EFFECTS OF LAND-USE VARIATIONS ON LANDSCAPE PATTERNS AND ESVS FROM 2000 TO 2022: A PERSPECTIVE ON URBAN AGGLOMERATIONS OF THE YELLOW RIVER BASIN, CHINA

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Abstract. Significant land use/cover changes due to urban agglomeration expansion affect ecological services. Taking the Yellow River urban agglomeration as an example, this study analyzed landscape pattern evolution at patch and landscape scales. The Markov - FLUS model simulated the 2030 - 2035 land use pattern in the southern Yellow River Basin urban agglomerations in China. The equivalent factor approach determined the historical evolution and trend of Ecosystem Service Values (ESVs). The following results were obtained: 1) Construction land use grew (28% transfer rate), while cropland and forest land decreased (44.08% and 13.66% transfer rates). 2) Water and impervious areas increased the most, grassland and shrub areas declined the most. 3) Urban landscape expansion showed a generally uniform distribution, stable proportion structure, and complex patch shapes; human activities caused spatial heterogeneity. 4) Future land use change follows the current pattern. 5) The 2030 - 2035 ESV forecast shows an 8.15% - 7.93% drop compared to 2022 and adjusting regulation and support service values can increase ESVs. This study helps to understand urban expansion and ESV losses in rapidly developing areas and improve urban planning regulations.
Keywords: *landscape patterns, Markov-FLUS model, dynamic attitudes towards land use, land-use transfer matrix*

Introduction

Resources on land have to be available for human survival and advancement (Lourenco et al., 2020). Land use, particularly the ongoing expansion of urban construction land, results in changes to the land-use structure and has been a widely studied topic globally. With the acceleration of global urbanization, there is a growing need for higher standards in the rational use of land resources, control of urban expansion, and the achievement of sustainable development. To accommodate urban growth, human intervention on land has been increasing. Due to the cost of ecologically productive croplands, forests, and vegetation, both vertical (inner-city redevelopment) and horizontal (inward and outward growth) land-use patterns have intensified significantly (Shi et al., 2009). Moreover, land use, as a significant human activity, has

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a substantial impact on ESVs. The development and expansion of cities (Wang et al., 2023) have a significant effect on ecological diversity and ecological service functions. Numerous studies have shown that changes in land use and urban development have led to a decrease in ESVs. This situation demands urgent attention considering sustainable ecological development.

In terms of land use, numerous studies have focused on optimizing the land-use structure and enhancing land-use efficiency (Szymańska-Walkiewicz et al., 2023; Yang et al., 2023). At the same time, research related to urban expansion mostly focused on the dynamics (He et al., 2008), scale (Zeng et al., 2015); and spatial patterns of urban development (Sahana et al., 2018), as well as its impacts on the environment, society, and the economy (Redman and Jones, 2005; Yin et al., 2011). Many researchers have paid particular attention to the environmental sustainability challenges of urban expansion, including air quality (Tao et al., 2015), water resources (Chang et al., 2015), waste disposal (Leao et al., 2004), and energy consumption (Li et al., 2019). However, it is worth noting that urban expansion often requires a large amount of land resources (Jiang et al., 2013), resulting in the destruction or loss of existing ecosystems (Tang et al., 2021). For example, large-scale urban construction and industrial development can lead to the reduction in wetlands, forests, and cropland, thereby diminishing ecological services such as water conservation (Tefera and Sterk, 2010), species conservation (Camagni et al., 2002), and carbon storage (Wang et al., 2020). Simultaneously, urban expansion can disrupt the continuity and integrity of the ecosystem (Liu et al., 2022), resulting in the formation of isolated fragments (Kadhim et al., 2022). Habitat fragmentation can disrupt species migration and gene flow (Miles et al., 2019), which in turn affects biodiversity and ecosystem stability. These factors have a significant impact on ESVs, but their relationship with ESVs has been overlooked in previous studies (Pennekamp et al., 2018).

In the past, most research have been committed to making contributions to the evolution of ESVs and changes in land use (Li et al., 2018). Commonly used analysis models include multiple linear regression models, GM (1,1) models (Wang et al., 2021), BP neural networks (Pal et al., 2009), and others. These methods, which are based on mathematical statistics or empirical reasoning, primarily utilize historical data to analyze future trends in structural evolution. However, there are few studies on the impacts of land-use change on landscape patterns and ESVs. Currently, the predominant methods primarily utilize identification-oriented products, such as the IMAGE model (Doelman et al., 2018), LUSs model (Letourneau et al., 2012), CLUMondo model (Zhu et al., 2020), and FLUS model (Liu et al., 2017; Chen et al., 2021). The IMAGE model, LUSs model, and CLUMondo model have not been fully implemented, and one or more of them may not yet be complete.

Therefore, they cannot be used to effectively evaluate land-use changes and its impact on ecology. The FLUS model combines human and natural factors, organically integrating "top-down" system dynamics with "bottom-up cellular automata" to achieve a detailed simulation of large-scale land-use changes in the future. Its practicality has been validated in numerous research cases (Zhang et al., 2023; Qiao et al., 2023). Thus, the FLUS model is applicable for studying land-use changes and ESVs at the basin scale. During the last decade, number of studies have focused on the quantitative analysis of ESVs loss at national and regional scales (Da et al., 2017). Past studies may have overemphasized the extent of ESVs loss (Zank et al., 2016), but this bias has been addressed through spatial assessment at a 500 m resolution (Kubiszewski et al., 2017).

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However, using a lower resolution may result in underestimation or overestimation of ESV because this method relies on less precise land-use data. Thus, we utilized and established the Markov-FLUS model of urban expansion with a 30-meter resolution. Such a high resolution provides more details about the losses of ESVs in terms of quantity and location.

Studies of land-use changes in the Yellow River Basin are significant because the Yellow River, known as the "Mother River" of the Chinese nation, originates from the Qinghai-Tibet Plateau and flows through nine provinces and regions (Chen et al., 2020). With a watershed area of 795,000 km^2, it is the second-largest watershed in China. With only 2% of the country's water resources, the Yellow River Basin supports nearly 9% of the country's population, 13% of its food production, and 25% of its coal resources. The area is densely populated with a high concentration of human activity (Chen et al., 2012). The middle and lower reaches of the Yellow River are home to 60% of the population. This region has the highest population density and the largest urban development scale in the Yellow River basin. In recent years, urban expansion in these regions has increased and has been dominated by urban agglomerations (Li et al., 2021). This trend has brought cities closer together and has made certain land-use patterns more common (Webber et al., 2008). The urban agglomeration in the Henan section of the Yellow River Basin has become the most densely populated area in the entire basin due to its concentration of agriculture and industry (Zhao et al., 2022). The land-use changes caused by urban development not only alters the urban development pattern but also the landscape pattern and ESVs (Estoque and Murayama, 2013; Hegazy and Kaloop, 2015). The impact of this change on human and natural ecosystems is significant and far-reaching (Peng et al., 2016). The unique geographical location of this region also leads to contradictions and conflicts in the development of the population, urbanization, agriculture, and economy in the area. Understanding the changes associated with these factors and their impacts on ecosystem service values (ESVs) is crucial for both the Yellow River Basin and similar geographic areas.

Taking the urban agglomeration in the Henan section of the Yellow River Basin as an example, this study aimed to (1) systematically analyze the spatiotemporal variation characteristics of land use/land cover (LULC) change from 2000 to 2022; (2) analyze changes in landscape patterns using class-level indexes (NP, PD, Area_MN) and landscape-level indexes (LSI, CONTAG, SHDI, SHEI); (3) simulate and predict the land-use patterns of the Henan urban agglomeration in 2030 and 2035 using the Markov-FLUS model; (4) assess the spatiotemporal changes in ESVs at the grid level and explore the impact mechanism of the comprehensive index of land-use degree on ESVs. To enhance the comprehension of spatially-varying urban expansion and associated losses in ESVs in rapid developing areas, an analysis of the Markov-FLUS model and landscape pattern index was conducted. The study revealed an accelerated urban expansion rate in the Henan section of the Yellow River basin, leading to a decrease in ecosystem service values. The findings could serve as a guide for the development of urban agglomerations to optimize land-use patterns and provide ecological protection for sustainable development. Section 2 presents the materials and methods used in the study and describes the study location. Section 3 describes the results and analysis of the study. Section 4 discusses the interrelationship between the study's findings and its limitations. Section 5 draws conclusions and presents prospects. The research framework of the study is as follows (*Fig. 1*):

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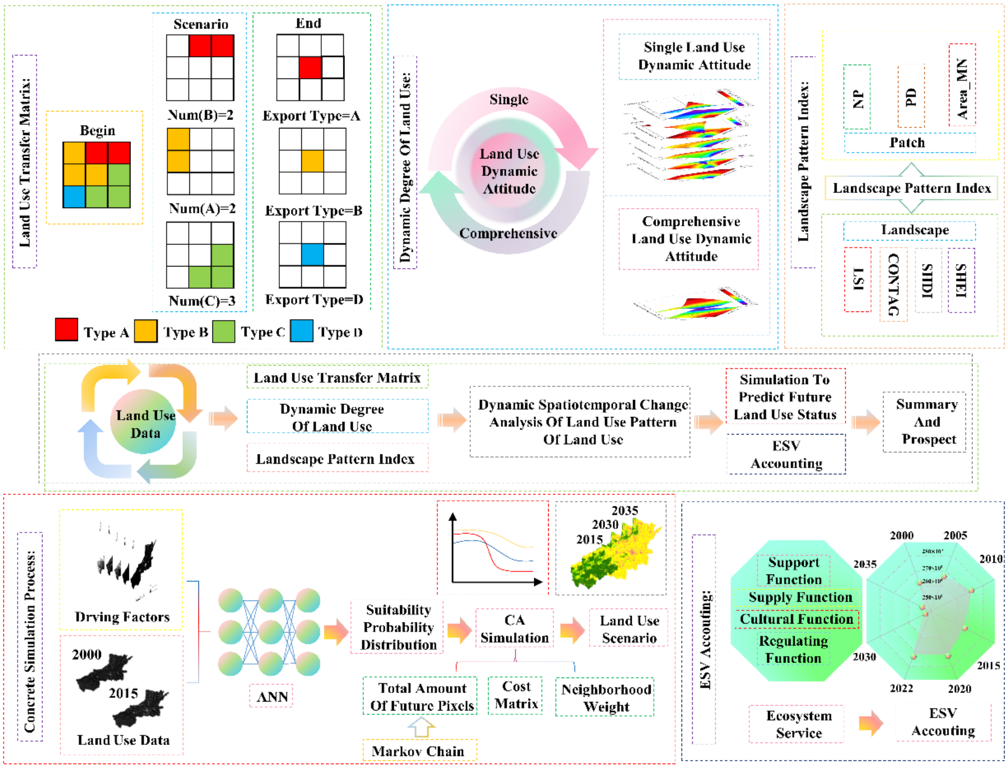

