



# Regional differences and convergence of urban land green use efficiency in China under the constraints of carbon neutrality

Xianxian Fan<sup>1</sup> · Xin Jiang<sup>2</sup>

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## Abstract

Exploring the regional differences and convergence of urban land green use efficiency (ULGUE) is of great significance for urban green development and the goal of carbon neutrality. Based on the panel data of 282 prefecture-level cities in China from 2006 to 2019, this paper uses the SBM-Undesirable model to calculate ULGUE in China, then uses Dagum Gini coefficient decomposition, coefficient of variation and panel data model to reveal the regional differences and convergence of ULGUE. The results show that ULGUE in China increased from 0.441 to 0.555 in 2006–2019. The number of cities in the medium–low efficiency range is dominant, accounting for more than 54%. There are differences in ULGUE among the three major regions, which shows the distribution pattern of west > east > central. ULGUE in China has significant spatial agglomeration characteristics, and its overall, intra-regional and inter-regional differences show a downward trend. Over-variable density is the main source of the overall difference, with an average contribution rate of 49.71%. ULGUE across the country and in the three regions of east, central and west in China exist significant  $\sigma$  convergence, absolute  $\beta$  and conditions  $\beta$  convergence. The research results are helpful to objectively evaluate ULGUE in China, and provide decision-making reference for promoting the green, low-carbon and sustainable use of urban land and achieving the goal of carbon neutrality.

**Keywords** Urban land green use efficiency · SBM-Undesirable model · Dagum gini coefficient · Convergence model

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✉ Xin Jiang  
jiangxin199566@foxmail.com  
Xianxian Fan  
fanxianxian95@163.com

<sup>1</sup> College of Economics and Trade, Hunan University, Changsha 410079, Hunan, China

<sup>2</sup> School of Economics, Anhui University, Jiulong Road, Hefei 230610, China

## 1 Introduction

In response to global climate change, it has become the consensus of the international community to implement carbon emission reduction and increase carbon sinks. As one of the countries with the highest carbon emissions in the world, China's carbon emission reduction actions play a pivotal role in the global carbon emission reduction process. In 2020, China proposed the strategic goal of "achieving carbon peak by 2030 and carbon neutrality by 2060". The concept of carbon neutrality was proposed by the UK in 2010 in the PAS 2060 "Specification on Carbon Neutral Commitments". According to the IPCC's, 2018 Special Report on Global Warming of 1.5 °C, carbon neutrality is defined as offsetting anthropogenic CO<sub>2</sub> emissions through CO<sub>2</sub> removal technologies over a period of time, or net-zero CO<sub>2</sub> emissions. Studies have shown that net carbon emissions mainly depend on land use and changes in land cover caused by human activities (Campbell et al, 2000). Land use has a dual effect on carbon emission and absorption. The change in land use mode or structure can directly or indirectly affect the carbon emission and absorption process between the terrestrial ecosystem and the atmosphere (Lai et al., 2016). Among them, urban construction land is the main source of carbon emissions from land use (Ribeiro et al., 2019; Zhang & Xu, 2017). Forest and other ecological land are important means of carbon sequestration. The increase of ecological land is conducive to reducing the concentration of CO<sub>2</sub> in the atmosphere and is an important way to achieve carbon neutrality (Zhao et al., 2010; Keenan et al., 2016; Karkkainen et al., 2020; Weng et al., 2021; Marle et al., 2022).

However, in the past ten years, the rapid urbanization process in China has led to the rapid expansion of urban construction land, while ecological land is largely occupied (Wang et al., 2018). From 2006 to 2019, the area of urban construction land in China expanded from 3.1766 million hectares to 5.8308 million hectares, an increase of 83.55%, with an average annual growth of 5.66%. The proportion of green space only increased from 9.9% to 11.43%, resulting in the carbon emission of urban construction land far greater than the carbon sink of urban green area, which greatly hindered the carbon neutralization process (Liu et al., 2014; Peng et al., 2017; Shaker et al., 2019; Yu et al., 2014). Implementing the goal of carbon neutrality into the process of urban land utilization and reasonably measuring urban land green use efficiency (ULGUE) have become the key breakthrough.

Scholars' research on urban land use efficiency mainly focuses on countries such as Europe (Masini et al., 2019), Ethiopia (Koroso et al., 2020), Vietnam (Jalilov et al., 2021), and China. There is a lot of evidence from China, and scholars have carried out a series of studies on urban land use efficiency in different regions of China from the perspective of economy, green and low carbon. From an economic perspective, Chen et al. (2016) calculated the construction land use efficiency of 336 cities in China based on urban construction land input and economic output. From a green perspective, scholars have considered the economic, social or environmental benefits and environmental costs of land use under environmental constraints, and have calculated provincial regions (Liu et al., 2020; Lu et al., 2018), resource cities (Song et al., 2022), the Yellow River Basin (Xue et al., 2022), megacities (Zhu et al., 2019), urban agglomerations (Yu et al., 2019) and other geographic scales of urban land use efficiency in China. From a low-carbon perspective, scholars have measured the urban land use efficiency of urban agglomerations such as Beijing-Tianjin-Hebei, Yangtze River Delta and Pearl River Delta (Tan et al., 2021; Lu et al., 2022b) by taking carbon emissions as the expected output of land use. The measurement methods of

urban land use efficiency mainly include LIP and LOP within the framework of urban scaling law (Jiao et al., 2020), interacting criteria (Zhang et al., 2020), SFA model (Liu et al., 2020), DEA model (Chen et al., 2016; Gao et al., 2022), SBM model (Lu et al., 2018; Tan et al., 2021), etc. Scholars have also carried out relevant research on the influencing factors of urban land use efficiency. Kroll and Haase (2010) found that economic processes have a greater impact on land use than population changes, and the spatial agglomeration effect of economic transformation on urban land use efficiency is also a factor that cannot be ignored (Wu et al., 2017). Regional economic integration has a significant positive spatial spillover effect on urban land use efficiency, which can significantly improve urban land use efficiency (Gao et al., 2020). Urban form (He et al., 2020), environmental regulation (Zhang et al., 2021), transportation infrastructure (Lu et al., 2021), and industrial agglomeration (Zhang et al., 2022b) are also factors that affect urban land use efficiency. With the continuous adjustment of urban development goals, carbon emissions have become the primary factor hindering the intensive use of urban land (Wang et al., 2019).

This paper summarizes representative literature on ULGUE, reporting its research methodology, study area, and study content (Appendix Table 6). In a word, existing literatures have measured urban land use efficiency from different perspectives and geographical scales, and analyzed its influencing factors, but there are still some deficiencies in indicators selection and research content. First, the indicator system of urban land use efficiency needs to be optimized. Most of the existing studies focus solely on green or low carbon, and relatively lack the literatures on ULGUE around the carbon neutral goal. Second, the research on ULGUE in China is not thorough and comprehensive. Particularly, regional differences and convergence of ULGUE in China have not been comprehensively and systematically investigated.

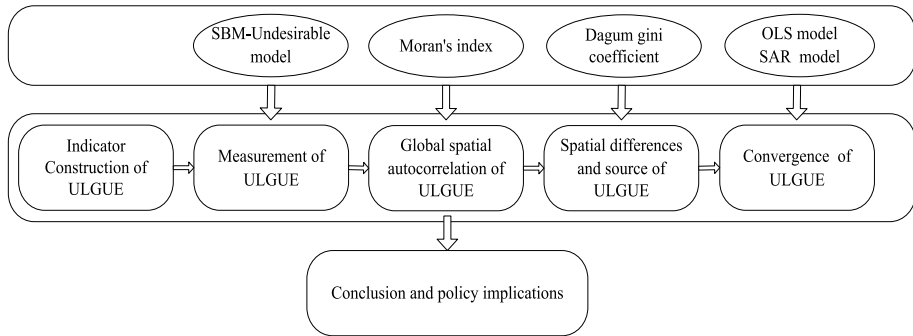
In view of this, based on the goal of carbon neutrality, this paper first introduces the carbon sink of urban green space and the carbon emissions of urban construction land into the urban land use output system as ecological benefits and environmental costs, and uses the SBM-Undesirable model to calculate the ULGUE of 282 prefecture-level cities in China in 2006–2019, and then analyzes its time and spatial patterns. Furthermore, we use Dagum Gini coefficient to calculate the regional difference and its sources in China's ULGUE, and use the convergence model to analyze the convergence of China's ULGUE. In general, the purpose of this paper is to explore the regional differences and convergence of ULGUE in China, objectively evaluate its development level, and provide policy reference and inspiration for promoting urban land green use and achieving carbon neutrality. Figure 1 shows the research methods and analytical framework in this paper.

