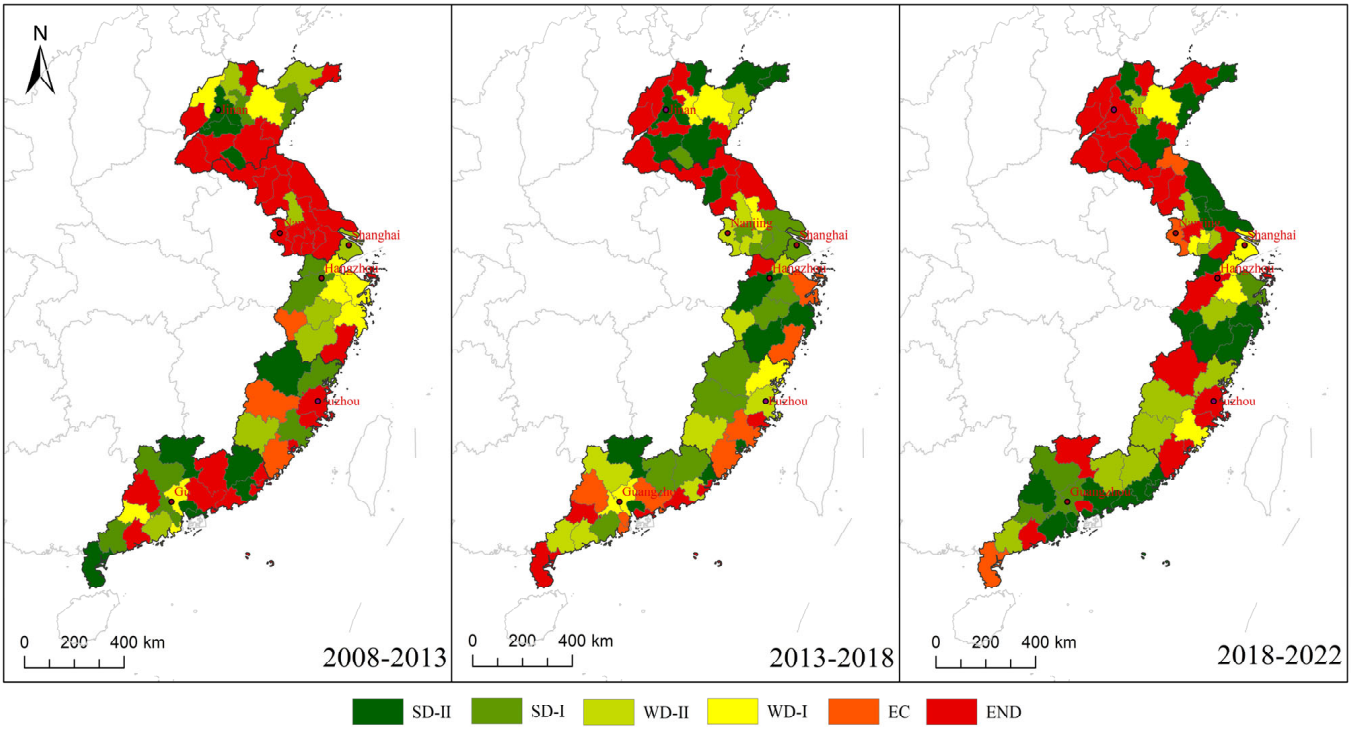

Figure 7. Spatiotemporal distribution of decoupling relationship between carbon emissions and innovation cities from 2008 to 2022.

From 2013 to 2018, within the study area, the decoupling relationship between carbon emissions and innovation city development among cities has undergone significant improvement. Notably, the proportion of expansive negative decoupling has decreased markedly, from an initial 43.7% to 25.4%. Concurrently, there has been an increase in the number of cities categorized as strong decoupling type 2, strong decoupling type 1, and weak decoupling type 2, highlighting the remarkable efficacy of reducing carbon emissions during the progression of innovation city development. According to Figure 7, cities such as Jinan, Jining, and Dezhou in Shandong Province, as well as Nantong, Suzhou, Wuxi, Zhenjiang, Changzhou, and Nanjing in Jiangsu Province, have exited the END status. These cities have increasingly shifted their focus towards the ecological environment, residents' quality of life, public facilities, and green economy.

