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Research on the Spatial Pattern of Carbon Emissions and Differentiated Peak Paths at the County Level in Shandong Province, China

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Abstract: In the pursuit of China's carbon peak and carbon neutrality objectives, county-level areas assume a pivotal role in orchestrating diverse initiatives for low-carbon development. However, empirical evidence is limited. This paper aims to fill this gap by exploring the driving factors of carbon peak and carbon peak path at the county level, using Shandong Province as a case study. Employing data related to economic development, industrial structure, land utilization, energy consumption, and emission characteristics, a principal component analysis (PCA) was utilized to extract the following five driving factors of carbon peak: green transformation, urbanization, industrial construction, energy consumption, and environmental constraints. Subsequently, K-means clustering identified five cluster areas: (1) agricultural transformation pending area, (2) low-carbon lagging area, (3) industrial transformation area, (4) low-carbon potential areas, and (5) low-carbon demonstration area. Based on these areas, this study further elucidates spatial combination models of carbon peak within the urban system, spanning central cities, coastal cities, resource-based cities, and agricultural cities. The paper enhances comprehension of the integral role county-level areas play in achieving China's carbon reduction objectives. By providing nuanced insights into diverse developmental trajectories and spatial interactions, the study contributes to effective low-carbon strategy formulation. The findings underscore the importance of considering specific county attributes in urban areas to devise precise optimization strategies and trajectories, ultimately facilitating the realization of carbon peak goals.

Keywords: carbon emission; driving factors; differentiated peak paths; cluster analysis; county; Shandong

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1. Introduction

The greenhouse effect and ecological environmental issues resulting from carbon emissions have presented significant challenges to sustainable development in recent years [1,2]. China, in particular, has experienced rapid industrialization and urbanization since the 1980s, resulting in substantial socioeconomic progress. However, this growth has been accompanied by a continuous increase in the scale and intensity of carbon emissions [3,4]. China has held the title of the world's largest CO_2 emitter since 2007, contributing to a staggering 28% of global carbon emissions in 2019 [5]. Consequently, China's forthcoming endeavors to curtail emissions will play a pivotal role in the global pursuit of limiting global warming to 1.5 °C [6]. Acknowledging the escalating importance of carbon reduction, China has established ambitious targets, aiming to peak CO_2 emissions before 2030 and achieve carbon neutrality by 2060 [7]. Given regional variances, burden-sharing complexities, policy innovation, and the enhancement of local competitiveness and development, individual provinces have emerged as key actors in realizing the dual carbon strategy within this strategic framework [8,9]. Therefore, it is imperative to gain a scientific understanding of the spatial disparities and evolutionary trends in regional carbon emissions, accounting for the diverse development objectives and priorities of different stakeholders. This knowledge is vital for formulating effective strategies for carbon control and emission reduction, particularly in light of the dual challenges posed by economic growth and future "dual carbon" targets.

In response to the increasingly pressing global issue of climate change, which has garnered significant international attention, scholars have made substantial progress in addressing the challenges of carbon reduction. In the early stages of this research, a primary focus was on accurately predicting the scale of carbon emissions. This involved the development of diverse measurement methods and frameworks to assess and quantify various aspects related to carbon emissions [10–13]. Subsequent studies delved into regional carbon emission measurements, using them to comprehensively examine the multifaceted factors contributing to variations in carbon emissions. Researchers, for instance, constructed various frameworks to investigate the role of carbon emissions, analyzing driving factors such as population, per capita GDP, energy consumption intensity, and carbon intensity [13]. Notably, these studies identified an inverted 'U' curve relationship between GDP and carbon emissions, signifying diminishing marginal benefits of carbon emissions as the economy reaches a certain level of growth [14]. Analyses of energy consumption characteristics across different countries have revealed that energy intensity plays a significant role in controlling carbon emissions [15]. Additionally, researchers have identified population growth as a driver of carbon emissions scale, particularly in urban areas with significant population agglomeration [16]. Panel statistics analysis has underscored the pivotal role of the secondary industry in urban carbon emissions, emphasizing the optimization of industrial structure as a crucial pathway toward achieving low-carbon development [17]. Furthermore, various measures, such as the promotion of industrial structure rationalization, the adoption of innovation development strategies, and the enhancement of technological innovation, have proven to be effective in reducing carbon emissions [18].

As China's carbon reduction efforts have garnered global attention, an increasing volume of research has been dedicated to understanding various aspects of carbon emissions within the country. This includes studying carbon emissions from different industries, regions, and energy consumption patterns [19]. Additionally, scholars have delved into the exploration of the technological, policy, and economic factors necessary for transitioning China's energy production and consumption towards a low-carbon trajectory [20,21]. Moreover, researchers have examined the establishment and development of carbon market mechanisms in China [21,22] and evaluated the effectiveness and impact of China's carbon reduction policies [23,24]. Many of these studies have relied on regional and provincial panel data to offer empirical evidence through heterogeneity analysis across provinces and thus support provincial energy transition and industrial upgrading policies. As carbon reduction research continues to advance in terms of spatial and temporal granularity, an increasing number of studies are examining the spatial distribution and evolutionary characteristics of regional carbon emissions from a space–time perspective. These endeavors aim to unveil the effects and influences of human activities on carbon emissions by scrutinizing factors such as city size, economic development patterns, level of international cooperation [25], urban land use, industrial structure, consumption behavior [26], and the selection of action paths for reducing carbon emissions [27].

In summary, research on carbon emissions at the provincial level has provided valuable insights into regional characteristics and underlying influences. Additionally, studies examining spatiotemporal patterns and evolution across multiple regions, scales, and timeframes are gaining prominence. However, it is crucial to recognize two key limitations. Firstly, using cities as spatial analysis units might overlook variations in socioeconomic and industrial development within cities and counties. While micro-county units are considered more appropriate for studying resource utilization and administration, research focused on them remains scarce, potentially restricting our comprehension of local carbon emission dynamics. Secondly, the absence of comprehensive analysis on dominant factors driving carbon peak scenarios hampers the classification of regional carbon peak types and formulation of differentiation paths for carbon emission peak types. Addressing these limitations represents a significant enhancement to the current research within urban contexts. This effort will lead to a deeper understanding of carbon emissions at a more intricate and granular level, thereby facilitating the development of effective carbon reduction strategies. Furthermore, a comprehensive analysis of the predominant factors influencing carbon emissions will provide substantial support for categorizing, formulating, and executing emission peak trajectories across diverse regions.

