

Article

How Does the Intensive Use of Urban Construction Land Improve Carbon Emission Efficiency?—Evidence from the Panel Data of 30 Provinces in China

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Abstract: China actively explores the green development road by promoting the intensive use of urban construction land and low carbon emissions. This research evaluates urban construction land intensity and carbon emission efficiency by using a multifactor comprehensive evaluation method and SBM model and measures the spatial characteristics of between urban construction land intensity and carbon emission efficiency by Moran's I and LISA scattering. The result shows that (1) the average value of urban construction land intensity was constantly improving from 0.11 in 2000 to 0.29 in 2021, (2) the value of carbon emission efficiency generally showed a fluctuating downward from 0.89 in 2000 to 0.66 in 2009 and then a fluctuating upward to 0.84 in 2021, with many provinces located in the Level III and IV carbon emission efficiency intervals, (3) the land development, road density, technology development, and fixed asset investment have a negative impact on carbon emission efficiency, while the greening level and tax have a positive promotion effect, and (4) the correlation and spatial features between urban construction land intensity and carbon emission efficiency in 30 provinces have consistency, as well as heterogeneity in the temporal and spatial development trends. Policy implications are accordingly proposed.



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Keywords: urban construction land; intensity; carbon emission efficiency; spatiotemporal evolution; spatial correlation; technology efficiency

1. Introduction

China is faced with the contradiction between the over-expansion of urban space and the inefficiency of land use, as well as the conflict between the increase in carbon emissions and the commitments to carbon emission reduction in the acceleration of industrialization and urbanization [1]. Compared with Western countries that have achieved industrialization and carbon emission reduction ahead of schedule, China's modernization faces a more difficult dual task of intensive land use and carbon emission reduction. On the one hand, urban built-up areas have increased from about 22,649 km² in 2000 to 63,196 km² in 2021, there are problems of inefficient land use, such as idle land and repeated construction on land, and intensive land use has become the guiding principle to crack the shortage of urban construction land resources and inefficient land use.

On the other hand, the intensive use of urban construction land is also accompanied by the negative externalities of carbon emissions. As the world's largest carbon emitter, China has put forward the strategic goal of 'striving to peak carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060' [2], which urgently requires China to improve the carbon emissions efficiency on land use [3]. Urban construction land is the main carrier of human and socio-economic activities, which is not only the land type with the highest

concentration of factor inputs but also the land type with the highest carbon emissions [4]. Urban construction land is the typical land type that can better reflect the land use intensity and carbon emission efficiency. It is of great theoretical and practical significance to explore the basic laws of urban construction land intensity and carbon emission efficiency in China to promote the development of the intensive use and low-carbon emission output of urban construction land.

2. Literature Review

2.1. Research Progress on the Evaluation of Urban Construction Land Intensity

Land rent theory, diminishing returns to land theory, location theory, and so on, which were put forward by Western scholars, have laid the theoretical foundation for the study of the intensive use of urban construction land. The core of the thinking of the intensive use of urban construction land is to improve the unit land revenue by increasing the input of capital, technology, labor, and other factors [5]. The current evaluation indexes and evaluation methods of land intensity have not been unified. According to different factors such as research scale, research purpose, index validity, data availability, etc., scholars have constructed the index system dimensions including input–output [6], economic, environmental, and social benefits [7], pressure–state–response [8], and use of the entropy weighting method, hierarchical analysis method, and principal component analysis method. Then, the urban construction land intensity is evaluated based on the multifactor. The space for further research on urban construction land intensity is based on long-time-series panel data, with the evaluation criteria shifting from static indicators to the dynamic coupling of the comprehensive application of econometrics, remote sensing (RS), geographic information system (GIS), and other methods [9,10].

2.2. Research Progress on Carbon Emission Efficiency Evaluation

Land use is the second major cause of CO₂ increase in the atmosphere, second only to fossil fuel combustion [11,12]. Land use affects the natural and anthropogenic carbon flux processes carried by different land use types through changes in the natural cover of the land surface and the intensity of human activities [13]. As carbon emissions from urban construction land use are non-desired outputs, carbon emission efficiency can be measured at the cost of carbon emissions. It can make up for the weakness of indicators such as the total carbon emissions and carbon emission intensity, as these two indicators do not take into account the role of carbon emissions as a cost on desired outputs [14]. The current carbon emission efficiency evaluation refers to the IPCC accounting framework [15]. It takes energy consumption as the basis for carbon emission measurement [16], combines advanced means such as remote sensing technology [17], and selects a series of DEA models [18], the Malmquist method [19], etc., to measure carbon emission efficiency and analyze its spatiotemporal characteristics. The SBM (slacks-based measure) model not only solves the problem that the radial model (DEA) measurement of inefficiency does not include slack variables but also incorporates the non-desired outputs directly into the outputs [20]. The space for further research is to reasonably determine the parameters for carbon emission measurement [21], to scientifically construct the multifactor input–output index system of urban construction land use, and to select or optimize suitable models such as Charnes–Cooper–Rhodes (CCR), Banker–Charnes–Cooper (BCC), Stochastic Frontier Analysis (SFA), and slacks-based measure (SBM) [1,22].

2.3. Research Progress on the Spatial Correlation Between Urban Construction Land Intensity and Carbon Emissions

Although the research on the causal mechanisms between the intensive use of land and its carbon emissions is insufficient, scholars generally agree that there is a significant correlation [23,24]. From the perspective of the input and output of land use, the input of labor, capital, technology, energy, and environmental protection on land brings economic, social, and ecological benefits, as well as unexpected effects such as carbon emissions. The

intensive use of urban land has been interpreted from such three aspects as land use structure, land use intensity, and land use efficiency, while land use intensity comprehensively measures the multi-factor input and output effects per unit area. The carbon emissions efficiency of land use can also be measured with the method of input–output analysis. The influencing factors, interaction mechanism, and spatial relationship between urban construction land intensity and carbon emissions efficiency can be measured under the condition of multiple inputs and outputs with econometric methods.

The study on the correlation between urban construction land intensity and carbon emission efficiency employs spatial econometric models such as the Logarithmic Mean Divisia (LMDI), Spatial Autoregressive Model (SAR), and Spatial Autoregressive Combined Model (SAC) to verify the spatial correlation and interaction mechanism [25–28] and applies the Moran index [29], LISA cluster analysis [22], etc., to study the global spatial autocorrelation and local spatial autocorrelation features. There are also some differences in the research conclusions of the spatial correlation characteristics. Urban construction land intensity and its carbon emission efficiency are dynamically changing, but the trend of the two changes is not generally consistent [30]. The overall correlation between the urban construction land intensity and carbon emission efficiency is negative [26]. Further research can deepen the analysis of spatial correlation characteristics, the coupling degree, and the explanation of the causes based on the use of multiple econometric models to explain the interaction mechanism between the urban construction land intensity and carbon emission efficiency [23,24,31,32].

In summary, the existing studies provide a comprehensive research idea for the study of urban construction land intensity and carbon emission efficiency. Still, there is room for further improvement, (1) the analysis of the spatiotemporal evolution characteristics of urban construction land intensity and carbon emission efficiency at the national level, provincial scale, and in a long time series is insufficient, (2) the robustness test and factor-driven effects of the correlation between urban construction land intensity and carbon emission efficiency need to be enriched further, (3) the explanation of spatial correlation characteristics between urban construction land intensity and carbon emission efficiency at the overall and local levels needs to be improved, and (4) the policy implications need to be further supplemented. The theoretical mechanism and logical framework proposed in this study are shown in Figure 1.

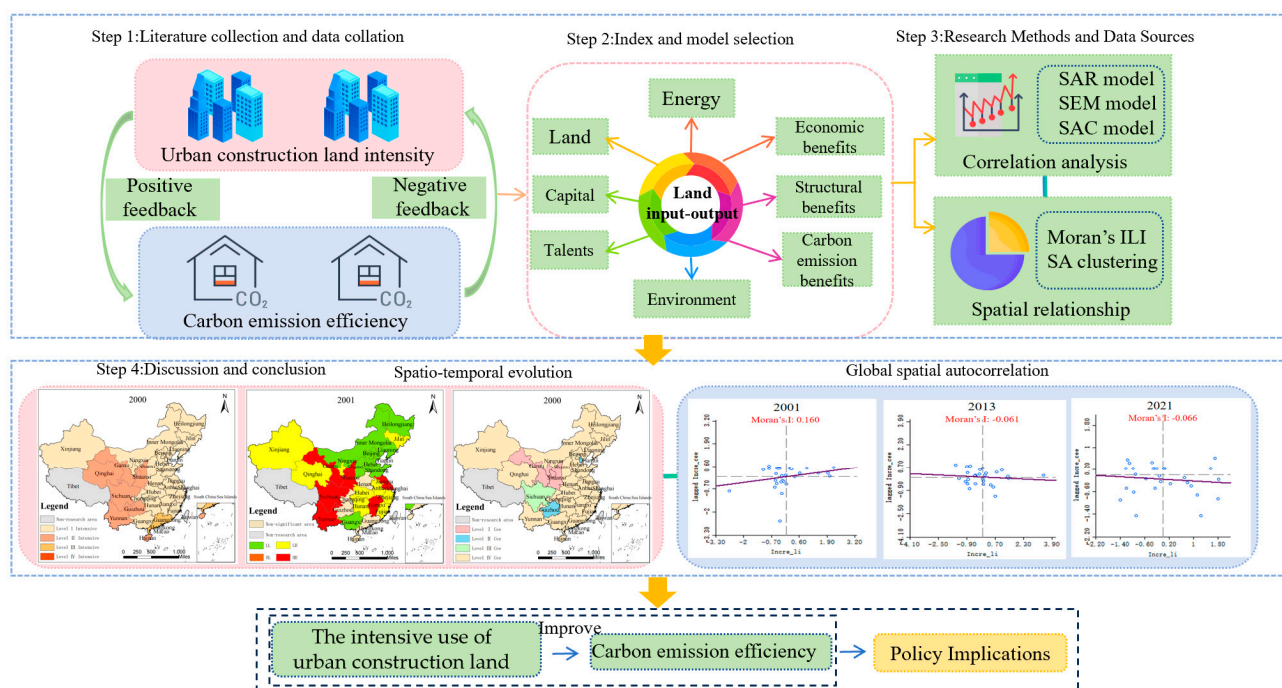


Figure 1. The theoretical mechanism and logical framework.

