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Cultivated Land Green Use Efficiency and Its Influencing Factors: A Case Study of 39 Cities in the Yangtze River Basin of China

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Abstract: In recent years, the Chinese government pays more and more attention to agricultural development and ecological protection. While improving the cultivated land green use efficiency(CLGUE) is the key to promote the sustainable development of agriculture. This study aims to study the current situation and influencing factors of agricultural production from the perspective of green utilization efficiency of cultivated land. It takes 39 cities in the upper, middle and lower reaches of the Yangtze River basin in China as an example. The CLGUE values in those 39 cities from 2011 to 2020 were specifically measured, using the Super-SBM model, kernel density estimation and geographic detector method. Their temporal and spatial heterogeneity was described, and the influencing factors were detected at both single and interactive levels. The results showed that: （1） From 2011 to 2020, the green utilization efficiency value of cultivated land in the Yangtze River Basin showed an upward trend on the whole; （2） There is a clear spatial heterogeneity the CLGUE values in the Yangtze River Basin cities, as shown by: downstream region > midstream region > upstream region; (3) Cultivated land resource endowment, socioeconomic development, and agricultural production technology are important factors affecting the variability of CLGUE values. However, there are some differences in the degree and direction of influence of different influencing factors on different sample subgroups.

Keywords: CLGUE; kernel density estimation; geographic detector method; Yangtze River Basin; regional differences

1. Introduction

At the present stage, sudden challenges such as international trade frictions and extreme climate disasters occur frequently. High-quality agricultural development is an inevitable requirement to adapt to the current economic situation(Chen et al., 2023). Cultivated land resources are the material basis for human survival and development. However, in the process of urbanization and industrialization, many countries, including China, its cultivated land resources are facing a sharp drop in the total area. These problems such as idle barren phenomenon and a variety of different degrees of pollution, seriously restricted the sustainable development of agriculture(Hu et al., 2021). For example, the amount of arable land per capital in the world dropped from 0.41 hectares in 1960 to 0.21 hectares in 2019(Masini et al., 2019), and China's arable land area reduced by 6.36 percent in the five years through the third National Land Survey. The sharp decrease of cultivated land area and the huge population base have brought great challenges to the global agricultural development. In addition, with the improvement of science and technology, the input of pesticides, fertilizers, agricultural film and other production factors in the agricultural production process also increases the total global carbon emissions, thus bringing environmental problems such as global warming, which is contrary to the concept of green and sustainable development(Qiu et al., 2023). Therefore, on the basis of efficient and reasonable utilization of cultivated land resources, the concept of green and low-carbon production is the focus of sustainable agricultural development. Scientific and reliable index of farmland utilization efficiency can be used as an important decision-making reference to promote the optimization of agricultural layout and sustainable development(Zhu et al., 2019).

As a composite system of the interaction between society, economy and ecological environment, the CLGUE is expected to maximize the comprehensive benefits of society, economy and ecological environment with reasonable input elements such as pesticides and fertilizers(Ma and Liu, 2019; Zhang and Jiao, 2015). The CLGUE values are calculated through the input and output of cultivated land, and the spatial imbalance characteristics of cultivated land utilization and time are revealed, so as to provide decision-making basis for the optimal allocation of cultivated land resources more scientifically, and further promote the high-quality development of China's agriculture. With the deepening of the concept of sustainable development, the ecological environment index can not be ignored more and more in the calculation of cultivated land utilization efficiency, which is embodied in the name of "green utilization efficiency of cultivated land". Xie Hualin et al. defined "green utilization efficiency of cultivated land" as "the maximum economic and ecological benefits that can be realized in the utilization process of cultivated land under certain economic and environmental costs"(Xie et al., 2018).

Existing studies related to land use efficiency can be summarized into several characteristics:(1) In the construction of the index system, the evaluation index of land use efficiency gradually changes from the simple "input" and "output" index(Song et al., 2022) to the "non-desirable output"(Feng et al., 2023; Huang, 2018; Lu et al., 2020) index with ecological value as the core. (2) In terms of research method selection, the method is gradually transferred from early qualitative analysis to quantitative analysis in recent years, and data envelope analysis (DEA)(Koroso et al., 2020; Liu and Zhao, 2022; Zhu et al., 2019), random frontier production function(Liu et al., 2020), SBM (Kuang et al., 2018; Lu et al., 2020; Zang et al., 2021). Other methods(Ferreira and Feres, 2020; Qu et al., 2021) are mostly used for empirical analysis. (3) In terms of the research subjects, most of focuses were urban land(Ji and Zhang, 2020; Koroso et al., 2020; Liu et al., 2020), followed by agricultural land(Muñoz Gielen and Mualam, 2019; Qiu et al., 2023; Zhao et al., 2021), and a small number of studies involved forests and grassland(Li et al., 2020). In general, the existing studies on the CLGUE are less on urban land use efficiency. In the selection of indicators, there are problems such as incomplete index selection, focusing on economic benefits while ignoring ecological efficiency and social benefits. Most of the research areas are based on traditional provincial administrative regions(Zang et al., 2021; Hu et al., 2018; Huang, 2018), economic coordinated development urban agglomeration(Zhang et al., 2022; Song et al., 2022) or a relatively broad view of China(Liu and Ke, 2019; Liu and Zhao, 2022), which rarely analyzed from the perspective of grain production. Although Liu Mengba(Liu et al., 2022), Gai Zhaoxue(Gai et al., 2017) and others studied the spatial and temporal evolution characteristics of cultivated land utilization efficiency in grain production areas, they essentially took the province as the decision-making unit. As for the exploration of the influencing factors of cultivated land utilization efficiency value, the mainstream methods adopted in the existing literature are mediation effect analysis(Liu and Wang et al., 2022), Tobit regression (Liu et al., 2023; Song et al., 2022)and obstacle identification method(Gou et al., 2021).