In this study, Shandong Province serves as an illuminating case study, offering a comprehensive microcosm of substantial significance. Being one of China's economic powerhouses, Shandong exemplifies the intricate interplay between economic growth and its corresponding environmental consequences. The province's unique composition encompasses a wide range of industrial, agricultural, and residential activities across various counties, including urban, suburban, and rural areas. These activities work in synergy to contribute to its overall carbon emissions. The unveiling of the intricate carbon emission patterns within this distinctive geographic context is pivotal, not only for crafting localized mitigation strategies but also for yielding invaluable insights into broader trends. The primary focus of this paper is to comprehensively address the closely interrelated influencing factors of the carbon peak pathway. To achieve this, we establish an evaluation index system for carbon peak trends, which incorporates key elements such as population, economy, land usage, and carbon emissions. The framework is established using principal component analysis (PCA) and k-means cluster analysis. Specifically, two key questions will be answered: (1) What are the key factors driving carbon peak? (2) What is the spatially differentiated pattern of carbon peak features, and how does the typical spatial combination model manifest in different types of cities? (3) What are the pathways to achieve different types of carbon peaks, considering their varying levels of development and differences in industrial structure?

2. Methodology and Data

2.1. Study Area and Data Source

Shandong Province, situated along the eastern coast of China, was selected as the study area. It is important to note that Shandong has consistently reported carbon emissions per capita and intensity figures that surpass the national average. As a province with a large population and considerable economic importance, Shandong stands out due to its diverse industrial landscape, high levels of energy consumption, and significant agricultural activities, all of which contribute significantly to its substantial carbon emissions. The administrative division of Shandong Province consists of 17 prefecture-level cities and 139 county-level administrative divisions, encompassing both counties and county-level cities.

This study utilized four data sources. Firstly, vector data for administrative divisions were acquired from the map of Shandong (http://www.sdmap.gov.cn/ (accessed on 8 August 2023)). Secondly, socioeconomic data primarily from the 2018 Shandong Statistical Yearbook, along with relevant statistical yearbooks and communiqués at the municipal level, were supplemented. District gross national product (GDP) was revised using data from the fourth economic census. Thirdly, data on land use status and change were based on the latest results of the third land survey. Fourth, data on carbon emissions in 2017 were obtained by processing energy data from the China Bureau of Statistics using the apparent energy consumption estimation method. Finally, county-level energy consumption data for the year 2017 was sourced from the study conducted by Chen et al. (2022). (https://figshare.com/articles/dataset/City-_and_county-level_spatio-temporal_energy_consumption_and_efficiency_datasets_for_China_from_1997_to_2017/19196780/1 (accessed on 8 August 2023)) [28].

2.2. Data and Methods

2.2.1. Hotspot Analysis of Carbon Emissions: Getis–Ord Statistic

We initially performed a normality test on carbon emissions at the county level in 2017. The results of this test indicated that carbon emissions did not conform to a normal distribution. This deviation from normality made them suitable for the application of the Getis–Ord Gi* statistics. Subsequently, we employed the Getis–Ord statistic to identify hotspots of carbon emissions. This statistical test is designed to determine whether clusters of emissions are statistically significant. The resulting z-scores signify either high or low values of neighboring features. High z-scores do not necessarily indicate statistically significant hotspots. To be classified as a statistically significant hotspot, a feature should exhibit both a high z-score and be surrounded by other features with high z-scores. A positive z score indicates a hotspot, and the larger the z scores, the more intense the clustering, while a z score indicates a cold spot and the smaller the z score indicates a more intense clustering of low values (cold spot). The Getis–Ord General G and Getis–Ord local statistics are given as Equations (1) and (2):

$$G(d) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}x_i x_j}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j} \tag{1}$$

$$G_i^*(d) = \frac{\sum_{j=1}^{n} w_{ij}x_i}{\sum_{j=1}^{n} x_i} \tag{2}$$

where n is the number of spatial units, x_i is the attribute value for feature i, x_j is the attribute value for feature j, and w_{ij} is the spatial weight between feature i and j.

2.2.2. Influencing Indicators System for Carbon Peak

Based on the existing literature [17,18,29], this paper selects influencing factors closely related to carbon emissions and carbon peak and constructs the carbon peak trend evaluation index system. As presented in Table 1, the index system encompasses the following 12 indicators: per capita carbon emissions, population size, economic level, and industrial structure (regional GDP, per capita GDP, government budget, residents' savings depository balance, second industry, territorial industry), land use (land), and energy consumption and environmental protection (energy consumption, PM2.5). From a theoretical standpoint, the variables do not strictly adhere to an absolute normal distribution. However, considering that the kurtosis absolute value is less than 10 and the skewness absolute value is less than 3, and when examining the normal distribution plot, it can be reasonably characterized as broadly conforming to a normal distribution.

Table 1. Carbon peak evaluation index system.

NO.	Indicator	Description	Mean	Std. Dev.	Max	Min	Kurtosis	Skewness
X1	Per capita carbon emissions	The amount of carbon dioxide emissions produced by an individual on average (metric tons per person)	0.09	0.05	0.41	0.01	7.38	2.13
X2	Population size	The total count of individuals living in a given area or region. (Number of individuals)	74.49	31.42	175.63	21.91	0.66	0.92

Table 1. *Cont.*

NO.	Indicator	Description	Mean	Std. Dev.	Max	Min	Kurtosis	Skewness
X3	Construction land	The percentage of land area dedicated to construction or urban development. (%)	0.19	0.14	0.95	0.06	3.18	3.32
X4	Government general budget	The total amount of money spent by the local government from the general budget. (CNY 100 million)	53.43	32.95	23.10	18.65	9.83	2.70
X5	Residents' savings deposit balance	The total balance of savings deposits held by urban and rural residents, measured in CNY 10 thousand. (CNY 100 million)	340.37	227.36	1173.12	90.74	2.30	1.26
X6	Regional GDP	The total value of goods and services produced within a specific region, measured in the local currency. (CNY 100 million)	441.91	331.63	2765.69	84.10	6.93	3.10
X7	Per capita GDP	The average value of goods and services produced per person within a given region, measured in the local currency. (Unit of currency per person)	7.28	5.55	34.62	1.79	5.68	2.13
X8	Secondary industry	The percentage contribution of the secondary industry (manufacturing, construction) to the overall economic output. (%)	0.45	0.10	0.66	0.08	1.42	−0.91
X9	Tertiary industry	The percentage contribution of the tertiary industry (services, commerce) to the overall economic output. (%)	0.50	0.12	0.89	0.28	1.14	1.09
X10	Energy consumption	The quantity of standard coal consumed per CNY 10 thousand of GDP (tons of standard coal per CNY 10 thousand GDP)	1.58	0.80	6.06	0.06	9.20	2.33
X11	PM2.5 emissions	The overall quantity of particulate matter with a diameter of 2.5 μm or less released into the atmosphere in a year (10 thousand metric tons)	5.69	2.68	13.65	0.11	0.151	−0.80
X12	Environmental protection penalty	The total count of legal cases or instances where penalties have been imposed for violating environmental protection regulations. (Count)	17.27	32.37	198.00	0.00	9.28	2.80

