

Evaluation, simulation, and optimization of land use spatial patterns for high-quality development: A case study of Zhengzhou city, China

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Abstract: High-intensity land use and resource overloaded-induced regional land use spatial pattern (LUSP) are essential and challenging for high-quality development. The empirical studies have shown that a scientific land uses spatial layout, and the supporting system should be based on a historical perspective and require better considering the double influence between the current characteristics and future dynamics. This study proposes a comprehensive framework that integrates the resource environment carrying capacity (RECC) and land use change (LUC) to investigate strategies for optimizing the spatial pattern of land use for high-quality development. China's Zhengzhou city was the subject of a case study whose datasets include remote sensing, spatial monitoring, statistics, and open sources. Three significant results emerged from the analysis: (1) The RECC has significant spatial differentiation but does not follow a specific spatial law, and regions with relatively perfect ecosystems may not necessarily have better RECC. (2) From 2020 to 2030, the construction land and farmland will fluctuate wildly, with the former increasing by 346.21 km² and the latter decreasing by 295.98 km². (3) The study area is divided into five zones, including resource conservation, ecological carrying, living core, suitable construction, and grain supply zones, and each one has its LUSP optimization orientation. This uneven distribution of RECC reflects functional defects in the development and utilization of LUSP. In addition, the increase in construction land and the sharp decline of farmland pose potential threats to the sustainable development of the study area. Hence, these two elements cannot be ignored in the future high-quality development process. The findings indicate that the LUSP optimization based on dual dimensions of RECC and LUC is more realistic than a single-dimension solution, exhibiting the LUSP optimization's effectiveness and applicability.

Keywords: land use spatial pattern; resource environment carrying capacity; land use change; spatial optimization; high-quality land development; Zhengzhou city

Received: 2021-12-29 **Accepted:** 2022-09-21

Foundation: National Natural Science Foundation of China, No.42071358, No.41671406; Fundamental Research Funds for the Central Universities, No.CCNU22QN018; The Self-Determined Research Funds of CCNU from the Colleges' Basic Research and Operation of MOE, No.CCNU20TS035

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1 Introduction

Land use spatial pattern (LUSP), defined as the organization of geospatial elements formed by natural evolution and human intervention over time (Paikan and David, 2005; Ge and Lu, 2021), is crucial for regional development (Li *et al.*, 2021b). Land use spatial pattern optimization aims to facilitate resource utilization efficiency by adjusting the allocation of geospatial elements (Yue and Wang, 2009; Li *et al.*, 2018b; Li *et al.*, 2021a). The sustainable development goals articulated convincingly that regional development potential depends on efficiency and justice (David *et al.*, 2013; Liu *et al.*, 2016), indicating that the primary pursuit of land use spatial pattern optimization is to enhance quality (Camara *et al.*, 2020). The criteria of LUSP quality were divided into two levels: status and dynamics (Li *et al.*, 2021a). It holds that only the development mode with both high efficiency and sustainability can be termed high-quality land development (Ju and Zhang, 2018; Li and Li, 2019; Fang *et al.*, 2021). A significant number of studies have been conducted on either status or dynamics of LUSP during recent decades. However, the research paradigm of land use spatial pattern optimization for high-quality land development has not yet been established.

The LUSP represents the modes and degrees of geospatial element utilization and describes the current characteristics of the human-nature system relationship (Li *et al.*, 2017b; Shan and Fang, 2018). The principal contradiction of Chinese society is the disharmony of unbalanced and inadequate development and the people's ever-growing need for a better life (Chen *et al.*, 2020b). This reality is embodied in human nature system relationship theory by the coordination degree of spatial resource allocation mode and regional carrying capacity (Li *et al.*, 2017b). This coordination degree depends on the objective characteristics of resource environment elements, which environmentalists call a 'mutual-feed paradox' (Zhou *et al.*, 2020). These studies believe that resource environment elements directly represent the current land use spatial state and fundamentally impact its future evolution (Sun *et al.*, 2020). Unplanned land use can lead to the loss of prominent agricultural land, urban traffic congestion, and ecological degradation, reducing the resources-environment carrying capacity (RECC) (Carlesi *et al.*, 2013). New land use and spatial planning strategies must be developed to meet upcoming challenges. Reorganizing the land-use spatial pattern is one powerful solution that can facilitate more sustainable development implications (Lane, 2010). For example, some scholars have investigated the mutual relationship between land use and RECC. Chen *et al.* (2020a) reported that the places with greater land use change are more prone to RECC. Similar to this proposition, some scholars believe that the RECC is affected by urban development, underground space mining, and increasing changes in blue-green space (Tong *et al.*, 2018). Whether land use activities can meet the requirements of the RECC is a hot topic, and studying the coupling relationship between RECC and land use helped to focus on this issue. However, relatively few researchers have discussed the relationship between land use and the RECC paradox in a single system. The existing experience shows that if land use spatial pattern optimization is conducted only by considering the current status or future evolution, it is likely that resources and opportunities will be allocated to regions with insufficient carrying capacity or even threaten sustainability (Chen *et al.*, 2020a).

In recent years, China's natural resources sector has begun to regard land use spatial pattern optimization based on RECC as a crucial way of ensuring land development quality (Li

et al., 2018a; Niu *et al.*, 2020). Officials urge the reallocation of resources and opportunities based on recognizing the limits of human activities that can be carried out to balance the region's carrying capacity and future development potential (Zhang *et al.*, 2018). Over 70% of the world's cities suffer from resource overuse and environmental degradation (Neus and Wolfgang, 2021). Together, they have demonstrated that the unreasonable LUSP causes overexploitation and waste of resources and that the service value of a regional geospatial system is damaged (Velenturf and Jopson, 2019). Multiple case studies on LUSP development demonstrate that human activities represented by road traffic and urban construction have become the dominant driving factors of land use change in most metropolitan areas (Wu *et al.*, 2021e). Most of these studies have revealed a widely accepted truth that the unreasonable LUSP leads to excessive human intervention in land use spatial evolution (Chen, 2022). Understanding the LUSP of any region usually requires a hierarchical and long-time series approach, which examines the status and potential of LUSP on the resource environment system and land use change (Qi *et al.*, 2020).

UNESCO defines the RECC as "the intensity of human activities that a region can sustain while maintaining an acceptable standard of living and development." In the progress of urban civilization, entities of territorial space, as geospatial carriers, consume geospatial resources and accumulate many artificial exploit activities in the meantime (Yan and Liu, 2017). The carrying capacity of geospatial resources and environmental systems determines aspects—including the control scale, development intensity, and suitable use type—directly and indirectly (Wang and Liu, 2019). These aspects are not always coordinated or matched in various regions and periods. Other empirical studies have indicated that RECC is not always distributed in areas with well-preserved ecosystems but performs better in some urban subcenters (Wang and Liu, 2019). Notably, areas with low RECC are typically densely populated and industrially concentrated, which should improve utilization restrictions and industrial transfer measures. Recently, research on the RECC has attracted the attention of scholars from different disciplines as one of the propositions that cannot be ignored (Niu *et al.*, 2020). These researchers determine the limitation of the regional carrying capacity of human development activities using a complex evaluation method. This method analyzes the carrying capacity of subsystems, including resources, environment, and social economy, by constructing an index system (Niu and Jiang, 2021). Specifically, many investigations concluded that resource environment protection positively impacts LUSP in the regions of the Chinese Yangtze river, northeast of Iran, and Wroclaw, Poland (Ali and Amin, 2016; Sun *et al.*, 2020). These studies also believe that the degradation of urban land resources is related to expanding construction land and economic growth (Long and Zhang, 2019).