Based on the current research status on the utilization efficiency of cultivated land, this paper makes a further expansion and innovation. Firstly, the selection of indicators is more scientific and comprehensive. In the input indicators, land, labor, capital and technology, a total of seven indicators comprehensively evaluate the input in the process of farmland utilization. The food security coefficient is selected as the social output measurement index from the output index, while most of the existing studies ignore this index, or simply make the social output index by the total grain output(Ma et al., 2022). Compared with the total grain output, the index of food security coefficient can better reflect the actual supply level of local grain, so as to better reflect the contribution of cultivated land to the food security of the whole society. In terms of "non-desirable" output indicators, the carbon emissions of various carbon sources in the process of cultivated land utilization are fully considered. Secondly, in the selection of research areas, the Yangtze River Basin, an important major grain producing area for exploration in chosen, breaking the boundary of the traditional provincial administrative unit, and measuring the green utilization efficiency value of cultivated land from the perspective of grain production. Combining with the differences in agricultural production structure, economic development level and the number of permanent resident population in different regions in the upper, middle and lower reaches of the Yangtze River basin, the heterogeneity of the CLGUE values in the three basins is analyzed in space, so as to improve the utilization level of cultivated land

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according to different local conditions. Thirdly, the detection of the influencing factors of the CLGUE is more comprehensive. In addition to the detection of individual influencing factors one by one as in existing studies(Kuang et al., 2021), this paper also uses geographical detectors to further explore the interaction among the influencing factors based on the realistic consideration that cultivated land utilization efficiency is often influenced by multiple factors. Interaction probing of the influence factors revealed that the interaction influence of any two factors is consistently greater than that of the individual factor.

2. Research Design

2.1. Research Methods

2.1.1. Super-efficient SBM models including non-desired outputs

The super-efficient SBM model is a new model that combines super-efficiency and SBM models. It solves the problem of multiple effective decision units with an efficiency value of 1 based on the traditional SBM model's ability to incorporate non-desired outputs into the model(Zang et al., 2021). The model is able to avoid the missing information of the effective decision unit and thus calculate its efficiency value x =greater than one, so that the effective decision units with efficiency value is greater . The basic principle of the Super SBM model containing non-desired outputs is as follows: Assuming that n is the number of decision units in the arable land use process, m is the number of input factors, s_1 is the number of desired outputs, and s_2 is the number of non-desired outputs. X 、 y^a and $y^b$are the vectors represented by input, output and undesired output respectively. The expression of this model is as follows:

$$\rho = \min \frac{1 + \frac{1}{m}\sum_{i=1}^{m}\frac{D_i^c}{x_{ih}}}{1 - \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1}\frac{D_r^a}{y_{rh}^a} + \sum_{k=1}^{s_2}\frac{D_k^b}{y_{kh}^b}\right)}$$

$$\text{S.T.}\begin{cases} x_{ik} \geq \sum_{j=1,j\neq h}^{n} \lambda_j x_{ij} - D_i^c, \quad i = 1, \cdots m \\ y_{rh}^a \gg \sum_{j=1,j\neq h}^{n} \lambda_j y_{rj}^a + D_r^a, \quad r = 1, \cdots s_1 \\ y_{kh}^b \gg \sum_{j=1,j\neq h}^{n} \lambda_j y_{kj}^b + D_k^b, \quad k = 1, \cdots s_2 \\ 1 - \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1}\frac{D_r^a}{y_{rh}^a} + \sum_{k=1}^{s_2}\frac{D_k^b}{y_{kh}^b}\right) > 0 \\ D^a \geq 0, D^b \geq 0, D^c \geq 0 \end{cases}$$

where ρ is the green land use efficiency index of the decision unit, and D^a, $D^b$and D^c represent the desired output, non-desired output, and slack variables of the input variables, respectively, as the weight vector.

2.1.2. The kernel density estimation method for exploring spatial disequilibrium

In order to study the spatial non-equilibrium characteristics of the CLGUE for 39 cities in the upstream and midstream and downstream of the Yangtze River basin, kernel density estimation method is selected in this paper, which uses non-parametric estimation to describe the dynamic

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distribution of data. This method is characterized by not making any prior assumptions about the sample data, but directly studying the distribution characteristics of the data through the data sample itself. The advantage of this method is that it can effectively avoid the subjectivity caused by the function setting in parameter estimation, thus increasing the objectivity and realism of the results. Assuming that $'X_1, X_2, \cdots, X_n'$ is an independent identically distributed sample of the unit variable X, the kernel density estimate of the probability density function that X obeys is:

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} k(\frac{X_i - \bar{x}}{h})$$

$k(x)$ is the kernel function, n is the observed value, and h is the bandwidth as the mean value.