***Figure 1.** Research framework of the study*

Materials and methods

Study area

The terrain of the Yellow River basin is high in the west and low in the east. The average elevation of the western river source area is over 4,000 meters. This region consists of a range of high mountains with year-round snow cover and glacial landforms. The central area is situated at an elevation between 1 km and 2 km above sea level. The area is characterized by loess landforms, and soil erosion is a serious issue. Henan Province, located in Central China, covers a total land area of 167,000 km^2 and is situated between the following coordinates: 31°23′–36°22′ N and 110°21′–116°39′E. Henan Province experiences a continental monsoon climate, with an annual average temperature ranging from 10.5 to 16.7℃ and an annual precipitation ranging from 407.7 to 1295.8 mm. During periods of rain and heat, the climate, water, and soil conditions in the province are conducive to crop growth. The Henan section of the Yellow River Basin is situated in the middle and lower reaches of the Yellow River Basin, extending from Yangjia Village, Yuling Town, Lingbao city in the west, to Dongba Head, Lankao County, Kaifeng city in the east. These areas are crucial for connecting the "nine-curve Yellow River" and are important for the national strategy related to the Yellow River (Guo et al., 2022). Moreover, the Henan section serves as a crucial ecological barrier for the North China Plain and is also a highly developed economic area within the basin (Gao et al., 2023). However, in recent years, the pattern of land-use has undergone significant changes due to the large population density and the rapid expansion of urban agglomerations. Therefore, in this study, all the prefecture-level cities in the Yellow River watershed in the Henan Section are the focus of the research. This includes 10

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provincial cities under the jurisdiction of Zhengzhou, Kaifeng, Luoyang, Hebi, Anyang, Jiaozuo, Puyang, Xinxiang, Sanmenxia, and the Jiyuan Demonstration Zone (*Fig. 2*), with a total area of 65,000 km^2, representing 18.9% of the province's total area. The terrain is elevated in the west and lower in the east, and the climate is characterized by a continental monsoon climate that transitions from the northern subtropical zone to the warm temperate zone (Xu and Ma, 2009).

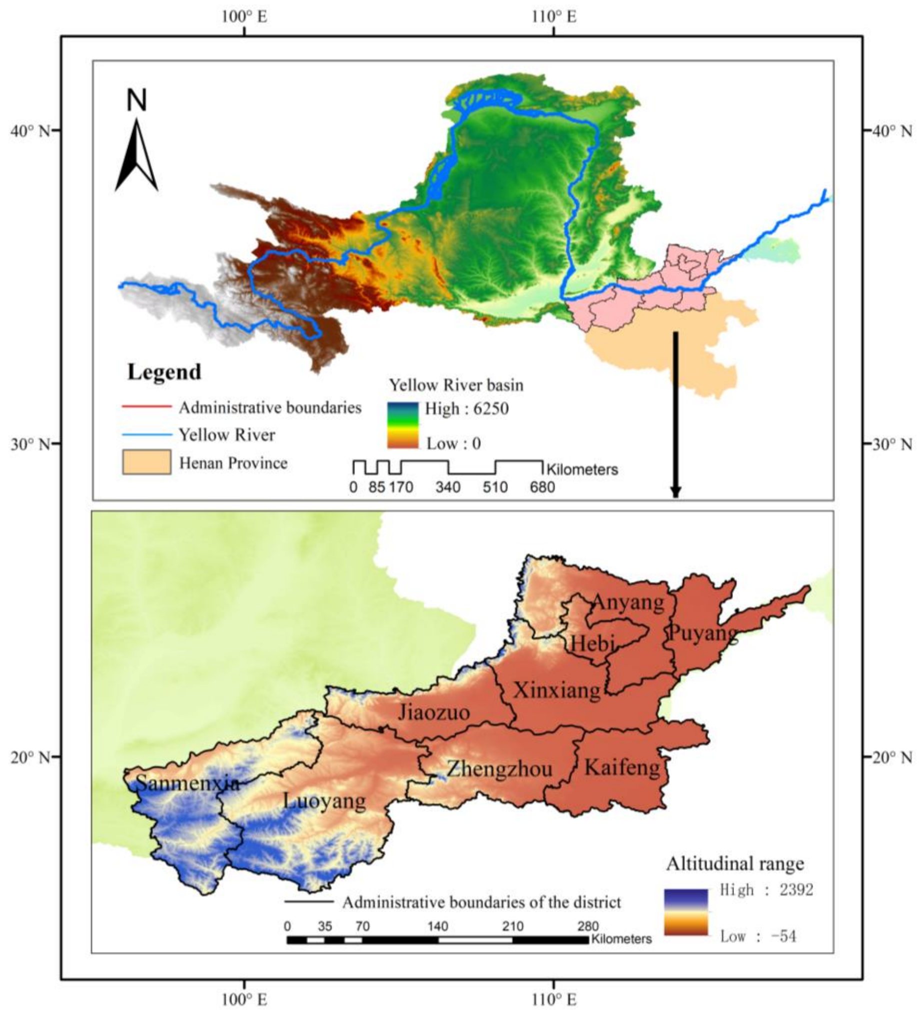

Figure 2. *Geographical location diagram of the urban agglomeration in the Henan section of the Yellow River Basin*

Methods

Analysis of land-use changes based on land-use transfer matrix

The land-use transfer matrix (Szymańska-Walkiewicz et al., 2023) includes not only regional area data at a certain point in time but also regional area information regarding transfers at the beginning and end of a certain period, thus reflecting the dynamic process of mutual transformation between regional areas. The formula is cited from the research by Lambin (1997). The general form of the land-use transfer matrix (1) is as follows:

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$$S_{ij}=\begin{bmatrix} S_{11} & S_{12} & \dots & S_{1\kappa} \\ S_{21} & S_{22} & \cdots & S_{2\kappa} \\ \dots & \dots & \cdots & \dots \\ S_{n1} & S_{n2} & \cdots & S_{n\kappa} \end{bmatrix} \tag{Eq.1}$$

where *S* represents the area; *n* is the number of land-use types before and after the transfer; *ij* (*i*,*j*= *1*,*2*... *n*), respectively represent the types of land-use before and after the transfer; and S_{ij} represents the area of the land class converted to the j_{th} land class before the transfer. Each row of elements in the matrix represents the flow information of class *i* before the transfer to the class at the destination after the transfer, and each column of elements represents the source information of class *j* after the transfer from the class at the origin before the transfer.

Calculation of the variation in LULC within a specific time frame using the LULC dynamic degree formula

The land-use dynamic degree (Huang et al., 2018) is defined as the rate of change of the total land area that was converted into other types of land use. The dynamic expresses in a comprehensive manner the dynamic change in land use for a given region. However, the dynamic attitudes towards single land-use types and comprehensive land use are different.

1) Dynamic Attitude Towards Single Land-use Type

The dynamic attitude of a single land-use type describes the quantitative changes in a certain land-use type within a specific time range in particular research area. The formula is cited from the research by Wang et al. (1999). Its expression (2) is as follows:

$$K = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\% \tag{Eq.2}$$

where (2) K represents the dynamic range of a LULC type during the study period; U_a and U_b represent the area of a LULC type at the beginning and end of the study period, respectively, in hectares hm^2. *T* is the length of the study period, expressed in $yr-1$.

2) Comprehensive Land-use Dynamic Attitude

Comprehensive dynamic analysis of land use describes the overall rate of change in land use within a research area and can be utilized to examine regional variations in land-use dynamics. The formula is cited from the research by Zhu et al. (2001). The expression (3) is as follows:

$$LC = \left[\frac{\sum_{i=1}^{n} \triangle LUi{-}j}{2\sum_{i=1}^{n} LUi}\right] \times \frac{1}{T} \times 100\% \tag{Eq.3}$$

where (3), *LUi* is the area of Class *i* land-use type at the monitoring start time; *⊿LUi-j* is the absolute value of the area of Class *i* land-use type converted to non-Class *i* land-use type during the monitoring period; and *T* is the length of the monitoring period. When the time period of *T* is set as the year, the value of *LC* is the annual change rate of land use in the study area.

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Changes in landscape patterns based on LULC patterns

The landscapes pattern index is a quantitative research tool used to establish the relationship between landscape structure and ecological processes. Landscape patterns and changes are represented and explained through an index of landscape characteristics (Abbas et al., 2022). These patterns are commonly utilized to analyze the evolution of landscape patterns during urban and rural construction and development. Each landscape pattern index has a specific correlation, and an analysis of a particular index can characterize the landscape pattern characteristics (Corry, 2005). Based on the classification system of landscape indices, this study followed the principle of fully reflecting pattern information while avoiding redundancy and duplication, in line with relevant literature. Additionally, 7 landscape pattern indices were selected at the landscape level, considering the actual situation of urban agglomeration in the southern part of the Yellow River Basin. Fragstats 4.2 software was utilized to quantitatively analyze changes in landscape patterns within cities in the southern part of the Yellow River Basin Group. The landscape pattern indices at the classlevel included the patch number (NP), patch density (PD), patch average area (Area_MN) and the landscape pattern indices at the landcape level included landscape shape index (LSI), spread index (CONTAG), Shannon diversity index (SHDI) and the Shannon evenness index (SHEI) (*Table 1*).

Table 1. *Landscape pattern indices and descriptions*

Index	Formula	Description
Patch Number (NP)	$NP = N_i$	N_i--the number of patches of a Clasi landscape type;
Patch Density (PD)	$PD = \frac{N_i}{A}$	A-- total area of landscape or patch, hm^2; PD--patch density, per hm^2;
Shannon Diversity Index (SHDI)	$SHDI = -\sum_{i=1}^{m} (P_i \ln P_i)$	P_i-- ratio occupied by landscape patch type i;
Shannon Uniformity Index (SHEI)	$SHEI = \frac{-\sum_{i=1}^{m} (P_i \times \ln P_i)}{\ln m}$ $(0 \leq SHEI \leq 1)$	m--total number of patch types in the landscape;
Mean Patch Area (Area_MN)	$Area\_MN = \frac{A}{NP}$	P--perimeter of landscape type;
Landscape Shape Index (LSI)	$LSI = \frac{P}{2\sqrt{\pi \times A}}$	P_i--percentage of the area occupied by type i plaques; g_{ik}--the number of adjacent plaques of type i and type k;
CONTAG	$CONTAG = \left[1 + \frac{\sum_{i=1}^{m}\sum_{i=1}^{m}\left[\left(P_i\left(\frac{g_{ik}}{\sum_{i=1}^{m} g_{ik}}\right)\right)\right]\left[\ln(P_i)\left(\frac{g_{ik}}{\sum_{i=1}^{m} g_{ik}}\right)\right]}{2\ln(m)}\right](100)$	

Predicting LULC changes via the Markov-FLUS model

Due to its high accuracy in long-term quantitative prediction, the Markov model has been widely used in the GeoSOS-FLUS V2.3 software to predict changes in land-use efficiency (Munthali et al., 2020; Chen et al., 2020). In view of the numerous factors considered for land-use prediction, we selected five key driving factors: population

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density, digital elevation, slope, gross domestic product (GDP), and soil type. Additionally, we took into account the social development status, as well as natural and economic conditions in the study area. The area and cell number of land-use types simulated by the Markov-FLUS model in 2015 were compared with actual data. The kappa coefficient and FOM index were utilized as indicators to evaluate the simulation results. After evaluating the accuracy to meet the prediction requirements, the future change trend of the land-use structure was predicted.