Previous studies have successfully simulated regional land use change. Researchers simulate future land use change using cellular automata and other models based on evolution and transformation rules of land use. Many analyses use geospatial models and statistics to measure the dynamics of land use change, such as Cellular Automata (CA), Markov Chain (Wu *et al.*, 2019), Artificial Neural Network (ANN) (Saeedi, 2018), and the Future Land Use Simulation (FLUS). Some studies use these models to simulate the changing trends of future land use under various scenarios, such as natural development, farmland protection, ecological protection (Gidey *et al.*, 2017). Then, it examines the evolution of territorial space from different development perspectives. Other studies identified areas with a high risk of expan-

sion of urban built-up areas and shrinkage of farmland in the future on the premise of simulating land use change and then proposed a reference scheme to optimize LUSP (Lu *et al.*, 2015). The literature review above indicates that the RECC and LUC have a profoundly close relationship with the supply of territorial space and are mutually influential and restrictive. However, it is still unclear how to apply current RECC and future LUC to LUSP optimization research, despite the prevalence of unscientific LUSP-related resource and environment problems.

Sporadic studies investigated LUSP optimization from a single RECC or LUC perspective, providing fruitful references for RECC measurement and LUC simulation. However, these cases cannot consider the dual characteristics of the current situation and future dynamics of territorial space. They are unable to satisfy the refined needs of high-quality land development. Consequently, the main objective of this paper is to systematically analyze the LUSP optimization strategy using a comprehensive approach that simultaneously considers the current state and future dynamics of LUSP. It intends to address three key research questions: (1) What are the dominant drivers of the current state and future dynamics of SPLD? (2) How can SPLD be scientifically optimized under the premise of weighing the current state and future dynamics? (3) What implications can LUSP optimization strategies have for high-quality land development? The states and dynamics of LUSP are characterized by RECC and land use change, which serve as the basis for LUSP optimization analysis.

2 Materials and methods

2.1 Study area

Zhengzhou City is located in the north-central part of Henan Province in Central China (34°16'N–34°58'N, 112°42'E–114°14'E) on the lower reaches of the Yellow River (Figure 1). The terrain is characterized by high elevations in the southwest and low in the northeast. The total area of Zhengzhou city is 7580.92 km², of which the urban built-up area is 1181.51 km², under the jurisdiction of 12 county-level administrative areas, including Zhongyuan (ZY), Erqi (EQ), Guancheng (GC), Jinshui (JS), Shangjie (SJ), Huiji (HJ), Zhongmou (ZM), Gongyi (GY), Xingyang (XY), Xinmi (XM), Xinzheng (XZ), Dengfeng (DF). As the capital of Henan Province, the urbanization process of Zhengzhou has developed rapidly in recent years, and the GDP growth rate in the 10 years from 2010 to 2020 exceeded 197%. At the same time, practical problems such as overexploitation of resources, increased environmental coercion, ecological degradation, and population surge associated with rapid economic growth have successively emerged. According to the Seventh China Population Census data, the permanent population of Zhengzhou is 12.606 million, and the urban population is 9.879 million (Li *et al.*, 2021a). Although Zhengzhou's economic productivity and people's living standards have been significantly improved, there are still many contradictions between urbanization–agriculture–ecology (Ju *et al.*, 2018). The key to achieving high-quality development is how to reasonably trade-off to reorganize and optimize Zhengzhou SPLD based on scientific measurements of the current conditions of the land system.

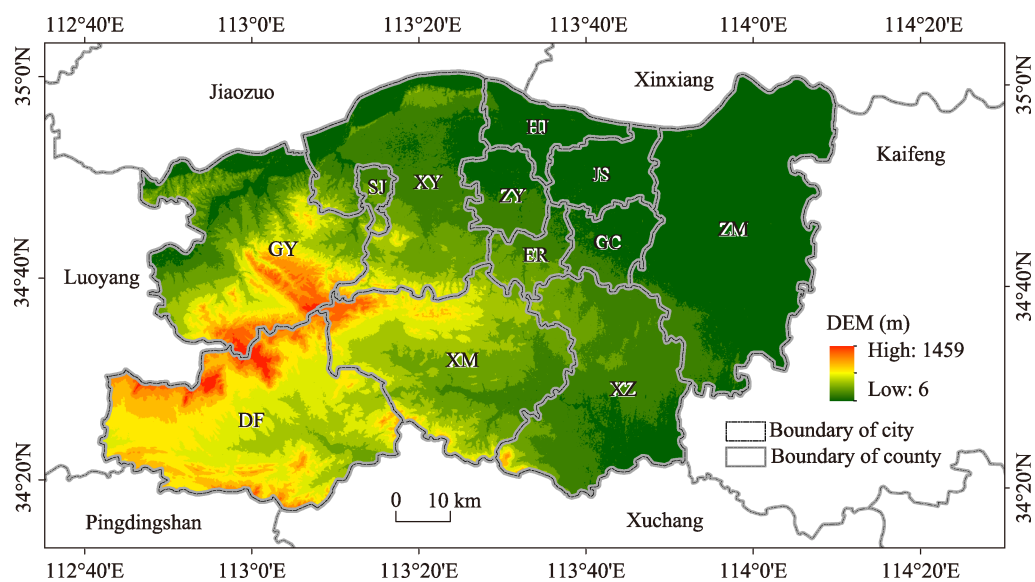


Figure 1 Location of Zhengzhou, Henan province, central China

2.2 Data sources and processing

This study utilized remote sensing, monitoring, open-source, and statistical data (Lin *et al.*, 2021). Table 1 summarizes the data and sources used in this research. Preprocessing was conducted according to the attribute characteristics of each data, as shown below: (1) Remote sensing involves a digital elevation model, Geo-information and information standard product (Globeland30), and Landsat TM remote sensing image, including VFC, NPP, and NDVI. These images were processed using ENVI software and ArcGIS, which involves the geometric correction, projection, and extraction. (2) Monitoring, including climate, atmosphere, and geological condition, from the National Meteorological Science Data Center, Atmospheric Composition Analysis Group, and National Earth System Science Data Center. (3) Open-source, Points of interest (POI) (Wu *et al.*, 2021c), and Traffic network were acquired using Python programming language and online map-related application interface service. Monitoring and open-source data were georeferenced to the Universal Transverse Mercator (UTM) projection coordinate system. The raster data were uniformly set to resolution at 30 m × 30 m. (4) Statistics, the data on population, GDP, citizen income, and water resources were provided by the Henan Provincial Statistics Bureau and Water Resources Bureau and processed by standardization and spatial mapping.

2.3 Methodology

This research introduces remote sensing, monitoring, statistical, and some open-source data based on the essential data system reference provided by the dual evaluation guide (Wu *et al.*, 2021a). Matrix standardization and the EWM-TOPSIS model assign weights and quantify indicators to evaluate the carrying capacity of the resource, environment, and socio-economic system. On this basis, the CA-Markov model was applied to simulate and predict the spatial-temporal dynamics of land use patterns under the business as usual and carrying capacity protection scenario. The K-means method was then employed to analyze the regional differences and land use dynamics. Figure 2 depicts the technical research route.

