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Spatio-temporal characteristics and typical patterns of eco-efficiency of cultivated land use in the Yangtze River Economic Belt, China

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Abstract: Identifying the dynamics of the eco-efficiency of cultivated land use (ECLU) is important to balance food security and environmental protection. The Yangtze River Economic Belt (YREB) is a vital region of national strategic development in China. However, the spatio-temporal characteristics and typical patterns of the ECLU in the YREB remain unclear. This study aims to reveal the spatio-temporal characteristics of the ECLU by using the super-efficiency slack-based measure (SBM) and a spatial autocorrelation model. The typical patterns of the ECLU were classified based on a decision tree algorithm. The results indicate that the overall ECLU increased from 0.78 to 0.87 from 2000 to 2019, dropping sharply in 2003 before rising again. Different reaches had similar trends. The local indicators of spatial association (LISA) cluster reflect that the spatial distributions of high-high and low-low agglomeration varied dramatically among these years. The ECLU was divided into three typical patterns considering the restriction of agrochemicals and water resources (RAW), cultivated land and agrochemicals (RCA), as well as technology (RT). Most cities belonged to the low ECLU category in RT pattern. Fully understanding the spatio-temporal characteristics and classification of the ECLU will provide a reference for decision-makers to improve the ECLU in different regions.

Keywords: ecological efficiency; cultivated land use; super-efficiency SBM; carbon emissions; classification; Yangtze River Economic Belt, China

1 Introduction

Cultivated land is important to society as it provide food and ecosystem services (Arowolo *et al*., 2018; Lai *et al*., 2020). In China, there is only 7.5% cultivated land of the world, but feeds the population accounts for 22% of the world (Kuang *et al*., 2020). In 2021, the national grain yield reached 683 million tons, having achieved continuous growth in the past

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eighteen years (NBSC, 2022). In the face of the rapidly increasing grain yield, the protection of cultivated land and the environment is under great stress (Lu *et al*., 2019; Zhang *et al*., 2019; Zhao *et al*., 2021) mainly as a result of intense agricultural activities (Tsoraeva *et al*., 2020). An increase in grain yield is generally related to an excessive agricultural input of pesticides, agricultural films, fertilizers, and agricultural mechanization, for example (Liu *et al*., 2020; Zou *et al*., 2020). The *National Soil Pollution Survey Bulletin* documented that 19.40% of the cultivated land in China (around 23.6 million hectares) has been polluted (Ministry of Environmental Protection and Ministry of Land and Resources, 2014). According to *The Second National Pollution Source Census Bulletin*, in 2017, China's agricultural machinery emissions of nitrogen oxides reached 1.89 million tons, around 1.42 million tons of plastic films were used, and the residual plastic films accumulated over numerous years amounted to 1.18 million tons (Ministry of Ecology and Environment of the People's Republic of China, 2020). These have been the prominent causes of the degradation of cultivated land (Liu *et al*., 2022). Accordingly, the cultivated land use has gradually become "three-high mode" (high consumption, pollution, and emissions). This unsustainable land use has persisted for a long time, resulting in an increasing waste of natural resources and significant environmental pollution.

The concept of "eco-efficiency" has been considered in recent decades to measure the environmental costs of socioeconomic activities (Caiado *et al*., 2017; Rybaczewska-Błażejowska and Gierulski, 2018), was first proposed by Schalteegger and Sturm (1990). Nowadays, it has been widely used in many fields such as industry (Han *et al*., 2021; Liu *et al*., 2021), tourism (Liu *et al*., 2017; Peng *et al*., 2017), energy use (Peng *et al*., 2020), and agriculture (Godoy-Durán *et al*., 2017; Deng and Gibson, 2019; Coluccia *et al*., 2020). Notably, some recent studies have combined the socioeconomic and ecological efficiency of cultivated land use (Liu *et al*., 2020; Wang *et al*., 2022). These studies mainly focused on the spatio-temporal dynamics and influential factors of the eco-efficiency of cultivated land use (ECLU) (Liu *et al*., 2021; Yang *et al*., 2021; Yin *et al*., 2022), the relationship between the ECLU and urbanization (Hou *et al*., 2019; Liu *et al*., 2022) at different scales (e.g., provincial, watershed, and individual city). Several methods can be used to calculate eco-efficiency, such as data envelopment analyses (DEA), stochastic frontier analyses (SFA), life cycle assessment (LCA), slack-based measure (SBM), and super-efficiency SBM (Vásquez-Ibarra *et al*., 2020; Luo *et al*., 2022). The SBM is a derivative model of DEA, and the super-efficiency SBM deals with the measurement error problem effectively with the value is over 1, which cannot be achieved with traditional DEA model (Ma *et al*., 2022). Therefore, the super-efficiency SBM has been widely applied to measure eco-efficiency (Chen *et al*., 2021). However, most previous studies have only proposed policy recommendations to improve the ECLU (Hou *et al*., 2019; Ke *et al*., 2022). Few studies have divided the ECLU into different patterns according to the input factors of the cultivated land to improve the ECLU of the regions through precise improvements of different input factors for these patterns.

The Yangtze River Economic Belt (YREB) is an important area due to its contribution to economic development, ecosystem services, and food production in China (Wang *et al*., 2020). The area is also subject to intense conflicts between economic development, agricultural production, and environmental protection (Zhang and Chen, 2021). The government began attempting to mitigate this conflict and promote environmental protection in 1998 following a severe flooding event of the Yangtze River, which causing serious casualties and crop damage (Lyu *et al*., 2018). This study aims to investigate the spatio-temporal characteristics of the ECLU in the YREB from 2000 to 2019, and accordingly classify its typical patterns related to input factors. Specifically, an index system to measure ECLU is established by considering the input factors, and expected and unexpected output ones. Subsequently, the spatio-temporal characteristics of the ECLU can be revealed with the super-efficiency SBM and a spatial autocorrelation model. Finally, the typical patterns of the ECLU can be identified based on the classification method of a decision tree algorithm.

2 Methodology and data sources

2.1 Study area

The YREB extends from the west to the east of China. The region includes nine provinces, namely Sichuan, Guizhou, Yunnan, Hubei, Hunan, Jiangxi, Jiangsu, Zhejiang, Anhui, and the two municipalities of Chongqing and Shanghai (Figure 1). The YREB covers an area of approximately 2.05 million km^2, hosts around two-fifths of the total population in China, and contributes over 40% of the GDP (Jin *et al*., 2018). The YREB became one of China's strategic development regions for grain production and ecological protection after the *Yangtze River Economic Belt Development Plan Outline* was issued (Political Bureau of the Central Committee of the Communist Party of China, 2016). However, the YREB faces severe resource and environmental problems due to human activities (Zhang *et al*., 2020). The overuse of fertilizers, pesticides, and agricultural films on cultivated land increases carbon emissions and aggravates environmental pressures (Sun *et al*., 2018; Luo *et al*., 2019; Zhou and Lei, 2020). Understanding the spatio-temporal characteristics and typical patterns of the ECLU is therefore crucial for the sustainability of the YREB.