2.2.3. Identifying Key Factors Driving Carbon Peak: PCA

The carbon emission level is a complex and extensive system with multiple interacting factors and significant differences exist among its elements. Principal component analysis (PCA) [30] aims to identify a few new variables (principal components) that are independent of each other through variable transformation, with minimal information loss. These new variables represent a linear combination of the original variables, reflecting the information contained in the original variable index to the greatest extent while being independent of each other. In this study, principal component analysis was conducted for the 12 indicators, and the principal components with a cumulative contribution rate of 85% and above were extracted as the main factors influencing carbon peak. Given that a large number of variables make any worthwhile judgment and interpretation impossible, the method of Quartimax rotation in PCA that yields the most interpretable results was applied to the matrix. The composite score of the main factor was then calculated as follows:

$$\begin{cases} z_1 = l_{11}x_1 + l_{21}x_2 + \ldots + l_{p1}x_p \\ z_2 = l_{12}x_1 + l_{22}x_2 + \ldots + l_{p2}x_p \\ z_m = l_{1m}x_1 + l_{2m}x_2 + \ldots + l_{pm}x_p \end{cases} \tag{3}$$

In this context, z_m represents the score of the m-th principal component, x_p denotes the standardized value of the p-th original variable, and l_{pm} stands for the loading coefficient of the p-th original variable in the m-th principal component.

2.2.4. Segmenting Carbon Peak Area Systems: K-Means

The principal components obtained from principal component analysis are saved as variables, and the principal element score is calculated using Formula (3). Subsequently, the K-means clustering algorithm is applied to cluster the dominant factors, with three to eight different clustering schemes attempted. The cluster schemes with shorter class spacing are selected, and the results are visualized in ArcGIS to analyze the spatial distribution of the carbon peak area.

The Kruskal–Wallis test (K–W test) is employed to examine whether there are significant differences in the overall distributions of multiple independent samples. In this context, it is used to assess the various components across different clustering areas. The significance level, denoted as α, is set to 0.05. If the p-value from the test is less than 0.05, the null hypothesis is rejected, indicating that there is a significant difference in the visitation rates of tourists from different household life cycles at the 0.05 significance level. Conversely, if the p-value is greater than 0.05, it suggests that there is no significant difference.

The clustering process involves the random selection of K samples as initial cluster centers, calculating the distance or similarity between samples using formula (2), and then allocating the samples to homogenous clusters based on the principle of the nearest center distance.

$$d\left(X'_{mj}, X'_{nj}\right) = \sum_{K=1}^{q} \left(X'_{mj} - X'_{nj}\right)^2 \tag{4}$$

In this context, K represents the number of categories, q denotes the dimensions of cluster indicators, and X'_{mj} and X'_{nj} refer to the standard values for the j indicators of units in group m and group n, respectively.

3. Results

3.1. Spatial Pattern of Carbon Emissions at the County Level

In this study, we employed the natural breaks method to examine the spatial distribution of the carbon emissions at the county level in Shandong for the year 2017, as depicted in Figure 1a. The findings revealed that there is an east–west pattern of carbon emissions, with the highest emissions observed in east coast cities. Carbon emissions in each city exhibit a looped pattern, featuring lower emissions in the inner city, substantial increases in the surrounding counties, and subsequent declines in the outermost counties. Moreover, the global spatial autocorrelation results demonstrated that the Getis–Ord General G value for carbon emissions was greater than 0 and passed the significance test, signifying the presence of spatial autocorrelation in this study. Then, using Getis–Ord GI* analyses, we found that carbon emissions exhibited a notable spatial clustering pattern. As illustrated in Figure 1b, the hot spots are situated in the northeast, specifically in Dongying, Qingdao, and Weihai. These counties rely on coastal cities to leverage port trade and have developed industries with high carbon emissions, notably in the petrochemical sector. On the other hand, the cold spots are dispersed in the outermost counties of inland cities in the west and center, primarily encompassing rural areas with comparatively lower socio-economic levels.

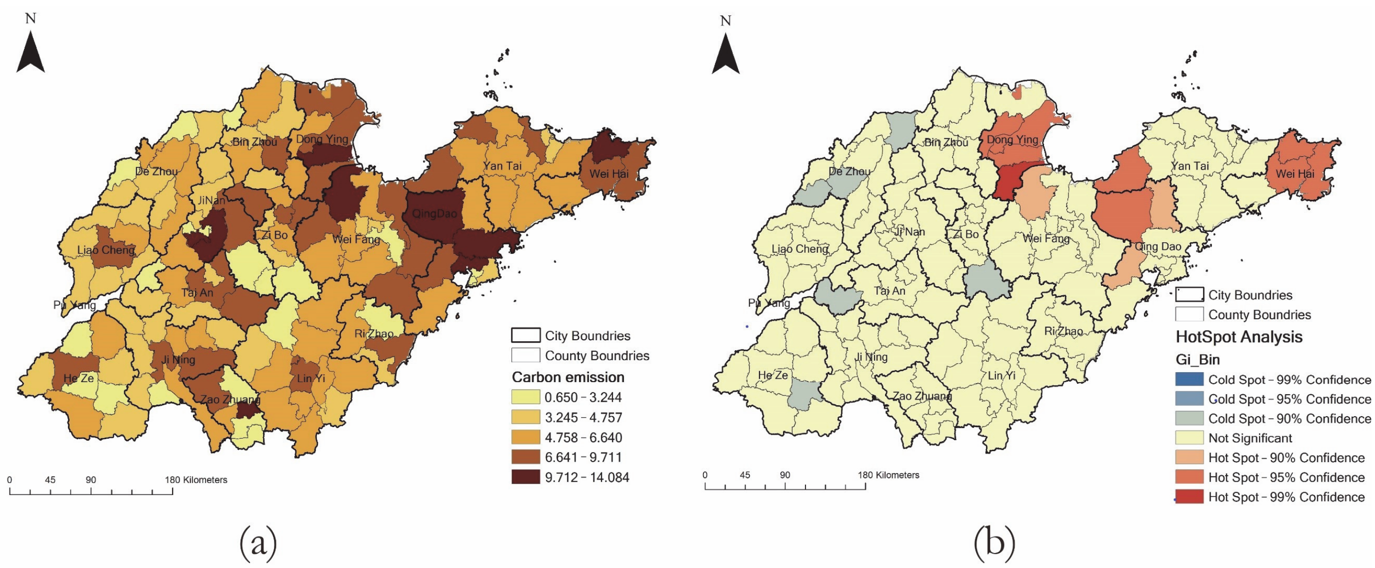

Figure 1. Spatial pattern of carbon emissions in 2017 (**a**) Spatial distribution of carbon emissions (**b**) cold and hot spot of carbon emissions.