Table 1 Data used in this research

Data type	Data name	Data source
Remote sensing	DEM	ASTER GDEM (asterweb.jpl.nasa.gov/gdem.asp)
	Land use	Globeland30 (http://globeland30.org/)
	VFC	Landsat TM (https://glovis.usgs.gov/)
	NPP	Landsat TM (https://glovis.usgs.gov/)
	NDVI	Landsat TM (https://glovis.usgs.gov/)
Monitoring	Climate	National Meteorological Science Data Center (http://data.cma.cn/)
	Atmosphere	Atmospheric Composition Analysis Group (https://sites.wustl.edu/acag/)
	Geological condition	National Earth System Science Data Center (http://www.geodata.cn/)
Open-source	Point of interest	Amap API (https://lbs.amap.com/)
	Traffic network	OpenStreetMap (https://www.openstreetmap.org/)
Statistics	Population	Henan Provincial Statistics Bureau (http://tjj.henan.gov.cn/)
	GDP	Henan Provincial Statistics Bureau (http://tjj.henan.gov.cn/)
	Citizen income	Henan Provincial Statistics Bureau (http://tjj.henan.gov.cn/)
	Water resource	Water Resources Bureau (http://zzsl.zhengzhou.gov.cn/)

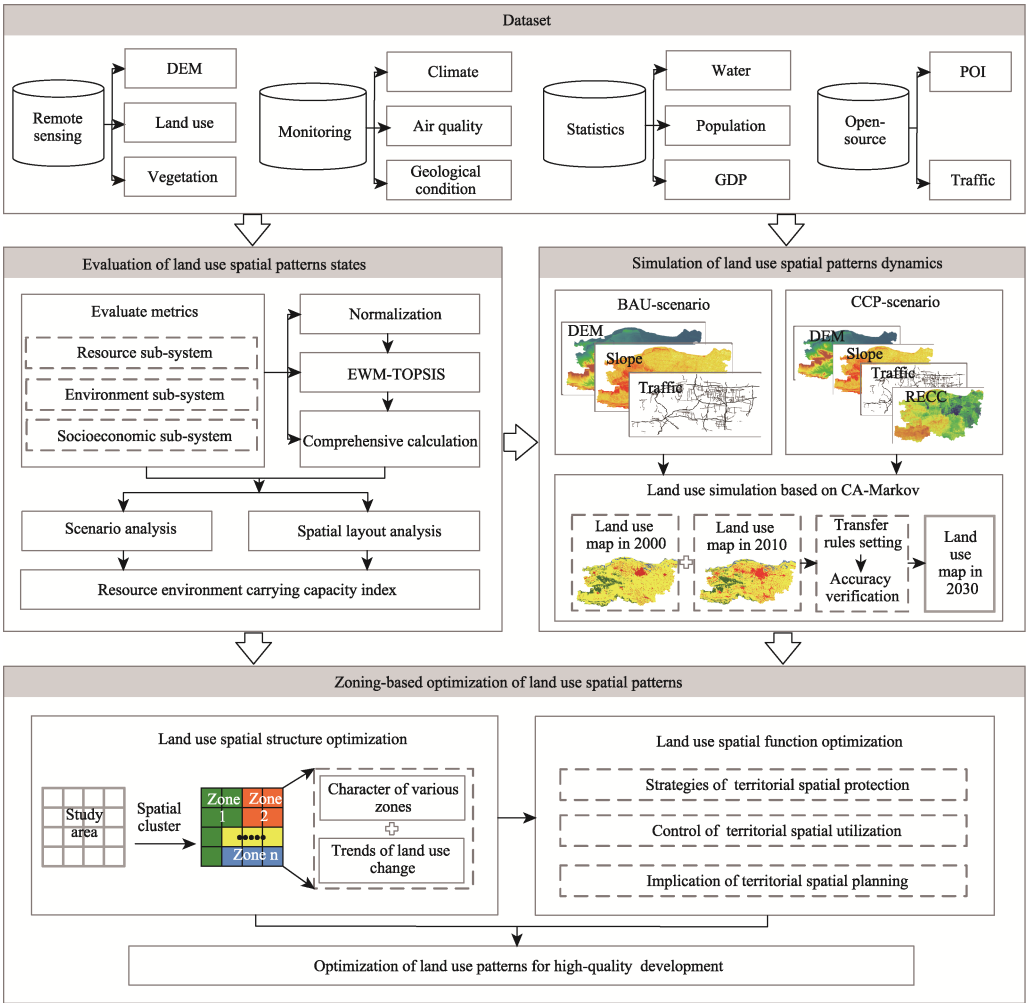


Figure 2 Flowchart of research methodology

2.3.1 Evaluation of LUSP states

(1) Selection of RECC indicators

The carrying capacity of the resource environment system is the total of various natural and social elements in the region in the objective world (Huang *et al.*, 2021). RECC analysis aims to explain the potential of multiple components to carry out human activities and the intensity of economic and social development. Based on the connotation of RECC, the carrying capacity of resources, environment, and society are the core components of the comprehensive carrying capacity of the resource environment system, and they influence one another (Liao *et al.*, 2020). The supporting capacity of resources and environment provided by specific ecosystems to the human social system includes integration, continuous carrying, and spatio-temporal change. It is affected by human activities, social goals, and feedback (Wu *et al.*, 2022). The maintenance of the regional resource structure must meet sustainable development needs (Hu *et al.*, 2020), and the regional environmental function should continue to be capable of producing a steady-state effect (Cheng *et al.*, 2016). After a comprehensive and detailed analysis, it is discovered that natural background factors limit the resource and environmental carrying capacity. Consumption of resources for social and economic development will inevitably affect the atmosphere and water environment (Bao *et al.*, 2020). This paper proposes a RECC evaluation index framework consisting of three subsystems, resource, environment, and social economy based on existing literature research, combined with quantification and availability of data and actual characteristics of the study area. The evaluation indicators of RECC are listed in Table 2.

Table 2 Indicators of RECC

Objective	Category	Index		Impact
		First-level index	Second-level index	
Resource environment carrying capacity	Resource carrying capacity	Land resources	Relief of land surface, R1	Negative
			Degree of land use mix, R2	Positive
			Area of farmland per capita, R3	Positive
		Water resources	Water resources per capita, R4	Positive
			Water consumption per unit of GDP, R5	Negative
		Public resources	Density of the road network, R6	Positive
			Density of POI, R7	Positive
	Environment carrying capacity	Atmosphere environment	Level of air quality, E1	Negative
		Ecological environment	Vegetation fractional coverage, E2	Positive
			Vegetation net primary productivity, E3	Positive
			Normalized difference vegetation Index, E4	Positive
		Disaster risk to the environment	Flooding risk, E5	Negative
			Ecological sensitivity, E6	Negative
	Socioeconomic carrying capacity	Social factor	Level of urbanization, S1	Positive
			Population density, S2	Negative
		Economic factor	GDP per capita, S3	Positive
			Per capita net income, S4	Positive

(2) Calculation of RECC index

The dimension evaluation index data of different dimensions are dimensionless and processed by the matrix standardization method (Ye *et al.*, 2016). This step aims to convert data values carrying various dimensions into [0, 1] so they can be compared in the same dimension.

The calculation equation is as follows:

$$r_{ij} = [v_{ii} - \min(v_{ij})] / [\max(v_{ij}) - \min(v_{ij})] \quad (1)$$

$$r_{ij} = [\max(v_{ij}) - v_{ij}] / [\max(v_{ij}) - \min(v_{ij})] \quad (2)$$

where Eq. (1) is the calculation method of positive indicators, and Eq. (2) is the calculation method of negative indicators, r_{ij} and v_{ij} for the standardization of index values and original values, respectively, $\max(v_{ij})$ and $\min(v_{ij})$ are the maximum and minimum values of the indicator, respectively.

EWM-TOPSIS model evaluates the carrying capacity of resources and environment in Zhengzhou city, which aims to enhance the objectivity of carrying capacity evaluation. The entropy weight approach is a mathematical one that calculates a comprehensive index based on considering the amount of information provided by each index (Wu *et al.*, 2021d). It has strong operability and objectivity, improving the distinguishing significance and difference of indicators, avoiding the analysis difficulties caused by too small a difference of indicators, and accurately reflecting all kinds of information (Li, 2021). The weight of the TOPSIS model is a predetermined value, which measures the index weight with some subjective arbitrariness (Wu *et al.*, 2021d). The combination of the entropy weight method and the TOPSIS model can effectively consider the change degree of indicators, objectively reflect the importance of indicators, and eliminate the subjective initiative determined by the weight of the TOPSIS model.

