

Understanding the change of land space utilization efficiency with different functions and its coupling coordination:

A case study of Urban Agglomeration in the Middle Reaches of the Yangtze River, China

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Abstract: Land spaces function in capacities of urban development, agricultural production, and ecological conservation, among many others. Research of land space utilization efficiency (LSUE) and coupling coordination relationships among its subsystems are significant for sustainable land space development. In this study, taking the Urban Agglomeration in the Middle Reaches of the Yangtze River (UAMRYR) as the study area, we establish a measurement index system to evaluate the LSUE (2000–2018) and analyze its coupling coordination degree by utilizing an improved coupling coordination model. The main results include the following. (1) The average efficiency levels of urban space and agricultural space in the UAMRYR increased 2000–2018, while the average efficiency of ecological space declined. (2) The spatial pattern of the LSUE values varied greatly, with the distributions of high-efficiency and low-efficiency levels significantly different. (3) The coupling degree of LSUE includes three types, i.e., high-level coupling, break-in, and antagonism. Each coupling degree type was characterized by change over time. (4) The proportion of areas with high coupling coordination and moderate coupling coordination increased from 2000 to 2018, while the proportion of areas with basic coupling coordination, moderate imbalance, and serious imbalance declined during this period. Given that the spatial differentiation of the LSUE and its coupling coordination, it is necessary to implement a differential land space development strategy in the UAMRYR. This study is helpful to promote the efficient utilization and coordinated development of land space utilization systems.

Keywords: land use; utilization efficiency; coupling coordination; sustainable development; Urban Agglomeration in the Middle Reaches of the Yangtze River

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1 Introduction

Since the reform and opening-up of China in recent years, the economy has developed rapidly (Han *et al.*, 2020). GDP increased from 362.41 billion yuan to 9030.95 billion yuan from 1978 to 2018 with an annual average increase of 31.99% and the average urbanization level rose from 17.9% to 59.58% in the forty years (Wang *et al.*, 2020; Lai and Zhu, 2022). This rapid development has caused a variety of issues. Urban space has been expanding in a disorderly fashion, with demand for construction land rapidly increasing (Xu *et al.*, 2019; Li *et al.*, 2020b). At present, about 15%–30% of the stock construction land in China is idle or being inefficiently utilized (Jiao *et al.*, 2020). Furthermore, environmental impacts are often ignored when utilizing land space resources (Hanaček and Rodríguez-Labajos, 2018; Yang *et al.*, 2020a). Large amounts of industrial wastewater, nitrogen oxides, dust, sulfur dioxide, and other pollutants are discharged, causing serious environmental problems (Nin *et al.*, 2016; Zou *et al.*, 2020; Oliveira-Andreoli *et al.*, 2021). With the rapid development of urbanization and industrialization in China, some agricultural production spaces and ecological conservation spaces are co-opted for development, which poses threats to the food security and ecological security of the country (Su *et al.*, 2016; Zhou and Li, 2017; Wang *et al.*, 2021b). In addition, the excessive utilization of production materials, such as pesticides and chemical fertilizers, have led to the deterioration of water quality, soil compaction, heavy metal pollution, and reduction of biodiversity, resulting in the structure and function of regional ecosystems being seriously degraded (He *et al.*, 2019; Liang *et al.*, 2019; Zou *et al.*, 2020). These issues indicate that the traditional mode of driving economic growth through the consumption and extensive utilization of land space resources is unsustainable. Therefore, improving land space utilization efficiency (LSUE) has become an inevitable choice to ensure sustainable development.

LSUE is a significant indicator for measuring regional land space development and utilization quality (Liu *et al.*, 2019a; Yang *et al.*, 2020a). Various studies to date have primarily focused on the measurement methods (Lewis and Brabec, 2005; Blancard and Martin, 2014; Yang *et al.*, 2020a), spatial differences (Lu *et al.*, 2018; Luo *et al.*, 2020; Tan *et al.*, 2021) and their influencing factors (Xie *et al.*, 2018a; He *et al.*, 2020; Yang *et al.*, 2021). Others have explored the optimal utilization path and development strategies of land space resources from regional and national perspectives (Liu *et al.*, 2019a; Dong *et al.*, 2020; Chilombo and Van Der Horst, 2021). Overall, these studies only targeted the LSUE in a single land use type, such as urban construction land (Lu *et al.*, 2018; Tan *et al.*, 2021; Zhao *et al.*, 2021a), industrial land (Xie *et al.*, 2018a; Jiang, 2021), cultivated land (Wang *et al.*, 2015; Kuang *et al.*, 2020), development zones (Huang *et al.*, 2017; Sun *et al.*, 2020), or urban agglomeration areas (Yu *et al.*, 2019; Ding *et al.*, 2021). With new urbanization and regional coordinated development strategies, these studies are insufficient to promote optimal utilization and sustainable development of land space. In particular, the interactions and coupling coordination between urban efficiency, agriculture efficiency, and ecological efficiency is neglected.

The Urban Agglomeration in the Middle Reaches of the Yangtze River (UAMRYR) is an important part of the Yangtze River Economic Belt of China. The total GDP of the UAMRYR reached 7027.547 billion yuan in 2018¹, a core role in China's economic devel-

¹Data come from the China Statistical Yearbook.

opment. The UAMRYR is a key area for promoting the economic rise of the central China region, a pioneering area for new urbanization, and a demonstration area for inland opening and cooperation (Sun *et al.*, 2018; Zheng and He, 2021). Because of the prominent strategic position and rapid urbanization development, land use in this region has become increasingly intense (Yang *et al.*, 2020a). Therefore, it is of great importance to coordinate land use among urban development, agricultural production, and ecological conservation in the UAMRYR.

In this study, we establish a measurement index system for the LSUE covering urban space, agriculture space, and ecological space with the undesirable externalities explicitly considered. An improved coupling coordination model is applied to investigate the interaction between the three land uses. The main objectives in this study include (1) evaluating the LSUE values using an SBM-Undesirable model; (2) revealing spatio-temporal characteristics of the LSUE 2000–2018 in the UAMRYR; (3) exploring the coupling coordination of the three subsystems. This research will be of significance for promoting the coordinated development of land resources, thereby ensuring the healthy and stable development of the economy and society.

2 Theoretical framework

2.1 Analysis of the land space utilization system

2.1.1 Structure and function of the land space utilization system

Land space is a complex territorial system composed of three subsystems, i.e., urban space utilization, agricultural space utilization, and ecological space utilization (Wang *et al.*, 2018; Jin *et al.*, 2020). The urban space utilization system has several functions, including supporting economic development, industrial agglomeration, social stability, and living services, and providing land, assets, and capital (Liu *et al.*, 2019a; Kurowska *et al.*, 2021). The land types of the urban space utilization system include urban construction land, industrial and mining land, and other construction lands. The agricultural space utilization system plays an important role in ensuring national food security and maintaining social stability (Tudor, 2014; Zhao *et al.*, 2021b). The agricultural space utilization system provides grain, cotton, oil, fishing, animal husbandry, and a variety of raw materials for human survival and development. The system also has a strong social security function by accommodating labor force demand and providing a living space for rural residents (Yang *et al.*, 2020b). These areas include cultivated land (paddy fields, drylands) and rural residential land. An ecological space utilization system can provide some indispensable substances for human survival, e.g., organic matter, air, and water (Wu *et al.*, 2018; Fu *et al.*, 2021). The system performs functions such as soil conservation, climate regulation, and biodiversity protection (Liu *et al.*, 2019b; Grêt-Regamey and Weibel, 2020; Li *et al.*, 2020a). These areas include forests, grasslands, water bodies, and other non-developed lands.

2.1.2 Interaction mechanisms of land space utilization system

The three subsystems interact to provide a basis for sustainable development (Figure 1). The urban space utilization system provides economic benefits including a variety of social security services (Liu *et al.*, 2020a). It provides means of production (e.g., fertilizer, pesticide,

seeds, plastic film), funds, and related technical support for agricultural space. A series of ecological space capacities, including restoration, protection, and governance, can be carried out by financial and technical support provided by the urban space subsystem. The agricultural space utilization system provides basic material resources, such as grain, cotton, linen, and oil for human survival and production, which plays a basic role in guaranteeing the high-quality development of urban space. The agricultural space utilization system also has some ecological service functions and can promote ecological space-efficient utilization. The ecological space utilization system supports human survival and production by providing natural products and services, which support the urban and agricultural subsystems. The three subsystems interact with each other and promote the stable and sustainable development of the overall land space utilization system.

2.2 Workflow of this study

We designed a workflow of this study (Figure 2) for the objectives which were proposed in the Introduction. First, we established the measurement index system of LSUE from the perspective of input and output. Second, the SBM-Undesirable model was used to quantitatively measure the level of LSUE and examine the spatio-temporal characteristics of land space subsystem efficiencies. Third, we modeled the coupling coordination relationship among land space subsystem efficiencies. Fourth, land space development strategies based on the spatial differences are proposed to promote the efficient utilization and coordinated development of the overall land space utilization system. Additionally, this paper concentrates on the administrative division of the Urban Agglomeration in the Middle Reaches of the Yangtze River at the county level from 2000 to 2018, including 165 counties (or districts) in total.