2.1.3. Geographical detector

Geographic detector is a research method used to reveal spatial heterogeneity and its driving factors. Its core idea is that if an independent variable has an important impact on the dependent variable, then the independent variable and the dependent variable should have similar spatial distribution. The magnitude of influence is measured by q. A larger value of q indicates a greater effect of the independent variable on the dependent variable, and the smaller the effect otherwise. The expression is as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2}$$

N and N_h represent the number of regions and the number of sub-regions, respectively σ^2 and σ_h^2 represent the variance of arable land use efficiency of regions and sub-regions, respectively.

2.2. Overview of the study area

Most of the Yangtze River basin is located in the subtropical monsoon region, with a warm and humid climate. Therefore, the region has superior light, heat, water and soil conditions for agricultural production, which is the most important agricultural production base in China. There are more than 24.6 million hectares of cultivated land, accounting for a quarter of China's total cultivated land area, and the value of agricultural production accounts for 40% of China's total agricultural output, as well as 40% of the country's total grain production. The Chengdu Plain, Jianghan Plain, Dongting Lake area, Poyang Lake area, Chaohu Lake area and Taihu Lake area located in this basin are the main commercial food bases in China.

The upstream Yangtze River Basin contains six cities including Chengdu, Yibin, Panzhihua, Luzhou, Chongqing, and Yichang. Midstream is from Yichang to Hukou County, Jiujiang City. The main cities include Wuhan, Xiangyang, Ezhou, Huanggang, Jingzhou, Enshi, Xianning, Huangshi, Yueyang and Jiujiang. Below Hukou is downstream, where the main 23 cities are Nanchang, Hefei, Maanshan, Tongling, Anqing, Chizhou, Wuhu, Huangshan, Nanjing, Zhenjiang, Yangzhou, Suzhou, Wuxi, Changzhou, Nantong, Taizhou, Shanghai, Hangzhou, Jiaxing, Huzhou, Ningbo, Shaoxing and Zhoushan. The study area map is shown in Figure 1.

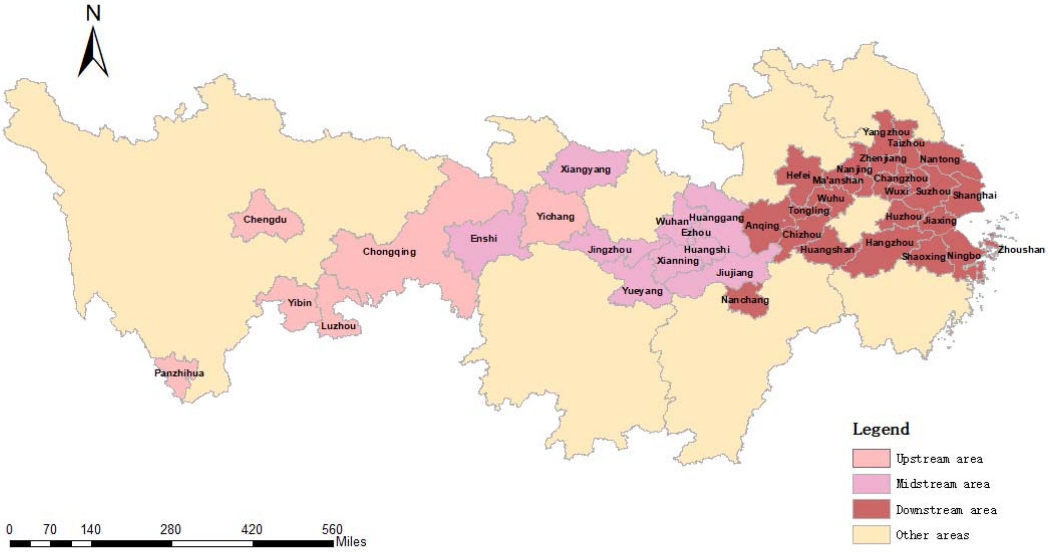


Figure 1. Study area map

2.3. Indicator System

2.3.1. Input Indicators

Referring to the existing studies on the values of CLGUE by Lu Xinhai(Lu et al., 2018) and Liang Liutao(Liang et al., 2019), seven input indicators including cultivated land area and number of laborers were selected in this paper, which involve four major dimensions of land, labor, capital and technology. The selected indicators and their related descriptions are shown in Table 1 below.

Table 1 Description of input and output indicators

Tier 1 Indicators	Tier 2 Indicators	Indicator Description	Abbreviations
Input Indicators	cultivated land	Year-end arable land area/thousand hectares	I_1
	Workforce	Number of people employed in agriculture / 10,000	I_2
	Irrigation	Effective irrigated area/thousand hectares	I_3
	Farm Machinery	Total power of agricultural machinery / million kilowatts	I_4
	Pesticides	Pesticide use / million tons	I_5
	Fertilizer	Fertilizer equivalent pure application amount / million tons	I_6

	Agricultural film	Amount of agricultural film used/ton	I_7
Desired Output Indicators	Economic output	Gross agricultural product/billion yuan	Y_1
	Social Output	Food security factor	Y_2
Non-desired output indicators	Carbon Emissions	Total carbon emissions/ton	E

2.3.2. Desired Output Indicators

In the selection of output indicators, Ke Nan(Ke et al., 2021), Lu Xinhai(Lu et al., 2018), and Zang Junmei(Zang et al., 2021) selected the two indicators of total agricultural output value and total grain production from the two major levels of economic and social benefits, respectively. This paper further expands on this basis by selecting the gross agricultural output value as the indicator of economic benefits, the coefficient of food security as the indicator of social benefits, which can reflect the level of food supply in the region more scientifically than the total food production. The food security factor is calculated as total food production/total resident population/400kg, which is derived from the internationally defined safety line of 400kg of food possession per capita per year.

