

Article

Regional Collaborative Governance for Carbon Mitigation and Energy Sustainability: A Spatial Analysis of Drivers and Policy Differentiation Across City Clusters

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Abstract

Accurately identifying carbon reduction drivers based on regional variability is important for balancing different carbon reduction targets and advancing sustainable development. This paper first defines and quantifies carbon emission reduction capacity. It then combines cluster analysis and spatial modeling to analyze the drivers of carbon emission reduction capacity at different administrative levels. The results show that the mean values of carbon emission reduction capacity for the different plates, in descending order, are Plate II > Plate I > Plate III > Plate IV. The internal spatial relationships within the plates are relatively weak, while the synergies and spillover effects between the plates are more significant. Moreover, economic development has the largest positive impact on carbon emission reduction capacity in Shandong Province. Industrial structure has the largest effect on the carbon emission reduction capacities of Plates I, II, and III, with positive effects in Plates I and III but a negative effect in Plate II, while population size has the largest negative effect on the carbon emission reduction capacity of Plate IV. These findings could provide theoretical references and practical support for governments to formulate regionally differentiated carbon emission reduction policies and promote coordinated carbon emission reduction and high-quality regional development.

Keywords: carbon emission reduction capacity; prefectural cities in Shandong Province; improved gravity model



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1. Introduction

Reducing carbon dioxide emissions is a primary means of controlling and mitigating global warming and an inevitable requirement for global sustainable development [1]. From the signing of the United Nations Convention on Carbon Emissions from Climate Change in 1992 and the subsequent Kyoto Protocol, the Paris Climate Agreement, etc., the international community has made tremendous efforts to realize carbon emission reduction targets [2]. As the world's leading carbon emitter, China has committed to

international climate governance by pledging to peak its carbon emissions before 2030 and achieve carbon neutrality by 2060 [3,4]. However, regional disparities in resource endowment and economic development induce spatial correlation and heterogeneity in emissions, necessitating region-specific collaborative reduction strategies. Within this national framework, Shandong Province ranks first in carbon emissions across China due to its massive industrial system, population size, and economic output [5]. As one of the important provinces along the eastern coast of China, its prefectural cities exhibit significant regional differences in terms of location, economic development, industrial structure, cultural traditions, and more [6]. This paper takes a sample of 16 prefecture-level cities in Shandong Province to explore the drivers of regional synergistic carbon emission reduction based on the spatial perspective, with a view to enrich and improve the relevant theories. Meanwhile, it can provide theoretical references and practical bases for the formulation of provincial, regional, and even national emission reduction policies, which will help to enhance the overall capacity and efficiency of responding to climate change and realize the goal of regional low-carbon sustainable development.

Based on different carbon emission reduction indicators and different research scales, there have been numerous investigations into the spatiotemporal patterns of carbon emissions. Xiao et al. examined the spatiotemporal dynamics of carbon mitigation efficiency in 136 countries from the perspectives of developed and developing countries [7]. Hong et al. examined the intrinsic mechanism of the impact of drivers on carbon emission intensity using Chinese provincial panel data from 2010–2019 [8]. Yang et al. constructed a multi-objective assessment system to characterize China's provincial carbon emissions [9]. Wu et al. analyzed the spatiotemporal variations in total emissions, per-capita emissions, and emission intensity in the Yangtze River Economic Belt and bidirectional effects with drivers [10]. Wang et al. explored the spatial and temporal distribution trends of carbon emissions in 19 urban agglomerations in China along with their driving mechanisms [11]. Thus, the spatial and temporal distribution of different carbon emission indicators is somewhat different and one-sided in explaining the characteristics of regional carbon emission reductions [10,12]. While these studies provide valuable baseline insights into historical emission trends, their reliance on single-dimensional indicators yields a fragmented and somewhat static understanding of regional carbon dynamics. By frequently isolating emission outputs from the broader socioeconomic system, previous research fails to holistically quantify a region's actual dynamic capability to reduce carbon while maintaining economic efficiency and social equity. This highlights an urgent need to transition from tracking simple emission metrics to evaluating composite, multidimensional carbon emission reduction capacity. Therefore, it is necessary to construct and scientifically quantify a comprehensive indicator to reflect the intrinsic links between carbon emissions and resources, factors, and societal and related economic activities in a certain region. In addition, the realization of carbon emission reduction targets cannot rely solely on terminal management measures in the energy and industrial sectors. It is even more important to strengthen integrated resource allocation and synergistic development among prefectural cities, which are important vehicles for policy implementation and carbon emission reduction actions, from a provincial perspective, so that integrated intra- and inter-regional development can be regulated at the macro level.

Extensive research has been conducted to explore the drivers of CO₂ emissions in order to control carbon emissions and develop effective policy actions [13]. Decomposition analysis, STIRPAT modeling, and panel Granger causality tests are the more widely used approaches [14]. Liu et al. identified the drivers of carbon emissions by constructing a decomposition model of carbon emission influencing factors through structural decomposition analysis while forecasting carbon emissions [15]. Qin et al. explored the

differences in carbon emissions in China across spatial and temporal dimensions and their drivers with the Logarithmic Mean Division Index (LMDI) method [16]. Bey et al. investigated the main drivers of carbon emissions in Italian regions with the extended STIRPAT model [17]. Wang et al. explored the causal relationship between carbon emissions and their drivers with panel Granger causality modeling [18]. Chen et al. adopted a dynamic panel approach to uncover the mechanisms behind carbon emissions in the Yangtze River Delta (2000–2017) [19]. Demography, urbanization rate, energy, and economic development are the main drivers of carbon emissions based on a literature analysis [20–22]. Furthermore, it was found that China's digital economy, which entered a mature stage of development after 2011, has become a key force in the implementation of China's major national strategies, with significant implications for innovation-driven development and carbon emission reduction [23,24]. However, it is controversial whether it contributes to changes in carbon emissions (whether it is a facilitating or inhibiting effect) due to differences in definitions, research methodologies, and regions [25,26]. Furthermore, while the identification of isolated drivers has matured, the literature remains deeply fragmented regarding the interactive and scale-dependent effects of emerging factors. Most existing frameworks evaluate these drivers within rigid, static, regional boundaries, struggling to capture whether factors like the digital economy act as catalysts or inhibitors across different tiers of urban development. This exposes a critical gap in systematically mapping the differentiated localized driving mechanisms required for targeted urban carbon reduction. Thus, further investigation is needed to assess how various factors, particularly the digital economy, drive urban carbon reduction.

Comprehensive analysis of carbon emission factors indicates that as with carbon emissions, they have obvious spatial dependence, i.e., spatial correlation, generating a siphon effect or spillover effect on neighboring regions [27,28]. Therefore, spatial autocorrelation, regression analysis, and spatial econometric modeling were further employed to analyze the spatial patterns influencing carbon emissions [6,29,30]. Liu et al. applied regression methods to examine how urban spatial organization affects CO₂ emissions [6]. Su et al. applied spatial econometrics to analyze regional differences in China's agricultural emissions [31]. Liu et al. applied spatial econometric techniques to assess how emissions vary across time and space in Chinese counties, along with their key determinants [32]. Huang et al. investigate the spatial spillover effects of environmental regulations on carbon emission reduction with spatial Durbin models and panel threshold models [33]. However, current spatial analyses predominantly rely on simple geographic adjacency, largely overlooking the underlying functional network structures and asymmetrical spillover directions between cities. Treating regions as relatively homogeneous spatial units obscures the complex synergistic relationships and block-level (plate) interactions that dictate actual resource allocation. Consequently, previous studies fail to adequately capture how specific urban clusters functionally collaborate or compete, creating a blind spot in designing actionable, cross-regional, collaborative mitigation policies.