3.2. Driving Factors of Carbon Peak at the County Level

The 12 variables presented in Table 1 after nine iterations when a Quartimax rotation method was selected. The Kaiser–Meyer–Olkin (KMO) measure resulted in a value of 0.696, and the Bartlett spherical assay p-value was 0.000, both meeting the criteria for factor analysis (KMO > 0.5, $p < 0.05$). Subsequently, five common factors were extracted based on the principle of eigenvalue > 1 and cumulative interpretation of over 80% (Table 2).

Table 2. Principal component weight results.

Component	Eigenvalues	Percentage of Variance (%)	Cumulative Variance Explanation Rate (%)
Component 1	3.38	28.168	28.168
Component 2	2.622	21.851	50.018
Component 3	1.856	15.463	65.481
Component 4	1.284	10.699	76.18
Component 5	1.189	7.454	83.635

To improve the interpretability of the common factor on the carbon peak at the county level, we applied rotation to the load matrix, resulting in the rotated component matrix presented in Table 3. In general, the components derived from the PCA encompass urbanization, industrial economy, energy consumption, and other classical factors that influence carbon emissions during socio-economic development. Additionally, these factors include characteristic indicators that reveal the trend of low-carbon transformation in the region such as ecological conservation and green innovation.

Table 3. Rotated component matrix.

NO.	Indicator	Component 1	Component 2	Component 3	Component 4	Component 5
X1	Per capita carbon emissions	−0.318	0.185	0.703	0.398	−0.370
X2	Population size	0.052	0.594	−0.725	−0.042	0.133
X3	Construction land	0.784	0.096	0.274	−0.298	0.091
X4	Government general budget	0.178	0.832	−0.002	−0.174	−0.100
X5	Residents' savings deposit balance	−0.027	0.801	−0.087	0.211	0.171
X6	Regional GDP	0.012	0.730	0.159	−0.545	−0.129
X7	Per capita GDP	0.311	0.478	0.682	−0.182	−0.173
X8	Secondary industry	−0.874	0.046	0.103	−0.080	0.166
X9	Tertiary industry	0.880	0.218	0.025	0.010	−0.058
X10	Energy consumption	−0.044	−0.070	0.057	0.935	−0.033
X11	PM2.5 emissions	−0.106	0.018	−0.150	−0.023	0.952
X12	Environmental protection penalty	−0.510	0.264	−0.705	0.140	−0.025

Component 1 can be named "Green Transformation Component". It is characterized by its high correlations with certain indicators, notably X3 construction land (0.784), X9 tertiary industry (0.880), and X8 secondary industry (−0.874), while X1 per capita carbon emissions (−0.318) exhibits a relatively low correlation. These indicators collectively signify a shift in counties away from traditional industrialization pathways towards more energy-efficient and low-carbon service sectors. Based on the component scores (Figure 2a), a notable loop effect was observed in each city, with the highest scores found in the central counties and gradually decreasing towards the outer areas. This observation highlights that the impact of green transformation was most pronounced in the urban core areas.

Component 2 can be named the "Urbanization Component". It is characterized by its high correlations with indicators, notably X2 population size (0.594), X4 government general budget (0.832), X5 residents' savings deposit balance (0.801), and X6 regional GDP (0.730). These correlations unveil patterns of urbanization closely associated with the size of regional population concentrations and levels of economic affluence. An examination of the component scores (Figure 2b) reveals that the eastern urban counties exhibit higher levels of urbanization compared to their western counterparts. Within each city, most of these counties comprise newly developed urban areas and enjoy certain advantages in terms of overall population and socio-economic development.

Component 3 can be named the "Industrial Construction Component". It exerts a discernible positive influence on indicators such as X1 per capita carbon emissions (0.703) and X7 per capita GDP (0.682). Moreover, the indicator X8 secondary industry (0.103) demonstrates a relatively high positive correlation. Conversely, indicators such as X2 population size (−0.725) and X12 environmental protection penalty (−0.705) exhibit negative impacts. These patterns unveil an industry-centric development model within the region, accompanied by associated carbon emissions and environmental pollution challenges. Based on the component scores (Figure 2c), it becomes evident that the level of industrial development in the counties of eastern and northern cities generally surpasses that in the southern and western regions. This discrepancy is particularly pronounced in the majority of counties in northern and eastern cities, such as Dongying, Yantai, and Weihai, as well as in parts of Jinan and Zibo in central cities.

Component 4 can be named the "Energy Consumption Component" with X10 energy consumption (0.935) being the only significant positive factor. Additionally, X3 construction land (−0.298), X6 regional GDP (−0.545), and X7 per capita GDP (−0.182) serve as significant negative indicators. These findings highlight the substantial challenges associated with achieving sustainable development due to serious structural and efficiency problems in the utilization of energy resources in the examined areas. When examining the component scores (Figure 2d), it becomes apparent that the overall spatial pattern of energy consumption and industrial construction components displays a degree of convergence, implying a reliance of industrial construction on energy consumption. However, the energy consumption and industrial construction in Jinan, Weihai, and Qingdao do not exhibit consistency, suggesting that the counties in these cities are largely free from high energy consumption.

