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Spatial Effects of Economic Modernization on Carbon Balance in China

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Abstract: Exploring the impact of economic modernization on carbon balance is an essential endeavor to achieve carbon neutrality and combat climate change. However, the spatial impact of economic modernization on carbon balance remains ambiguous. Therefore, this study aims to explore the spatial spillover effects of agricultural modernization, industrialization, and urbanization on carbon balance during the economic modernization process in China, taking 30 provinces and cities in China as examples from 2010 to 2021. This study utilizes the spatial Durbin model to derive the following results: In the past decade, the carbon balance ratio has shown a fluctuating and decreasing dynamic evolution trend. There is an increase in regions with serious carbon deficits. Further investigation into the spatial spillover effect of carbon balance unveils that for every 1% increase in the carbon balance ratio of a province, neighboring provinces experience a decrease of 0.833%. Additionally, the spatial spillover effects of the three modernizations in China on the carbon balance ratio behave differently. Agricultural modernization and urbanization demonstrate negative spatial spillover effects on the carbon balance in neighboring regions, while industrialization exerts a significant positive spatial spillover effect on the carbon balance of neighboring regions. Regarding control variables, the level of innovation solely contributes to local carbon balance realization without generating a trickle-down effect, whereas infrastructure development operates inversely. At the same time, there are differences in the spatial effects of agricultural modernization and industrialization on the carbon balance between the eastern region and the central and western regions. The study underscores the importance of economic modernization and development processes focusing on fostering synergistic growth between economic and environmental benefits within both local and neighboring areas.

Keywords: agricultural modernization; industrialization; urbanization; carbon emissions; carbon sinks

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1. Introduction

Global warming is a challenge to global sustainable development [1–3], with carbon dioxide identified as its primary driver [4–6]. Sustainable development is crucial for enhancing human well-being, as it entails development that satisfies present needs while safeguarding the capacity of future generations to meet their own needs [7,8]. Recognizing this, item 13 of the United Nations Sustainable Development Goals emphasizes the urgent need for action to address climate change and its consequences. China, as a major developing nation, has implemented a range of measures aimed at reducing carbon emissions and enhancing carbon sinks, including setting the China dual carbon strategy [4,9], striving to peak carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060. These efforts are integral to mitigating climate change amidst rapid economic modernization in China. However, the modernization of China's economy has led to improved production efficiency, albeit with a corresponding rise in energy consumption pressure to some extent. Consequently, the eco-efficiency regarding carbon balance remains unclear.

Agricultural modernization, industrialization, and urbanization, collectively known as the three modernizations, are recognized as prominent and concentrated facets of economic modernization [10]. Agricultural modernization is pivotal for advancing the modernization of economic development. Industrialization is an indispensable force for economic modernization. Urbanization enhances resource utilization efficiency, accelerates economic growth, and serves as the primary driver of economic modernization. Research on their impact on carbon balance can be categorized into three areas. First is the examination of economic modernization's effect on carbon emissions [11,12]. Some studies suggest that economic modernization significantly contributes to carbon emissions and plays a crucial role in their escalation [13,14]. The advancement of modernization inevitably entails substantial energy consumption [15], thereby exacerbating the pressure on carbon emissions. Conversely, other research indicates that economic modernization can effectively mitigate carbon emissions [16,17]. The three modernizations drive economic structural transformation, industrial upgrading, and technological innovation [18]. In particular, technological innovations, such as the adoption of energy-efficient equipment and the application of cleaner energy technologies, have greatly improved the efficiency of energy utilization, which has reduced energy consumption, thereby alleviating the burden on carbon emissions [19]. Additionally, some studies highlight the stage-specific characteristics of economic modernization's impact on carbon emissions [20,21]. For instance, Wang et al. [22] observed that the impact of urbanization on carbon emissions in OECD countries adheres to the environmental Kuznets curve, revealing the time-varying and intricate nature of its influence.

The second category is the influence of economic modernization on carbon sinks [23,24]. Existing research indicates that, on the one hand, the beneficial effects on carbon sinks resulting from agricultural modernization, emphasizing forest preservation and conservation, as well as from industrialization and urbanization involving urban greening, are noteworthy [25,26]. Conversely, the progression of the three modernizations inevitably triggers a range of environmental challenges, such as land degradation, environmental pollution [27,28], and heightened land use intensity [29], which severely hinder the realization of carbon sink functions. In summary, while the three modernizations significantly impact carbon emissions and carbon sinks, their effect on carbon balance remains unclear.

The third category comprehensively considers carbon sources and sinks, specifically examining the impact of the three modernizations on carbon balance [30]. Zhang et al. [31] noted a clear positive effect on carbon balance from the modernization of irrigated agriculture, while Ding and Li [32] found that land expansion due to industrialization and urbanization impedes achieving carbon balance. These studies focus on individual aspects of economic modernization and ignore their combined effects on carbon balance. Spatial autocorrelation is an analytical technique used to assess the spatial distribution patterns and interdependencies within data. The presence of spatial correlation among regions is consistently anticipated. If variable values become increasingly similar as distance decreases, they exhibit positive spatial correlation; conversely, if they diverge, they indicate negative spatial correlation [33]. China's vast size and significant geographical variations lead to spatial correlation effects from agricultural modernization, industrialization, and urbanization [34]. Breaking down spatial and temporal barriers in the development process could result in a spatial spillover effect on carbon balance. Some studies have found their spatial spillover effects on carbon sinks and emissions [35,36], but only a limited number of studies have delved into the spatial spillover effects on carbon balance. Thus, there is an urgent necessity to elucidate the spatial spillover effect of economic modernization on carbon balance.

To sum up, as a symbol of economic modernization, the three modernizations all need to be integrated into the research system. At the same time, related studies often ignore their spatial effects on carbon balance. To fill the gaps in these aspects, this study aims to examine the spatial spillover effects of agricultural modernization, industrialization, and urbanization on carbon balance using panel data from 30 provinces and cities in China spanning from 2010 to 2021. Since 2010, when China put forward its 12th Five-Year Plan, the country has undergone a major shift in its economic development and structure over the past decade, which has been manifested in the three modernizations of the economy in China. This has also profoundly changed the energy structure in China. Due to the lack of data on Hong Kong, Macao, Taiwan, and Tibet, 30 provinces and cities in China (including 22 provinces, 4 municipalities directly under the central government, and 4 autonomous regions) were selected as the samples for this study. By evaluating the spatial correlation effect to understand how economic modernization affects the carbon balance of local and neighboring areas, policymakers can strategize fitting measures for the integrated and coordinated progression of these areas. Meanwhile, studying the spatial spillover effects of the three modernizations on the carbon balance can provide policymakers with some reference for formulating policies related to the synergistic development of economic and environmental benefits.