ESVs evaluation model based on correction factors

The equivalent factor approach, which multiplied the land use type area in the study area by the land use type value of the land use type in the unit area, was the most appropriate method to evaluate the ecosystem service value because the study area was small-scale.

The coefficient of the standard equivalent was updated based on a review of pertinent literature combined with the real circumstances of the research area. The formula is cited from the research by Xie et al. (2001):

$$D = \frac{\sum_{i=1}^{n} m_i p_i q_i}{M} \quad \text{(Eq.4)}$$

where i is the crop type, m_i is the planting area of i different crop kinds (hm^2), and D is the value of ecosystem services expressed as one standard equivalent factor (yuan /hm^2). M is the total planted area of all crops (hm^2); q_i is the yield per unit area of i crops (kg /hm^2); and p_i is the national average price (yuan/kg) of i crops in a given year.

The method was modified to incorporate attribute data from the National Bureau of Statistics and the macroeconomic database of Henan Province. This resulted in the equivalent factor of ecosystem service value of 1629.42 yuan /hm^2 for Henan Province.

To obtain the table of ecological service value per unit area (yuan /hm^2) of the provincial ecosystem in the southern segment of the Yellow River basin, certain parameters in the revised table of equivalent factor of ecosystem ecosystem service value in Xie ’s (2001) could be modified based on relevant literature (Li et al. 2021) and combined with the actual situation of the study area. The updated ESVs coefficient of land-use types (Xie et al., 2001) are summarized in the following *Table 2*:

Data sources and processing

The data used in the study mainly included historical and projected land use statistics:

(1) Six periods of land-use vector data from 2000, 2005, 2010, 2015, 2020 and 2022, spatial resolution 30m, were selected for research. The research data were collected from Wuhan University's Annual Land-cover dataset with a resolution of 30 metres spanning in China (Yang and Huang, 2021). Based on 335,709 scenes of Landsat data on Google Earth Engine, the research team led by Yang produced the annual China Land Cover Dataset (CLCD). With reference to its classification system and considering the nature and characteristics of land-use in the Henan section of the Yellow River Basin, land was divided into the following 7 categories: cropland, forest, grassland, shrub, impervious, water and barren.

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Table 2. *ESVs coefficient of land-use types in the study area(yuan/hm^2)*

Types of Ecosystem service		Cropland	Forest, Shrub	Grassland	Impervious	Barren	Water
1st level	**2nd level**						
Provision services	Food supply	3601.02	1645.71	1140.59	0.00	16.29	2134.54
	Raw material supply	798.42	3780.25	1678.30	0.00	48.88	1189.48
	Water resources supply	-4252.79	1955.30	928.77	0.00	32.59	21247.64
Regulation services	Gas regulation	2900.37	12432.47	5898.50	0.00	211.82	6191.80
	Climate regulation	1515.36	37199.66	15593.55	0.00	162.94	10477.17
	Environmental purification	439.94	10900.82	5148.97	0.00	668.06	26526.96
	Regulation of water flows	4871.97	24343.53	11422.23	0.00	391.06	217690.51
Support services	Maintenance of soil	1694.60	15137.31	7185.74	0.00	244.41	5279.32
	Maintenance of nutrient cycle	505.12	1156.89	554.00	0.00	16.29	407.36
	Biological diversity	554.00	13784.89	6533.97	0.00	228.12	16994.85
Cultural services	Esthetic landscape	244.41	6045.15	2884.07	0.00	97.77	10933.41

(2) The land use forecast data mainly included the driving force data of land use change: DEM data, which is derived from the Global Digital Elevation Model (GDEM) data, was obtained from the geospatial data cloud (http://www.gscloud.cn), from which slope data were further derived by ArcGIS spatial calculation. Soil type, GDP and population density data were obtained from the Resources and Environmental Science and Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/); the spatial resolution was 1 km. According to the FLUS model requirements for input data, the baseline data was designated as land-use data. The number of rows, coordinate system, and resolution of each dataset were standardized to ensure that all raster data complied with the model construction requirements.

Results

Spatiotemporal analysis of land-use change

To discern the link between land - use change and ESVs in the study area, data from six periods (2000, 2005, 2010, 2015, 2020, and 2022) were selected. The land - use transfer matrix was employed to explore spatiotemporal changes.

Geographically, the Henan section of the Yellow River Basin spanned both the middle and lower reaches. The study area's urban agglomeration, located in Henan Province (a major agricultural region), had forest and cropland as dominant land - use types, sharing similarities with northeastern regions. Between 2000 and 2022, the land - use structure changed significantly (*Fig. 3*). Notably, 44.08% of cropland and 13.66% of forest land were transferred out. Development land, with a 28% transfer rate, expanded by 13,776.53 km², showing a dramatic increase in proportion. Evidently, the Henan region of the Yellow River Basin faced two major pressures: poor ecological flow in the lower reaches and severe soil erosion in the middle reaches.

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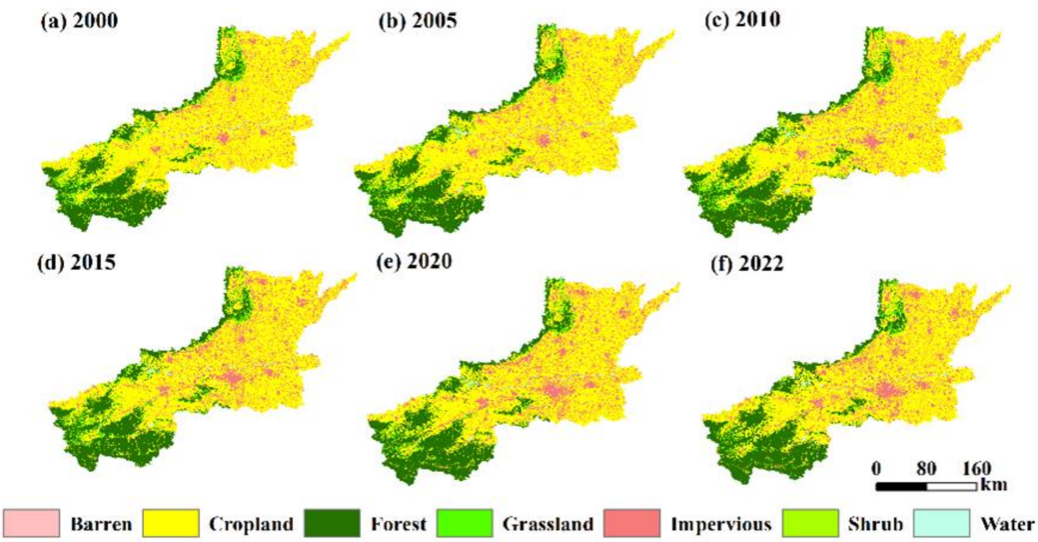

Figure 3. *Variations of regional LULC during 2000-2022 of the urban agglomeration of the Henan section of the Yellow River Basin*

A Sankey map illustrated land - use transfer types and relationships in the study area. As shown in *Figure 4*, cropland and impervious surfaces were the main transfer sources. From 2000 to 2022, large - scale or frequent transfers occurred, characterized by a significant increase in impervious land. This indicated that accelerated urbanization tightened the connection between urban construction expansion and urban agglomeration, driving the rapid growth of impervious land. Thus, it further confirmed the substantial impact of urban development on land - use dynamics and the overall urban landscape pattern.

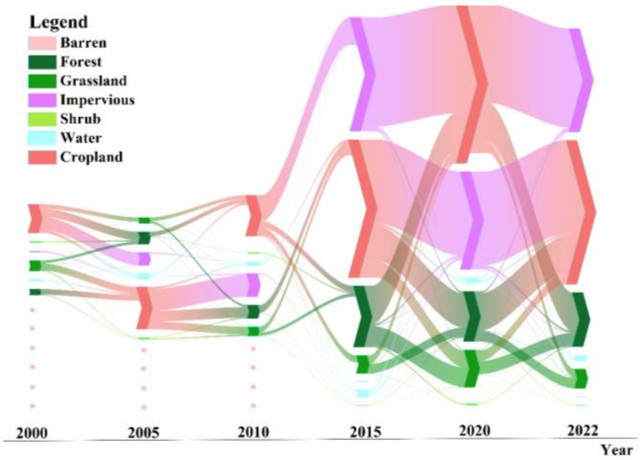

Figure 4. *Land-use transfer Sankey map from 2000 to 2022*

In terms of land - use transfer (*Table 3*), the area of land-use type conversion in the Henan section of the Yellow River Basin from 2000 to 2022 was 49,606.84 km². Generally, the most significant conversions were between cropland and impervious land, followed by cropland and forest. Over 22 years, the converted area of cropland was 21,868.97 km², impervious land 10,160.327 km², and forest 6,777.81 km². Among

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them, 11,353.47 km² of cropland was converted to impervious ground, accounting for 51.92% of cropland's total transfer area and 22.87% of the overall converted area. Impervious ground was mainly converted into cropland (9,442.73 km²), accounting for 92.93% of its converted area and 20.48% of the total converted area. Forests were primarily converted into cropland, accounting for 63.80% of forest's converted area.

Table 3. *Land-use transfer matrix from 2000 to 2022 (km^2)*

Land Type	Cropland	Forest	Grassland	Impervious	Shrub	Water	Barren	Total
Cropland	——	4557.23	2047.47	11353.47	23.88	629.72	3257.19	21868.97
Forest	4324.52	——	1408.15	174.91	151.50	47.11	671.60	6777.81
Grassland	1626.03	1432.73	——	93.49	72.99	17.99	951.79	4195.01
Impervious	9442.73	170.68	76.59	——	1.68	354.18	114.46	10160.32
Shrub	28.31	217.43	101.27	0.04	——	0．00	148.48	495.53
Water	444.68	51.90	15.89	284.20	0.00	——	84.00	880.67
Barren	1277.68	1092.39	539.60	1870.42	88.65	359.80	——	5228.53
Total	17143.95	7522.36	4188.96	13776.53	338.70	1408.80	5227.53	49606.84

Ultimately, the construction of urban agglomerations had not only brought about rapid economic and social development but also profoundly changed the land-use pattern. Especially with the large-scale expansion of impervious, there was a high frequency of conversion of cropland and forest, making it challenging for the land to revert to its original land use due to changes in land-use patterns. Therefore, it was necessary to further analyze the dynamic degree of land-use and its impact on landscape patterns to explore its ecological response.

