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Dynamic Interactions of Urban Land Use Efficiency, Industrial Structure, and Carbon Emissions Intensity in Chinese Cities: A Panel Vector Autoregression (PVAR) Approach

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Abstract: Climatic and environmental issues have attracted considerable attention worldwide. Clarifying the interactions between urban land use efficiency (ULUE), industrial structure (IS), and carbon emissions intensity (CEI) is of considerable importance in promoting resource–economy–environment coordination. The temporal and spatial characteristics of ULUE, IS, and CEI were analyzed based on panel data from 309 cities in China from 2006 to 2021. A PVAR model was established to analyze the long-term and short-term dynamic and causal relationships among the three variables. ULUE, IS, and CEI showed an upward trend, but significant spatial heterogeneity existed. The three variables had a long-term cointegration relationship. Overall, ULUE had a positive effect on IS, and IS had a promotional effect on ULUE. ULUE and IS had bidirectional inhibitory effects on CEI. This indicates that improving ULUE, upgrading IS, improving energy efficiency, and reducing CEI may be necessary measures to mitigate the environmental impact of human activities. These research results can provide theoretical and policy support for promoting the coordination of resources, the economy, and the environment, and for achieving the promotion of urban high-quality green and sustainable development.

Keywords: urban land use efficiency; industrial structure; carbon emissions intensity; panel vector autoregression; China

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1. Introduction

Against the background of the increasing severity of global climate change and environmental problems, it is necessary to break the bottleneck of resources and environment and achieve green economic transformation [1]. This has become a common goal worldwide. Therefore, finding a way to transform the external environment is an ongoing global development task [2]. With the acceleration of global industrialization and urbanization, more and more countries have begun to focus on the impact of carbon emissions on land use, industrial transformation, and upgrading [3]. Globally, land resources are important for environmental protection and economic development [4]. ULUE focuses more on the efficiency of the use of land as a specific production factor. It refers to the ability to use land resources strategically and efficiently during the urban planning and construction processes. This reflects the degree of maximization of economic, social, and environmental benefits in the use of urban land resources. It not only emphasizes the economic output of land but also encompasses social welfare and environmental sustainability, making it one of the key objectives pursued in urban planning and management [5]. Urbanization is accelerating, leading to differences in land use between urban and rural areas worldwide. Simultaneously, there have been substantial changes in resource demand and ecological pressure, and irrational land use will aggravate environmental pollution and cause tension between people and land. These have become common challenges for all countries worldwide [6]. In this context, improving ULUE is a more effective way of promoting long-term sustainable urban development. There is a positive correlation between the transformation and upgrading of IS and high-quality economic development [7]. This continuous IS upgrading is accompanied by a large increase in carbon emissions and resource consumption. This has led to environmental problems and resulted in widespread concern. Therefore, examining IS provides an important direction for addressing global challenges and has a profound effect on economic growth, technological innovation, and international cooperation and exchange [8,9]. As economies worldwide experience swift growth, the insatiable appetite for non-renewable energy sources has precipitated a dramatic escalation in greenhouse gas emissions. This phenomenon has not just exacerbated the trajectory of global warming but has also catapulted climate change to the forefront of the most critical environmental concerns of our time. The emission of CO_2 stands out as a principal catalyst for both the warming of our planet and the deterioration of our environment. Climate change is a global challenge that transcends national borders, and it demands that we take effective measures while pursuing economic growth. This includes promoting a green, low-carbon sustainable development model to address the severe challenges posed by climate change.

China is the top carbon emitter globally and accounted for approximately 30.19% of global carbon emissions in 2022 [10,11].Since the historic initiation of reform and opening up in 1978, the economy of China has burgeoned, securing its position as second-largest in the world [12,13]. Yet, this meteoric economic ascent has not been without environmental repercussions; the ecological strain has become increasingly evident, and the capacity of the environment to sustain such growth is under intense scrutiny [14,15]. China's traditional growth model, characterized by substantial investment and voracious energy consumption, has often overlooked environmental considerations, leading to a dramatic escalation in carbon emissions [16]. This paradigm, predicated on environmental sacrifice, is now recognized as unsustainable. It poses a dual threat; domestically, it endangers ecological integrity, while internationally, it draws the attention of the world due to the far-reaching implications of carbon emissions. In the intermediate stage of industrial development, the key to achieving the goals of carbon peaking and carbon neutrality lies in promoting the in-depth optimization and upgrading of the industrial structure [17]. This process can significantly improve the allocation efficiency of production factors, as well as effectively improve the utilization efficiency of resources, reduce energy consumption, and thereby reduce carbon dioxide emissions. Therefore, closely integrating the industrial structure with the control of carbon emissions not only has far-reaching theoretical value, but also has urgent practical significance. In addition, the adjustment of the land use structure and the evolution of ecosystem types have a decisive impact on the dynamic balance of regional carbon stocks, which in turn has an important impact on regional carbon emission levels and industrial layout [18]. In addition, ULUE, IS, and CEI are important components of the environmental economic system, and there may be interactions among them. The enhancement of ULUE facilitates the upgrading of IS, leading to enhanced energy utilization efficiency and a reduction in CEI [19,20]. Conversely, changes in IS also influence land use patterns by modifying industrial layouts and energy consumption structures, which subsequently affects CEI. Moreover, improvements in ULUE are typically accompanied by a reduction in CEI, as more efficient land use minimizes the ecological damage associated with urban expansion and encourages the adoption of green buildings and low-carbon technologies to further decrease carbon emissions [21]. Exploring the intrinsic relationship between ULUE, IS, and CEI plays a vital role in formulating scientific land-management policies, optimizing industrial layout, and achieving regional sustainable development, and provides a solid foundation for building a green and low-carbon economic system.

In the existing literature, the dynamic interaction influence of ULUE, IS, and CEI in cities has rarely been mentioned. Examining the existing literature on the relationship of ULUE and IS, researchers have reached different conclusions due to the use of diverse samples and models. Industrial structure transformation and upgrading can promote effective land use efficiency [19]. However, Li et al. found that industrial structure upgrading has had a negative effect on land use efficiency based on the spatial Durbin model [22]. Liu et al. adapted the panel data of 31 provinces in China, combining the STIRPAT model with the spatial Durbin model together to analyze the relationship of IS and ULUE, and the results showed that a "U" relationship exists between industrial structure upgrading and land use efficiency [23]. Meanwhile, some researchers have found a nonlinear relationship between industrial structure upgrading and land use efficiency [9]. Wang et al. found that the relationship between IS and ULUE follows an inverted U-shape. In the research on ULUE and CEI, land use change is an important reason for carbon emission changes [24]. Land use urbanization has had a positive impact on CEI [25]. How to efficiently utilize land resources to reduce carbon emissions is a very important research topic. Xie et al. found that the increases in industrial land use efficiency have had negative impacts on CEI based on the STIRPAT model [26]. Zhang et al. showed that there is an inverse U-shaped relationship between land-intensive use and carbon emissions and that IS plays an intermediary role in this mechanism [27]. In recent years, the relationship between IS and CEI has been examined by constructing empirical test models at different spatial scales [28,29]. Hu et al. studied the influencing factors of CEI based on the EKC model, and found a negative structural effect of industrial structure on CEI [30]. However, its absolute value is too small and it has a limited effect on suppressing carbon emissions. Numerous scholars have underscored the pivotal role of industrial restructuring and upgrading as a strategic conduit for expediting economic progress and attaining the ambitious objectives encapsulated by the "dual carbon" targets [12]. Su et al. used a STIRPAT-PLSR model to explore the driving forces behind carbon emissions and found that increasing the proportion of tertiary industries significantly inhibits regional carbon dioxide emissions [31]. However, to date, most prior studies have found that secondary-sector growth significantly impacts carbon emissions [32]. Song studied 30 provinces in China and showed that different regions have different impacts on carbon efficiency. The upgrading of IS in the eastern region has a positive effect on CEI and a negative effect on CEI in the central region [33].