While contemporary studies have significantly advanced the understanding of emission reduction factors, several research gaps remain unaddressed. First, carbon emissions exhibit strong associations with a variety of economic, social, and environmental factors, and existing research on carbon emissions is limited to only one aspect, which cannot fully reflect its multidimensional impact on the region [34]. Therefore, this paper proposes an innovative carbon emission reduction capacity (CERC) indicator, integrating economic, energy, social equity, environment, and other aspects, so as to explore how spatial interactions shape regional pathways toward lower emissions. Second, what are the variations in the drivers of CERC at different spatial scales? What are the driving effects and extent of neighborhood versus self on CERC? The spatial and temporal complexities and poten-

tial drivers behind CERC have not yet been fully recognized and addressed by previous studies. This paper conducts research related to CERC drivers at two administrative levels, provincial and prefectural, to minimize the uncertainty generated by the spatio-temporal variability of CERC. Third, some studies have conducted comparative subregional analyses of carbon emissions based on geographic location (three regions: east, central, and west). However, limited research has explored regional variations in carbon emission reduction drivers by integrating spatial network relationships in the context of spatial econometrics. Therefore, there is an urgent need to compare the drivers of CERC at different scales from a spatial network perspective to translate research insights into implementable climate solutions while fostering regional joint mitigation mechanisms. Employing plate clustering to analyze CERCs across city clusters in Shandong Province, this paper proposes appropriate carbon emission reduction measures by identifying the driving factors of the overall provincial and different plate CERCs. This methodology can serve as a reference for other regions nationwide and their urban agglomerations in formulating regionally coordinated carbon reduction strategies.

2. Methodology

First, this paper constructs an indicator system by integrating energy, the economy, the population, social equity, and the environment to define and quantify CERC from two perspectives: efficiency and equity. Second, using the modified gravity model, we quantify inter-prefectural spatial correlations based on the CERC spatial correlation diagnosis, and further spatial clustering analysis is conducted. Finally, it applies the spatial econometric model to examine the CERC drivers for Shandong Province as a whole and its plates separately, with their spatial effects decomposed into direct and indirect effects for comparison. For the specific research framework, see Figure 1.

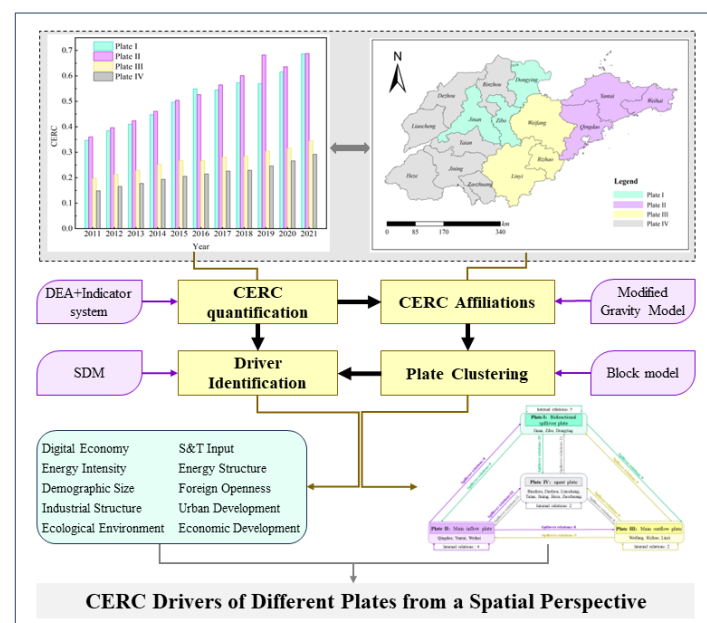


Figure 1. Roadmap for identifying the factors affecting carbon emission reduction capacity.

2.1. CERC Quantification

While existing carbon emission indicators are often one-sided, focusing on single aspects, they fail to fully capture the intrinsic multidimensional links between carbon emissions, resources, society, and economic activities. To address this gap, the CERC serves as an innovative and comprehensive indicator that integrates economic, energy, social equity,

and environmental dimensions into a single framework. Furthermore, unlike traditional metrics, the CERC scientifically quantifies mitigation capacity from two distinct perspectives: efficiency and equity. It evaluates efficiency via the SBM model while assessing equity and potential by incorporating individual equality, historical carbon responsibility, and sustainable development levels (see Table 1). The specific methodology and indicator treatment are described in detail in the baseline study for this research, which is our previously published paper [5]. The SBM model, a more advanced approach, prevents input or output variable relaxation from overestimating carbon emission efficiency [35]. Our analysis covers 16 prefectural cities in Shandong Province as DMUs, utilizing 2011–2021 panel data to build the SBM model and assess carbon emission efficiency. Inputs comprise capital stock, labor, and energy consumption; outputs are GDP (desired) and carbon emissions (non-desired) (see Table 1).

Combined with literature research and expert consultation, a multi-perspective, multi-level indicator system is constructed in consideration of individual equality, historical responsibility, sustainable development, and other factors to ensure the scientificity and reasonableness of the carbon emission reduction potential indicators. This framework characterizes individual equality by GDP per capita, historical carbon responsibility by per capita cumulative CO₂ emissions, and sustainable development level by the Comprehensive Environmental Pollution Index (CEPI). The entropy weight method was further applied for calculation, and the specific index system is shown in Table 1.

The Shandong Province prefecture-level city CERC model, based on efficiency–equity–sustainability perspectives, is presented in Equation (1).

$$CERC_{it} = \omega \times Equity_{it} + (1 - \omega) \times Efficiency_{it} \quad (1)$$

where $CERC_{it}$ is the CERC of prefectural city i in year t . ω is the weight, with a value of 0.5. For prefectural city i in year t , $Equity_{it}$, $Efficiency_{it}$ represent its carbon emission reduction potential and efficiency, respectively. The equal weights were set based on the theoretical framework of “strong sustainability,” where environmental justice and technical efficiency are defined as equally foundational and non-substitutable pillars. Furthermore, similar to established composite metrics like the UN’s Human Development Index (HDI), equal weighting is adopted to minimize subjective bias and provide a standardized, objective benchmark when no absolute consensus exists for asymmetric weights.

Table 1. Carbon emission reduction capacity indicator system. (The content in Table 1 is collated from our previously published papers [5], which are the preliminary studies of the present manuscript).

Criteria Level	Primary Indicators	Secondary Indicators	Unit
Carbon emission efficiency	Inputs	Capital stocks	CNY 10 ⁸
		Total labor force	10 ⁴ persons
	Expected outputs Unexpected outputs	Total energy consumption	10 ⁴ tons of standard coal
		GDP	CNY 10 ⁸
		CO ₂ emission	10 ⁶ tons
Carbon reduction potential	Economic development	GDP per capita	CNY 10 ⁸
	Historical emissions	Historical cumulative CO ₂ emissions per capita	10 ⁶ tons
		Industrial wastewater discharge	10 ⁴ tons
		Industrial ammonia nitrogen emissions	tons
	Comprehensive Environmental Pollution Index	Industry Industrial smoke (dust) emissions	tons
		Industrial SO ₂ emissions	tons
		Industrial solid waste emissions	10 ⁴ tons
	Lives	Domestic wastewater discharge	10 ⁴ tons
		Domestic ammonia nitrogen emissions	tons
		Domestic SO ₂ emissions	tons
		Domestic smoke emissions	tons

2.2. Construction in CERC's Spatial Correlation Network

2.2.1. Improved Gravitational Model

Establishing a spatial network underpins network analysis, while the quantification of the spatial correlation relationship is the core of spatial network construction. Regarding the construction of the spatial correlation network, traditional spatial weight matrices (such as binary adjacency or simple geographic distance matrices) primarily focus on physical proximity and often assume symmetrical relationships. However, CERC is deeply influenced by dynamic socio-economic interactions, population flows, and economic disparities. Therefore, we selected the modified gravity model because it organically integrates economic and demographic variables with geographic distance [36,37]. This allows us to accurately capture the multi-dimensional, asymmetrical spatial linkages and spillover directions between cities, which traditional distance-based models fail to reflect. The improved gravity model is shown in Equation (2):

$$y_{ij} = k_{ij} \frac{\sqrt[3]{P_i CERC_i G_i} \sqrt[3]{P_j CERC_j G_j}}{D_{ij}^2}$$

$$k_{ij} = \frac{CERC_i}{CERC_i + CERC_j}$$

$$D_{ij} = \frac{d_{ij}}{|g_i - g_j|}$$
(2)

Here, i and j denote prefecture-level cities, while P_i , $CERC_i$, G_i , and g_i represent the total population, CERC, GDP, and GDP per capita of city i , respectively. Here, y_{ij} , k_{ij} , D_{ij} , and d_{ij} denote the CERC correlation relationship, CERC coefficient, comprehensive economic geographic distance, and geographic distance between prefecture-level cities i and j , respectively. In cases where $g_i = g_j$, the economic distance approaches infinity, implying complete spatial isolation in terms of economic–geographical attributes, which can be mathematically adjusted by adding a minute constant $\sim 10^{-4}$.

