

THE IMPACT OF LAND USE SYSTEM CHANGE ON ECOSYSTEM SERVICE VALUE IN RAPIDLY URBANIZED AREAS IN CHINA

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Abstract. Land use system change is the primary reason for the variation of ecosystem service value (ESV). This study analyzes the effects of land use category (LUC) and land use intensity (LUI) on ESV simultaneously in Guangzhou city with 3 rapid urbanization stages. Firstly, ESV is assessed using the LUC value equivalent method and sensitivity analysis; meanwhile, bivariate spatial autocorrelation and time path models are applied to characterize the impact of LUI with three aspects, configuration LUI, carrying LUI2, output LUI3, on ESV utility. The conclusion was drawn that: (1) the changes in LUC and LUI continued to intensify. The ESV showed significant four-zone effects, with the development zones P1-P3 showed an “inverted U-shaped” trend, and only the ecosystem zone P4 showed a “positive U-shaped” structure; (2) the ESV utility was significantly inhibited by negative pressure from LUI, with the uneven impact evolution from LUI1 to LUI2 and then to LUI3; (3) the overall fragmentation of ESV time path was high, showing a significant positive correlation with the comprehensive change of LUI1 and LUI2 paths, and significant spatial proximity effects and boundary effects; it also showed a significant negative correlation with the change rate of LUI3 paths, a significant cross-boundary displacement effects and uneven impacts.

Keywords: *ecosystem service value, land use category, land use intensity, bivariate spatial autocorrelation, LISA time path, LISA spatiotemporal migration*

Introduction

The ecosystem services value (ESV) refers to the life support products and services obtained directly or indirectly through the structure, processes, and functions of the ecosystems (Li, 2011). The main indicators include supply services, regulating services, supporting services, and aesthetic landscape services (Chen et al., 2025; Zhang et al., 2025). As ESV research at different scales in various regions develops and progresses, researchers have found that land use system (LUS), as the foundation of ecosystem composition, influences the value of ecosystem services by altering the structure, processes, and functions of ecosystems, making LUS the most significant factor affecting ESV. Since 2010, China has undergone a transformation characterized by accelerating urbanization and high-quality development. With the frequent migration of populations in urban areas, the rapid expansion of artificial surfaces, and the high development of human production activities, significant changes have occurred in land use systems, leading to intense erosion

and destruction of ESV over certain periods, which in turn has generated a series of contradictions and conflicts between ecological service functions and socioeconomic development. Therefore, exploring the synergistic evolution mechanism between land use system and ESV, and scientifically measuring their response relationships and spatial patterns, is the basis for rationally allocating limited land resources and efficiently utilizing them (Li et al., 2011). It is also an important prerequisite for formulating ecological compensation policies and improving the value of regional ecosystem services (Lai et al., 2015; Lei et al., 2019; Zhan and Li, 2025). It can provide theoretical and decision-making support in resolving the conflicts between comprehensive urban development and environmental protection.

The ESV is closely related to human well-being. In the 1990s, Costanza et al. (1997) first put forward the the estimation principle and method model of ESV. It has established the connection between land use category (LUC) and ESV, and made a preliminary evaluation of global scale ESV, providing an important research foundation for later scholars. Chinese scholars Xie et al. (2015a, b), based on the Costanza model and combining the actual situation of China, established an ESV value scale for land use and proposed an improved method for economic value calculation. These studies have attracted extensive references from scholars both domestically and internationally. Many scholars have proposed corrections to the scaling factors based on the actual ecological and socio-economic development conditions of their research areas, conducting relevant studies on the assessment of ESV in urban regions (Zhou et al., 2021; Pan et al., 2021; Li et al., 2021; Ran et al., 2021; Zhang and Jin, 2024; Liu et al., 2024), promoting the rapid development of ESV accounting in China. It can be observed that in most of these studies on the impact of LUC on ESV, a single LUC change is often considered for its effect on ESV. Although some studies have proposed a series of influencing factors, they still focus on the relationship between changes in ESV quantity and LUC and their derived indicators (such as composition, structure, and function), often overlooking the mechanisms and characteristics of spatial pattern evolution of ESV caused by multidimensional changes in land use intensity (LUI).

Different region's land use systems, apart from exhibiting varying degrees of configuration intensity, also show diverse and different intensities in utilization strength such as carrying capacity and productivity, leading to different patterns and effects on ESV (Wang et al., 2022). For example, the intensity of human disturbance and ecological adaptability of different types of land use in various regions differ (He et al., 2024), and the changes in ESV caused by their transfer also vary; population migration and mobility lead to changes in the intensity of land use carrying (Chen et al., 2023), which may reduce ESV in some areas but increase it in adjacent areas; while an increase in the intensity of land use output generally reduces ESV. Moreover, land use changes at different time scales exhibit distinct characteristics, showing significant differences in their impact on ESV (Wang et al., 2024; Luan and Ma, 2024; Wu et al., 2025). However, current research primarily focuses on larger scales such as provincial or municipal levels, mainly focusing on explicit LUC and their estimation and impact methods on ESV (Guo et al., 2024; Xie et al., 2025), overlooking the influence of implicit land configuration intensity, carrying capacity, output intensity, and other utilization strengths, failing to reveal the spatial details of multi-dimensional LUI impacts; simultaneously, statistical associations and static spatial pattern analyses based on ideal assumptions provide less research on the dynamic changes in spatial agglomeration of ESV, unable to uncover multiple potential reasons for agglomeration

changes in smaller scales of spatial patterns and the coupling evolution mechanisms over longer periods.

Since 2010, China has comprehensively accelerated its urbanization process, leading to another round of economic growth in major cities (Yu et al., 2019; Peng et al., 2020). However, the contradiction between population and land use has become increasingly prominent (Li et al., 2024; Qi et al., 2024). The urbanization process, characterized by the expansion of artificial surfaces, population migration, and GDP growth, has led to the fragmentation and degradation of regional habitats, profoundly impacting the ecosystem service functions. For example, the continuous expansion of urban areas has eroded large tracts of farmland and forest, and the high density of population and intensive production activities have led to ecosystem degradation and a reduction in biodiversity, which can also cause soil erosion and weaken the value of related ecosystems, such as soil and water conservation. Changes in LUC can stimulate shifts in ecosystem structure and function, disrupting ecosystem balance and causing a series of issues including environmental degradation and the decline of ecosystem service functions (Duan et al., 2005). Changes in LUI are becoming the primary factors eroding and damaging ecosystems. However, traditional studies, due to idealized statistical analyses and static spatial feature descriptions, are unable to reveal the potential directions of changes in LUC or reflect its implicit coupling with ecosystem services and spatiotemporal evolution patterns.