2. Materials and Methods

2.1. Framework for Analysis

In this study, agricultural modernization, industrialization, and urbanization serve as explanatory variables, while the carbon balance ratio acts as the response variable. We include a set of control variables (level of innovation, infrastructure, openness, and economic development) in our analysis (Figure 1). Agricultural modernization, characterized by excessive chemical fertilizer inputs, leads to land degradation and environmental pollution [27,28], thereby impacting regional carbon balance. However, it also encourages water-saving irrigation and reduces energy consumption, thereby mitigating carbon emissions to some extent [19]. Rapid industrialization contributes significantly to carbon emissions due to high energy consumption [15], yet advancements in production efficiency and technological innovation alleviate this pressure. Urbanization emerges as a prominent human activity influencing ecosystems and social systems [37,38]. The intensified land use and socio-economic activities associated with urbanization contribute to increased carbon emissions, while urban expansion diminishes natural landscape areas, affecting carbon sink functionality [29]. However, new urbanization initiatives can also enhance ecological environments and positively influence carbon balance evolution [39]. The effects of the three modernization processes on carbon balance operate through driving forces and pressures. According to the first law of geography, things are spatially correlated [40]. The economic activities in the region not only affect themselves but also extend their influence to neighboring regions or even across different regions; that is to say, spatial spillover effects are generated [41]. The spatial Durbin model (SDM), as a model to analyze the correlation of spatial units, can present the spatial spillover effect of variables in a region more comprehensively. Primarily, agricultural modernization, industrialization, and urbanization effectively stimulate industrial clustering, fostering inter-regional exchanges and cooperation, thereby expediting the cross-regional flow of technological factors and human resources, which in turn influences the carbon balance of neighboring regions [42]. However, concurrently, distortions in factor markets and mismatches in resources during the three modernization processes might impede technological innovation, consequently negatively affecting the carbon balance of neighboring regions [43].

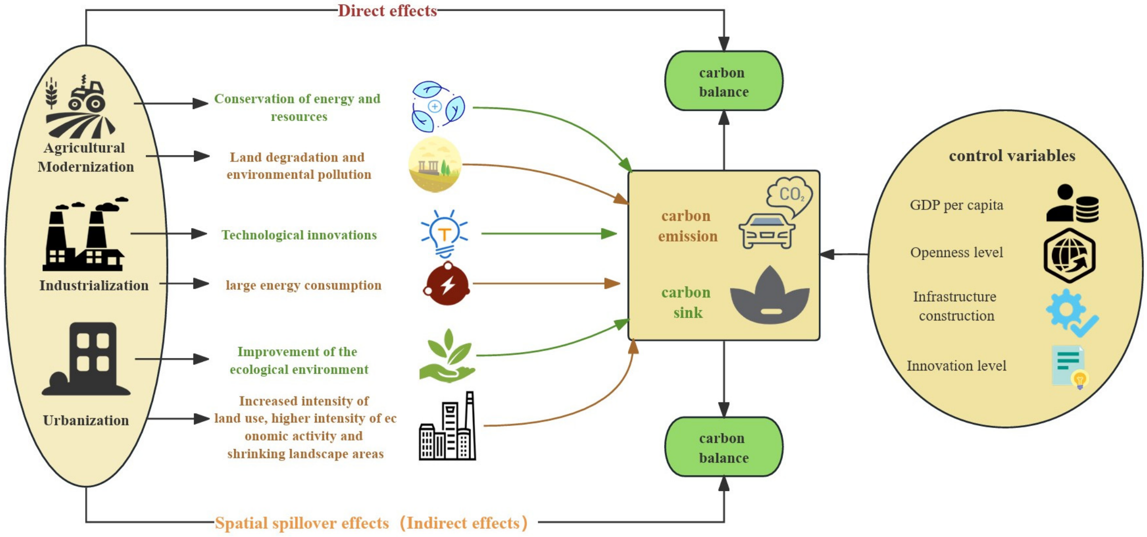

Figure 1. Analytical framework.

2.2. Data Sources

Land use/land cover data are from the National Cryosphere Desert Data Center (http://www.ncdc.ac.cn, accessed on 25 August 2023). The dataset uses 335,709 Landsat images from Google Earth Engine, combined with stabilized samples extracted from the China Land Use Dataset (CLUD) and visually interpreted samples from satellite time-series data, Google Earth, and Google Maps to collect training samples to construct an annual land cover product (CLCD) for China from 1985 to 2022. Indicators related to agricultural modernization, industrialization, and urbanization are from China Rural Statistical Yearbook, China Statistical Yearbook, and China Energy Statistical Yearbook. Due to the lack of data from Hong Kong, Macao, Taiwan, and the Tibet Autonomous Region, the study sample was finalized for 30 provinces and cities.

2.3. Construction of the Indicator System for the Three Modernizations

In terms of constructing indicators for the three modernizations, this study adopts a systematic and scientific approach, selecting specific indicators to build an index for the three modernizations (Table 1). (1) Agricultural modernization is structured around three key aspects: the level of agricultural mechanization, agricultural output, and the living standards of rural residents [44]. (2) Industrialization is assessed based on inputs and outputs at the regional level [10,45]. (3) Urbanization, which enhances resource utilization efficiency and accelerates economic growth [46], is not only a key driver of economic modernization but also a significant factor in altering carbon sources and sinks [47]. In this study, urbanization is evaluated across three dimensions: population, economy, and living standards of urban residents [48]. To establish the weight of each indicator, the entropy method is utilized, which computes both the objective weight and the entropy weight by considering the variances among indicators.

Table 1. Construction of the indicator system for the three modernizations.

Types	Indicators	Description	Attributes
Agricultural Modernization Index (AMI)	Per capita disposable income of rural residents (CNY/person) [44]		+
	Engel's coefficient of rural residents (%) [49]	Rural residents' food expenditures as a percentage of consumption expenditures	−
	Degree of agricultural mechanization (kW/ha) [49]	Total power of agricultural machinery divided by area of cultivated land	+
	Grain yield (t/ha) [44]	Grain production divided by area sown to grain	+

Table 1. *Cont.*

Types	Indicators	Description	Attributes
Industrialization Index (II)	Number of industrial enterprises above scale (number) [10]		+
	Industrial profit (million CNY) [50]		+
	R&D Expenditure (%) [10]	R&D expenditure as a percentage of regional GDP	+
	Industrialization rate (%) [51]	Value added of industry as a percentage of GDP	+
Urbanization Index (UI)	Share of urban population (%) [10]	Urban population as a percentage of total regional population	
	Per capita disposable income of urban residents (CNY/person) [52]		+
	Engel's coefficient of urban residents (%) [52]	Urban residents' food expenditure as a percentage of consumption expenditure	-
	Employment urbanization rate (%) [53]	Urban employment as a percentage of total employment	+

Since the indicators in Table 1 encompass various dimensions of socio-economic data, directly quantifying these data to gauge the development level of the three modernizations is not feasible. Therefore, as a first step, all measurements are standardized into common units through normalization [10]. Following normalization, features across different dimensions become numerically comparable, significantly enhancing the accuracy of the results by utilizing the equations:

$$\text{Positive indicators}: \ t_{ij} = (x_{ij} - x_{i\min})/(x_{i\max} - x_{i\min}) \tag{1}$$

$$\text{Negative indicators}: \ t_{ij} = (x_{i\max} - x_{ij})/(x_{i\max} - x_{i\min}) \tag{2}$$

where t_{ij} represents the standardized value of the jth evaluation indicator in the evaluation index for the ith evaluation object. Meanwhile, x_{ij} denotes the value of the ith evaluation object before it undergoes standardization to the jth evaluation indicator. Additionally, $x_{\max}$ refers to the maximum value within the jth evaluation value, whereas $x_{\min}$ signifies the minimum value within the jth evaluation value.