2.2.2. Spatial Cluster

The spatial region is segmented into plates based on the spatial cluster analysis–block model based on network cohesion analysis, with new perspectives on internal plate structure to explore the interactions between the plates. Based on prior research, spatial correlations divide the network into four distinct categories: the main inflow, the main outflow, the bidirectional spillover, and the agent plate.

Using the block model, this study groups 16 prefecture-level cities in Shandong Province to examine the functions and positions of distinct regional plates. The CERC spatial relationship matrix was first binarized. Then, the convergent correlation method (CONOR) in UCINET 6.232 software was employed for clustering, and the segmentation depth was set to a maximum of 2 with a convergence threshold of 0.2. Finally, prefectural cities were divided into four plates (see Table 2).

Table 2. Basis of block model plate division (compiled from Reference [38]).

Proportion of Internal Relationships	Proportion of Relationships Received	
	≈ 0	$= 0$
$\geq (g_k - 1)/(g - 1)$	Bidirectional spillover plate	Main inflow plate
$\leq (g_k - 1)/(g - 1)$	Main outflow plate	Agent plate

Note: g_k is the number of prefectures in the plates; g is the total number of prefectures, here 16.

2.3. Spatial Econometric Modeling

Spatial econometric models enable examination of the spatial interaction effects and spatial structural characteristics between different regions in regressions of panel data. This

study employs the spatial Durbin model to examine the driving factors of CERC across Shandong Province and its sub-regions.

2.3.1. Spatial Econometric Model Setup

1. The extended STIRPAT model

The STIRPAT model, an extension of the IPAT framework (I = PAT) proposed by Ehrlich and Holdren, assesses the environmental impact of human activities. In this equation, I denotes environmental influence, P represents population, A stands for affluence, and T refers to technology (see Equation (3)):

$$\ln I = \ln a + b \ln P + c \ln A + d \ln T + \ln e$$

(3)

In this model, a serves as the coefficient, while b, c, and d correspond to the exponential parameters for P, A, and T, respectively, with e accounting for random error.

The CERC is affected by many factors, such as demographic size, technological level, energy structure, economic development, and so on. Meanwhile, with the gradual maturation of information technology development, such as the Internet, the digital economy also exerts some influence on carbon emissions. Specifically, the digital economy indicator represents the level of application of digital technologies that contribute to low-carbon energy transition and dual-carbon goals by optimizing resource utilization and increasing production efficiency. It is characterized by three levels and five indicators, including digital industrialization (total per capita telecommunication services, employment share in information/computer-related sectors) and industrial digitization (China’s Digital Inclusive Finance Index) and digital economic access (proportion of Internet users, proportion of cell phone users), which is calculated using the entropy weighting method. Therefore, this paper extends the STIRPAT model using panel data covering 16 prefecture-level cities in Shandong Province between 2011 and 2021 (see Table 3).

Table 3. Extended STIRPAT model indicators.

Symbols	Variables	Indicator Description	Unit
y	CERC	CERC value	-
x1	Digital Economy	Digital Economy Index	-
x2	Demographic Size	Population	10 ⁴ persons
x3	Economic Development Level	GDP per capita	CNY 10 ⁴
x4	Industrial Structure	Percentage of secondary industry	%
x5	Urbanization Level	Urbanization rate	%
x6	Energy Consumption Intensity	Energy consumption per unit of GDP	ton tec/CNY 10 ⁴
x7	Energy Consumption Structure	Coal consumption	%
x8	Foreign Openness Degree	Ratio of total import and export	%
x9	Ecological Environment	Green space per capita	10 ⁴ /square meters per person
x10	S&T Input Level	R&D investment	%

2. The Spatial Durbin Model (SDM)

The SDM serves as the most comprehensive model capable of simplifying into a spatial autoregressive or error model when specific conditions are met. The SDM considers that the region is affected by both its neighbors and the self, i.e., exogenous and endogenous interactions between regions. This is crucial for our research, as a region’s CERC is affected not only by its own socio-economic factors but also by the driving factors of neighboring regions (exogenous interaction effects). Thus, the model measures not only the spatial correlation between the explanatory variables but also the spatial dependence brought about by the explanatory variables of neighbors and the home region (see Equation (4)):

$$Y = \alpha + \lambda WY + \beta X + \theta WX + \varepsilon \quad (4)$$

Here, y represents an $n \times 1$ column vector of explanatory variables. X denotes an $n \times k$ matrix of predictors. W corresponds to an $n \times n$ spatial weight matrix. ε is a random error vector of $n \times 1$. α is the constant term coefficient. λ denotes the regression parameter for the spatially lagged explanatory variable, while β represents the coefficient of the explanatory variable itself. θ denotes the regression coefficient associated with the spatial lag of the explanatory variable.

Integrate the extended STIRPAT framework with SDM to derive an extended STIRPAT-SDM framework (see Equation (5)):

$$\ln Y = \alpha + \lambda W \ln Y + \beta \ln X + \theta W \ln X + \varepsilon \quad (5)$$

2.3.2. Spatial Econometric Model Decomposition

Because variables in the SDM are all spatially lagged, their regression coefficients encompass not only impacts of local explanatory variables on dependent variables but also influences from neighboring areas. However, the regression coefficients in the SDM fail to explicitly indicate their marginal effects. Thus, the SDM regression coefficients were separated into direct, indirect, and combined impacts through the partial derivative decomposition approach (see Equation (6)):

$$\begin{bmatrix} \frac{\partial Y}{\partial X_{1k}} & \cdots & \frac{\partial Y}{\partial X_{nk}} \end{bmatrix} = \begin{bmatrix} \frac{\partial Y_1}{\partial X_{1k}} & \cdots & \frac{\partial Y_1}{\partial X_{nk}} \\ \vdots & \vdots & \vdots \\ \frac{\partial Y_n}{\partial X_{1k}} & \cdots & \frac{\partial Y_n}{\partial X_{nk}} \end{bmatrix} = (I - \lambda W)^{-1} \begin{bmatrix} \beta_k & W_{12}\theta_k & \cdots & W_{1n}\theta_k \\ W_{21}\theta_k & \beta_k & \cdots & W_{2n}\theta_k \\ \vdots & \vdots & \ddots & \vdots \\ W_{n1}\theta_k & W_{n2}\theta_k & \cdots & \beta_k \end{bmatrix} \quad (6)$$

where the direct impact corresponds to the mean value of the matrix's diagonal entries, which indicates an average comprehensive effect of a regional explanatory variable on the interpreted variable. The indirect impact is derived from the mean of off-diagonal entries in the matrix, which represents the average combined effect of the explanatory variables in a region on the interpreted variables in neighborhoods through spatial interactions. The overall impact combines direct and indirect influences, representing the average aggregated influence of explanatory variables from one region on dependent variables across all regions.

2.3.3. Spatial Econometric Model Examination

Spatial econometric models exist in multiple forms, and this study selects them through the following diagnostic tests. First, the spatial effects are diagnosed by the Lagrange Multiplier (LM). If the LM-lag test confirms the presence of a lag effect, the spatial lag model (SLR) will be adopted. When the LM-error test confirms an error effect, the spatial error model will be adopted. If both LM-lag and LM-error tests are significant, indicating both lag and error effects, the SDM model is applied. Diagnosis of random and fixed effects was then carried out using the Hausman (Hausman) test. Finally, a Likelihood Ratio (LR) test was conducted to assess whether the model was reduced from mixed fixed effects to either individual or time fixed effects and whether it degenerated from SDM to SAR or SEM. Based on the test results, the optimal spatial econometric model is ultimately determined.