Guangzhou City is located in the central part of Guangdong Province, China, and is a typical economically developed city and a pilot city for rapid urbanization. The issues between land use and ecosystems are becoming increasingly prominent, making it significant to explore the synergistic development pattern of LUC changes and ESV. This study aims to uncover internal information about LUS changes in Guangzhou over a long-term scale. Based on the ESV assessment, it applies spatiotemporal geographic statistical methods such as bivariate spatial autocorrelation, LISA time path, and LISA spatiotemporal migration to analyze the response relationship and pattern evolution of LUI and ecosystem service value. This can further reveal the mechanism by which changes in LUI during rapid urbanization affect ESV, providing a reference for the rational allocation of land resources and ecological environment construction in megacities. Therefore, this study focuses on the following questions: (1) Does the LUC determine the value of ecosystem services, and if so, does the LUI determine the realization of ESV utility? What aspects can these potential influencing factors be summarized? (2) How reliable and sensitivity are the assessment of ESV based on changes in LUC? (3) How to measure the coupling impact of LUI on ESV utility, and what spatiotemporal evolution patterns do they exhibit in rapidly urbanized areas?

Materials and methods

Study area and study data

Guangzhou City is the political, economic, technological, educational, and cultural center of Guangdong Province, China. It is the largest and oldest international trading port, as well as one of the starting points of the Maritime Silk Road and a frontier of China's reform and opening up. Guangzhou has a diverse land type with terrain gradually decreasing from north to south; the northeastern part is a mid-low mountainous area; the central part is a hilly basin; and the southern part is a coastal alluvial plain.

Guangzhou comprises 11 districts. According to its urban development plan of from 2010 to 2020, these districts can be divided into 4 major types: P1 Old City Development

Area (Liwan, Yuexiu, Tianhe, Haizhu), P2 Complex Integration Area of Urban and Rural Landscapes (Baiyun, Huadu, Huangpu), P3 Key Urban Development Area (Nansha, Panyu), and P4 Urban Ecological Protection Area (Zengcheng, Conghua). The location map is shown in *Figure 1*. During the period, the city experienced the rapid urbanization process from spatial expansion to population concentration and then to economic coordination (data sources: <https://www.webmap.cn/mapDataAction.do?method=globalLandCover>).

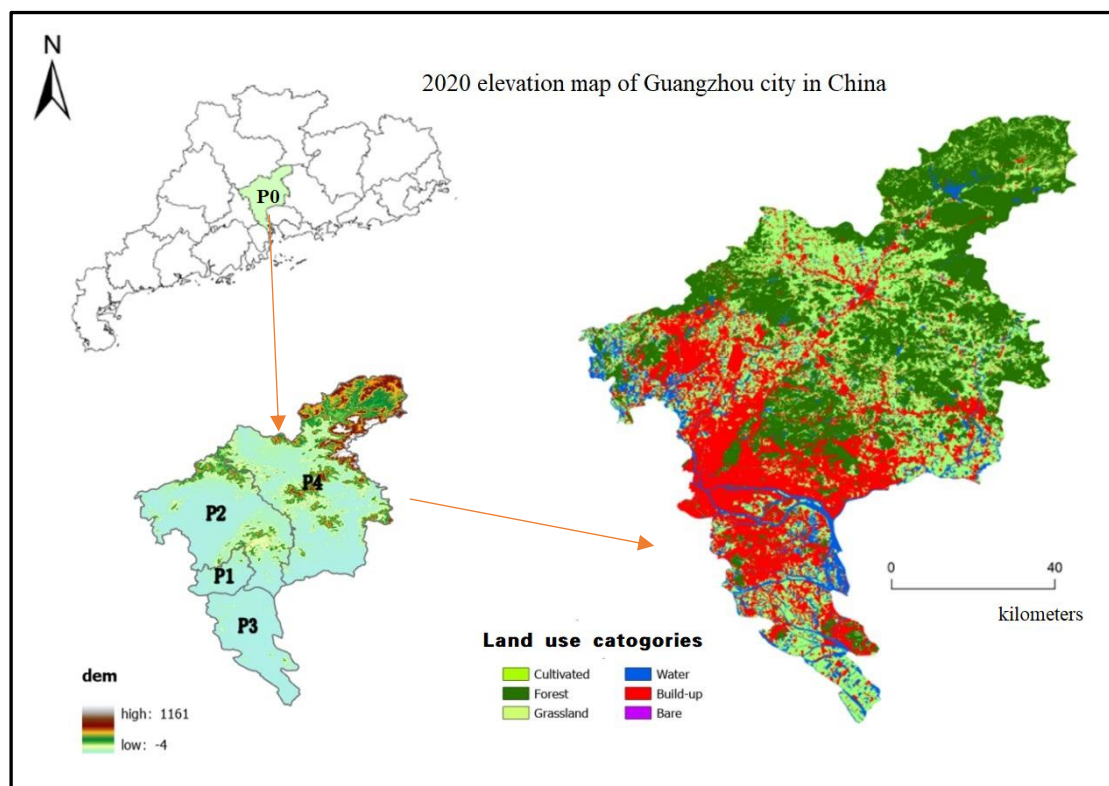


Figure 1. Location map of Guangzhou in 2020 years

Therefore, the study period includes 2 phases interval of every 5 years from 2010 to 2020 in Guangzhou City. Among them, the 30-m resolution land use data comes from the Global Land Surface Data (GlobalLand30) from 2010 to 2020; the population density grid data comes from the WorldPop website, with a resolution of $1 \text{ km} \times 1 \text{ km}$ from 2010 to 2020; the GDP grid data comes from the Institute of Resources and Environmental Sciences of the Chinese Academy of Sciences, with a resolution of $1 \text{ km} \times 1 \text{ km}$ from 2010 to 2020; the resident population data and district GDP data come from the Guangzhou Statistical Yearbook from 2010 to 2020.

Land use change estimation

Classification of land use catogories

The LUC data originates from the Global Surface Cover Data (GlobalLand30), which is the outcome of the key project “Global Surface Cover Remote Sensing Mapping and Key Technology Research” under the National 863 Program. This data utilizes images from the U.S. LandSat (TM5, ETM+) and China’s Environment Disaster Reduction Satellite (HJ-

1), employing a comprehensive method based on pixel classification-object extraction-knowledge verification for extraction. The overall accuracy of the 2010 data was 83.50%, with a Kappa coefficient of 0.78, while the overall accuracy of the 2020 data was 85.72%, with a Kappa coefficient of 0.82 (Jun et al., 2015). Data in 2015 were derived from the first annual land cover product derived from Landsat in China, established by Wuhan University between 1985 and 2019. Through reprojecting, registration and cropping, the land use data of Guangzhou city in 2010, 2015 and 2020 with a resolution of 30 m were obtained; then through reclassification, the LUC in Guangzhou city were divided into cultivated land, forest land, grassland, wetland, artificial surface, bare land, and water body; finally obtained the area of land use through computing the number of pixels from the RS image for each category.