In summary, most studies investigated the effects of ULUE and IS on CEI using time series or panel data for bivariate analysis. Meanwhile, relatively few studies have systematically analyzed the impact mechanisms among ULUE, IS, and CEI by constructing a relationship between the three. The relationship between ULUE, IS, and CEI is not clear when analyzed as a system. Additionally, the interaction between ULUE, IS, and CEI may follow a dynamic spatiotemporal mechanism, which is affected not only by the internal factors of the land system and environmental changes in a specific period, but also by adjustments in different periods.

Additionally, since the research has predominantly focused on broader scales such as provinces or river basins, there is also a notable gap in studies that delve into the dynamics between ULUE, IS, and CEI from the vantage point of individual cities. By choosing 309 cities from across China as research subjects, we are able to present a more accurate depiction of the current state and challenges faced by Chinese cities in these critical areas. This granular analysis offers a more intricate lens to discern the subtle yet profound interplay between urban evolution and the stewardship of environmental and material resources. During the period of 2000–2021, the economy and urbanization process of China grew rapidly, and urban land use efficiency and industrial structure upgrading became key factors in promoting economic development. In addition, 2021 is the year when the national carbon emission trading market was officially launched, which is of great significance to the study of carbon emissions. Therefore, to deepen our understanding of this, we regarded ULUE, IS, and CEI as systems, using the PVAR model to innovatively examine the dynamic interactions among them, which are of considerable practical importance for achieving green and sustainable development in China and beyond.

Compared with previous studies, the academic contribution of this paper is mainly reflected in two aspects: First, from the perspective of resources, economy, and environment, the three indicators of ULUE, IS, and CEI are innovatively combined and incorporated into statistical research, which will make up for the lack of quantitative analysis of the relationship between the three in the existing literature. As well as further exploring the temporal and spatial differences of the three variables in China's urbanization and industrialization process, we provide detailed comparative analysis across different regions from the urban level in China. Second, this study also uses the PVAR model to clarify the causal relationship between ULUE, IS, and CEI through the Granger causality test. The long-term and short-term dynamic relationship between the three variables is analyzed through impulse response diagrams and variance decomposition. It aims to provide reference for green and sustainable development in various regions, and for future policy formulation and development model selection. In addition, it provides innovative perspectives and practical paths for achieving global carbon reduction goals and addressing climate change. Especially in China, this study has opened up a new dimension of thinking for achieving the national strategic goals of achieving a carbon emissions peak by 2030 and carbon neutrality by 2060. The rest of this article is as follows. The data and variables selection in this study are introduced and the econometric specifications of the regression models are laid out in Section 2. Section 3 introduces our results, which include the comparison of variables in time and space, as well as the testing and final results from the PVAR model. The discussion and associated policy recommendations are introduced in Section 4. The last section introduces the conclusions. The research flowchart is as Figure 1:

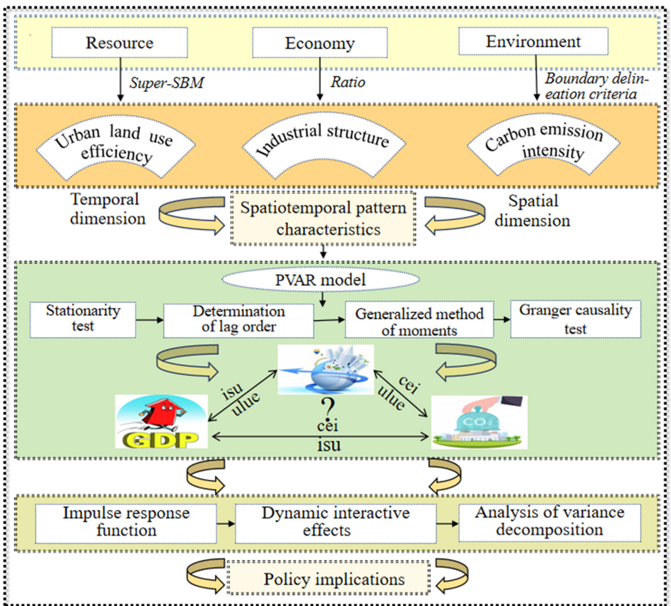

Figure 1. Research flowchart.

2. Materials and Methods

2.1. Data Resources and Variable Selection

2.1.1. Data Resources

Due to the limited access to original data for some cities, the analysis used panel data from 309 cities in China from 2006 to 2021. The data were taken from the National Bureau of Statistics of China, the China City Statistical Yearbook (2007–2022), the Provincial and Municipal Statistical Yearbook revised by the provincial statistical bureaus from 2007 to 2022, the China Environmental Statistics Yearbook (2007–2022), and the China Energy Statistical Yearbook, additionally including the China Agricultural Statistical Yearbook, China Animal Husbandry Yearbook, and China Forestry and Grassland Statistical Yearbook from 2007 to 2022. The statistics data come from official statistics, which ensures the accuracy of the analysis results. The calculation methods for the three indicators are detailed as follows.

2.1.2. ULUE

This study proposes an evaluation system for ULUE in terms of input and output dimensions (Table 1).

Table 1. Index system for ULUE.

Index	Variable	Measurement Method	Unit
Input	Land	Urban construction land area	km^2
	Capital	Total investment in fixed assets	10^4 yuan
	Labor force	Total employed persons in secondary and tertiary industry	10^4 people
	Resource	Total water supply	10^4 m^3
Expected output	Economic output	Added value of secondary and tertiary industry	10^4 yuan
		Disposable income of urban residents	10^4 yuan
	Social output	Number of students enrolled in colleges and universities	people
		Number of hospital health beds	sheet
	Environmental output	Green coverage rate	%
Unexpected output	Sulfur dioxide emissions	Estimated sulfur dioxide emissions	t
	Smoke and dust emissions	Estimated smoke and dust emissions	t
	Wastewater discharge	Estimated water emissions	10^4 t

Land, capital, labor force, and resources were selected as input indicators for ULUE. The rational planning and management of urban construction land directly impact the spatial structure of urban development and the intensive use of land resources, thereby reflecting the status of urban land use. Fixed-asset investment reflects the economic input of cities in land development and infrastructure construction. Employment in secondary and tertiary industries constitutes a significant portion of urban economic activities, and the number of employees in these sectors can reflect the employment-driving effect of ULUE. The total urban water supply is fundamental to the operation and development of the city and serves as an important natural resource factor for measuring urban land use efficiency. Therefore, the urban construction land area, total investment in fixed assets, employment in secondary and tertiary industries, and total urban water supply were selected as input indicators [34,35].

Economic, social, and environmental benefits were selected as the first-level indicators of the expected output indicators. To measure the level of economic output in relation to urban land use we used the added value of the secondary and tertiary industries, which are crucial for urban economic vitality and innovation capacity. The number of students enrolled in colleges and universities along with the number of hospital beds were chosen as indicators of social benefit output. This is because the enrollment figures in higher education and the availability of hospital beds are vital components of urban social services in education and healthcare. Their quantity and quality directly impact the quality of life and social welfare of urban residents. To assess environmental development in urban land use, the green coverage rate was selected as an indicator of environmental benefit output [6,36].

Based on the prior literature, the emissions of three traditional pollutants, namely, sulfur dioxide, industrial wastewater, and industrial smoke (dust), were included as unexpected output indicators [11].

2.1.3. IS

Changes in IS reflect the level of economic development and technological progress. Therefore, upgrading IS is of considerable importance in improving economic efficiency, promoting sustainable development, and enhancing international competitiveness. IS is a process that is carried out from primary to secondary and tertiary industries. In this study, the proportion of the sum of secondary and tertiary industry output values to the GDP was used as an indicator to measure IS [7]. This reflects changes in the quantity of IS.

2.1.4. CEI

The core issue in city-scale carbon emission estimation is determining the estimation scope. The idea of delineating emission sources was first proposed by the World Resources Institute in its guidelines for the preparation of corporate greenhouse gas inventories to avoid double counting [37]. Therefore, based on prior research, the emission factor coefficient was used to calculate the sum of all direct emissions within the jurisdiction of cities and energy-related indirect emissions outside the jurisdiction of cities [38,39].