The specific calculation formula of the EWM method is as follows:

$$w_j = \frac{1 - e_j}{n - \sum_{j=1}^n e_j} \quad (3)$$

where $e_j = -\frac{1}{\ln m} \sum_{i=1}^m P_{ij} \ln P_{ij}$ is information entropy, the characteristic proportion of the index

is $P_{ij} = \frac{r_{ij}}{\sum_{i=1}^m r_{ij}}$, when $P_{ij}=0$, $\ln P_{ij}=0$.

where e_j is the entropy of the indicator j , w_j is the weight value of the indicator j .

The RECC of Zhengzhou is measured with the application of the TOPSIS model based on the entropy weight method to determine the weight, and the steps are as follows:

Evaluation matrix weighting based on entropy weight:

$$Z_{ij} = r_{ij} \times w_j \quad (4)$$

where Z_{ij} is the weighted normalized decision matrix, w_j is the entropy weight.

Determining positive and negative ideal solutions:

$$Z_i^+ = \max\{z_{ij}\} \quad (5)$$

$$Z_j^- = \min\{z_{ij}\} \quad (6)$$

where Z_i^+ and Z_j^- are the positive and negative ideal solutions, which are the maximum and minimum values of the weighted normalized decision matrix z_{ij} , respectively.

Distance calculation:

$$D_i^+ = \sqrt{\sum_{j=1}^m (z_{ij} - Z_j^+)^2}, (i = 1, \dots, n) \quad (7)$$

$$D_i^- = \sqrt{\sum_{j=1}^m (z_{ij} - Z_j^-)^2}, (i = 1, \dots, n) \quad (8)$$

Euclidean distance is applied in this study to calculate the distance between the positive and negative ideal solutions. D_i^+ is the Euclidean distance from z_{ij} to positive ideal solutions, while D_i^- is negative ideal solutions.

Numeration of the closeness between the evaluation object and the ideal solution is:

$$C_i = \frac{D_i^-}{D_i^- + D_i^+} \quad (9)$$

where C_i is the comprehensive evaluation index of carrying capacity, with the value range of [0, 1]. When $C=1$, the RECC is the highest; when $C=0$, the RECC is the lowest.

Urban development must be pursued without destroying ecological systems' balance and virtuous cycle (Luo *et al.*, 2020). Specifically, it is of great significance to determine the safe scale of urban ecological land use and its supporting RECC for the development of Zhengzhou city (Zhang *et al.*, 2021). The RECC calculation system was constructed from RCC, ECC, and SCC through standardized indices and determining weights. RECC computation formula is as follows:

$$\text{RECC} = \sqrt[3]{\text{RCC} \times \text{ECC} \times \text{SCC}} \quad (10)$$

2.3.2 Simulation of LUSP dynamics

Cellular automata (CA) is a dynamic grid model that can simulate the evolution of the complex spatiotemporal system (Li *et al.*, 2017a). The Markov chain analysis is a stochastic process model that uses the transition probability to simulate land use change between two land use types (Mondal and Southworth, 2010). The CA-Markov model, a combination of CA and Markov chain, added CA's advantages in simulating complex systems and Markov chain in long-term prediction and was utilized to simulate land use change (Wu *et al.*, 2021e).

Land use change simulation based on CA has always been a hot issue in geographic information science (Wu *et al.*, 2019). In order to explore the possibilities of future land use change, this paper simulates land use change under different scenarios by assuming two different land use development directions, namely business as usual (BAU) and carrying capacity protection (CCP). Under the BAU scenario, land use types will ultimately follow the evolutionary laws of history. However, under the CCP scenario, it aims to predict the future trend of land use changes under the control of the protection of the resource and environmental carrying capacity. For example, the simulation will protect ecologically sensitive

land types such as forests and water in low RECC areas and will not be converted into other land types. Hence, in CCP scenario simulation, in addition to all suitability maps based on the BAU scenario, the RECC index, derived from the results of the RECC evaluation, is also included. In this study, the land use transfer matrix is computed using the Markov model, and the suitability maps contain elevation, slope, distance from the railway, and distance from the main road. The Multi-Criteria Evaluation (MCE) module was applied to generate suitability maps of BAU and CCP scenarios, which were then used as the transformation rule of cellular automata to simulate the evolution of land use patterns in 2030. Utilizing the Markov analysis module of the IDRISI software to investigate the operation results, base period (2000), and end period (2020) land use data, one can obtain the transfer area matrix of the land use type. The transition matrix is the transition rule of the Ca-Markov model operation.

The CA model calculation formula is as follows:

$$CA = (L, S, N, f) \quad (11)$$

where L is the cell grid, d is the dimension of space, S is the set of possible states of a cell, and N is the neighborhood set of cells; f is the cellular transformation rule.

The Markov model calculation formula is as follows:

$$S_{(t+1)} = P_{ij} \times S_t \quad (12)$$

where $S_{(t+1)}$ and S_t are two consecutive state vectors at the time $t+1$ and t , respectively.

2.3.3 Zoning-based optimization of LUSP

The K-means is the most commonly used and simplest clustering method (Celebi *et al.*, 2013). Almost all data mining software includes one realization of it. This algorithm is easy to implement, general, and explainable. The main parameters that need to be adjusted are only the number of clusters. Furthermore, the rapid convergence and good clustering effect are advantages of K-means. Therefore, it is more suitable for territorial spatial planning clustering analysis (Jiang *et al.*, 2019).

K-means clustering analysis aims to divide the observed objects into several subsets. Each subset constitutes a cluster, so the clustering objects should be as different as possible. The K points are randomly selected as the initial clustering center in the K-means algorithm. The distance between each data object and the clustering center is then calculated. Afterward, the data objects are classified into the class containing the nearest clustering center lies. It is indicated that the data object adjustment is over if the two adjacent clustering centers do not change. Furthermore, such circumstance also showed that the clustering criterion function has converged. At each iteration, the classification of each sample must be verified. If not, it is necessary to adjust. The basic principles and steps are as follows (Li *et al.*, 2020):

$$\text{sample set: } D = [x_1, x_2, \dots, x_m] \quad (13)$$

Initial clustering centers were selected into k in the study area, $[\mu_1, \mu_2, \dots, \mu_k]$.

The Euclidean distance is calculated from each cluster object (x_i) to its center (μ_i). Then assign x_i to the class where the nearest cluster center is located. To divide the data cluster class. The calculation formula is as follows:

$$c^{(i)} = \arg \min_j \|x^{(i)} - \mu_j\| \quad (14)$$

where $c^{(i)}$ represents the class with the closest distance between sample i and classes k , the value of $c^{(i)}$ is 1 to k . μ_j is the center point of the sample belonging to the same category.

These algorithms also minimize the square error of clusters. The sum of squared error (SSE) is the most intuitive and frequently used criterion function given by:

$$SSE = \sum_{i=1}^K \sum_{x_j \in P_i} \|x_j - c_i\|_2^2 \quad (15)$$

The new centroid μ_j for all sample points in c_j is recalculated by:

$$\mu_j = \frac{\sum_{i=1}^m 1\{c^{(i)} = j\} x^{(i)}}{\sum_{i=1}^m 1\{c^{(i)} = j\}} \quad (16)$$

where j is the new classes that are redistributed.

The iterative calculation is conducted until the clustering center does not change, output the result: $c = [c_1, c_2, \dots, c_k]$.