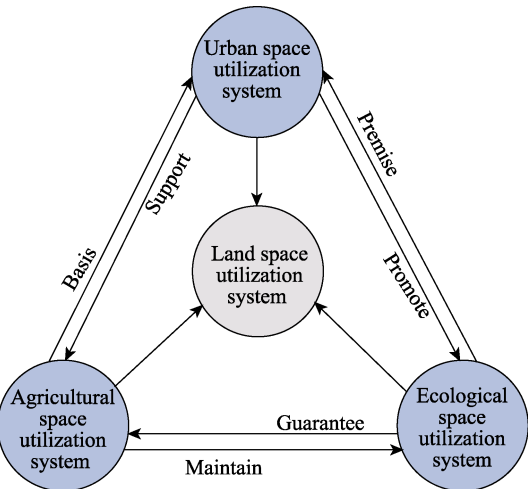


Figure 1 The interaction of land space utilization sub-systems

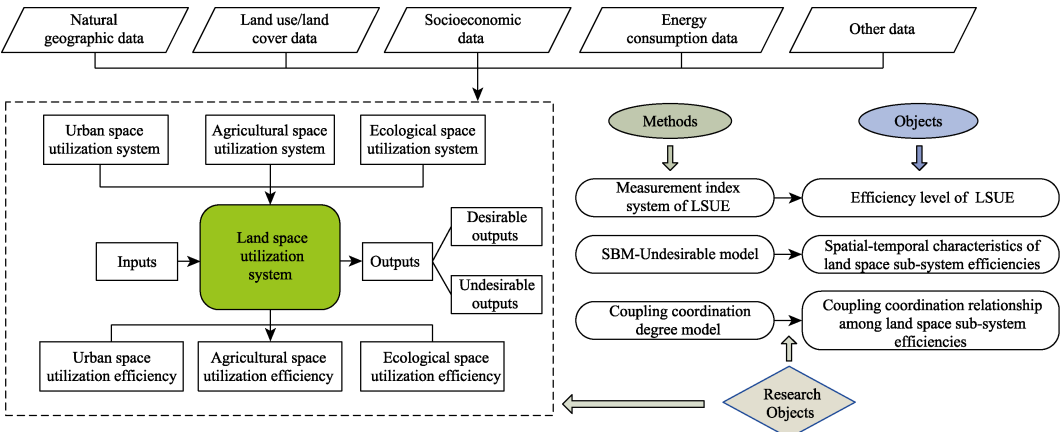


Figure 2 The workflow of this study

3 Materials and methods

3.1 Study area

The UAMRYR is situated in central China, covering three provinces: Hubei, Hunan, and Jiangxi (Figure 3). The UAMRYR's total area is about 326,900 km² and the region is composed of three metropolitan areas, i.e., Wuhan Metropolis, Poyang Lake City Group, and Changsha-Zhuzhou-Xiangtan Metropolis. UAMRYR is in a basin, with the surrounding areas higher elevation and the center flat terrain. The land space types in the UAMRYR include urban, agricultural, and ecological space, accounting for 4.86%, 36.77%, and 58.37% of the total area, respectively. In recent years, the UAMRYR has developed rapidly and has become an important agricultural and industrial production base of China. The GDP of the region was 694.21 billion yuan in 2000 and it reached 7.03 trillion yuan in 2018, with an average growth rate of 13.90%¹. Moreover, the urbanization level in this region increased from 19.23% in 2000 to 54.71% in 2018.

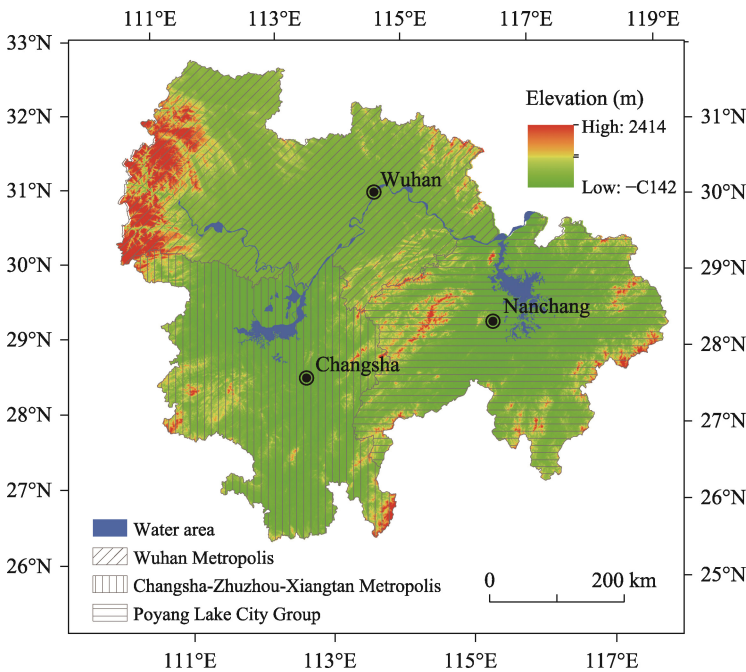


Figure 3 Location and elevation of the Middle Reaches of the Yangtze River (UAMRYR)

3.2 Measurement index system of land space utilization efficiency

There are not only interactions between the three subsystems, but also significant differences in utilization objectives. Therefore, the measurement indicators of different space utilization efficiency should be designed according to their functional characteristics. The measurement index of urban space utilization efficiency was mainly used to measure the quality of urban space utilization, which was divided into two parts: urban space inputs and outputs of social, economic, and environmental aspects, which included eight variables. We selected urban

¹ Data come from China Statistical Yearbook.

construction land areas to characterize land input (AI-1). Fixed asset investment reflects the scale, structure, and cost of the government's investment in urban space, so we used the total fixed-asset investment to characterize the capital input (AI-2). The number of employees in the secondary and tertiary industries was used to represent the input of labor (AI-3). As GDP is an important indicator that characterizes regional economic development, we selected the GDP of the secondary and tertiary industries to represent the economic output (AO-1). The employment of urban residents maintains social stability and promotes social development. Therefore, the average salary of urban employees was used to represent the social output of urban space utilization (AO-2). Urban space not only results in the production of industrial products and economic benefits but also causes pollution (Tan *et al.*, 2021; Zhang *et al.*, 2021). Based on existing research (Yue and Li, 2017; Lu *et al.*, 2018; Sun *et al.*, 2018; Yu *et al.*, 2019), we chose industrial wastewater discharge (AO-3), industrial sulfur dioxide discharge (AO-4), and the amount of solid waste (AO-5) to represent the negative environmental outputs.

The measurement indicators of agricultural space utilization efficiency also include two parts, i.e., agricultural inputs and outputs of social, economic, and environmental aspects, with a total of nine variables. Inputs variables comprise three parts: land, labor, and means of production. The sown area of crops can better reflect the production and utilization of agricultural land than the area of cultivated land at the end of the year (Yang *et al.*, 2021), so the sown area of crops is used to characterize the land input for agricultural space utilization (BI-1). We selected the number of employees in the primary industry to characterize the input of labors for agricultural space utilization (BI-2). The means of production used in agricultural space primarily refer to various machinery, fertilizers, pesticides, and seeds needed for agricultural production (Kuang *et al.*, 2020; Xie *et al.*, 2018b). We selected the total power of agricultural machinery (BI-3), the amount of agricultural film used (BI-4), and the amount of chemical fertilizer (BI-5) to characterize the input of agricultural production materials.

Among the outputs, the total agricultural output value reflects the economic benefits brought by various crops (Han and Zhang, 2020), therefore, we choose the annual agricultural output value to represent the economic output (BO-1). The per capita annual income of farmers reflects the well-being of rural residents, which plays an important role in maintaining the stability and development of rural society (Liu *et al.*, 2020b). Based on this, we select the per capita annual income as the social output for agricultural space (BO-2). However, because of agricultural machinery, plowing activities, and the use of agricultural films, fertilizers, and pesticides, pollution is inevitable. Referring to existing literature (Feng *et al.*, 2015; Xie *et al.*, 2018b; Kuang *et al.*, 2020; Yang *et al.*, 2022), we choose agricultural non-point source pollution and carbon emissions as the undesirable outputs in this study. The main sources of agricultural non-point pollution are chemical fertilizers, organic fertilizers, and farmland wastes. The calculation method was as follows. First, we calculated the total nitrogen (TN), total phosphorus (TP), and chemical oxygen demand (COD) resulting from agricultural production (Table 1). Then, we converted to equal standard emissions based on the formula: equal standard pollutant emissions = initial pollutant emissions/pollutant emission assessment criteria. According to Feng *et al.* (2015), the emission assessment standards of COD, TN, and TP were set as 20 mg/L, 1 mg/L, and 0.2 mg/L, respectively.

Table 1 Composition and measurement of agricultural non-point source pollutions

Pollution source	Measurement	Reference
Chemical fertilizers	Nitrogen fertilizer, phosphorus fertilizer, compound fertilizer \times TN/TP pollution coefficient \times loss rate	Li <i>et al.</i> (2011)
Organic fertilizers	Rural population and the number of pigs, cattle, sheep, and poultry \times (1 - the rate of utilization) \times Fecal and urine excretion coefficient \times pollution coefficients of COD, TN, and TP	Chen <i>et al.</i> (2006); Pan and Ying (2013)
Farmland wastes	Crop straw, fruit, and vegetable outputs \times pollution coefficients of COD, TN, and TP	Li <i>et al.</i> (2011)

Carbon emissions from agricultural production mainly come from the two aspects. One aspect is the use of means of agriculture production, such as chemical fertilizers and plastic film for agriculture. Another aspect is carbon emissions from the use of electricity and fossil fuels for agricultural machinery and irrigation. The estimation formula is:

$$C = \sum E_i \times \varepsilon_i \quad (1)$$

where C is the total carbon emission from agricultural production, E_i is the carbon emission from various carbon sources, and ε_i is the carbon emission coefficient corresponding to carbon sources. According to relevant research, the carbon emission coefficients are summarized in Table 2.