2.2. Research Methods

2.2.1. The Undesired Super-Efficiency SBM

The undesired super-efficiency SBM model was proposed by Tone and combines the DEA and SBM models to enhance the practicality of the efficiency model, which improves the practicality and accuracy of efficiency analysis [40]. Compared with the DEA and SBM models, a notable feature of the undesired super-efficiency SBM model is that it allows efficiency values greater than one, which makes the efficiency comparable. In addition to this, the Super-r-efficiency SBM model considers slack variables and radial problems and evaluates the efficiency of decision-making units with unexpected outputs. This provides a more detailed approach to efficiency assessment, making it a better super-efficiency model [41]. Therefore, this study used a nonradial and nonangular super-efficiency SBM model to measure ULUE. The expressions are as follows:

$$\min\theta = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\overline{x_i}}{x_{i0}}}{\frac{1}{S_1+S_2}\left(\sum_{r=1}^{S_1}\frac{\overline{y_r^g}}{y_{r_0}^g}\right)+\sum_{r=1}^{S_2}\frac{\overline{y_l^g}}{y_{l_0}^g}} \tag{1}$$

$$\text{S.t} = \begin{cases} \overline{x} \geq \sum_{j=1,j\neq 0}^{n}\lambda_j x_j,\ (i = 1,2,\cdots,m) \\ \overline{y}^g \leq \sum_{j=1,j\neq 0}^{n}\lambda_j y_j^g,\ (r = 1,2,\cdots,S_1) \\ \overline{y}^b \geq \sum_{j=1,j\neq 0}^{n}\lambda_j y_j^b,\ (k = 1,2,\cdots,S_2) \\ \overline{x} \geq x_0,\ \overline{y}^g \leq y_0^g,\ \overline{y}^b \geq y_0^g,\ \lambda \geq 0 \\ \sum_{j=1,j\neq 0}^{n}\lambda_j = 1 \end{cases} \tag{2}$$

In this paper, θ represents urban land use efficiency; n represents the number of decision-making units; λ represents the weight vector; m, S_1, and S_2 represent the number of inputs, expected outputs, and unexpected outputs, respectively; and x, y^g, and y^b represent the vectors of input, output, and unexpected output, respectively. The variable with "-" indicates the projection value and the variable with a subscript 0 is the evaluated decision unit.

2.2.2. PVAR Model

The PVAR model was developed by Love et al. and is an extension of the VAR model used to study the interaction among variables [42]. It treats each variable as an endogenous variable, thereby capturing the dynamic interrelationships between variables while considering potential endogeneity issues, it can solve the endogenous problem of variables by introducing variable lag, a problem that has been ignored in most of the literature [43]. This has the advantages of both panel data and the VAR model but also considers individual fixed effects and time effects. The PVAR model effectively addresses the issues of individual heterogeneity and temporal effects in the data by combining time series analysis with panel data analysis, as well as effectively describing the short-term response and long-term movement trends among variables, forming a robust analysis of multivariable dynamic relationships. This can improve the accuracy of the results [44]. Therefore, the PVAR model was used to study the dynamic interactions among ULUE, IS, and CEI more accurately as it can avoid the endogenous influences that may arise among the three variables during the analysis process, clearly depicting the transmission mechanisms formed by various shocks. The PVAR model is expressed as follows:

$$Y_{it} = T_0 + \sum_{j=1}^{K} T_j Y_{it-j} + a_i + \beta_i + \varepsilon_{it} \tag{3}$$

where Y_{it} represents a vector composed of ULUE, IS, and CEI variables; i and t represent city and year, respectively; j represents the lag period; T_0 represents the intercept term vector; T_j represents the parameter matrix of the jth order of lag; ε_{it} represents the random disturbance term; a_i represents the individual fixed effect vector; and β_i represents the time effect vector. Among them, the size of the individual fixed effects can indicate the strength of heterogeneity among 309 cities in China, and the size of the time effects can describe the strength of specific shock effects. To ensure the accuracy of parameter estimation, ULUE, IS, and CEI were logarithmically processed before model estimation.

2.2.3. Time Series Clustering

This study is based on the longitudinal and latitudinal coordinates of 309 cities in China from 2006 to 2021. The step time was set to 1 year, and a space–time cube containing time and space characteristics was generated through the aggregation point. Time series clustering was used to divide the positions of the space–time cube into three groups (Figure 2). The time series within the groups are highly similar, including numerical similarity and change trend similarity [45]. The main purpose of this research was to use time series clustering to find the areas where values are clustered throughout the cycle. Therefore, numerical similarity was used for the analysis. For two given time series, their numerical similarity can be expressed as follows:

$$\Delta = \left(z_1^{(n)} - z_1^{(m)}\right)^2 + \cdots + \left(z_i^{(n)} - z_i^{(m)}\right)^2 \tag{4}$$

$$\Omega_m = \left(z_1^{(m)}, z_2^{(m)}, \cdots, z_i^{(m)}\right)$$

$$\Omega_n = \left(z_1^{(n)}, z_2^{(n)}, \cdots, z_i^{(n)}\right)$$

where $z_i^{(n)}$, $z_i^{(m)}$ represent the ULUE (IS, CEI) of the m and n time series (Ω_m, Ω_n) in the i time step, respectively.

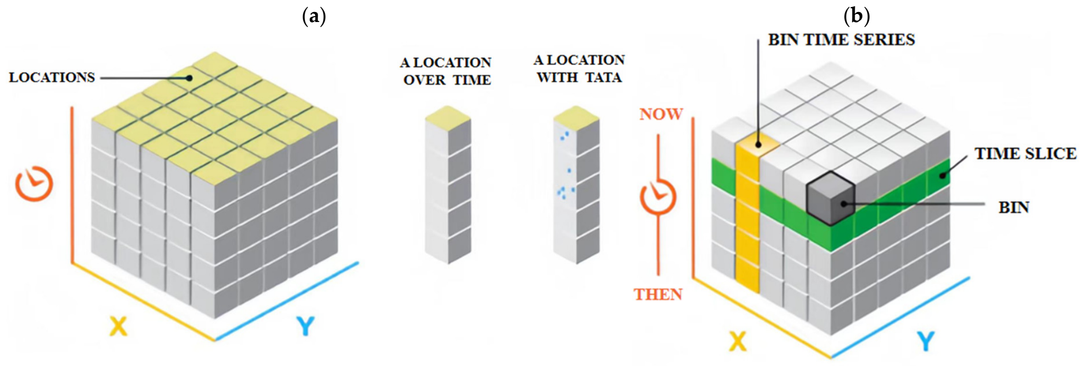

Figure 2. The space–time cube: (**a**) the grid cube; (**b**) each bin has a location ID, a time-step ID, and a count.

3. Results

3.1. Spatiotemporal Variation in ULUE, IS, and CEI

To further explore the spatial distribution characteristics of ULUE, IS, and CEI for 309 cities in China from 2006 to 2021, the natural breaks method was used to divide the calculation results into four categories, from high to low. We selected two time periods from 2006 to 2021 to show the results.

The ULUE in Chinese cities showed an overall upward trend (Figure 3). There were 80 cities with values of ULUE more than 0.88 in 2006. These were mainly distributed in the eastern region, followed by the central region, and then the western region. Meanwhile, the ULUE on the eastern section of the Hu Line was higher than that of the western section. Over time, the change in urban land use efficiency in the eastern region of the Hu Line was significantly higher than that in the western region. From 2006 to 2021, the spatial pattern of the ULUE in China exhibited imbalanced characteristics. Overall, ULUE in the eastern region was significantly higher than that in the western and central regions, with Shanghai and Guangdong having the highest ULUE values. This indicates the reasons for the differences in ULUE levels across different regions may include that the eastern region has made rapid strides in the reform of land marketization, which has facilitated the efficient utilization of land resources. As well as this, the ULUE is influenced by the level of economic development, with regions that have a higher economic level exhibiting greater ULUE. Cities with faster ULUE growth, such as Anhui and Yunnan, are concentrated in the central region. Cities with lagging growth in ULUE were mainly located in the western regions, such as Inner Mongolia and Xinjiang.