From 2018 to 2022, the decoupling relationship within the study area still necessitated improvement, despite the rapid increase in the proportion of strong decoupling type 2, which rose from 19.7% to 31%, reaching its peak during the survey period. These cities are primarily located in the eastern Jiangsu Province, including Yancheng, Taizhou, and Nantong, as well as in the southern Zhejiang Province, encompassing Quzhou, Lishui, Wenzhou, and Taizhou. However, there has also been a notable increase in the proportion of expansive negative decoupling, which has risen from 25.4% to 35.2%. This indicates that some cities lack sufficient momentum for the transformation of traditional economic industries, and energy-intensive industries characterized by high pollution and high emissions still exist abundantly. Therefore, these cities should promptly transition towards green and low-carbon industrial development.

Primarily, the coexistence of multiple decoupling types between innovation city development and carbon emissions at the prefecture-level city scale is a notable characteristic within the study area. This phenomenon of coexisting decoupling types is expected to persist in the long term, with the proportions of strong decoupling and weak decoupling continuing to rise among the decoupling types. Research indicates that the spatiotemporal distribution of decoupling relationships among prefecture-level cities is significantly correlated with the mitigation of carbon emissions and the advancement of innovation initiatives in various cities. Figure 8 illustrates that type 2 strong decoupling is predominantly observed in eastern Shandong (driven by the "Blue-Yellow Economic Zone" policy promoting the marine economy and low-carbon industries), the coastal regions of Jiangsu (linked to the Jiangsu Coastal Development Strategy prioritizing renewable energy and smart manufacturing), southern Zhejiang (facilitated by the Digital Economy Innovation Zone policy accelerating tech-driven decarbonization), and coastal Guangdong (supported by the Greater Bay Area initiative integrating green finance and urban sustainability frameworks). This distribution is closely tied to national macro-policies, such as vigorously promoting the green economy, facilitating industrial restructuring, accelerating the transition from old to new growth drivers, enhancing energy efficiency, and fostering the construction of ecological civilization. In contrast, western Shandong and northwestern Jiangsu (exacerbated by the 2010s "Heavy Industry Revitalization Plan" that prioritized GDP growth over emission controls), where the industrial structure is heavily reliant on heavy industries, have long struggled with persistently high carbon emissions and have yet to join the ranks of innovation cities. Their decoupling status remains in an undesirable END state for an extended period, necessitating targeted policies for these cities.