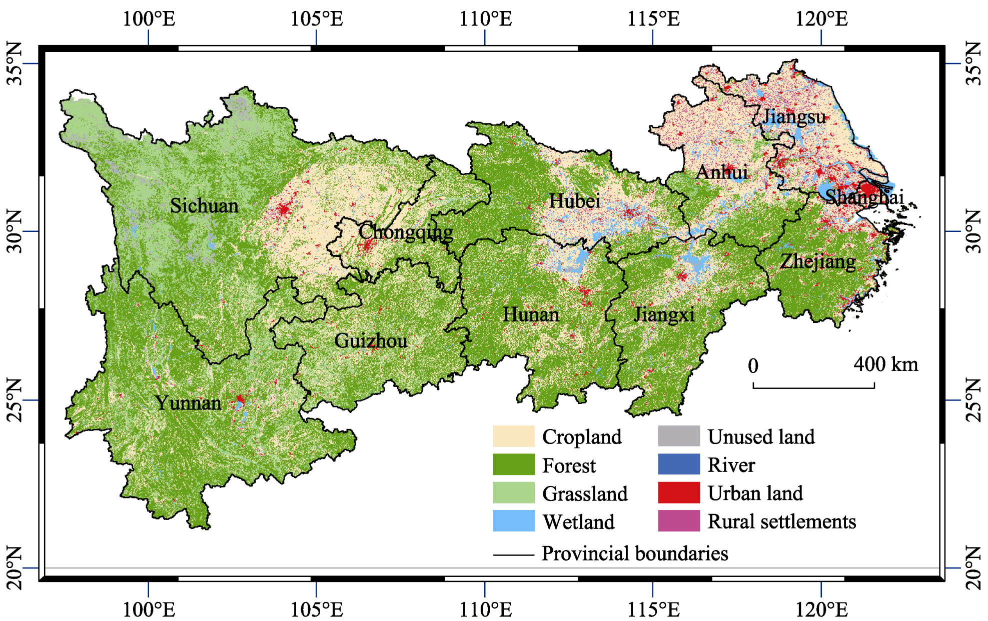

Figure 1 Administrative divisions and land uses in the Yangtze River Economic Belt (YREB) (2015)

The YREB is divided into three parts based on the natural resource endowment and socioeconomic development: the upper, middle, and lower reaches (Table 1). The upper reaches are dominated by mountains and plateaus while the middle and lower reaches are dominated by plains (Cui *et al*., 2021). The level of socioeconomic development is highest in the lower reaches, followed by the middle reaches, and the upper reaches (Zhang *et al*., 2021).

Table 1 Regional divisions in the Yangtze River Economic Belt (YREB)

Reaches	Provinces / Municipalities
Upper	Provinces of Sichuan, Guizhou, Yunnan, and the municipality of Chongqing
Middle	Provinces of Hubei, Hunan, Jiangxi
Lower	Provinces of Jiangsu, Zhejiang, Anhui, and the municipality of Shanghai

2.2 Definition of the eco-efficiency of cultivated land use

The definition of eco-efficiency is constantly developing. Schmalleger and Sturm (1990) applied it in the enterprise sector and defined it as the ratio of the added economic value to the added environmental impact. The World Business Council for Sustainable Development (WBCSD) (1992) interpreted eco-efficiency as satisfying human production and life resource consumption while minimizing the resource input and environmental impact. According to the Organization for Economic Cooperation and Development (OECD) (1998), eco-efficiency refers to the maximization of human welfare while ensuring a smaller loss of resources and lesser impact on the environment. The core of eco-efficiency is therefore the ratio of the added value of economic and social to the added resource consumption and environmental impact. In this study, the ECLU involves maximizing the expected output and simultaneously minimizing the input factors and negative ecological influence over a process of limited cultivated land use. Specifically, the ECLU consists of the input factors (resource, labor, capital, and technology), the expected output (the gross output value of agriculture and grain yield), and the unexpected output (carbon emissions).

2.3 Methods

2.3.1 Super-efficiency SBM model

Stochastic frontier analyses (SFA) and Data envelopment analyses (DEA) are widely used to measure eco-efficiency. The difference between these two methods is that SFA applies to multi-input and single-output situations while DEA applies to multi-input and multi-output situations ones (Yang and Deng, 2019; Vásquez-Ibarra *et al*., 2020). DEA was proposed by Charnes (1978), but most of the traditional DEA models are based on radial and angle measurements which fail to fully consider the slack variable. Moreover, it does not consider the negative environmental effects caused by unexpected outputs (Yang *et al*., 2021). In this regard, Tone (2001) proposed the SBM model. The SBM model solves the problems of slack of input-output variables effectively (Zhou *et al*., 2018). In addition, the super-efficiency SBM model obtains efficiency values exceeding 1 so that effective values are still comparable (Han *et al*., 2017). Therefore, this study adopted the super-efficiency SBM model to measure the ECLU in the study area. The model can be represented as:

$$p^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2} \frac{s_r^b}{y_{r0}^b}\right)} \tag{1}$$

$$\text{s.t.} \begin{cases} x_0 = X\lambda + \overline{s}, y_0^g = Y^g\lambda - s^g, y_0^b = Y^b\lambda + s^b \\ \overline{s} \geqslant 0, s^g \geqslant 0, s^b \geqslant 0, \lambda \geqslant 0 \end{cases} \tag{2}$$

where, assuming that n decision-making units (DMU) are considered, each DMU consists of input factors (m), expected outputs (s_1), and unexpected outputs (s_2); s^-, s^g and s^b are the slack variables of input variables and λ is the weight vector.

In this study, we used the MAXDEA8 software to construct the unified efficiency frontier from 2000 to 2019, assuming that the expected and unexpected output weight ratio was 1:1 following Liu *et al*. (2021). The global reference method made the results comparable between these years.