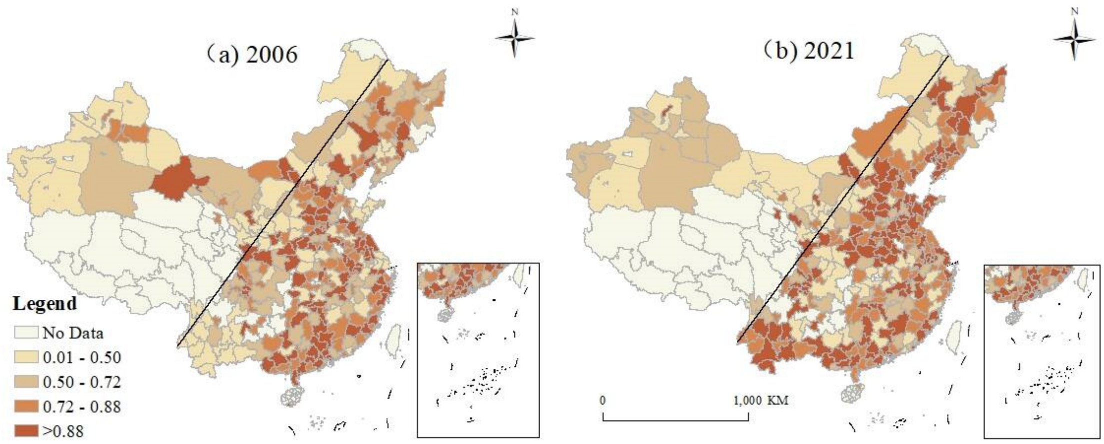

Figure 3. Spatial distribution of ULUE in Chinese cities. (**a**) Spatial distribution of ULUE in Chinese cities in 2006; (**b**) Spatial distribution of ULUE in Chinese cities in 2021.

As shown in Figure 4, the overall IS in Chinese cities continuously improved from 2006 to 2021. This indicates that the IS of China has been upgraded. There was a coupling with the spatial variation trend of ULUE from a macroscopic point of view. Compared with ULUE, the Hu Line played a smaller role. Overall, the IS changes in the areas east and west of the Hu Line were smaller than those of ULUE. The number of cities with an IS above 89.58% increased from 95 to 145 during this period. The scope of cities that were above 89.58% gradually expanded from regional central cities, such as Beijing and Hangzhou, to subcentral cities. Over time, subcentral cities tend to connect individual regions to cover the entire region in their development process from an overall perspective. The disparities in industrial structure levels among various regions may be attributed to differences in resource availability and geographical environments; therefore, IS development in the eastern region is the fastest as the improvement of infrastructure and market mechanisms has promoted the development of high-tech industries and modern service industries. This has eliminated backward production capacity and promoted industrial structure. IS in the central and western regions also improved significantly. This may be because the Central Rise Strategy and Western Development Strategy of China had achieved results. Meanwhile, market demand and consumption upgrading have led to the westward transfer of capital, technology, labor, and other resource factors, which has promoted the upgrading of IS.

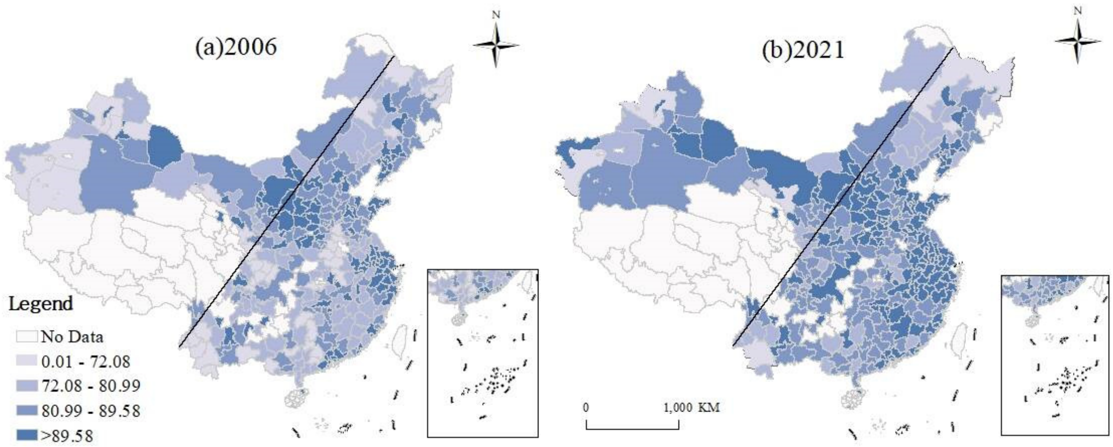

Figure 4. Spatial distribution of IS in Chinese cities. (**a**) Spatial distribution of IS in Chinese cities in2006; (**b**) Spatial distribution of IS in Chinese cities in 2021.

As shown in Figure 5, during the study, the overall CEI in the cities of China showed a pronounced upward trend. The number of cities with a CEI above 3110.12 increased from six to two hundred and eighty-seven. Compared to ULUE and IS, the overall degree of change in CEI was the most substantial and included more cities. The Hu Line of CEI played the most significant role. The increase in CEI in the eastern region of the Hu Line was significantly higher than that in the western region. There was a difference in the distribution of CEI in different regions of China. Overall, the CEI of the eastern region was significantly higher than that of the central and western regions. This may be because of the high population density, developed technology, and concentrated transportation and industries in the eastern region. During this period, the CEI was low in the western region, and the western region lagged behind other regions in economic development. This may be because the western region's industrialization process occurred relatively late. The western region has abundant renewable energy resources, which can reduce dependence on traditional fossil energy, improve environmental quality, and reduce greenhouse gas emissions.

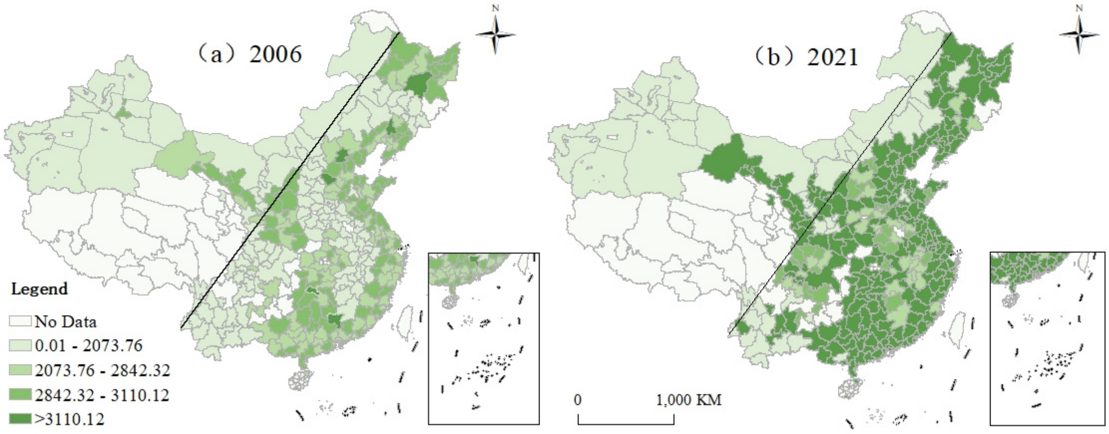

Figure 5. Spatial distribution of CEI in Chinese cities. (**a**) Spatial distribution of CEI in Chinese cities in 2006; (**b**) Spatial distribution of CEI in Chinese cities in 2021.