In this study, a total of 2060 grids were created with $2 \text{ km} \times 2 \text{ km}$ as the basic unit of spatial clustering. Six index layers were constructed as input attribute parameters of K-means clustering. These six indicators include RCC, ECC, SCC, and RECC, representing the status quo of territorial space and the changing area of construction land and farmland from 2020 to 2030 under the CCP scenario (Zheng *et al.*, 2020). Eventually, the spatial statistics method converted raster data into shapefile grid data.

When the RCC value is relatively high for the various zoning unit, it is divided into resource conservation zone (RCZ). An ecological carrying zone (ECZ) is defined when the ECC value is relatively high. When the SCC value is relatively highest, it is regarded as the living core zone (LCZ). While the construction land area is the largest, it can be divided into a suitable construction zone (SCZ). Finally, when the farmland area is the largest, it is divided into a grain supply zone (GSZ).

3 Results

3.1 Results of LUSP states evaluation

Figure 3 illustrates each subsystem's carrying capacity and the resource environment. From the subsystem point of view, the RCC, ECC, and SCC spatial distribution rules in Zhengzhou city are entirely different. The spatial distribution variation within each subsystem is also significant. The RCC's spatial distribution is characterized by "high in the east and low in the west," and Zhongmou County, the easternmost county, has the best resource endowment conditions (Figure 3a). In contrast, the spatial distribution of ECC is precisely opposite to that of the RCC, showing a characteristic of "high in the west and low in the east" (Figure 3b). Notably, the SCC lacks the same spatial transition law as the former. Its spatial distribution is irregular, and its value is better in the central and northwest parts of the region (Figure 3c). The areas with the highest RCC, ECC, and SCC indices are 1627.39 km^2 , 3320.39 km^2 , and 1692.96 km^2 , respectively, representing less than 50% of the total area. Most regions of Zhengzhou city lack sufficient resource endowment, an excellent natural environment, and a sound socioeconomic foundation simultaneously.

From the whole RECC point of view, the spatial distribution of RECC in Zhengzhou city is significantly different, exhibiting a spatial differentiation pattern of “high in the west and low in the east” (Figure 3d). An interesting phenomenon is that the distribution of RECC is not entirely consistent with that of a single RCC, ECC, and SCC. For example, the Dengfeng District, which is located west of Zhengzhou, has a relatively superior ECC, and its RCC and SCC are very low, preventing it from getting a good RECC. However, the Guancheng District, situated in the middle of Zhengzhou, has a non-poor RCC, ECC, and SCC simultaneously, thus becoming the region with the highest RECC index. To measure the differences in RECC grades, it divided the RECC index into five grades, from low to high, based on the natural breakpoint method. The regions with low, lower, medium, higher, and high RECC are not evenly distributed, representing 15.30%, 27.06%, 21.96%, 26.05%, and 9.62%, respectively. It is simple to determine that the middle and lower RECC grade area is 5186.65 km², constituting more than half of the entire region. The illustration above indicates very few areas with high RECC in Zhengzhou city. Most regional territorial space is threatened by resource over-exploitation and environmental degradation.

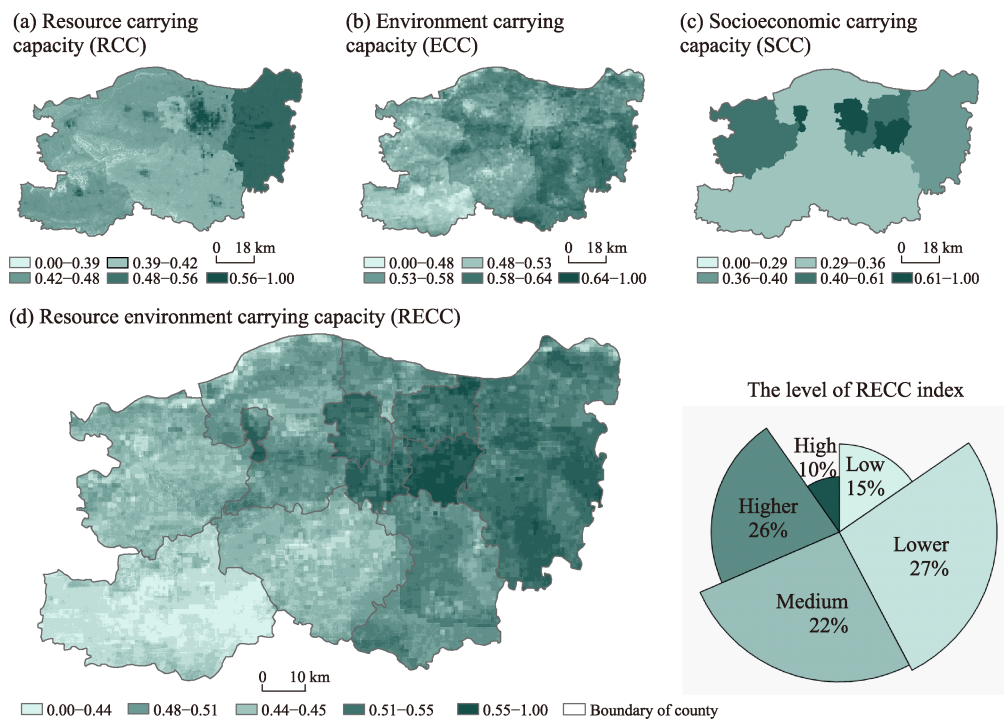


Figure 3 Resource environment carrying capacity index of Zhengzhou city

3.2 Results of LUSP dynamics simulation

Table 3 displays the validation of simulated land use change results based on the Kappa index. All Kappa statistics exceeded the 0.75 significant thresholds, indicating high accuracy between the simulated and actual land use maps in 2020. It is substantial evidence that the selected land use simulation model is applicable. Consequently, the integrated CA-Markov model can forecast the LUC dynamics in the study area.

Table 3 Results of Kappa statistics of the CA-Markov model

Scenario	Kappa for no	Kappa for location	Kappa for standard	Kappa for location Strada
BAU	0.7858	0.7661	0.7429	0.7661
CCP	0.7873	0.7679	0.7447	0.7679

As shown in Figure 4, the spatiotemporal trends of land use differ between regions. The land use structure and spatial patterns are local and different under the two scenarios of BAU and CCP. Compared to 2020, the construction land and grassland area under the BAU scenario increased by 346.21 and 39.79 km², respectively, while the farmland, forest, and water decreased by 295.98, 68.10, and 21.79 km², respectively. Furthermore, the increased construction land was mainly converted from farmland. In contrast, the construction land and grassland area under the CCP scenario improved by 287 and 39.89 km², whereas the farmland, forest, and water areas dropped by 239.27, 67.46, and 20.04 km², respectively. The increase in grassland was the largest, reaching 26.3%. The enhanced construction land was also transformed from farmland, primarily distributed in the central region of Zhengzhou city. The decreased farmland was mainly changed to grassland in the west and construction land in the central region.