Measurement of land use intensity

China has been advancing its urbanization process since 2000, leading to the proposal of new urbanization construction. During this period of rapid development, many cities have followed a general sequence of spatial expansion, population migration, and economic improvement, demonstrating characteristics distinct from conventional urbanization processes. Therefore, scholars have proposed three indicators to characterize urbanization levels: spatial urbanization, population urbanization, and economic urbanization. Correspondingly, changes in LUC serve as a three-dimensional spatial carrier for spatial planning and development practices, acting as an intermediary variable for the coordination of urbanization development and ecological service value, exhibiting corresponding change patterns (Sun et al., 2020), namely land use configuration intensity LUI1, land use carrying intensity LUI2, and land use output intensity LUI3. Therefore, this study comprehensively employs spatial correction coefficient analysis methods to analyze LUI in three aspects. These computation process are shown in *Table 1*.

Table 1. Calculation method of LUI

LUI	Computational formula	Variable significance	Describe the indicators
LUI1_ (Eq.1)	$LUI1 = \frac{100 * \sum_i^n M_i X_i}{M_z}$	n is the number of land-use categories; X_i is the grading index of land-use category i ; M_z is the total area	M_i is the total area of land-use category i
LUI2_ (Eq.2)	$LUI2 = \frac{100 * \sum_i^n O_i}{M_z}$		O_i is the total population carrying the population
LUI3_ (Eq.3)	$LUI3 = \frac{100 * \sum_i^n G_i}{M_z}$		G_i is the total economic output

(1) Land allocation intensity

The intensity of land allocation is to set the grading index for different types of land use and express the degree of land use development in the study area by combining the area, which reflects the structure of the common effect of land resources endowment and human interference activities to a certain extent (Xu et al., 2019). Referring to the research of Zhuang and Liu (1997), this study assigns the artificial surface category index value as 4, the cultivated land category index value as 3, the forest land, grassland, wetland, and water body category index value as 2, and the bare land category index value as 1. *Equation 1* is shown in *Table 1*. Wherein the area of land-use is obtained through computing the number of pixels from the RS image for each category.

Following the research method of Zhuang and Liu (1997), in this study, the grading index for artificial surfaces is assigned a value of 4, the grading index for farmland is assigned a value of 3, the grading indices for forest land, grassland, wetland and water bodies are assigned a value of 2, and the grading index for bare land is assigned a value of 1.

(2) Land carrying intensity

The Chinese Academy of Sciences Comprehensive Natural Resources Investigation Committee defines land carrying capacity as: “the population that a country or region can sustainably and stably support over different time scales in the future, based on foreseeable technological, economic, and social development levels and corresponding material living standards” (T. R. Malthus; K. Wicksell). In this study, land carrying intensity is expressed as the current population carrying capacity of land resources (optimum population), calculated by dividing the population number by the land area, also known as the population density per unit area of land. *Equation 2* is shown in *Table 1*.

(3) Land output intensity

The land output rate refers to the average annual output value per unit of land, which is an important indicator reflecting the efficiency of land use. Taking into account the conditions of various industries, this study defines the land output rate as the ratio of regional GDP to land area, serving as a comprehensive economic indicator reflecting the level of industrial productivity in a region, with the unit being yuan/hm². *Equation 3* is shown in *Table 1*.

ESV assessment based on land use categories equivalent

Land use categories value equivalent on ESV

Ecosystem services are further divided into 11 subcategories as shown in *Table 2*. Costanza et al. (1997) developed a value equivalent table for ecosystem services per unit area based on biomass and land cover area. Subsequently, Xie et al. (2015a, b) proposed a value equivalent table for ecosystem services in China, tailored to the country's specific conditions. This study revises the value equivalents based on the table proposed by Xie et al. (2015a,b) incorporating the actual conditions of the study area. The revised formula is as *Equation 4*:

$$E_i = \frac{c}{c_0} * E_{i0} \quad (\text{Eq.4})$$

where E_i is the equivalent factor of the modified LUC of category i , c and c_0 are the yield per unit area of grain in Guangzhou and the whole country, respectively, and E_{i0} is the equivalent factor of the same LUC determined by Xie et al. (2015a,b). In 2020, the national grain yield per unit area was 5734 kg/ha; the grain yield per unit area in Guangzhou was 5749 kg/ha. The grain purchase price at the end of 2020 was 3156.05 yuan/ton. The economic value provided by natural ecosystems is one-seventh of the economic value of food production services provided by existing unit area cultivated land (Wu, 2021). Therefore, the economic value of one ecological service value factor in Guangzhou is calculated to be 2592.01 yuan/hm². Therefore, the value coefficient of ecological services per unit area of different ecosystem units can be obtained, as shown in *Table 2*.

Table 2. Value coefficient of ecosystem services in Guangzhou

	LUC	Meadow	Plough	Artificial surface	Forest land	Waters	Bare land
LUC areas (km)	Area	20856.8	188649	185209	253034	51236.7	87.4
	Area proportion%	2.98	26.98	26.49	36.19	7.33	0.01
ESV coefficient	Food production	987.52	3534.30	0.00	753.64	2079.00	0.00
	Raw material production	1455.30	233.89	0.00	1715.17	597.71	0.00
	Water supply	805.61	-6834.71	0.00	883.57	21543.63	0.00
	Gas regulation	5119.54	2884.61	0.00	5639.29	2001.04	51.97
	Climatic regulation	13539.48	1481.29	0.00	16891.87	5951.14	0.00
	Clean the environment	4469.85	441.79	0.00	5015.59	14423.06	259.87
	Hydrological regulation	9927.22	7068.60	0.00	12318.07	265696.12	77.96
	Soil conservation	6237.00	25.99	0.00	6886.69	2416.84	51.97
	Maintain nutrient circulation	467.77	493.76	0.00	519.75	181.91	0.00
	Biodiversity	5665.27	545.74	0.00	6262.99	6626.81	51.97
	Aesthetic landscape	2494.80	233.89	0.00	2754.67	4911.64	25.99

The value of ecosystem services in Guangzhou can be calculated by combining Table 2 and Equation 5.

$$ESV = \sum M_i * E_i * V \quad (Eq.5)$$

where ESV is the ecosystem service value (yuan), M_i is the area of the i th LUC, E_i is the economic value of an ecological service value factor in Guangzhou, and V is the equivalent factor after the modification of the i th LUC.

Value equivalent sensitivity analysis

Due to the uncertainty of the value coefficient of various ecosystem services, this study adjusts the value coefficient of ecological services of various types of land use by $\pm 50\%$ and uses sensitivity to reflect the response of ESV to the change of ecosystem service value coefficient. The calculation formula is as Equation 6:

$$CS = \left| \frac{(ESV_j - ESV_i) / ESV_i}{(VC_{jx} - VC_{ix}) / VC_{ix}} \right| \quad (Eq.6)$$

ESV is the calculated ecosystem service value, VC is the value coefficient, i and j represent the initial value and adjusted value (up or down adjusted by 50%), and x represents various types of land use. When $CS \geq 1$, it indicates that the ESV is elastic relative to the value coefficient; when $CS < 1$, the ESV is inelastic, and the larger the CS value (but less than 1), the more suitable the selected ecosystem service value coefficient is for the study area.