3.2. Time Series Clustering Analysis of ULUE, IS, and CEI

The time series cluster of ULUE, IS, and CEI from 2006 to 2021 is shown in Figure 6. The data were clustered according to the similarity of the values in the time series data. Therefore, ULUE, IS, and CEI were clustered based on time series. The number of clusters was three, which were divided into high, medium, and low. The cluster distribution patterns of the three variables have certain similarities. Medium and high clusters are mainly distributed in the central and eastern regions and are predominantly concentrated in urban agglomerations. Urban agglomerations are characterized by large populations, active economies, and developed industries. Carbon emissions are high and concentrated. Low clusters were mainly distributed in the western region, such as Yunnan, Xinjiang, and Inner Mongolia, and showed a concentrated and contiguous distribution pattern. This may be because these regions have complex and diverse geographical environments, an uneven distribution of resources, and are lagging in technological innovation and economic development.

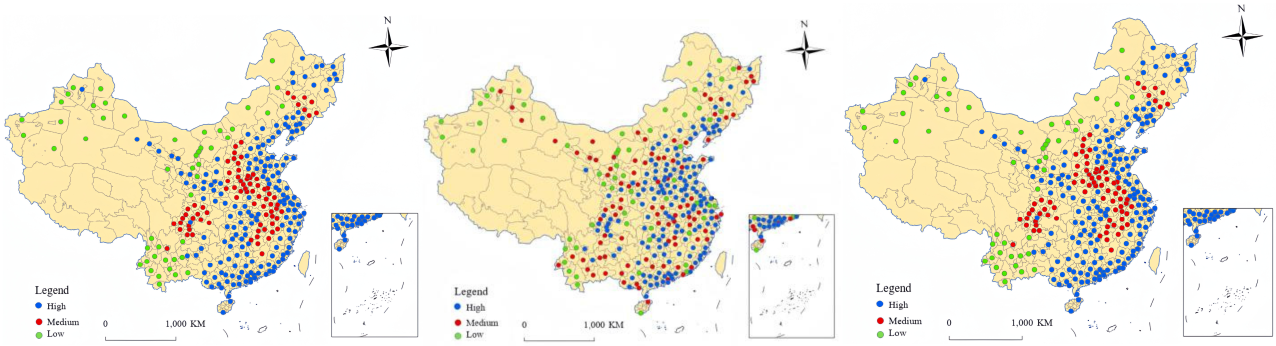

Figure 6. Time series cluster of ULUE, IS, and CEI from 2006 to 2021.

3.3. Analysis of ULUE, IS, and CEI

3.3.1. Panel Unit Root and Panel Cointegration Tests

The descriptive statistical analysis of ULUE, IS, and CEI is shown in Table 2. It was crucial to conduct unit root testing on panel data to avoid regression errors caused by panel data non-stationary phenomena before model estimation. Therefore, three unit root tests were used to confirm data stationarity [46,47]. All three variables passed the significance test at the 1% level. This indicated that they were stationary and could be used for the parameter estimations. After that, a panel cointegration test was performed to analyze the balanced relationship between the variables over time (Table 3). The original hypothesis of Gt was that there is no cointegration relationship. Ga's original hypothesis was that at least one set of cointegration relationships exists. Thus, ULUE, IS, and CEI had a long-term cointegration relationship. Based on these findings, it could be assumed that the PVAR model could be developed (Table 4).

Table 2. Descriptive statistics of empirical variable data.

Variable	Obs	Mean	Std. Dev.	Min	Max
lnULUE	4944	−0.1477137	0.333958	−10.714	1.1067
lnIS	4944	1.937149	0.0492624	1.5563	3.34161
lnCEI	4944	3.419364	0.2197135	2.7301	3.8138

Table 3. Results of the unit root test.

Variables	LLC Test	IPS Test	HT Test	Conclusion
lnULUE	−24.386 ***	−1.097 ***	0.204 ***	Smooth
lnCEI	−23.404 ***	−10.407 ***	0.608 ***	Smooth
LnIS	−53.173 ***	−12.846 ***	0.109 ***	Smooth

*, **, and *** denote significance at 10%, 5%, and 1% confidence levels, respectively.

Table 4. Results of the panel cointegration test.

t	Value	Z-Value	*p*-Value
Gt	−1.801	−7.038	0.000
Ga	−4.525	4.176	1.000
Pt	−23.735	−5.467	0.000
Pa	−6.597	−14.697	0.000

3.3.2. Determining the Optimal Lag Order

It was necessary to determine the lag order of the variables when establishing the PVAR model. Setting the lag order is important for the model, which suggests that the past values of a variable can serve as exogenous variables for its future values. In this way, we can reduce the endogeneity issues caused by simultaneity to a certain extent. The Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), and Hannan–Quinn Information Criterion (HQIC) were used to determine the optimal lag order [48]. According to the three-criteria value minimization principle, the lag order of the model was set to the first order (Table 5) [49].

Table 5. Results of optimal lag order determination.

Lag	ATC	BIC	HQIC
1	−5.0590 *	−3.6704 *	−4.5622 *
2	−5.4769	−3.9952	−4.9518
3	−5.8932	−4.2434	−5.3240
4	−5.8592	−4.1221	−5.2383
5	−5.7823	−3.8837	−5.1004

Note: * denotes the optimal lag order chosen for the corresponding criterion.

3.3.3. Granger Causality Test

A Granger causality test was performed using stationary panel data to determine the statistical causal relationship between ULUE, IS, and CEI. The data are listed in Table 6. With ULUE investment as the dependent variable, IS and CEI were Granger causes at the 10% significance level. With IS as the dependent variable, CEI was a Granger cause at the 5% significance level. When CEI was the dependent variable, ULUE and IS were Granger causes at the 5% significance level. This means that there was a single causality between

ULUE and IS and a two-way causality between ULUE and CEI. IS and CEI also established a two-way causal relationship between them.

Table 6. Results of Granger causality test.

Equation	Excluded	Ch2	df	Prob > chi2	Conclusion
h_lnULUE	h_lnIS	3.3729	1	0.066	reject
	h_lnCEI	12.119	1	0.000	reject
	ALL	73.904	2	0.000	reject
h_lnIS	h_lnULUE	1.3205	1	0.251	accept
	h_lnCEI	10.633	1	0.001	reject
	ALL	12.945	2	0.002	reject
h_lnCEI	h_lnULUE	7.8603	1	0.005	reject
	h_lnIS	3.8568	1	0.050	reject
	ALL	7.8791	2	0.019	reject

3.3.4. GMM Estimation of the PVAR Model

A generalized method of moments (GMM) estimation was performed based on the previously determined optimal lag order (Table 7). It combines the advantages of the instrumental variables method and the difference GMM method, effectively addressing endogeneity issues in dynamic panel data models. The GMM uses lagged variables as instruments and takes into account potential serial correlation and heteroskedasticity, providing a more effective estimation method.

Table 7. Results of GMM estimation.

	h_lnULUE	h_lnCEI	h_lnIS
h_lnULUE	0.0232	−0.0262 **	0.0115 *
	(0.0314)	(0.0093)	(0.100)
h_lnCEI	−1.9563 ***	1.1937 ***	−0.5876 ***
	(0.5620)	(0.1647)	(0.1802)
h_lnIS	4.1193 *	−1.4087 **	1.5977 **
	(2.2430)	(0.7173)	(0.7775)

*, **, and *** denote significance at 10%, 5%, and 1% confidence levels, respectively.

In the ULUE equation, the co-efficient for the current period was 0.0232, which is positive. However, the co-efficient was not significant. This indicated that the cumulative effect of intensive land-resource use was relatively weak and had not yet exerted its real effect. The impact of IS and CEI on each other was significantly positive during the current period. This shows that the evolution process of ULUE, IS, and CEI had a self-reinforcing effect. IS had a significant negative effect on ULUE during this study period. Simultaneously, CEI had a significantly positive effect on ULUE. This may be because industrial structure upgrading improves the comprehensive utilization efficiency of urban land resources by optimizing urban land use structure and employment structure, adjusting the allocation of land and labor factors.