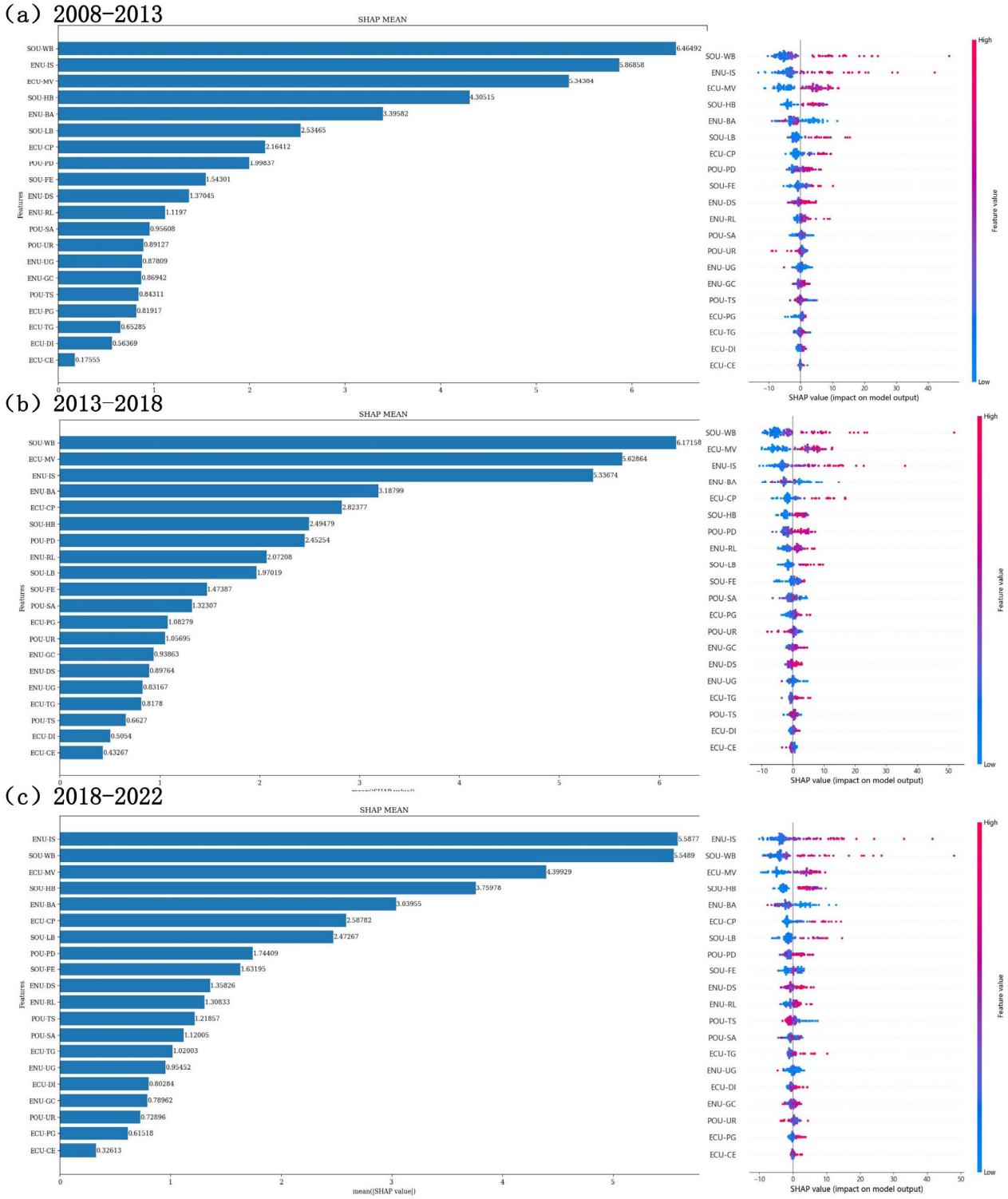

Figure 8. SHAP model results for factors influencing the decoupling of carbon emissions and innovation cities.

4.3. Influencing Factors

By applying the SHAP model, we examined the crucial components driving the decoupling between carbon emissions and innovation cities. Shapley values were used to measure the individual impact of every element. Those factors with substantial contributions were identified as critical in enabling the decoupling process, and the detailed analysis of those elements is presented in Figure 8.

Between 2008 and 2013, the elements with the greatest impact on decoupling degree, ranked in descending order, were SOU-WB, ENU-IS, BCU-MV, SOU-HB, and ENU-BA. From 2013 to 2018, the most influential factors, listed in descending order, were SOU-WB, ECU-MV, and ENU-IS. From 2018 to 2022, ENU-IS, SOU-WB, BCU-MV, and SOU-HB became the primary drivers of decoupling.

From the environment, population, society, and economy dimensions of this analysis, we discern different factors affecting decoupling in three time intervals. In the environmental dimension, during the study period, the expansion of industries and increased proportion of built-up areas had heightened environmental pressures, significantly impacting the decoupling process and resulting in a significant negative correlation between ENU-IS and the decoupling degree. Meanwhile, the enhancement of the ENU-BA system contributed to improving land-utilization efficiency and decreasing transportation needs, along with the related carbon emissions, resulting in a positive relationship.

In the population dimension, POU-PD demonstrated considerable influence from 2008 to 2022. The increase in population density may have led to an increase in carbon emissions from transportation and living. This results in a negative increase in the degree of decoupling. Therefore, in the long term, policy makers should encourage residents to adopt a lifestyle of low daily consumption, which will ultimately help reduce carbon emissions.