Table 2 Agricultural carbon emission coefficients

Carbon source	Coefficients	Units	References
Chemical fertilizers	0.896	kg·kg ⁻¹	West and Marland (2002)
Plastic film	5.170	kg·kg ⁻¹	Li <i>et al.</i> (2011)
Agricultural machinery	0.190	kg·kw ⁻¹	Tian <i>et al.</i> (2012)
Agricultural plowing	312.580	kg·km ⁻²	Tian and Zhang (2013)
Agricultural irrigation	20.476	kg·hm ⁻²	Li <i>et al.</i> (2011)

The measure indicator of ecological space utilization efficiency is the ability to maintain regional water and soil conservation, climate regulation, environmental purification, and biodiversity. In this study, we take the proportion of ecological land area as the input variable (CI-1); forests, grasslands, garden lands, water bodies, and marshland are defined as ecological land (Wang *et al.*, 2018; Chen *et al.*, 2019). Socio-economic development inevitably consumes energy, which has some impacts on the ecological environment. Therefore, we chose energy consumption per unit GDP as the energy inputs (CI-2). We selected the ecosystem service value as the output variable (CO-1), which is referred to in the research results of Xie *et al.* (2015). The calculation is:

$$ESV = \sum S_k \cdot VC_k \quad (2)$$

where ESV is the total value of ecosystem services, S_k represents the land area of the k th land type, and VC_k represents the evaluation value coefficient of the k th land type.

3.3 SBM-Undesirable model

Data envelopment analysis (DEA) is widely used to measure efficiency, as proposed by Charnes *et al.* (1978), which is referred to as the Charnes-Cooper-Rhodes (CCR) model. In

Table 3 The measurement index system of the land space utilization efficiency

Criteria		Level indicators	Units	Attributes
Urban space utilization efficiency (A)	Inputs	Urban construction land area (AI-1)	ha	+
		Total investment in fixed assets (AI-2)	100 million yuan	+
		People employed in secondary and tertiary industries (AI-3)	persons	+
	Outputs	GDP of secondary and tertiary industries (AO-1)	100 million yuan	desirable output
		Average wages of urban workers (AO-2)	yuan	desirable output
		Discharge of industrial wastewater (AO-3)	tons	undesirable output
		Emissions of industrial SO ₂ (AO-4)	tons	undesirable output
		Emissions of solid waste discharge (AO-5)	tons	undesirable output
Agricultural space utilization efficiency (B)	Inputs	The sown area of crops (BI-1)	ha	+
		People employed in primary industry (BI-2)	person	+
		Total power of agricultural machinery (BI-3)	10,000 kilowatts	+
		Amount of agricultural film (BI-4)	tons	–
		Amount of chemical fertilizer (BI-5)	tons	–
	Outputs	The annual output value of agriculture (BO-1)	100 million yuan	desirable output
		Per capita annual income of farmers (BO-2)	yuan	desirable output
		Agricultural non-point source pollution (BO-3)	ton	undesirable output
Ecological space utilization efficiency (C)	Inputs	The proportion of ecological land area (CI-1)	%	+
		Energy consumption per unit of GDP (CI-2)	tons	–
	Outputs	Ecosystem service value (CO-1)	yuan	desirable output

traditional DEA models, the efficiency measurements of homogeneous units are mainly based on the radial and angle levels to minimize inputs and maximize outputs. However, it ignores the undesirable outputs in the evaluation process. To end this, Tone (2001) overcame this problem by developing a slack-based measure (SBM) model based on non-radials and non-angles, which can measure the inefficiency incorporating the desirable and undesirable outputs at different rates. The specific computational formulas are:

$$\begin{aligned} \min \rho &= \frac{\frac{1}{m} \sum_{i=1}^n (x^- / x_{i0})}{\frac{1}{r_1 + r_2} \left(\sum_{s=1}^{r_1} y^{d-} / y_{s0}^d + \sum_{q=1}^{r_2} y^{u-} / y_{q0}^u \right)} \\ \text{s.t. } x^- &\geq \sum_{j=1, \neq 0}^n x_{ij} \lambda_j; y^{d-} \leq \sum_{j=1, \neq 0}^n y_{sj}^d \lambda_j; \\ y^{d-} &\geq \sum_{j=1, \neq 0}^n y_{qj}^d \lambda_j; x^- \geq x_0; y^{d-} \leq y_0^d; y^{u-} \geq y_0^u; \\ \lambda_j &\geq 0, i = 1, 2, \dots, m; j = 1, 2, \dots, n, j \neq 0; \\ s &= 1, 2, \dots, r_1; q = 1, 2, \dots, r_2 \end{aligned} \tag{3}$$

where ρ is the value of LSUE, n is the number of evaluation units, the evaluation index con-

sists of input index (m) and output index (desirable output index r_1 and undesirable output index r_2), x , y^d , and y^u are the elements of the input matrix, including desirable output matrix and undesirable output matrix, respectively. The vectors of x^- , y^{d-} , and y^{u-} are the input relaxation vector, the desirable output relaxation vector, and the undesirable output relaxation vector, respectively; λ is the weight vector.

3.4 Coupling coordination degree model

The concept of coupling originates from physics, which is widely used to describe the interaction between two or more subsystems (Zhang *et al.*, 2008; Li *et al.*, 2012; Tang, 2015). The classical formula of the coupling degree model is:

$$C = \sqrt[n]{\left\{ (u_1, u_2, \dots, u_n) / \left[\prod (u_i + u_j) \right] \right\}} \quad (4)$$

where u_1, u_2, \dots , and u_n represent the measure functions of each subsystem.

This model is simple and practical. However, the measurement of the coupling degree is zero when one subsystem's value is zero. In addition, the numerical range of the measurement is usually narrow and lacks a strict hierarchy. Referring to existing research (Zhang *et al.*, 2008; Liu *et al.*, 2018; Tomal, 2021), we derived an improved coupling degree model as follows:

$$C = \left[2 - \frac{3 \times (U_1^2 + U_2^2 + U_3^2)}{(U_1 + U_2 + U_3)^2} \right]^K \quad (5)$$

where K represents the adjustment coefficient and $K \geq 3$. The value range of C is $[0, 1]$. The larger it is, the higher the coupling degree is. When the values of U_1, U_2 and U_3 are equal, the value of C is 1, indicating that the coupling degree is the highest. When the value of C is 0, the subsystems are completely uncoupled and are in an independent state.

Based on the coupling degree measurement model, we expanded the connotation of the model and constructed the coupling coordination degree model. The calculation formulas are:

$$U = \alpha U_1 + \beta U_2 + \gamma U_3 \quad (6)$$

$$D = \sqrt{C \times U} \quad (7)$$

where C is the coupling degree, D represents the coupling coordination degree, U is the comprehensive value of the LSUE, and α, β and γ are the weight coefficients of U_1, U_2 , and U_3 , respectively.

3.5 Data sources

The data in this study include land use, Digital Elevation Model (DEM) data, and socioeconomic data. Land use data were derived from the Resources and Environmental Data Center of The Chinese Academy of Sciences (<http://www.resdc.cn>) in 2000, 2005, 2010, 2015, and 2018, with a resolution of $30 \text{ m} \times 30 \text{ m}$. We reclassified the land use types into six categories (i.e., arable land, woodland, grassland, water, construction land, and unutilized land). The DEM data at a 30 m spatial resolution were derived from the website of the Geospatial Data Cloud, Chinese Academy of Sciences (<http://www.gscloud.cn>). Moreover, with the help of surface analysis in ArcGIS, topographic factors, such as elevation and slope, were obtained

based on DEM data. Socioeconomic data include Gross Domestic Product (GDP), population, urban development, agricultural production, medical and health, and environment. These data were collected from the Statistical Yearbooks for Hubei, Hunan, and Jiangxi provinces in 2001, 2006, 2011, 2016, and 2019. Energy consumption data, such as coal, petroleum, and natural gas, were derived from the Chinese Energy Statistical Yearbook and City Statistical Yearbook in the study area.

4 Results

4.1 The evolution of land space utilization efficiency in the UAMRYR

Based on Formula (3), we measured urban space utilization efficiency in the UAMRYR from 2000 to 2018. Then we calculated the regional and integral average efficiency of the study area, as shown in Figure 4. It was found that the urban efficiency continuously improved from 2000 to 2018, increasing from 0.556 in 2000 to 0.703 in 2018, with an average increase of 6.06%. From the perspective of regions, the efficiency of three sub-metropolitan areas all improved 2000–2018. The efficiency of the Wuhan metropolitan area increased from 0.528 in 2000 to 0.682 in 2018, with an average increase of 6.68%. The efficiency of Changsha-Zhuzhou-Xiangtan urban agglomeration increased from 0.582 in 2000 to 0.745 in 2018, with an average increase of 6.36%. The efficiency of Poyang Lake urban agglomeration increased from 0.572 in 2000 to 0.695 in 2018, with an average increase of 5.01%. The average value of urban space use efficiency was highest in the Changzhou-Zhuzhou- Xiangtan urban agglomeration, the second-highest in the Poyang Lake urban agglomeration, and the lowest in the Wuhan Metropolitan area.