2.4. Data

The nighttime light data fitted to the carbon emissions in this paper are derived from two sources. They are partly derived from the U.S. military weather satellite DMSP-OLS and partly from the NPP-VIIRS sensor provided jointly by NASA and NOAA, with raw data

obtained from the EOG platform: <https://eogdata.mines.edu/products/vnl/> (accessed on 13 January 2024). The CEADs database provides municipal-level CO₂ emission records for Shandong Province between 2011 and 2017 (CEADs, 2020). The CERC assessment metrics and variables in this study were sourced from Shandong's Provincial Statistical Yearbook and municipal statistical yearbooks. Using harmonized nighttime light data to fit and estimate carbon emissions has been widely applied in numerous studies, and the relevant data processing workflows and application scenarios have been extensively published in authoritative peer-reviewed journals [39–41]. Figure 2 is the fitting flowchart of DMSP_OLS and VIIRS_VNL satellite data. Table 4 lists the R² results of fitting nighttime light data with historical carbon emission data.

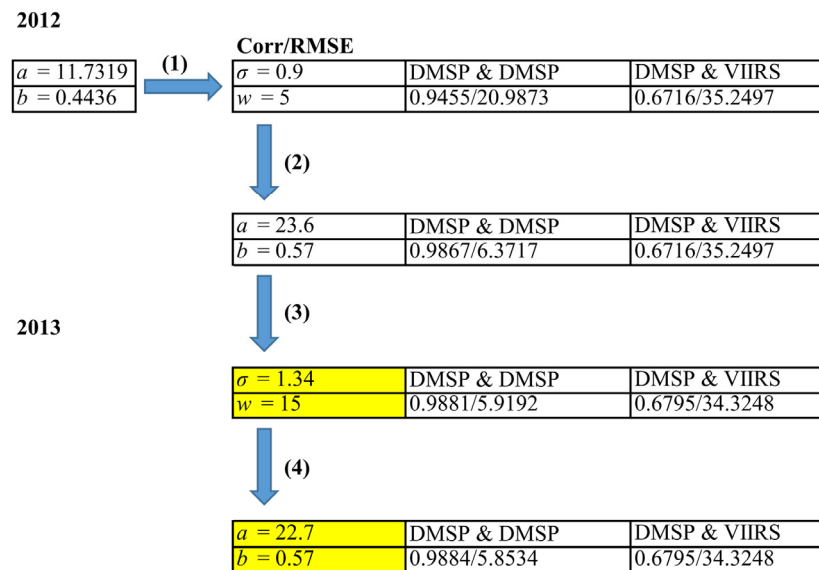


Figure 2. Flowchart of DMSP_OLS and VIIRS_VNL satellite data fitting.

Table 4. R² of fitting results for historical carbon emissions and nighttime light data.

Plates	Cities	R ²
Plate I	Jinnan	0.835
	Zibo	0.814
	Dongying	0.918
Plate II	Qingdao	0.825
	Yantai	0.947
	Weihai	0.981
Plate III	Weifang	0.88
	Rizhao	0.894
	Linyi	0.917
Plate IV	Binzhou	0.871
	Dezhou	0.956
	Liaocheng	0.868
	Taian	0.846
	Jining	0.922
	Heze	0.904
	Zaozhuang	0.894

3. Results

3.1. CERC Temporal and Spatial Trends

Using carbon emission performance and reduction capacity as criteria, the CERCs for Shandong's 16 municipalities were calculated during 2011–2021 (see Figure 3).

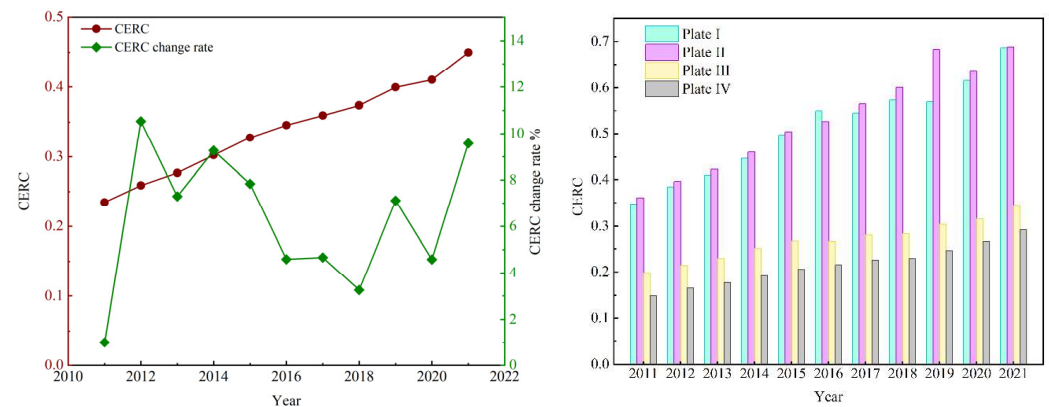


Figure 3. Carbon emission reduction capacity and growth rate in Shandong Province, 2011–2021. (The left figure is derived from our previously published reference [5], which presents the preliminary research findings of this manuscript.).

From Figure 3, the CERC mean value of Shandong Province exhibited consistent growth between 2011 and 2021, rising from 0.235 to 0.450, with an approximate twofold increase. The CERC mean value growth rate in Shandong fluctuated between 3.26% and 10.53%, averaging approximately 6.87%. The order of CERC means after plate clustering is Plate II > Plate I > Plate III > Plate IV. The order of the CERC mean growth rate is Plate I > Plate IV > Plate II > Plate III. The CERC for Plate IV, while lower overall, has a greater rate of growth over the study period, with an increase from 0.149 in 2011 to 0.292 in 2021. This implies that cities in Plate IV possessed higher CERC improvement potential, while this could also be due to the spillover-driven effect of other plates.

3.2. Spatial Cluster Analysis

First, the global Moran index was applied to assess the spatial linkage of CERC across Shandong Province, with significant positive spatial correlation, as shown in Table 5. Then, Shandong's 16 cities were grouped into four plates based on inter-city CERC correlations, with their specific attributes clarified (see Figure 4).

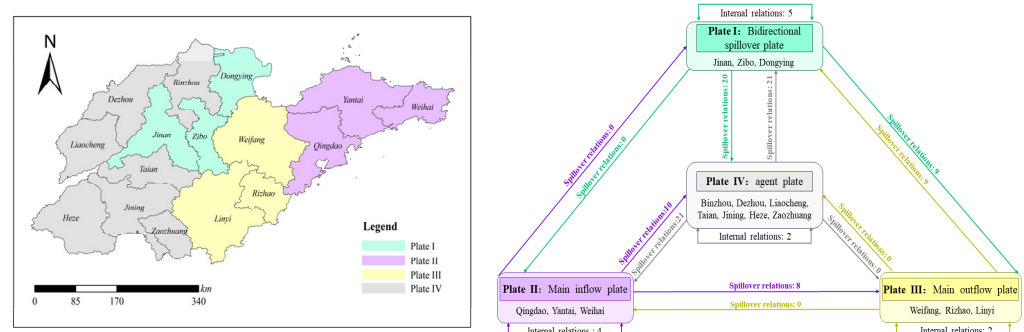


Figure 4. Spatial clustering and characterization of carbon emission reduction capacity.

Table 5. Spatial correlation of carbon emission reduction capacity in Shandong Province.

Year	Moran's I	z	p-Value
2011	0.604	4.605	0.002
2012	0.655	5.122	0.002
2013	0.682	5.639	0.003
2014	0.661	5.610	0.003
2015	0.688	5.655	0.010
2016	0.701	5.347	0.020
2017	0.681	5.820	0.004
2018	0.672	5.805	0.003
2019	0.670	6.274	0.000
2020	0.663	5.987	0.001
2021	0.656	5.599	0.003

3.2.1. Results of Spatial Clustering

From Figure 4, for Shandong's urban CERC networks, external reception consistently outweighs internal connectivity, indicating a significant spillover effect in four plates. Plate I (Jinan, Zibo, and Dongying) demonstrates higher actual than desired internal linkages, with stronger reception than delivery, qualifying as a bidirectional spillover plate. In Plate II (Qingdao, Yantai, and Weihai), actual internal connections surpass desired relationship proportions, while it receives more relationships from external plates than it delivers; hence, Plate II is the main inflow plate. The actual internal relationships in both Plate III (Weifang, Rizhao, and Linyi) and Plate IV (Binzhou, Dezhou, Liaocheng, Tai'an, Jining, Heze, and Zaozhuang) are smaller than the desired internal relationships, while Plate IV delivers much larger relationships externally than Plate III. Therefore, Plate IV is the agent plate while Plate III is the main outflow plate. Notably, the CERC network in Shandong Province exhibits weaker inter-plate spatial linkages, while the synergies and spillovers among the plates are more significant. This highlights the importance of leveraging the core city's spillover influence within the region to foster coordinated growth, thereby strengthening low-carbon transition dynamics across the area.