## 2 Research methods and data

### 2.1 Study area and data source

This paper takes 282 prefecture-level cities in China as the study area. Due to the unbalanced regional development in China, cities in different regions have great differences in location conditions and policies, which may lead to great differences in ULGUE. According to the geographical location of the city, this paper is divided into three regions: the east, the central and the west.<sup>1</sup> Cities in the eastern region have strong economic strength, high

<sup>1</sup> The eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan and Guangxi Zhuang Autonomous Region. The central region includes Shanxi



**Fig. 1** Analytical framework and methodology

population density and urbanization level, and land use is mainly construction land and cultivated land. The central region is in the transition period of urbanization, and the land use is mainly cultivated land, with a large proportion of forest land and grassland. Although the level of economic development and urbanization in the western region is relatively backward, it is rich in land resources. The land use is mainly grassland and forest land, followed by construction land. In order to speed up the development of the central and western regions and narrow the differences between the central and eastern regions, the strategy for the rise of the central region and the strategy for the development of the western region have been put forward, which has had a profound impact on the economic development and land use in the central and western regions. The indicator data of ULGUE are mainly from the China Urban Statistical Yearbook (CUSY) (2005–2020) and the China Urban Construction Statistical Yearbook (CUCSY) (2005–2020). When using the panel data model to analyze the convergence, except for the data of environmental regulation from the local government work report (2006–2019), the rest of the data are from the China Urban Statistical Yearbook (CUSY) (2005–2020). A few missing data are from the statistical bulletin issued by the Bureau of Statistics or supplemented by interpolation.

## 2.2 Research methods

### 2.2.1 SBM-undesirable model

In this paper, the SBM-Undesirable model including undesired outputs is used to estimate ULGUE in China (Tone, 2004). Considering each city as a production decision-making unit (DMU), assuming constant returns to scale,  $x'_{k'n}$ ,  $y'_{k'm}$  and  $b'_{k'i}$  are the input, expected output and undesired output elements of each decision-making unit, respectively. The SBM model is set as follows in Eq. (1):

Footnote 1 (continued)

Province, Inner Mongolia Autonomous Region, Jilin Province, Heilongjiang Province, Anhui Province, Jiangxi Province, Henan Province, Hubei Province and Hunan Province. The western region includes Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Ningxia Hui Autonomous Region, Qinghai and Xinjiang Uygur Autonomous Region.

$$\rho = \min \frac{1 - \frac{1}{N} \sum_{n=1}^N \frac{s_n^x}{x_{k'n}^x}}{1 + \frac{1}{M+I} \left( \sum_{m=1}^M \frac{s_m^y}{y_{k'm}^y} + \sum_{i=1}^I \frac{s_i^b}{y_{k'i}^b} \right)} \quad s.t. \begin{cases} \sum_{t=1}^T \sum_{k=1}^K \lambda_k^t x_{kn}^t + s_n^x = x_{k'n}^t & (n = 1, 2, \dots, N) \\ \sum_{t=1}^T \sum_{k=1}^K \lambda_k^t y_{km}^t - s_m^y = y_{k'm}^t & (m = 1, 2, \dots, M) \\ \sum_{t=1}^T \sum_{k=1}^K \lambda_k^t b_{ki}^t + s_i^b = b_{k'i}^t & (i = 1, 2, \dots, I) \\ s_n^x \geq 0, s_m^y \geq 0, s_i^b \geq 0, \lambda_k^t \geq 0 \end{cases} \quad (1)$$

In Eq. (1),  $\rho$  is the value of ULGUE, which is between 0 and 1. When  $\rho=1$ , it indicates that the decision-making unit is at the best production frontier; when  $0 < \rho < 1$ , it indicates that the production of the decision-making unit is inefficient, with redundant input or insufficient output.  $N, M$  and  $I$  represent the number of input variables, expected output variables and undesired output variables, respectively. Vectors  $s_n^x$  and  $s_m^y$  represent the redundancy of input and expected output, respectively, and  $s_i^b$  represents the deficiency of undesired outputs.  $\lambda_k^t$  is the weight variable of each decision-making unit.

### 2.2.2 Global spatial autocorrelation

Global spatial autocorrelation is to examine the spatial agglomeration of research objects from a global perspective, which can be used to determine whether the variables under investigation are spatially dependent. This paper uses global Moran's I to measure the global spatial correlation of ULGUE in Chinese cities. The calculation formula is seen in Eq. (2):

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

In Eq. (2),  $S^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n}$ ,  $w_{ij}$  are the spatial weights between city  $i$  and city  $j$ , and  $x_i$  is the observed value of city  $i$ . Moran's I is between [- 1, 1].

### 2.2.3 Dagum Gini coefficient

The Dagum Gini coefficient and its decomposition include the total Gini coefficient  $G$ , the intra-regional difference contribution  $G_w$ , the inter-regional difference contribution  $G_{nb}$  and the hypervariable density contribution  $G_r$ , and satisfy  $G = G_w + G_{nb} + G_r$ . It can reflect the differences and contribution of variables within and between regions. Therefore, this paper selects the Dagum Gini coefficient and its decomposition as the core tool to explore the regional differences of ULGUE in China. The specific logic and calculation formula are seen in Eq. (3) to Eq. (9):

Overall Gini coefficient:

$$G = \sum_{j=1}^k \sum_{h=1}^k \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |y_{ji} - y_{hr}| / 2n^2 \bar{Y} \quad (3)$$

In Eq. (3),  $n$  is the number of cities;  $k$  is the number of regions.  $\bar{Y}$  is the average of ULGUE,  $y_{ji}(y_{hr})$  is ULGUE of cities  $i(r)$  in group  $j(h)$ , and  $n_j(n_h)$  is the number of cities in group  $j(h)$ .

Intra-regional Gini coefficient:

$$G_{jj} = \frac{1}{2\bar{Y}_j} \sum_{i=1}^{n_j} \sum_{r=1}^{n_j} |y_{ji} - y_{jr}| / n_j^2 \tag{4}$$

Inter-regional Gini coefficient:

$$G_{jh} = \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |y_{ji} - y_{hr}| / n_j n_h (\bar{y}_j + \bar{y}_h) \tag{5}$$

Contribution of intra-regional differences:

$$G_w = \sum_{j=1}^k G_{jj} p_j s_j \tag{6}$$

Contribution of interregional differences:

$$G_{nb} = \sum_{j=2}^k \sum_{h=1}^{j-1} G_{jh} (p_j s_h + p_h s_j) D_{jh} \tag{7}$$

Contribution of hypervariable density:

$$G_t = \sum_{j=2}^k \sum_{h=1}^{j-1} G_{jh} (p_j s_h + p_h s_j) (1 - D_{jh}) \tag{8}$$

where,

$$\left\{ \begin{array}{l} p_j = n_j / n \\ s_j = n_j \bar{Y}_j / n \bar{Y} \\ d_{jh} = \int_0^\infty dF_j(y) \int_0^y (y-x) dF_h(x) \\ p_{jh} = \int_0^\infty dF_h(y) \int_0^y (y-x) dF_j(x) \\ D_{jh} = (d_{jh} - p_{jh}) / (d_{jh} + p_{jh}) \end{array} \right. \tag{9}$$

In Eq. (4) to (9),  $D_{jh}$  is the mutual influence of ULGUE between groups  $j$  and  $h$ ,  $d_{jh}$  is the difference in ULGUE between the groups.  $F_j(F_h)$  is the cumulative density distribution function of group  $j(h)$ .