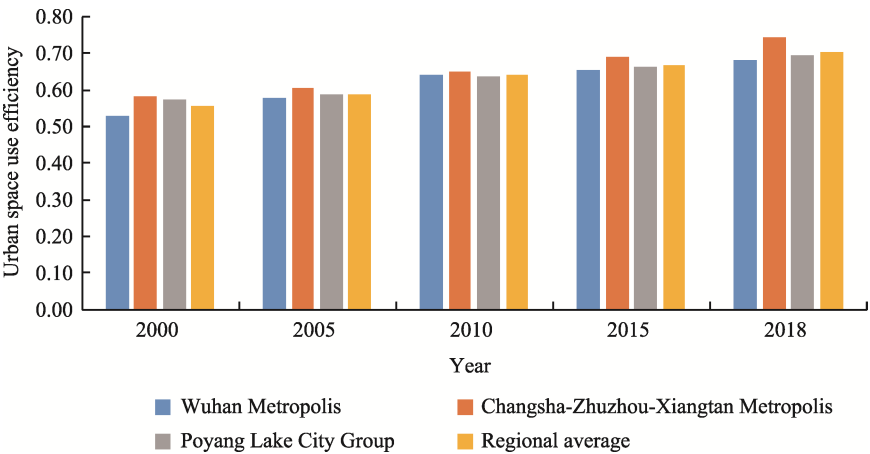


Figure 4 The results of urban space use efficiency in the UAMRYR from 2000 to 2018

Based on Formula (3), we measured agriculture space utilization efficiency in the UAMRYR 2000–2018. Then we calculated the regional and integral average efficiency of the study area, as shown in Figure 5. It is found that agriculture efficiency continuously improved from 2000 to 2018. The efficiency value increased from 0.495 in 2000 to 0.686 in 2018, with an average increase of 8.53%. From the perspective of regions, the agricultural space utilization efficiency of the three sub-metropolitan areas all improved 2000–2018. The

efficiency of the Wuhan metropolitan area increased from 0.550 in 2000 to 0.746 in 2018, with an average increase of 7.91%. The efficiency of Changsha-Zhuzhou-Xiangtan urban agglomeration increased from 0.460 in 2000 to 0.672 in 2018, with an average increase of 9.96%. The efficiency of Poyang Lake urban agglomeration increased from 0.445 in 2000 to 0.613 in 2018, with an average increase of 8.33%. The average value of agriculture efficiency was the highest in the Wuhan Metropolitan area, the second-highest in the Changzhou-Zhuzhou-Xiangtan urban agglomeration, and the lowest in Poyang Lake urban agglomeration.

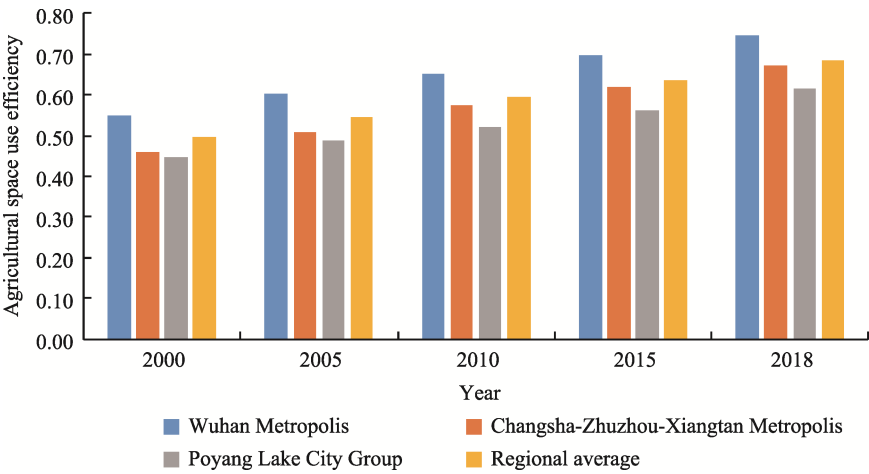


Figure 5 The results of agricultural space use efficiency in the UAMRYR from 2000 to 2018

We also measured ecological space use efficiency in the UAMRYR 2000–2018 based on Formula (3) and calculated the regional and integral average efficiency, as shown in Figure 6. It is found that the average efficiency in the UAMRYR declined from 0.661 in 2000 to 0.612 in 2018. From the perspective of regions, the ecological efficiency of the three sub-metropolitan areas all declined from 2000 to 2018. The efficiency of the Wuhan metropolitan area declined from 0.720 in 2000 to 0.678 in 2018. The efficiency of Changsha-Zhuzhou-Xiangtan urban agglomeration declined from 0.639 in 2000 to 0.570 in 2018.

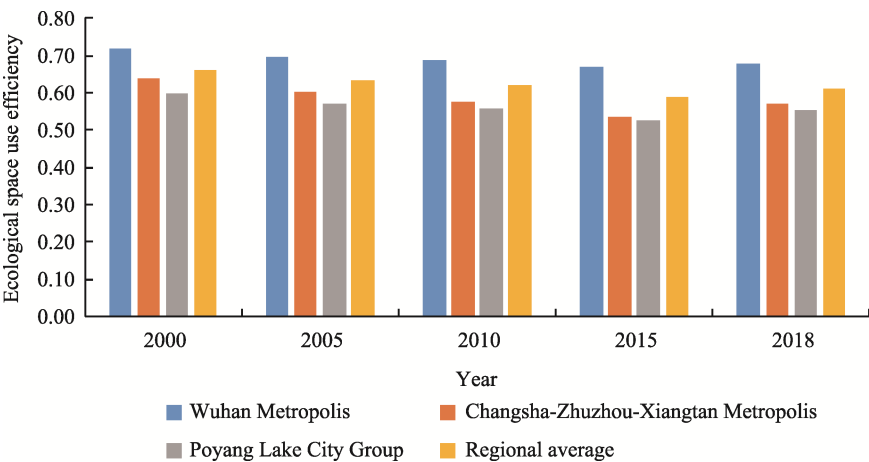


Figure 6 The results of ecological space use efficiency in the UAMRYR from 2000 to 2018

The efficiency of Poyang Lake urban agglomeration declined from 0.598 in 2000 to 0.553 in 2018. The average value of ecological efficiency was highest in the Wuhan metropolitan area, the second-highest in the Changsha-Zhuzhou-Xiangtan urban agglomeration, and the lowest in Poyang Lake urban agglomeration.

4.2 Spatio-temporal characteristics of land space utilization efficiency in the UAMRYR

4.2.1 Urban space utilization efficiency

Figure 7 depicts the spatio-temporal variations of urban space utilization efficiency in the study area for the selected five years. In addition, to compare the efficiency level of different areas, we divided the efficiency values into four categories: high efficiency (0.75–1.00], medium-high efficiency (0.50–0.75], medium-low efficiency (0.35–0.50], and low efficiency (0.00–0.35]. Overall, the number of counties (districts) with high and medium-high efficiency levels increased, while the number of counties (districts) with medium-low and low-efficiency levels decreased 2000–2018. This indicates that urban space use efficiency in the UAMRYR showed a significant improving trend during the study period. Areas with high-efficiency levels were mainly distributed in Wuhan, Changsha, Nanchang, and their surrounding counties. It is worth noting that the efficiency in some counties (districts) of Yichang and Xiangyang increased after 2015. The main reasons may be the increasing input of production factors, optimization of industrial structure, and rapid improvement of economic development level in these areas. Areas of low efficiency were primarily distributed around the UAMRYR and some counties (districts) bordering Hubei and Jiangxi. These areas are mostly mountainous with a high elevation and large slope gradient, which is not conducive to the development and utilization of urban space. Being far away from the central cities, some favorable factors, such as industrial agglomeration, factor inputs, and preferential policies are limited, resulting in the urban efficiency remaining at a lower level.

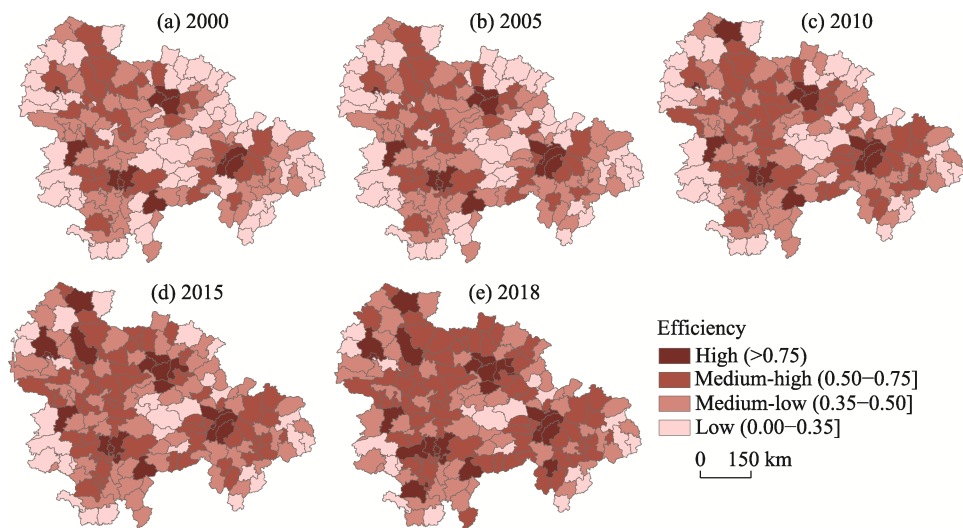


Figure 7 Spatio-temporal variations of urban space use efficiency in the UAMRYR from 2000 to 2018