3. Research Methods and Data Sources

3.1. Evaluation Methods for Urban Construction Land Intensity

Intensive land use was firstly proposed on agricultural land by classical political economists such as David Ricardo (1772–1823) in the theory of land rent, which evaluates the input of production factors such as land, capital, and labor and the output of economic benefits on a certain area of land. Then, Weber's industrial location theory, Kristal's central location theory, and so on have involved the connotation of the intensive use of urban land. As the development of concept connotation and land use practice has proceeded, previous scholars have extended the input variables to land, capital, labor, technology, environment, energy, and so on and extended the output variables to economic, social, and environmental benefits.

Based on the existing research [26] and the evaluation indexes on construction land intensity in China with available data, this research has modified the evaluation indexes in the following ways: Firstly, guideline layers were constructed from the input–output dimensions. Secondly, variables such as the land development rate, road density, population density, ground average land energy, ground average science and technology, ground average environment protection investment, and ground average investment in fixed assets were used to indicate the production factors input on land, while variables such as the ground average secondary sector output, ground average tertiary output, ground average profit tax, and green area coverage were adopted to indicate the social, economic, and environmental output. Thirdly, the multifactor comprehensive evaluation method was applied to calculate the weight.

The land intensity model for urban construction is as follows:

$$P_j = \sum_{i=1}^n x'_{qij} \times w_i \quad (1)$$

where P_j is the intensity value of the evaluation unit j , x'_{qij} is the standardized value of the i th indicator in province j in year q , and w_i is the weight of the i th indicator. The basic formulas for data standardization using the method of extreme deviation and calculation of weights using the entropy weight method are as follows:

Data standardization:

$$y_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \quad (\text{positive indicator}) \quad (2)$$

$$y_{ij} = \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}} \quad (\text{negative indicator}) \quad (3)$$

where y_{ij} is the standard value of the indicator, x_{ij} is the original value of the indicator, x_{imin} is the minimum value of the i th indicator, and x_{imax} is the maximum value of the i th indicator.

Data panning (after normalization, for data 0):

$$y_{ij} + 0.001 \quad (4)$$

Calculation of the weight of the j th indicator in year i using p_{ij} :

$$p_{ij} = \frac{y_{ij}}{\sum_{i=1}^m y_{ij}} \quad (5)$$

Calculation of the information entropy, denoted by e_j :

$$e_j = -K \sum_{i=1}^m p_{ij} \ln p_{ij}, \quad k > 0, \quad 0 \leq e_{ij} \leq 1 \quad (6)$$

where $K = 1/\ln m$ and $m = \text{number of cities} \times \text{year}$

Calculation of the information entropy redundancy using g_i

$$g_i = 1 - e_j \quad (7)$$

Calculate the weights, denoted by w_i :

$$w_i = \frac{g_j}{\sum_{i=1}^n g_j} \quad (8)$$

3.2. Building the Land Carbon Efficiency Non-Expected Output SBM (Slacks-Based Model)

The traditional DEA model is suitable for analyzing the efficiency of multi-input and multi-output problems, but it cannot deal with the problem of non-desired outputs, whereas carbon emissions, as an environmental burden, is a kind of ‘cost’ for urban construction land use and also a kind of ‘non-desired output’. Therefore, this research cites the non-angular, non-radial, non-expected output SBM model [18], which is suitable for this research for the accurate measurement of carbon emission efficiency. The specific formula is as follows:

$$\rho = \min \frac{1 - \frac{1}{i} \sum_{i=1}^i \frac{s^-_{ki}}{x_{ki}}}{1 + \frac{1}{s_1 + s_2} (W^{s_1} \sum_{k=1}^{s_1} s^{s_1}_{kj} / y^{s_1}_{kj} + W^{s_2} \sum_{k=1}^{s_2} s^{s_2}_{kj} / y^{s_2}_{kj})} \quad (9)$$

s.t.

$$\begin{cases} x_{ki} = \lambda X + s^-_{ki} \\ y^{s_1}_{kj} = \lambda Y^{s_1} - s^{s_1} \\ y^{s_2}_{kj} = \lambda Y^{s_2} + s^{s_2} \\ s^-_{ki} \geq 0, s^{s_1} \geq 0, s^{s_2} \geq 0, \lambda \geq 0 \end{cases}$$

where ρ is the decision unit efficiency value; s is the slack variable of input and output; x_{ki} is the j th input of unit i ; y_{kj} is the j th output of unit k ; s_1, s_2 represent the desired output and non-desired output, respectively; W^{s_1}, W^{s_2} is the relative weight of the desired output and non-desired output, according to the number of outputs being set to 5/6 and 1/6, respectively, and λ being the vector of weights; s^-, s^{s_1}, s^{s_2} represents the amount of redundancy in inputs, the insufficiency of desired outputs, and the redundancy of non-desired outputs, respectively, and is set to $\sum \lambda = 1$, then, let ρ be the pure technical efficiency (ρ_t) or else be the comprehensive efficiency (ρ_c); $\rho_s = \rho_c / \rho_t$ represents the efficiency of the scale.

3.3. Spatial Measurement Models

Considering the actual existence of provinces as individual factors influencing the regression variables, firstly, Matlab 2022 was used to conduct regression analyses of mixed effects, individual fixed effects, time fixed effects, and two-way fixed effects models in order to test the overall fit, the significance of individual coefficients, and spatial correlation of residuals in the different models. Since the ordinary panel model cannot describe the spatial interaction of economic variables between different regions [33], a spatial econometric model is introduced when discussing the impact of the intensive use of urban construction land on carbon emission efficiency. The spatial lag model (SAR), spatial error model (SEM), and spatial autoregressive mixed model (SAC) were used to regress the two-way fixed effects model.

$$\begin{cases} y = pWy + X\beta + \varepsilon \\ \varepsilon \sim (0, \sigma^2 1_n) \end{cases} \quad (10)$$

$$\begin{cases} y = X\beta + \mu \\ \mu = \lambda Wu + \varepsilon \\ \varepsilon \sim (0, \sigma^2 1_n) \end{cases} \quad (11)$$

where y is the explanatory variable; p is the spatial autoregressive coefficient; W is the spatial matrix of variables; X is the set of explanatory variables; β is the regression coefficient of the explanatory variables; ε is the random error; μ is the term of the sequence of random errors concerning the normal distribution of spatial errors; and λ is the coefficient of spatial error, whose value reflects the degree of spatial correlation of the residuals.

This study constructs the following three kinds of spatial weight matrix [33].

The first is based on the Queen adjacency rule, and the geographical neighbor weight matrix is constructed by using map boundary vector data:

$$W_{ij} = \begin{cases} 1, & \text{when provinces } i \text{ and } j \text{ share a common boundary} \\ 0, & \text{when provinces } i \text{ and } j \text{ have no common boundary or } i = j \end{cases} \quad (12)$$

The second weight matrix developed in this study is termed the economic distance weight matrix, which is founded on the reciprocal of the absolute value of the economic gap. In this context, w_{ij} represents the reciprocal of the absolute difference between the per capita GDP of province i and that of province j during the specified sample years.

$$W_{ij} = \begin{cases} 1/|\bar{X}_i - \bar{X}_j|, & \text{when } i \neq j \\ 0, & \text{when } i = j \end{cases} \quad (13)$$

Recognizing the limitations of the previously mentioned single-geographical and economic weight matrices, this study constructs a third type of comprehensive weight matrix for geographical economics, which is based on the ratio of the GDP of each neighboring province to the total GDP of all neighboring provinces.

$$W_{ij} = \begin{cases} X_i / \sum_{k \in I_i} X_k, & \text{when provinces } i \text{ and } j \text{ share a common boundary} \\ 0, & \text{when provinces } i \text{ and } j \text{ have no common boundary or } i = j \end{cases} \quad (14)$$

The subsequent spatial econometric analysis is only based on the geographical proximity weight matrix and the comprehensive weight matrix of the geographical economy for consideration.