Change analysis based on dynamic degree towards land use

The dynamic degree model of land use could quantitatively reflect the regional differences in the intensity and rate of land-use change and had a positive impact on predicting future trends in land-use change. Specifically, the single dynamic degree could express the changes in land-use of a specific type in a particular region, while the comprehensive dynamic degree was more focused on the annual change rate of all land-use types in the entire region. *Figures 5 and 6* displayed the comprehensive dynamic attitude and the single dynamic attitude, respectively, in the form of mapping graphs. The XYZ axis represented the year, buffer distance, and dynamic attitude, respectively.

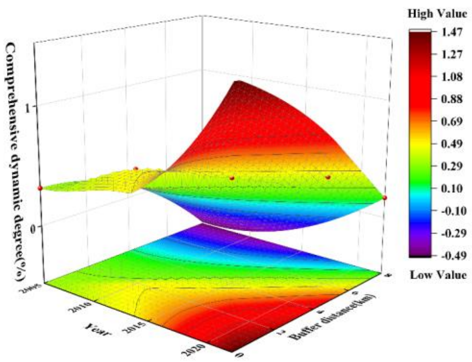

Figure 5. *Comprehensive degree of land-use dynamics calculated*

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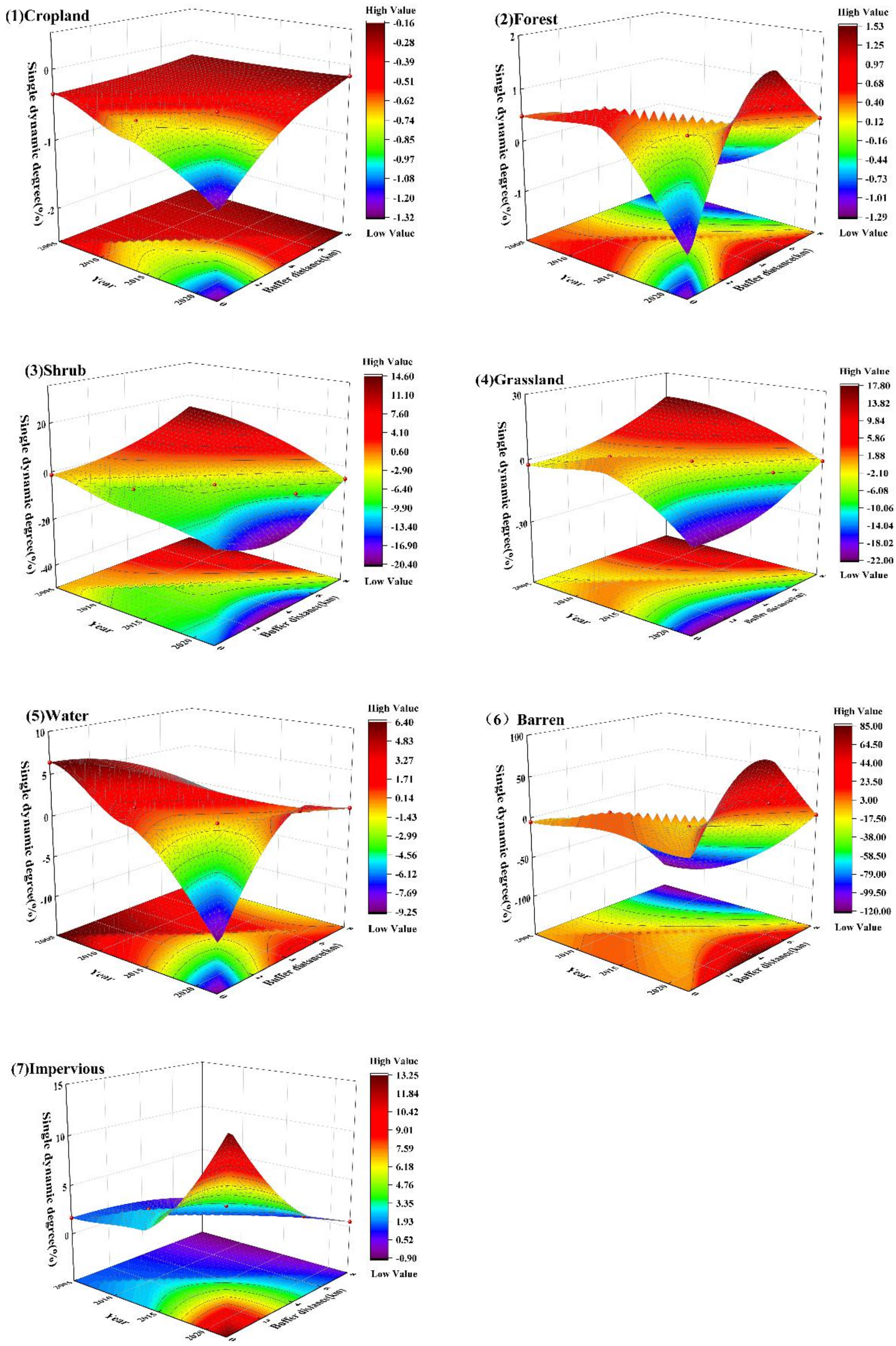

Figure 6. *Single degree of land-use dynamics calculated*

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A declining trend and a wide variety of changes were evident in the research area's comprehensive dynamic attitude of land use (*Fig. 5*). Over the past 22 years, the overall land-use dynamic degree suffers several main stages: a sharp increase, a slow decline, a moderate increase, and a sharp decrease. In general, the dynamic attitudes on land-use that were complete in 2000-2005, 2010-2015, and 2015-2020 exceeded the average level by 0.36%. The period from 2005 to 2010 had the most overall dynamic attitude, at 0.48%. This was followed by 0.42% from 2015 to 2020, 0.41% from 2010 to 2015, and 0.32% from 2000 to 2005. With a mere 0.17% growth, the smallest comprehensive dynamic attitude was noted between 2020 and 2022, which could be attributed to the impact of the COVID-19 pandemic and the relatively short research period. According to the findings, the research area's land-use was most active from 2005 to 2010 and least active from 2020 to 2022. The majority of land-use types varied spatially as one got farther away, showing varying dynamic attitudes about land-use. Therefore, the buffer zone of 1 to 10 km was chosen. Regarding the single land type change rate, cropland and shrub land displayed negative growth trends, with average values of -0.43% and -5.70%, respectively; the negative growth trend then slowed (*Fig. 6*). Forest and impervious, on the other hand, maintained a growth trend.

Additionally, the category-level intensity analysis revealed that the greatest increases in zones were caused by impervious surfaces and water, whereas the largest losses were attributed to shrub and grassland. Despite regulations aimed at conserving the countryside, there was a significant shift from cropland to impervious in both zones, as urban growth became a larger portion of the economy.

Temporal and spatial variations in landscape patterns

Changes in land use would inevitably shift result to changes in landscape patterns. In this study, the changing process of urban landscape pattern expansion was analyzed in this study using the landscape pattern index. In order to analyze and compare changes in the relevant landscape pattern indices in different periods and reveal changes in the evolution characteristics of the southern segment of the Yellow River Basin at the urban agglomeration class level, three indices, NP, PD, and Area_MN, at the class level were selected based on changes in patch fragmentation degree, patch aggregation degree, and patch complexity in the southern segment of the Yellow River Basin from 2000 to 2022.

Fig. 7 showed the change trend of the landscape pattern index from 2000 to 2022. The X-axis indicated the year, the Y-axis represented the landscape pattern index, and the Z-axis represented the landscape pattern index value in order to more intuitively display the shifting trend of the landscape pattern index. In sections 3.3.1 at patch class level index (NP, PD, Area_MN) and 3.3.2 at landscape level index (LSI, CONTAG, SHEI, SHDI), particular changes in landscape patterns were discussed to better explain the points.

Analysis of the evolutionary characteristics of landscape patterns at the class level

Features such path aggregation, fragmentation, and evolutionary traits were examined in order to comprehend changes in the landscape patterns in the Yellow River Basin over the study period.

(1) Patch aggregation

The degree of fragmentation was showed by the number of patches (PD) in each square kilometer of the studied area. The degree of fragmentation increased with increasing PD. As seen in *Fig. 8*, both NP and PD displayed a declining tendency,

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suggesting that artificial development and building caused patches to become more concentrated and reduced the degree of fragmentation during the process of developing urban agglomerations in the Yellow River Basin's Henan portion.

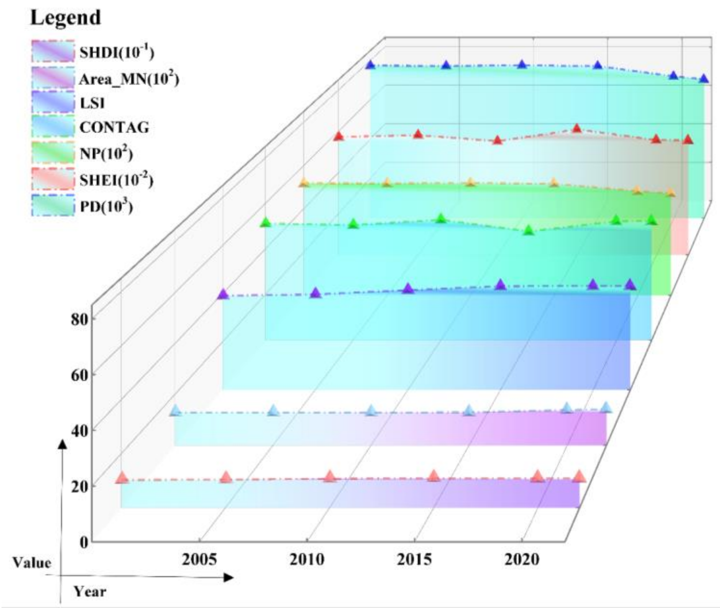

Figure 7. *Variation trend of the landscape pattern indices*

(2) Degree of patch fragmentation

AREA_MN, which measured the ratio of a patch's total area to the total number of plaques of the same type, can indicate the level of fragmentation to some extent. The distribution of patch types was concentrated, and the AREA_MN showed an increased trend from 2000 to 2005, as illustrated in *Figure 8*. The distribution of patch types became more spread and the AREA_MN showed a decreasing tendency between 2005 and 2010. From 2010 to 2022, the average patches exhibited a rising tendency, suggesting that most plaque types were large and centralized.

(3) Class-level patch evolution characteristics

The NP, PD, and AREA_MN indicated that patches would tend to aggregate and become more intensively dispersed, and the degree of fragmentation reduced as a result of artificial development and construction.

Analysis of the evolutionary characteristics of the landscape pattern at the landscape level

Four indices, CONTAG, LSI, SHDI, and SHEI, were chosen to analyze and compare their changes in different periods based on the changes in landscape complexity and diversity of the urban agglomeration in the Henan section of the Yellow River Basin from 2000 to 2022 (*Fig. 8*).