4.2.2 Agricultural space utilization efficiency

Figure 8 shows the spatio-temporal variations of agricultural space utilization efficiency in

the study area for the selected five years. Moreover, in order to compare the efficiency level of different areas, we divided the efficiency values into four categories: high efficiency (0.75–1.00], medium-high efficiency (0.50–0.75], medium-low efficiency (0.35–0.50], and low efficiency (0.00–0.35]. Overall, the number of counties (districts) with high and medium-high efficiency levels increased, while the number of counties (districts) with medium-low and low-efficiency levels decreased 2000–2018. At the end of 2000, the number of counties (districts) with high efficiency, medium-high efficiency, medium-low efficiency, and low efficiency was 9, 54, 62, and 40, respectively. At the end of 2018, the number of counties (districts) with high efficiency and medium-high efficiency increased to 22 and 94, the amount of medium-low efficiency declined to 48, while only one county was at low efficiency. Areas with high efficiency were distributed in the Jiangnan Plain (e.g., Jianli County, Zhongxiang City, and Chibi City), Dongting Lake Plain (e.g., Yueyang County and Huarong County), and Poyang Lake Plain (e.g., Yugan County and Boyang County). These areas have flat terrain and fertile soil, as well as abundant light, heat, and water, resulting in high agricultural outputs and high agricultural production efficiency. Areas with low efficiency are concentrated in the marginal areas of the region and mountainous areas bordering Hubei and Jiangxi Provinces. Only two counties (Zigui and Xingshan) had low efficiency at the end of 2015, and only one county (Zigui) had low efficiency at the end of 2018, indicating that agricultural space utilization efficiency in the UAMRYR primarily was at high and medium-high levels after 2015.

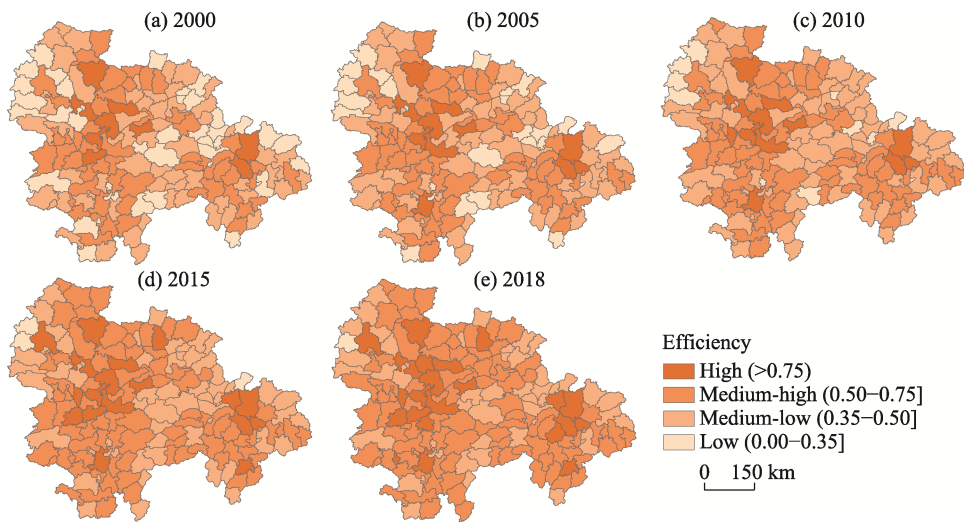


Figure 8 Spatio-temporal variations of agricultural space use efficiency in the UAMRYR from 2000 to 2018

4.2.3 Ecological space utilization efficiency

Figure 9 depicts the spatio-temporal variations of ecological space utilization efficiency in the study area for the selected five years. Overall, the number of counties (districts) with high and medium-high efficiency levels decreased first and then increased, the number of counties (districts) with medium-low efficiency levels was stable, and the number of counties (districts) with low-efficiency levels increased first and then decreased. Areas with high-efficiency levels were mainly distributed in the surrounding areas of the region and

border areas of Hubei and Jiangxi. The main reason may be that the terrain in these areas is mountainous with rich ecological resources, and some functions such as water and soil conservation, air purification, water conservation, and biodiversity are robust. Also, urbanization and industrialization in these areas are relatively low and the ecological environment is relatively preserved. Areas with low efficiency are primarily located in the central area of the UAMRYR, especially in the surrounding areas of Wuhan, Changsha, and Nanchang.

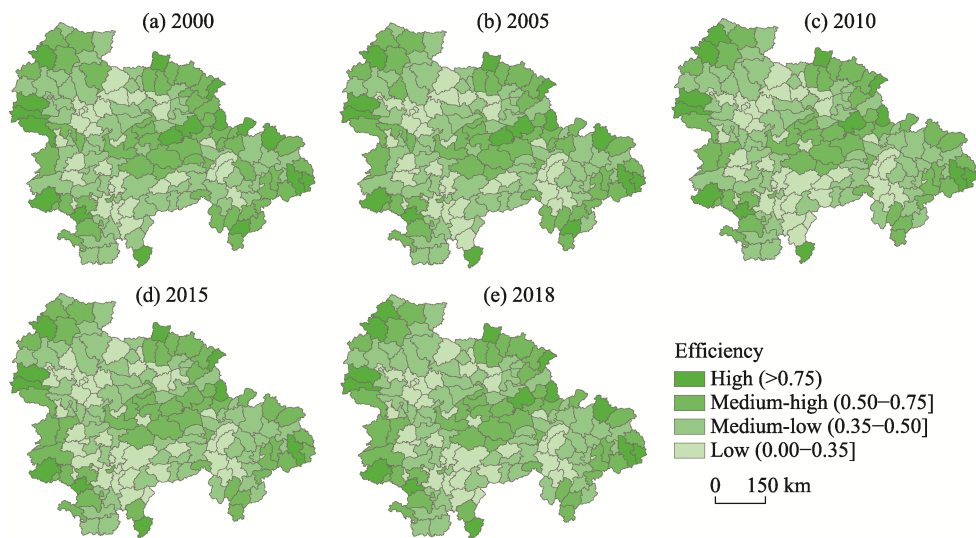


Figure 9 Spatio-temporal variations of ecological space use efficiency in the UAMRYR from 2000 to 2018

4.3 Coupling coordination of land space utilization efficiency

The coupling degrees of the LSUE were calculated based on formula (5) and were visualized with ArcGIS 10.2 software as shown in Figure 10. To analyze the intensity of interaction among urban efficiency, agricultural efficiency, and ecological efficiency, we divided the coupling degrees of LSUE into three categories: high-level coupling state (>0.80), break-in state (0.50–0.80], and antagonism state (0.00–0.50]. The coupling degrees of the LSUE were generally at the break-in stage and high coupling stage 2000–2018 (Figure 11). This suggests that land space sub-systems have obvious interactive effects with one another. The counties (or districts) with high-level coupling stages were mainly distributed in a strip from the northwest to southeast of the study area, and these areas gradually expanded over time. Areas with break-in stages were distributed in a wide range, covering the entire UAMRYR, whereas areas with antagonism stage were few, mainly distributed around the study area and at the border of Hubei and Jiangxi provinces. The proportion of the counties (or districts) at the high-level coupling stage of the three efficiencies increased during the study period, from 50.91% in 2000 to 58.79% in 2018 (Figure 11). The proportion at the break-in stage fluctuated, whereas the proportion of the counties (or districts) at the antagonism stage declined over time from 14.55% in 2000 to 6.06% in 2018. In sum, the charge in proportions for coupling stages indicated that the interactive effects of the three subsystems were increasing over time.

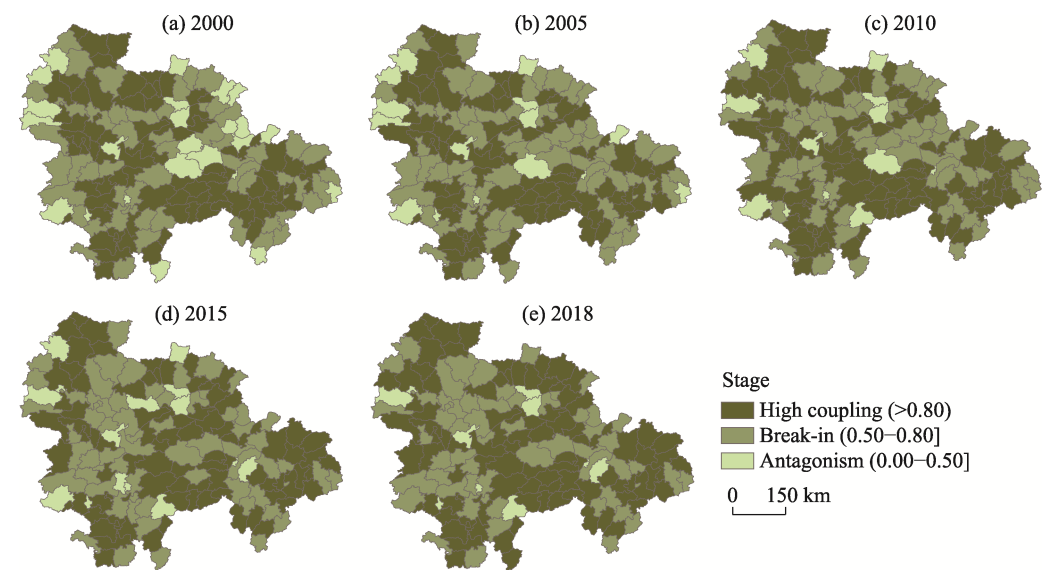


Figure 10 Spatio-temporal variations of coupling degree in the UAMRYR from 2000 to 2018