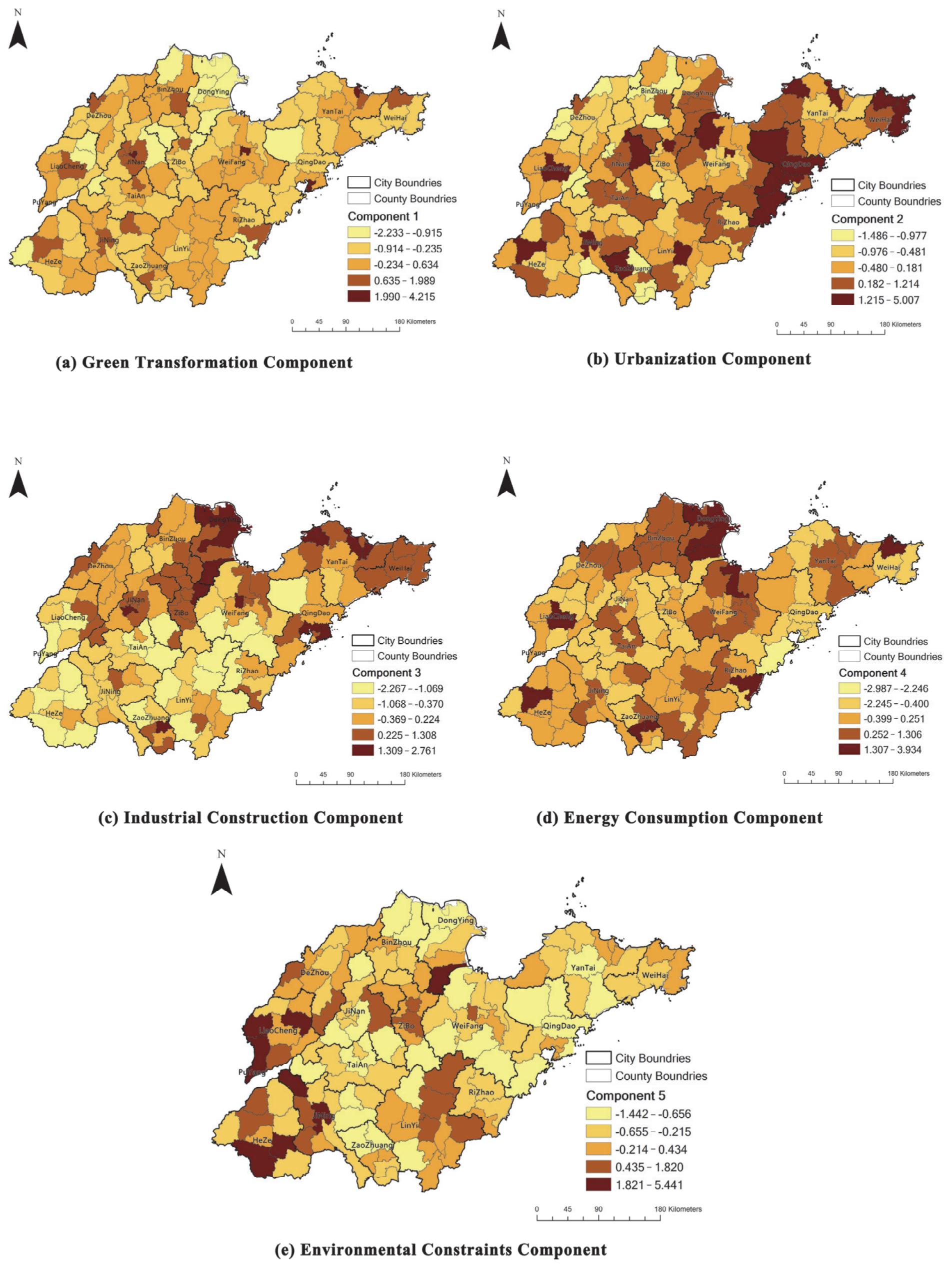

Figure 2. Spatial pattern of component of carbon peak at the county level.

Component 5 can be named the "Environmental Constraints Component" characterized mainly by X11 PM2.5 emissions (0.952) with dominant influence, and the negative indicator X1 per capita carbon emissions (−0.370) with relatively high coefficients. These findings indicate a close relationship between the regional carbon emissions problem and the ecological environment. Based on the component scores (Figure 2e), the environmental restriction level is highest in the west and south, particularly in certain counties of Liaocheng, Heze, and Jining. Notably, these regions exhibit lower levels of socio-economic development, indicating that the industrial development of these counties is more challenging and has a more pronounced ecological impact.

In general, PCA extracted 5 components, including urbanization, industrial construction, and energy consumption, which are classical influencing factors that reflect the long-term social and economic development and accumulation in the region [15,17,19]. Additionally, the components of green transformation and environmental constraints depict the region's capacity to transform and develop in line with China's ecological civilization principles, especially following the introduction of carbon-neutral strategies [31,32].

3.3. Carbon Peak path at the County Level

The carbon emission peak characteristics of county-level regions in Shandong Province can be categorized into five cluster areas (Table 4, Figure 3). The spatial pattern of the carbon peak is illustrated in Figure 4.

Table 4. Identification of clusters.

Cluster Area	Component 1 Green Transformation component	Component 2 Urbanization Component	Component 3 Industrial Construction Component	Component 4 Energy Consumption Component	Component 5 Environmental Constraints Component
Agricultural transformation Pending area	−0.19	−0.52	−0.23	0.03	−0.25
Low-carbon lagging area	−0.03	0.27	−0.35	0.06	2.36
Industrial transformation area	−0.02	0.71	1.36	2.48	−0.23
Low-carbon potential area	−0.43	1.32	0.13	−0.63	−0.36
Low-carbon demonstration area	2.61	−0.27	0.69	−0.96	−0.27

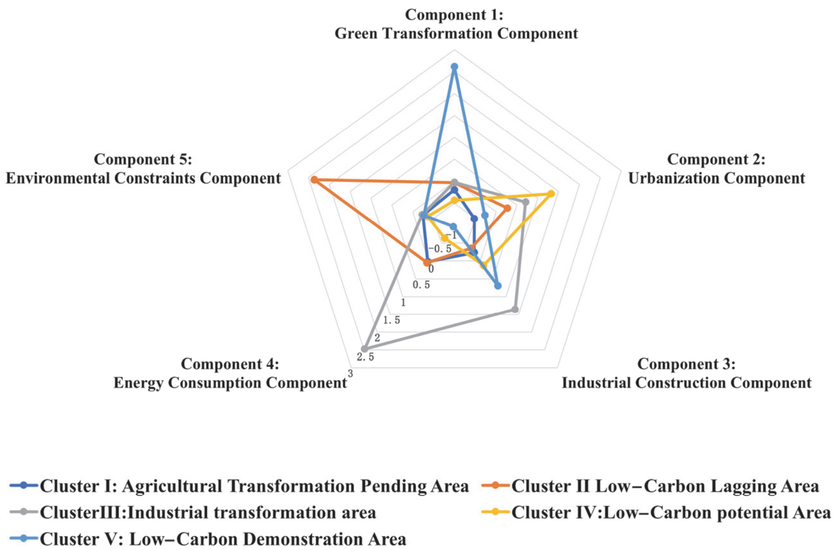

Figure 3. Radar chart of the average scores of components for cluster areas.

Cluster I, referred to as the "Agricultural Transformation Pending Area", comprises 79 counties, accounting for 58.1 percent of the total. These areas are primarily concentrated in eastern Shandong Province, with the majority located in inland regions. At the city level, they are mainly situated in peripheral urban and rural fringe areas. The scores of these areas are relatively balanced, but they all remain at a low level, particularly exhibiting the lowest scores for urbanization component (Component 2), which further highlights the underdeveloped status of regional development. Additionally, the subpar scores for industrial construction component (Component 3) and the green transformation component (Component 1) indicate structural obstacles associated with a single economic structure and a weak industrial base.