### 2.2.4 Convergence model

The convergence model includes  $\sigma$  convergence and  $\beta$  convergence, where  $\sigma$  convergence is used to test the stock difference of ULGUE, and  $\beta$  convergence is used to test the incremental difference of ULGUE. The economic meaning of  $\sigma$  convergence is

that the dispersion of ULGUE keeps decreasing with time, and its measurement methods include standard deviation, coefficient of variation method and Theil index. In this paper, the coefficient of variation method commonly used by scholars is used to measure the  $\sigma$  convergence. The specific calculation formula is seen in Eq. (10):

$$\sigma_t = \frac{\sqrt{\left[ \sum_i^{n_t} \left( ULGLUE_{it} - \overline{ULGLUE_{it}} \right)^2 \right] / n}}{\overline{ULGLUE_{it}}} \tag{10}$$

In Eq. (10),  $\sigma_t$  is  $\sigma$  the convergence coefficient of ULGUE in period  $t, n$  is the number of cities in the survey area. When there is  $\sigma_t < \sigma_{t-1}$ , it means that ULGUE tends to converge, otherwise it tends to diverge.

$\beta$  convergence means that areas with low ULGUE can catch up with areas with high ULGUE at a faster growth rate. With the passage of time, ULGUE in different cities will eventually reach the same steady state level.  $\beta$  convergence can be divided into absolute  $\beta$  convergence and conditional  $\beta$  convergence. The difference between absolute  $\beta$  convergence and conditional  $\beta$  convergence lies in whether a series of factors that have an important impact on ULGUE are considered. Absolute  $\beta$  convergence refers to the convergence trend of ULGUE without considering other factors. Absolute  $\beta$  convergence is set as Eq. (11):

$$\ln \frac{ULGLUE_{i,t+1}}{ULGLUE_{it}} = \alpha + \beta \ln ULGLUE_{it} + \mu_i + \eta_t + \varepsilon_{it} \tag{11}$$

In Eq. (11),  $\ln \frac{ULGLUE_{i,t+1}}{ULGLUE_{it}}$  is the growth rate of ULGUE at city  $i$  in period  $t + 1, \mu_i$  is a city fixed effect,  $\eta_t$  is a year fixed effect, and  $\varepsilon_{it}$  is a random disturbance term.  $\beta$  is the focus coefficient of this paper. If  $\beta < 0$ , it means that ULGUE in China has a convergence trend. If the total number of observation years is  $T$ , the convergence rate is  $v = -\ln(1+\beta)/T$ . If  $\beta > 0$ , it means that there is a divergence in ULGUE in China.

Considering that ULGUE may have spatial correlation. This paper further uses the spatial lag model to carry out the convergence research, and the specific model settings are seen in Eq. (12):

$$\ln \frac{ULGUE_{i,t+1}}{ULGUE_{it}} = \alpha + \delta W \ln \frac{ULGUE_{i,t+1}}{ULGUE_{it}} + \beta \ln ULGUE_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{12}$$

In Eq. (12),  $\delta$  is the spatial lag coefficient and  $W$  is the spatial weight matrix. This paper selects the reciprocal of the square of the geographical distance between cities to construct the geographical weight matrix.

The relative  $\beta$  convergence model introduces a series of control variables ( $X_{i,t+1}$ ) that affect ULGUE based on the absolute  $\beta$  convergence model. Referring to Lu et al., (2022a, 2022b), Xue et al., (2022) and Chen et al., (2018), this paper selects the economic development level (PGDP), technology investment (TECH), environmental regulation (ER), foreign direct investment (FDI), industrial structure upgrading (IND), transportation infrastructure (INFRA) and population density (POP) as control variables. Table 1 shows the descriptive statistics of the above control variables.

**Table 1** Descriptive statistics for main variables

Variable	Mean	SD	Min	Max	Definition
PGDP	10.48	0.696	4.071	12.46	ln(GDP per capita)
TECH	0.015	0.015	0.001	0.207	Science and technology expenditure/financial expenditure
ER	0.006	0.002	0	0.023	Frequency of environment-related words/total word frequency
FDI	0.018	0.019	0	0.204	Total actually utilized foreign capital/GDP
IND	0.921	0.509	0.094	5.168	Output value of tertiary industry/secondary industry
INDRA	16.02	6.933	0.390	60.07	Road mileage/urban area
POP	0.043	0.034	0.001	0.276	Registered residence population/ urban area

### 2.3 Indicator of ULGUE

Based on the research of existing scholars, this paper introduces urban green space carbon sink, urban construction land carbon emissions and other indicators to build ULGUE indicator system. See Table 2 for specific indicator selection.

Input indicators mainly include capital, labor and land. Capital input is represented by the capital stock calculated by the perpetual inventory method  $K_{it} = K_{it-1}(1 - \delta) + I_{it}$ . Among them, the depreciation rate  $\delta$  is 9.6%,  $I_{it}$  represents the total investment in fixed assets,  $K_{it-1}$  is measured by dividing the investment in fixed assets by 10% in the base period. This paper takes 2006 as the base period. The secondary and tertiary industries are the main industrial components of urban land use. Therefore, labor input is represented by the number of employees in the urban secondary and tertiary industries at the end of the year. The land input is selected from the urban construction land.

Expected output includes three dimensions of economy, society and ecological environment. Among them, the economic and social benefits are measured by the added value of the secondary and tertiary industries and the average wage of urban workers. The ecological benefit is expressed by the carbon sink of urban green space. The calculation formula of urban green space carbon sink is  $Cs = fs \times As$ , where  $Cs$  is the carbon summation of urban green space;  $fs$  is the carbon sink coefficient of urban green space (Shi, 2013);  $As$  is the total urban green space area.

Undesired outputs mainly include carbon emission output and industrial pollution. Among them, the carbon emission output is represented by the carbon emission of urban construction land. The industrial pollution output is represented by the comprehensive index of industrial wastewater discharge, industrial sulfur dioxide discharge and industrial smoke and dust discharge.

## 3 Results and analysis

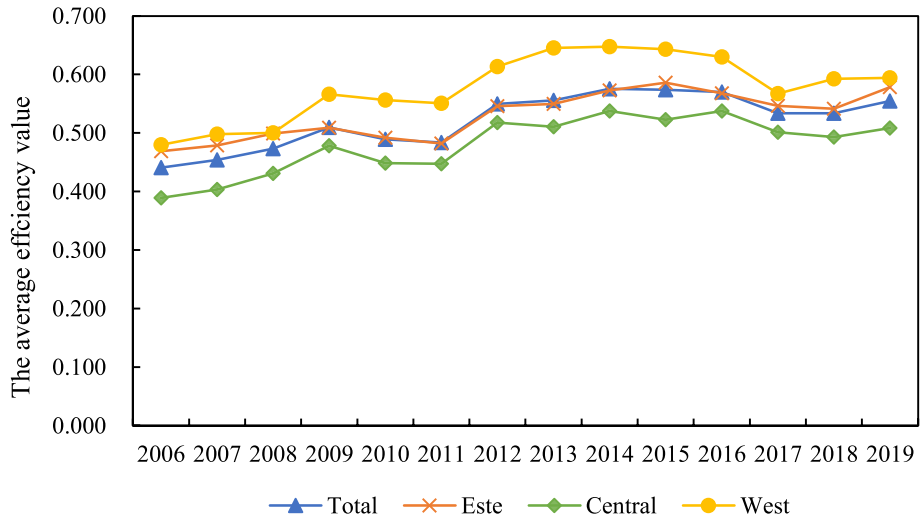
### 3.1 Measurement results analysis of ULGUE

In this paper, we use the SBM-Undesirable model to calculate ULGUE in China, and obtain the values of ULGUE in 282 prefecture-level cities from 2006 to 2019. Figure 2 shows the change trend of the mean value of China's ULGUE. From 2006 to 2019,