Based on the results of coupling degree in the UAMRYR, we calculated the coupling coordination of the three efficiencies by formulas (6) and (7) at the county level in the study area 2000–2018. Referring to existing research (Cheng *et al.*, 2019; Yang *et al.*, 2020b), we divided the coupling coordination degree into five states: high coupling coordination (0.800–1.000], moderate coupling coordination (0.600–0.799], basic coupling coordination (0.400–0.599], moderate imbalance (0.200–0.399], and serious imbalance (0.000–0.199]. Spatio-temporal distribution was visualized with ArcGIS 10.2 software as shown in Figure 12. Spatially, the spatial pattern characteristics were similar to that of the coupling degree in the UAMRYR. The areas in various coupling coordination states showed a relatively random distribution in the study area. During the study period, the total number of counties (or districts) with moderate coupling coordination and basic coupling coordination types accounted for more than 90% of areas (Figure 13). From the perspective of temporal scale, the proportion of counties (or districts) with high coupling coordination and moderate coupling coordination increased, while the proportion of counties (or districts) with basic coupling coordination, moderate imbalance, and serious imbalance declined 2000–2018. For instance, the change of moderate imbalance was 4.85%→2.42%→1.21%→0.00%→0.00% over time, the change of basic coupling coordination was 49.09%→42.42%→32.73%→33.33%→24.24%, and that of moderate coupling coordination was 45.45%→55.15%→63.64%→62.42%→69.09%. This indicated that the coupling coordination degree of the LSUE in the UAMRYR has shown a good trend during the study period.

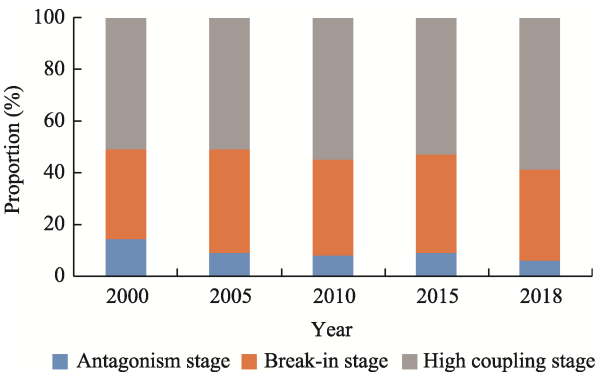


Figure 11 The proportion of areas at different coupling stages 2000–2018 in the UAMRYR

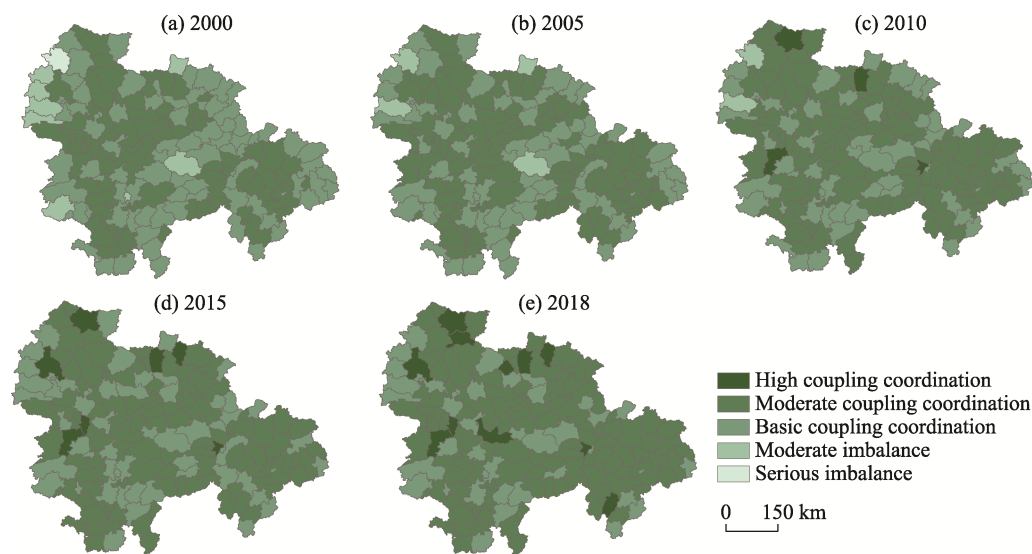


Figure 12 Spatio-temporal variations of coupling coordination degree in the UAMRYR from 2000 to 2018

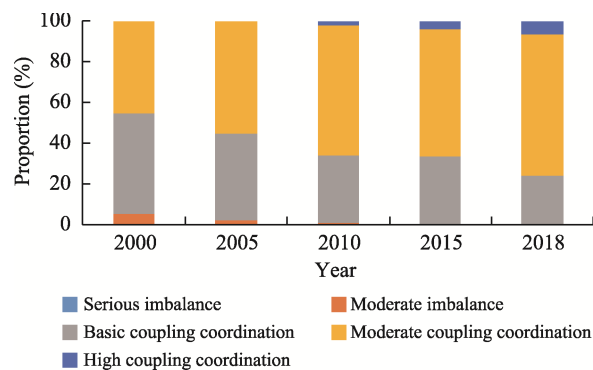


Figure 13 The proportion of areas at different coupling coordination stages 2000–2018 in the UAMRYR

5 Discussion

5.1 Factors influencing land space utilization efficiency

The LSUE levels are influenced by multiple factors, such as natural geographic factors, socioeconomic development level, and regional policies (Wang *et al.*, 2015; Yue and Li, 2017; Liu *et al.*, 2020a; Yang *et al.*, 2021). Natural geographic factors, including topography, climate, hydrology, and location conditions are the basis for land space utilization, which fundamentally affect the LSUE (Liu *et al.*, 2021a; Zhou *et al.*, 2017; Zhang *et al.*, 2020). Specifically, elevation and topographic variation directly restrict the development and utilization of urban space (Birhane *et al.*, 2019). Likewise, for agricultural space, the differences in natural conditions such as slope, elevation, temperature, and precipitation are the basis to determine agricultural production activities (Pan and Ying, 2013; Liu *et al.*, 2020b). From the perspective of location condition, the better is it, the greater the land space development intensity (Wang *et al.*, 2021a). The distance from the central city and main traffic arteries has a significant influence on the development and utilization of urban space through factors

such as land prices and agglomeration effects (Lu and Ke, 2018; Gao *et al.*, 2020; Qu *et al.*, 2020). The distance to rivers, main roads, and the nearest rural settlements can affect agricultural space development and affects drive its spatio-temporal trends (Liu *et al.*, 2020b; Ma *et al.*, 2021). For the ecological space, the farther away from the main roads and residential areas, the less disturbance from human activities, and the higher of ecosystem service values (Chen *et al.*, 2020; Ouyang *et al.*, 2021).

The socio-economic development level directly affects the degree of land space development and utilization, which has a direct impact on the investment capacity of urban space, determines its development and utilization intensity, and thus plays an important role in mediating efficiency (Lu *et al.*, 2018; Gao *et al.*, 2020; Zhao *et al.*, 2021a). For agricultural space, the impact of socioeconomic development on agricultural efficiency includes two aspects. First, the socio-economic development level affects the input of means of production, such as labor force, machinery, seeds, and plastic films for agricultural production, and directly affects the utilization efficiency (Yang *et al.*, 2021). Second, the level of agricultural science and technology advances in rapid socioeconomic developing regions is generally high, which will further promote the optimization of agricultural space (Xie *et al.*, 2018b; Kuang *et al.*, 2020). For ecological space, the socio-economic development and urban land expansion will inevitably co-opt large amounts of ecological space, which results in environmental pollution and ecological deterioration, thus affecting ecological space utilization efficiency (Wang *et al.*, 2018; Zheng and He, 2021).

In addition, some policy systems have an important influence on LSUE. Regional integration can upgrade and optimize the urban industrial structure, reduce carbon emissions, and improve urban space utilization efficiency by promoting factor flow and regional cooperation (Gao *et al.*, 2020; Wen *et al.*, 2021). With industrialization and urbanization, the area of cultivated land is decreasing and its quality is degraded, which poses a great threat to the country's food security (Deng *et al.*, 2015; Yang *et al.*, 2021). To this end, the government has formulated a series of measures and policies to protect cultivated land, which plays an important role in improving farmland utilization efficiency and ensuring national food security. Faced with the reality of environmental deterioration in recent years, the government introduced a series of ecological compensation policies, which improved ecological efficiency and promoted sustainable development (Hu *et al.*, 2019; Lu *et al.*, 2021). Also, some environmental systems, such as carbon emissions permit trading systems and environmental pollution control investments, have impacts on LSUE (Xian *et al.*, 2020; Fan *et al.*, 2021).

5.2 Policy implications

Based on this study's findings, several policy implications can be drawn. First, because of the different patterns of coupling and coordination relationships among land space sub-system efficiencies, a differential land space development strategy should be implemented that varies by region. Areas surrounding the UAMRYR with high ecological efficiency should actively explore an eco-priority growth path to promote sustainable socio-economic growth. For the rapidly developing economic areas, such as Wuhan, Changsha, and Nanchang, it is necessary to optimize the industrial structure and further improve urban space utilization efficiency (Liu *et al.*, 2021b). Investments should be increased for ecological space protection and promote the coordinated development of urban construction and

ecological conservation in these areas. For agricultural production bases in the central UAMRYR, the government should strengthen the cultivated land protection to further improve agricultural production and food security. Further, scientific and technological innovation strategies should be advanced. This will be helpful to drive the transformation of secondary and tertiary industries to gradually eliminate enterprises with high energy consumption and low output. It will also promote the large-scale modernization of agricultural production to reduce production costs and increase outputs. Finally, the government should strengthen regional cooperation and integrated development to improve the LSUE in the whole region.