Analysis of the impact of land use intensity change on ESV

Bivariate LISA analysis

The spatial correlation between two variables is investigated by the double variable space correlation (Ma et al., 2019). This study uses it to reveal the spatial distribution correlation and dependence characteristics between LUC and ESV, that is, the analysis

of the influence of general LUC changes on ESV values. The calculation equations is as *Equations 7 and 8*:

$$I_i = \frac{(x_i - x_{ave}) \sum_j^n Q_{ij} (x_j - x_{ave})}{S^2} \quad (\text{Eq.7})$$

$$S^2 = \frac{1}{n} \sum_{i=1}^n (x_i - x_{ave})^2 \quad (\text{Eq.8})$$

where n denotes the total number of grid cells, x_i represents the value of the i -th grid cell, $(x_i - x_{ave})$ is the difference between the value of the i -th grid cell and the average value, Q_{ij} is the standardized spatial weight matrix, and S^2 is the variance.

When calculating the autocorrelation index in a bivariate space, we typically use the correlation coefficient as an indicator of the degree of correlation between two variables. The correlation coefficient is a standardized measure with a range of -1 to 1. When the correlation coefficient equals 1, it indicates that there is a perfect positive correlation between the variables; when the correlation coefficient equals -1, it indicates that there is a perfect negative correlation between the variables; and when the correlation coefficient is 0, it indicates that there is no linear correlation between the variables. It is a very important tool in geographic information science that helps us gain a deeper understanding of the relationships between spatial variables and enables us to make data predictions and decisions based on correlations.

LISA time path calculation

The LISA time path can effectively combine temporal and spatial attributes by leveraging the spatiotemporal migration trend in Moran scatter plots using the local spatial correlation index, enabling static LISA to present dynamically. The geometric characteristics of the LISA time path include the relative length of the LISA time path, curvature, and direction of movement. The relative length of the LISA time path helps reveal the dynamic features of the local spatial structure of the study unit, while curvature reflects the variability in the direction of local spatial dependence, and the direction of movement maps the dynamic changes in the spatial integration of the study unit. *Equations 9 and 10* for relative length and curvature are as follows:

$$\Gamma_i = \frac{n \times \sum_{t=1}^{T-1} d(L_{i,t}, L_{i,t+1})}{\sum_{i=1}^n \sum_{t=1}^{T-1} d(L_{i,t}, L_{i,t+1})} \quad (\text{Eq.9})$$

$$\Lambda_i = \frac{\sum_{t=1}^{T-1} d(L_{i,t}, L_{i,t+1})}{d(L_{i,t}, L_{i,T})} \quad (\text{Eq.10})$$

In the formula: Γ denotes the relative length, Λ is the curvature, n is the number of study units, T is the number of study years, $L_{i,t}$ is the LISA coordinate of plot i in year t; $d(L_{i,t}, L_{i,T})$ is the migration distance of study unit i from year t to the final year.

Analysis of LISA spatiotemporal transition mode

The changes in the LISA time path at different stages show its transition characteristics, which can be divided into four conversion modes (as shown in *Table 3*), and further describe the evolution process of local spatial correlation index among different types.

Table 3. The classification of spatiotemporal transition types

Types	Transition pattern	Symbols
Type I	Self transition, neighborhood stability	HH→LH, LH→HH, LL→HL, HL→LL
Type II	Self stabilization, neighborhood transition	HH→HL, LH→LL, LL→LH, HL→HH
Type III	Self transition, neighborhood transition	HH→LL, LH→HL, LL→HH, HL→LH
Type IV	Self stabilization, neighborhood stabilization	HH→HH, LH→LH, LL→LL, HL→HL

Results

Land use system change estimation

Changes in land use categories

In the study area, 7378 grids of 1 km × 1 km were created. On this basis, the area of different LUC in 2010, 2015 and 2020 were statistically analyzed. According to the spatial distribution characteristics of land use changes in the 11 administrative districts of Guangzhou City, combined with the urbanization strategy and natural historical conditions outlined in the “Guangzhou City 2010-2020 Territorial Space Plan,” it is divided into four major development zone types. And then, the changes are obtained on a two phases basis (Phase I for 2010–2015 and Phase II for 2015–2020), the LUC transition matrix in the two phases are as shown in *Table 2* and *Figure 2*.

The results indicate that the average rate of change in land use categories reached 14.53% in Phase I and increased to 19.71% in Phase II, showing an accelerating trend of change. Specifically, grasslands experienced a sharp decline in Phase I but increased slightly in Phase II. The total area of cultivated land and forest land continued to decrease, with significant spatial displacement due to the “compensation for occupation” scheme. The total area of artificial surfaces continued to rise, with an total increase of 355.39 m² in Phase II. Water bodies and bare land showed a decreasing trend in Phase I but a recovery trend in Phase II. Overall, the changes sequentially demonstrated the characteristics of continuous expansion of urban Artificial surface, significant local displacement of cultivated and forest land in the middle stage, and slow displacement of grassland, water bodies, and bare land.

Table 2. LUC transition matrix in Phase I and Phase II (unit: km²)

LUC		Meadow		Plough		Artificial surface		Forest land		Water		Bare land	
Region		I	II	I	II	I	II	I	II	I	II	I	II
P0	Guangzhou	-180.55	111.22	-151.36	-138.89	168.31	355.39	230.93	-402.12	-67.68	75.54	0.58	-0.10
P1	Liwan	-2.65	0.28	1.78	-3.33	113.46	90.18	-7.07	0.77	-37.08	20.92	0.00	0.00
	Yuxiu	-0.25	0.19	1.38	-1.38	0.04	0.18	-8.30	-0.65	1.50	-1.32	0.00	0.00
	Tianhe	-2.72	1.27	6.30	-18.53	-1.55	-6.40	-10.75	-75.88	0.10	0.01	0.01	-0.01
	Haizhu	-0.23	0.01	-3.73	-1.73	-26.85	34.02	-0.50	-0.95	0.18	0.06	0.01	-0.01
P2	Baiyun	-14.37	5.59	-329.80	-90.22	27.40	85.82	1018.77	-1015.01	-11.64	9.90	0.04	-0.04
	Huadu	-37.74	20.48	87.89	136.70	-8.62	8.42	24.50	-81.88	-16.40	20.91	0.17	-0.17
	Huangpu	-14.42	7.01	-39.85	-113.99	-27.27	8.17	-732.79	27.67	-1.30	2.50	0.09	-0.09
P3	Nansha	-8.58	3.52	34.10	-34.65	29.59	27.65	-10.71	5.74	-2.78	9.57	0.06	-0.06
	Panyu	-19.43	4.84	-6.74	-64.49	30.87	33.30	-23.29	7.09	8.39	-8.09	0.11	-0.11
P4	Zengcheng	-22.16	16.82	-20.92	121.27	21.09	34.09	-56.43	59.34	-4.76	12.24	0.06	0.42
	Conghua	-58.01	51.21	118.22	-68.54	10.15	39.94	37.51	671.64	-3.88	8.84	0.05	-0.05