2.4. Carbon Balance Ratio (CBR)

The carbon balance ratio (CBR_i) characterizes the match between carbon emissions (C_{ei}) and carbon sequestration (C_{si}), reflecting whether the carbon sequestration capacity of a region can meet the demand for human carbon emissions. The ratio of carbon absorption to carbon emission reflects the surplus, balance, or deficit of carbon balance [54]. The formula is as follows:

$$CBR_i = \frac{C_{si}}{C_{ei}} \tag{3}$$

Among them, carbon sequestration mainly comes from forest land, grassland, water, cropland, and unutilized land. Its stability is high, so it is measured using the area of different land categories multiplied by the corresponding carbon absorption coefficient. The formula is as follows:

$$C_{si} = \sum_{k=1}^{n} A_k \times \delta_k \tag{4}$$

where A_k represents the area of the kth land-use type; δ_k represents the carbon absorption coefficient of the kth land-use type. The carbon absorption coefficients of forest land, grassland, water, cropland, and unutilized land are selected as shown in Table 2 [55].

Carbon emissions mainly come from urban land and construction land. In this study, carbon emissions from energy consumption are used to replace carbon emissions from urban land and construction land [56–58], and the data are obtained from provincial statistical yearbooks.

Table 2. Carbon absorption coefficients.

Land Types	Forestland	Grassland	Water	Unused Land	Wetland
Carbon absorption coefficient	0.0578	0.0021	0.0252	0.0005	0.00006132
Unit	kg/(m^2·a)	kg/(m^2·a)	kg/(m^2·a)	kg/(m^2·a)	kg/(m^2·a)

2.5. Control Variables

Carbon balance is influenced by various factors, such as the degree of innovation, economic advancement, and openness to global interactions. Therefore, besides the fundamental explanatory variables of the three modernizations, this study incorporates the following control variables.

(1) Level of economic development (GDPPC). This is gauged by the per capita GDP of each province and city.
(2) Level of innovation. This is assessed by the count of effective invention patents in each province and city.
(3) Openness. This is evaluated by the total foreign investment in each province and city.
(4) Infrastructure. This is measured by the density of highways in each province and city.

2.6. Spatial Autocorrelation Test

Moran's I coefficient is commonly utilized to gauge the global spatial autocorrelation, which effectively portrays the overarching tendency of the spatial correlation among carbon balance ratios across 30 provinces and cities in China. Moran's I ranges [−1, 1]. A value nearing 1 indicates a robust positive spatial autocorrelation in the carbon balance ratio, while a value approaching −1 suggests a significant negative spatial autocorrelation. When the value equals 1, the carbon balance ratio exhibits a random distribution pattern. The formula for computing the global Moran index is as follows:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \sum_{i=1}^{n} (x_i - x)^2} \quad (5)$$

where I is the global Moran index, n is the number of spatial units, x_i is the observed value of each spatial unit, $\overline{x}$ is the average value of x_i, and w_{ij} is the spatial weight [59].

The local spatial autocorrelation relationship delineates the type and extent of spatial correlation between a particular area and its neighboring areas. The formula for local spatial autocorrelation is as follows:

$$I_i = \frac{1}{S^2} \sum_{i \neq j}^{n} w_{ij}(x_j - \overline{x})(x_i - \overline{x}) \quad (6)$$

$$S^2 = \frac{1}{n} \sum_{i=1}^{n} (x_i - \overline{x})^2 \quad (7)$$

2.7. Spatial Durbin Model (SDM)

The SDM assumes spatial dependence, meaning that the relationship between observations not only depends on their characteristics but also their spatial locations. The SDM holds significant importance in analyzing spatial dependence and explaining relationships and variations in spatial data. Its limitation lies in the requirement for appropriate modeling of spatial structures and strict demands on the spatial distribution of data [60].

Spatial dependence and heterogeneity are observed in the carbon balance ratio, suggesting potential interaction effects with agricultural modernization, industrialization, and urbanization. These interactions can manifest as the endogenous interaction effect, the interaction effect between error terms, and the exogenous interaction effect, corresponding to the spatial lag model, spatial error model, and spatial Durbin model, respectively. Additionally, depending on the temporal dynamics of panel data, fixed-effects models and random-effects models can be distinguished [41,61]. The general expression of the spatial Durbin panel model is as follows:

$$CBR_{it} = \alpha + \rho WCBR_{it} + \beta X_{it} + \gamma WX_{it} + \delta WC_{it} + \theta C_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{8}$$

CBR_{it} denotes the vector consisting of the carbon balance ratio for the ith province in year t; X_{it} and denotes the vector consisting of the independent and control variables for the ith province in year t; α denotes a constant, and ρ, β, and θ denote the spatial autoregressive coefficients of the carbon balance ratio, the independent variables, and the control variables, respectively; γ and denotes the spatial lag coefficients. μ_i denotes individual fixed effects, λ_t denotes time-fixed effects, and ε_{it} denotes a random disturbance term. W denotes the spatial weight matrix [62].

3. Results

3.1. Spatial and Temporal Variations in CBR

Overall, China's carbon balance ratio has shown a fluctuating downward trend, from 1.36 to 1.26. Carbon sinks have been relatively stable, while carbon emissions have grown significantly (Figure 2) (Table 3).