(1) Landscape complexity improvement

The intricacy of the overall terrain shape may be reflected in the LSI. According to *Figure 7*, the LSI had risen gradually over the last 22 years, increasing by 10.18% in 2022 when compared to that in 2000. The LSI index described the landscape as becoming more disorderly and complex, suggesting that artificial construction had

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impacted the rapid economic development of the urban agglomeration in the Yellow River Basin's Henan section. As a result, the overall shape of the landscape patch had become more complex and irregular.

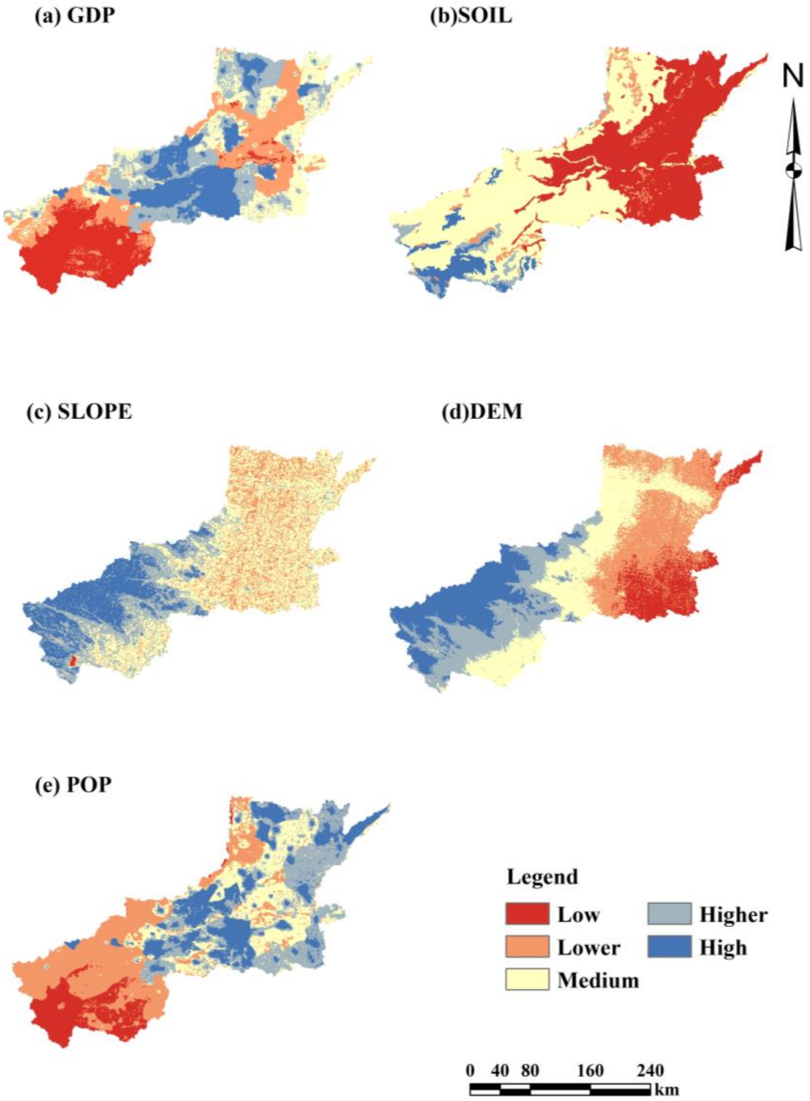

Figure 8. *The main spatial driving factors of land-use change*

(2) Landscape diversity enhancement

From various angles, the major impacts of one or more land-use categories on the entire region were reflected in the SHDI and SHEI. The landscape was more varied and the greater the uncertainty in the information content.

The richness of the terrain was reflected in the SHDI. The SHDI grew and subsequently decreased over the course of the trial. Between 2000 and 2015, both of them and landscape richness rose. Over the next seven years, the study area's land-use degree had been simple, with patches typically consisting of a single use.

The unequal distribution of patches in the landscape was reflected in the SHEI. The closer the value was to 1, the more uniform the landscape distribution, indicating that there would no obvious dominant type in the landscape. From 2000 to 2022, the SHEI

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in the southern section of the Yellow River Basin fluctuated greatly, but the amplitude was low, and the overall landscape types tended to be evenly distributed.

The SHDI and SHEI variation trends were generally positive, and both increased over the study period. This suggested that between 2000 and 2022, the proportional structure tended to be stable, the distribution of landscape types tended to be uniform, and the landscape diversity of urban agglomerations in the southern section of the Yellow River Basin increased.

(3) Variation trend of CONTAG

There were other minor patches in the landscape in addition to dominant patch types with significant connectedness, as demonstrated by the little change in CONTAG. Plaque types generally exhibited an agglomeration tendency.

(4) Landscape-level landscape pattern evolution characteristics

The landscape types of urban agglomerations in the Henan section of the Yellow River Basin tended to be diverse and complex.

The findings demonstrated the usefulness of the landscape pattern index in detecting changes in the urban landscape over time, and an examination of the process of urban landscape expansion proved that human activity was primarily responsible for the spatial heterogeneity of this process. The primary representation of this human component was the alteration in land-use mode brought about by human disturbances. Then, in what direction would the study area's future land-use change? To investigate potential changes in land-use, the Markov-FLUS model was utilized.

Predictions of future LULC changes based on the Markov-FLUS model

To investigate how LULC would evolve in the future, land-use scenarios in 2030 and 2035 were simulated using the Markov-FLUS model. Spatial factors from the research region's land-use data from 2000 and 2015 powered the FLUS model. This generated a simulation map, which was then evaluated for accuracy by comparing it with the real land-use map (*Fig. 8*). Two indices were used to conduct the simulation accuracy test. The first, the FOM index, was chosen for a thorough analysis, while the second was chosen for the test mode of conventional remote sensing image categorization using the Markov-FLUS model implementation.

The five indices that were found to be the geographical drivers of the land-use change were population density, GDP, slope, soil type, and DEM (*Fig. 8*). After verification, the comprehensive kappa coefficient was 0.79 and the FOM index was 0.04, both of which met the accuracy standards of the model.

Using the accuracy-verified Markov-FLUS model, the land-use types in the Yellow River Basin's Henan region were predicted for 2030 and 2035 (*Fig. 9*). The land-use structure in 2030 (*Fig. 9*) was still dominated by agriculture and forestland, per the study area's predicted land-use. 60.38% of the land was made up of farmland, 22.08% was made up of forest, 11.24% was made up of impermeable land, 3.13% was made up of grassland, and very little was made up of shrub land and water. Cropland and forest made up the majority of the land-use structure in 2035, accounting for 60.42% and 20.71%, respectively, with the impermeable surface coming in second at 15.04%. It followed logically from Figure 9 that the impervious surface would keep growing in the future. The analysis of the simulation results indicated that future land use change would follow the current trend of land use change, with cropland area continuing to decline and construction land area continuing to increase, if the land use types from 2000 to 2022 continued to develop and converted at the current rate.

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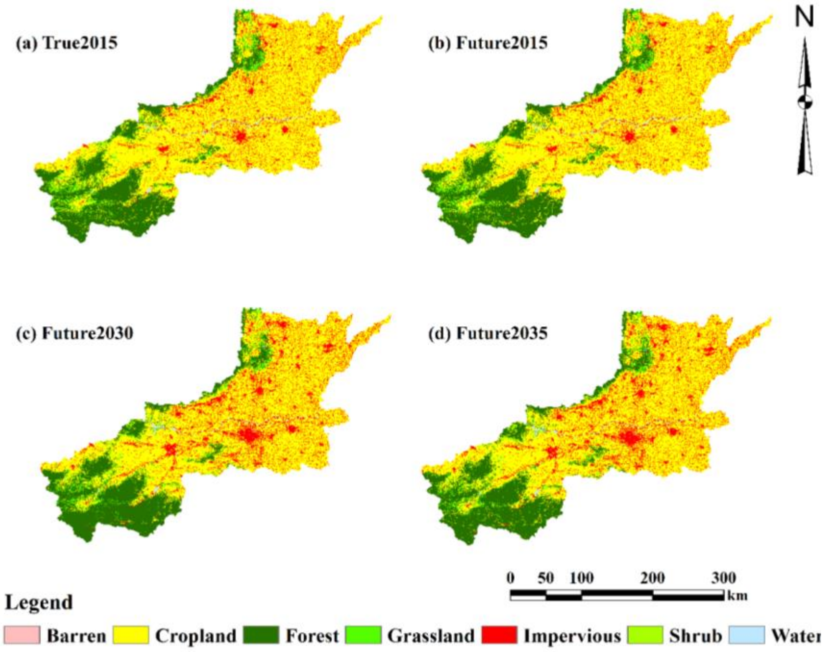

Figure 9. *Land-use simulation and prediction*

Spatio-temporal variation characteristics of ESVs

Spatio-temporal variation characteristics of ESVs as a whole

The equivalent factor technique was utilized to analyze ESVs in order to assess the influence of urban growth on ESVs. The equivalent service value of unit area was used to compute the overall ecosystem service value of land type area. According to the study, there would be a decrease in the value of ecosystem services in the forecast years of 2030 and 2035. This suggested that inappropriate urban expansion would unavoidably jeopardize the establishment of ecological security patterns (*Fig. 10*).

1) From a spatial viewpoint

From the standpoint of ecosystem service types of the whole study area, the ecosystem service value of the urban agglomeration in the Yellow River Basin was primarily composed of regulatory services, which made up 69.04%–69.33% of the total, on average 69.16%; support services came in second, making up 21.82-22.11%, on average 21.94%. According to *Figure 10*, supply services made up 4.95%–5.08% while cultural services made up 3.79%–3.96%. Each service item's value varied within the overall cost while considering time change. The value of supply, adjustment, support, and cultural services would change by 6.99%, 3.93%, 2.61%, and 8.86%, respectively, in 2022 compared to 2000.

2) From a temporal viewpoint

The ESV of the southern Yellow River Basin climbed to a maximum of 301.50×10^9 yuan in 2010, with an average annual growth rate of 4.17×10^9 yuan. The ESV of this region first showed a trend of rising and then dropping from 2000 to 2022. The ESV trended downward from 2010 to 2022 and was predicted to hit its lowest value in that year. There had been a 1.11×10^9 yuan annual decline to 288.22×10^9 yuan. The overall ESV was predicted to drop by 2.97%–3.34% for 2030 and 2035 compared to 2022.