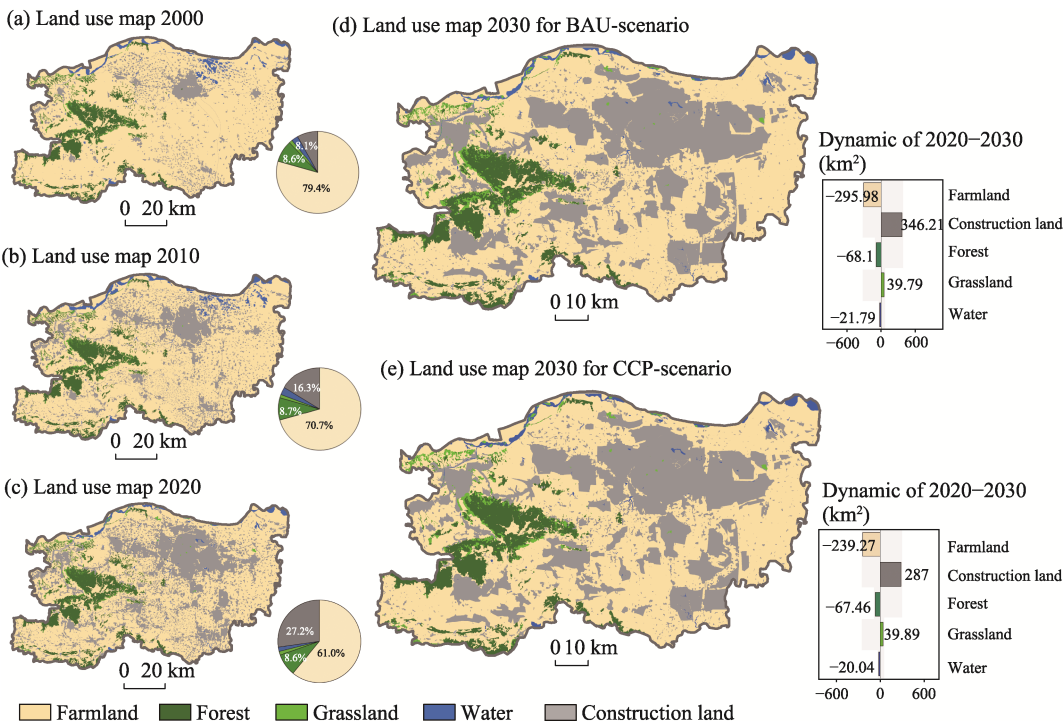


Figure 4 The historic and simulated land use of Zhengzhou city

3.3 Results of zoning-based LUSP optimization

The training results obtained by comparing the number of different clusters show that the slope of the sum of squares curve has the smallest when the number of clusters is 5. It is indicated that based on the K-means spatial clustering method, the study area is most suitable

ble to be divided into five types of zoning. Consequently, the study area is further divided into several regions based on the optimal number of clusters and the index characteristics of each region.

Figure 5 depicts the results of LUSP zoning. Significant differences exist in various zones' area, proportion, and spatial distribution. The area of the GSZ is 2906.52 km², represents the most significant proportion (38.32%) of Zhengzhou city, and is distributed in the regions near the peripheral farmland. The LCZ covers 1554.71 km², or 20.50% of Zhengzhou city, and is located in the study area's central part and other scattered county center areas. Additionally, the SCZ is primarily distributed in the edge region adjacent to LCZ, with an area of 945.40 km², accounting for 12.5% of the total area of Zhengzhou city. The area of the RCZ is 1450.24 km², or 19.12% of the study area, and it is dispersed in a scattered form in the study area between urban built-up areas and farmland-concentrated areas. Furthermore, the ECZ consists mainly of mountains in the west and waters along the northern and southern edges, which cover an area of 727.65 km² and account for 9.59% of the study area, and the primary land use type is forest and water.

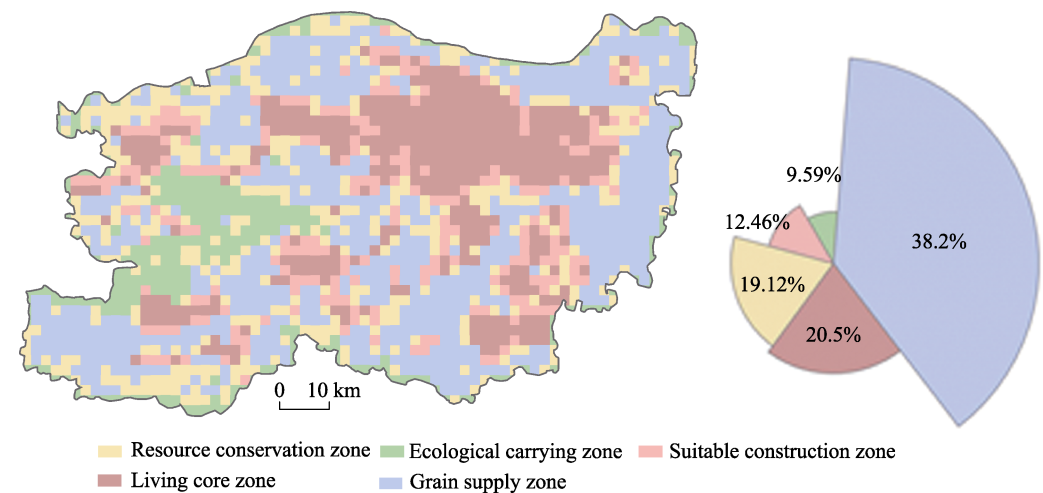


Figure 5 Distribution of land use spatial pattern zones in Zhengzhou city

Table 4 displays the land use change in 2020–2030 in land use spatial pattern zones. From the perspective of various land use types, in the CCP scenario, construction land and farmland have the most significant changes, reaching -14.03% and 16.82% , respectively. From 2020 to 2030, the construction land LCZ will expand by 1697.75 km² or 22.40% of the total area. The most significant change in farmland is the LCZ, which will decrease by 1644.54 km² from 2020 to 2030, accounting for 21.69% of the total area. In addition, the BAU scenario trend is identical to that of the CCP. From the perspective of each zone, the most significant land use change between 2020 and 2030 is in the ECZ, and the smallest is in the SCZ. Under the BAU scenario, the farmland in the ECZ decreased by 146.48 km², and the construction land increased by 13.83 km², while the land use change in the SCZ only rose by 27.73 km², a change of only 0.37%. On the other hand, under the CCP scenario, the farmland and construction land areas in the ECZ decreased and increased by 141.28 km² and 14.6 km², respectively, while the changes in the SCZ were -641.99 km² and 688.06 km², respectively.

Table 4 Land use change in 2020–2030 of land use spatial pattern zones in Zhengzhou city

Land use	Scenario	ECZ (km ²)	GSZ (km ²)	LCZ (km ²)	RCZ (km ²)	SCZ (km ²)	2020–2030 (km ²)	2020–2030 (%)
Farmland	BAU	−146.48	1120.38	−1663.74	81.71	−707.35	−1315.48	−17.35%
	CCP	−141.28	1195.65	−1644.54	168.72	−641.99	−1063.44	−14.03%
Forest	BAU	−78.97	−65.18	4.40	−134.51	−28.40	−302.68	−3.99%
	CCP	48.33	−118.96	−36.94	−147.00	−45.24	−299.80	−3.95%
Grassland	BAU	123.63	−2.13	−1.25	57.66	−1.07	176.84	2.33%
	CCP	17.24	74.58	40.08	20.82	24.58	177.29	2.34%
Water	BAU	−16.97	−18.46	−21.32	−25.64	−14.44	−96.84	−1.28%
	CCP	−17.50	−18.42	−19.25	−20.68	−13.30	−89.14	−1.18%
Construction land	BAU	13.83	−988.87	1720.33	25.99	766.88	1538.16	20.29%
	CCP	14.60	−1057.67	1697.75	−67.64	688.06	1275.09	16.82%
2020–2030 (km ²)		−183.58	120.92	75.51	−40.58	27.73		
2020–2030 (%)		−2.42%	1.60%	1.00%	−0.54%	0.37%		

4 Discussion

This section addresses the three relevant research questions outlined in the introduction in the order they were proposed based on the results presented above and the information collected from the literature review. The discussion section concludes with some policy implications to help facilitate high-quality land development in Zhengzhou city.