5.3 Limitations

This paper has some limitations. First, the coupling and coordination relationships of LSUE were based on limited available data, leaving some important influencing mechanisms remain unclear. Future studies should select specific factors and models to reveal the key mechanisms driving the coupling coordination of the LSUE. Second, the conclusions in this paper are only based on land space optimal utilization. How to guide land space optimal utilization based on the utilization efficiency and to solve specific issues in practice, such as through the improvement of policy regulations, warrants more study.

6 Conclusions

In this paper, taking the UAMRYR as the study area, we establish a measurement index system to quantify the LSUE by using the SBM-Undesirable model 2000–2018. An improved coupling coordination model was applied to investigate the coupling coordination degree of the LSUE. The main conclusions included the following. (1) The average efficiencies of urban space and agricultural space in the UAMRYR both increased from 2000 to 2018, while the average efficiency of ecological space declined. (2) The spatial pattern of the LSUE varies greatly. Areas with a high level of urban space utilization efficiency were mainly distributed in Wuhan, Changsha, Nanchang, and their surrounding areas, while areas with low-efficiency levels were primarily distributed around the UAMRYR and some areas bordering Hubei and Jiangxi. Areas with a high level of agricultural space utilization efficiency were mainly distributed in the central UAMRYR, while areas with low efficiency concentrated in the marginal areas of the region. Areas with a high level of ecological space utilization efficiency were mainly distributed in the surrounding areas of the UAMRYR and the borders of Hubei and Jiangxi, while areas with low efficiency are mainly located in the central areas. (3) The coupling degree of LSUE in the UAMRYR includes three types, i.e., high-level coupling, break-in degree, and antagonism. The proportion of areas at the high-level coupling stage of the three efficiencies increased during the study period, from 50.91% in 2000 to 58.79% in 2018. The proportion at break-in degree fluctuated through the period. The proportion of areas at the antagonism degree level declined over time, from 14.55% in 2000 to 6.06% in 2018. (4) The proportion of areas with high coupling coordination and moderate coupling coordination continuously increased, while the proportion of areas with basic coupling coordination, moderate imbalance, and serious imbalance during 2000–2018. These findings can promote the efficient utilization and coordinated development of land space systems. Given the spatial differentiation of the LSUE and its coupling

coordination degree, it is necessary to implement a land space development strategy that differs by region in the UAMRYR.

References

- Birhane E, Ashfare H, Fenta A A *et al.*, 2019. Land use land cover changes along topographic gradients in Hurgumburda national forest priority area, northern Ethiopia. *Remote Sensing Applications: Society and Environment*, 13: 61–68.
- Blancard S, Martin E, 2014. Energy efficiency measurement in agriculture with imprecise energy content information. *Energy Policy*, 66: 198–208.
- Charnes A, Cooper W W, Rhodes E, 1978. Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2: 429–444.
- Chen M, Chen J, Lai S, 2006. Inventory analysis and spatial distribution of Chinese agricultural and rural pollution. *China Environmental Science*, 6: 751–755. (in Chinese)
- Chen W, Chi G, Li J, 2019. The spatial association of ecosystem services with land use and land cover change at the county level in China, 1995–2015. *Science of The Total Environment*, 669: 459–470.
- Chen W, Chi G, Li J, 2020. The spatial aspect of ecosystem services balance and its determinants. *Land Use Policy*, 90: 104263.
- Cheng X, Long R, Chen H *et al.*, 2019. Coupling coordination degree and spatial dynamic evolution of a regional green competitiveness system: A case study from China. *Ecological Indicators*, 104: 489–500.
- Chilombo A, Van Der Horst D, 2021. Livelihoods and coping strategies of local communities on previous customary land in limbo of commercial agricultural development: Lessons from the farm block program in Zambia. *Land Use Policy*, 104: 105385.
- Deng X, Huang J, Rozelle S *et al.*, 2015. Impact of urbanization on cultivated land changes in China. *Land Use Policy*, 45: 1–7.
- Ding T, Yang J, Wu H *et al.*, 2021. Land use efficiency and technology gaps of urban agglomerations in China: An extended non-radial meta-interactive effects of urban land-use efficiency, industrial transformation, and carbon emissions. *Journal of Cleaner Production*, 270: 122547.
- Fan Q, Qiao Y, Zhang T *et al.*, 2021. Environmental regulation policy, corporate pollution control and economic growth effect: Evidence from China. *Environmental Challenges*, 5: 100244.
- Feng Y, Peng J, Deng Z *et al.*, 2015. Spatial-temporal variation of cultivated land utilization efficiency in China based on the dual perspective of non-point source pollution and carbon emission. *China Population, Resources and Environment*, 25(8): 18–25. (in Chinese)
- Fu B, Stafford-Smith M, Wang Y *et al.*, 2021. The Global-DEP conceptual framework: Research on dryland ecosystems to promote sustainability. *Current Opinion in Environmental Sustainability*, 48: 17–28.
- Gao X, Zhang A, Sun Z, 2020. How regional economic integration influence on urban land use efficiency? A case study of Wuhan metropolitan area, China. *Land Use Policy*, 90: 104329.
- Grêt-Regamey A, Weibel B, 2020. Global assessment of mountain ecosystem services using earth observation data. *Ecosystem Services*, 46: 101213.
- Han H, Zhang X, 2020. Static and dynamic cultivated land use efficiency in China: A minimum distance to strong efficient frontier approach. *Journal of Cleaner Production*, 246: 119002.
- Han Y, Liu Z, Ma J, 2020. Growth cycles and business cycles of the Chinese economy through the lens of the unobserved components model. *China Economic Review*, 63: 101317.
- Hanaček K, Rodríguez-Labajos B, 2018. Impacts of land-use and management changes on cultural agroecosystem services and environmental conflicts: A global review. *Global Environmental Change*, 50: 41–59.
- He J, Pan Z, Liu D *et al.*, 2019. Exploring the regional differences of ecosystem health and its driving factors in China. *Science of The Total Environment*, 673: 553–564.
- He S, Yu S, Li G *et al.*, 2020. Exploring the influence of urban form on land-use efficiency from a spatiotemporal heterogeneity perspective: Evidence from 336 Chinese cities. *Land Use Policy*, 95: 104576.

- Hu Y, Huang J, Hou L, 2019. Impacts of the grassland ecological compensation policy on household livestock production in China: An empirical study in Inner Mongolia. *Ecological Economics*, 161: 248–256.
- Huang Z, He C, Zhu, S, 2017. Do China's economic development zones improve land use efficiency? The effects of selection, factor accumulation and agglomeration. *Landscape and Urban Planning*, 162: 145–156.
- Jiang H, 2021. Spatial-temporal differences of industrial land use efficiency and its influencing factors for China's central region: Analyzed by SBM model. *Environmental Technology & Innovation*, 22: 101489.
- Jiao L, Xu Z, Xu G *et al.*, 2020. Assessment of urban land use efficiency in China: A perspective of scaling law. *Habitat International*, 99: 102172.
- Jin G, Shi X, He D *et al.*, 2020. Designing a spatial pattern to rebalance the orientation of development and protection in Wuhan. *Journal of Geographical Sciences*, 30(4): 569–582.
- 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.
- Kurowska K, Adamska-Kmieć D, Kowalczyk C *et al.*, 2021. Communication value of urban space in the urban planning process on the example of a Polish city. *Cities*, 116: 103282.
- Lai P, Zhu T, 2022. Deflating China's nominal GDP: 2004–2018. *China Economic Review*, 71: 101709.
- Lewis G M, Brabec E, 2005. Regional land pattern assessment: Development of a resource efficiency measurement method. *Landscape and Urban Planning*, 72: 281–296.
- Li B, Zhang J, Li H, 2011. Research on spatial-temporal characteristics and influencing factors decomposition of agricultural carbon emission in China. *China Population, Resources and Environment*, 21(8): 80–86. (in Chinese)
- Li S, Zhang H, Zhou X *et al.*, 2020a. Enhancing protected areas for biodiversity and ecosystem services in the Qinghai–Tibet Plateau. *Ecosystem Services*, 43: 101090.
- Li Y, Li Y, Zhou Y, *et al.*, 2012. Investigation of a coupling model of coordination between urbanization and the environment. *Journal of Environmental Management*, 98: 127–133.
- Li Z, Luan W, Zhang Z *et al.*, 2020b. Relationship between urban construction land expansion and population/economic growth in Liaoning Province, China. *Land Use Policy*, 99: 105022.
- Liang L, Wang Z, Li J, 2019. The effect of urbanization on environmental pollution in rapidly developing urban agglomerations. *Journal of Cleaner Production*, 237: 117649.
- Liu C, Xu Y, Lu X *et al.*, 2021a. Trade-offs and driving forces of land use functions in ecologically fragile areas of northern Hebei Province: Spatiotemporal analysis. *Land Use Policy*, 104: 105387.
- Liu J, Hou X, Wang Z *et al.*, 2021b. Study the effect of industrial structure optimization on urban land-use efficiency in China. *Land Use Policy*, 105: 105390.
- Liu J, Jin X, Xu W *et al.*, 2019a. Spatial coupling differentiation and development zoning trade-off of land space utilization efficiency in eastern China. *Land Use Policy*, 85: 310–327.
- Liu J, Jin X, Xu W, *et al.*, 2020a. 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 W, Jiao F, Ren L *et al.*, 2018. Coupling coordination relationship between urbanization and atmospheric environment security in Jinan City. *Journal of Cleaner Production*, 204: 1–11.
- Liu Y, Li T, Zhao W *et al.*, 2019b. Landscape functional zoning at a county level based on ecosystem services bundle: Methods comparison and management indication. *Journal of Environmental Management*, 249: 109315.
- Liu Y, Zou L, Wang Y, 2020b. Spatial-temporal characteristics and influencing factors of agricultural eco-efficiency in China in recent 40 years. *Land Use Policy*, 97: 104794.
- Lu S, Lu W, Shao W *et al.*, 2021. The transboundary ecological compensation construction based on pollution rights: Ways to keep the natural resources sustained. *Resources Policy*, 74: 102401.
- Lu X, Ke S, 2018. Evaluating the effectiveness of sustainable urban land use in China from the perspective of sustainable urbanization. *Habitat International*, 77: 90–98.
- Lu X, Kuang B, Li J, 2018. Regional difference decomposition and policy implications of China's urban land use