2.3.2 Spatial autocorrelation model

The spatial autocorrelation model (global and local) is an essential instrument for correlating the research object and its position (Cliff and Ord, 1973). The global spatial autocorrelation mainly reflects the correlation of attribute values in the entire region, and local spatial autocorrelation reveals the spatial heterogeneity (Fotheringham, 2009). Correspondingly, the Moran's *I* and local indicators of spatial association (LISA) are commonly used to represent the global and local spatial autocorrelation (Anselin, 1995). The formulae for calculating the global autocorrelation and local spatial autocorrelation are as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(X_i - \overline{X}\right)\left(X_j - \overline{X}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i=1}^{n}(X_i - \overline{X})^2} \tag{3}$$

$$I_i = \frac{n\left(X_i - \overline{X}\right)\sum_{j=1}^{n} W_{ij}\left(X_j - \overline{X}\right)}{\sum_{i=1}^{n}(X_i - \overline{X})^2} \tag{4}$$

where I and I_i are global Moran's I and LISA, respectively; n is the total number of regions; X_i and X_j are the value of the ECLU in regions i and j; $\overline{X}$ is the average of ECLU in each region; W_{ij} is the spatial relation in regions i and j. Moreover, the values of Moran's I and LISA are usually tested with the Z-test (Cliff, 1981):

$$Z(I) = \frac{I - E(I)}{S(I)}, S(I) = \sqrt{Var(I)} \tag{5}$$

$$Z(I_i) = \frac{I_i - E(I_i)}{S(I_i)}, S(I_i) = \sqrt{Var(I_i)} \tag{6}$$

where $E(I)$, $Var(I)$ and $E(I_i)$, $Var(I_i)$ represent the expected and variance of I and I_i, respectively.

In this study, the spatial correlation of the ECLU in the YREB from 2000 to 2019 was determined using the GeoDa software. The value of Moran's *I* ranges from –1 to 1, representing a negative (closer to –1) or positive (closer to 1) spatial correlation. When the value is 0, there is no spatial correlation.

2.3.3 The decision tree

The decision tree extracts patterns by summarizing large data sets (Quinlan, 1986). It has the advantages of easy understanding of data sets and implementation of the information. The aim of using a decision tree is to employ the information gain as the test attribute (Myles *et al*., 2004):

$$Gain\left(D,a\right)=Ent\left(D\right)-\sum_{v=1}^{v}\frac{|D^{v}|}{D}Ent\left(D^{v}\right) \tag{7}$$

$$Ent\left(D\right)=-\sum_{k=1}^{|y|}p_{k}log_{2}p_{k} \tag{8}$$

where a is the attribute of sample D, D^v represents the v-th value in sample D, $Ent(D)$ is the information entropy, and p_k is the proportion of class k samples in the sample set. The smaller the $Ent(D)$, the higher the purity of information. Each branch node selects the attribute that maximizes the information gain to divide the samples.

In this study, the attributes of the decision tree were the cultivated land (farm crop sown areas), labor force (workers in the primary industry), agrochemicals (the amounts of fertilizers, pesticides, and agricultural films), water resources (effective irrigation areas), and technology (the total power of agricultural machinery). The ECLU was divided into high and low efficiency according to the average value of the ECLU which was 0.73, by C5.0 decision tree algorithm. 80% of the data set was used as the training set and 20% of the data set became the testing set to train and predict the decision tree. In the identified decision tree, we tried to select the branch containing each cultivated land input factor. The attribute value range of each node was the allocation of input factors in this pattern.

2.3.4 Index system and data sources

The index system of the ECLU includes the input factors, expected, and unexpected outputs (Table 2). The input factors include (1) resources (farm crop sown areas and effective irrigation areas), (2) labor force (workers in the primary industry), (3) agrochemicals (the amounts of fertilizers, pesticides, agricultural films), and (4) technology (the total power of agricultural machinery). The expected outputs are the economic output (gross output value of agriculture) and social output (grain yield). The unexpected output is the ecological influence (carbon emissions from cultivated land use).

This study was conducted at a prefecture-level and comprised data from 126 cities. The data were acquired from the *Statistical Yearbook* and *Statistical Bulletin on National Economic and Social Development* from 2001 to 2020. The smoothing data processing and average estimation methods were used to calculate for some missing data (the amounts of pesticides and agricultural films in Sichuan, Guizhou, and Yunnan provinces). The areas of Tianmen, Xiantao, Qianjiang, and the Shenlongjia Forestry District in Hubei Province were excluded from the calculations due to data unavailability.

Table 2 The index system of the eco-efficiency of cultivated land use

Types	First-level indicators	Secondary indicators	Unit
Input	Resource	Farm crop sown areas	10^3 ha
		Effective irrigation areas	10^3 ha
	Labor force	Workers in the primary industry	10^4 persons
	Agrochemicals	Fertilizers	ton
		Pesticides	ton
		Agricultural films	ton
	Technology	Total power of agricultural machinery	10^4 kW
Expected output	Economic	Gross output value of agriculture	10^8 yuan
	Social	Grain yield	10^4 ton
Unexpected output	Environmental	Carbon emissions	10^4 ton

The carbon emissions from cultivated land use were measured based on the carbon source and coefficient according to existing studies (Li *et al*., 2011; Kuang *et al*., 2020) and included the following six aspects (Table 3).

Table 3 Carbon source and coefficients of carbon emissions from cultivated land use

Carbon source	Coefficient	Unit	Source
Fertilizer	0.8956	kg/kg	West and Marland, 2002
Machinery	0.18	kg/kW	West and Marland, 2002
Pesticide	4.9341	kg/kg	Post and Kwon, 2000
Agricultural film	5.18	kg/kg	Li *et al*., 2011
Farm crop sown area	3.126	kg/ha	Li *et al*., 2011
Effective irrigation area	20.476	kg/ha	Li *et al*., 2011

3 Results

3.1 Spatio-temporal characteristic of the eco-efficiency of cultivated land use

The overall value of the ECLU followed a fluctuating increasing trend, increasing from 0.78 in 2000 to 0.87 in 2019 (Figure 2). Specifically, the overall value of the ECLU dropped sharply from 2000 to 2003, followed by a slight increase until 2017, before rising dramatically from 2017 to 2019. Similar trends could be observed in the upper, middle, and lower reaches. In addition, the growth rates of the values of the ECLU from 2000 to 2019 were 12.99% (overall), 5.49% (upper reaches), 5.13% (middle reaches), and 26.98% (lower reaches), respectively, indicating that the growth rate of the value of the ECLU in the lower reaches was the fastest.

The value of the ECLU was the highest in the upper reaches, followed by the middle reaches, and finally the lower reaches. Moreover, the value of the ECLU in the upper reaches was higher than the overall, dropping from 2000 to 2011 and then rising from 2011 to 2019; the highest and lowest values were 0.97 in 2019 and 0.68 in 2011. The values of the ECLU in the middle and lower reaches were lower than the overall value. The value of the

ECLU in the middle reaches dropped from 2000 to 2003 and then rose from 2003 to 2019; the highest and lowest values were 0.82 in 2019 and 0.60 in 2003. In the lower reaches, the value of the ECLU dropped from 2000 to 2003, and then rose from 2003 to 2018, followed by a slight decrease in 2019. The highest and lowest values in the lower reaches were 0.87 in 2018 and 0.52 in 2003.