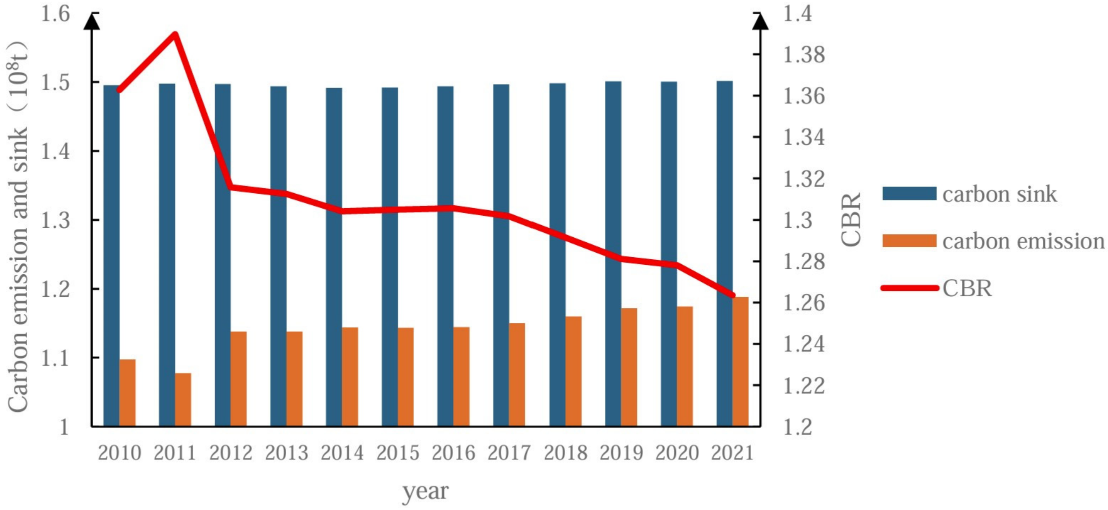

Figure 2. Line graph of the time evolution of carbon emissions, carbon sinks, and carbon balance.

Table 3. Table of the time evolution of carbon emissions, carbon sinks, and carbon balance.

Year	Carbon Sink (10^8 t)	Carbon Emission (10^8 t)	CBR
2010	1.4952	1.0971	1.3628
2011	1.4974	1.0775	1.3898
2012	1.4971	1.1378	1.3158
2013	1.4935	1.1379	1.3125
2014	1.4913	1.1436	1.3040
2015	1.4918	1.1431	1.3050
2016	1.4937	1.1441	1.3055
2017	1.4967	1.1498	1.3017
2018	1.4978	1.1599	1.2914
2019	1.5009	1.1716	1.2811
2020	1.5002	1.1739	1.2780
2021	1.5015	1.1884	1.2635

Spatial visualization using ArcGIS was employed to categorize the carbon balance into five types: severe carbon deficit (0, 0.6), slight carbon deficit (0.61, 0.9), carbon balance (or tending to carbon balance) (0.91, 1.1), slight carbon surplus (1.11, 2), and carbon surplus (2.01, 5.28).

In terms of spatial distribution, carbon deficit regions are primarily concentrated in the eastern part of the country, including Liaoning, Hebei, Tianjin, Shandong, Shanxi, Anhui, and Jiangsu, situated in the Bohai Economic Zone and the Yangtze River Delta region. The number of regions with severe carbon deficits has somewhat increased between 2010 and 2021. Xinjiang and Liaoning have consistently experienced carbon deficits during this period, transitioning from slight deficits to severe deficits. In the Beijing–Tianjin–Hebei region, Beijing has shifted from a carbon deficit to a slight carbon surplus. Carbon surplus areas are predominantly located in southwest and southeast China, including Qinghai, Sichuan, Yunnan, Guangxi, Jiangxi, and Fujian, with Guizhou transitioning from a slight surplus to a surplus between 2016 and 2021. Gansu has maintained a carbon balance from 2010 to 2021, while Jilin shifted from a slight surplus to a balance between 2010 and 2016 (Figure 3).

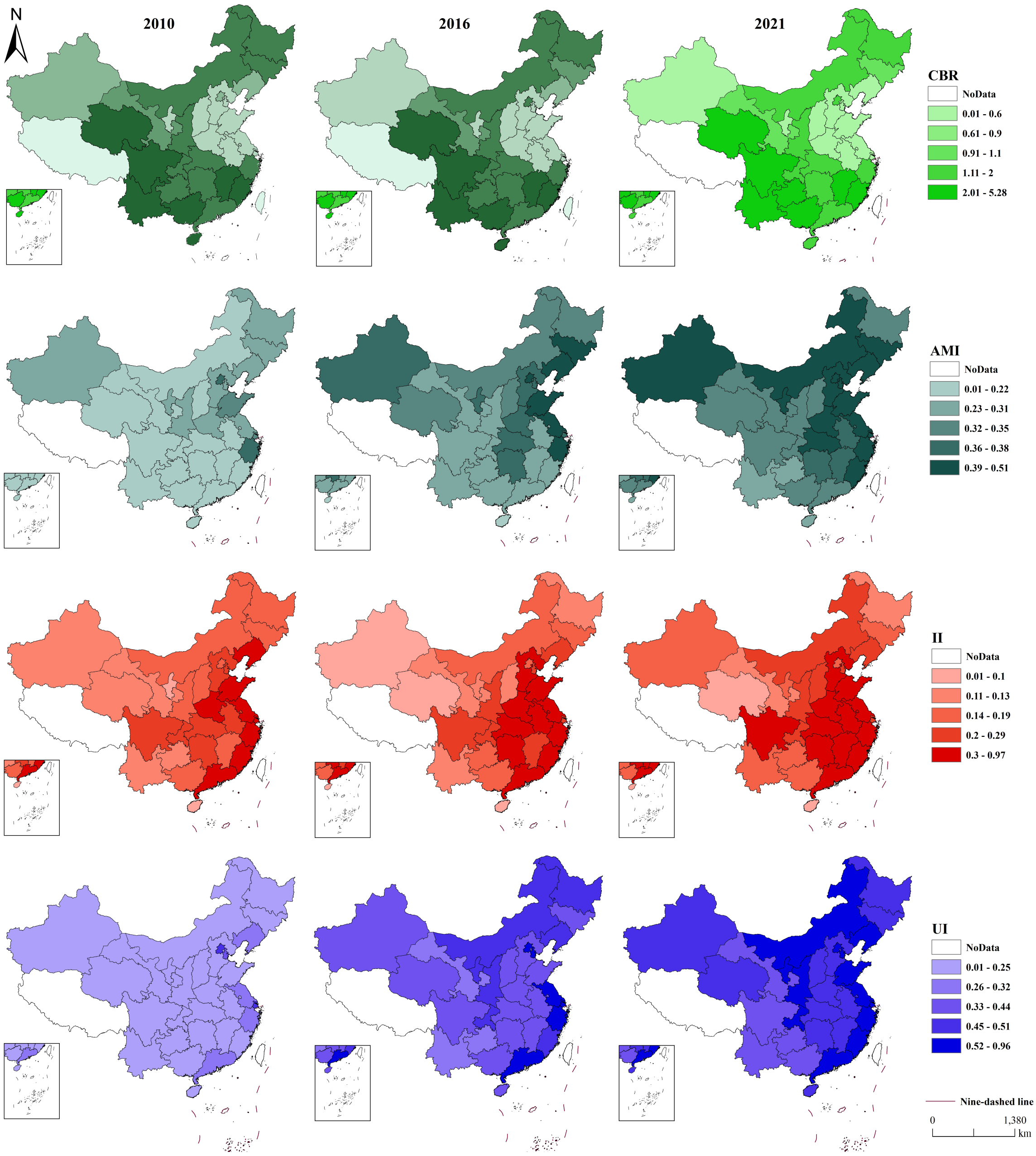

Figure 3. Spatial map of carbon balance, a spatial map of the three modernizations.