At the same time, when the SAC model does not consider the influence of the lag term of the explained variable on itself, that is, the spatial lag coefficient of the model $\rho = 0$, the SEM model of the spatial error can be obtained, such as Formula (11). When the SAC model excludes the influence of the disturbance term, that is, the spatial error term coefficient $\lambda = 0$, the SAR model is obtained, as shown in Formula (10). Since the OLS model is a non-spatial econometric model, it does not consider the spatial correlation between different provinces, so it can be regarded as the result of excluding the influence of the spatial lag term and spatial error term in the SAC model. The spatial lag model (SAR) and the spatial error model (SEM) are combined to establish the generalized spatial autoregressive model (GSAR) (see Equation (15)), and ten factors, the land development rate, road density, population density, per capita energy, per capita science and technology, per capita environmental protection, per capita fixed asset investment, per capita net carbon emission, industrial structure, per capita profit and tax, and green land coverage are taken as variables in the GSAR model. In the GSAR model, the influence of the above variables on carbon emission efficiency is examined in terms of spatial lag and spatial error effects.

$$\begin{cases} cf = pW_{ij}cf + \beta_1 ldr_{i,t} + \beta_2 pd_{i,t} + \beta_3 ei_{i,t} + \beta_4 ti_{i,t} + \beta_5 epi_{i,t} + \\ \beta_6 pi_{i,t} + \beta_7 nce_{i,t} + \beta_8 is_{i,t} + \beta_9 pda_{i,t} + \beta_{10} pgc_{i,t} + \mu_{i,t} + \tau_t + \omega_i \\ \mu = \lambda W \mu + \varepsilon \\ \varepsilon \beta_1 \sim (0, \sigma^2 I_n) \end{cases} \quad (15)$$

where cf is the explanatory variable, including carbon emission efficiency under intensive use; W_{ij} and W_{2ij} are the spatial lag term and spatial error term based on the spatial distance weight matrix of the centers of the two provinces i, j ; $ldr_{i,t}$, $pd_{i,t}$, $ei_{i,t}$, $ti_{i,t}$, $e pi_{i,t}$, $pi_{i,t}$, $nce_{i,t}$, $is_{i,t}$, $pda_{i,t}$, $pgc_{i,t}$ represents the variables of the land development rate, road density, per

capita energy, per capita science and technology, per capita environmental protection, per capita investment in fixed assets, per capita net carbon emission, industrial structure, per capita profit and tax, and the greenland coverage in the year t of province i , with the meanings of these variables. The meanings of the variables are consistent with the descriptions of the indicators in Table 1; $is_{i,t}$ is the level of industrial structure, expressed as the ratio of the value added of the secondary and tertiary industries; $\beta_{1\sim 10}$ is the regression coefficients of the ten variables; τ_t, ω_i is the time and spatial fixed effects; λ and p are the autocorrelation and autoregression coefficients of spatial error, which are transformed into the SAR model when $\lambda = 0$ and into the SEM model when $p = 0$.

Table 1. Evaluation indicators and weights for urban construction land intensity in China.

Guideline Layer (Weights)	Indicator Layer	Description of Indicators	Indicator Properties	Indicator Weights
Land input intensity (0.762)	Land development rate	Built-up area/urban area	+	0.024
	Road density	Road area/built-up area	+	0.174
	Population density/(10,000 persons/km ²)	Year-end resident population/built-up area	+	0.031
	Ground average land energy/(million tce/km ²)	Urban energy consumption/built-up area	-	0.003
	Ground average Science and Technology/(million CNY /km ²)	Urban R&D expenditure/built-up area	+	0.253
	Ground average Environment protection investment/(million CNY /km ²)	Total investment in environmental pollution control/built-up area	+	0.233
	Ground average investment in fixed assets/(million CNY/km ²)	Investment in fixed assets/built-up area	+	0.044
Land output intensity (0.238)	Ground average secondary sector output/(billion CNY/km ²)	Value added of secondary industry/built-up area	+	0.029
	Ground average Tertiary output/(billion CNY/km ²)	Value added of tertiary industry/built-up area	+	0.051
	Ground average profit tax/(million CNY/km ²)	Urban tax revenue/built-up area	+	0.097
	Green area coverage	Green space/built-up area	+	0.061

3.4. Spatial Autocorrelation

Exploring the correlation between land intensity and carbon emission efficiency can reveal the degree of correlation and spatial aggregation of the attributes and visually corroborate the intrinsic link between land intensity and carbon emission efficiency. This research cites bivariate global and local autocorrelation methods [34] to portray the bivariate spatial correlation between the growth of urban construction land intensity and the growth of carbon emission comprehensive efficiency. The bivariate global spatial autocorrelation index (DGM) is defined as follows:

$$DGM = n \sum_i^n \sum_j^n w_{ij} Y a_i Y b_j / \left((n-1) \sum_i^n \sum_j^n w_{ij} \right) (i \neq j) \quad (16)$$

where $Y a_i$ and $Y b_j$ are the urban construction land intensity in province i and the increase in carbon emission comprehensive efficiency in province j , respectively; $\sum_i^n \sum_{j \neq i}^n w_{ij}$ is the spatial weight matrix based on the spatial distance of each province's central coordinates.

The DGM index can observe the global correlation of variables, and the larger the absolute value, the stronger the correlation. Still, it cannot characterize the spatial correlation pattern and distribution of different provinces. Hence, it needs to be supplemented

by the local spatial autocorrelation index (DLM), and the significance level of the index is calculated by using the LISA scatter plot to reveal the correlation between the neighboring provinces of a local region. Positive values for the DLM index indicate spatial clusters of similar values around the region, while negative values indicate spatial clusters of non-similar values, as defined below:

$$DLM = \frac{Ya_i - \bar{Ya}}{\sigma_a} \sum_{i=1}^n w_{ij} \frac{Yb_j - \bar{Yb}}{\sigma_b} (i \neq j) \quad (17)$$

where $\bar{Ya}$, $\bar{Yb}$, σ_a , and σ_b are the regional mean and variance of the increased value in urban construction land intensity and carbon emission efficiency, respectively; $\sum_{i=1}^n w_{ij}$ is the spatial weighting matrix from province j to other provinces.

3.5. Data Sources and Descriptive Statistics

Data are from *China Statistical Yearbook*, *China Statistical Yearbook of Urban Construction*, *China Statistical Yearbook of Environment*, *China Statistical Yearbook of Fixed Assets*, and *China Statistical Yearbook of Energy*, 2001–2022. Data for such indicators as the area of the urban area, the built-up area, the area of the road, the area of the green area, the resident population, the tax income, the expenditure on research and experimentation, and the secondary and tertiary industries are from *China Statistical Yearbook of Urban Construction* and *China Statistical Yearbook*; data on fixed asset investment are from *China Yearbook of Fixed Asset Investment*; data on investment in environmental protection and pollution control are from *China Statistical Yearbook of Environment*; and data on energy consumption are from *China Statistical Yearbook of Energy*. This study uses panel data from 30 Chinese provinces (excluding Tibet, Hong Kong, Macao, and Taiwan due to data limitations), covering the period from 2000 to 2021. Descriptive statistics for the calculated provincial indicators are presented in Table 2.

Table 2. Descriptive statistics on the numerical values of evaluation indicators of urban construction land intensity in 30 provinces of China, 2000–2021.

Symbol	Variable	Unit	Min	Max	Mean	Std.dev.
ldr	Land development rate		0.04	0.77	0.29	0.15
rd	Road density		0.05	20.77	3.19	5.32
pd	Population density	Million people/km ²	0.88	12.88	3.71	2.01
ei	Ground average energy	million tce/km ²	0.01	27.19	8.47	3.89
ti	Ground average science and technology	million/km ²	31.20	174,480.81	7335.51	23,614.09
epi	Ground average environmental protection investment	million/km ²	32.39	5176.77	1129.06	974.30
fai	Ground average investment in fixed assets	million/km ²	6355.30	259,663.28	71,208.66	51,430.56
nce	Ground average net carbon emissions	million tons/km ²	1.25	19.07	6.10	2.80
sii	Ground average secondary sector output	billion/km ²	0.41	10.84	4.20	2.25
tii	Ground average tertiary sector output	billion/km ²	0.65	25.50	4.86	3.58
pda	Ground average profit tax	million/km ²	77.77	85,165.98	10,076.30	10,803.92
pgc	Percentage of green coverage		0.09	2.38	0.46	0.25

4. Results Analysis

4.1. Results of Urban Construction Land Intensity Evaluation

Based on the distribution law of the intensity value, the cluster analysis method was used to divide the urban construction land intensity values of 2000, 2003, 2006, 2009, 2012, 2015, 2018, and 2021 into four grades, with a level I intensive degree interval of [0.042:0.142), a level II intensive degree interval of [0.142:0.237), a level III intensive degree interval of [0.237:0.356), and a level IV intensive degree interval of [0.356–0.356). The higher the result of the evaluation level, the higher the degree of intensity.

As is shown in Figure 2, from 2000 to 2021, the intensity of urban construction land in China generally increased, which shows an overall trend of the intensive use of urban construction land in China. Meanwhile, the number of provinces in China's urban construction land intensity intervals changed from 2000 to 2021. The number of provinces in the level I intensity interval decreased abruptly from 22 in 2000 to 3 in 2021, the number of provinces in the level II intensity interval increased from 7 in 2000 to 17 in 2012 and then decreased to 10 in 2021 in fluctuation, and the number of provinces in the level III and IV intervals increased from 1 in 2000 to 7 in 2021 and from 0 in 2000 to 10 in 2021, respectively.