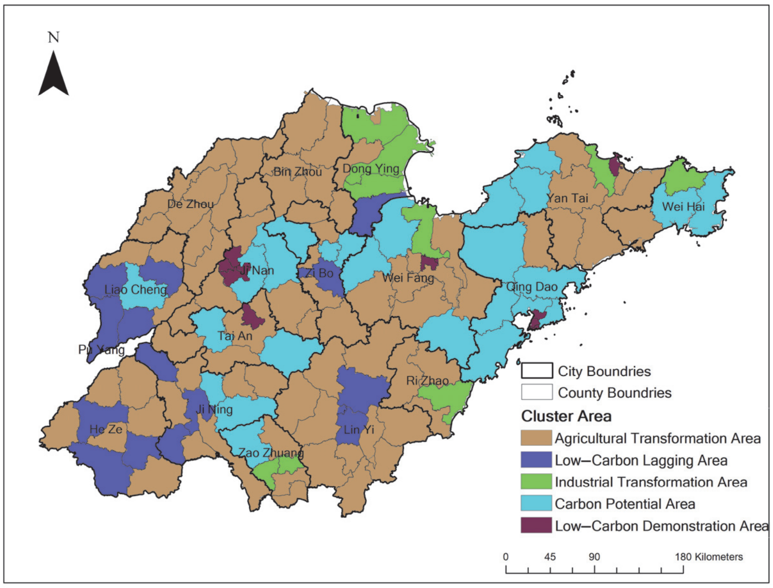

Figure 4. The spatial pattern of carbon peak at the county level in Shandong Province.

Cluster II, referred to as the "Low-Carbon Lagging Area", comprises 15 counties, accounting for 11 percent of the total. These areas are primarily located in the western part of Shandong Province, with some scattered in the central area. Although the urbanization component (Component 2) score falls within the middle range, indicating an average level of socio-economic development in the affected areas, the notably low score for the industrial construction component (Component 3), along with high scores for energy consumption component (Component 4) and environmental constraints component (Component 5), indicates that the traditional industrial structure is the primary factor influencing regional carbon emissions and environmental protection.

Cluster III, referred to as the "Industrial Transformation Area", comprises 11 counties, accounting for 8.1 percent of the total. These areas are typically situated in coastal port cities in eastern Shandong Province. The scores for industrial construction component (Component 3) and energy consumption component (Component 4) in this category are significantly higher than in other types, indicating that the leading industrialization process has contributed to a good level of economic development in the region. However, it is crucial to highlight that the elevated score for the environmental constraints component (Component 5) also signifies their significant reliance on the secondary sector, where the scale and intensity of industrial carbon emissions are significantly higher than in equivalent units, leading to a sharp contradiction between environmental pollution and ecological protection.

Cluster IV, referred to as the "Low-Carbon Potential Area", consists of 22 counties, accounting for 16.2 percent of the total. This category is primarily concentrated in the outskirts of Jinan and Qingdao, the most developed cities in Shandong Province, with some scattered in the central areas of the main cities in the east and south. The urbanization component (Component 2) scores in these areas are the highest, aligning with their long-term development factors, such as population, capital, and land agglomerations, reflecting their favorable social and economic conditions. Although the low scores for environmental constraints component (Component 5) and energy consumption component (Component 4) partly indicate the trend of green transformation through regional industrial structure upgrading and efficient energy utilization, the very low score for green transformation component (Component 1) indicates that regional development is still in the transitional stage of structural optimization.

Cluster V, referred to as the "Low-Carbon Demonstration Area", consists of 9 counties, accounting for 6.6 percent. These areas are all located in the urban centers of leading cities in the province, including Jinan, Qingdao, Yantai, and Weifang. Compared to other types, this cluster shows higher scores for industrial construction component (Component 3) and the green transformation component (Component 1), while exhibiting a significant negative influence of energy consumption component (Component 4) and environmental constraints component (Component 5). These findings suggest that the region has successfully departed from the traditional path of urbanization and industrialization and currently finds itself in the latter stages of the "inverted U-shaped" relationship between economic development and carbon emissions. As a result, this cluster area has achieved a remarkable level of economic development with low carbon emissions. The low-carbon model in this region is evidently effective, as the transformation of the industrial structure has largely been accomplished, and a clear decoupling of carbon emissions from economic growth is observed.

In general, areas with a high level of low-carbon development, such as the low-carbon demonstration area and low-carbon potential area, show the potential to reach peak emissions in the near future. These areas should capitalize on their demonstrating functions and play a pivotal role in promoting low-carbon development in their surrounding regions [33]. On the other hand, regions mainly driven by industrial and agricultural sectors, facing challenges in achieving peak emissions, share common difficulties stemming from traditional urbanization and industrial development models. These challenges comprise resource dependency, energy waste, and backward industries [14,34].

4. Discussion

4.1. Typical Spatial Combination Model of Carbon Peak Based on Urban System Division of Labor

At the county level, the spatial pattern of carbon peak exhibits distinct typical spatial combination models (Figure 5). This study provides valuable insights for further delineating the characteristics of inner-city types, thus supplementing existing research conducted at the urban and provincial levels [27,35]. When viewed from the city-level typology perspective, it aligns with the division of labor within the urban system, underscoring the significant influence of the urban spatial development model on carbon dioxide emissions and the need for a comprehensive understanding of low-carbon sustainable development [36].

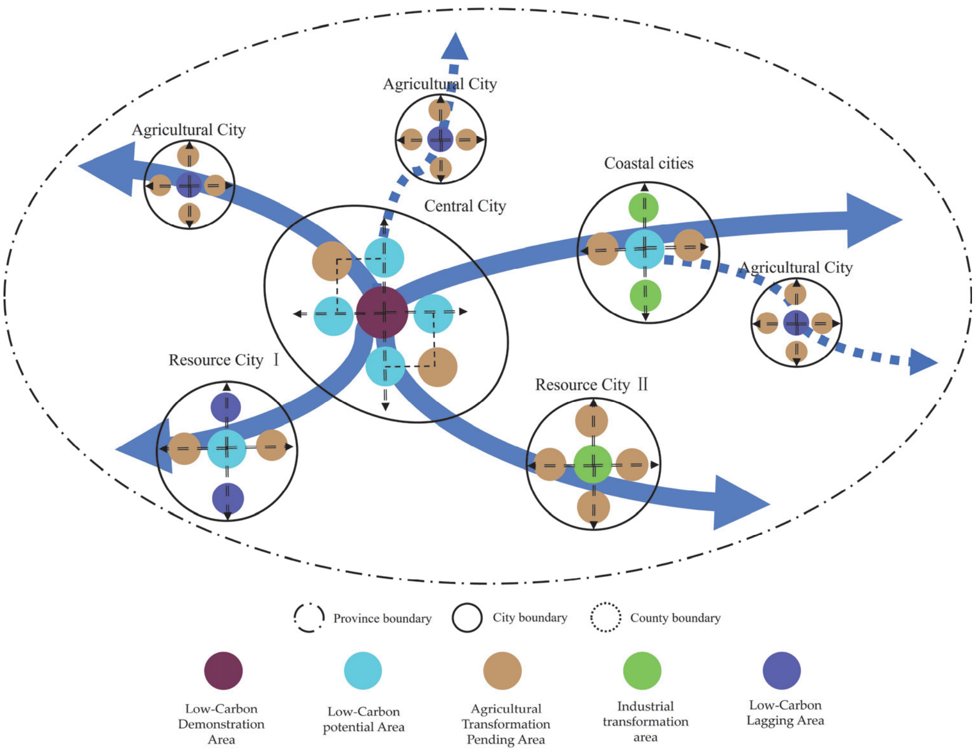

Figure 5. Typical spatial combination model of carbon peak based on urban system division of labor.