**Table 2** The index system of ULGUE

Layer of criteria	Layer of factors	Layer of indicators (unit)	References	Data sources
Input	Capital	Capital stock (100 million yuan)	Liu & Zhao, (2022)	CUSY
	Labor	Number of employees in urban secondary and tertiary industries at the end of year (10,000 people)	Yu et al., (2019)	CUSY
Expected Output	Land	Urban construction land area (square kilometers)	Tan et al., (2021)	CUCSY
	Economic Benefits	Added value of secondary and tertiary industries (100 million yuan)	Tang et al., (2021)	CUSY
	Social Benefits	Average wages of urban workers (yuan)	Lu et al., (2018)	CUSY
	Ecological Benefits	Urban green space carbon sink (10,000 tons)	Ke et al., (2021)	CUCSY
Undesired Output	Carbon Output	Carbon emissions from urban construction land (10,000 tons)	Glaeser and Kahn (2010); Li et al., (2013)	CUSY & CUCSY
	Industrial Pollution	Composite index of industrial wastewater, sulfur dioxide and soot emissions	Lu et al., (2020)	CUSY



**Fig. 2** Average value of ULGUE in China

ULGUE in China showed an overall fluctuating upward trend, with its average value rising from 0.441 in 2006 to 0.555 in 2019. It means that ULGUE in China has been improved, and the green and low-carbon transformation of Chinese cities has achieved certain results. From the perspective of time evolution, the change of ULGUE in China can be divided into two stages. The period from 2006 to 2015 is a period of continuous improvement. Although some years have declined during this period, the overall trend remains upward. From 2015 to 2019, there was a “V” trend of change. This may be because although China’s land use mode from 2006 to 2015 is dominated by land development, the local government has also implemented large-scale ecological protection and restoration projects, which has greatly increased the area of ecological land dominated by forests, shrubs and grasslands, and high-quality ecological land has been protected and restored, and the ecological environment has improved significantly, improving ULGUE in China. Since 2015, China’s urbanization process has accelerated, and the area of urban construction land has expanded rapidly. China’s land use has changed from ecological land to urban construction land, resulting in the decline of ULGUE. However, this downward trend has not continued. In 2019, ULGUE in China rebounded, which benefited from the implementation of the green development concept such as “green water and green mountains are golden mountains and silver mountains” in China.

Further through the comparison of the results of the three regions in east, central and west, we find that the average value of ULGUE in the west is the highest. The average in the eastern region takes the second place, and the average in the central region is the lowest. It is noteworthy that after 2016, the average of ULGUE in the eastern region has gradually caught up with that in the western region, and the overall gap between the eastern region and the western region has become smaller and smaller. It shows that ULGUE in the eastern region has great growth potential. This is mainly because although the eastern region is economically developed, and cities have absolute advantages in economic growth, basic public service facilities, public service level and other aspects, which can attract the inflow of factors and improve economic and social benefits, the carbon emissions brought by the economic and social development of the eastern region cannot be ignored. During

the sample survey period, the carbon emissions of urban construction land in the eastern region accounted for about 60% of the national total, which is the main source of carbon emissions of urban construction land in China. The carbon emission of urban construction land in the western region is low, accounting for only about 14%. Therefore, ULGUE in the western region is better than that in the eastern region. However, due to the gradual transfer of the traditional industrial structure within the cities in the eastern region to the central and western regions, the advanced industrial structure with high-end manufacturing and modern service industries as the economic pillar has been initially realized. The effect of carbon reduction and pollution reduction of industrial structure optimization is increasingly obvious, which is conducive to the improvement of ULGUE. The strategy of developing the western region has given the western region more development opportunities, increased economic investment in urban construction, and increased carbon emissions, resulting in a decline in ULGUE. Therefore, ULGUE in the eastern region tends to catch up with that in the western region.

### 3.2 Spatial characteristics of ULGUE

To investigate the spatial differences of ULGUE in China, this paper uses the natural breakpoint method in ArcGIS to visualize the spatial characteristics based on ULGUE in 2006, 2010, 2015 and 2019. The results are shown in Fig. 3. On the whole, the number of cities with low efficiency (0–0.25) dropped from 57 in 2006 to 3 in 2019, and the proportion dropped from 20 to 1%. The medium–low efficiency value (0.25–0.50) decreased from 158 in 2006 to 151 in 2019, and the proportion decreased from 56 to 54%, and the number of cities with medium–high efficiency values (0.50–0.75) decreased from 28 in 2006 rising to 80 in 2019, the proportion rose from 10 to 28%. The number of cities with high efficiency values (0.75–1.0) increased from 39 in 2006 to 48 in 2019, and the proportion increased from 14 to 17%. This shows that ULGUE in China is mainly concentrated in the medium–low and medium–high efficiency areas, showing a distribution trend of “more in the middle and less at both ends”. At the same time, there is a certain degree of regional heterogeneity in the spatial distribution pattern of ULGUE. The low-level types are distributed in the central and northeast regions in a patchy manner. This is mainly because there are prominent inefficient and idle problems in urban land use in the central and northeast regions, and the degree of land intensive use lags behind the level of ecological efficiency, resulting in low ULGUE (Fu & Li, 2019). The high level type is mainly distributed in the southwest in a scattered manner, and in the northwest and southeast in a flaky manner. This is mainly because most cities in southwest China are affected by natural conditions, and land resources cannot be effectively developed and utilized, resulting in large differences in ULGUE (Zhu & Gao, 2022). The southeast and northwest regions have significant positive spatial dependence and spatial aggregation, and under the guidance of the national green development concept, the blind and extensive expansion of urban land is increasingly reduced, idle land is continuously reused, and the urban green coverage rate is significantly improved, making ULGUE in the southeast region at a high level.

To further determine the spatial agglomeration characteristics of ULGUE in China, according to Eq. (2), this paper calculates the global Moran's I, and the calculation results are shown in Table 3. It can be seen that the global Moran's I of ULGUE is significantly positive, and the global Moran's I of ULGUE in 2006–2019 is between 0.024 and 0.045, showing a fluctuating upward trend. It shows that there is a significant spatial positive

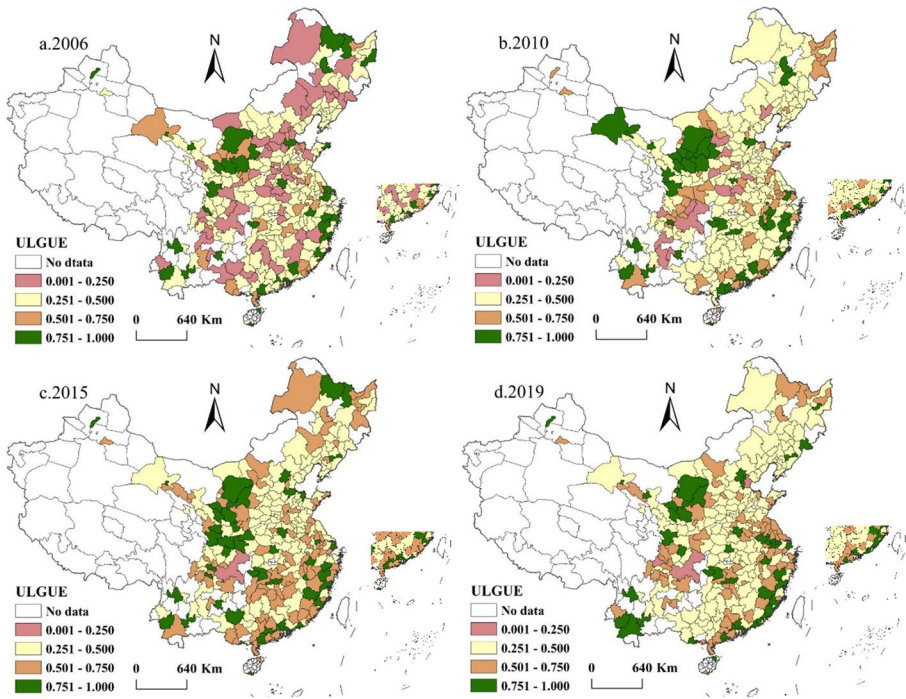


Fig. 3 Spatial distribution of ULGUE in China

autocorrelation in ULGUE, the spatial agglomeration characteristics are obvious, and the trend is increasing.