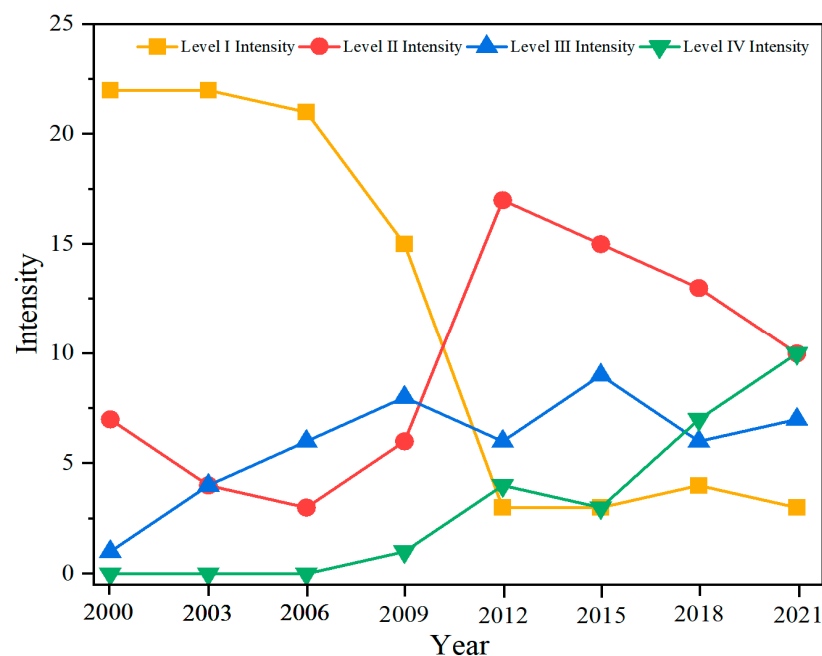


Figure 2. Number of provinces in each range of urban construction land intensity in China, 2000–2021.

As shown in Figure 3, three provinces that were in the Level I intensity in 2021 in China are Liaoning and Jilin in the northeast region and Ningxia in the northwest region; the causes of this may be factors such as relatively insufficient economic development, wide land area, sparsely population, etc. Except for a few provinces in the eastern region, the provinces have relatively high intensity levels. For example, Beijing, Shanghai, and Guangdong were in the IV intensity interval in 2021 thanks to the developed economy and efficient land use. Sichuan, Yunnan, Guizhou, Gansu, and Qinghai in the western region were in the level IV intensity interval in 2021, which may have been affected by infrastructure investment, the introduction of talent, and the undertaking of industrial transfer from the east.

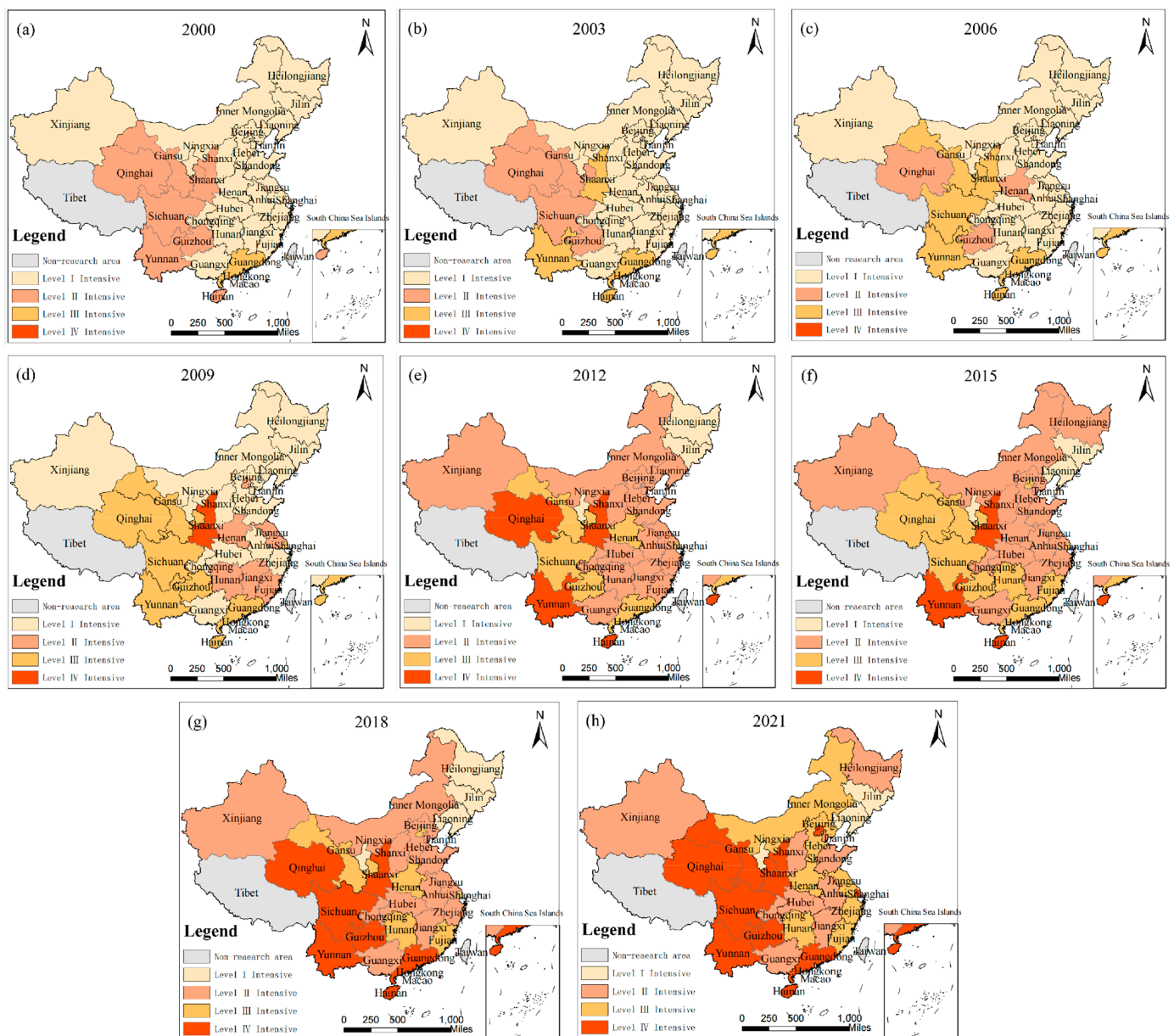


Figure 3. Spatial evolution of urban construction land intensity in 30 provinces of China, 2000–2021.

4.2. Results of Carbon Emission Efficiency Evaluation

This study uses the Dearun computing platform to calculate the carbon emission efficiency scores for urban construction land in 30 Chinese provinces from 2000 to 2021. These scores encompass scale efficiency, technical efficiency, and overall efficiency. The scale efficiency of carbon emission represents the matching degree between the input scale of urban construction land and the output scale of carbon emission. The technical efficiency of carbon emission is a measure of the output efficiency per unit of carbon emission under the influence of technological progress; the comprehensive efficiency of carbon emission reveals the level of the intensive use of urban construction land to achieve the output efficiency per unit of carbon emission. The comprehensive efficiency is the product of the scale efficiency and technical efficiency.

The development trends of the scale efficiency, technical efficiency, and comprehensive efficiency of 30 provinces from 2000 to 2021 are shown in Figure 4. The overall trend of the number of provinces with a scale efficiency, technical efficiency, and combined efficiency value of 1 from 2000 to 2021 is a fluctuating decrease followed by a fluctuating

increase, with more than 77 percent of the provinces having comprehensive efficiency, technical efficiency, and scale efficiency at the fully effective level of efficiency by 2021. The comprehensive efficiency, technical efficiency, and scale efficiency have the same trend of change. The technical efficiency curve is closer to the comprehensive efficiency curve than the scale efficiency curve, indicating that technical efficiency is the main factor influencing the change in the comprehensive efficiency of carbon emissions. The scale efficiency of most provinces is larger than that of technical efficiency and comprehensive efficiency, illustrating that there is still room for further improvement in technical efficiency.