2.3.3. Non-desired output indicators

The non-desired output refers to the total carbon emission in the process of cultivated land utilization, such as carbon emission generated in the process of agricultural machinery use, fertilizer, pesticide, agricultural film, etc. The formula for measuring the carbon emission in the process of arable land use is as follows.

$$E = \sum E_i = \sum M_i \cdot \sigma_i$$

In the above equation, E represents the total carbon emission of the decision unit. H represents the carbon emission of the ith carbon source in the process of root utilization. M represents the base data of the ith carbon source, and O refers to the carbon emission coefficient of this carbon source. Referring to the existing studies, the carbon emission coefficients of individual carbon sources in the process of cultivated land utilization are summarized as shown in Table 2 (Hu et al., 2020).

Table 2. Carbon emission factors for each carbon source

Carbon Source	Carbon emission factor
plowing	$312.6kg/km^2$
Workforce	0.18kg/kw
Irrigation	$25kg/km^2$
Farm Machinery	4.9341kg/kg
Pesticides	0.8956kg/kg
Fertilizer	5.18kg/kg

2.4. Data source

The data for this study are mainly obtained from the 2011-2020 statistical yearbooks of each prefecture-level city and the statistical yearbooks of the provinces where each prefecture-level city is located. The cultivated land area data of each prefecture-level city for some years are obtained from the national land survey data of the second and third surveys released by the Ministry of Natural Resources of China.

3. Analysis of the results of measuring the values of CLUE

3.1. Time-series evolutionary characteristics of CLUE

In this paper, the Super SBM model was constructed with the help of Matlab software to measure the specific values of CLUE in 39 cities in the Yangtze River Basin during 2011-2020, and the statistics are shown in Table 3 below. The mean value of CLUE in the upstream cities of this study area during the study period is 0.6625, the mean value of efficiency in the midstream cities is 0.7592, and the mean value of efficiency in the downstream cities is 0.8340. It can be seen that the values of CLUE in the Yangtze River Basin as a whole show that the upstream area < midstream area < downstream area. Table 3 shows that the values of CLUE in the upstream, midstream and downstream of the Yangtze River Basin show an overall upward trend during 2011-2020, but the trend varies from basin to basin. The mean CLGUE of the six cities in the upstream region of the Yangtze River changed more slowly, always fluctuating above and below the mean value. The overall change in the midstream region was more dramatic, and the downstream cities were basically in a stable to slightly increasing trend during the study period.

From the overall varietal trend of the CLGUE values in the three major regions of the Yangtze River Basin, there is a slight decline in efficiency values overall among the six cities in the upper reaches ,except for Yichang. The efficiency values of the other five cities have increased in fluctuation. The remaining eight cities in the midstream of the Yangtze River, including Ezhou, Huanggang, and Huangshi, showed an increase in cropland efficiency during the study period, with Huangshi showing the most significant increase in cultivated land efficiency. Among the 10 midstream cities, Enshi and Xiangyang are among those whose efficiency values have declined overall, but the downward trend is not significant. The remaining eight cities in the midstream of the Yangtze River, including Ezhou, Huanggang, and Huangshi, showed an increase in cultivated land efficiency during the study period, with Huangshi showing the most significant increase. Among the 23 cities in the downstream, the efficiency values decreased in Anqing, Huangshan, Taizhou, Tongling, Yangzhou and Shaoxing, while the values of CLGUE in other cities showed an increasing trend, with the rate of increase being more obvious in Chizhou, Jiaxing and Maanshan.

According to the calculation principle of Super-SBM model, it is known that the efficiency value greater than 1 is an efficient decision unit, and conversely, the efficiency value less than 1 is an inefficient decision unit. From Table 3, it can be seen that the only city with cultivated land use efficiency value greater than 1 in the upstream cities is Yichang, accounting for 16.67%. The midstream cities with efficiency values always greater than 1 are Enshi and Xianning. The efficiency values in Ezhou and Wuhan are less than 1 only in 2017. Huangshi is an obvious increase in efficiency values, with efficiency values less than 1 in 2011-2015 and greater than 1 after 2015, with a comprehensive assessment of midstream cities accounting for about 40% of effective decision-making units. The cities in the downstream of the Yangtze River Basin with efficiency values always greater than 1 include Nanjing, Shanghai, Zhenjiang, Suzhou, Changzhou, Hangzhou, Huzhou, Ningbo, Shaoxing and Zhoushan, and the cities with efficiency values greater than 1 in most years include Tongling and Wuxi, accounting for about 52.17% of the cities in the dowmstream with efficiency values greater than 1. This shows that in the percentage of effective decision units, the downstream region > midstream region > upstream region.