3.2.2. Plates Characterization

Plate density matrices and image matrices were calculated to intuitively analyze the correlation of CERCs between plates (see Table 6).

Table 6. Density matrix and image matrix of different plates in Shandong Province.

Plate	Density Matrix				Pixel Matrix			
	Plate I	Plate II	Plate III	Plate IV	Plate I	Plate II	Plate III	Plate IV
Plate I	0.67	0.00	1.00	0.95	1	0	1	1
Plate II	0.00	0.67	0.89	0.48	0	1	1	1
Plate III	1.00	1.00	0.50	0.00	1	1	1	0
Plate IV	1.00	1.00	0.00	0.05	1	1	0	0

From Table 6, the spatial relationships between Plate I and Plate II include two aspects, partly intra-plate correlations and partly spillover effects of Plate III and Plate IV. It shows that the prefecture-level cities in Plate I and II have higher CERC and economical intensity, whose industrial structure is upgraded and optimized as a priority. This leads to high industrial agglomeration, scientific and technological innovation, and production efficiency, resulting in a large energy resource gap, which needs to be replenished by relevant factor flows from other plates. The spatial relationships of Plate III are derived only from Plate

I and Plate II, while Plate IV contains as many as seven prefectures; its lack of intra-plate correlations contrasts with Plate III. This aspect explains that the increase in CERCs of Plate I, II, and III comes from the spatial spillover effect of Plate IV, i.e., elements such as energy, resources, and talent provided by prefectural cities within Plate IV. Another aspect suggests that the optimal allocation of resource factors may not be well-played between prefectural cities within Plate IV. Its excessive spillovers to external plates restrict the synergistic effects of CERCs at the prefecture level within Plate IV. Therefore, it is necessary to realize the enhancement of CERC in Shandong Province, which requires not only the synergistic enhancement of the spatial network and the plates but also differentiated synergistic carbon emission reduction within each plate, i.e., exploration of driving factors within the plates.

3.3. Spatial Econometric Model Selection

Given observed spatial linkages among prefectural cities, spatial econometric model selection was conducted through correlation tests (see Table 7).

Table 7. Spatial econometric model examination.

Test Methods	Test Content	Shandong	Plate I	Plate II	Plate III	Plate IV
	Moran Index	8.71 ***	1.77 *	1.36 *	1.98 **	3.66 ***
LM test	LM-Error	60.41 ***	2.04 *	5.12 *	3.17 *	5.34 **
	LM-Lag	3.58 *	2.74 *	1.03 *	2.89 *	5.93 **
Robust LM test	LM-Error	57.43 ***	1.05 ***	4.09 *	1.83 *	1.056 *
	LM-Lag	0.59 *	3.11 *	1.003 *	3.55 *	1.65 *
Hausman test	FE-RE	437.67 ***	114.71 ***	0.08 ***	348.62 ***	970.98 ***
LR test	both-time/time-ind	129.89 ***	16.84 ***	295.98 ***	121.77 ***	75.88 ***
	both-ind/time-both	143.16 ***	69.75 ***	292.5 ***	75.50 ***	55.37 ***
	SDM-SAR	125.55 ***	59.63 ***	56.06 ***	96.35 ***	56.30 ***
	SDM-SEM	180.05 ***	40.45 ***	54.66 ***	81.51 ***	63.06 ***

Note: ***, **, and * represent significance at the 0.01, 0.05, and 0.1 levels, respectively.

From Table 7, Moran's I statistic for CERC in Shandong Province as well as all plates is greater than 0 with the significance test passed, demonstrating significant positive spatial dependence for all. Results from the LM test indicate that both standard and robust versions of LM-Error and LM-Lag terms are statistically significant, confirming the presence of spatial error and lag effects. Therefore, the SDM model is the appropriate choice. The Hausman test demonstrated that the model rejected random effects with $p < 0.01$, suggesting the fixed-effects SDM model as the preferred option. As the fixed-effects model includes time-fixed, individual-fixed, and double-fixed for time and individual, further diagnosis using the LR test is required. The results show that Shandong Province should choose the time fixed-effects model while the four plates should choose the double fixed-effects model of time and individual. Finally, further testing showed that the SDM model collapses to the SAR or SEM model based on LR, all of which rejected the original hypothesis. Ultimately, Shandong Province chose the SDM-time fixed-effects model, while the four plates chose the SDM-both fixed-effects model for the subsequent regression and decomposition analyses.

4. Discussion

4.1. CERC Influences Factor Regression Analysis

This paper conducts a regression analysis of CERC and its influencing factors in Shandong Province and the four plates with SDM-time and SDM-both fixed-effects models, respectively (see Table 8). From Table 8, the R^2 of Shandong Province and the four plates are 0.965, 0.881, 0.700, 0.705, and 0.798, respectively, where the majority of coefficients show statistical significance ($p \leq 0.10$). These results demonstrate that the models have better fit and can be analyzed for correlation.

Table 8. Regression analysis and robustness test of carbon emission reduction capacity.

Symbols	Shandong		Plate I		Plate II		Plate III		Plate IV	
	Original	Replacement	Original	Replacement	Original	Replacement	Original	Replacement	Original	Replacement
x1	0.068 **	0.063 **	0.164 ***	0.166 ***	−0.193 ***	−0.213 ***	0.366 ***	0.396 *	−0.103 **	−0.125 *
x2	0.159 ***	0.142 ***	0.813 ***	0.660 ***	1.330 *	2.558 ***	1.266	1.766	−2.473 ***	−0.281 ***
x3	0.044	0.045	−0.559 **	−0.565 **	1.598 ***	1.223 **	−1.097 *	−0.209 *	1.157 ***	0.513 ***
x4	0.450 ***	0.479 ***	3.473 ***	3.437 ***	1.801 ***	1.753 ***	9.056 ***	4.108 ***	−0.624 ***	−0.034 *
x5	−0.028 ***	−0.028 *	0.103 **	0.107	−0.830 *	−0.766 *	−0.267 *	−0.214 *	−0.228 **	−0.131 *
x6	−0.300 ***	−0.336 ***	0.085	0.091	−0.567	−0.483	−0.098	−0.091	−0.124 *	0.009 *
x7	−0.029	−0.019	−0.008	−0.004	0.475	−0.507	−0.570 ***	−0.104 *	−0.098 ***	−0.104 *
x8	−0.050 ***	−0.027 **	−0.224 ***	−0.225 ***	−0.452 ***	−0.155 **	−0.173	−0.117	−0.023	0.049
x9	−0.031	−0.004	0.183	0.194	−0.34	−0.293	3.426	3.995	0.022	0.001
x10	−0.008	−0.022	−0.298 ***	−0.298 ***	−0.231 ***	−0.264 ***	−0.331	0.012	0.032	−0.085
W*x1	−0.031	−0.047	0.050 *	0.055 *	−0.006	0.003	0.758 ***	0.617 **	0.018	−0.143
W*x2	0.093	0.048	1.475 ***	1.044 ***	2.911 ***	4.696 ***	−0.024	1.311	4.270 ***	0.219 *
W*x3	0.034	0.049	−2.145 **	−2.076 **	2.525 **	−0.591 *	−6.922 ***	−2.638 *	−3.303 ***	−0.648 *
W*x4	0.426 ***	0.535 ***	5.157 ***	4.874 ***	2.233 ***	2.975 ***	28.450 ***	8.045 ***	−5.042 ***	−2.009 ***
W*x5	0.008	−0.025	−0.069	−0.062	−2.217 **	−3.521 ***	−1.728 ***	−0.104 *	0.708 *	0.154 *
W*x6	1.065 ***	1.220 ***	1.010 ***	1.054 ***	−1.228	−2.92	0.572 **	0.348 *	−0.770 **	−0.404 ***
W*x7	−0.021	−0.009	0.313 ***	0.334 ***	0.752	−1.012	−2.717 ***	−0.445 *	0.248 ***	0.542 *
W*x8	−0.118 **	−0.091 *	−0.393	−0.393	−0.967 ***	−0.245 *	−1.183 ***	−0.553 **	−0.483 *	−0.376 *
W*x9	0.060	−0.002	−2.172 ***	−2.128 ***	−0.400 ***	−0.074 *	3.222	3.497	0.041	−0.023
W*x10	−0.016	0.016	−0.022	−0.015	−0.051	0.092	−1.470 ***	−0.093 *	0.475 ***	0.341 *
R2	0.965	0.964	0.881	0.881	0.7009	0.759	0.7048	0.676	0.7981	0.651

Note: ***, **, and * represent significance at the 0.01, 0.05, and 0.1 levels, respectively.