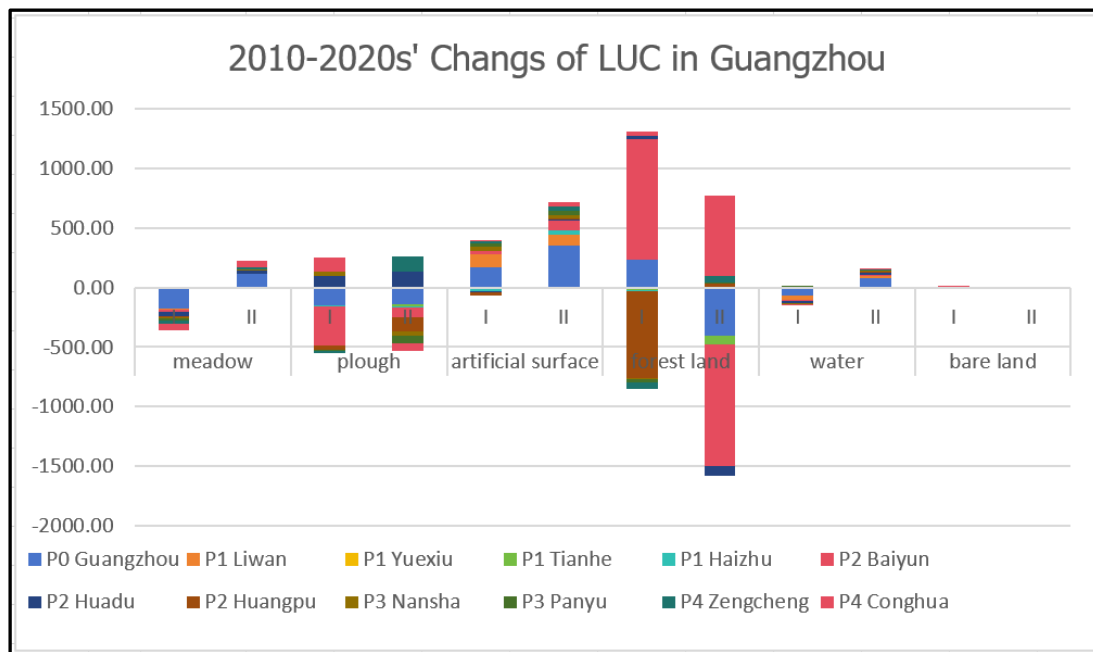


Figure 2. Changes in LUC in Phase I and Phase II (unit: km^2). P1 Old City Development Area (Liwan, Yuexiu, Tianhe, Haizhu), P2 Complex Integration Area of Urban and Rural Landscapes (Baiyun, Huadu, Huangpu), P3 Key Urban Development Area (Nansha, Panyu), and P4 Urban Ecological Protection Area (Zengcheng, Conghua)

Changes in land use intensity

The land use allocation LUI1, the carrying LUI2, and the output LUI3 intensity are calculated based on the fomalus in *Table 1*, and their changes every five years from 2010 to 2020 are statistically analyzed as shown in *Figure 3*.

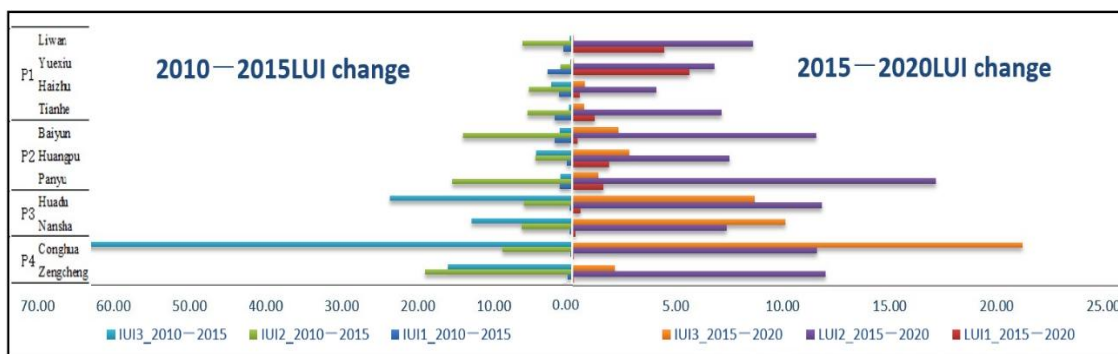


Figure 3. Changes in LUI of allocation, carrying and output from 2010 to 2020

Based on the average intensity of LUI1, LUI2, LUI3, the comprehensive utility level of land use can be reflected. *Figure 3* shows that the intensity of land use has generally shown a significant increase. Among them, the change rate of allocation intensity LUI1 increased from 0.45 in period 1 to 9.41 in period 2; the change rate of carrying capacity intensity LUI2 increased from 1.36 in period 1 to 11.60; the change rate of output intensity LUI3

decreased from 8.62 in period 1 to 4.40 in period 2, but locally such as P1 it rose to 10.33, showing a significant enhancement and polarization trend of the four zoning effects.

Assessment of ESV based on land use categories equivalent method

According to the changes in LUC and combined with the comprehensive calculation of *Table 4*, the total value of ecosystem services in Guangzhou City from 2010 to 2020 can be obtained; by analyzing the sensitivity coefficients of value coefficients for various LUC in Guangzhou City using *Equation 3*, the range is between 0 and 0.48, indicating that the results are valid and credible.

Table 4. The sensitivity coefficient of ESV in 2020

LUC	Meadow	Plough	Artificial surface	Forest land	Waters	Bare land
ESV sensitivity coefficient	0.03	0.05	0	0.43	0.48	0

The total ESV value was evaluated based on the land categories equivalent method on the basis of sensitivity analysis, and the results are shown in *Figure 4*.