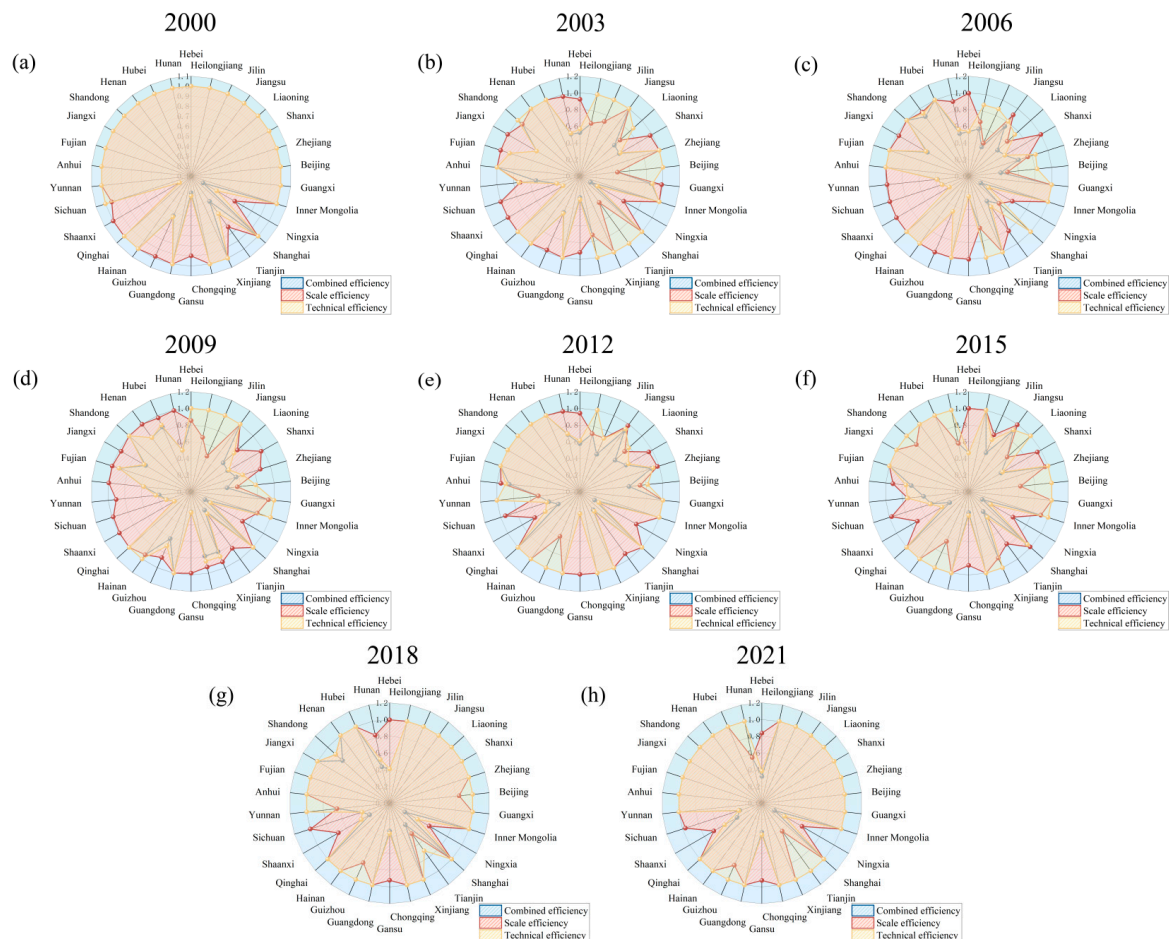


Figure 4. Carbon emission efficiency value of urban construction land in China, 2000–2021.

In order to further explore the features of the scale efficiency, technical efficiency, and comprehensive efficiency of carbon emissions from the intensive use of urban construction land in time and space, the efficiency values in 2000, 2003, 2009, 2012, 2015, 2018, and 2021 were selected, and these three types of efficiency values were classified into four grades using cluster analysis.

The scale efficiency values are divided into four intervals: the level I scale efficiency interval value is $[0:0.53)$, the level II scale efficiency interval value is $[0.53:0.7)$, the level III scale efficiency interval value is $[0.7:1)$, and the level IV scale efficiency interval value is $[1]$. As can be seen from Figure 5a, the carbon emission scale efficiency of 30 provinces from 2000 to 2021 is mainly located in the zone of levels III and IV. The number of provinces in the level I and II scale efficiency interval accounts for a relatively low and stable number, which indicates that the carbon emission efficiency as a whole is at a high level. In 2021, 22 provinces had reached full-scale efficiency and 8 provinces had not reached full-scale efficiency.

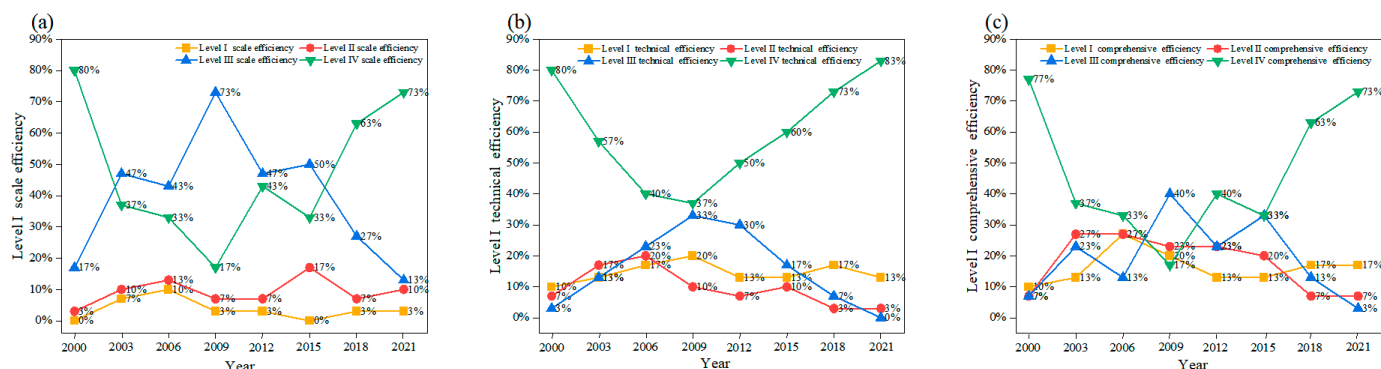


Figure 5. (a) Percentage of the number of provinces in each interval of the carbon emission scale efficiency of urban construction land in China, 2000–2021. (b) Percentage of provinces in each interval of the technical efficiency of carbon emissions from urban construction land in China, 2000–2021. (c) Percentage of provinces in each interval of the comprehensive efficiency of carbon emissions from urban construction land in China, 2000–2021.

The technical efficiency values are divided into four intervals: the level I technical efficiency interval is $[0:0.45)$, the level II technical efficiency interval is $[0.45:0.56)$, the level III technical efficiency interval is $[0.65:1)$, and the level IV technical efficiency interval is $[1]$. As shown in Figure 5b, similar to the scale efficiency values, the number of provinces in the level III and IV technical efficiency intervals accounts for a large proportion, and their fluctuation trend is significant in the opposite direction. The number of provinces located in the level I technical efficiency interval and the level II technical efficiency interval accounts for a lower and more stable proportion, fluctuating within the range of 0–20%, respectively. In 2021, 25 provinces have reached full technical efficiency, accounting for 83 percent of the total. Almost all the developed eastern provinces with better economic development are in the level IV technical efficiency interval. In contrast, the regions with insufficient efficiency are mainly in the central and western provinces, such as Ningxia, Gansu, Shanxi, Hebei, and Sichuan, which are technologically backward in production and management or rely on energy and other non-technical factors for development.

The comprehensive efficiency values are divided into four intervals: the level I comprehensive efficiency interval is $[0:0.39)$, the level II comprehensive efficiency interval is $[0.39:0.60)$, the level III comprehensive efficiency interval is $[0.60:1)$, and the level IV comprehensive efficiency interval is $[1]$.

As can be seen from Figure 5c, similar to the scale efficiency and technical efficiency, the number of provinces in the level IV technical comprehensive interval accounts for a large proportion and its fluctuation trend is significant, while the proportion of the number of provinces located in the level I, level II, and level III comprehensive efficiency intervals is relatively stable.

In 2021, 22 provinces have reached full comprehensive efficiency, accounting for 73 percent of the total. The provinces with insufficient comprehensive efficiency are Hebei, Ningxia, Sichuan, Gansu, and Shanxi in the level I comprehensive efficiency interval, Tianjin and Hunan in the level II comprehensive efficiency interval, and Guizhou in the level III comprehensive efficiency interval.

As shown in Figure 6, from 2000 to 2021, the provincial carbon emission efficiency generally shows a trend of fluctuating decrease and then fluctuating increase. Provinces in the level I comprehensive efficiency interval are relatively stable and mainly located in the central regions such as Sichuan, Gansu, Shaanxi, and Ningxia. The number of provinces with levels II and III shows a trend of first increasing and then decreasing; these provinces are mainly located in the southwestern region. The number of provinces with level IV comprehensive efficiency is much more significant, showing a fluctuating decrease and then a fluctuating increase. Eastern provinces are mainly found in the level IV comprehensive efficiency interval.