4.1.1. Regression Analysis in Shandong Province

From Table 8, the coefficients of digital economy, demographic size, and industrial structure are significantly positive, indicating their significant contribution to increasing the local CERC. The advancement of digitalization complements both population expansion and industrial structure refinement. Initially, digital economic progress accelerates industrial transformation, enhances data-driven decision making for structural optimization, and fosters novel low-emission sectors. The optimization of industrial structure, meanwhile, provides practical situations and needs for the sustainable development of the digital economy. The two mutually promote the improvement of living quality and standards, which, by popularizing environmental awareness and supporting a variety of low-carbon behaviors, facilitate environmentally sustainable and climate-friendly societal progress. Yu et al. also demonstrated that digitalization lowers carbon intensity through industrial structure optimization, which is consistent with this paper [42]. The coefficients of urbanization level, energy consumption structure, and foreign openness are significantly negative, indicating that they have a significant inhibitory effect on local CERC enhancement. The rising urbanization level would increase the resource and energy demand somewhat, i.e., the coal consumption demand would also increase, which might increase local carbon emission. This is consistent with Song et al., where urban construction accelerates the expansion of the urban scale and the clustering of related industries, which could result in carbon emission increases [43]. Therefore, it is necessary to minimize the inhibitory effect on the local CERC through policy guidance, industrial adjustment, technological innovation, and other measures in the process of economic development, energy structure adjustment, and foreign opening up.

From Table 8, the influencing factors of neighboring prefectural cities also significantly affect the local CERC through spatial interaction. Among them, industrial structure and energy intensity coefficients remain significantly positive, i.e., neighboring prefectures will promote the local CERC due to the enhancement of these two influencing factors. This occurs as neighboring cities' industrial structure optimization and energy consumption intensity reduction can reduce their own carbon emissions. Cross-regional cooperation further enables optimal resource allocation and production capacity deployment, and it can promote the transfer and popularization of advanced technologies, contributing to the realization of regional carbon emission reduction. This is consistent with Yu et al.'s finding that in the mid-Yellow River industrial structure, particularly secondary industry, upgrading enhances neighbors' carbon emission efficiency [44]. Meanwhile, foreign openness is

significantly negative, which could inhibit the increase of local CERC. It is possible that the increase in foreign investment and trade activities in neighboring prefectures could stimulate the demand for resources and energy, which in turn would stimulate local energy consumption and economic growth with increased local carbon emissions. Consequently, neighboring areas' development exerts dual effects on local carbon emissions. Therefore, when the relevant carbon emission reduction action programs are formulated, it is necessary to fully consider the mutual influences and synergistic effects between regions so as to promote the enhancement of the overall regional CERC.

4.1.2. Regression Analysis by Plates

From Table 8, matching Shandong's regression outcomes, Plate I digital economy, demographic size, and industrial structure coefficients show significantly positive values. Furthermore, contrary to Shandong Province, urbanization level has a significant contribution to the CERC in Plate I. Exceptionally, prefectural cities in Plate I have higher urbanization rates, all exceeding the average in Shandong Province [45]. Higher urbanization levels, in turn, are often accompanied by more concentrated lifestyles and work styles, which help to improve the efficiency of public transport systems, social infrastructure, and energy resource use, thus contributing to local CERCs. This is consistent with Liu et al.'s finding that there is a negative impact on carbon emissions as urbanization levels increase [46]. Compared with Shandong Province, besides foreign openness, the economic development level and S&T investment level also have a significant inhibiting effect on the CERC enhancement of Plate I. This is because Jinan is the provincial capital for the regional economic development center of Shandong Province, while Zibo and Dongying are energy- and industry-oriented cities, and they are in the economic and industrial transformation and upgrading stage. Technology inputs and economic restructuring are bound to have a positive impact on energy efficiency, thereby reducing local carbon emissions.

Similar to Plate I, the coefficients of demographic size and industrial structure are significantly positive in Plate II. Unlike Plate I, Plate II's economic development level substantially affects its CERC. Qingdao, Yantai, and Weihai are coastal cities in Shandong Province, with marine characteristic resources and geographical advantages, and their industries are mainly developed in fishery, the service industry, and port logistics. Also, their improving economic development level boosts local energy consumption efficiency, especially clean energy and energy-saving technologies, which in turn contributes to CERC promotion. Compared with Shandong Province and Plate I, its digital economy significantly inhibits Plate II's CERC enhancement, except for urbanization level, foreign openness, and S&T investment level. This likely results from Plate III prefectures undergoing rapid early-stage digital economy development, especially in Qingdao, where the continued production capacity expansion and financial gains through productivity improvements could increase energy demand and carbon emissions [47]. To mitigate the rebound effect of early digitalization, it is crucial to adopt "green" computing technologies and integrate renewable energy sources into IT infrastructure, thereby decoupling digital economic growth from carbon emissions. Furthermore, the dampening spatial effect of neighboring prefectures' openness can be explained by interregional value-added chains. As neighbors upgrade their industries via investment of funds from outside prefecture-level cities, energy-intensive segments are often outsourced to local prefectures, resulting in the transboundary transfer of environmental costs between prefecture-level administrative regions.

Similar to Plate I, the coefficients of digital economy and industrial structure in Plate III are significantly positive, while economic development level is significantly negative. Its urbanization level is similar to Plate II, which inhibits the local CERC. Notably, the coefficient on the energy consumption structure in panel III is significantly negative, showing that

lower shares of coal consumption contribute to local CERCs. While Weifang, Rizhao, and Linyi are all typical regions with less abundant fossil energy resources, they possess the potential to develop renewable energy sources (e.g., wind, solar, biomass, etc.). Yang et al. found that clean energy could reduce local carbon emissions, considering it the most important measure to reduce carbon emissions [48]. Therefore, Plate III should actively explore and utilize local new energy sources and reduce its dependence on fossil energy sources, especially coal, thus contributing to the enhancement of local CERCs.

Similar to Shandong Province and the other plates, the coefficients on the economic development level are significantly positive, while those for digital economy, urbanization level, energy intensity, and energy consumption structure are significantly negative in Plate IV. Specifically, the coefficients for demographic size and industrial structure are significantly negative in Plate IV. Notably, the increase in demographic growth and secondary industry may not necessarily lead directly to carbon emission increases but also depends on various factors such as the local energy consumption structure, technology application, ecological and environmental protection, and so on [46]. Meanwhile, the prefectures in Plate IV are inland cities, and are mostly energy-oriented cities, now urgently confronting energy industry restructuring. In addition, compared with other plates, their economic development level and urbanization level are relatively low, so their demographic factors contribute to carbon emissions. This aligns with Liu et al.'s western China findings of demographic contributions to carbon emissions [46].