3.2. Spatial Distribution of Agricultural Modernization, Industrialization, and Urbanization

The period 2010–2021 is not only a period of big changes in the carbon balance pattern but also a period of rapid development of agricultural modernization, industrialization, and urbanization. (1) Overall, there was a substantial increase in the average value of agricultural modernization, rising from 0.184 to 0.323 across 30 provinces and cities. The average value of industrialization increased from 0.173 to 0.205, while urbanization experienced a remarkable growth from 0.137 to 0.427. These developments were driven by the rapid economic progress experienced during this period. Notably, urbanization recorded the highest increase, reaching an impressive 211.679%, surpassing the other two aspects. (2) The degree of the three modernizations has obvious spatial heterogeneity. The high value of agricultural modernization is mostly concentrated in the eastern coastal region. It spread to the central and western regions with a point, among which the growth of agricultural modernization in Xinjiang and Inner Mongolia has been especially remarkable in 12 years. The high value of industrialization is mainly concentrated in the southeast coastal region and Bohai Rim, which is the core of the expansion to the central and western regions. Among them, the city cluster in the middle reaches of the Yangtze River shows a more significant growth in industrialization. High urbanization is concentrated in the Southeast Coast, Beijing–Tianjin, and Pearl River Delta regions and spreads to the central and western regions (Figure 3).

3.3. Spatial Autocorrelation Test

Table 4 shows the results of the global spatial correlation analysis of the CBR for the period 2010 to 2021. During this period, the CBR consistently shows positive global Moran's I values, which are consistently significant at the 1% confidence level, thus refuting the null hypothesis and indicating a robust spatial clustering effect of the CBR from 2010 to 2021. Analyzing the trend of the Moran's I value, it can be found that the Moran's I value showed an increasing trend from 2010 to 2012, a steady decrease from 2012 to 2018, followed by fluctuations, and then an increase again from 2018 to 2021. Overall, the fluctuating downward trend of Moran's I value indicates that the degree of agglomeration of the CBR of the 30 provinces and cities in China is gradually weakening.

Table 4. Moran's I value for carbon balance ratio (CBR) from 2010 to 2021.

Year	I	z	*p*-Value	Year	I	z	*p*-Value
2010	0.084	3.184	0.001	2016	0.080	3.096	0.001
2011	0.085	3.221	0.001	2017	0.076	2.996	0.001
2012	0.087	3.264	0.001	2018	0.073	2.929	0.002
2013	0.085	3.216	0.001	2019	0.075	2.980	0.001
2014	0.084	3.186	0.001	2020	0.068	2.818	0.002
2015	0.080	3.086	0.001	2021	0.076	2.991	0.001

Although the global Moran's I value measures the spatial correlation of the CBR, it does not differentiate between high and low-value clustering situations. Therefore, to analyze the spatial heterogeneity of the CBR, this study employs Moran's scatter plot to examine its local clustering.

Figure 4 depicts the local spatial correlation of CBR in 2010, 2013, 2017, and 2021, with 30 provinces and cities identified by numbers from 1 to 30. The Moran index of the 30 provinces and cities is concentrated in the first and third quadrants. This indicates that low CBR provinces and cities exhibit clustering patterns with neighboring low CBR provinces and cities (L-L), while high CBR cities tend to cluster together (H-H). Further observation of the Moran scatterplot reveals that the provinces and cities falling into quadrants I and III remain relatively stable over the study period, each accounting for about 33% of the total number of provinces and cities. This phenomenon underscores the significant spatial correlation characteristics of CBR and establishes a basis for further investigation into spatial spillover effects.

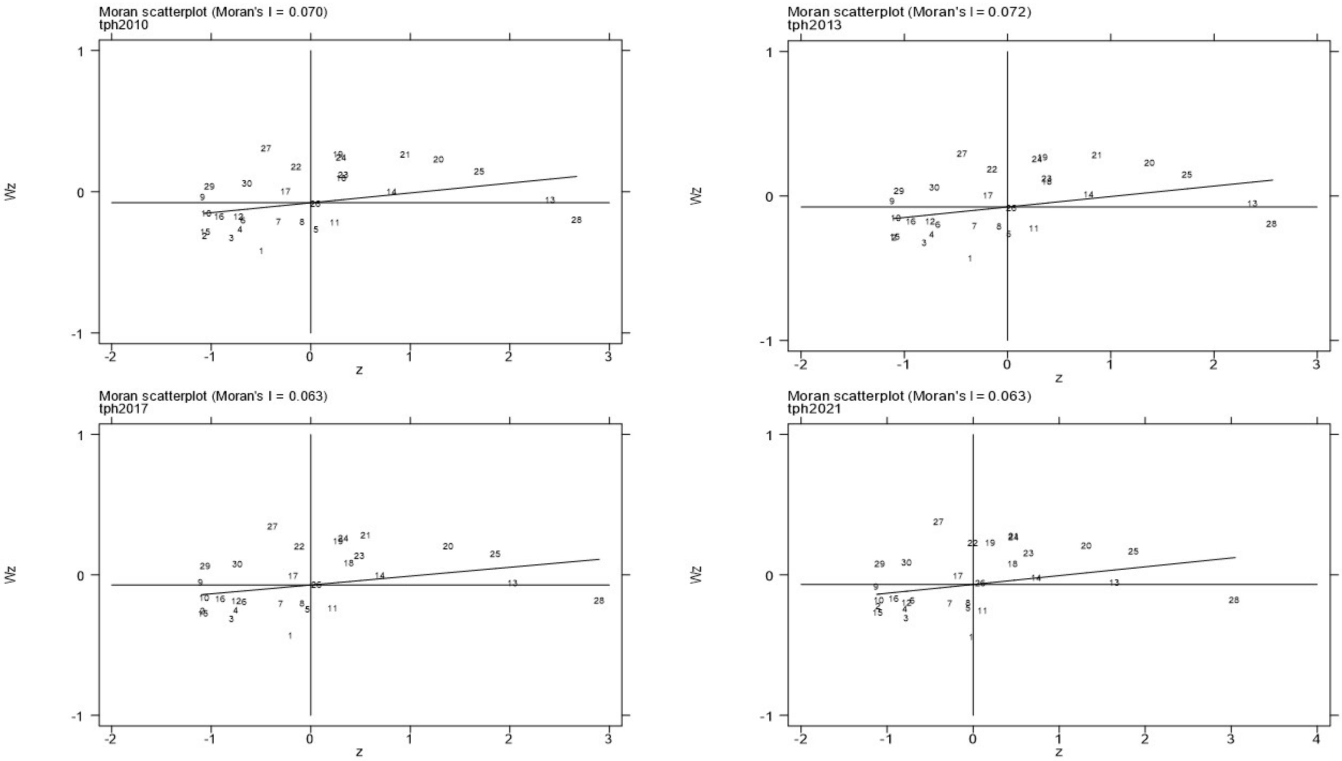

Figure 4. Moran scatter plot. Note: When the diagonal line slopes from bottom left to top right, it indicates a positive correlation. When the diagonal line slopes from the upper left to the lower right, it indicates a negative correlation.