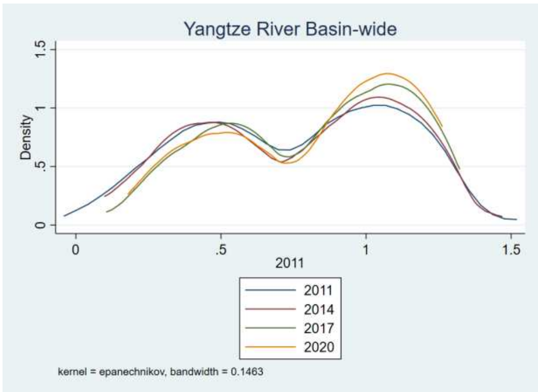
Table 3. The values of GLGUE in 39 cities in the upstream, midstream and downstream of the Yangtze River Basin from 2011 to 2020

Watershed	City	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Upstream	Chengdu	1.1023	1.1153	1.1196	1.1163	1.1205	1.1067	1.1084	1.1152	1.1114	1.1107
	Luzhou	0.5817	0.5666	0.5361	0.5119	0.6461	0.6705	0.6661	0.6419	0.6518	0.6922
	Panzhihua	0.4316	0.4353	0.4124	0.4149	0.4186	0.4200	0.4119	0.4371	0.4476	0.4536
	Yibin	0.5724	0.5771	0.5629	0.5906	0.5655	0.5905	0.5971	0.5850	0.5841	0.5951
	Yichang	1.1368	1.1067	1.0916	1.0820	1.0586	1.0583	1.3226	1.0524	1.0488	1.0502
	Chongqing	0.1061	0.1075	0.1045	0.0995	0.1556	0.1586	0.1056	0.1637	0.1672	0.1799
Average value		0.6552	0.6514	0.6379	0.6359	0.6608	0.6674	0.7020	0.6659	0.6685	0.6803
Midstream	Ezhou	1.0896	1.1505	1.1252	1.1793	1.2708	1.3141	0.5215	1.3172	1.3114	1.2626
	Enshi	1.0848	1.0961	1.0966	1.0788	1.103	1.1195	1.0199	1.1259	1.1288	1.0427
	Huanggang	0.4515	0.4718	0.4648	0.4536	0.4996	0.5153	0.4894	0.4833	0.5322	0.5363
	Huangshi	0.6631	0.6628	0.5996	0.5909	0.7593	1.0156	1.0453	1.0216	1.0173	1.0298
	Jingzhou	0.4804	0.384	0.4862	0.4813	0.4847	0.4875	0.4704	0.4902	0.4934	0.5127
	Jiujiang	0.2316	0.2406	0.2791	0.2880	0.3626	0.3563	1.2129	0.3522	0.3777	0.382
	Wuhan	1.0138	1.0031	1.0209	1.0364	1.059	1.0716	0.5409	1.0713	1.0624	1.0607
	Xianning	1.1287	1.628	1.1276	1.0473	1.1205	1.2194	1.2603	1.2244	1.1975	1.2093
	Xiangyang	0.6718	0.6444	0.6132	1.0002	0.6077	0.568	0.4312	0.6492	0.6637	0.6424
	Yueyang	0.2665	0.2612	0.2404	0.2452	0.2573	0.2593	0.2920	0.2870	0.3000	0.3185
Average value		0.7082	0.7543	0.7054	0.7401	0.7525	0.7927	0.7284	0.8022	0.8084	0.7997
	Anqing	0.3541	0.3323	0.2977	0.3144	0.3245	0.3205	0.3562	0.3401	0.3223	0.339
	Chizhou	0.7999	0.9977	1.0133	1.0771	1.1095	1.1584	0.6776	1.0949	1.0769	1.1107
	Hefei	0.2739	0.29	0.2584	0.2687	0.3506	0.348	0.4033	0.3573	0.3508	0.3433
	Huangshan	0.5981	0.5759	0.5309	0.5535	0.5525	0.5681	0.5747	0.5699	0.5235	0.5047