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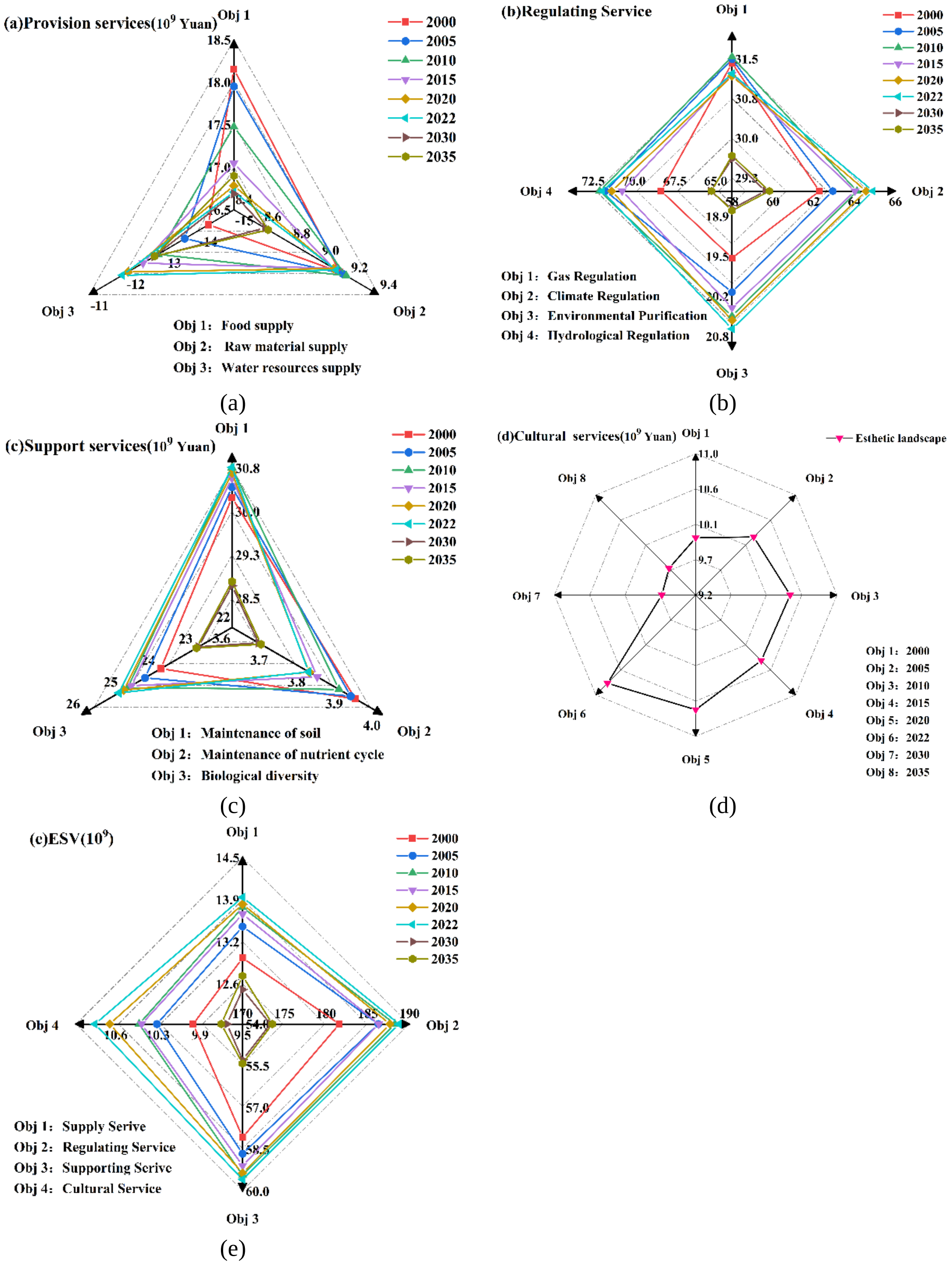

Figure 10. *Variations in ESVs from 2000 to 2035*

It was discovered that the area of land used for urban building was steadily growing. As the body of knowledge about urban ecosystem services had grown, so too had the value and quantification of the recreational service function that urban green space offers. As a result, in the Yellow River Basin ESVs assessment, attention must be paid specifically to the ecosystem service value of construction land.

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Spatio-temporal variation characteristics of ESVs in details

1) From a spatial viewpoint

It was clear from each city's total ESVs diagram in *Figure 11* that Puyang City had a comparatively low total ESVs compared to Luoyang City (*Fig. 11*), which had a leading total ESVs. Luoyang City's high overall ESVs could be attributed to its sustained high level of contribution from several support service categories from 2000 to 2035. Conversely, Puyang City's lower overall ESVs could be attributed to the low contribution of different service categories, particularly cultural services (*Fig. 12a,b*).

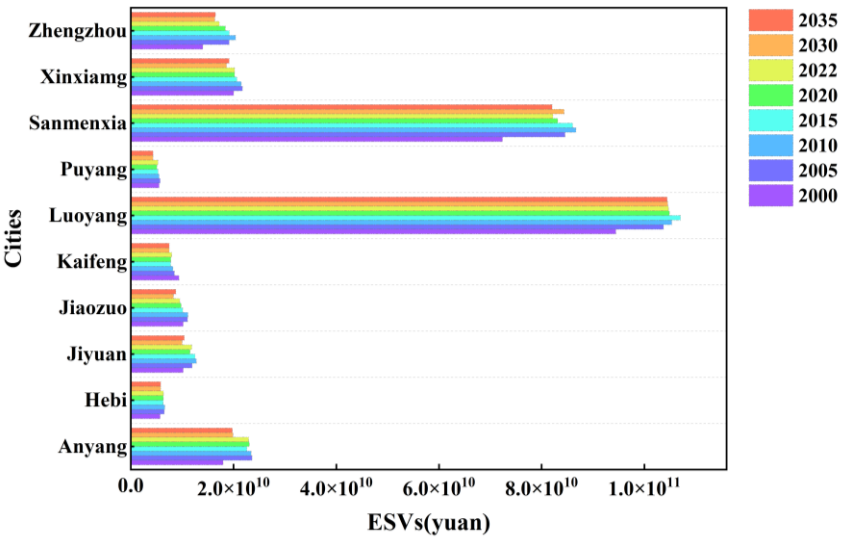

Figure 11. *ESVs rankings by city from 2000 to 2035*

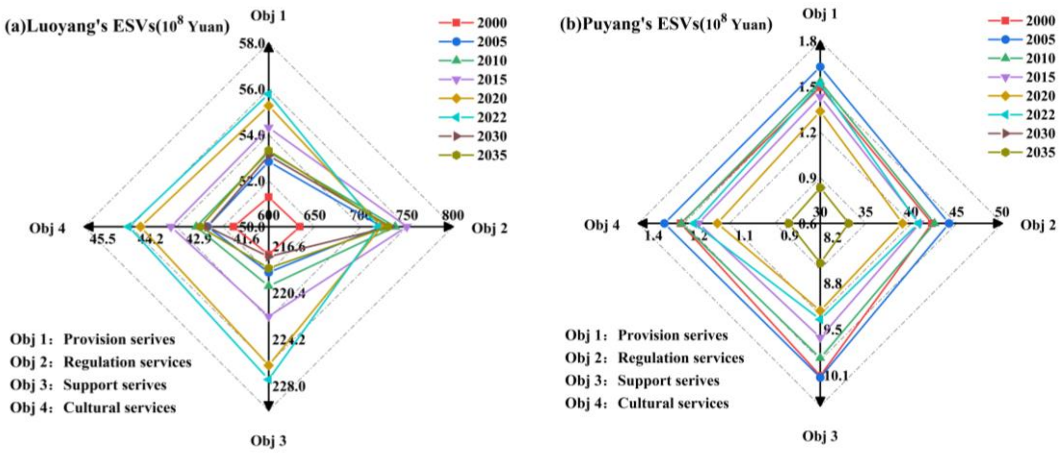

Figure 12. *Types of ecosystem services in Luoyang and Puyang*

2) From a temporal viewpoint

When looking at the research area's ESVs from 2000 to 2035, the analysis revealed that in 2000, the overall ESVs was at a very low level and peaked in 2010. After looking into the different kinds of ecosystem services in more details, we discovered that the major factor contributing to the high total ESVs in 2010 was the larger

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contribution of regulation services; in contrast, the significant reduction of regulation services in 2000 caused the total ESVs to fall (*Fig. 13*).

Overall, the value of regulation services and support services contributed the most to the increase in total ESVs.

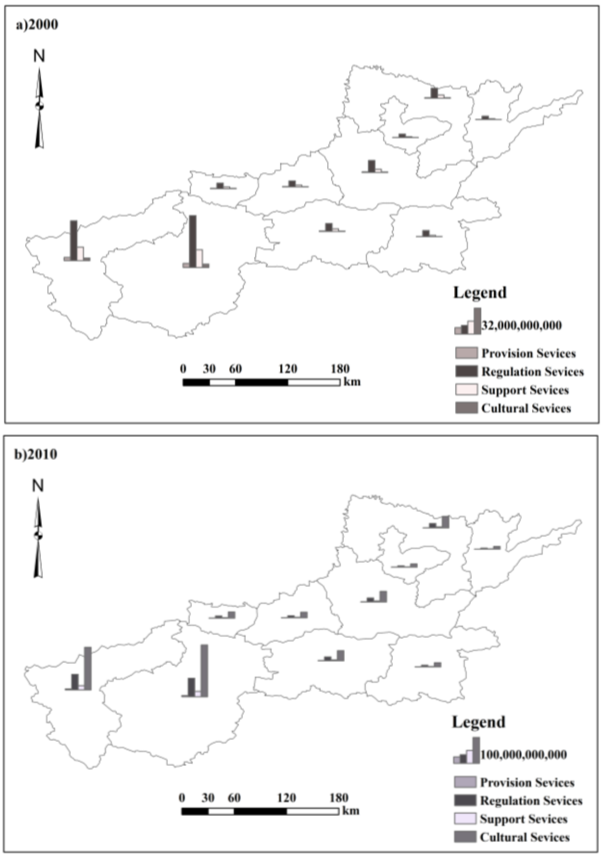

Figure 13. *Histograms of ecosystem service types in 2000 and 2010*

Discussion

As one of the regions with the largest population density and rapid economic and social development, the urban agglomeration in Henan section of the Yellow River Basin had experienced significant changes in land use and land-cover over the past two decades. To better understand the impacts of land-use evolution on landscape patterns and ecological service values in this region, we analyzed the land - use evolution and trends from 2000 to 2022, investigated landscape pattern changes, predicted land-use scenarios in 2030 and 2035 using the Markov-FLUS model, and calculated the evolution process and future trends of ESVs. Results showed that land-use changes had a profound influence on landscape patterns and ESVs.