From Table 8, neighboring regions' socioeconomic indicators generate local-level CERC spillovers via spatial interaction. The economic development level of neighbors in Plates I, III, and IV has a depressing effect on the local CERC, which is attributable to growth in economic development level that promotes the expansion of industrial capacity together with resources and energy demand, which in turn depresses the local CERC. Meanwhile, the low-carbon technology effects of economic growth around neighbors in Plate II might bring spillover effects to the local area, thus contributing to local CERC enhancement. Besides Plate IV, the industrial structure of the neighboring regions in other plates has a significant promotion effect on local CERCs. This might occur because industrial structure adjustment and optimization, industrial clustering, and the popularization of low-carbon technologies in neighboring regions have a spillover effect on the local area, which promotes low-carbon development and diversification of the local industry. For most of prefectures in Plate IV, they are still dependent on high-carbon industries with slower green and low-carbon technology development overall, thus inhibiting local CERCs.

Therefore, the drivers of CERCs differ among plates; hence, differentiated and synergistic carbon reduction strategies should be followed. Plate I needs to accelerate and promote economic structure optimization, upgrading, and transformation to maximize economic development and scientific and technological progress in the promotion of urban carbon emission reduction. Plate II requires intensive promotion of technological innovation and the development of marine renewable energies (tidal and wind energy, etc.) to achieve low-carbon sustainable development in cities. Plate III should aggressively explore new local energy resources for lowering fossil energy dependence, especially coal, to facilitate CERC enhancement. When promoting local CERCs, Plate IV should take into account factors such as population, industrial structure, energy, and technology to formulate carbon reduction strategies.

4.2. Decomposition of Carbon Emission Reduction Capacity Drivers

4.2.1. Intermediation Effects in Shandong Province

Shandong's CERC spatial effects underwent three-way decomposition via SDM-time modeling: direct, indirect, and total (see Table 9).

Table 9. Spillover effects and robustness test of carbon emission reduction capacity.

Spillover Effect	Variables	Shandong		Plate I		Plate II		Plate III		Plate IV	
		Original	Replacement	Original	Replacement	Original	Replacement	Original	Replacement	Original	Replacement
Direct effect	x1	0.070 **	0.066 **	0.163 **	0.166 ***	−0.265 ***	−0.246 ***	0.389 *	0.417 *	−0.101 **	−0.120 *
	x2	0.156 ***	0.141 ***	0.773 ***	0.641 ***	0.658	1.760	1.134	1.626	−2.430 ***	−0.282 ***
	x3	0.043	0.044	−0.479	−0.508	1.206 ***	0.425 *	−1.206	−0.223	1.237 ***	0.540 ***
	x4	0.442 ***	0.463 ***	3.307 ***	3.322 ***	1.635 **	1.258 *	9.433 *	4.101 **	−0.547 **	−0.088 *
	x5	−0.033	−0.036	0.103 *	0.106 *	−0.276	−0.438	−0.288	0.218	−0.239 **	−0.136 *
	x6	−0.331 ***	−0.396 ***	0.062	0.079	−0.258	−0.950	−0.09	−0.085	0.144 **	0.101 *
	x7	−0.018	−0.005	−0.015	−0.008	0.392	−0.315	−0.592	0.126	−0.104 ***	−0.098 *
	x8	−0.047 ***	−0.022 *	−0.217 ***	−0.222 ***	−0.240 ***	−0.120 *	−0.183	−0.118	−0.018	0.0578
	x9	−0.031 ***	−0.004 *	0.255	0.242	−0.298 ***	−0.315 ***	3.684 *	4.280 *	0.023 *	0.011 *
	x10	−0.021	−0.011	−0.295 ***	−0.296 ***	−0.293 ***	−0.327 ***	−0.322	0.053	0.026	−0.102
Indirect effect	x1	−0.039	−0.055	0.037	0.046	0.162 **	0.116 *	0.802 **	0.653 *	0.037	−0.108
	x2	0.053	−0.002	1.416 ***	1.017 ***	1.512 ***	2.722 ***	−0.22	1.063	−3.892 ***	−0.186 *
	x3	−0.012	0.017	−2.017 **	−1.971 *	0.985 *	−0.625 *	−7.110 **	−2.653 *	−3.206 ***	−0.657 *
	x4	0.304 ***	0.305 ***	4.803 ***	4.596 *	0.43	1.696	29.281 ***	8.103 **	−4.796 ***	−1.882 ***
	x5	−0.069	0.008	−0.089	−0.081	−1.295 **	−2.458 ***	−1.777 ***	−0.097 *	0.726	0.147
	x6	0.991 ***	1.073 ***	1.033 **	1.088 *	−0.639	−1.764	0.593 *	0.367 *	−0.711 **	−0.386 ***
	x7	−0.014	−0.014	0.319 ***	0.343 ***	0.273	−0.603	−2.771 **	−0.474 *	0.243 ***	0.529 *
	x8	−0.097 **	−0.067	−0.394	−0.398	−0.508 ***	−0.134 *	−1.209 ***	−0.564 **	−0.481	−0.382
	x9	0.057 ***	0.001 *	−2.176 ***	−2.149 ***	−0.089	0.089	3.71	3.987	0.0368	−0.028
	x10	−0.108	−0.012	0.001	0.004	0.145 **	0.218 ***	−1.470 ***	−0.031 *	0.459 ***	0.306 *
Total effect	x1	0.031	0.012	0.201 ***	0.212 ***	−0.103 ***	−0.130 ***	1.191 **	1.071 *	−0.064	−0.228
	x2	0.208 **	0.138 *	2.188 ***	1.658 ***	2.170 **	4.482 ***	0.914	2.689	−6.323 ***	−0.467 *
	x3	0.055	−0.061	−2.495 **	−2.479 *	2.191 ***	−0.200 *	−8.316 *	−2.876	−1.968 ***	−0.117 *
	x4	0.746 ***	0.769 ***	8.110 ***	7.917 ***	2.065 ***	2.955 ***	38.714 **	12.203 **	−5.343 ***	−1.795 **
	x5	0.036	0.041	0.0139	0.025	−1.572 **	−2.896 ***	−2.064 **	−0.121 *	0.487	0.011
	x6	0.660 ***	0.677 ***	1.095 **	1.167 *	−0.897	−2.714	0.503	0.281	−0.567	0.387
	x7	−0.016	−0.015	0.303 **	0.335 *	0.665	−0.919	−3.363 **	−0.599 *	0.139 *	0.627 *
	x8	−0.144 ***	−0.089 **	−0.611 *	−0.620 *	−0.748 ***	−0.254 **	−1.393 **	−0.681 *	−0.499	−0.323
	x9	0.026	0.004 *	−1.921 **	−1.907 *	−0.387 ***	−0.225 ***	7.393	8.267	0.059	−0.028
	x10	−0.013	−0.013	−0.295 **	−0.292 *	−0.147 ***	−0.108 *	−1.792 **	−0.022 *	0.486 **	0.204 *

Note: ***, **, and * represent significance at the 0.01, 0.05, and 0.1 levels, respectively.

From Table 9, the economic development level has a significant spatial spillover effect, with significantly positive coefficients for direct, indirect, and total effects, indicating its positive contribution to the CERCs of both local and neighbors. The coefficients of the direct effects of urbanization development level and foreign openness are both significantly negative, while their indirect effects are significantly positive. This implies that their significantly positive spatial spillover generates enhanced CERC in neighboring regions. The energy consumption structure's direct, indirect, and total effect coefficients are all statistically negative, indicating that energy decarbonization not only contributes to the enhancement of local CERCs but also to CERCs in neighboring regions. Furthermore, demographic size and digital economy have a significant direct effect, while the indirect effect fails the significance level test. This shows that the two make a significant contribution to the local CERC, with weaker spatial spillover effects. Notably critical to carbon emission reduction is the digital economy, which requires enhancing its radiation-driven effect on neighbors by building regionally shared digital infrastructure, promoting the mobility and sharing of population, especially technical talent, resources, and capital, and optimizing the industrial layout and restructuring to reduce inter-regional disparities.

4.2.2. Intermediation Effects Across Plates

The spatial effects of CERCs in different plates were decomposed into direct, indirect, and total effects through SDM-both models (see Table 9).