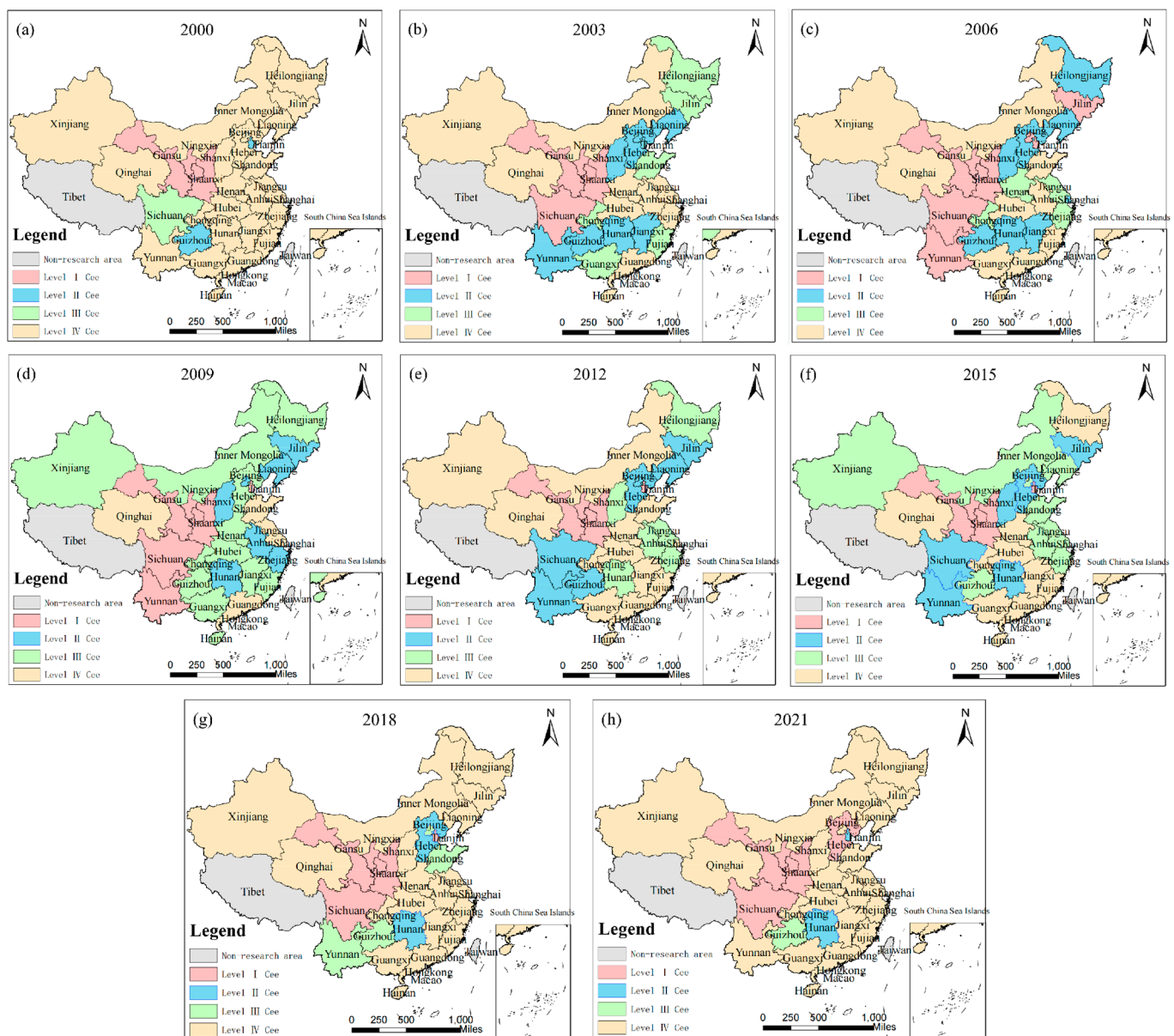


Figure 6. Spatial evolution of the comprehensive efficiency of carbon emissions from urban construction land in China, 2000–2021.

4.3. Analysis of the Correlation Between Urban Construction Land Intensity and Carbon Emission Efficiency

4.3.1. Ordinary Panel Model Measures and Spatial Correlation Analysis

As shown in Table 3, both the individual fixed effects model and the time fixed effects model LM test results pass the significance test, indicating a spatial correlation and that the choice of spatial measurement model will be more accurate. The goodness of fit and Log-L value of the two-way fixed effects model are 0.1050 and 519.97, respectively, which indicate that the two-way fixed effects model fits better than other models; this research will use the two-way fixed effects model to study the intensive factors affecting the efficiency of carbon emissions. The LM-lag statistic is significantly larger than the LM-err statistic, so the spatial autoregressive model becomes the best choice of the model. The spatial autoregressive model is a better choice for this research.

Table 3. Estimation and test results of the ordinary panel model of urban construction land intensity.

Variable	Mixed Effect	Individual Fixed Effect	Time Fixed Effect	Two-Way Fixed Effect
ldr	−2.94 ** (−2.25)	−1.73 (−1.32)	−3.76 *** (−2.73)	−4.62 *** (−3.56) **
rd	0.93 (0.70)	0.17 (0.12)	0.86 (0.57)	−3.67 (−2.29)
ei	−51.45 (−0.79)	14.50 (0.45)	−41.29 (−0.64)	20.79 (0.71)
ti	−4.48 *** (−4.57)	−0.53 (−0.83)	−4.83 *** (−4.97)	−0.93 (−1.54)
epi	3.13 ** (2.14)	0.75 (0.89)	3.01 (2.05) **	0.16 (0.21)
fai	−0.70 (−0.70)	−1.81 ** (−2.25)	−2.25 * (−1.61)	−5.33 *** (−6.09)
nce	107.64 * (1.65)	9.84 (0.31)	90.82 (1.40)	−21.58 (−0.74)
is	−0.03 (−1.23)	0.07 *** (3.07)	−0.05 ** (−2.01)	0.01 (0.16)
pda	7.09 *** (4.85)	3.35 *** (2.84)	7.18 *** (4.97)	3.31 *** (2.96)
pgc	12.35 *** (4.69)	3.45 ** (2.14)	12.94 *** (4.87)	4.01 *** (2.71)
R-squared	0.1350	0.0912	0.1450	0.1050
Log-likelihood	−50.99	442.75	−33.06	519.97
LM-lag	0.33	57.85 ***	9.65 ***	1.55
Robust LM-lag	3.50 *	0.29	8.35 ***	0.47
LM-err	3.93 **	133.59 ***	2.82 *	1.12
Robust LM-err	7.10 ***	76.03 ***	1.52	0.04

Note: *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively, as in the following table; *t*-test values are in parentheses.

4.3.2. Analysis of the Results of Spatial Panel Modeling

In this research, the two-way fixed effects model is regressed again using the SAR and SEM models, and the results are shown in Table 4. Compared with the ordinary two-way fixed effects model, the regression goodness of fit values of the SAR and SEM models are 0.8587 and 0.8573, respectively, indicating substantial improvement. Meanwhile, the Log-L value increases somewhat and the overall fitting effect is better. In comparing specific coefficients, except for the variables environmental protection investment (epi) and industrial structure (is), the positivity and negativity of the coefficients of the other variables are consistent with the original estimation model. Still, most of the T-values have a certain magnitude of improvement, which suggests that the two models mentioned above have improved the results of the coefficient regression of the bidirectional fixed effects model more significantly. In addition, although the spatial lag term and the spatial error term passed the 5% and 1% tests, respectively, the goodness of fit of the SAR is higher than that of the SEM, the log-likelihood value is slightly lower than that of the SEM, and the overall fitting effect is better. This research launches the analysis of the significance of variables with the results of the SAR model and the findings are as follows: (1) the land development rate (ldr) passes the 1% significance level test and the coefficient is negative; (2) road density (rd) passes the 5% significance level test and the coefficient is negative; (3) the ground average science and technology investment (ti) passes the 10% significance level test and the coefficient is negative; (4) the ground average investment in fixed assets (fai) passes the 1% significance level test and the coefficient is negative, (5) the ground average profit tax (pda) passes the 1% significance level test and the coefficient is positive; and (6) the percentage of green coverage (pgc) passes the 5% significance level test and the coefficient is positive.

Table 4. Spatial metrological estimation and test results of the bidirectional fixed effect model of urban construction land intensity influencing factors on carbon emissions efficiency.

Variable	SAR	SEM
ldr	−6.69 *** (−4.74)	−6.77 *** (−3.65)
rd	−3.50 ** (−2.07)	−3.65 ** (−2.14)
ei	17.89 (0.60)	13.79 (0.47)
ti	−1.13 * (−1.83)	−1.03 * (−1.69)
epi	−0.83 (−1.03)	−0.75 (−0.94)
fai	−0.538 *** (−6.23)	−5.32 *** (−6.17)
nce	−19.19 (−0.65)	−15.26 (−0.53)
is	−0.04 (−1.29)	−0.04 (−1.35)
pda	4.20 *** (3.59)	4.28 *** (3.69)
pgc	3.11 ** (2.11)	3.10 ** (2.13)
W*dep.var.	−0.27 ** (−2.01)	
Spat.aut.		−0.39 *** (−2.75)
R-squared	0.8587	0.8573
Log-likelihood	545.59	546.81

Note: *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively, as in the following table; *t*-test values are in parentheses.

The SAC model divides the total spatial effect into direct and indirect effects, and the total effect is the sum of the direct and indirect effects. In this research, the spatial autoregressive mixed model SAC is used to regress the two-way fixed effects model again, and the results are shown in Table 5. Overall, the indirect effects of variables on the impact of carbon emission efficiency are larger than the direct effects; this is mainly attributed to two reasons. The first is the spatial spillover effect, where the spatial econometric model considers geographical proximity and interaction relationships. The carbon emission efficiency of a certain region is directly affected by a certain variable or may be indirectly affected by multiple variables from neighboring regions, resulting in more significant indirect effects than direct effects. The second is the spatial path dependence effect, where the impact of variables on carbon emission efficiency may be achieved through a series of intermediate steps or pathways, which may involve interactions and feedback between multiple regions, resulting in indirect effects being more significant than direct effects. Road density, the ground average science and technology investment, the ground average environmental protection investment, and the ground average fixed asset investment significantly negatively affect carbon emission efficiency. Road density has a significant positive effect on carbon emission efficiency. Profit tax has a significant positive direct effect on carbon emission efficiency, and the percentage of green coverage has a significant positive direct effect and a significant negative indirect effect on carbon emission efficiency. The ground average energy, ground average net carbon emissions, and industrial structure have no significant effect on carbon emission efficiency. By comparing the total effect results of the SAC model with those of the SAR model and SEM model, it is found that, except for the positive and negative coefficients of road density (rd) and percentage of green coverage (pgc) in the SAC model, which are opposite to those of SAR model and SEM model, the coefficients of the other variables are consistent with each other.

Table 5. Spatial effect decomposition of the test results of the bidirectional fixed effect model of urban construction land intensity influencing factors on carbon emissions efficiency.