In its long-term development trajectory, Shandong Province has established a dual-core development pattern with Jinan and Qingdao as the central cities. Jinan is striving to position itself as a financial, logistics, science, technology, and innovation center, focusing on the headquarters economy, service economy, high-end equipment manufacturing, and high-tech industries. On the other hand, Qingdao is leveraging its advantages in openness, aligning with the national Belt and Road strategy, and prioritizing the development of modern service industries, advanced manufacturing, and emerging marine sectors, with the aim of becoming a globally competitive coastal city. As a result, both cities have effectively decoupled social and economic development from carbon emissions, establishing themselves as the "low-carbon demonstration zones" at their core, encircled by "low-carbon spheres of influence", with the "Agricultural Transformation Pending Area" situated at their periphery.

In addition to the construction of dual-core development pattern, the spatial pattern of carbon peak in Shandong Province is also influenced by geographical conditions. Shandong Peninsula is located in the transition area between land and sea. The region has different development conditions and resource endowments, which leads to different development paths in the region. For instance, certain coastal cities have leveraged port trade advantages to progressively cultivate leading industries with high carbon emissions, notably in the petrochemical sector [37]. In the northern region, Dongying is primarily reliant on the Shengli Oilfield, which stands as China's most significant domestic crude oil source. Since the 1960s, it has progressively developed related industrial clusters [38]. Furthermore, coastal cities such as Yantai, Qingdao, and Rizhao have capitalized on China's reform and opening-up policies, along with the forces of economic globalization. These cities have emerged as pivotal locations for national overseas crude oil imports and have established multiple storage and transportation facilities and processing zones, centered around their core trade functions [39]. Their distinctive spatial combination model revolves around the concept of "Low Carbon Potential Area", which is surrounded by the "Industrial Transformation Area" and the "Agricultural Transformation Pending Area". While some counties have made notable economic development progress, and a few exhibit potential for a transition toward a low-carbon economy, the majority of counties face significant challenges associated with industrial transformation.

Shandong Province encompasses several resource cities in its central and western regions, including Taian, Linyi, and Zibo, which boast abundant mineral and agricultural resources. These cities play pivotal roles in industries such as coal, steel, and agricultural products, thereby contributing to the local economy's growth. While certain cities have achieved notable progress in low-carbon development, resulting in a framework with "Low Carbon Potential Area" at its core, surrounded by "Low Carbon Lagging Area" and "Agricultural Transformation Pending Area". On the other hand, some cities still adhere to conventional dynamics of "Industrial Transfer Pending Area" at their core, with an array of "Agricultural Transfer Pending Area" zones surrounding them. In general, these cities grapple with multifaceted challenges in their pursuit of low-carbon development, primarily attributable to their economic structure, energy reliance, and environmental pressures.

The western region of Shandong Province lies within the Huang-Huai Hai impact plain, renowned for its favorable agricultural conditions and historical significance as a crucial grain production hub in China. Within these agricultural cities, the prevailing feature consistently consists of the "Low-Carbon Lagging Areas", encircled by a concentrated and contiguous expanse of the "Agricultural Transformation Pending Area". This agricultural sector is characterized by density and continuity, yet it also grapples with the challenge of transitioning agricultural production patterns.

In general, this typical model, based on various divisions of labor, provides valuable insights into the distinct characteristics and potential of different counties within the city. Such an approach is indispensable for comprehending carbon emission patterns and effectively achieving carbon reduction targets. Particularly, when examining carbon emissions through the lens of urban-rural duality, the introduction of this typical model serves as a crucial complementary tool [39,40]. Traditional urban and rural dual structures may not adequately account for the functional orientation and development of certain counties. By delving into the specific attributes and potential of different counties, we can more accurately identify the primary sources and impacts of carbon emissions, thus enabling the formulation of targeted strategies effective carbon emission reduction.

4.2. Exploring Differentiated Paths for Peak Optimization and Policy Implications

By considering the differences in resource endowments and developmental stages, we can assess the influencing factors of carbon emissions in different counties and their evolving trends. This analysis provides valuable support for the classified design and implementation of carbon peak paths. By understanding these factors and their interplay, policymakers can devise targeted strategies to achieve carbon peak goals efficiently and effectively in different counties.

The low-carbon demonstration areas are primarily situated in the central regions of central cities. The low-carbon model implemented in this area is operating effectively and should serve as a catalyst for promoting low-carbon development in the surrounding counties. These counties should prioritize decoupling carbon emissions from economic growth in order to achieve regional emissions peak targets. This can be accomplished by fostering green industries, adopting clean energy sources, disseminating energy-saving and emission-reduction technologies, strengthening carbon market mechanisms, and providing incentives for businesses to take actions that reduce emissions.

The low-carbon potential areas have substantial potential for low-carbon development but have yet to achieve its carbon peak targets. These counties are typically located on the outskirts of a central city or at the core of a coastal or resource city. It means that they are influenced by the low-carbon demonstration area and contribute to the radiation effect for low-carbon development in the surrounding region. These counties need innovative solutions to address energy demand during rapid urbanization and industrialization. This involves transforming high-energy consumption and high-emission development patterns, encouraging green production practices among businesses, and establishing green supply chains.

The low-carbon lagging areas are typically situated on the outskirts of resource cities or at the core of agricultural cities. These areas will continue to prioritize social and economic development in the foreseeable future. However, as these regions undergo industrial upgrading, their existing resource-intensive development model is likely to intensify the conflict between economic growth and carbon emissions. This, in turn, will necessitate increased efforts for carbon reduction and achieving emissions peak targets. To effectively tackle this challenge, it is advisable for these regions to capitalize on their latecomer advantages and expedite their peak process through the implementation of innovative policies and market-driven mechanisms that foster low-carbon transformation and optimize industrial economies, thereby circumventing the conventional industrialization path of "pollute first, treat later". Additionally, these regions should address the complex task of ensuring economic stability and employment, taking cautionary measures to prevent potential issues such as economic downturns and population outflows while concurrently pursuing their low-carbon development objectives.