3.4. Spatial Spillover Effects of the CBR

The results of the spatial correlation test show that the CBR has a strong spatial dependence. To further analyze its spatial spillover effect, tests were conducted under the geospatial weight matrix to select an appropriate spatial effect model.

The ex ante test was conducted first. The Lagrange multiplier (LM) test was conducted to prove the existence of specific spatial effects, as shown in Table 5, and the results were all significant at the 1% level, which rejects the original hypothesis, indicating that both the spatial lag term and the spatial error term exist in the sample. As a result, the Spatial Durbin Model (SDM) was initially chosen to accommodate both effects. Then, the post hoc test was conducted, which was divided into three steps. The first step passes the Hausman test to determine whether to use a fixed effects model or a random effects model. The second step was a likelihood ratio (LR) test to test whether the spatial Durbin model degenerates into a spatial autoregressive model and a spatial error model. The Wald test was performed in the third step to further verify whether the results of the second step were robust. In particular, the Hausman test yielded a critical value of 17.64, which was significant at the 5% level, and thus the fixed effects model was used. In addition, the test scores of the LR test were 101.48 and 93.88, which were both significant at the 1% level, and the results of the Wald test were both significant at the 1% level, which indicates that the spatial Durbin model does not degenerate into the spatial error model and the spatial lag model. Therefore, this paper chose the fixed effect spatial Durbin model for empirical analysis.

Table 5. Pre-test and post-test results.

Test		Statistic
LM	Spatial error:	
	Lagrange multiplier	693.614 ***
	Robust Lagrange multiplier	221.39 ***
	Spatial lag:	
	Lagrange multiplier	489.310 ***
	Robust Lagrange multiplier	17.090 ***
Hausman		17.64 **
LR	Lagrange multiplier	101.48 ***
	Robust Lagrange multiplier	93.88 ***
Wald	Lagrange multiplier	19.01 ***
	Robust Lagrange multiplier	19.17 ***

Note: *** and ** indicate 1% and 5% significance levels, respectively. z-values are in paren-theses.

3.5. SDM Model Regression Results

The spatial correlation coefficient is −0.833, which is significant at a 1% level. This indicates that there is a significant negative correlation between CBRs. For every 1% increase in CBR in the province, CBR in neighboring provinces decreased by 0.833%. The CBR between provinces showed mutual exclusion.

The impacts of the three modernizations on CBR were decomposed into direct effects, indirect effects, and overall effects (Table 6). The direct effect represents the impact of local agricultural modernization, industrialization, and urbanization on local CBR. The indirect effect shows the impact of local agricultural modernization, industrialization, and urbanization on CBR in neighboring areas. The total effect represents the overall impact of the three modernizations on CBR. As can be seen from the table below, the direct effects of the three modernizations on CBR are all significantly negative, indicating that regional agricultural modernization and industrialization all have a dampening effect on CBR. The advancement of agricultural modernization and industrialization promotes the increase in carbon emissions. Meanwhile, it crowds out the space of vegetation landscape, reduces carbon absorption, and the carbon absorption capacity is gradually difficult to meet the local demand for carbon emissions, which makes the tendency of the carbon balance of payments deficits increase. The indirect effect coefficient of agricultural modernization and urbanization is significantly negative, indicating that there is a negative spatial spillover effect of agricultural modernization and urbanization on CBR. The indirect effect of industrialization was significantly positive, indicating that the impact of industrialization on CBR had a positive spatial spillover effect. The overall regression coefficients of agricultural modernization and urbanization were −4.686 and −9.880, which were both significant at a 1% level. This indicates that agricultural modernization and urbanization have a significant negative effect on CBR.

Table 6. Direct effects, indirect effects, and total effects.

CBR	Direct	Indirect	Total
AMI	−1.284 ***	−3.401 ***	−4.686 ***
	(−3.30)	(−2.680)	(−3.990)
II	−2.529 ***	6.217 **	3.688
	(−4.480)	(2.190)	(1.250)
UI	−0.576 ***	−9.304 ***	−9.880 ***
	(−4.190)	(−4.860)	(−5.170)
GDPPC	0.148	5.756 ***	5.903 ***
	(0.460)	(3.580)	(3.680)
Openness	−0.148 ***	0.891 ***	0.742 ***
	(−3.550)	(3.510)	(3.510)

Table 6. *Cont.*

CBR	Direct	Indirect	Total
Infrastructure	−0.470 *** (−2.930)	2.807 *** (4.130)	2.337 *** (3.470)
Innovation	2.520 *** (4.770)	−9.943 *** (−3.530)	−7.422 ** (−2.530)
Spatial rho	−0.833 *** (−3.300)		
sigma2_e	0.144 *** (13.170)		

Note: *** and ** indicate 1% and 5% significance levels, respectively. z-values are in parentheses.

Among the control variables, the indirect effects of GDPPC, Openness, and Infrastructure were significantly positive, and there was a positive spatial spillover effect. This indicates that the improvement of the local economic development level, the expansion of openness, and the improvement of infrastructure can effectively promote the carbon balance of the neighboring areas. The direct effect of Innovation is significantly positive, and the indirect effect is significantly negative, with a negative spatial spillover effect. The improvement of Innovation in most regions can only satisfy the increase in local CBR and cannot have a trickle-down effect on the CBR of neighboring regions.

3.6. Robustness Testing

3.6.1. One-Period Lagged Explanatory Variables

In this study, the core explanatory variables were selected with one lag to test the robustness of the spatial Durbin model. The spatial correlation coefficients remain significantly negative after one period of lagging for AMI, II, and UI. The direct effects of the three types of modernization on CBR are all significantly negative, the indirect effect coefficients of agricultural modernization and urbanization were significantly negative, and the indirect effect of industrialization was significantly positive, and the conclusions were consistent with the empirical results of the original model (Table 7). Therefore, the model setup is robust and reliable.