### 3.3 Regional differences and sources of ULGUE

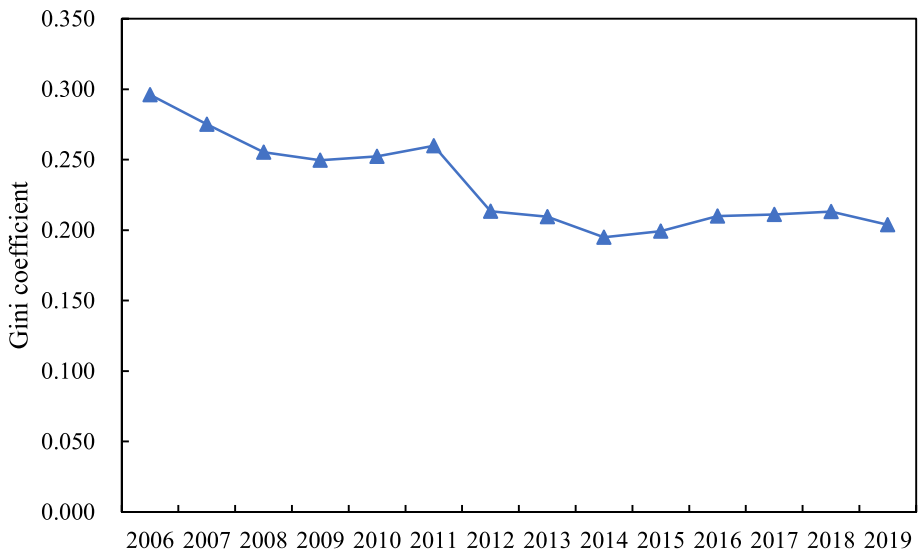
The above introduces the calculation results and spatial distribution of ULGUE in China. In this part, to explore the regional differences and sources, we use Dagum Gini coefficient and its decomposition method to analyze ULGUE across the country and in the three regions of the east, central and west in China from 2006 to 2019 (See Appendix Table 7 for detailed calculation results).

Figure 4 shows the evolution trend of the overall difference of ULGUE from 2006 to 2019. The total Gini coefficient is in the range of  $[0.204, 0.296]$ , showing a downward trend, indicating that the overall difference in ULGUE is narrowing. From the perspective of changing trend, the period from 2006 to 2014 was a decline stage, and the period from 2014 to 2019 was stable. This is mainly because the strategies such as the development of the west and the rise of the central region have achieved remarkable results, promoting the balanced development among regions, and driving the reduction of the differences in ULGUE. After 2014, the Chinese government proposed to guide urban development with the concept of new urbanization and ecological civilization construction. Under the guidance of green development, a new development pattern of “green water and green mountains are golden mountains and silver mountains” has been set up across the country. The

**Table 3** Global Moran's I of ULGUE in China

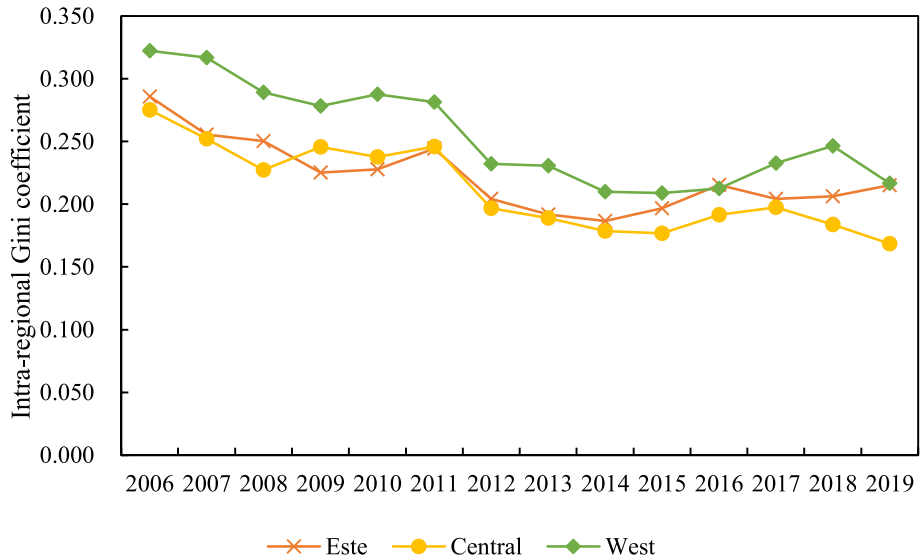
Year	Moran's I	P value	Z Score
2006	0.027***	0.000	5.942
2007	0.026***	0.000	5.745
2008	0.021***	0.000	4.819
2009	0.032***	0.000	6.917
2010	0.038***	0.000	8.088
2011	0.036***	0.000	7.563
2012	0.039***	0.000	8.308
2013	0.039***	0.000	8.308
2014	0.042***	0.000	8.895
2015	0.039***	0.000	8.286
2016	0.042***	0.000	8.762
2017	0.028***	0.000	6.147
2018	0.024***	0.000	5.332
2019	0.045***	0.000	9.314

Note: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Fig. 4** Evolution trend of overall differences of ULGUE in China

concept of green land use has gradually taken the leading position, making the overall difference stable.

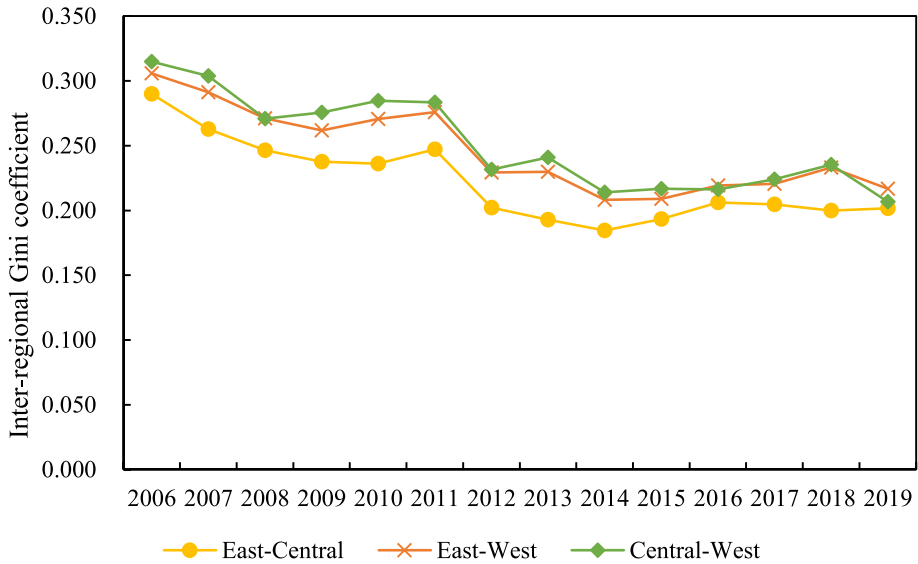
Figure 5 shows the evolution trend of intra-regional differences in ULGUE from 2006 to 2019. The Gini coefficient of the eastern region has dropped from 0.286 in 2006 to 0.215 in 2019, with a decline rate of 24.72%. The Gini coefficient of the central region dropped from 0.275 in 2006 to 0.168 in 2019, with a decline rate of 38.84%. The Gini coefficient of the western region dropped from 0.322 in 2006 to 0.217 in 2019, with a decline rate of 32.76%. Based on the above information, the internal differences in the eastern, central



**Fig. 5** Evolution trend of intra-regional differences of ULGUE in China

and western regions were markedly narrowed. Looking further at the position of the curve in three regions, the western region was the highest. The curves of the eastern and central regions crossed in some years. From 2009 to 2011, the central region was higher than the eastern region, and the eastern region was higher than the central region in other years. On average, the western region had the largest intraregional variation, followed by the eastern region and finally the central region. This is mainly due to the great differences in economic development and land use among cities in the western region due to the influence of natural geographical environment. Therefore, although the average level of ULGUE in the western region is at a high level, the efficiency value of some cities, especially Chongqing, has been at a low level, which has widened the gap between ULGUE in the western region, resulting in more prominent differences within the western region.