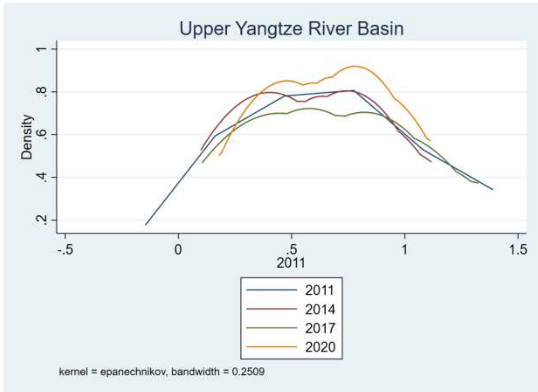
Downstream	Jiaxing	0.6349	0.5539	0.5223	0.5113	0.5285	0.5874	0.7915	1.0051	1.0147	1.0265
	Maanshan	0.5433	0.5236	0.5472	0.5611	1.0119	1.0079	1.1401	1.015	1.0234	1.015
	Nanchang	0.3673	0.3385	0.415	0.459	0.5019	0.4804	0.3404	0.5034	0.477	0.4586
	Nanjing	1.1219	1.1366	1.1352	1.1368	1.1363	1.1401	1.195	1.1362	1.1452	1.1545
	Shanghai	1.1458	1.085	1.0468	1.0447	1.0257	1.075	1.1251	1.1372	1.2642	1.2419
	Taizhou	0.4951	0.4495	0.5017	0.5678	0.5667	0.5083	0.454	0.4788	0.4595	0.481
	Tongling	1.3722	1.3191	1.3698	1.4684	1.246	1.1003	0.7115	1.134	1.1416	1.1389
	Wuhu	0.4148	0.4034	0.4079	0.4404	0.4895	0.4482	1.0489	0.4561	0.4526	0.4876
	Yangzhou	0.796	1.0003	0.82	0.7709	0.7957	0.7371	0.6956	0.7314	0.6948	0.7085
	Zhenjiang	1.0023	1.0565	1.0022	1.0088	1.0721	1.0668	1.0262	1.0399	1.0198	1.0083
	Suzhou	1.0012	1.0119	1.0151	1.0109	1.0041	1.0121	1.0086	1.0116	1.1158	1.1445
	Wuxi	1.0056	1.0322	1.0354	1.0391	1.0347	1.042	0.4335	1.0299	1.0092	1.0082
	Changzhou	1.0671	1.058	1.0471	1.0369	1.0345	1.0298	1.0639	1.0104	1.1455	1.1153
	Nantong	0.364	0.3538	0.3772	0.375	0.4559	0.4352	0.4698	0.428	0.4556	0.4567
	Hangzhou	1.0326	1.0501	1.0562	1.0633	1.0583	1.0696	1.0042	1.0798	1.0838	1.084
	Huzhou	1.0586	1.0835	1.0645	1.0464	1.0502	1.0625	1.0118	1.0522	1.0537	1.056
	Ningbo	1.0491	1.0411	1.0351	1.0279	1.0168	1.0113	1.0818	1.0315	1.018	1.0223
	Shaoxing	1.071	1.0584	1.0566	1.057	1.0304	1.0163	1.0384	1.0152	1.0057	0.932
	Zhoushan	1.004	1.0081	1.0098	1.008	1.037	1.074	1.0861	1.0901	1.0768	1.083
Average value		0.8075	0.8156	0.8072	0.8195	0.8449	0.8391	0.8147	0.8586	0.8665	0.8661

3.2. Spatial evolutionary characteristics of CLGUE

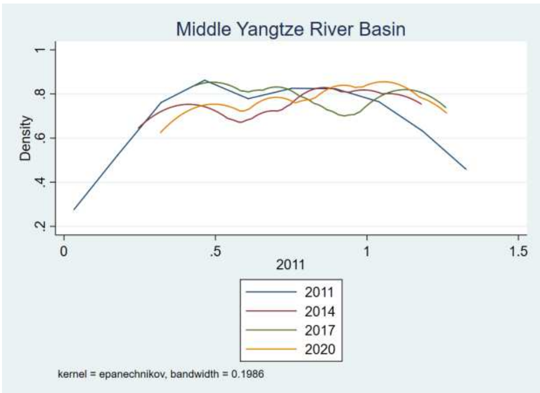
In order to accurately capture the dynamic evolution characteristics of the CLGUE values in the upstream, midstream and downstream of the Yangtze River Basin, this study used the software STATA 15.0 to plot the kernel density curves of CLGUE in 2011, 2014, 2017 and 2020 which is shown in Figure 2.



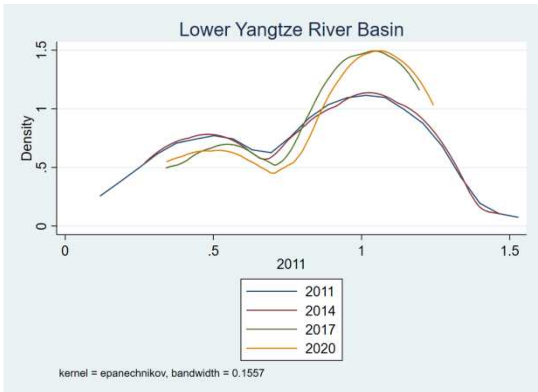
(a)



(b)



(c)



(d)

Figure 2. Kernel Density Curve for the values of CLGUE in the Yangtze River Basin

Figure 2a shows the kernel density curve about the CLGUE values in all cities in the Yangtze River Basin, with double peaks clearly visible in all study years, indicating a clear polarization of CLGUE values in 39 cities in the Yangtze River Basin. In terms of time, from 2011 to 2020, there is a year-by-year shortening of the right tail of the nuclear density curve and a narrowing trend in the extension of the distribution, implying that the spatial gap about the values of CLGUE in the Yangtze River Basin is gradually narrowing. At the same time, the peaks of both peaks of the curve are gradually shifting to the right, which indicates that the values of CLGUE in the study area are increasing and the utilization level is improving. The height of the peak on the right side of the efficiency value greater than 1 is increasing year by year, which indicates that the data here are becoming more and more intensive, representing more and more cities with efficient use of cultivated land. Figure 2b shows the kernel density curves of CLGUE values in the upstream of the Yangtze River Basin cities, and the set of curves as a whole shows a flat and wide feature, which shows that the CLGUE values in the upstream of the Yangtze River Basin vary widely among cities. However, the fluctuation of the trailing degree of the right tail of the curve indicates that the degree of difference among cities has been changing over time, gradually increasing from 2011 to 2014. It increases from