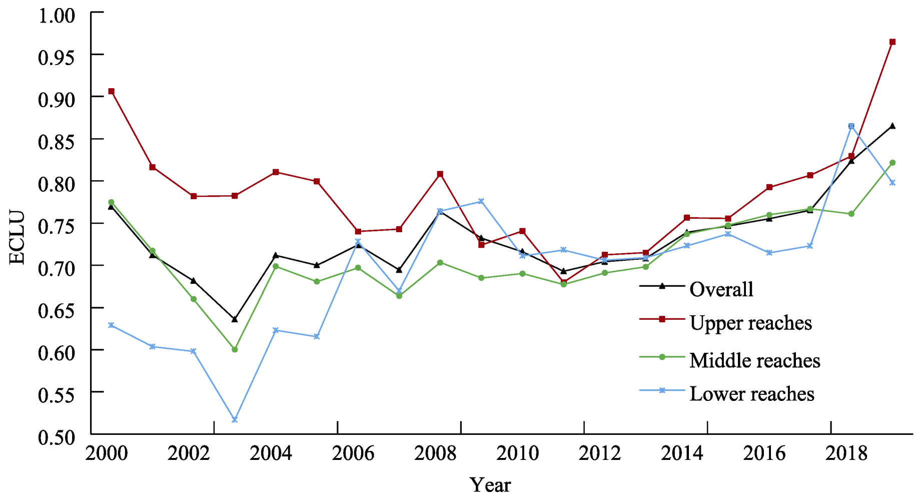

Figure 2 The value of eco-efficiency of cultivated land use in the Yangtze River Economic Belt

The number of cities with an effective ECLU (value over 1) showed that the overall values decreased first and then increased from 2000 to 2019, as well as the upper, middle, and lower reaches (Table 4). In 2000, 2005, and 2019, effective ECLU values were mainly recorded in cities in the upper reaches with 59.26% (2000), 62.5% (2005) and 47.27% (2019), respectively. In cities in the lower reaches, effective ECLU values were mainly recorded from 2010 to 2015 with 50% (2010) and 55.56% (2015).

Table 4 The number of cities with effective values of eco-efficiency of cultivated land use

Year	Region			
	Overall	Upper reaches	Middle reaches	Lower reaches
2000	27	16	8	3
2005	8	5	1	2
2010	14	4	3	7
2015	18	4	4	10
2019	55	26	13	16

The overall values of ECLU were classified into four levels based on the natural break method: low (0.32–0.60], medium-low (0.60–0.75], medium-high (0.75–0.90] and high (0.90–1.87] (Figure 3). The results showed that numerous cities with the medium-low and low ECLU, which were scattered in the overall of the YREB. The cities with medium-high and high ECLU values were mainly concentrated in the western and eastern upper reaches. Since 2010, the area of medium-high and high ECLU had increased in the middle and lower reaches.

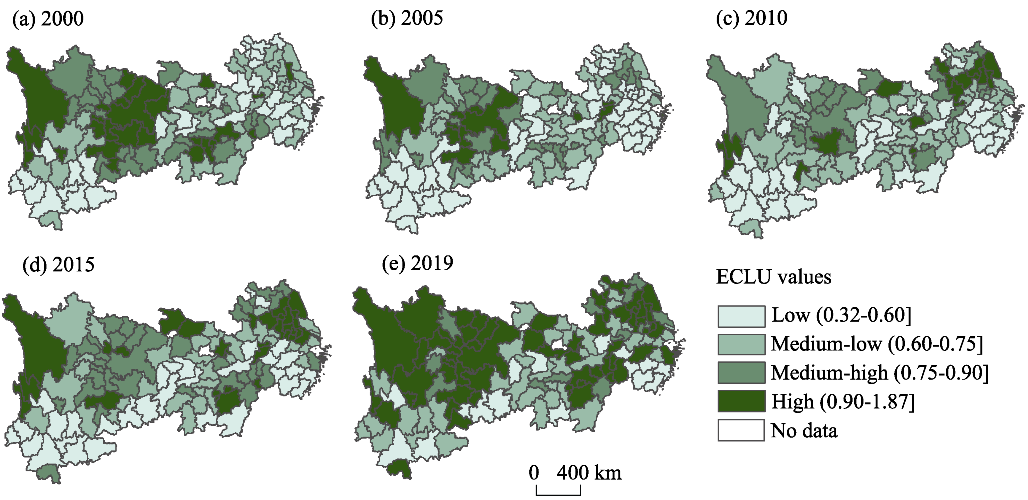

Figure 3 Spatial characteristics of the eco-efficiency of cultivated land use in the Yangtze River Economic Belt

3.2 Spatial correlation characteristics of the eco-efficiency of cultivated land use

The global Moran's *I* values of the ECLU in each year were all significant at a 1% level. The results were all greater than 0, showing a positive spatial autocorrelation in the YREB (Table 5). Moreover, the global Moran's *I* decreased by 50.98% from 2000 to 2019, indicating that the spatial autocorrelation of the ECLU weakened during the later years of the study period. Particularly, a sharp decrease was observed in 2019, reflecting that the overall spatial pattern of the ECLU changed dramatically.

Table 5 Global Moran's *I* of the eco-efficiency of cultivated land use

Year	Moran's *I*	SD	Z-Value
2000	0.408***	0.057	7.386
2005	0.397***	0.055	7.394
2010	0.395***	0.056	7.294
2015	0.389***	0.058	6.936
2019	0.200***	0.057	3.771

Note: ***, **, * significant at 1%, 5% and 10% level

The LISA cluster was further investigated to reveal the local characteristics of the ECLU in the YREB (Figure 4). The spatial patterns of the ECLU differed from each other significantly. Overall, the majority of cities concentrated in High-High (H-H) and Low-Low (L-L) agglomerations, with a few cities in High-Low (H-L) and Low-High (L-H) agglomerations, reflecting a positive spatial autocorrelation. In 2000, the proportions of H-H and L-L agglomerations were 15.09% and 19.84%, showing that the regional value was similar to the neighbor cities. The eastern upper reaches belonged to the H-H agglomerations, while the L-L agglomerations were located in the southern upper reaches and most of the lower reaches. Since 2010, the area of H-H agglomerations had reduced sharply and were sparsely distributed in a few cities in the upper, middle, and lower reaches. Since 2005, the area of L-L agglomerations in the upper and lower reaches had decreased. Simultaneously, the area of L-L agglomerations in the middle reaches had increased since 2015.