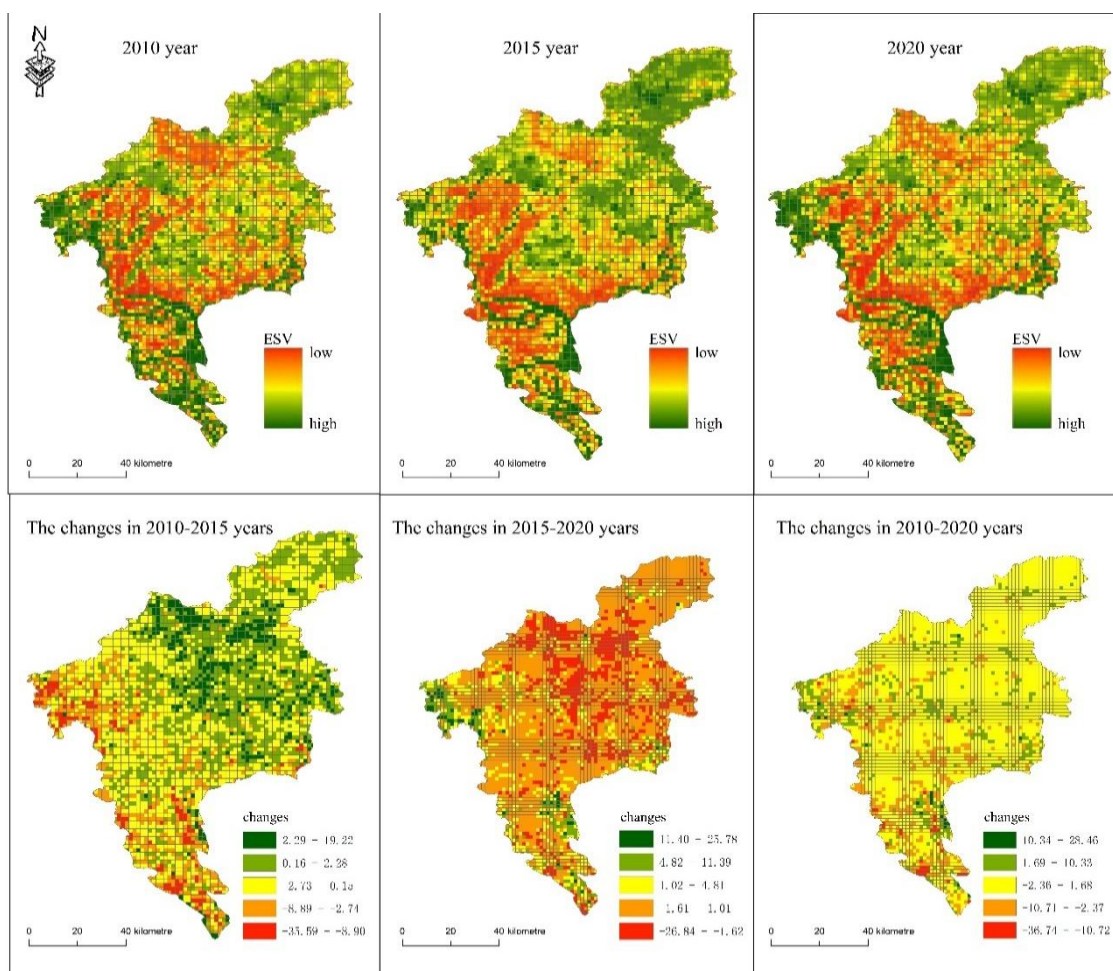


Figure 4. Spatiotemporal changes of ESV in Guangzhou from 2010 to 2020

As can be seen from *Figure 4*, the high-value areas of Guangzhous ESV are concentrated in the northeastern forested areas and the southern Pearl River waters and wetland parks, while the low-value areas are mainly concentrated in the western and southern plains and the northern Conghua urban area. During the period from 2010 to 2015, the ESV values in the northern and northeastern parts of the study area increased, while the ESV values in the western and southern parts of the study area showed a decreasing trend; from 2015 to 2020, the ESV values in the western part of the study area and the Pearl River Basin showed an increasing trend, while the ESV values in Conghua urban area, Zengcheng urban area, and Nansha urban area showed a decreasing trend.

The per capita ESV of each district is calculated by combining the data of the permanent population in each district. The results are shown in *Table 5*.

Table 5. The total ESV and per capita ESV of different regions in Guangzhou

Region	Total ESV (unit: yuan)				Per capita ESV (unit: yuan)			
	2010	2015	2020	Changes	2010	2015	2020	Changes
P0	3.7E+10	3.39E+10	3.47E+10		2941.31	2511.49	2268.11	
P1	1.2E+09	1.002E+09	9.81E+08		939.48	733.71	659.28	
P2	1.1E+10	8.81E+09	1.02E+10		10337.06	7559.31	7622.92	
P3	8.5E+09	6.25E+09	7.39E+09		18820.06	6809.31	6486.32	
P4	1.6E+10	1.789E+10	1.61E+10		22413.5	23102.84	19484.92	

Overall, during the period of 2010-2020, the total ESV and per capita ESV in Guangzhou City showed a decreasing trend, with a more pronounced decline in per capita ESV; during the period of 2010-2015, the ecological environment suffered significant damage, while from 2015 to 2020, the trend of destruction tended to ease, but still reflecting that the deficit area of total ESV is larger than the surplus area. Among them, the internal variance value of ESV in Zone P1-P4 is relatively low, while the inter-class variance value is relatively high, indicating a significant zoning effect. The total ESV and per capita ESV values show a trend of $P4 > P2 > P3 > P1$. The total ESV of Zones P1, P2, and P3 shows a “U-shaped” change, while the total ESV of Zone P4 shows an “inverted U-shaped” change, reflecting a sharp decline in ESV during the urban spatial expansion period, followed by an increase in total ESV during the urban spatial displacement period, but with a clear trend of continuous decline in per capita ESV.

Analysis of the impact of land use intensity changes on ESV

Bivariate LISA analysis

In order to explore the spatial coupling relationship between ESV and LUI1 configuration, LUI2 bearing, and LUI3 output, the double variable spatial autocorrelation LISA distribution relationship was calculated, as shown in *Table 6*.

The results show that from 2010 to 2020, the bivariate LISA values of ESV and LUI are both negative and the significance P values are very high, indicating that there is a significant spatial negative correlation between the three aspects of LUC and ESV in Guangzhou. Among these, it showed that the impact on ESV followed the pattern $LUI1 > LUI2 > LUI3$, but the impact gap was gradually narrowing, gradually showing a comprehensive impact.

From the 2020 bivariate LISA spatiotemporal distribution map of ESV and LUI (*Fig. 5*), it can be seen that in the LISA maps of ESV and LUI1, HH and LH are mainly

distributed in P1 zone, mostly showing significant correlation ($P < 0.05$), while LL and HL are mainly distributed in P4 Conghua area, with sporadic distribution in P3 zone, mostly showing significant correlation ($P < 0.05$).

Table 6. Two-variable Moran I index

Year	ESV and LUI1	ESV and LUI2	ESV and LUI3
2010	-0.228	-0.111	-0.008
2015	-0.197	-0.127	-0.104
2020	-0.14	-0.093	-0.072