Figure 6 shows the evolution trend of inter-regional differences in ULGUE from 2006 to 2019. First, from the perspective of change trend, the Gini coefficients of east-central, east-west and central-west all show an obvious downward trend, from 0.290, 0.306 and 0.315 in 2006 to 0.202, 0.217 and 0.207 in 2019, with a decline rate of 30.47%, 29.16% and 34.35% respectively. This shows that the inter-regional differences are narrowing significantly. Secondly, according to the comparison of Gini coefficient between regions, the inter-regional differences are from large to small in the order of west-central, east-west and east-central. The possible reason for the large difference between the western and central regions is that the western region has rich ecological resources, and according to “the National Main Functional Area Plan”, the restricted development zones and prohibited development zones are mostly located in the western region, which provides effective support for the improvement of ULGUE in the western region. The industrial structure of the central region is dominated by agriculture and heavy industry. Urban development depends more on the expansion of construction land, and the industry is relatively unified, which affects the efficient and green use of urban land resources, leading to large differences between the western and central regions.



**Fig. 6** Evolution trend of inter-regional differences of ULGUE in China

Figure 7 reports the sources of differences and their contribution rates of ULGUE from 2006 to 2019. From the perspective of evolution trend, the variation trend of the regional differences' contribution rate is flat and there is no obvious fluctuation. Specifically, the contribution rate of intra-regional differences increased slightly from 34.08% in 2006 to 34.09% in 2019, with an increase of only 0.04%, indicating that intra-regional differences have not changed much. The contribution rate of hypervariable density and regional disparity fluctuated significantly. The contribution rate of hypervariable density decreased slightly from 50.08% in 2006 to 48.93% in 2019, with a decrease of 2.28%. The contribution rate of inter-regional differences increased slightly from 15.84% in 2006 to 16.97% in 2019, with an increase of 7.14%, indicating that the contribution rate of inter-regional differences has an expanding trend. From the perspective of contribution rate, hypervariable density has the highest contribution rate, with an average contribution rate of 49.71%, followed by intra-regional difference contribution rate, with an average contribution rate of 33.72%, and inter-regional difference contribution rate, with an average contribution rate of 16.57%. The overall difference of ULGUE in China is mainly caused by over-variable density. This is mainly because the number of cities with ULGUE in an isolated state is high, leading to more isolated groups entering the ranks of higher or lower level groups. Based on the previous analysis, this phenomenon is most obvious in the western region. Specifically, many cities in the western region have reached the highest efficiency level, such as Zigong, Ziyang, Bazhong and Yuxi, which have separated from other cities in the western region and entered the ranks of high-level groups. However, some cities have been at a low level of efficiency. In particular, Chongqing has been at the lowest level of efficiency, and then fell into the low level group. As a central city in the western region, Chongqing, with the continuous expansion of its economic scale, has led to the rapid expansion of the built-up areas, excessive investment in land resources, and serious industrial pollution emissions, which have inhibited its ULGUE.

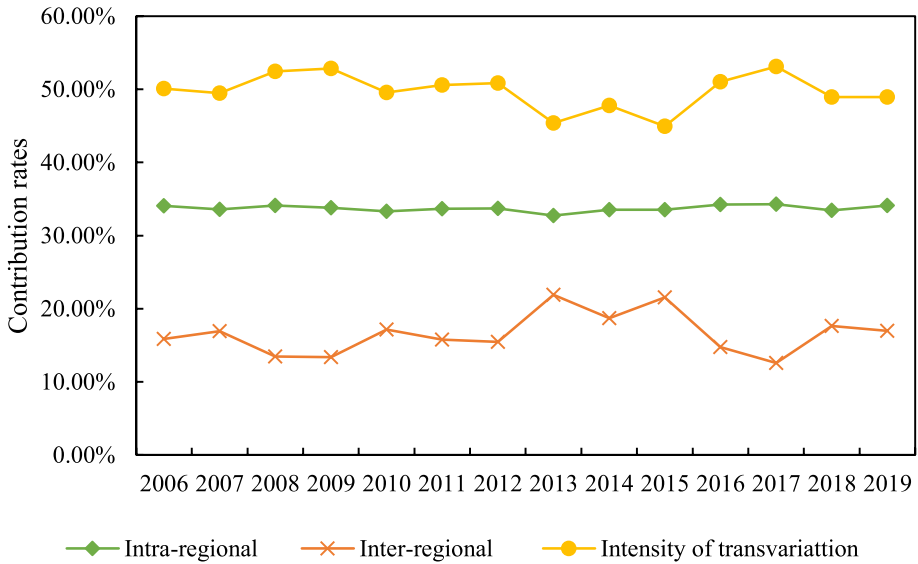


Fig. 7 Evolution trend of regional difference contribution rate of ULGUE in China

### 3.4 Convergence analysis of ULGUE in China

After investigating the spatial and temporal distribution and regional differences of ULGUE in China, this part further uses the convergence model to explore the convergence characteristics of ULGUE in China. Specifically, it is to examine whether the cities with low efficiency level have a higher development speed, which can accelerate to catch up with the cities with high efficiency level.  $\sigma$ convergence, absolute  $\beta$  convergence and conditional  $\beta$  convergence are three common convergence models.

#### 3.4.1 $\sigma$ convergence analysis

According to Eq. (10), this paper calculates the variation coefficient of ULGUE from 2006 to 2019, which is used to test  $\sigma$ convergence. Figure 8 shows the evolution trend of the variation coefficient of ULGUE at the national, eastern, central and western levels. At the national level, the variation coefficient of ULGUE showed a significant downward trend from 2006 to 2019. The variation coefficient decreased from 0.577 in 2006 to 0.392 in 2019, with a decline of 32.17%. At the regional level, the variation coefficient of the eastern, central and western regions also showed a rapid decline. The variation coefficient in the eastern region decreased from 0.553 in 2006 to 0.404 in 2019, a decrease of 0.149, with a decline of 26.92%. The variation coefficient of the central region (0.599) in 2019 decreased by 0.214, with a decline of 38.26%, compared with that in 2006 (0.345). The variation coefficient in the western region decreased from 0.608 in 2006 to 0.404 in 2019, with a decrease of 33.56%. To sum up, ULGUE across the country and in the three regions of the east, central and west in China have the characteristics of  $\sigma$  convergence. It shows that the regional differences of ULGUE in China cities are gradually narrowing and tend to converge among regions.