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2014 to 2017, and then decreases in 2020. However, compared with 2011, there is still a significant trend of reduction in the degree of difference of the CLGUE values among cities in the upstream of the Yangtze River Basin. Figure 2c shows the kernel density curves about the CLGUE values in the midstream of the Yangtze River Basin cities. Like (b) this set of curves also has the same flat and wide characteristics, but the degree of difference in efficiency values is relatively flatter for cities in the midstream compared to the upstream. The right tail of the curve shortens significantly from 2011 to 2014 showing that the degree of difference in efficiency values among cities has decreased.However, the difference among cities is always relatively smooth from 2014 to 2020. In addition, the overlap of the kernel density curves in each year after 2014 is high, indicating that the distribution of efficiency values of cities in the midstream region has always been relatively smooth with little fluctuation since 2014.Figure 2d shows the kernel density curve about the values of CLGUE in the downstream of the Yangtze River Basin, and the main feature of this graph is the existence of double peaks. However, the effect of the double peaks decreases year by year, and the right peak with efficiency values greater than 1 increases significantly and the right tail trails less after 2017. This shows that more and more cities in the downstream region show efficient use of cultivated land, and the degree of difference in efficiency values among cities is becoming smaller.

4. Analysis of influencing factors

4.1. Selection of impact factor indicators

The temporal evolution and spatial distribution pattern of cultivated land use efficiency are influenced by various factors such as natural conditions, cultivated land resource endowment, economic development level and agricultural production conditions. Combining the existing research results and the current situation of Yangtze River basin as well as the availability of indicator data(Pang et al., 2018), this paper selects the following indicators: (1) cultivated land resource endowment: per capita cultivated land area, replanting index, and the proportion of paddy land area; (2) social economy: per capita GDP, urbanization rate(Yan et al., 2021), and the proportion of secondary and tertiary industries(Zhao et al., 2021); (3) agricultural production conditions: chemical fertilizer, pesticide, agricultural film, total power of agricultural machinery and effective irrigation area per unit of cultivated land. In this paper, the values of CLGUE in 39 cities in the Yangtze River Basin in 2020 and the above indicators are selected for detection.

4.2. Analysis of the role of impact factors

Combined with the characteristics of the geographical detector, the data of each indicator should be converted from continuous data to category data before detecting the magnitude of the influence of each indicator on the values of CLGUE. In this study, K-means cluster analysis(Yu et al., 2019) was performed on all the influencing factors using SPSS Statistics 26.0 software, and the influencing factors were classified into five categories. After that, the processed data and efficiency values were imported into GeoDetector software for detection, and the magnitude of q-values in the detection results was used to determine the degree of influence of the impact factors on the green use efficiency values of cultivated land. The larger the q-value, the greater the influence of the influence factor, and vice versa, the smaller the influence. Q-values of each influence factor in the detection results are organized as shown in Table 4 below.

Table 4. Detection results of each impact factor

Impact Dimension	Impact Factor	Yangtze River Basin-wide	Upstream	Midstream	Downstream
cultivated land	per capita cultivated land areaX_1	0.2809	0.3651	0.4279	0.2609

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resource endowment	replanting indexX_2	0.1680	0.0244	0.1840	0.5139
	the proportion of paddy land areaX_3	0.2620	0.2609	0.3252	0.4254
social economy	per capita GDPX_4	0.1967	0.2747	0.3088	0.2572
	urbanization rateX_5	0.2064	0.9332	0.3660	0.1547
	The proportion of secondary and tertiary industriesX_6	0.1390	0.0058	0.2550	0.0877
Agricultural production conditions	Total power of agricultural machinery per unit of cultivated landX_7	0.0388	0.2675	0.0357	0.1013
	Fertilizer use per unit of cultivated landX_8	0.0629	0.2682	0.2697	0.2375
	Pesticide use per unit of cultivated landX_9	0.0219	0.3063	0.4310	0.0712
	Effective irrigated area per unit of cultivated landX_{10}	0.1901	0.4835	0.5168	0.1658
	Amount of agricultural film used per unit of cultivated landX_{11}	0.0149	0.1654	0.2234	0.2446

As can be seen from Table 4, among the 11 influencing factors, the various influencing factors that have some influence effect on the efficiency value in descending order are: cultivated land area per capita (0.2809) > paddy land area share (0.2620) > urbanization rate (0.2064) > GDP per capita (0.1967) > effective irrigated area (0.1901) > replanting index (0.1680) >secondary and tertiary industries share (0.1390). Among them, three factors, namely, per capita cultivated land area, proportion of paddy land area and urbanization rate, have the most obvious effect on the values of CLGUE in the whole Yangtze River Basin. In addition, four factors, namely GDP per capita, effective irrigated area, replanting index and the proportion of secondary and tertiary industries, also have some influence, and various influencing factors together cause the spatial heterogeneity of the values of CLGUE in the Yangtze River Basin. The four influencing factors of fertilizer, pesticide, agricultural film and total agricultural machinery power per unit of cultivated land under the dimension of agricultural production technology had insignificant effects on the spatial heterogeneity of the values of CLGUE in the Yangtze River Basin.

From the above detection results, there are some differences in the factors affecting the values of CLGUE in the upstream, midstream and downstream of the Yangtze River Basin. The dominant influencing factors in the upstream of the Yangtze River Basin are urbanization rate (0.9332) and effective irrigated area per unit (0.4835), in addition to per capita cultivated land area and pesticide use per unit of cultivated land, which are also more important influencing factors.