Variable	Direct Effect	Indirect Effect	Total Effect
ldr	−6.21 *** (−4.57)	−33.44 *** (−2.82)	−39.65 *** (−3.19)
rd	−3.95 ** (−2.27)	35.04 *** (3.56)	31.09 *** (3.23)
ei	15.62 (0.53)	110.91 (0.64)	126.53 (0.69)
ti	−0.97 (−1.59)	−11.54 ** (−2.58)	−12.51 ** (−2.68)
epi	−0.72 (−0.89)	−9.80 ** (−2.34)	−10.52 ** (−2.45)
fai	−5.27 *** (−6.08)	−4.95 (−1.18)	−10.23 ** (−2.41)
nce	−17.30 (−0.59)	−108.38 (−0.66)	−125.68 (−0.74)
is	−0.03 (−1.19)	−0.08 (−0.56)	−0.11 (−0.80)
pda	4.27 *** (3.71)	−2.74 (−0.35)	1.52 (0.19)
pgc	3.38 ** (2.22)	−18.19 * (−1.83)	−14.81 (−1.45)

Note: *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively, as in the following table; *t*-test values are in parentheses.

4.4. Analysis of the Spatial Relationship Between Urban Construction Land Intensity and Carbon Emission Efficiency

The global spatial autocorrelation method from the GeoDa software 1.18.0 was used to obtain the double Moran's I scatter plot of the increased value of intensity and carbon emissions efficiency from 2001 to 2021 (Figure 7). Arcgis was used to plot the land at the $p < 0.05$ level of significance for the years 2001–2021. Local spatial autocorrelation LISA plots of the combined increase in intensity and carbon emissions efficiency (Figure 8). In Figure 8, quadrants I–IV are the HH, LH, LL, and HL quadrants, respectively. The areas falling in quadrants I and III represent the positive (negative) increase in intensity and the positive (negative) increase in the comprehensive carbon emission efficiency, and the two growth trends are spatially positively correlated; the opposite is true for quadrants II and IV. The Moran's I index values from 2001 to 2021 are generally negative except for a few years, indicating a negative correlation between urban construction land intensity growth and comprehensive carbon emission efficiency growth. Double Moran's I scattering from 2001–2021 is distributed in the four quadrants, and only a few provinces are non-significantly clustered. The scatter plot concentration is in the LH quadrant, the LL quadrant, and the HL quadrant, indicating that the relationship between land intensity and comprehensive carbon emissions efficiency is mainly decrease–growth, decrease–decrease, and increase–decrease, and the scatter plot distribution shifts from relatively concentrated to relatively dispersed, indicating that there is a tendency to expand the increase value and decrease value of urban construction land intensity and the comprehensive carbon emissions efficiency with the growth of the year.

(1) Explanation of the characteristics of HH clustering. The number of provinces clustering in HH decreased from seven in 2001 to three in 2021. The clustered provinces changed from Gansu, Sichuan, Yunnan, Shaanxi, Jiangsu, Jiangxi, and Shanghai in 2001 to Sichuan, Jiangsu, and Shanghai in 2021, which showed that an increase in carbon emission efficiency accompanied the growth of land intensity. The growth of both land intensity and carbon emission efficiency is a win–win situation. Shanghai is the center of China's international economy, finance, trade, shipping, and science and technology innovation; Jiangsu Province is one of the provinces with the highest level of comprehensive

development in China; and Sichuan is a major clean energy province in China that is rich in natural gas resources and abundant in hydropower.

(2) Explanation of the characteristics of LH clustering. The number of provinces clustering in LH remained at 7–9 from 2001 to 2021. LH was generally the quadrant with more clustered provinces. In 2021, LH clustering included Heilongjiang and Jilin in the eastern region, Zhejiang and Hebei in the east region, Hunan and Anhui in the central region, and Xinjiang and Ningxia in the western region. The characteristics of LH clustering showed that land intensity decreased while carbon emission efficiency increased. Zhejiang Province actively practiced the concept of ecological civilization and maintained high-quality economic development while reducing urban construction land intensity and increasing carbon emission efficiency. Provinces clustering in LH have the potential and space to improve land intensity.

(3) Explanation of the characteristics of LL clustering. From 2001 to 2021, LL clustering fluctuated among 6–11 provinces. In 2021, LL clustering included Liaoning in the northeast, Tianjin and Shandong in the east, Shanxi, Henan, and Jiangxi in the central region, and Chongqing in the western region. Provinces in the central region accounted for a larger proportion. The characteristics of LL clustering were that, while urban construction land intensity decreased, the carbon emission efficiency decreased. Provinces in the LL cluster were faced with the double task of improving urban construction land intensity and carbon emission efficiency.

(4) Explanation of the characteristics of HL clustering. HL-clustered provinces increased from 0 in 2001 to 9 in 2021. The clustered provinces in 2021 included Guangdong, Hainan, and Beijing in the eastern region, Shaanxi in the central region, and Qinghai, Gansu, Inner Mongolia, Yunnan, and Guizhou in the western region. The number of provinces in the western region accounted for a larger proportion of the total number of provinces. The characteristics of HL clustering manifested that while land intensity increased, the carbon emission efficiency decreased. HL-clustered provinces were faced with an urgent need to improve carbon efficiency.

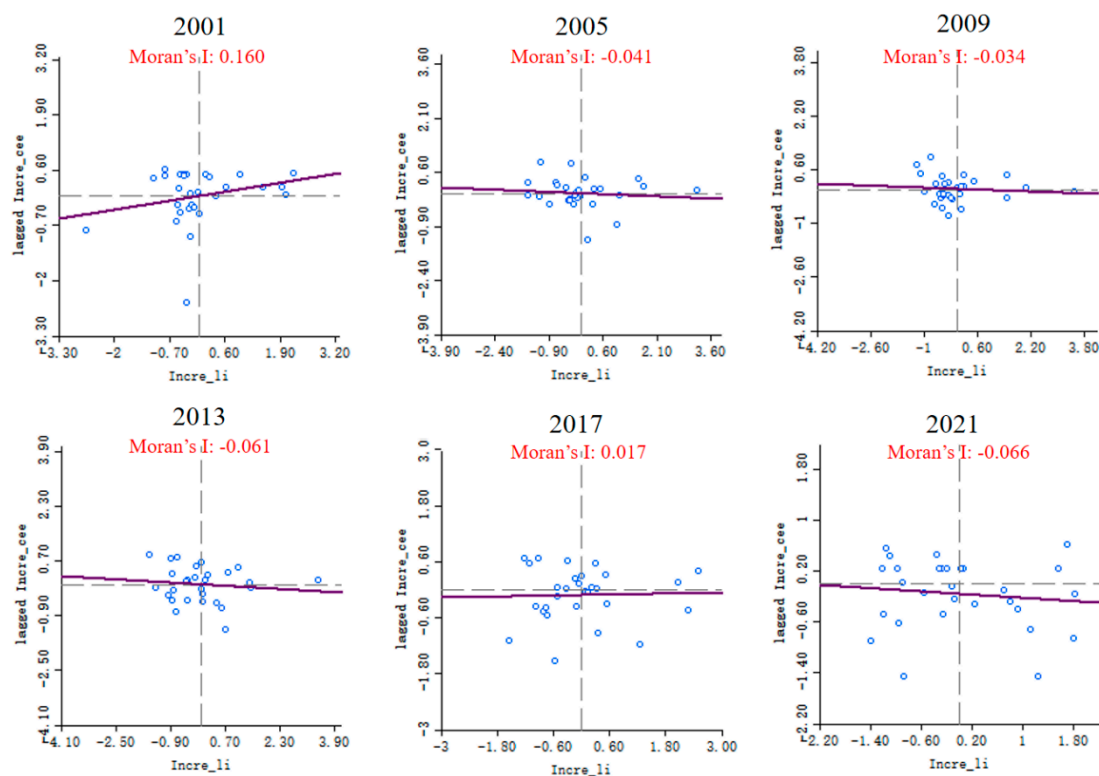


Figure 7. Scatterplot of global spatial autocorrelation Moran index of urban construction land intensity and comprehensive efficiency growth of carbon emission in 30 provinces of China, 2000–2021.