From Table 9, there are positive direct effects of the digital economy, demographic size, industrial structure, and urbanization level in Plate I, while there are negative direct effects of foreign openness and S&T investment level. Therein, it is the industrial structure that has the largest direct effect on the local CERC. Specifically, there are positive indirect effects of demographic size, industrial structure, energy intensity, and energy structure, while economic development level and ecological environment have negative indirect effects. This indicates that local economic development may have stimulated and driven consumer demand in neighborhoods, resulting in increasing their production, transportation, and other activities, which in turn increase carbon emissions. Moreover, Huang et al. demonstrated an inverted U-shaped association between environmental regulation and carbon emissions, whereby as environmental regulation is strengthened its impact on carbon emissions shifts from facilitation to suppression [33]. This is consistent with this paper, suggesting that environmental regulation in Plate I needs to be strengthened urgently to further expand its breadth and depth for contributing to the realization of carbon reduction targets.

There are positive direct effects of economic development level and industrial structure in Plate II, while there are negative direct effects of the digital economy, foreign openness, ecological environment, and S&T investment level. Industrial structure has the largest direct effect on local CERCs. Fang et al. demonstrated that deep integration between productive services and manufacturing synergistically enhances carbon emission reduction [49]. This is consistent with the actual development of Qingdao, Yantai, and Weihai in Plate II. Also, there are positive indirect effects of the digital economy, demographic size, economic development level, and S&T investment level, while there are negative indirect effects of urbanization level and foreign openness. With the development of local urbanization and the introduction of foreign capital and technology, it may increase the local demand for energy resources in its surrounding areas, and, at the same time, some relatively outdated production technologies will be transferred to other areas, which will inhibit the enhancement of the CERC in nearby areas.

Only digital economy, industrial structure, and ecological environment have significant positive direct effects in Plate III, with the largest direct effect of industrial structure

on local CERC, while other influencing factors are insignificant. Moreover, the digital economy along with industrial structure positively affect neighboring regions indirectly. Hong et al. found that the digital economy is widely integrated into the whole process of enterprise production, which promotes the industrial structure's digital transformation and upgrading, contributing to the suppression of carbon emissions, in line with Plate III [8]. Economic development level, urbanization development level, energy structure, foreign openness, and S&T investment level have a negative indirect effect. The increase in local coal consumption stimulates and directs the demand for coal resources in neighbors, thus having an inhibiting effect not only on local CERC enhancement but also neighbors.

In Plate IV, economic development level, energy intensity, and ecological environment have significant positive direct effects, while digital economy, demographic size, industrial structure, urbanization development level, and energy structure have negative direct effects. Therein, demographic size has the largest direct effect on local CERC, followed by economic development level. Liu et al. found that positive spatial spillovers from the digital economy require appropriate economic foundations in the neighborhood to accelerate digital element flows [23]. The economic development level of prefectures in Plate IV is lower than the average in Shandong Province. Therefore, they urgently need to enhance economic development by optimizing industrial and energy structures to maximize the digital economy's positive spatial spillover effects. In addition, there are positive indirect effects of energy structure and S&T investment level on neighbors, while demographic size, economic development level, industrial structure, and energy intensity have negative indirect effects, with the industrial structure having the largest indirect effect, followed by demographic size and economic development level.

Overall, the plates should adopt different synergistic carbon reduction strategies to maximize the province's CERC. Plate I should focus on the impact of industrial structure on local CERCs while further strengthening environmental regulation intensity to avoid inhibitory effects on neighboring CERCs. Plate II should avoid the transfer of outdated technology to the periphery while strengthening the in-depth integration of the service industry with the manufacturing industry while realizing the sharing of technological resources between regions to collaboratively enhance the CERC of the entire region. Plate III should strengthen the breadth and depth of the digital economy's application to assist in industrial restructuring and advancement; meanwhile, it should actively promote clean energy utilization in order to avoid the reduction of the CERC. Plate IV should control its demographic size and economic growth rate while continuously adjusting and optimizing its industrial structure towards high-tech service industries so as to drive up the overall plate CERC.

4.3. Robustness Test

(1) Replacement explanatory variables in Shandong Province

Based on the literature search, this paper adopts foreign investment instead of foreign openness to characterize regional openness to the outside world for the model robustness test in Shandong Province. Table 9 shows the model's R^2 at 0.964, and the coefficient of import and export investment is consistent with the original SDM-time model, both of which have a dampening effect on the local CERC and a boosting effect on the neighboring regions. This demonstrates strong robustness in the constructed spatial econometric model, ensuring credible results.

(2) Replacement explanatory variables across plates

Based on the literature search, this paper adopts foreign investment instead of foreign openness to characterize regional openness to the outside world for the model robustness test across plates, shown in Table 9. From Table 9, the R^2 of the robustness test are close to

the original fits, while the coefficients of the import and export investment are consistent with the original regression, both of which have a dampening effect on the local CERC and a boosting effect on neighbors. This indicates that the spatial econometric model constructed in this paper has good robustness, which ensures the credibility of its results.

5. Conclusions

Using 2011–2021 carbon emission data from Shandong's 16 cities, this study extends prior research. Firstly, the CERC indicator was creatively proposed and scientifically quantified by comprehensively considering various aspects, such as energy, the economy, society, and the environment. Second, combining the improved gravity model with the spatial econometric model, considering both geographic variability and spatial correlation, the clustering analysis of Shandong Province and the identification of the drivers of CERCs in different plates were carried out. Finally, comparative analyses of CERC drivers were conducted at two administrative levels, provincial and prefecture, respectively. This study could offer an empirical foundation for Shandong's government to shape regional synergistic carbon policies and methodological guidance for other nations in conducting related research.

It is found that Shandong Province's CERC steadily grew during 2011–2021. while the magnitude of the CERC in different plates is in the following order: Plate II > Plate I > Plate III > Plate IV. Cluster analysis classifies Plate I as bidirectional spillover, Plate II as main inflow, Plate III as main outflow, and Plate IV as an agent. Meanwhile, it is found that the internal spatial relationships of the plates are relatively loose, while the synergistic and spillover effects among the plates are more significant. This suggests that while promoting regional synergistic development, it is necessary to exert the driving effect of the central cities within the plates.

The regression of CERC drivers in Shandong Province and the four plates through the SDM model found that the impact effects are also regionally differentiated due to resource endowment and development stage differences. Specifically, Plate I should accelerate industrial structure upgrading and transformation, strengthen environmental regulation intensity, and maximize the contribution of economic development and technological progress to urban carbon emission reduction. Plate II should vigorously promote technological innovation and marine renewable energy (tidal and wind energy, etc.), together with the deeper integration of services and manufacturing and the sharing of technological resources between regions, in order to synergistically improve the overall CERC. Plate III should actively develop renewable energy and reduce dependence on fossil energy, especially coal, while strengthening the breadth and depth of digital economy applications to assist its upgrading transformation, thus avoiding CERC reductions. Plate IV should control its demographic size and economic development rate while continuously optimizing its industrial structure towards high-tech service industries so as to boost the CERC. As for the Shandong Provincial Government, it should comprehensively consider the linkage effect of neighboring regions and fully utilize their respective complementary strengths to maximize the effect of carbon emission reduction.

Although this study provides valuable insights into the regional collaborative governance and driving mechanisms of CERC of Shandong Province, several limitations remain to be addressed in future investigations. First, due to the inherent publication lag of official statistical data and municipal-level carbon inventories, the study period was restricted to 2011–2021; this temporal constraint, alongside potential uncertainties regarding data quality and the macro-level nature of indicator construction, may slightly limit the generalizability of the findings, requiring future research to extend the temporal scope as newer data become available. Second, while this paper establishes differentiated macro-level

strategies for the four identified plates, the proposed policy recommendations remain relatively broad. Finally, the current spatial econometric approach relies on static model assumptions, primarily identifying static driver relationships without fully clarifying the dynamic interaction mechanisms of inter-city factor flows. To bridge these gaps and systematically address these uncertainties, our future work will employ spatial system dynamics modeling. This advanced approach will allow us to simulate complex, dynamic correlations both among the different plates and across individual cities within them. By tracking the concrete spatial flows of energy, resources, capital, and technological talent, we aim to formulate highly specific, optimized, and quantifiable synergistic emission reduction pathways tailored to individual prefectural cities, thereby maximizing regional mitigation efficiency from both micro and macro perspectives.

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