4.1 The dominant factors of LUSP

Judging the advantages and disadvantages of LUSP is a complex process involving natural, social, and economic factors. Previous research has confirmed that land use spatial patterns can be represented by the current status and the future trend of two dimensions of indicators. For instance, the resource abundance, environmental quality, availability of public infrastructure, economic development level, and potential have been proven to be correlated with the current characteristics of LUSP (Che and Zhou, 2021). Furthermore, the direction of land use type transfer and the amplitude of land use change are essential manifestations of LUSP’s future evolution dynamics. These factors are a macro judgment based on a holistic view, which may not be able to target LUSP’s core picture in a concise system.

This study analyzes the fluctuation difference of the index values in the RECC evaluation system using the theory of index dimension reduction. Moreover, it describes the land use dynamics under BAU and CCP scenarios during 2000–2030 to better understand the main drivers of LUSP. The heat map of RECC evaluation index values (Figure 6a) shows that the dispersion degree of R2 (degree of land use mix), E1 (the level of air quality), and S2 (population density) is the highest among the 17 indices, that is, their variance is the largest. Based on the contribution principle of variance to the importance of indicators, these three indicators significantly impact the RECC. Besides, they determine the current basis of the LUSP more than any other indicator. The LUC in 2000–2030 (Figure 6b) shows that the construction land is the land class with the most considerable growth rate, where its value increased from 613.18 km² in 2000 to 2065.37 km² in 2020, representing about 19.16%.

Notably, this trend will continue, most likely increasing by 11.58% in the next decade. On the other hand, farmland is the land category with the most significant decline representing about 18.45% in 2020–2030. This percentage is expected to decrease further in the future.

The above screening results of LUSP’s dominant factors suggest that human activities are the most critical source of LUSP’s influence. The reason is that the characteristics of these five dominant factors are all triggered or highly influenced by human activities (Zhang *et al.*, 2017). Specifically, Zhongmou county and Guancheng district have the lowest degree of land use mix in Zhengzhou. The former is dominated by farmland, while the latter is dominated by construction land. However, LUSP, dominated by a single type of land use, is exceptionally vulnerable to climate change and public emergencies. Accordingly, relevant managers should consciously guide the diversification of land use in these regions. The extreme air quality index and population density in the Dengfeng county and Guancheng district have exceeded reasonable standards ($AQI \leq 200$, 100 person/km²). This means that there are unreasonable human activities in these regions, including environmental degradation and over-exploitation of resources, which have led to the collapse of the LUSP and other practical problems. In addition, human activities most affect land and farmland construction (Jin *et al.*, 2021). Whether their development dynamics are increasing or decreasing, if the range of change is not controlled within a reasonable range, it is bound to cause an imbalance of LUSP and even lead to risks such as urban sprawl and agricultural output decline.

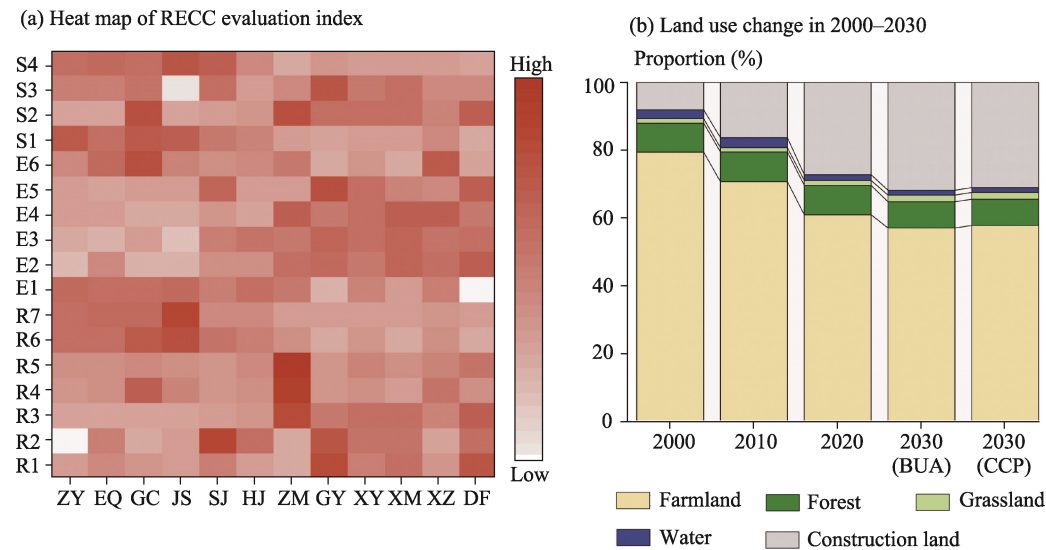


Figure 6 Heat map of RECC evaluation index (a), and land use change (b) in 2000–2030

4.2 The effectiveness of optimization scheme for LUSP

High-efficiency optimization strategies are essential for improving the stability and development quality of LUSP (Fang and Wang, 2020). That is, the greater the validity, the greater the reliability of the optimization scheme to improve the LUSP pattern. Therefore, this section proposes a method that combines land use change scenario simulation and field discrimination to test the uncertainty of the LUSP optimization effect caused by different reference factors. Moreover, this section compares the simulation results of the land use change

of RECC. The layers of the simulated land use change results of BAU and CCP are superimposed. In addition, hot spot analysis is used to explore the spatial distribution of such differences. Furthermore, the LUSP zoning method mentioned above is used again to input the simulation results of the two scenarios as relevant attribute indices into the spatial clustering model. Some findings are shown in Figure 7.

It can be seen that the hot spots of the differences between the LUC scenario simulation results are mainly concentrated in the rectangular positions in Figure 7, including regions of mountainous and hilly areas in the west and urban core areas in the east. In order to examine the reasons for this difference, field discrimination is conducted by taking the current land use map of the region as a reference. The primary land use types in hot spot A are forest and grassland, which account for more than 60% of the total rectangular area. Based on the CCP scenario, the LUSP optimization scheme divides the extensive ecological land distribution areas into ecological carrying ones. This region’s most suitable territorial space function provides essential element support for the ecosystem. Furthermore, this inference conforms to the principle that “land development should be consistent with the orientation of territorial spatial function” proposed by other studies. However, under the BAU scenario, this region’s forest and grassland are reduced. After spatial clustering using the relevant indicators of this scenario, it can be observed that this region is not entirely divided into ecological carrying areas but is more defined as grain supply areas. It can be seen that this optimization scheme deviates from the territorial spatial function positioning of this region. In hot spot B, the main current land category is construction land, which also accounts for more than 60% of the total rectangular area. In the LUSP optimization scheme based on the CCP scenario, most areas with a large amount of urban construction land are defined as living core areas, and these areas are the main places for residents’ daily activities and social and industrial production. According to the location theory of urban development, the suitable territorial spatial function of the core urbanized area is to provide public resources for residents’ life. Nevertheless, in the BAU scenario, some territorial spatial functions of resource protection and food supply are also included in the LUSP optimization scheme. Thus, this optimization strategy can be considered a groundless delusion and is not feasible.