Effect of LULC changes on ESVs

Over the past 20 years, the dominant land - use type changes in the study area were conversions between cropland and impervious surfaces (*Fig. 5, Table 3*). An analysis of *Table 3* revealed that changes in land - use values, driven by human and natural factors, were a significant determinant of ecosystem value changes, consistent with previous

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research (Jiang et al., 2019; Li et al., 2021; Wang et al., 2022). The growth rate of forestland was lower than that of impervious surfaces and reversing cropland loss was difficult. From 2000 to 2022, the average growth rate of forestland was 2.19%, while that of impervious surfaces was 9.67%, over four times higher; moreover, 51.92% of cropland was converted to impervious surfaces. Forests had a relatively high ecological service values, and any changes to their extent would inevitably result in significant changes to their ecological service values. This was also one of the main causes of the drop in ecological service values seen in the research area. The ecological service value of agriculture per unit area differed by 12,872.42 yuan/hm^2 when compared to the impervious surface. This difference also affected the ecological service value. Analyses of ESV changes indicated that alterations in ecological service functions mainly occurred in regulatory services, closely related to cropland and forest changes in land - use. Thus, land - use changes significantly affected ESVs. Optimizing the land - use pattern to further enhance ESVs is crucial for the sustainable development of the urban agglomeration in the Henan section of the Yellow River Basin.

Impact of landscape pattern changes on ESVs

There were geographical differences in how the value of ecosystem services was impacted by landscape pattern. The response status of the landscape pattern index would also differ depending on the ecological service values of different times and types of landscapes. The rapid changes in landscape types brought about by population increase and urbanization impacted ecosystem function and structure, as well as the value of ecosystem services. Among them, total ESVs were positively correlated with LSI, Area_MN, and SHDI, and showed no negative correlation with NP and PD, landscape index than SHDI. It implied that many factors, such as discrete fragmentation of landscape patches, diverse shapes and poor accessibility, would contribute to the decline in regional ecological value, and that the development of forest land and water landscape types was also correlated with years with high ecosystem service value. In terms of service type, there was a clear inverse relationship between supply service, regulating service, support service, cultural service and NP and PD. which turned out the degree of landscape fragmentation, increased with the number of patches and would be comparatively high. The service function and value would also be impacted by the mutual transfer of different landscapes, particularly when it came to the widespread conversion of cropland to construction land, the dispersion and fragmentation of cropland and water bodies, and the intricate land structure and landscape space configuration. As a result, the total loss of ESVs within the research scope reached 10.44×10^9 yuan in 22 years.

Forestland area made up a significant percentage of the development period from 2000 to 2022; as a result, its landscape indices were mostly stable while other landscape types experienced increases or decreases. Concentrated urban development resulted from the annual growth in the area of building land and the decrease in the degree of separation among them caused by urban development. The degrees to which grasslands and water regions were separated from one another as a result of human activity clearly declined at a pace of 10.9% and increased at a rate of 7.58%, and their shapes steadily became more complex. Sharp variations in ESVs were caused by the degree of landscape pattern fragmentation, agglomeration, and diversity in the Yellow River Basin. Furthermore, the value of regulating and supporting services was greatly impacted by the topography of development sites and water bodies. The future land-use

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structure was simulated using the FLUS model, and the prediction results demonstrated a clear decline in ESVs. Therefore, the primary means of preventing the degradation of the ecological environment, significant reductions in wetland area, and declines in biodiversity in the Yellow River basin were to restrict construction land, increase water bodies, and optimize land-use patterns (Li et al., 2021).

Future scenarios of land-use patterns

The Markov-FLUS model's prediction findings could accurately depict the dynamic changes in land-cover that would occur in the Henan region of the Yellow River Basin in the future. The dynamic changes in land-cover types in 2030 and 2035 were forecasted by analyzing the land-use change from 2000 to 2015; the findings demonstrated that the land-use types usually exhibited a pattern of transition to urban landscapes. In the Yellow River Basin, human activity had resulted in a decrease in grassland and water bodies and a constant growth in construction land. If urbanization was allowed to continue expanding and develop, it may lead to more serious ecological damage and environmental pollution, resulting in new human-generated soil and water loss and aggravating the deterioration of the ecological environment.

Our research validated earlier discoveries that significant land-use changes associated with urban growth could harm ecosystems, which was also confirmed by research in other regions (Kroll et al., 2012).

Conclusions

The urban agglomeration in the Henan region of the Yellow River Basin was confronted with expanding land-use changes and the need for ecological conservation as the region with the highest population density in the basin. Considering this, land-use data from the Henan section's urban agglomeration was evaluated, and the land-use variations from 2000 to 2022 were investigated. Land-use scenarios for 2030 and 2035 were predicted using the Markov-FLUS model, and the effects of land-use changes on landscape patterns and ecological service values were examined. The results were as follows:

(1) An review of the existing land-use situation revealed a large rise in the amount of impermeable land, of which 51.92% resulted from the conversion of arable land. The research area's comprehensive dynamic attitude of land-use showed a declining trend and a wide changing range. Between 2000 and 2022, the growth of urbanization led to a rise in the demand for building land, a decline in farmland, and a clear strengthening of the urbanization trend.

(2) In order to analyze the changes in landscape patterns in urban agglomerations, seven typical landscape pattern indices were chosen from two perspectives: the class level and the landscape level. These selections were based on remote sensing land use monitoring data from 2000, 2005, 2010, 2015, 2020, and 2022. The findings demonstrated that the degree of fragmentation decreased, the patches tended to combine and become more intense, and the landscape types tended to diversify and become more complex.

(3) The Markov-FLUS model was used to simulate the land-use patterns in the study area in 2030 and 2035. The future land use change was mainly reflected in the continuation of the current trend of land use change: the construction land area would continue to show a rapid expansion trend, and the cultivated land would continue to

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decrease, which would lead to the decline of the quantity and quality of cultivated land, the difficulty of food security and urban pressure.

(4) Using the equivalent factor method to quantitatively evaluate the temporal and spatial characteristics of ecosystem service value from the grid level, the future forecast of ESVs in 2030-2035 would decrease by 8.15%-7.93% compared with 2022. On one hand, the recreational service function provided by urban green space had been valued and quantified as equivalent factor, while on the other hand, with the increasing consumption of Yellow River resources by human activities and inappropriate land-use, the ESVs were at a low level.

In summary, the ESVs in the Henan Urban Agglomeration of the Yellow River Basin had been drastically lowered due to the quick change in land-use value and the degradation of landscape patterns caused by human activities such as urban growth and land occupation. Significantly, the Yellow River Basin's ecosystem services were influenced by both natural and human factors to varying degrees. As a result, more accurate data and improved research techniques would be required in future studies to accurately quantify the value of the ecosystem and manage it more effectively across different regions. By exploring interactions between LULC and ESVs at the local level, we could propose more targeted land management as well as eco-governance strategies that could provide practical guidance for coordinating regional land development with ecosystem conservation. Furthermore, we verified the reliability of our findings in three aspects, namely the ESVs, landscape pattern indices, and the Markov-FLUS model, which may serve as valuable methodological references for future studies in this field.

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REFERENCES

[1] Abbas, Z., Zhu, Z., Zhao, Y. (2022): Spatiotemporal analysis of landscape pattern and structure in the Greater Bay Area, China. – Earth Science Informatics 15(3): 1977-1992.

[2] Camagni, R., Gibelli, M. C., Rigamonti, P. (2002): Urban mobility and urban form: the social and environmental costs of different patterns of urban expansion. – Ecological Economics 40(2): 199-216.

[3] Chang, Y. T., Liu, H. L., Bao, A. M., Chen, X., Wang, L. (2015): Evaluation of urban water resource security under urban expansion using a system dynamics model. – Water Supply 15(6): 1259-1274.

[4] Chen, Y., Syvitski, J. P. M., Gao, S., Overeem, I., Kettner, A. J. (2012): Socio-economic impacts on flooding: A 4000-year history of the Yellow River, China. – Ambio 41(7): 682-698.

[5] Chen, S., Feng, Y., Tong, X., Liu, S., Xie, H., Gao, C., Lei, Z. (2020): Modeling ESV losses caused by urban expansion using cellular automata and geographically weighted regression. – Science of the Total Environmennt 712: 136509.

[6] Chen, Y., Fu, B., Zhao, Y., Wang, K., Zhao, M. M., Ma, J., Wu, J., Xu, C., Liu, W., Wang, H. (2020): Sustainable development in the Yellow River Basin: Issues and strategies. – Journal of Cleaner Production 263: 121223.

[7] Chen, Z., Huang, M., Zhu, D., Altan, O. (2021): Integrating remote sensing and a markov-FLUS model to simulate future land use changes in Hokkaido, Japan. – Rem Sen 13(13): 2621.
[8] Corry, R. C. (2005): Characterizing fine-scale patterns of alternative agricultural landscapes with landscape pattern indices. – Lands Eco 20: 591-608.
[9] Da, Z., Huang, Q., He, C., Wu, J. (2017): Impacts of urban expansion on ecosystem services in the Beijing-Tianjin-Hebei urban agglomeration, China: a scenario analysis based on the shared socioeconomic pathways. – Res Cons & Rec 125: 115-130.
[10] Doelman, J. C., Stehfest, E., Tabeau, A., van Meijl, H., Lassaletta, L., Gernaat, D. E. H. J., Hermans, K., Harmsen, M., Daioglou, V., Biemans, H., van der Sluis, S., van Vuuren, D. P. (2018): Exploring SSP land-use dynamics using the IMAGE model: Regional and gridded scenarios of land-use change and land-based climate change mitigation. – Global Environmental Change 48: 119-135.
[11] Estoque, R. C., Murayama, Y. (2013): Landscape pattern and ecosystem service value changes: Implications for environmental sustainability planning for the rapidly urbanizing summer capital of the Philippines. – Landscape and Urban Planning 116: 60-72.
[12] FRAGSTATS (1995): Spatial Pattern Analysis Program for Quantifying Landscape Structure. – USDA Forest Service General Technical Report PNW-GTR-351.
[13] Gao, Q., Ge, J., Zhang, J., Ren, Z., Wu, D., Cheng, G., Zhang, K. (2023): Experimental study on the engineering characteristics of modified silt in the Yellow River alluvial plain. – Cons & Building Mat 398: 132491.
[14] Guo, P., Zhang, F., Wang, H. (2022): The response of ecosystem service value to land use change in the middle and lower Yellow River: A case study of the Henan section. – Eco Indicators 140: 109019.
[15] He, C., Okada, N., Zhang, Q., Shi, P., Li, J. (2008): Modelling dynamic urban expansion processes incorporating a potential model with cellular automata. – Landscape and Urban Planning 86(1): 79-91.
[16] Hegazy, I. R., Kaloop, M. R. (2015): Monitoring urban growth and land use change detection with GIS and remote sensing techniques in Daqahlia governorate Egypt. – International J of Sus Built Envi 4(1): 117-124.
[17] Huang, B., Huang, J., Pontius Jr, R. G., Tu, Z. (2018): Comparison of Intensity Analysis and the land use dynamic degrees to measure land changes outside versus inside the coastal zone of Longhai, China. – Eco Indicators 89: 336-347.
[18] Jiang, L., Deng, X., Seto, K. C. (2013): The impact of urban expansion on agricultural land use intensity in China. – Land Use Policy 35: 33-39.
[19] Jiang, Z., Sun, X., Liu, F., Shan, R., Zhang, W. (2019): Spatio-temporal variation of land use and ecosystem service values and their impact factors in an urbanized agricultural basin since the reform and opening of China. – Environmental Monitoring and Assessment 191: 739.
[20] Kadhim, N., Ismael, N. T., Kadhim, N. M. (2022): Urban landscape fragmentation as an indicator of urban expansion using sentinel-2 imageries. – Civ Eng J 89: 1799-1814.
[21] Kroll, F., Müller, F., Haase, D., Fohrer, N. (2012): Rural-urban gradient analysis of ecosystem services supply and demand dynamics. – Land Use Policy 29(3): 521-535.
[22] Kubiszewski, I., Costanza, R., Anderson, S., Sutton, P. (2017): The future value of ecosystem services: global scenarios and national implications. – Ecosystem Services 26: 289-301.
[23] Lambin, E. F. (1997): Modelling and monitoring land-cover change processes in tropical regions. – Progress in Physical Geography 21(3): 375-393.
[24] Leao, S., Bishop, I., Evans, D. (2004): Spatial-temporal model for demand and allocation of waste landfills in growing urban regions. – Computers, Envi and Ur Sys 28(4): 353-385.