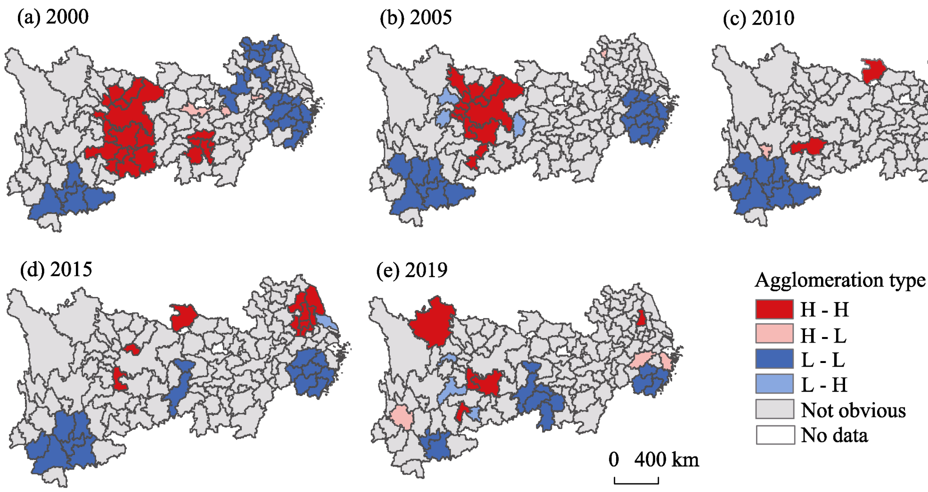

Figure 4 LISA cluster of the eco-efficiency of cultivated land use in the Yangtze River Economic Belt

3.3 Typical patterns of the eco-efficiency of cultivated land use

Three typical patterns were identified according to the classification results: "Restriction on agrochemicals and water resources" (RAW), "Restriction on cultivated land and agrochemicals" (RCA), and "Restriction on technology" (RT) (Figure 5).

In the RAW pattern (Figure 5a), the cultivated land exceeded 398.53 × 10^3 ha, the labor force ranged from 28.25 × 10^4 to 77.74 × 10^4 persons, and the technology consumption for total power of agricultural machinery amounted to less than 591.70 × 10^4 kW. The ECLU was majorly influenced by agrochemicals or water resources. In the RCA pattern (Figure 5b), the labor force was more than 77.74 × 10^4 persons, the technology consumption for total

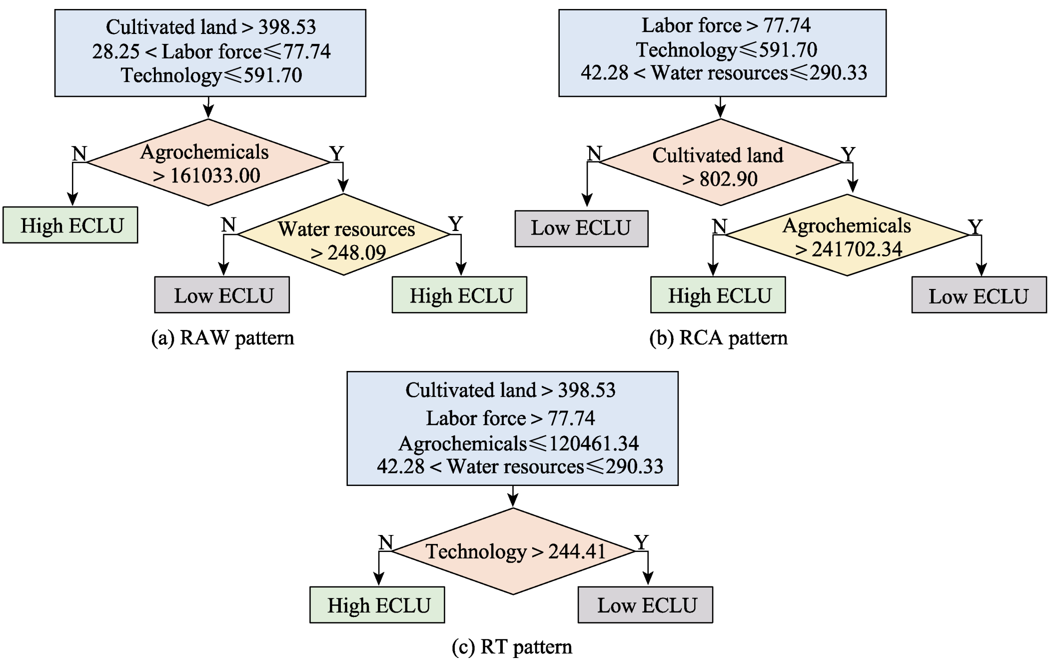

Figure 5 Typical patterns of the eco-efficiency of cultivated land use in the Yangtze River Economic Belt

power of agricultural machinery was less than 591.70 × 10^4 kW, and the water resources ranged from 42.28 × 10^3 to 290.33 × 10^3 ha. The ECLU was largely influenced by cultivated land or agrochemicals. In the RT pattern (Figure 5c), the cultivated land exceeded 398.53 × 10^3 ha, the labor force involved over 77.74 × 10^4 persons, agrochemicals amounted to less than 124061.34 tons, and the water resources ranged from 42.28 × 10^3 to 290.33 × 10^3 ha; technology was the only factor affecting the ECLU.

According to the distribution of the typical patterns of the ECLU (Figure 6), 74 cities fitted the typical classification. Most cities in the YREB belonged to the RT and RAW pattern, accounting for 55.41% and 25.68%, respectively. The proportions of low ECLU in each pattern were 5.41% (RAW pattern), 9.46% (RCA pattern), and 48.64% (RT pattern), indicating that most cities belonged to the low ECLU class in the RT pattern. Specifically, the cities with the RT pattern were widely distributed in Yunnan, Sichuan, Guizhou (upper reaches), Hubei, Jiangxi, Hunan (middle reaches), and Anhui, Zhejiang, and Jiangsu (lower reaches). The cities with the RAW pattern were widely distributed in Sichuan (upper reaches), Hubei, Hunan, Jiangxi (middle reaches), and Anhui, Jiangsu, and Shanghai (lower reaches). The cities with RCA pattern were the fewest. Fourteen cities had RCA patterns, mainly distributed in Yunnan, Sichuan, Guizhou (upper reaches), Hubei, and Hunan (middle reaches).