Table 7. Robustness test 1.

CBR	Direct	Indirect	Total
L1_AMI	−0.601 * (−1.800)	−3.534 *** (−3.950)	−4.135 *** (−5.340)
L1_II	−1.583 *** (−3.440)	3.872 ** (2.200)	2.289 (1.260)
L1_UI	−0.877 * (−1.760)	−9.523 *** (−5.550)	−10.401 *** (−6.140)
GDPPC	0.370 (1.090)	5.979 *** (4.380)	6.349 *** (4.670)
Openness	−0.153 *** (−3.610)	0.839 *** (4.400)	0.686 *** (3.870)
Infrastructure	−0.389 ** (−2.440)	2.158 *** (3.970)	1.769 *** (3.500)
Innovation	1.607 *** (3.720)	−7.410 *** (−4.340)	−5.803 *** (−3.310)
Spatial rho	−1.098 *** (−4.390)		
sigma2_e	0.139 *** (13.130)		

Note: ***, **, and * indicate 1%, 5% and 10% significance levels, respectively. z-values are in parentheses.

3.6.2. Exclusion of Some Samples

In this study, four municipalities were excluded, and the regression results of the remaining 26 provinces are shown in the table below. The spatial correlation coefficient is still significantly negative after excluding some samples. The direct effects of the three modernizations are still significantly negative. The spatial spillover effects of agricultural modernization and urbanization on the carbon balance ratio were still significantly negative, and industrialization was still significantly positive, which is consistent with the results of the original model (Table 8). The model is robust.

Table 8. Robustness test 2.

CBR	Direct	Indirect	Total
AMI	−1.766 *** (−5.240)	−5.274 *** (−3.320)	−7.040 *** (−4.570)
II	−1.720 *** (−2.780)	13.134 *** (2.820)	11.414 ** (2.390)
UI	−0.545 *** (−3.890)	−14.966 *** (−3.760)	−15.511 *** (−3.840)
GDPPC	1.144 *** (2.920)	15.732 *** (4.840)	16.876 *** (4.960)
Openness	−0.015 (−0.370)	1.283 *** (3.870)	1.268 *** (3.760)
Infrastructure	−1.004 *** (−5.500)	2.053 * (1.850)	1.049 (0.900)
Innovation	1.175 *** (3.070)	−18.149 *** (−3.860)	−16.398 *** (−3.370)
Spatial rho	−0.274 *** (−3.230)		
sigma2_e	0.121 *** (12.500)		

Note: ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively. z-values are in parentheses.

3.7. Heterogeneity Analysis

To delve deeper into the variations in the impact of the three modernizations on carbon balance across different regions, this study divides the 30 provinces into eastern, central, and western parts for empirical analysis (Table 9). The findings reveal significant disparities in the influence of the three modernizations on carbon balance between the eastern region and the central and western regions. Agricultural modernization exhibited a negative spatial spillover effect on carbon balance in the eastern region while displaying a positive spatial spillover effect in the central and western regions. Industrialization demonstrates a positive direct effect and spatial spillover effect in the eastern region, whereas the spatial spillover effect was insignificant in the central and western regions. Both the direct effect and spatial spillover effect of urbanization were significantly negative in the eastern, central, and western regions, but the spatial spillover effect coefficient was larger in the eastern region.

Table 9. Heterogeneity analysis.

	Eastern Region			Central and Western Regions		
CBR	Direct	Indirect	Total	Direct	Indirect	Total
AMI	−2.119 ** (−2.490)	−13.854 *** (−4.250)	−15.973 *** (−4.700)	−1.888 *** (−5.510)	3.369 *** (3.260)	1.481 (1.600)
II	5.705 *** (4.300)	19.458 *** (3.600)	25.164 *** (3.920)	−5.227 *** (−9.010)	2.950 (1.160)	−2.277 (−0.860)
UI	−1.900 *** (−2.680)	−11.281 *** (−4.510)	−13.181 *** (−4.840)	−1.835 *** (−2.580)	−5.890 *** (−2.600)	−7.725 *** (−3.400)
GDPPC	1.800 *** (2.650)	9.528 *** (3.650)	11.329 *** (3.820)	0.922 ** (2.470)	−1.130 (−0.750)	−0.208 (−0.130)
Openness	−0.487 * (−1.780)	2.906 *** (4.020)	2.419 *** (2.840)	0.000 (0.010)	−0.102 (−0.590)	−0.102 (−0.580)

Table 9. *Cont.*

CBR	Eastern Region			Central and Western Regions		
	Direct	Indirect	Total	Direct	Indirect	Total
Infrastructure	−1.238 *** (−2.890)	−0.508 (−0.450)	−1.746 (−1.390)	−0.312 * (−1.910)	2.083 *** (3.870)	1.771 *** (3.050)
Innovation	−3.569 *** (−2.890)	−19.668 *** (−3.990)	−23.238 *** (−3.990)	4.274 *** (8.340)	−3.087 (−1.320)	1.187 (0.480)
Spatial rho		−0.439 ** (−2.060)		−0.683 *** (−2.920)		
sigma2_e	0.046 *** (8.120)			0.044 *** (9.480)		

Note: ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively. z-values are in parentheses.

4. Discussion

4.1. Spatial Spillover Effects of Three Modernizations on the Carbon Balance in China

Agricultural modernization, industrialization, and urbanization exert significant direct negative effects on the local carbon balance ratio. This finding is consistent with the results of Wang et al. and Cheng et al. [63,64], who identified that industrialization and urbanization as single factors impact carbon balance. The implementation of these three modernizations leads to a rise in population and consumption demand, consequently increasing energy consumption and dampening the carbon balance [29]. Further investigation into spatial spillover effects reveals heterogeneity in how agricultural modernization, industrialization, and urbanization impact neighboring carbon balances. Agricultural modernization and urbanization notably decrease the carbon balance of neighboring areas. In line with our study, Zhang et al. [12] observed a pronounced siphoning effect of urbanization, particularly when it is in its early stages, resulting in increased carbon emission spillover to neighboring regions. The escalation of local agricultural modernization and urbanization induces land-use alterations in neighboring areas, fostering population mobility and growth [65]. This influx may heighten environmental pollution and energy consumption in neighboring regions, thereby impeding the realization of carbon sink functions and intensifying carbon emission pressure, leading to a decline in the carbon balance ratio of neighboring areas. Conversely, industrialization has a positive influence on the carbon balance of neighboring regions. This is attributed to the enhancement of regional industrial levels, which often stimulates spatial agglomeration and scale effects within industries [66]. Local industrial agglomeration reduces industrial costs in neighboring regions, thereby mitigating carbon emission pressures to some extent, resulting in a positive impact on neighboring carbon balances.