In the society dimension, SOU-WB exhibited a positive correlation with the decoupling index, which may be related to its ability to attract more professionals through higher social benefits, thereby reducing carbon emissions. Increasing other social welfare, in ways such as increasing the number of libraries, can enhance residents' awareness of environmental protection, enable more people to choose a low-carbon lifestyle, and further affect the decoupling process of carbon emissions and innovation cities.

In the economy dimension, both ECU-MV and ECU-CP are associated with the degree of decoupling. The increase in ECU-CP will affect people's consumption model, and with the prosperity of shopping malls, people may be more inclined to buy products with high energy consumption and high emissions, such as large household appliances, automobiles, etc., thereby indirectly increasing carbon emissions. Motor vehicles are one of the main sources of carbon emissions, and the increase in the ECU-MV number will lead to an increase in carbon emissions in the transportation sector. At the same time, it will lead to an increase in the consumption of fossil fuels such as oil, which has a significant negative impact on the decoupling process. The government should promote the green development of urbanization, optimize consumption patterns, improve energy efficiency, and lead by scientific and technological innovation to promote the reduction in carbon emissions. To develop effective emission reduction strategies, these factors need to be considered comprehensively.

5. Conclusions and Policy Recommendations

5.1. Conclusions

Based on the analysis presented above, against the backdrop of China's carbon peaking and carbon neutrality objectives, this paper delves into the spatiotemporal distribution characteristics of carbon emissions and the decoupling relationship between carbon emissions and innovation cities among prefecture-level cities in six coastal provinces and municipalities. Firstly, a comprehensive assessment is conducted on carbon emissions and the level of innovation in 71 prefecture-level cities within the study area. Following this, utilizing the Tapio decoupling model, an interpretation of the interplay between carbon emissions and innovation cities is provided, leading to the following conclusions.

From 2008 to 2022, the total carbon emissions within the study area exhibited a trend of increasing, fluctuating, and then increasing again. Spatially, the study area displayed

a pattern of higher carbon emissions in the north and lower emissions in the south, with particularly elevated levels in the central, western, and northern parts of Shandong, the northern section of Jiangsu, and the Yangtze River Delta region. Notably, while the carbon emissions of different cities and municipalities remained generally stable over time, specific locations experienced variations, marked by varying degrees of increases or decreases. These fluctuations can be primarily attributed to the transition from traditional to new economic drivers, the advancement of a green economy, and the impact of the COVID-19 pandemic.

Between 2008 and 2022, the level of smart cities in each city within the study area improved to varying degrees. However, as time progressed, the disparities in smart city development among these regions also widened. As of 2022, most northern cities in the study area, including the majority of cities in Shandong, the entire territory of Jiangsu, and Shanghai, along with all cities except Lishui, have entered the ranks of high-level innovation cities, forming a high-speed development belt centered on Jiangsu and Shanghai. Conversely, the western parts of Fujian and Guangdong have a lower degree of smart innovation cities, with the exception of the central region. Some cities achieved rapid development due to their focus on the green economy, industrial transformation, and the port economy, while cities with slower innovation progress need to adopt targeted policies to revise their development plans.

From 2008 to 2022, positive advancements were achieved in examining the decoupling status between carbon emissions and smart city development within the study area. The states transitioned from "Expansive Negative Decoupling (END)" and "Expansive Coupling (EC)" towards "Strong Decoupling (SD)" and "Weak Decoupling (WD)". During the period from 2008 to 2013, the decoupling situation within the study area was less than optimal, with 43.7% of the regions falling into the END state. Notably, Jiangsu and Shandong provinces had a preponderance of cities relying on high-energy consumption and high-emission development strategies. Between 2013 and 2018, the decoupling situation improved, with a notable decrease in the proportion of END states. City development strategies began to shift away from high-energy consumption and high-emission modes towards green economy and digital economy paradigms, placing greater emphasis on social welfare, ecological conservation, and infrastructure development. From 2018 to 2022, the proportion of type 2 strong decoupling increased rapidly, with coastal cities demonstrating even more favorable decoupling conditions.