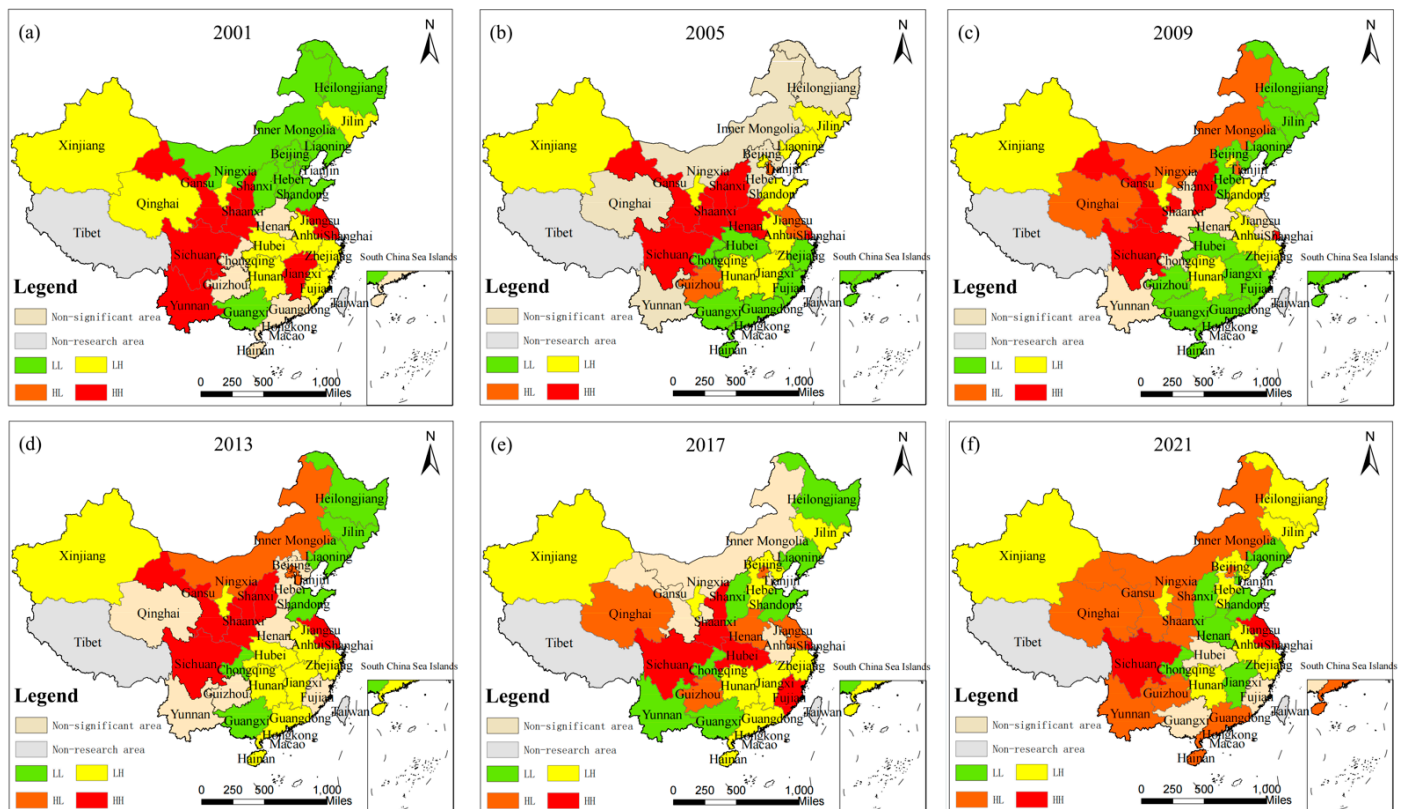


Figure 8. Global spatial autocorrelation LISA clustering of urban construction land intensity and comprehensive carbon emission efficiency growth in 30 provinces in China, 2000–2021.

(5) Explanation of non-significant correlation characteristics. The number of provinces with a non-significant correlation fluctuated from six in 2001 to three in 2021, and the number of provinces that had a non-significant correlation in 2021 included Guangxi and Fujian in the eastern region and Hubei in the central region, which showed that land intensity was not significantly correlated with the carbon emission efficiency.

5. Discussion

Previous researchers have made a series of analyses on the correlation and spatial relationship between urban construction land intensity and carbon emission efficiency. This study selected urban construction land in China as the research object and made an empirical analysis of the spatial and temporal characteristics and correlation between the land intensity and carbon emission efficiency of provincial units at the national level in a long time series. The main research contributions of this research are as follows.

Scholars have constructed a series of evaluation indicators for urban construction land intensity. However, the evaluation index system has not yet been unified, especially since the land input variable is not typically included [26]. Based on the previous research on the index system guideline layer from the perspective of inputs and outputs, this study constructed the input indexes, including land, capital, talents, science and technology, environmental protection, and energy, and the output indexes, including economic benefits, structural benefits, environmental benefits, and carbon emission benefits, to make the index system comprehensive and actionable. The land development ratio variable, equal to the area of the built-up area divided by the area of the urban area, is included as the land input indicator to symbolize the degree of land development, which contributes to making the index system more scientific. Based on the index system, this study collected the panel data of 30 provinces in China for more than 20 years to make an empirical analysis.

The data envelopment approach (DEA model) is the typical model that is widely used to test the input–output efficiency. However, previous studies regarding the DEA

model applications did not consider the simultaneous impact of undesirable outputs [35]. Carbon emission efficiency is the amount of carbon emission output per unit of input. This can compensate for the weakness of the total carbon emissions or intensity indicators that do not consider carbon emission as a cost to the desired output. Based on the DEA model, this study invokes the non-angle, non-radial, and non-expected output-oriented slacks-based measure (SBM) model [36], which is more applicable to accurately measuring carbon emission efficiency.

Scholars usually use ordinary panel models such as the fixed effect model, individual fixed effect model, time fixed effect model, and two-way fixed effect model to test whether there is a spatial correlation [37]. If there is spatial correlation, spatial econometrics models are used to test the spatial effects [38]. This research followed the typical ways to pass the significance test of correlation and used a series of different spatial panel models to make the test robust. For example, this research used the SAR model, the SEM model, and the SAC model to verify the role of factors influencing the carbon emission efficiency of urban construction land; furthermore, the use of Moran's index and LISA clustering is a further step to explore the spatial characteristics of urban construction land intensity and carbon emission efficiency.

The relationship between the intensive use of urban construction land and carbon emissions at the median level is highly heterogeneous. This study lacks in-depth analyses of the relationship between the intensive use of urban construction land and carbon emissions at the median level, the problems and factors affecting them, and the pertinence and operability of policy recommendations at the micro-level need to be improved.

In the follow-up study, we should pay more attention to the following points. (1) Most provinces are not yet in the ideal state of high urban construction land intensity and high carbon emission efficiency. Typical provinces in the LH, LL, and HL clustering regions should be selected for in-depth study of the problems and reasons for the lack of synergy between the intensive use of urban construction land and carbon emissions and to put forward policy recommendations to promote the synergistic development of land intensity and carbon emission efficiency on a micro-level. (2) Insufficient technical efficiency of carbon emissions from urban construction land is the main reason for the low overall carbon emissions efficiency. This study will analyze the factors influencing technical inefficiency in provinces across the eastern, central, and western regions of China. Furthermore, differentiated policy recommendations will be proposed to improve carbon emission technical efficiency in these regions, focusing on energy structure transformation, industrial upgrading, industrial transfer acceptance, and other relevant dimensions.

6. Patents

6.1. Conclusions

Chinese-style modernization actively promotes the synergistic development of urban construction land intensity and carbon emission efficiency. This research constructs an evaluation index of urban construction land intensity from the land input–output dimension, measures the urban construction land intensity of Chinese provincial units from 2000 to 2021, calculates the technical efficiency, scale efficiency, and comprehensive efficiency of carbon emission in provincial areas based on the SBM model of non-expected outputs (on the basis of which, the spatial econometric model is used to test the correlation between urban construction land intensity and carbon emission efficiency), and analyzes the characteristics of the spatial relationship by applying global and local autocorrelation methods to analyze the characteristics of the spatial relationship. The main conclusions are as follows:

(1) It is shown that urban construction land intensity in China is generally in an upward trend. In 2021, 57% of China's provinces are at Class III and above intensity. In terms of spatial distribution, provinces with a high value of urban construction land intensity in China are mainly located in Beijing, Shanghai, eastern coastal areas, and some western provinces.

(2) The overall provincial carbon emission efficiency from 2000 to 2021 shows a fluctuating downward and then a fluctuating upward trend. In 2021, the proportion of provinces at level III and level IV efficiency increases to 76%. Comprehensive efficiency, technical efficiency, and scale efficiency have the same development trend. Technical efficiency is the main reason influencing the change in the comprehensive efficiency of carbon emissions. There is still room for further improvement of technical efficiency.

(3) Different factor inputs in the process of the intensive use of urban construction land have different impacts on the carbon emission efficiency. The intensive use of land development, road density, technology development, and fixed asset investment have a negative impact on carbon emission efficiency, while greening level and tax have a positive promotion effect on carbon emission efficiency.

(4) Urban construction land intensity and carbon emission efficiency in China from 2001 to 2021 are generally negatively correlated. The local aggregation effect is obvious, and there is a shift from mainly LH and LL clustering to mainly LH, LL, and HL clustering. The increase in land intensity is not simply a high-input, high-output, and high-efficiency pattern in terms of carbon emission efficiency, and there exists a heterogeneity of correlation between land use intensity and carbon emission efficiency.

6.2. Policy Implications

(1) The central government and provincial and municipal governments should implement targeted and differentiated urban construction land use policies. For provinces such as Liaoning, Jilin, and Ningxia, where the intensity value is low, urban construction land intensity should be improved through the optimization of land scale, land structure, land layout, and factor inputs.

(2) On the one hand, China should strengthen carbon emission monitoring and early warning systems to tackle the dynamic nationwide differences in the carbon emission efficiency. On the other hand, for Hebei, Ningxia, Gansu, Shaanxi, and Sichuan, which have low carbon emission efficiency, the government should appropriately increase carbon emission reduction responsibility.

(3) Provinces with low carbon emission efficiency should optimize the structure and quantity of factor inputs of urban construction land, such as environmental protection funds, land greening, technological updating, energy consumption, and industrial development.

(4) It is necessary to promote the synergistic development of provincial land intensity and carbon emission reduction. For LH-clustered provinces such as Xinjiang, Ningxia, Heilongjiang, and Jilin, land intensity improvement is needed; for LL-clustered provinces such as Liaoning, Tianjin, Shanxi, and Shandong, the dual tasks of improving urban construction land intensity and carbon emission efficiency should be enhanced; and for HL clustered provinces such as Qinghai, Gansu, Inner Mongolia, and Shaanxi, measures to improve carbon emission efficiency should be made.

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