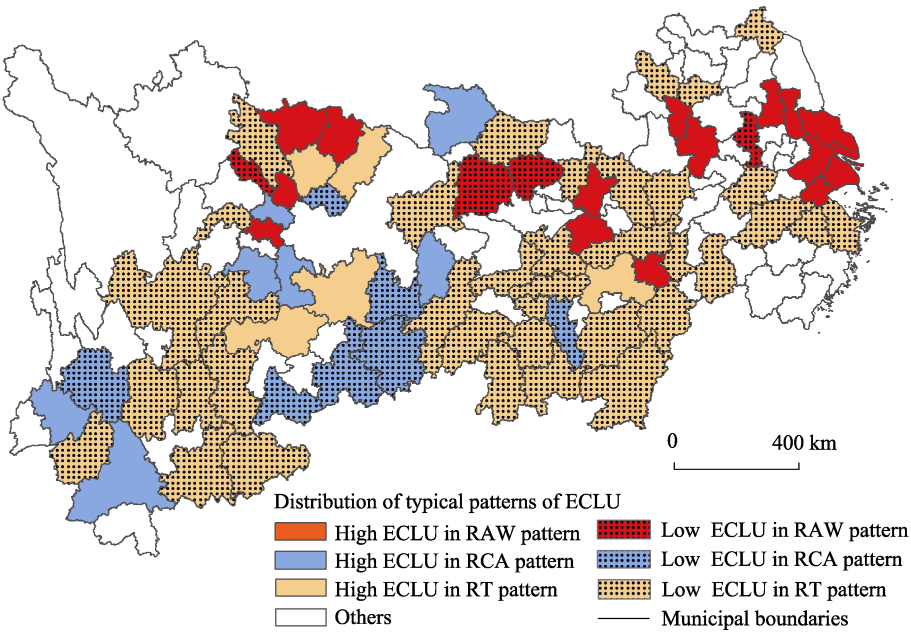

Figure 6 Distribution of typical patterns of eco-efficiency of cultivated land use in the Yangtze River Economic Belt

4 Discussion

4.1 Changes in the temporal characteristics

This study found that the ECLU in the YREB increased from 2000 to 2019, consistent with the results of existing studies (Luo *et al*., 2020; Yang *et al*., 2021). Furthermore, the gap of the ECLU in three reaches was decreasing and exhibiting an upward trend after 2003. The increase of the ECLU may have been due to the frequent implementation of cultivated land protection policies since 2003 (e.g., the most strictly implemented cultivated land protection system in 2005, the permanent essential farmland delineation in 2008, and the farmland protection and compensation policy in 2015) (Liu *et al*., 2017; Niu *et al*., 2019). This evidences that the implementation of these policies significantly improved the ECLU.

The growth rate of the ECLU in the lower reaches was the fastest from 2000 to 2019, indicating that cultivated land use had improved in the lower reaches. The early cultivated land use in the lower reaches major depended on large-scale mechanical use and extensive land use, which gained considerable economic and social benefits, but often at the expense of the environment (Liu *et al*., 2020). With an emphasis on the ecological environment (Guo *et al*., 2021), the original extensive development model was gradually abandoned on a regional scale, instead promoting low-carbon and intensively cultivated land use.

4.2 Changes in the spatial correlation characteristics

Previous studies have only measured the ECLU and explored its influence factors. In this study, considering the cities were not isolated (Zhou *et al*., 2019), the ECLU was influenced by adjacent cities. Hence, we explored the spatial correlation characteristics of the ECLU. The characteristics of local spatial autocorrelation showed that the ECLU in the YREB had a spatial proximity spillover effect. Therefore, when the ECLU values of neighbor cities were high (low), the region was more likely to become high (low) ECLU. The results showed that the areas of H-H and L-L agglomeration varied dramatically during the study period. Possible reasons behind this phenomenon included the differences in the speed of economic development, cultivated land resource endowment, and natural environment in the upper, middle, and lower reaches. Therefore, the natural conditions, economic level, and planting preferences of adjacent cities would impact the ECLU in the YREB.

4.3 Characteristics of the typical patterns

In addition, the input factors of cultivated land were treated as the attribute and the values of the ECLU as the category to train the decision tree and obtain three typical patterns. Each pattern had a corresponding path to mitigate the phenomenon of input factors mismatched. Specifically, in the RAW pattern, reducing the amounts of agrochemicals used or increasing the water resource input would contribute to improving the ECLU in different cities. Furthermore, the ECLU values would be improved in the RCA pattern by increasing the cultivated land areas and reducing the agrochemicals input, or by keeping the technology consumption for total power of agricultural machinery below 244.41×10^4 kW in the RT pattern. Moreover, it can be seen that the low ECLU values in the three patterns were mainly distributed in major grain-producing cities, which were under significant pressure from grain production (Xiao *et al*., 2021). The main grain-producing cities mainly use high input factors to increase planting income and yield (Zou *et al*., 2020). This method of cultivated land use achieved short-term and high-return economic benefits but reduced the ECLU. Therefore, it was necessary to control the input factors within a reasonable range to improve the ECLU.

5 Conclusions

This study used the super-efficiency SBM model to measure the ECLU in the YREB from 2000 to 2019. The value of the ECLU reflected that the trends were similar overall, as well as in the upper, middle, and lower reaches, individually. Particularly, the value of the ECLU declined from 2000 to 2003, followed by a slight increase until 2017, before increasing from 2017 to 2019. The growth rate in the lower reaches was the fastest. The number of cities with effective ECLU values decreased first and then increased from 2000 to 2019 in the upper, middle, and lower reaches of the region. The spatial characteristics of the ECLU showed that numerous cities with medium-low and low ECLU, which were scattered in the upper, middle, and lower reaches. The area of cities with medium-high and high ECLU values has increased in the middle reaches and lower reaches since 2010.

Moreover, the spatial autocorrelation model was used to explore the spatial relation of the ECLU in different cities. The global Moran's *I* showed that the ECLU values presented a positive spatial autocorrelation. There were significant differences between different cities for the local spatial autocorrelation of ECLU. Most cities concentrated in the H-H and L-L agglomerations. Therefore, cities with low ECLU values could break through restrictions and learn from cities with high ECLU values.

In addition, the decision tree algorithm was used to divide the ECLU into three typical patterns: "Restriction on agrochemicals and water resources" (RAW pattern), "Restriction on cultivated land and agrochemicals" (RCA pattern) and "Restriction on technology" (RT pattern). Most cities belonged to the low ECLU category in the RT pattern and each of the patterns was mainly distributed in major grain-producing regions in the upper, middle, and lower reaches. Regions could consider the corresponding typical patterns to adjust their input factor structure and improve their ECLU.

The limitations in this study were as follows: first, the index system of the ECLU should be further refined. We only selected the grain yield and gross output values of agriculture as the expected output. However, the value of ecological services in cultivated land use should also be considered as an expected output (Liu *et al.*, 2021; Zhang *et al.*, 2021). In addition, non-point source pollution generated by cultivated land use should also be considered as unexpected output (Yin *et al.*, 2022). Second, the value of carbon emissions was not accurately calculated as the carbon emissions coefficient of cultivated land use did not consider regional differences. Therefore, the selection and optimization of the index to make the ECLU more accurately will be the focus of future research.

References

Anselin L, 1995. Local indicators of spatial association: LISA. *Geographical Analysis*, 27(2): 93–115.

Arowolo A O, Deng X, Olatunji O A *et al.*, 2018. Assessing changes in the value of ecosystem services in response to land-use/land-cover dynamics in Nigeria. *Science of The Total Environment*, 636: 597–609.