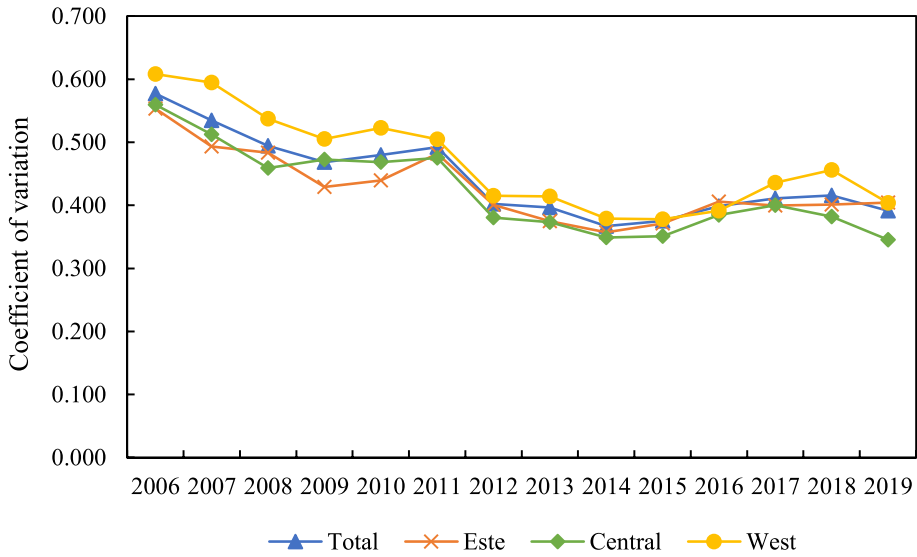


Fig. 8 Evolution trend of variation coefficient of ULGUE in China

Table 4 Absolute  $\beta$  convergence test results of ULGUE

Variables	Total	East	Central	West
	SAR model	SAR model	SAR model	OLS model
$\beta$	-0.365*** (-29.88)	-0.357*** (-18.347)	-0.427*** (-20.762)	-0.310*** (-5.511)
$\rho$	0.477*** (4.63)	0.329*** (3.078)	0.236** (1.973)	
$\nu$	0.035	0.034	0.043	0.029
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
$N$	3666	1469	1404	793
$R^2$	0.100	0.082	0.127	0.249

Note:  $t$  statistics in parentheses, \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

### 3.4.2 Absolute $\beta$ convergence analysis

According to the previous analysis, there is a spatial correlation in ULGUE. For this reason, the regression model is selected through LM test, LR test and Wald test. In this paper, OLS or SAR model is selected to test whether there is absolute  $\beta$  convergence in ULGUE. Table 4 shows the absolute  $\beta$  convergence test results of ULGUE in China. Overall, the  $\beta$  estimated coefficient is less than 0, and it has passed the 1% significance level test. It shows that ULGUE in China has an absolute  $\beta$ -convergence, and there is a catch-up effect between cities. Without considering the influence of a series of economic and social factors, ULGUE in China can converge to the same steady-state level over time. From a regional perspective, the  $\beta$  estimation coefficients in the eastern, central and western regions are all significantly negative, indicating that ULGUE also has an absolute  $\beta$  convergence at the regional level. From the perspective of convergence speed, the absolute

$\beta$  convergence rates of ULGUE across the country and in the three regions of the east, central and west in China are 0.035, 0.034, 0.043 and 0.029, respectively, showing the order of “central > national > eastern > western”. This is consistent with the convergence theory in neoclassical economics, that is, the central region of China with a low level of ULGUE has a faster convergence rate than other regions.

### 3.4.3 Conditional $\beta$ convergence analysis

Because the absolute  $\beta$  convergence test does not consider the heterogeneous impact of a series of economic and social factors on ULGUE, the absolute  $\beta$  convergence test results are not completely reliable. Therefore, it is necessary to further carry out the conditional  $\beta$  convergence test on ULGUE. Therefore, based on the absolute  $\beta$  convergence test, this paper adds the level of economic development, transportation infrastructure, environmental regulation, foreign direct investment, industrial structure upgrading, scientific and technological investment and population density as control variables to examine the conditional  $\beta$  convergence characteristics of ULGUE.

Table 5 shows the convergence test results of the condition  $\beta$  of ULGUE. According to the results in Table 5, it is easy to find that the convergence coefficients  $\beta$  at the whole and regional levels are all negative at 1% significance level. After considering a series of factors, such as economy, society and population, that may affect ULGUE in China, there is a significant condition  $\beta$  convergence, which changes towards their own steady level. Further comparing the convergence rate, the conditional  $\beta$  convergence rate of China as a whole and regions are 0.036, 0.036, 0.044 and 0.030 respectively. Compared with the absolute  $\beta$  convergence rate, the conditional  $\beta$  convergence rate of the whole, central and western regions has increased by 0.001, and that of the eastern region has increased by 0.002. It shows that after introducing a series of economic and social control variables, the convergence rate of ULGUE in China has accelerated.

## 4 Discussion

Land use is an important factor influencing carbon sources and sinks (Liu & Zhang, 2022; Deng et al., 2021; Wang et al., 2021; Zhang et al., 2018). Planning urban land use based on the carbon neutrality goal is an important direction for future low-carbon urban development (Feng et al., 2023). We construct a research framework on ULGUE under the carbon neutrality goal by introducing carbon source and sink from urban land use. We found that the overall level of green land use efficiency in Chinese cities is relatively low, with a large room for growth. This is mutually confirmed by Liang et al. (2019), Ji and Zhang (2020). Chen et al. (2022) found that low-carbon urban land use efficiency fluctuates around 0.9, which is at a high level. The reason for the difference may be that only economic output and carbon emissions are included in the urban land use efficiency index system as desired and undesired outputs, which fails to reflect the social and ecological benefits generated by land use and the carbon neutral process, and thus overestimates the true level of urban land use efficiency.

Additionally, we found significant differences in ULGUE among Chinese cities in the eastern, central, and western regions. Mainly because there are differences in natural conditions, urbanization process, population, and economic development levels among different regions in China. Among them, under the influence of natural conditions, urban terrain

**Table 5** Condition  $\beta$  convergence test results of ULGUE

Variables	Total	East	Central	West
	SAR model	SAR model	OLS model	OLS model
$\beta$	-0.373*** (-30.351)	-0.374*** (-19.129)	-0.438*** (-21.709)	-0.325*** (-5.573)
$\rho$	0.463*** (4.442)	0.345*** (3.258)		
PGDP	0.074*** (5.019)	0.144*** (4.741)	0.064 (1.189)	0.063* (2.164)
INFRA	-0.001 (-0.914)	-0.003** (-2.193)	0.000 (0.280)	0.001 (0.709)
ER	-1.947 (-1.215)	-0.045 (-0.018)	-3.210 (-1.591)	-1.698 (-0.447)
FDI	0.264 (1.106)	0.426 (1.390)	-0.079 (-0.175)	0.757 (0.394)
IND	-0.011 (-0.762)	0.050** (2.150)	-0.027 (-0.864)	-0.043 (-1.789)
TECH	-0.396 (-1.085)	-0.649 (-1.322)	-1.084 (-1.667)	1.036 (1.446)
POP	0.209 (0.291)	-0.390 (-0.501)	1.577 (1.540)	7.305 (1.807)
$v$	0.036	0.036	0.044	0.030
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
$N$	3666	1469	1404	793
$R^2$	0.095	0.067	0.345	0.260

Note:  $t$  Statistics in parentheses, \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

undulations, slopes, and other factors determine the way of urban land use, and affect the economic and environmental benefits of land use, thereby having a differential impact on ULGUE (He et al., 2020). At the same time, there are differences in the impact of urbanization levels on carbon emissions at different stages of urbanization development (Li et al., 2021), and the construction of new urbanization is more conducive to improving ULGUE (Zhang et al., 2022a). The increase in population growth and economic development level has accelerated the speed of urban land expansion, increased land use intensity, and exacerbated carbon emissions (Karakaya et al., 2019), which in turn will affect the ULGUE. Based on the influence of the above factors, we found that ULGUE in China shows a spatial pattern of West > East > Central, which is consistent with the findings of Lu et al., (2022a). Lu et al., (2022a) found that ULGUE of small cities in the western region is at a high level and that there are more small cities with high efficiency than in the east and central regions, which in turn leads to an overall higher ULGUE in the western region. Chuai et al. (2022) also found that the construction and industrial land in the eastern region is higher than other regions, resulting in higher carbon emissions levels. The proportion of vegetation land in the western region is relatively high, and two of the three provinces in China with carbon sinks greater than carbon emissions are located in the western region (Yunnan and Guizhou provinces). This also provides important support for our research conclusion.