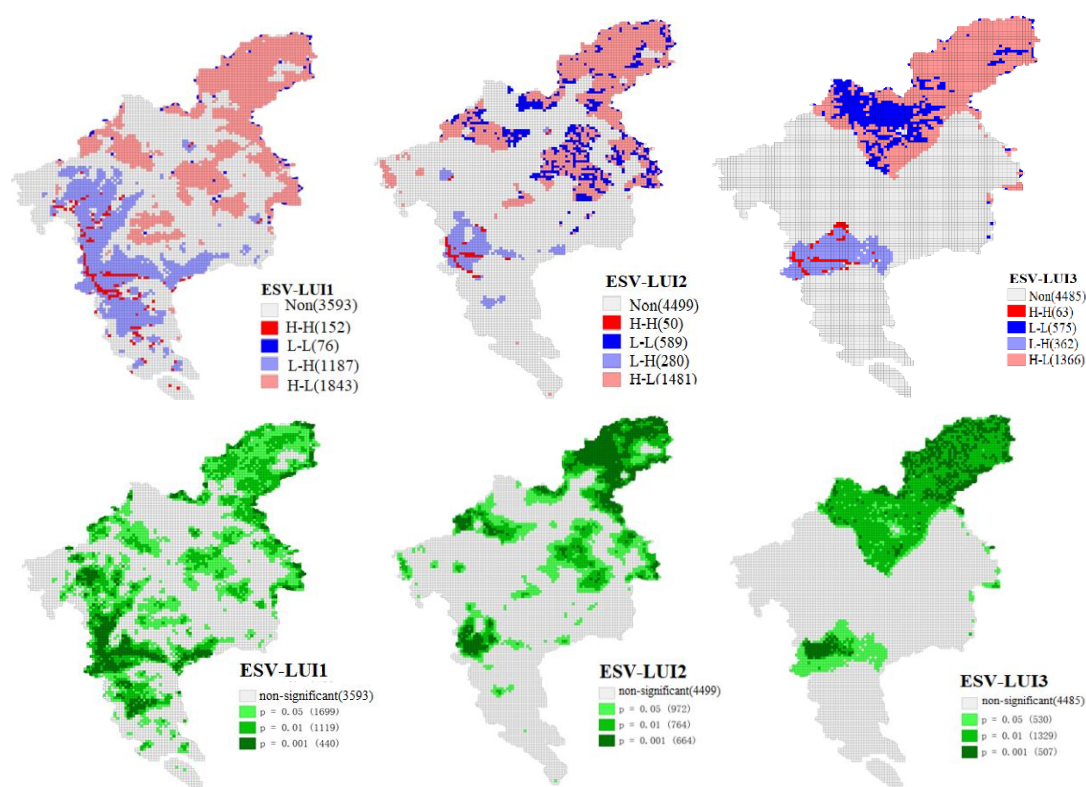


Figure 5. Bivariate LISA distribution and significance relationship between ESV and LUI in 2020

In the LISA maps of ESV and LUI2, HH and LH show linear and band-like distributions, mainly distributed in the Liwan and Yuexiu areas of P1 district, mostly showing highly significant correlations ($P < 0.01$); LL is sparsely distributed in P4 district; HL is mainly distributed in the northern part of P2 district, as well as in the northeastern and eastern parts of P4 district, mostly showing significant correlations ($P < 0.05$).

In the LISA maps of ESV and LUI3, there is an overall trend of spatial polarization correlation between P1 and P4 regions. HH and LH are mainly distributed in Liwan, Yuexiu, and Haizhu areas of the P1 region, showing highly significant correlations ($P < 0.01$); HL is mainly distributed in the P4 region, showing highly significant correlations ($P < 0.01$).

LISA time path calculation

Based on the local Moran index based on ESV and LUI, the LISA time path characteristics every 5 years during 2010-2020 are statistically obtained to obtain the evolution process of relative length and curvature at different development stages, as shown in *Table 7*.

Table 7. The characteristics of LISA spatiotemporal path for ESV and LUI

Variable	Relative length of LISA spatiotemporal path		
	2010-2015	2015-2020	Change rate
ESV	P3(1.67)>P2(1.03)>P4(0.82)>P1(0.67)	P3(1.44)>P2(1.12)>P4(0.84)>P1(0.64)	0.09
LUI1	P4(1.79)>P3(1.76)>P2(1.49)>P1(0.97)	P4(1.60)>P3(1.57)>P2(1.41)>P1(0.82)	0.15
LUI2	P1(4.75)>P3(1.16)>P2(1.06)>P4(0.59)	P1(4.65)>P3(1.15)>P2(1.14)>P4(0.55)	0.06
LUI3	P4(6.28)>P1(6.07)>P3(3.00)>P2(2.81)	P1(0.29)>P2(0.09)>P3(0.08)>P4(0.05)	4.41
Variable	Curvature of LISA spatiotemporal path		
	2010-2015	2015-2020	Change rate
ESV	P2(29.07)>P4(2.84)>P1(1.74)>P3(1.60)	P2(28.74)>P4(2.43)>P1(1.77)>P3(1.36)	0.25
LUI1	P3(1.31)>P1(1.21)>P2(0.97)>P4(0.90)	P3(1.10)>P1(1.00)>P2(0.99)>P4(0.98)	0.13
LUI2	P2(1.22)>P3(1.13)>P1(1.09)>P4(1.09)	P2(0.86)>P1(0.73)>P3(0.71)>P4(0.68)	0.39
LUI3	P1(1.07)>P3(1.03)>P4(1.02)>P2(0.91)	P1(0.27)>P2(0.19)>P3(0.07)>P4(0.02)	0.87

The spatial distribution of LISA time path characteristics of ESV and LUI is statistically analyzed on a grid basis as shown in *Figures 6 and 7*.