The above evidence shows that the LUC simulation results under the CCP scenario are

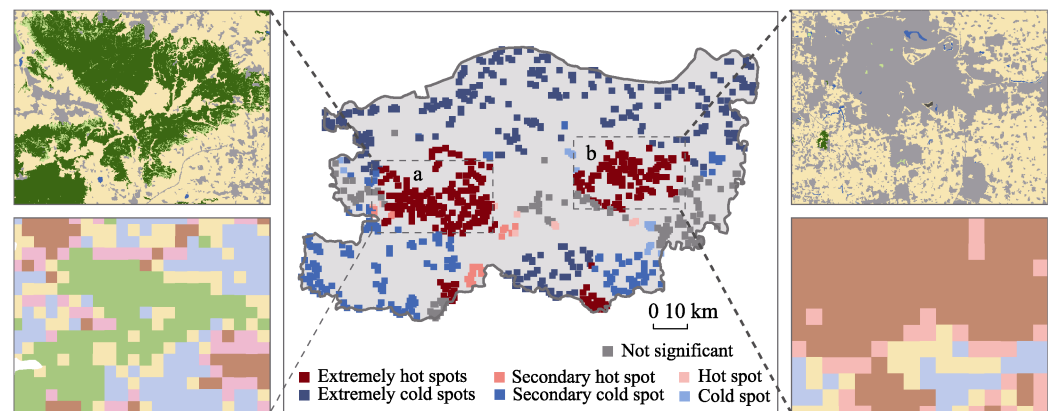


Figure 7 Differences in land use simulation between BAU and CCP scenarios

conducive to guiding the high-quality development of future territorial space (Wang and Fan, 2020). More importantly, the LUSP optimization scheme based on RECC and LUC has extremely qualified effectiveness. Furthermore, it has various advantages regarding urban development scale limitation and farmland protection because the area of farmland and construction land in the BAU scenario is less than that in the BAU scenario. Based on this result, the subsequent optimization of LUSP is more helpful in disciplining the disorderly expansion of urban construction land (Jin *et al.*, 2020). Additionally, it can reasonably guide the demarcation and adjustment of fundamental farmland control boundaries.

4.3 The implications regarding high-quality land development

This study indicates that, if not controlled, unreasonable LUSP would seriously jeopardize the resources and environmental sustainability. Policy interventions and reforms are urgently needed to facilitate high-quality development to avoid such a threat. To this end, this study has several policy-relevant implications.

Existing studies have pointed out that protection is the premise of development (Chen and Liang, 2020). Formulating a reasonable LUSP optimization strategy is the primary work of all government policies and development plans. Currently, the widely accepted research paradigm is “formulate a strategy for territorial space protection, control the development and utilization of territorial space, and put forward suggestions on territorial and spatial planning” (Chen *et al.*, 2019).

Combined with the results of RECC evaluation and LUSP optimization zoning, it is found that the RCZ and ECZ are areas with low RECC concentration. They have distributed vast ecological sources such as forests, waters, and grass, which contain vital land and water resources and public services. Special protection should be given to the ecosystem functions and ecological elements in the future development process. Some territorial space development activities unrelated to environmental protection should be restricted to make the construction of this region a focal point for achieving carbon neutrality.

In addition to the protection policies mentioned above, some unreasonable territorial space development and utilization still need to be abandoned. The LCZ's primary territorial spatial function is to provide conditions for residents' living, but excessive population aggregation and development of primary and secondary industries should be restricted. The proper development of modern urban agriculture is an appropriate direction for improvement based on ensuring its regional administrative status and urban functions. Additionally, the SCZ is a relatively suitable area for the evolution of urban structure and industrial transfer. The disorderly spatial expansion of urban built-up areas here should be strictly prohibited. While the GSZ is the lifeblood of food security in the study area, the relevant departments should formulate strict farmland protection policies to prevent the loss of farmland in this area. The specific approach is to take grain production as the main task and develop new green industries such as rural tourism.

The above enlightenment analysis will lose the practical application value if it only stays at the level of appeal for improvement. More importantly, the analysis is needed to provide a practical reference for future space planning and governance. Under the guidance of the Chinese central government, Zhengzhou city has been established as an important transportation hub and commercial trade center in the Belt and Road Initiative. This kind of urban

function positioning puts forward a high standard for the supply capacity of LUSP in Zhengzhou city. In the future, the LUSP will play a fundamental role in improving urban land space’s function and urban governance capacity and achieving realistic goals such as flood disaster emergency warning and response. In short, the relevant natural resource management departments should guide the optimization of LUSP according to local conditions and aim at the target to tap the development potential of higher quality. Based on the above discussion, some reference suggestions are given in Table 5.

There are many factors in addition to the LUSP, such as spatial planning orientation and economic investment intensity, which may affect the development quality of territorial space (Ge and Lu, 2021). Thus, local governments should restrict the rapid expansion of construction land and carry out strict farmland protection policies according to regional LUSP’s current situation and dynamic characteristics. Additional efforts should be made to protect ecological systematic service function and refine the spatial planning. Hence, careful consideration of the LUSP’s fundamental supply role in the follow-up regional planning and design and the strength of social and economic support is vital for future sustainable and high-quality development.

Table 5 The suitable modes of future land development in Zhengzhou city

Zone	Average RECC level	Primary land use type	Suitable development orientation
RCZ	Lower	Farmland	Ecosystem services, resource supply
ECZ	Low	Forest, Grassland	Environmental protection, carbon neutrality
LCZ	High	Construction land	Administrative functions, urban agriculture
SCZ	Higher	Construction land	Undertaking industrial transfer
GSZ	Medium	Farmland	Food production, rural tourism

4.4 The limitations and future research directions

While this research contributes a systematic analysis of the land use spatial patterns optimization, it can be enhanced in several aspects. As for research data, the vast majority of data used in this study are traditional spatial and statistical data. However, the reality shows that multi-source spatio-temporal big data-assisted geographical science research has become a substantial tide (Lin *et al.*, 2020). The follow-up research should use spatio-temporal big data rich in dynamics and higher precision, such as population migration and mobile phone signaling, to further improve the research’s refinement and timeliness (Wu *et al.*, 2021b). As for the research methods, the index selection in RECC evaluation and the suitability atlas input weight scaling in the CA-Markov scenario simulation method contain some unavoidable subjective interference. Eventually, higher-level semantic recognition methods should be used in future research to explore the truth closer to objective facts. In addition, the LUC scenario simulation only considers BAU and CCP. In the future, more scenarios, such as ecological and farmland protection, can be included to make the prediction results more comprehensive (Thompson *et al.*, 2020).

5 Conclusions

China’s economy has shifted from a high-speed growth stage to a high-quality development

one. The development model that sacrifices the ecological environment and human well-being have undergone fundamental changes. Systematically optimizing regional land use spatial patterns is critical for governmental organizations to pursue high-quality growth. Based on the evaluation of RECC and simulation of LUC, this study systematically examines the current characteristics and dynamics of LUSP, and a comprehensive LUSP optimization framework is proposed. The study's principal findings are as follows:

(1) The spatial distribution of the carrying capacity of resources and environmental systems in the study area was remarkably significant. The areas with higher RCC, ECC, and SCC indices were 1627.39, 3320.39, and 1692.96 km², respectively, while the area with higher RECC graded or above account for less than 30%. This result indicated that most of the study area's regional resources and environmental systems did not have sufficient capacity to carry out high-intensity human activities.

(2) The construction land and arable land area in the study area fluctuated wildly between 2000 to 2020. The increased construction land mainly came from decreased farmland, which will continue. The construction land will continue to increase by at least 280 km² by 2030, while the farmland will keep to decrease by 230 km² under business scenarios or to carry capacity protection.

(3) The whole region can be divided into five LUSP optimizing zones: resource conservation, ecological carrying, living core, suitable construction, and grain supply zones, and their proportions in the study area are 19.12%, 9.59%, 20.50%, 12.5%, and 38.32%, respectively. Furthermore, each zone has a specific optimization orientation of LUSP.

The optimization strategies in the carrying capacity protection scenario tend to be more reasonable through discriminant analysis. This approach can be applied to guide territorial spatial utilization within appropriate regions and decrease the damage to land development quality. In addition, it identified five dominant factors of LUSP, including the degree of land use mix, air quality, population density, increased construction land, and decreased farmland. This study indicated that a multidimensional spatio-temporal analysis framework considering these five factors is indispensable for better understanding and improving the quality of LUSP.

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