Regarding the source of regional differences in ULGUE, our results show that hyper-variable density is the main cause of regional differences. This is inconsistent with the findings of Lu et al. (2018), which found that the overall variation in ULGUE was mainly from inter-regional differences. The reason for the inconsistency may be that the conclusions of Lu et al. (2018) are obtained based on provincial panel data, which may ignore the uneven development between cities within each province. Specifically, there can be both cities with high and low efficiency values within provinces, resulting in some cities being out of the group. Therefore, when conducting research at the provincial level, the ULGUE is averaged, which weakens the phenomenon of urban outliers and leads to inaccurate sources of regional differences. Although there are spatial differences in ULGUE in China, these differences are decreasing and have  $\sigma$  convergence, absolute  $\beta$  and conditional  $\beta$  convergence, and the convergence rates differed among different regions. Liu and Zhao (2022) also reached a consistent conclusion that absolute  $\beta$  convergence of ULGUE with different rates of convergence under different locations, resource dependence degrees, and economic zones.

## 5 Conclusions and policy recommendations

In this paper, we use SBM-Undesirable model to measure ULGUE of 282 prefecture-level cities in China from 2006 to 2019, and analyze the regional differences and convergence of ULGUE in China with the help of Dagum Gini coefficient, coefficient of variation and convergence model. The following conclusions are obtained. First, ULGUE in China from 2006–2019 shows a fluctuating upward evolutionary trend. At the regional level, there are some differences in the efficiency values of the three major regions, with the highest in the west region and the lowest in the central region, and the fastest growth in the east region, which has the tendency to catch up with the west region. Second, the spatial distribution characteristics show that ULGUE in China exhibits obvious spatial clustering characteristics. The vast majority of cities have efficiency values in the medium–low and medium–high range. Cities with lower efficiency values are concentrated in the central and northeastern regions, while cities with higher efficiency values are concentrated in the northwestern and southeastern regions. Third, the overall differences in ULGUE are narrowing. For intra-regional differences, there are different evolutionary trends among the three major regions. Among them, the western region has the largest intraregional differences with a decreasing trend. The eastern region is the second, with an upward trend. The central region is the smallest, with a decreasing trend. For inter-regional differences, the largest inter-regional differences are found between the western and the central regions. For the contribution of the overall differences, the hyper-variance density accounts for about 50% and is the main cause. Fourth, the results of convergence analysis show that there are  $\sigma$  convergence, absolute  $\beta$  convergence and conditional  $\beta$  convergence for ULGUE in China. Among the absolute  $\beta$  convergence, the central region has the fastest convergence rate. In the conditional  $\beta$  convergence with the addition of control variables, the convergence speed has slightly increased. Based on the above conclusions, we propose the following policy recommendations.

First, improve the urban land development and utilization pattern with the orientation of increasing the carbon sink function of land use. By establishing a carbon sink impact assessment system, a carbon sink loss compensation mechanism, or a carbon sink space compensation mechanism, cities are incentivized to increase efforts to leave more white

space for future development and expand urban green space. Increase the restoration and protection of ecosystems such as forests, grasslands and woodlands, strictly control the transformation of urban ecological land into construction land too quickly, improve the urban ecological environment, integrate cities into nature, and improve the carbon sink capacity of urban green spaces, thus promoting the goal of carbon neutrality.

Second, different regions should take targeted measures to improve ULGUE according to their own development conditions. The eastern region can rely on its own economic advantages and increase the local government's financial and policy support for enterprise R&D to promote the R&D and innovation of carbon capture and carbon sequestration technologies. At the same time, the development of high-end manufacturing and modern service industries can be further promoted to achieve green production based on the advanced industrial structure, thus reducing carbon emissions and environmental pollution in the process of land use and improving the ecological benefits of land use. The central and western regions can improve the productivity of labor force by strengthening the construction of human resources and cultivating human capital that matches their industrial structure, thus improving the economic and social benefits of land use.

Third, in order to alleviate the overall differences in ULGUE in China, it is necessary to focus on solving the problems existing in cities with lower efficiency levels in regions with higher efficiency levels from the perspective of hypervariable density. This can be done by establishing a synergistic development mechanism for green urban land use between regions. While the traditional industries in the eastern region are transferred to the central and western regions, they also need to play a demonstration effect to spread some green technologies to the central and western regions by radiation, so as to form a good interaction mechanism between regions and promote the coordinated development of ULGUE in each region.

Compared with the existing literature, this paper incorporates the carbon neutrality goal into the urban land use system, which enriches the connotation of ULGUE, and the research findings are also helpful to provide a reference for decision-making to further improve ULGUE. However, there are some limitations in this paper. (1) There are controversies in academic circles about the social benefit indicators in the expected output of ULGUE, and only one of them is chosen to represent the social benefit in this paper. (2) The values of ULGUE measured by the SBM-Undesirable model in this paper are between 0 and 1. For cities that are already on the production frontier surface, their ULGUE has been equal to 1. Therefore, we cannot judge the variability of ULGUE in these cities. (3) Confined to the research framework of this paper, we were unable to characterize the local spatial autocorrelation of ULGUE in China, and we were also unable to further explore the drivers of spatial differences in ULGUE in China. These issues are also worthy of further research in the future.

## Appendix

See Tables 6, 7.

**Table 6** Representative literature of ULGUE

Authors	Research areas	Research contents	Research methods
Lu et al. (2018)	China's 31 provinces	Regional difference decomposition and policy implications	SBM-undesirable model
Yu et al. (2019)	China's 12 typical urban agglomerations	Assessment and influencing factors	SBM-UN model
Zhu et al. (2019)	China's 35 mega cities	Temporal-spatial characteristics	DEA-SBM model
Tang et al. (2021)	Yangtze River Delta urban agglomerations, China	Assessment and spatial-temporal evolution analysis	Global super-SBM model
Tan et al. (2021)	Yangtze River Delta, China	Regional differences and dynamic evolution	SBM-Undesirable model
Liu and Zhao (2022)	283 Chinese cities	Convergence analysis	DEA model
Song et al. (2022)	China's 115 resource-based cities	Estimation and driving mechanisms	DEA model
Xue et al. (2022)	Yellow River basin Chinese cities	Empirical investigation and influencing factors	Super-EBM model

**Table 7** Sources of variation and contributions of ULGUE

Year	Total	Intra-regional Gini coefficient			Inter-regional Gini coefficient			Contribution rates		
		East	Central	West	East-Central	East-West	Central-West	G_W	G_nb	G_t
2006	0.296	0.286	0.275	0.322	0.290	0.306	0.315	34.08%	15.84%	50.08%
2007	0.275	0.255	0.252	0.317	0.263	0.291	0.304	33.59%	16.93%	49.49%
2008	0.255	0.250	0.227	0.289	0.247	0.271	0.271	34.12%	13.46%	52.43%
2009	0.250	0.225	0.246	0.278	0.238	0.262	0.276	33.80%	13.35%	52.85%
2010	0.252	0.228	0.238	0.288	0.236	0.271	0.285	33.31%	17.13%	49.56%
2011	0.260	0.244	0.246	0.281	0.247	0.276	0.283	33.66%	15.76%	50.58%
2012	0.213	0.204	0.197	0.232	0.202	0.229	0.232	33.70%	15.46%	50.84%
2013	0.209	0.192	0.189	0.231	0.193	0.230	0.241	32.71%	21.90%	45.39%
2014	0.195	0.187	0.179	0.210	0.185	0.208	0.214	33.54%	18.70%	47.77%
2015	0.199	0.197	0.177	0.209	0.193	0.209	0.217	33.52%	21.52%	44.96%
2016	0.210	0.215	0.191	0.212	0.206	0.219	0.216	34.25%	14.74%	51.01%
2017	0.211	0.204	0.197	0.233	0.205	0.221	0.224	34.28%	12.60%	53.12%
2018	0.213	0.206	0.184	0.246	0.200	0.233	0.235	33.43%	17.64%	48.93%
2019	0.204	0.215	0.168	0.217	0.202	0.217	0.207	34.09%	16.97%	48.93%
Mean	0.232	0.222	0.212	0.255	0.222	0.246	0.251	33.72%	16.57%	49.71%

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**Author contributions** XF Conceptualization, Data curation, Methodology, Writing—original draft, XJ Writing—review & editing.

## Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.

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