The essence of the regional decoupling difference is the product effect of "policy execution force × technology reserve × market response". The Yangtze River Delta has formed a virtuous circle through policy innovation (such as Zhejiang's "hero per mu" reform), technological investment (Jiangsu's CNY 3 billion special fund), and market mechanisms (Shanghai Carbon Finance); the northern industrial belt needs to strengthen policy constraints (such as carbon quota tightening), technology introduction (hydrogen energy, CCUS), and ecological compensation to break through path dependence. Future regional policies should be differentiated, in ways such as focusing on supporting industrial green transformation in Shandong and Hebei and strengthening the expansion of carbon markets in the Yangtze River Delta, so as to narrow the regional gap in the decoupling process.

5.2. Policy Recommendations

This paper delves into the spatiotemporal evolution patterns and decoupling trends of carbon emissions and innovation city development across prefecture-level cities in six coastal provinces and cities in China. Such an exploration holds significant importance for establishing an evaluation theoretical framework of carbon emissions and innovation city development from a micro perspective. Meanwhile, it also possesses immediate practical

value for the planning of innovation cities at the prefecture level and the promotion of a sustainable low-carbon pathway. The results of this study can provide empirical support and actionable insights to promote the advancement of high-quality innovation city development, enhance urban–rural integration, and facilitate the decoupling process of carbon emissions.

Governments should focus on the mitigation potential of high-emission cities while integrating the reduction measures employed by low-emission cities to explore and implement cross-city emission reduction strategies. On one hand, high-carbon emission cities constitute key regions for carbon mitigation. Continuous efforts are imperative in advancing the low-carbon transformation of energy structures, optimizing industrial structures to decrease emissions, and comprehensively enhancing resource use efficiency, thereby curbing the growth of carbon emissions at the source. On the other hand, for low-emission cities, it is essential to augment the functionality of natural carbon sinks, including the establishment of nature reserves and strengthening land-use planning and management.

In the short term, policy makers need to prioritize the establishment of cross-city carbon emission reduction cooperation platforms, promote technology sharing between high-emission cities and low-emission cities, and achieve carbon intensity reduction through energy structure adjustment and industrial process optimization. For the weak innovation areas in the south, a special fund can be set up to support the research and development of green technologies, improve the carbon emission trading mechanism simultaneously, and use market means to stimulate low-carbon transformation. It is suggested that digital tools should be used to dynamically monitor urban carbon footprint, and differentiated control schemes should be developed based on seasonal emission characteristics to ensure that short-term emission reduction targets can be quantified and traceable.

In the long term, a three-part development framework of "industry–innovation–ecology" should be built: leading innovative cities in the north should continue to invest in basic research and cultivate low-carbon technology industry chains; southern cities can rely on ecological advantages to develop the carbon sink economy and establish ecological compensation mechanisms. Long-term planning needs to embed the dual transformation path of industrial digitalization and the green economy, in ways such as transforming traditional manufacturing through the industrial Internet and promoting intelligent emission reduction systems in transportation and construction.

Within the cities of the study region, there exists spatial heterogeneity in the levels of innovation cities, with those in the northern region significantly outperforming those in the southern region. Therefore, regions in the south with relatively lagging levels of innovation city development should be the focus of attention to narrow the development gap. When formulating policies, full consideration should be given to local characteristics, resource conditions, and competitive advantages. For example, in regions with limited economic infrastructure but rich ecological assets, prioritizing the growth of the service sector and fostering eco-friendly economic practices are essential for advancing innovation-driven urbanization. Conversely, in economically developed cities, optimizing resource allocation, advancing industrial digital transformation, and pursuing low-carbon development pathways are essential to ensure sustained and robust growth in innovation city levels. Furthermore, the expansion of transportation networks and the adjustment of industrial structures are also effective means of promoting the enhancement of innovation urbanization.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

SHAP	SHapley Additive exPlanations
END	Expansive Negative Decoupling
EC	Expansive Coupling
WD	Weak Decoupling
SD	Strong Decoupling

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