Caiado R G G, de Freitas Dias R, Mattos L V *et al.*, 2017. Towards sustainable development through the perspective of eco-efficiency: A systematic literature review. *Journal of Cleaner Production*, 165: 890–904.

Charnes A, Cooper W, Rhodes E, 1978. Measuring the efficiency of decision-making units. *European Journal of Operational Research*, 2(6): 429–444.

Chen Y, Ma L, Zhu Z, 2021. The environmental-adjusted energy efficiency of China's construction industry: A three-stage undesirable SBM-DEA model. *Environmental Science and Pollution Research*, 28(41): 58442–58455.

Cliff A D, Ord J K, 1973. Spatial Autocorrelation. London: Pion.

Cliff A D, Ord J K, 1981. Spatial Processes: Models and Applications. London: Pion.

Coluccia B, Valente D, Fusco G *et al*., 2020. Assessing agricultural eco-efficiency in Italian regions. *Ecological Indicators*, 116: 106483.

Cui X, Shen Z, Li Z *et al*., 2021. Spatiotemporal evolutions and driving factors of green development performance of cities in the Yangtze River Economic Belt. *Ecological Informatics*, 66: 101476.

Deng X, Gibson J, 2019. Improving eco-efficiency for the sustainable agricultural production: A case study in Shandong, China. *Technological Forecasting and Social Change*, 144: 394–400.

Fotheringham A S, 2009. "The problem of spatial autocorrelation" and local spatial statistics. *Geographical Analysis*, 41(4): 398–403.

Godoy-Durán Á, Galdeano-Gómez E, Pérez-Mesa J *et al*., 2017. Assessing eco-efficiency and the determinants of horticultural family-farming in southeast Spain. *Journal of Environmental Management*, 204: 594–604.

Guo Y, Fu B, Xu P *et al*., 2021. Mapping regional differences in payment for ecosystem service policies to inform integrated management: Case study of the Yangtze River Economic Belt. *Journal of Environmental Management*, 278: 111396.

Han J, Zhang A, Ke X, 2017. Identification of rural-to-urban farmland conversion efficiency patterns and land differential management strategies: The efficiency measurement and decision analysis based on undesirable output. *China Land Science*, 1(11): 16–24, 97. (in Chinese)

Han Y, Zhang F, Huang L *et al*., 2021. Does industrial upgrading promote eco-efficiency? A panel space estimation based on Chinese evidence. *Energy Policy*, 154: 112286.

Hou X, Liu J, Zhang D *et al*., 2019. Impact of urbanization on the eco-efficiency of cultivated land utilization: A case study on the Yangtze River Economic Belt, China. *Journal of Cleaner Production*, 238: 117916.

Jin G, Deng X, Zhao X *et al*., 2018. Spatiotemporal patterns in urbanization efficiency within the Yangtze River Economic Belt between 2005 and 2014. *Journal of Geographical Sciences*, 28(8): 1113–1126.

Ke N, Zhang X, Lu X *et al*., 2022. Regional disparities and influencing factors of eco-efficiency of arable land Utilization in China. *Land*, 11(2): 257.

Kuang B, Lu X, Zhou M *et al*., 2020. Provincial cultivated land use efficiency in China: Empirical analysis based on the SBM-DEA model with carbon emissions considered. *Technological Forecasting and Social Change*, 151: 119874.

Lai Z, Chen M, Liu T, 2020. Changes in and prospects for cultivated land use since the reform and opening up in China. *Land Use Policy*, 97: 104781.

Li B, Zhang J, Li H, 2011. Research on spatial-temporal characteristics and affecting factors decomposition of agricultural carbon emission in China. *Chinese Journal of Population, Resources and Environment*, 21(8): 80–86. (in Chinese)

Liu C, Gao M, Zhu G *et al*., 2021. Data driven eco-efficiency evaluation and optimization in industrial production. *Energy*, 224: 120170.

Liu J, Jin X, Xu W *et al*., 2020. A new framework of land use efficiency for the coordination among food, economy and ecology in regional development. *Science of The Total Environment*, 710: 135670.

Liu J, Zhang J, Fu Z, 2017. Tourism eco-efficiency of Chinese coastal cities: Analysis based on the DEA-Tobit model. *Ocean and Coastal Management*, 148: 164–170.

Liu M, Zhang A, Wen G, 2021. Temporal and spatial pattern and evolution trend of cultivated land use ecological efficiency in the main grain-producing areas in the Lower Yangtze Region. *China Land Science*, 35(2): 50–60. (in Chinese)

Liu M, Zhang A, Wen G, 2022. Regional differences and spatial convergence in the ecological efficiency of cultivated land use in the main grain producing areas in the Yangtze Region. *Journal of Natural Resources*, 37(2): 477–493. (in Chinese)

Liu X, Zhao C, Song W, 2017. Review of the evolution of cultivated land protection policies in the period following China's reform and liberalization. *Land Use Policy*, 67: 660–669.

Liu Y, Zhang A, Liu M, 2022. Analysis on the spatiotemporal pattern of coupling degree of urbanization and cultivated land use eco-efficiency in main grain producing areas in the mid and lower reaches in Yangtze River. *Chinese Journal of Agricultural Resources and Regional Planning*, 43(8): 106–118. (in Chinese)

Liu Y, Zhu J, Li E Y *et al*., 2020. Environmental regulation, green technological innovation, and eco-efficiency: The case of Yangtze River Economic Belt in China. *Technological Forecasting and Social Change*, 155: 119993.

Liu Y, Zou L, Wang Y, 2020. Spatial-temporal characteristics and influencing factors of agricultural eco-efficiency in China in recent 40 years. *Land Use Policy*, 97: 104794.

Lu H, Xie H, Lyu T *et al*., 2019. Determinants of cultivated land recuperation in ecologically damaged areas in China. *Land Use Policy*, 81: 160–166.

Luo Q, Luo L, Zhou Q *et al*., 2019. Does China's Yangtze River Economic Belt policy impact on local ecosystem services? *Science of The Total Environment*, 676: 231–241.

Luo X, Ao X, Zhang Z *et al*., 2020. Spatiotemporal variations of cultivated land use efficiency in the Yangtze River Economic Belt based on carbon emission constraints. *Journal of Geographical Sciences*, 30(4): 535–552.

Luo Y, Lu Z, Salman M *et al*., 2022. Impacts of heterogenous technological innovations on green productivity: An empirical study from 261 cities in China. *Journal of Cleaner Production*, 334: 130241.

Lyu H, Xu Y, Cheng W *et al*., 2018. Flooding hazards across southern China and prospective sustainability measures. *Sustainability*, 10(5): 1682.