The industrial transformation areas are typically located on the outskirts of coastal cities or at the core of resource cities. In these areas, there is often a prevailing development model characterized by "high emissions for high economic returns". This model tends to prioritize immediate economic growth while overlooking the environmental consequences linked to high energy consumption. This approach may result in short-term financial gains, but it is unsustainable in the long term and can impede progress toward carbon emissions reduction goals and peak targets. Furthermore, it exposes these regions to vulnerabilities and risks related to sustainable development, including heavy reliance on specific industries and environmental pollution. To address these challenges, these regions should shift their focus in economic development and low-carbon governance.

This shift involves reducing dependence on particular industries and improving energy efficiency. It requires active government intervention through policy support and guidance. Outdated, low-profitability, and highly pollutant industries should be phased out, while emerging, low-carbon industries should be nurtured and expanded. This comprehensive approach will contribute to improving the region's natural environment and building a more sustainable economic foundation for urban development.

As for the agricultural transformation pending area are typically located on the outskirts of various cities. These areas often face unique challenges due to their special status in the context of food security strategies, which may impose limitations on urban expansion and industrial development due to strict farmland protection policies. This complexity adds to the challenge of reversing the current situation of backward development. Therefore, it is advisable for these regions to focus on their regional endowments. While promoting orderly urbanization and industrialization, they should simultaneously strengthen the protection of agriculture and natural ecological environments around cities. Utilizing the "carbon sink" function and ecological compensation benefits of green landscapes and natural environments can create new driving forces for regional development.

5. Conclusions

County-level areas, as pivotal units responsible for coordinating diverse initiatives and driving low-carbon development, play a fundamental role in the realization of China's carbon peak and carbon neutrality objectives. Additionally, they serve as a vital complement to ongoing research conducted at the city level. This paper leverages disparities in resource endowments and developmental stages to analyze the magnitude, composition, and evolving patterns of carbon emissions across various regions. The goal is to provide support for the classification design and implementation of peak emission paths in various areas.

Firstly, the driving factors of carbon peak encompass the green transformation component, urbanization component, industrial construction component, energy consumption component, and environmental constraints component. These factors span a broad spectrum of social, economic, and environmental dimensions, offering a comprehensive understanding of the contributing elements to the surge in carbon surge. This analysis enhances readers' grasp of the intricacies of the issue and reflects a region's development over different periods and spatial contexts. Urbanization and industrial construction illustrate the trajectory of economic and social progress, while energy consumption relates to the regional energy structure and technological advancement. The transition towards green practices and environmental constraints are linked to future directions and potential limitations. This consideration of the spatiotemporal dimension underscores the gradual evolution of carbon emission patterns, necessitating the assessment of effects and influences across multiple stages [41,42].

Secondly, the carbon emission peak characteristics of county-level regions in Shandong Province can be classified into five cluster areas. Based on this classification, different paths and strategies for low-carbon development are delineated as follows. The "Low-Carbon Demonstration Area" and "Low-Carbon Potential Area" are strategically designed to pioneer the promotion of environmentally friendly development in neighboring regions and to facilitate a systematic transition towards achieving the carbon emission peak. In the case of "Low-Carbon Lagging Area", it is crucial to place paramount attention on social and economic development. Accelerating the achievement of emission peak targets achievement the advantages of backward development, deploying innovative policies, and market-oriented mechanisms to facilitate the transition towards low-carbon practices and optimizing industrial economies. Ensuring economic stability and safeguarding employment are imperative steps to mitigate potential challenges such as economic downturns and population decline. Additionally, the "Agricultural Transformation Pending Area" and "Industrial Transformation Area" belong to the category of regions facing significant challenges in achieving the carbon emission peak. These challenges are often rooted in conventional urbanization and industrialization, and they encompass issues such as resource dependency, energy inefficiency, and a lagging pace of industrial development.

Thirdly, typical spatial combination models of carbon peak at the county level, based on the division of labor within the urban system, were identified. The division of labor within the urban system encompasses central cities, eastern coastal cities, central and western resource-based cities, and agricultural cities. The carbon mixing patterns exhibited by these cities demonstrate the influence of urban positioning on carbon trajectories. In central cities, coastal cities, and certain developed resource-based cities, a typical spatial combination model emerges: the core of the central city serves as the focal point for either low-carbon demonstration or potential areas, encompassed by low-carbon lagging areas or industrial transformation areas undergoing development. This distributional model can be interpreted through the lens of Hirschman's trickle-down effect in regional economics [43]. Urban centers tend to function as "polarized" zones characterized by low energy consumption, minimal emissions, and high value-added industries. Consequently, advanced development factors like green production, innovative technologies, and low-carbon concepts diffuse to influence less developed regions. This developmental trajectory aims to shift from isolated and imbalanced growth patterns towards interconnected and harmonized systems. In terms of the under-development and traditional agricultural cities, the core comprises the "Low-Carbon Lagging Area" and the "Industrial Transformation Area", surrounded by the "Agricultural Transformation Pending Area". In these cities, the transition to a low-carbon economy often coincides with high energy consumption and emissions due to their reliance on energy sources such as coal, oil, and gas. Traditional economic frameworks constrict cities' sustainable development and impede the realization of low-carbon economic growth. Consequently, there's a surge in environmental pressures, leading cities to grapple with severe environmental issues such as air pollution and water scarcity. Addressing these challenges necessitates increased investment in green technologies and low-carbon innovation in the future. This investment is crucial for bridging the gap in technological upgrading and advancing the trajectory of low-carbon development.

The identification of typical models at the micro level, which concentrates on low-carbon development at the county level while considering the distinct attributes and potential of diverse regions within cities, serves as a robust complement to prior investigations conducted at the city and provincial levels [17,27]. This underscores the importance of understanding the fundamental patterns of variation within cities in order to achieve the overarching goal of carbon peak. Precise optimization strategies and trajectories must be devised by comprehensively comprehending these variations.

This study has limitations. Firstly, it relies on cross-sectional data, which cannot effectively capture the evolving driving factors and spatial pattern of carbon peak. Longitudinal studies conducted over time would be more influential in uncovering the dynamic trends in carbon emissions, including changes in carbon-intensity factors. Second, while conducting studies within provincial administrative units has its advantages for management and policy formulation, it may overlook cities located on the periphery of the administrative region. This could result in missing significant spatial interactions with neighboring cities or districts in adjacent provinces. Conducting larger-scale studies can mitigate the constraints imposed by boundary effects and provide a more comprehensive understanding. Thirdly, certain interpretations of carbon emissions remain at a qualitative level, such as the influence of trade on coastal carbon emissions. Conducting quantitative studies in future research endeavors could enhance the precision of these effects, further substantiating our findings. Lastly, the traditional k-means method does not account for the spatial dependence present within the geographical clusters. In subsequent research, we intend to integrate advanced spatial clustering methods to holistically address spatial dependence.

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