4.2. Divergence of Spatial Spillover Effects of Infrastructure Development and Innovation Levels on the Carbon Balance

Among the control variables, the direct effect and spatial spillover effect of the level of infrastructure development and the level of innovation on the carbon balance are particularly significant. The results of the study show that infrastructure development has a certain negative impact on the local carbon balance. To a certain extent, infrastructure construction threatens the stability of the ecosystem, leading to the acceleration of ecological degradation [67], thus affecting the realization of the carbon sink function. However, the improved level of infrastructure construction has a positive spatial spillover effect on the carbon balance of neighboring regions; for example, Bai et al. [68] found that intelligent transportation infrastructure construction and infrastructure management efficiency can effectively promote carbon emission reduction in neighboring regions. Higher levels of infrastructure construction can effectively play the role of factor agglomeration, improve the efficiency of the supply chain, increase the efficiency of energy use in neighboring regions, and promote carbon balance in neighboring regions. On the contrary, the level of innovation, although it can improve the local carbon balance ratio, has a negative effect on the carbon balance of neighboring regions, showing a significant siphoning effect. Wang and Guo [69] argue that the concentration of innovative technology industries leads to inter-regional technological barriers, which adversely affect the ecological environment and thus have a negative spatial spillover effect on the carbon balance. It is an established fact that the level of innovation improves the utilization of local resources and production efficiency and has a positive impact on carbon emission reduction, but the surrounding regions with lower levels of economic development are not strong enough to withstand the negative impacts of technological and innovative industrial agglomeration, i.e., heavier pressure on environmental governance, which restricts the radiation effect of the level of innovation in the central region, and thus shows a strong siphon effect.

4.3. Regional Heterogeneity in the Spatial Effects of Agricultural Modernization and Industrialization on the Carbon Balance

The spatial spillover effects of agricultural modernization and industrialization on the carbon balance in the eastern region and the central and western regions are heterogeneous. Among them, in the eastern region, agricultural modernization has a negative impact on the carbon balance of neighboring places. As Yang et al. [70] found, the eastern region has a higher dependence on carbon inputs in the development of agricultural modernization, and a strong demonstration of the eastern central region is prone to negatively affect the carbon balance of neighboring regions. The high population density in the east and the increase in agricultural modernization may mean over-intensive land use, while the high demand for yield and efficiency leads to excessive use of chemical fertilizers, pesticides, and machinery, resulting in increased environmental pollution and energy consumption [28], which will harm the carbon balance of the surrounding regions. On the contrary, the central and western regions, with lower population density, agricultural modernization to improve land use efficiency, and proactive ecological protection policies, can have a positive impact on the carbon balance of neighboring regions. For industrialization, its direct effect and spatial spillover effect are both positive in the eastern region, which is consistent with the findings of Liu et al. [71]. The higher degree of industrialization in the eastern region and the more mature development of the digital industry and green technology industry not only facilitates the coordinated development of the local industrial economy and the environment but also has a radiation effect on the neighboring regions [72], which has a good demonstration effect and thus promotes the balance of carbon balance between the local and neighboring regions. In contrast, the local industrialization in the central and western regions is not yet mature enough to bring positive spatial spillover effects to the neighboring regions.

4.4. Policy Recommendations

(1) Between 2010–2021, China's carbon emissions will grow at a relatively fast rate [30]. Therefore, continued attention to carbon emission control remains imperative, especially for regions with serious carbon deficits, such as the Bohai Economic Circle and the Lower Yangtze River Delta, as well as other industrial bases or urbanization frontiers. The expansion of industrial and urban land use is expected to have a negative impact on carbon balance, highlighting the importance of coordinating regional development with environmental management [73]. Meanwhile, actively promoting the development of new urbanization and information technology industries, along with the promotion of green and low-carbon industries, can effectively reduce carbon emissions [74]. In addition, research results show that carbon surplus areas are mainly located in the southwestern region with rich vegetation. Therefore, strategies focusing on forest protection, urban greening, and increasing vegetation cover in carbon-shortage areas are crucial for improving carbon sink capacity and promoting carbon balance [75]. (2) The spatial lag coefficient of the carbon balance is significantly negative, which indicates that there is a spatial lag overflow. The carbon balance among provinces is mutually exclusive and cannot play a good role in radiation and demonstration. Provinces and cities should focus on the local carbon balance and reduce the environmental and energy consumption pressure on the neighboring regions. (3) Attention should be directed towards addressing the negative externalities

arising from the modernization of agriculture, urbanization, and innovation levels. This involves reducing energy consumption and implementing comprehensive environmental pollution management strategies to mitigate the adverse impact on the carbon balance of neighboring regions. To counteract the negative effects of industrialization on local carbon balance, emphasis should be placed on developing green, low-carbon, and new technology industries. Simultaneously, leveraging the positive externalities of industrialization can further propel the synergistic development of both local and neighboring areas. This can be achieved through the aggregation and scalability effects of technology and service industries. Regarding infrastructure development, expediting the establishment of smart infrastructure and leveraging the supply chain effect can foster positive spatial spillovers, thereby enhancing the overall regional development landscape.

5. Conclusions

This study aims to explore the spatial effects of agricultural modernization, industrialization, and urbanization—key components of economic modernization—on the carbon balance. It seeks to uncover their local and neighboring impacts on the carbon balance. (1) The overall trend of the carbon balance ratio fluctuated downward from 2010 to 2021. The lack of focus on ecological protection and energy consumption reduction in the initial and intermediate stages of agricultural modernization, industrialization, and urbanization exacerbated this decline. However, the carbon balance ratio gradually stabilized in later stages due to a shift towards greener practices. (2) There is a significant disparity in carbon balance among provinces, hindering the generation of trickle-down effects. (3) The spatial spillover effects of the three modernization processes on the carbon balance ratio are diverse. Agricultural modernization and urbanization have negative spatial spillover effects on carbon balance, while industrialization has a positive effect due to its agglomeration and scalability. (4) There is regional heterogeneity in the spatial effects of agricultural modernization and industrialization on the carbon balance. The spatial spillover effect of agricultural modernization on carbon balance is negative in the eastern region, while it is positive in the central and western regions. Industrialization plays a positive radiative role in the eastern region, while the spatial spillover effect in the central and western regions is not significant. The study underscores the complexity and heterogeneity of these modernization effects on carbon balance and provides targeted recommendations to promote a balanced carbon pattern.

Although this study explores the spatial effects of agricultural modernization, industrialization, and urbanization on carbon balance, it has some limitations. Firstly, due to the data limitation, this study uses the data from 2010 to 2021, and the study area is limited to thirty provinces and cities in China; the study can be further extended by adding data from both time and space dimensions in the future. Secondly, the heterogeneity analysis only examines variations between the eastern, central, and western regions, overlooking other potential factors. Subsequent studies could explore additional perspectives, such as the impact of population density disparities on research outcomes.

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