ULUE had a significant positive effect on IS during the study period. This means that improvement in ULUE has provided the necessary space and resources for industrial development and promoted industrial linkage and technological innovation. This has supported the economy in moving toward higher quality and efficiency and more environmental protection and directional development. CEI is different from ULUE, and has had a significant negative effect on IS. This indicates that a development model driven by increased factor inputs and reliant on resource dependence is highly likely to result in a high-carbon lock-in effect. This then leads to substantial energy waste and low efficiency. This can, in turn, increase the costs of environmental governance, limit the capacity for sustainable development, and suppress the growth of emerging industries.

ULUE was significantly negatively correlated with current CEI. This shows that high-density urban land layouts play a positive role in reducing resource waste and contributing to global climate mitigation. Improvements in ULUE reduce direct and indirect carbon emissions by promoting greener and more sustainable urban development. IS has also had a significant negative impact on CEI. Despite industrial structures upgrading, the energy consumption structure still relies on fossil fuels. This may increase corresponding carbon emissions in the short term. Simultaneously, the different regions had significant differences in the energy structure and industrial upgrading paths. Some regions may still rely on high-carbon energy sources such as coal. In these areas, even if the IS is upgraded, carbon emissions may not be effectively reduced or may even increase, owing to the backward energy structure.

3.3.5. Analysis of Impulse Response Function

The GMM estimation results showed a prominent static relationship between ULUE, IS, and CEI. To further understand the dynamic change process between the three variables and determine their time-lag relationship, an impulse response analysis was performed on ULUE, IS, and CEI (Figure 7). This draws on the Monte Carlo method which was used to obtain impulse response diagrams of 309 cities across the country with a 10-period lag through 200 simulations. The impact of each variable on the other variables was also analyzed. The abscissa is the number of lag periods, and the ordinate is the degree of response. The blue lines indicate the 95% confidence interval, and the red line indicates the trend of the impulse response function.

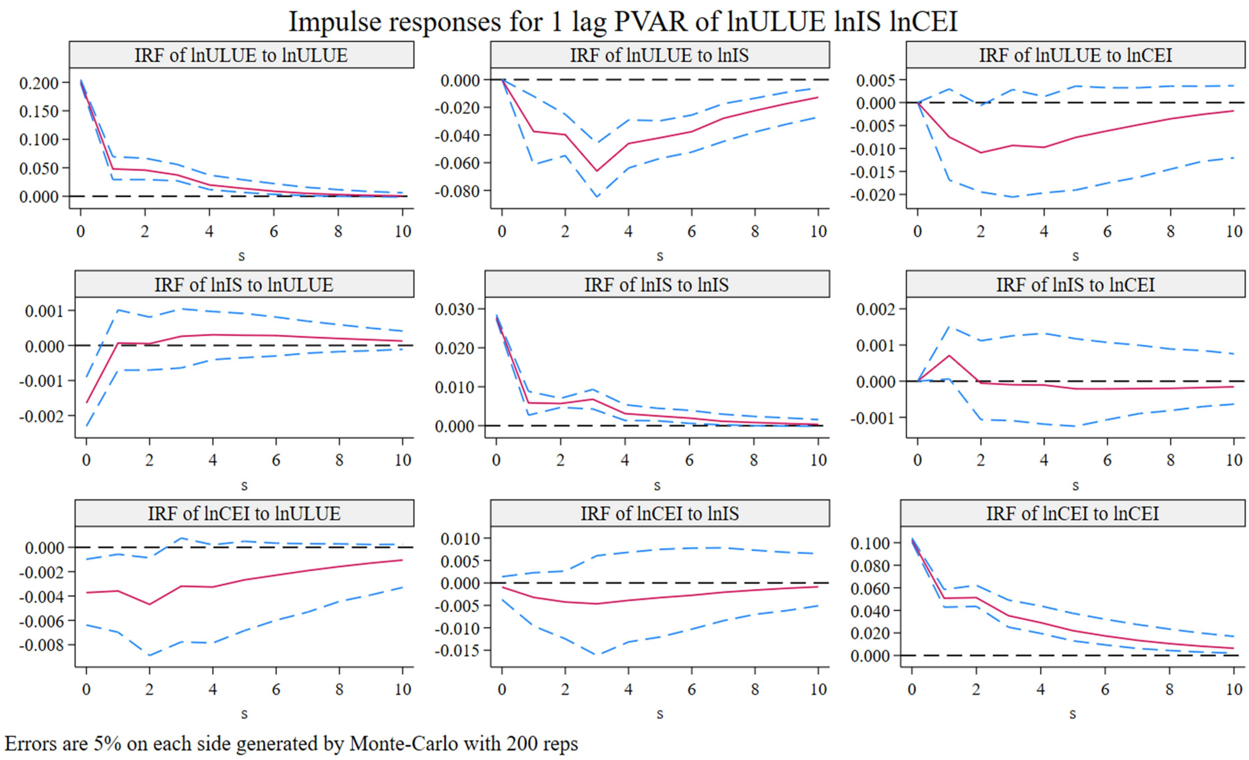

Figure 7. Impulse response diagrams.

ULUE showed a significant positive impact on itself as well as strong initial reactions during the sensing period. The impact gradually reached zero in the subsequent period. ULUE had a negative impact on IS, reaching its peak in the third period and gradually converging to zero. When facing the impact of CEI, the response of CEI and IS intensity was similar. They demonstrated significant negative effects gradually reaching zero. This indicates that improving ULUE can help balance the relationship between economic development and environmental benefits. In other words, an increase in urban land use efficiency is usually accompanied by an increase in the intensity of land use, reducing the consumption of energy and resources, which can reduce carbon emissions and thereby alleviate the pressure caused by climate change.

IS showed a significant positive impact on ULUE, peaking in the fourth period. Subsequently, the influence gradually decreased until it finally converged to zero. IS has a significant positive impact on improving ULUE by promoting the efficient agglomeration of economic activities, optimizing the urban spatial layout, encouraging the multifunctional and intensive use of land, and promoting the construction of smart and green cities. The comparison shows that the impulse response paths of IS to itself are similar to those of ULUE, and IS also has dynamic dependence. IS showed a significant positive impact for its shock in the first period. Subsequently, the impact gradually decreased and converged to zero in the 10th period. This indicates that IS also had a dynamic dependence. In contrast to ULUE, the impact of IS on CEI showed a significant positive reaction, reaching a maximum in the first period. IS upgrading had a negative impact on CEI and decreased slightly, tending to flatten after the second period. This means the upgrading of IS is usually accompanied by an increase in energy consumption and carbon emissions. Over time, technological progress and innovation may lead to the increased use of clean energy, thereby curbing carbon emissions.

CEI had a significant negative impact on ULUE; peaking occurred in the second period and gradually decreased. The responses of CEI to IS and LUUE were similar, showing a significantly negative reaction. Because land is the basic carrier of urban resources, the environment, the economy, and social development, it is also an important constraint on urban development. The use status and scheme of land resources are constraints and guidelines for regional structural adjustments. Industrial structure transformation and upgrading are often accompanied by the development of high-value-added, low-resource-consumption industries. This includes information technology, financial services, and high-end manufacturing industries. These industries generally use land more efficiently and create higher economic value on limited land, thereby improving land use efficiency. The interaction between them constitutes the reverse effect that promotes a decline in CEI in the future.

To avoid errors in the empirical research, we adjusted the variable order. By testing the model, we found that the empirical analysis results of this study were consistent with the above findings. Therefore, the model developed in this study is reliable, and the findings have strong explanatory power.

3.3.6. Analysis of Variance Decomposition

To better measure the degree of interaction between endogenous variables, this study selected 20 prediction periods for PVAR variance decomposition based on impulse response analysis and listed the first, fifth, tenth, fifteenth, and twentieth periods to analyze the interactions between ULUE, IS, and CEI (Table 8).