- efficiency under the environmental restriction. *Habitat International*, 77: 32–39.
- 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.
- Ma L, Long H, Tang L *et al.*, 2021. Analysis of the spatial variations of determinants of agricultural production efficiency in China. *Computers and Electronics in Agriculture*, 180: 105890.
- Nin M, Soutullo A, Rodríguez-Gallego L *et al.*, 2016. Ecosystem services-based land planning for environmental impact avoidance. *Ecosystem Services*, 17: 172–184.
- Oliveira-Andreoli E Z, Moraes M C P D, Faustino A D S *et al.*, 2021. Multi-temporal analysis of land use land cover interference in environmental fragility in a Mesozoic basin, southeastern Brazil. *Groundwater for Sustainable Development*, 12: 100536.
- Ouyang X, Tang L, Wei X *et al.*, 2021. Spatial interaction between urbanization and ecosystem services in Chinese urban agglomerations. *Land Use Policy*, 109: 105587.
- Pan D, Ying R, 2013. Agricultural eco-efficiency evaluation in China based on SBM model. *Acta Ecologica Sinica*, 33(12): 3837–3845. (in Chinese)
- Qu S, Hu S, Li W *et al.*, 2020. Temporal variation in the effects of impact factors on residential land prices. *Applied Geography*, 114: 102124.
- Su Y, Chen X, Liao J, *et al.*, 2016. Modeling the optimal ecological security pattern for guiding the urban constructed land expansions. *Urban Forestry & Urban Greening*, 19: 35–46.
- Sun X, Cheng S, Lang J *et al.*, 2018. Development of emissions inventory and identification of sources for priority control in the middle reaches of Yangtze River Urban Agglomerations. *Science of The Total Environment*, 625: 155–167.
- Sun Y, Ma A, Su H *et al.*, 2020. Does the establishment of development zones really improve industrial land use efficiency? Implications for China's high-quality development policy. *Land Use Policy*, 90: 104265.
- Tan S, Hu B, Kuang B *et al.*, 2021. Regional differences and dynamic evolution of urban land green use efficiency within the Yangtze River Delta, China. *Land Use Policy*, 106: 105449.
- Tang Z, 2015. An integrated approach to evaluating the coupling coordination between tourism and the environment. *Tourism Management*, 46: 11–19.
- Tian Y, Zhang J, 2013. Regional differentiation research on net-carbon effect of agricultural production in China. *Journal of Natural Resources*, 28(8): 1298–1309. (in Chinese)
- Tian Y, Zhang J, Li B, 2012. Agricultural carbon emissions in China: Calculation, spatial-temporal comparison and decoupling effects. *Resources Science*, 34(11): 83–91. (in Chinese)
- Tomal M, 2021. Evaluation of coupling coordination degree and convergence behaviour of local development: A spatiotemporal analysis of all Polish municipalities over the period 2003–2019. *Sustainable Cities and Society*, 71: 102992.
- Tone K, 2001. A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, 130: 498–509.
- Tudor M M, 2014. Utilization of land resources in agriculture: Opportunity or risk for romanian agri-food sector competitiveness. *Procedia Economics and Finance*, 8: 720–728.
- Wang G, Liu Y, Li, Y *et al.*, 2015. Dynamic trends and driving forces of land use intensification of cultivated land in China. *Journal of Geographical Sciences*, 25(1): 45–57.
- Wang H, Lu S, Lu B *et al.*, 2021a. Overt and covert: The relationship between the transfer of land development rights and carbon emissions. *Land Use Policy*, 108: 105665.
- Wang J, He T, Lin Y, 2018. Changes in ecological, agricultural, and urban land space in 1984–2012 in China: Land policies and regional social-economical drivers. *Habitat International*, 71: 1–13.
- Wang L, Zheng W, Tang L *et al.*, 2021b. Spatial optimization of urban land and cropland based on land production capacity to balance cropland protection and ecological conservation. *Journal of Environmental Management*, 285: 112054.
- Wang Z, Xu X, Wang H *et al.*, 2020. Does land reserve system improve quality of urbanization? Evidence from

- China. *Habitat International*, 106: 102291.
- Wen L, Chatalova L, Gao X *et al.*, 2021. Reduction of carbon emissions through resource-saving and environment-friendly regional economic integration: Evidence from Wuhan metropolitan area, China. *Technological Forecasting and Social Change*, 166: 120590.
- West T O, Marland G, 2002. A synthesis of carbon sequestration, carbon emissions, and net carbon flux in agriculture: comparing tillage practices in the United States. *Agriculture, Ecosystems & Environment*, 91.
- Wu X, Wang S, Fu B *et al.*, 2018. Land use optimization based on ecosystem service assessment: A case study in the Yanhe watershed. *Land Use Policy*, 72: 303–312.
- Xian Y, Wang K, Wei Y *et al.*, 2020. Opportunity and marginal abatement cost savings from China's pilot carbon emissions permit trading system: Simulating evidence from the industrial sectors. *Journal of Environmental Management*, 271: 110975.
- Xie G, Zhang C, Zhang L *et al.*, 2015. Improvement of the evaluation method for ecosystem service value based on per unit area. *Journal of Natural Resources*, 30(8): 1243–1254. (in Chinese)
- Xie H, Chen Q, Lu F *et al.*, 2018a. Spatial-temporal disparities, saving potential and influential factors of industrial land use efficiency: A case study in urban agglomeration in the middle reaches of the Yangtze River. *Land Use Policy*, 75: 518–529.
- Xie H, Chen Q, Wang W *et al.*, 2018b. Analyzing the green efficiency of arable land use in China. *Technological Forecasting and Social Change*, 133: 15–28.
- Xu G, Jiao L, Yuan M *et al.*, 2019. How does urban population density decline over time? An exponential model for Chinese cities with international comparisons. *Landscape and Urban Planning*, 183: 59–67.
- Yang B, Chen X, Wang Z *et al.*, 2020a. Analyzing land use structure efficiency with carbon emissions: A case study in the middle reaches of the Yangtze River, China. *Journal of Cleaner Production*, 274: 123076.
- 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.
- Yang B, Zhang Z, Wu H, 2022. Detection and attribution of changes in agricultural eco-efficiency within rapid urbanized areas: A case study in the urban agglomeration in the middle reaches of Yangtze River, China. *Ecological Indicators*, 144: 109533.
- Yang Y, Bao W, Liu Y, 2020b. Coupling coordination analysis of rural production-living-ecological space in the Beijing-Tianjin-Hebei region. *Ecological Indicators*, 117: 106512.
- Yu J, Zhou K, Yang S, 2019. Land use efficiency and influencing factors of urban agglomerations in China. *Land Use Policy*, 88: 104143.
- Yue L, Li W, 2017. Typical urban land use efficiency in China under environmental constraints based on DDF-Global Malmquist-Luenberger index modeling. *Resources Science*, 39(4): 597–607. (in Chinese)
- Zhang P, Su F, Li H *et al.*, 2008. Coordination degree of urban population, economy, space, and environment in Shenyang since 1990s. *China Population, Resources and Environment*, 18(2): 115–119. (in Chinese)
- Zhang Z, Li J, Luo X *et al.*, 2020. Urban lake spatial openness and relationship with neighboring land prices: Exploratory geovisual analytics for essential policy insights. *Land Use Policy*, 92: 104479.
- Zhao J, Zhu D, Cheng J *et al.*, 2021a. Does regional economic integration promote urban land use efficiency? Evidence from the Yangtze River Delta, China. *Habitat International*, 116: 102404.
- Zhao Q, Bao H X H, Zhang Z, 2021b. Off-farm employment and agricultural land use efficiency in China. *Land Use Policy*, 101: 105097.
- Zheng Z, He Q, 2021. Spatio-temporal evaluation of the urban agglomeration expansion in the middle reaches of the Yangtze River and its impact on ecological lands. *Science of The Total Environment*, 790: 148150.
- Zhou D, Xu J, Lin Z, 2017. Conflict or coordination? Assessing land use multi-functionalization using production-living-ecology analysis. *Science of The Total Environment*, 577: 136–147.
- Zhou Z, Li M, 2017. Spatial-temporal change in urban agricultural land use efficiency from the perspective of agricultural multi-functionality: A case study of the Xi'an metropolitan zone. *Journal of Geographical Sciences*, 27(12): 1499–1520.
- 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.