From the results of interaction detection in Table 5, it is clear that there is a significant interaction between the 11 selected impact factors and the values of CLGUE. The explanatory power of the interaction between any two influencing factors is greater than that of their individual influencing factors. This indicates that the multi-factor influence of the values of CLGUE in the Yangtze River Basin is better than the single-factor influence.

Table 5. Detection results of the interaction of influencing factors

X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}
X_2	0.2809									
X_3	0.7022	0.1680								
X_4	0.4053	0.4310	0.2620							
X_5	0.3398	0.4880	0.4575	0.1967						
X_6	0.5000	0.6071	0.4949	0.5418	0.2064					
X_7	0.4601	0.4050	0.3365	0.4490	0.3831	0.1390				
X_8	0.4108	0.4621	0.3320	0.4409	0.3745	0.3093	0.0388			
X_9	0.3930	0.3896	0.3718	0.3524	0.3568	0.3786	0.2051	0.0629		
X_{10}	0.4113	0.5044	0.4647	0.3458	0.4433	0.3554	0.2014	0.1964	0.0219	
X_{11}	0.5192	0.5896	0.4396	0.4572	0.6504	0.4377	0.4827	0.6900	0.4300	0.1901

5. Conclusion and Discussion

Based on the panel data of 39 cities in the upstream, midstream and downstream of the Yangtze River Basin from 2011 to 2020, this paper integrates the Super-SBM model, kernel density estimation and geographic probes to calculate the CLGUE values in each city in the study area. The efficiency value from 2011 to 2020 shows an overall upward trend. This is mainly caused by three factors. Firstly, in the aspect of input, it is mainly reflected in the reduction of labor force and the input of production factors. During the study period, the number of employees in China's primary industry decreased from 265 million to 177 million, dropping down by 33.21 percent. Secondly, at the level of economic output and social output, the continuous improvement of agricultural technology level brings about the improvement of crop output level per unit area. Thirdly, in terms of non-expected output, with the continuous promotion of the concept of green and low-carbon development in recent years, various industries have actively implemented the new development concept and gradually realized green transformation. The agricultural production process is no exception. With the vigorous promotion of new and renewable energy technologies, carbon emissions in the agricultural production process have also been declining.

What is more,the study reveals that there is a clear spatial heterogeneity the CLGUE values in the Yangtze River Basin cities, as shown by: downstream region > midstream region > upstream region. It is not difficult to see that the spatial distribution of the CLGUE values is basically in line with the overall economic development level of the upper, middle and lower reaches of the cities in the Yangtze River Basin. In other words, the green efficiency value of cultivated land in the areas with higher economic level is correspondingly higher. Related studies have also concluded that the CLGUE values are basically proportional to the level of economic development. The researchers interpreted this conclusion as an increase in non-farm payrolls(Fei et al., 2021). Areas with a higher level of economic development will also have higher urban rates, while a higher urban rate indicates that there are fewer agricultural workers. That is, there is less labor input in the process of farmland utilization. In addition to the above general reasons, according to the urban distribution characteristics in the Yangtze River basin, this study proves that this phenomenon should also be attributed to the flat terrain in the region,which is more conducive to the intensive use of cultivated land, so as to reduce the input in labor, irrigation, machinery and other aspects. In addition, economic development can often promote agricultural technological innovation and the transformation of scientific and technological achievements.

At the same time, it is found that the difference degree of green utilization efficiency of cultivated land in different cities of the Yangtze River. The development balance of cities in the middle and lower reaches regions is higher than that in the upper reaches of the Yangtze River. Influenced by the geographical location, industrial type and other factors, the development of cities within the Yangtze River basin is not balanced. The formation of urban agglomeration has a positive effect on promoting labor flow and industrial coordinated development.

The detection results of the influence factors show that the per capita cultivated land area, the proportion of paddy field area and the urbanization rate are the important factors affecting the difference of the CLGUE values. Among them, the per capital cultivated land area and urbanization rate mainly affect the CLGUE from the aspect of labor input, while the proportion of paddy field area affects the CLGUE from the aspect of economic output. A higher proportion of paddy fields will bring a higher economic output per unit area of farmland. In 2020, the average yield per mu of rice in China is 469.61 kg and the average yield of wheat is 382.82 kg. It is calculated that the per mu yield of rice in China is 22.67% higher than that of wheat in the same period. Combining with the interactive detection results of a single influencing factor and multiple influencing factors, the CLGUE is the result of the interaction of multiple factors, and the influence of any single factor on the CLGUE values is less than the result of the two influencing factors.

The above conclusions provide guiding suggestions for improving the CLGUE in the Yangtze River basin and promoting the sustainable development of agriculture. For the upper reaches of the Yangtze River, we should accelerate the improvement of the rural land transfer market, vigorously promote the construction of agricultural infrastructure, and promote the moderate scale of agricultural operation, so as to improve the green use efficiency of cultivated land from the aspect of intensive land use. For the middle and lower reaches of the region, science and technology should be rationally utilized, and the optimal ratio of various input elements should be scientifically evaluated for different types of cultivated land resource endowment. The top-level design will be transformed into real productivity, and actively promote the transformation of scientific and technological achievements to improve the output level of cultivated land. Finally, the concept of green and low-carbon development should be established in the process of agricultural production, and the total unexpected output such as carbon emissions in the use of cultivated land can be reduced through industrial transformation and structural adjustment, so as to realize the "low energy and high efficiency" of various factors.

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