The contribution gradually decreased from the ANOVA decomposition results of ULUE, and its contribution to itself became 39.4% in the 20th period. This implies that the economic value created per unit of land was reduced. This may be because, with the development of urbanization, urban land resources have become increasingly scarce. When there are insufficient land resources, land use efficiency may be limited. IS played a greater role in improving ULUE, but its contribution gradually decreased. The contribution of CEI to ULUE gradually increased. This may be because, with the acceleration of urbanization and industrialization, urban and industrial activities generally generate more carbon emissions. This includes emissions from transportation, energy consumption, and industrial processes. Therefore, urban and industrial development patterns with inefficient land use have led to a gradual increase in the contribution of carbon emissions. The contribution of CEI to ULUE reached 13% during the 20th period.

Table 8. Variance decomposition result.

Variable	Number of Periods	lnULUE	lnIS	lnCEI
lnULUE	1	0.939	0.061	0.000
	5	0.473	0.445	0.082
	10	0.404	0.473	0.122
	15	0.395	0.476	0.129
	20	0.394	0.477	0.130
lnIS	1	0.000	1.000	0.000
	5	0.000	0.919	0.081
	10	0.000	0.876	0.124
	15	0.000	0.868	0.132
	20	0.000	0.867	0.133
lnCEI	1	0.001	0.000	0.999
	5	0.001	0.002	0.997
	10	0.002	0.002	0.996
	15	0.001	0.003	0.996
	20	0.001	0.003	0.996

The variance contribution of IS is mainly from itself. However, this contribution gradually decreased in IS. This means that the contribution of a certain industry or sector to the overall economy has declined. This may be because upgrading the IS is a complex process, including cost increase, industrial chain extension, increase in the proportion of the service industry, international industrial division of labor, and technological evolution. In the 20th period, the contribution of IS to itself reached 86.7%. The contribution of IS to ULUE was 0% in the 20th period. This also verifies the unidirectional causal relationship between ULUE and IS; that is, IS was not the cause of ULUE. The contribution of CEI to IS gradually increased, reaching 13.3% during the 20th period. This may be due to increased energy demands, complex production processes, increased transportation, and untimely technological updates during the upgrading of industrial structures.

The variance contribution of CEI originates mainly from itself. Compared with ULUE and IS, its change in the contribution to itself was the smallest. The contribution of CEI to itself was maintained at 99.6% after the 10th period, which was the highest contribution among ULUE, IS, and CEI. This shows that factors such as the cities' IS, energy structure, and resident lifestyles have led to higher levels of CEI. These have had a greater impact on climate change and the environment. The contributions of CEI to ULUE and IS were both small at 0.1% and 0.3%, respectively, in the 20th period.

4. Discussion and Policy Implications

4.1. Discussion

Determining the relationship between resources, the economy, and environmental development is a prerequisite for improving the quality of development. This study focused on ULUE, IS, and CEI, examined their spatiotemporal evolution, and analyzed the static and dynamic interactive effects of the three variables. How to use and enhance land use efficiency, promote industrial structure upgrading, and reduce carbon emissions are subjects worthy of research. The mechanism diagram of ULUE, IS, and CEI is shown in Figure 8.

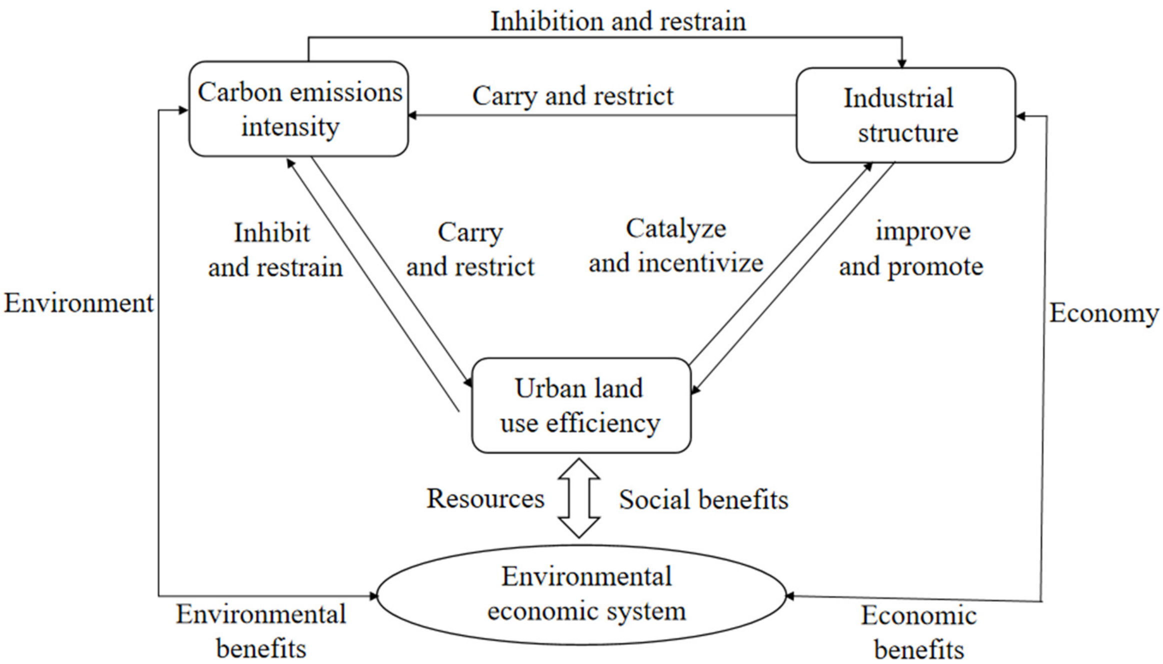

Figure 8. The mechanism diagram of ULUE, IS, and CEI.

The ULUE, IS, and CEI of Chinese cities had an overall upward trend, and there are substantial differences in their distribution in different regions of China. This also provides a complementary basis for optimizing land resource allocation, upgrading differentiated industrial structures, and reducing carbon emissions. This is consistent with the conclusions of Xiang et al. [50]. However, there are also different components. This study is not only based on ULUE, IS, and CEI but also on building a regionally coordinated development mechanism with complementary advantages and positive interactions. The regional comparative advantages played a key role. However, ULUE, IS, and CEI will also be used to conduct empirical research on the relationship between the three variables. Hence, this study differs from other research [51]. The empirical results are in accord with the reality of development in Chinese cities.

ULUE promotes the upgrading of IS, and IS upgrading has a positive effect on ULUE [19]. China has entered the middle stage of industrialization, the ULUE and IS of China has improved compared to the past, and improving ULUE can promote the IS to develop towards a higher-end, more environmentally friendly, and more technology-intensive direction, which can in turn further enhance the efficiency of land use. Industrial development is increasingly dependent on these resources. Faced with the discrepancy between increasing land demand and limited land supply in urban development, it is imperative to improve ULUE. The impulse response results of ULUE on IS are consistent with the research findings of Liu et al. who utilized the STIRPAT model and the spatial Durbin model to examine the relationship between the rationalization of industrial structure and land use efficiency [23]. The study results suggested that ULUE has an approximate "U-shaped curve" relationship with industrial structure optimization, but, unlike this, ULUE exerts a negative influence on the upgrading of IS. The spatial relationship between different land uses is a characteristic of the urban land use structure. The strategic use of urban land can improve the efficiency of resource allocation and promote industrial agglomeration. Hence, it is necessary to pay attention to scientificity, suitability, and sustainability in urban planning and land use, and to coordinate the relationship with the IS to promote optimization and upgrading.

ULUE inhibits CEI and CEI inhibits ULUE. Wang et al. showed that ULUE is negatively correlated with the spatial distribution of carbon emissions [16]. These findings confirm the results of the present study. Improving ULUE may reduce carbon emissions per unit of land through more intensive land use patterns and an optimized urban spatial structure. Land use change is also crucial to the impacts of ecological changes on the environment. Carbon emissions caused by land changes are closely related to global warming [52]. Therefore, carbon emissions must be reduced by improving the efficiency of urban land use while simultaneously promoting innovation in green technology and other policies to reduce carbon emissions. However, this may contradict the findings of Zhang et al., who proposed an inverse U-shaped relationship between intensive land use and carbon emissions, with industrial structure upgrading playing a mediating role in this mechanism [27]. This suggests that the relationship between ULUE and CEI may not be fixed but is jointly influenced by a variety of factors. Future research should pay more attention to the impact of different types of land use in different regions on carbon emissions, as well as how to optimize this relationship through policy intervention.