[25] Letourneau, A., Verburg, P. H., Stehfest, E. (2012): A land-use systems approach to represent land-use dynamics at continental and global scales. – Envi Mod & Sof 33: 61-79.
[26] Li, P. C., Yujun, S., Saeed, S. (2018): Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques-A case study of a hilly area, Jiangle, China. – PloS One 13(7): e0200493.
[27] Li, X., Zhou, Y., Yu, S., Jia, G., Li, H., Li, W. (2019): Urban heat island impacts on building energy consumption: A review of approaches and findings. – Energy 174: 407-419.
[28] Li, C., Wu, Y., Gao, B., Zheng, K., Wu, Y., Li, C. (2021): Multi-scenario simulation of ecosystem service value for optimization of land use in the Sichuan-Yunnan ecological barrier, China. – Eco Indicators 132: 108328.
[29] Li, N., Wang, J., Wang, H., Fu, B., Chen, J., He, W. (2021): Impacts of land use change on ecosystem service value in Lijiang River Basin, China. – Envi Sci & Pol Res 28: 46100-46115.
[30] Li, S., He, Y., Xu, H., Zhu, C., Dong, B., Lin, Y., Si, B., Deng, J., Wang, K. (2021): Impacts of urban expansion forms on ecosystem services in urban agglomerations: A case study of Shanghai-Hangzhou Bay urban agglomeration. – Rem Sens 13(10): 1908.
[31] Li, S., Zhao, X., Pu, J., Miao, P., Wang, Q., Tan, K. (2021): Optimize and control territorial spatial functional areas to improve the ecological stability and total environment in karst areas of Southwest China. – Land Use Policy 100: 104940.
[32] Liu, X., Liang, X., Li, X., Xu, X., Ou, J., Chen, Y., Li, S., Wang, S., Pei, F. (2017): A future land use simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects. – Landscape and Urban Planning 168: 94-116.
[33] Liu, Y., Gao, Y., Liu, L., Song, C., Ai, D. (2022): Nature-based solutions for urban expansion: Integrating ecosystem services into the delineation of growth boundaries. – Habitat International 124: 102575.
[34] Lourenco, I. B., Guimaraes, L. F., Alves, M. B., Miguez, M. G. (2020): Land as a sustainable resource in city planning: The use of open spaces and drainage systems to structure environmental and urban needs. – Journal of Cleaner Production 276: 123096.
[35] Miles, L. S., Rivkin, L. R., Johnson, M. T. J., Munshi-South, J., Verrelli, B. C. (2019): Gene flow and genetic drift in urban environments. – Mol Ecol 28(18): 4138-4151.
[36] Munthali, M. G., Mustak, S., Adeola, A., Botai, J., Singh, S. K., Davis, N. (2020): Modelling land use and land cover dynamics of Dedza district of Malawi using hybrid Cellular Automata and Markov model. – Rem Sens App: Soc & Envi 17: 100276.
[37] Pal, M. (2009): Extreme-learning-machine-based land cover classification. – Inter J of Rem Sen 30(14): 3835-3841.
[38] Peng, J., Du, Y., Liu, Y., Hu, X. (2016): How to assess urban development potential in mountain areas? An approach of ecological carrying capacity in the view of coupled human and natural systems. – Ecological Indicators 60: 1017-1030.
[39] Pennekamp, F., Pontarp, M., Tabi, A., Altermatt, F., Alther, R., Choffat, Y., Fronhofer, E. A., Ganesanandaamorthy, P., Garnier, A., Griffiths, J. I., Greene, S., Horgan, K., Massie, T. M., Machler, E., Palamara, G. M., Seymour, M., Petchey, O. L. (2018): Biodiversity increases and decreases ecosystem stability. – Nature 563: 109-112.
[40] Qiao, X., Li, Z., Lin, J., Wang, H., Zheng, S., Yang, S. (2023): Assessing current and future soil erosion under changing land use based on InVEST and FLUS models in the Yihe River Basin, North China. – Inter Soil & Wat Cons Res 12(2): 298-312.
[41] Redman, C. L., Jones, N. S. (2005): The environmental, social, and health dimensions of urban expansion. – Population & Environment 26(6): 505-520.
[42] Sahana, M., Hong, H., Sajjad, H. (2018): Analyzing urban spatial patterns and trend of urban growth using urban sprawl matrix: A study on Kolkata urban agglomeration, India. – Sci of the Tot Envi 628: 1557-1566.

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DOI: http://dx.doi.org/10.15666/aeer/2303_50955121

[43] Shi, L., Shao, G., Cui, S., Li, X., Lin, T., Yin, K., Zhao, J. (2009): Urban three-dimensional expansion and its driving forces-A case study of Shanghai, China. – Chinese Geographical Science 19: 291-298.
[44] Szymańska-Walkiewicz, M., Matela, M., Obolewski, K. (2023): Patterns of effects of land-use structure on lake water quality in coastal lake catchments of the southern Baltic Sea. – Ecohydrology & Hydrobiology 7(25): 1642-3593.
[45] Tang, L., Ke, X., Chen, Y., Wang, L., Zhou, Q., Zheng, W., Xiao, B. (2021): Which impacts more seriously on natural habitat loss and degradation? Cropland expansion or urban expansion? – Land Degradation & Development 32(2): 946-964.
[46] Tao, W., Liu, J., Ban-Weiss, G. A., Hauglustaine, D. A., Zhang, L., Zhang, Q., Cheng, Y., Yu, Y., Tao, S. (2015): Effects of urban land expansion on the regional meteorology and air quality of eastern China. – Atmospheric Chemistry & Physics 15(15): 8597-8614.
[47] Tefera, B., Sterk, G. (2010): Land management, erosion problems and soil and water conservation in Fincha'a watershed, western Ethiopia. – Land Use Policy 27(4): 1027-1037.
[48] Wang, X. L., Bao, Y. H. (1999): Study on the methods of land use dynamic change research. – Progress in Geography 18(1): 81-87.
[49] Wang, Z., Cao, J., Zhu, C., Yang, H. (2020): The impact of land use change on ecosystem service value in the upstream of Xiong'an new area. – Sustainability 12(14): 5707.
[50] Wang, L., Sun, J., Wu, Q. (2021): Nonlinear total least-squares variance component estimation for GM (1, 1) model. – Geodesy and Geodinamics 12(3): 211-217.
[51] Wang, Z., Zeng, J., Chen, W. (2022): Impact of urban expansion on carbon storage under multi-scenario simulations in Wuhan, China. – Envi Sci & Pol Res 29(30): 45507-45526.
[52] Wang, C., Liu, S., Zhou, S., Zhou, J., Jiang, S., Zhang, Y., Feng, T., Zhang, H., Zhao, Y., Lai, Z., Cui, S., Mao, X. (2023): Spatial-temporal patterns of urban expansion by land use/land cover transfer in China. – Ecological Indicators 155: 111009.
[53] Webber, M., Barnett, J., Wang, M., Finlayson, B., Dickinson, D. (2008): The Yellow River in transition. – Envi Sci & Pol 11(5): 422-429.
[54] Xie, G. D., Zhang, Y. L., Lu, C. X., Zheng, D., Cheng, S. K. (2001): Study on valuation of rangeland ecosystem services of China. – J of Nat Res 16(1): 47-53.
[55] Xu, J., Ma, Y. (2009): Response of the hydrological regime of the Yellow River to the changing monsoon intensity and human activity. – Hydro Sci J 54(1): 90-100.
[56] Yang, J., Huang, X. (2021): The 30 m annual land cover dataset and its dynamics in China from 1990 to 2019. – Ear Sys Sci Data 13(8): 3907-3925. https://doi.org/10.5194/essd-13-3907-2021.
[57] Yang, M., Gao, X., Siddique, K. H. M., Wu, P., Zhao, X. (2023): Spatiotemporal exploration of ecosystem service, urbanization, and their interactive coercing relationship in the Yellow River Basin over the past 40 years. – Sci of the Tot Envi 858: 159757.
[58] Yin, J., Yin, Z., Zhong, H., Xu, S., Hu, X., Wang, J., Wu, J. (2011): Monitoring urban expansion and land use/land cover changes of Shanghai metropolitan area during the transitional economy (1979-2009) in China. – Environmental Monitoring & Assessment 177: 609-621.
[59] Zank, B., Bagstad, K. J., Voigt, B., Villa, F. (2016): Modeling the effects of urban expansion on natural capital stocks and ecosystem service flows: a case study in the Puget Sound, Washington, USA. – Landscape & Urban Planning 149: 31-42.
[60] Zeng, C., Zhang, M., Cui, J., He, S. (2015): Monitoring and modeling urban expansion-A spatially explicit and multi-scale perspective. – Cities 43: 92-103.
[61] Zhang, Y., Zheng, M., Qin, B. (2023): Optimization of spatial layout based on ESV-FLUS model from the perspective of "Production-Living-Ecological": A case study of Wuhan City. – Eco Mod 481: 110356.
[62] Zhao, L., Zhao, C., Huang, J. (2022): Spatial Dynamics and Determinants of Population Urbanization in the Upper Reaches of the Yellow River. – Land 11(9): 1420.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2303_50955121

[63] Zhu, H. Y., Li, X. B., He, S. J., Zhang, M. (2001): Spatio-temporal Change of Land Use in Bohai Rim. – Acta Geographica Sinica 56(3): 253-260.
[64] Zhu, W., Gao, Y., Zhang, H., Liu, L. (2020): Optimization of the land use pattern in Horqin Sandy Land by using the CLUMondo model and Bayesian belief network. – Science of the Total Environment 739: 139929.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
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