Ma L, Zhang R, Pan Z *et al*., 2022. Analysis of the evolution and influencing factors of temporal and spatial pattern of eco-efficiency of cultivated land use among provinces in China: Based on Panel Data from 2000 to 2019. *China Land Science*, 36(3): 74–85. (in Chinese)

Ministry of Ecology and Environment of the People's Republic of China *et al.*, 2020. The Second National Pollution Source Census Bulletin. Beijing.

Ministry of Environmental Protection and Ministry of Land and Resources, 2014. National Soil Pollution Survey Bulletin. Beijing.

Myles A J, Feudale R N, Liu Y *et al*., 2004. An introduction to decision tree modeling. *Journal of Chemometrics: A Journal of the Chemometrics Society*, 18(6): 275–285.

National Bureau of Statistics of China, 2022. Announcement of the National Bureau of Statistics on 2021 grain output data. http://www.stats.gov.cn/tjsj/zxfb/202112/t20211206_1825058.html.

Niu S, Fang B, 2019. Cultivated land protection system in China from 1949 to 2019: Historical evolution, realistic origin exploration and path optimization. *China Land Science*, 33(10): 1–12. (in Chinese)

OECD, 1998. Eco-efficiency. https://www.oecd-ilibrary.org/environment/eco-efficiency_9789264040304-en.

Peng B, Wang Y, Wei G, 2020. Energy eco-efficiency: Is there any spatial correlation between different regions? *Energy Policy*, 140: 111404.

Peng H, Zhang J, Lu L *et al*., 2017. Eco-efficiency and its determinants at a tourism destination: A case study of Huangshan National Park, China. *Tourism Management*, 60: 201–211.

Political Bureau of the Central Committee of the Communist Party of China, 2016. Yangtze River Economic Belt Development Plan Outline. Beijing.

Post W M, Kwon K C, 2000. Soil carbon sequestration and land-use change: Processes and potential. *Global Change Biology*, 6(3): 317–327.

Quinlan J R, 1986. Induction of decision trees. *Machine Learning*, 1(1): 81–106.

Rybaczewska-Błażejowska M, Gierulski W, 2018. Eco-efficiency evaluation of agricultural production in the EU-28. *Sustainability*, 10(12): 4544.

Schaltegger S, Sturm A, 1990. Ökologische rationalität: ansatzpunkte zur ausgestaltung von ökologieorientierten managementinstrumenten. *Die Unternehmung*, 44: 273–290.

Sun C, Chen L, Tian Y, 2018. Study on the urban state carrying capacity for unbalanced sustainable development regions: Evidence from the Yangtze River Economic Belt. *Ecological Indicators*, 89: 150–158.

Tone K, 2001. A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, 130(3): 498–509.

Tsoraeva E, Bekmurzov A, Kozyrev S *et al*., 2020. Environmental issues of agriculture as a consequence of the intensification of the development of agricultural industry. In: E3S Web of Conferences, 215: 02003.

Vásquez-Ibarra L, Rebolledo-Leiva R, Angulo-Meza L *et al*., 2020. The joint use of life cycle assessment and data envelopment analysis methodologies for eco-efficiency assessment: A critical review, taxonomy and future research. *Science of The Total Environment*, 738: 139538.

Wang K, Wang J, Wang J *et al*., 2020. Investigating the spatiotemporal differences and influencing factors of green water use efficiency of Yangtze River Economic Belt in China. *PLOS ONE*, 15(4): e0230963.

Wang Q, Lang H, Zhong J *et al*., 2022. Progress review on land science research in 2021 and prospects for 2022. *China Land Science*, 36(3): 104–115. (in Chinese)

WBCSD, 1996. Eco-efficient leadership for improved economic and environmental performance. World Business Council for Sustainable Development.

West T O, Marland G, 2002. Net carbon flux from agricultural ecosystems: methodology for full carbon cycle analyses. *Environmental Pollution*, 116(3): 439–444.

Xiao Q, Zhou Z, Luo Q, 2021. Spatial-temporal differentiation and spatial effects of grain production in the Yangtze River Economic Belt. *Chinese Journal of Agricultural Resource and Regional Planning*, 42(12): 89–101. (in Chinese)

Yang B, Wang Z, Zou L *et al*., 2021. Exploring the eco-efficiency of cultivated land utilization and its influencing factors in China's Yangtze River Economic Belt, 2001–2018. *Journal of Environmental Management*, 294: 112939.

Yin Y, Hou X, Liu J *et al*., 2022. Detection and attribution of changes in cultivated land use ecological efficiency: A case study on Yangtze River Economic Belt, China. *Ecological Indicators*, 137: 108753.

Zhang C, Chen P, 2021. Industrialization, urbanization, and carbon emission efficiency of Yangtze River Economic Belt: Empirical analysis based on stochastic frontier model. *Environmental Science and Pollution Research*, 28(47): 66914–66929.

Zhang D, Jia Q, Xu X *et al*., 2019. Assessing the coordination of ecological and agricultural goals during ecological restoration efforts: A case study of Wuqi County, Northwest China. *Land Use Policy*, 82: 550–562.

Zhang J, He J, Zhang G *et al*., 2020. Ecological benefit, spatial spillover and fiscal transfer of farmland in watershed: Evidence from the Yangtze River Economic Belt. *Issues in Agricultural Economy*, (12): 120–132. (in Chinese)

Zhang S, Hu W, Li M *et al*., 2021. Multiscale research on spatial supply-demand mismatches and synergic strategies of multifunctional cultivated land. *Journal of Environmental Management*, 299: 113605.

Zhang Z, Yu Y, Wang D *et al*., 2021. Socio-economic drivers of rising CO_2 emissions at the sectoral and sub-regional levels in the Yangtze River Economic Belt. *Journal of Environmental Management*, 290: 112617.

Zhao C, Zhou Y, Jiang J *et al*., 2021. Spatial characteristics of cultivated land quality accounting for ecological environmental condition: A case study in hilly area of northern Hubei province, China. *Science of The Total Environment*, 774: 145765.

Zhou C, Shi C, Wang S *et al*., 2018. Estimation of eco-efficiency and its influencing factors in Guangdong province based on Super-SBM and panel regression models. *Ecological Indicators*, 86: 67–80.

Zhou X, Lei K, 2020. Influence of human-water interactions on the water resources and environment in the Yangtze River Basin from the perspective of multiplex networks. *Journal of Cleaner Production*, 265: 121783.

Zhou Y, Kong Y, Sha J *et al*., 2019. The role of industrial structure upgrades in eco-efficiency evolution: Spatial correlation and spillover effects. *Science of The Total Environment*, 687: 1327–1336.

Zou L, Liu Y, Wang Y *et al*., 2020. Assessment and analysis of agricultural non-point source pollution loads in China: 1978–2017. *Journal of Environmental Management*, 263: 110400.