IS initially promotes CEI, and CEI inhibits IS. IS is closely related to economic development, and IS upgrading and optimization promote CEI in the short term [53,54]. To upgrade the IS, large resource investments and energy consumption may be required. IS is mainly manifested in the gradual decline in the proportion of primary and secondary industries and the gradual dominance of tertiary industry. At present, China still takes secondary industry as its leading industry, which is the main source of CEI [48]. However, as IS is gradually upgraded, carbon emissions will decrease. Substantial amounts of money, human, and material resources are required to reduce carbon emissions. This may cause waste and the uneven distribution of resources, affecting the sustainability of IS. Therefore, it is necessary to take measures to promote IS in a low-carbon direction, promote economic growth, and reduce carbon emissions. In addition, although some of our research findings are consistent with the existing literature, for instance, the widely held view that the upgrading of IS helps to improve CEI, Song's (2019) study offers a more nuanced perspective, suggesting that this relationship does not hold in all regions. This indicates that it may be worthwhile to reconsider existing theories to account for such regional differences and the factors that contribute to these disparities in future research [48].

This study has several limitations. While the PVAR model effectively reveals the dynamic interactions between the variables, non-experimental research cannot entirely eliminate the potential for omitted variable bias or reverse causality. Furthermore, due to limitations in data acquisition, we mainly focus on research at the prefecture-level-city level; thus, this study did not include some autonomous prefectures in the southwestern region, and there are significant regional differences among cities in China which we may not have fully considered the impact of on ULUE, IS, and CEI. Future research should consider more nuanced regional divisions to more comprehensively capture specific regional heterogeneity. Lastly, econometric models are varied and complex; this study only employed the PVAR model and therefore exploring other models to investigate this topic should be a focus for future research.

4.2. Policy Implications

Based on the study findings, we have sought a green and sustainable development path that coordinates "resources–economy–environment" and achieves positive interaction among the three variables. This would promote the strategic and intensive use of land resources, achieve economic growth, reduce carbon emissions, and cope with climate change. The following policy recommendations are proposed.

Among the different regions of China, the eastern region should focus on high-level innovation capacity, geographical location, and technical advantages, focusing on the development of the modern service industry and advanced manufacturing industry. It should also promote the multifunctional development and full use of construction land. The central region should transform the factor drive into an innovation drive, accelerating the integration of traditional heavy industry and the green transformation of industry. Simultaneously, we should actively explore the mechanism of improving the efficiency of urban land use and promoting the integration of cities and industries to optimize industrial structure. In addition, the western region should construct a green mode of industrial transfer according to talent and natural resource endowments. Additionally, we should encourage cooperation and coordination among different regions in land resource management, industrial structure optimization, and carbon emission control in order to achieve complementary advantages and positive interactions between regions.

Research findings suggest that improving ULUE can suppress CEI. Efficient use of urban land is the key to achieving green development and reducing greenhouse gas emissions. In the short term, optimizing urban planning and land use policies. As the leaders of land resource allocation, local governments should establish a regular land-resource assessment system based on respecting the market mechanism as well as comprehensively consider factors such as the local economic development level, resources, and environmental conditions, so as to formulate a scientific and reasonable land supply strategy. In the long term, they should promote the intensive use of urban land resources and encourage multifunctional land use to achieve a sustained increase in land use efficiency. By advocating mixed land use and multifunctional integration in key areas, such as industrial land reconstruction areas, near rail transit stations, and around public spaces, we can not only improve the efficiency of land use, but also stimulate the vitality and sustainability of cities. In this way, we can effectively avoid the waste and idleness of land resources and correct improper resource allocation.

Industrial upgrading is a crucial pathway to curb carbon emissions and promote sustainable economic development. The research results indicate that there is a bidirectional causal relationship between industrial structure and carbon emissions. Therefore, enterprises should be encouraged to pursue technological innovation and industrial upgrading through financial incentives and tax breaks. Local governments should actively advocate for and support the robust growth of clean high-tech industries such as big data and finance, thereby facilitating the evolution of industrial structures towards higher-end and more environmentally friendly directions. In the long term, it is essential to develop high-value-added, low-energy-consumption industries, gradually decreasing reliance on high-energy-consumption sectors. To reduce carbon emissions per unit of GDP by improving energy efficiency and promoting clean energy, traditional industries with high pollution levels should be encouraged to undergo necessary transformations or to relocate to cities with lower economic levels to achieve green industrial upgrading. Moreover, accelerating the development of strategic emerging industries and establishing a green manufacturing and service system is key to achieving environmentally friendly growth. By nurturing green, low-carbon enterprises with international competitiveness, we can not only effectively mitigate environmental pollution but also foster sustainable urban development.

This research finds that the optimization and upgrading of the industrial structure are the key drivers in enhancing land use efficiency. It helps alleviate the over-reliance on land resources and propels the transformation of urban land use patterns from extensive to intensive and efficient models. The government should formulate strategic plans and policies to guide the industrial structure towards higher levels and greater added value. By extending the industrial chain, for example, in the manufacturing sector, companies can be encouraged to expand their focus towards research and development as well as brand marketing, thereby enhancing the technological sophistication of their products and brand value while the economic output and benefits of land use can be effectively improved. Through these measures, we can achieve the harmonious development of the economy, society, and environment, laying a solid foundation for building more prosperous, livable, and sustainable cities.

5. Conclusions

Using the PVAR model, this study examined the dynamic relationships among ULUE, IS, and CEI in 309 cities in China from 2006 to 2021. The following conclusions were drawn.

The ULUE of Chinese cities generally increased during the study period; ULUE increased the most in the central region and showed a spatial pattern that was higher in the eastern region and lower in the western region. The eastern and central regions morphed into vibrant epicenters of efficient land utilization, whereas the western region, though showing promise, treads slightly behind in this rapid ascent. The CEI of Chinese cities was distributed in a hierarchical pattern, and, over time, the development trend shifted from individual areas to cover the entire region. Concurrently, while the central and eastern regions sustained a moderate to high level of carbon emissions, the western region presented a commendably lower carbon footprint. The disparities in IS across various regions witnessed a consistent reduction. The ULUE, IS, and CEI exhibited spatial coupling characteristics. Middle and high values were mainly concentrated in the central and eastern regions, whereas those in the western region were relatively low.

From the Granger causality test and GMM, ULUE, IS, and CEI had dynamic effects. There was a symmetrical effect of the one-way interaction between ULUE and IS. ULUE had a significant positive effect on IS. Improvement in ULUE produces an agglomeration effect that improves the standards of industrial chains and promotes the upgrading of urban industrial structures. Ultimately, the direct and indirect carbon emissions from land use were reduced. In addition, there was a complex two-way interaction between ULUE and CEI. During the study period, the causal relationship between CEI and IS was the same, the difference being that the improvement of ULUE played a restraining role in CEI, while IS promoted the growth of CEI to a certain extent. CEI had an inhibitory effect on the IS.

From the impulse response function and analysis of the variance decomposition, ULUE, IS, and CEI all had positive impacts on themselves but the contributions of ULUE, IS, and CEI showed a downward trend. In particular, the negative impact of ULUE on IS and CEI reveals that the improvement of ULUE may have an inhibitory effect on IS and CEI, which is of great significance for achieving green and sustainable development. At the same time, the contribution of IS to ULUE gradually decreased, while the contribution of CEI to ULUE increased. The impact of IS on ULUE was positive, and the impact of IS on CEI was positive in the short term. The contribution of CEI to IS gradually increased. Simultaneously, CEI had a negative impact on both ULUE and IS, and the contributions of ULUE and IS to CEI were relatively small.

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