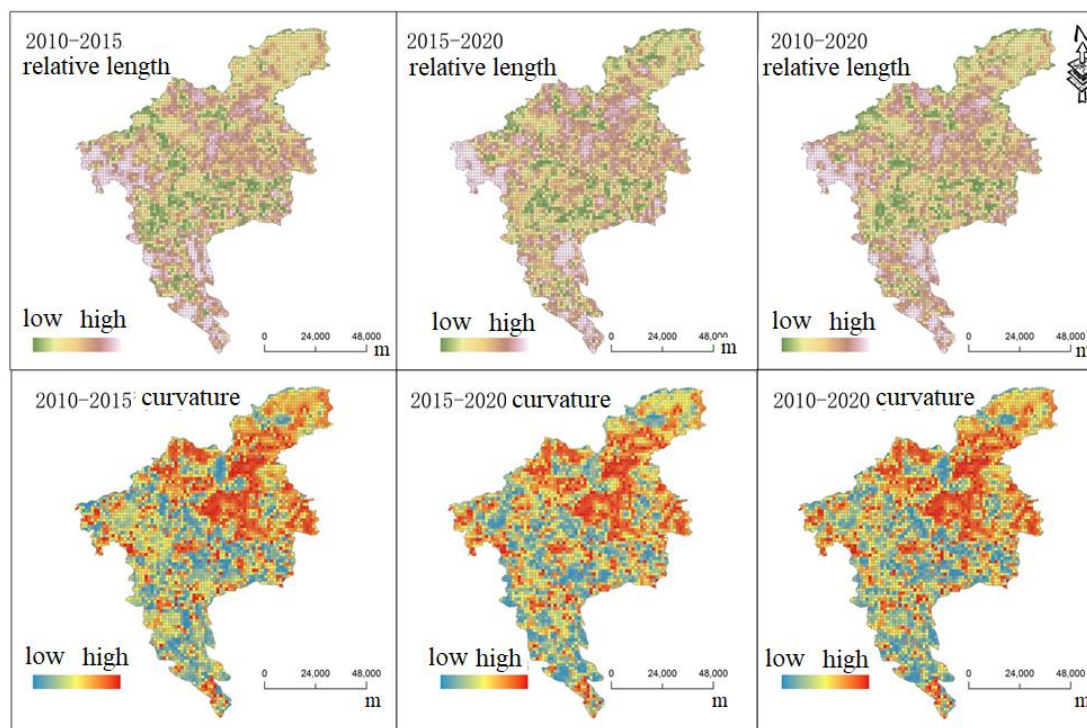
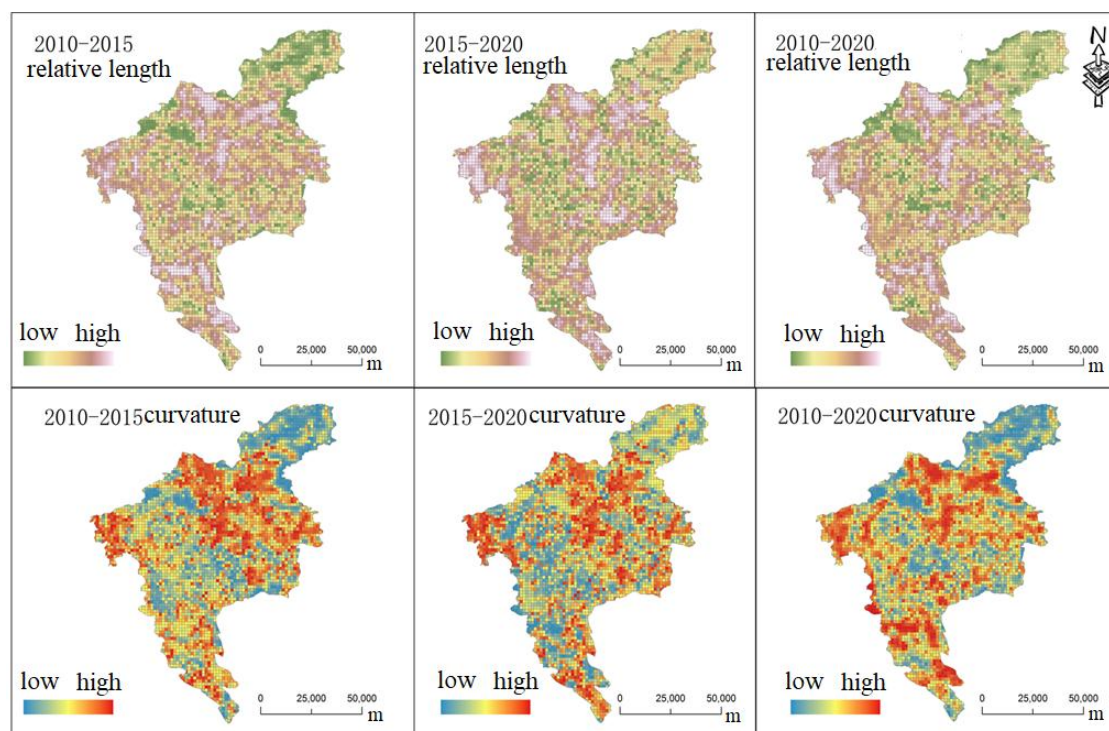


Figure 6. LISA time path characteristics of ESV

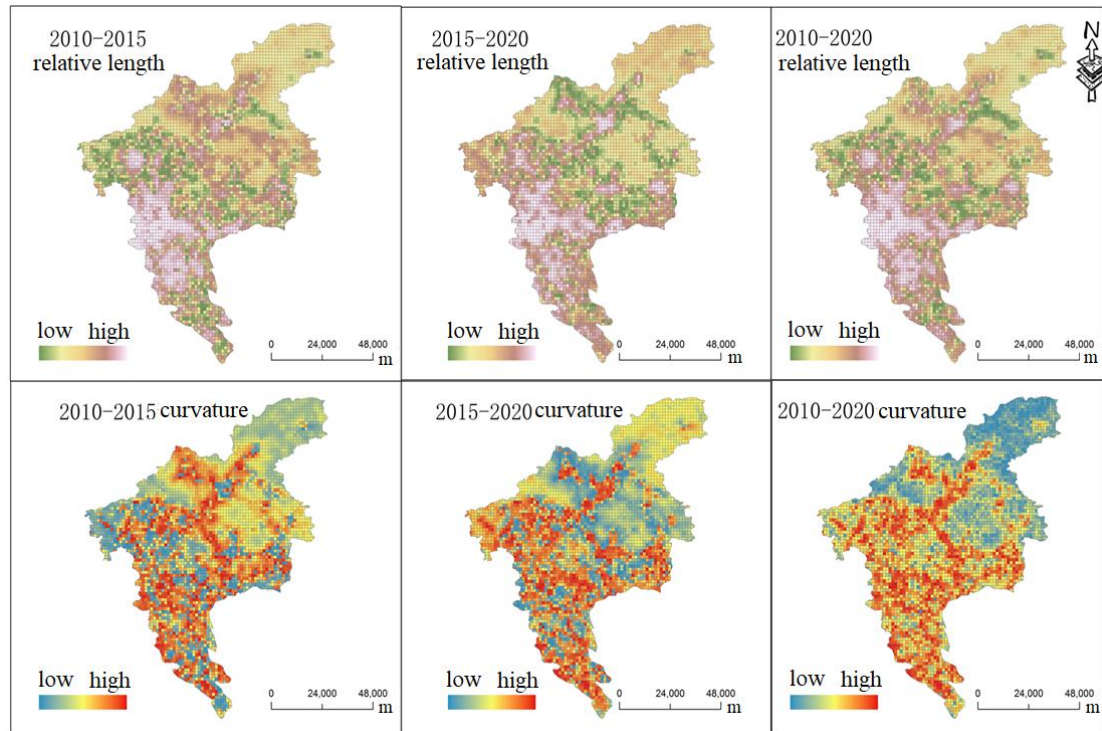
As can be seen from *Figure 6*: During 2010-2015, the LISA time path of ESV was high fragmentation, with more dynamic path structures in the P2 and P3 regions; the curvature from the central P2 region to the northern P4 region was significant, showing strong directionality, with the highest value at Huadu in P2 reaching 83.28, indicating intense local changes. Other regions exhibited a curvature below 10. From 2015 to 2020, the ESV path experienced localized displacement, with reduced fragmentation in the P1 and P3 regions while the fragmentation in the P4 region increased significantly, showing a pronounced boundary effect; the overall length and curvature showed slight decreases but exhibited localized displacement patterns.

As can be seen from *Figure 7*: By 2010-2015, the LUI1 and ESV paths were spatially adjacent, exhibiting similar fragmentation, but showed more extended behavior with stronger directionality, with P4 and P3 regions displaying more dynamic local spatial structures; the path extension of LUI2 was at a moderate level, with significant partition effects, and the P1 region exhibited a pronounced dynamic local spatial structure; the curvature of P2 and P3 regions showed a polarized effect, with significant direction dependence; the local spatial structure of LUI3 in P4 and P1 regions was more extended, with an average value exceeding 6, showing significant zonal and polarization effects.

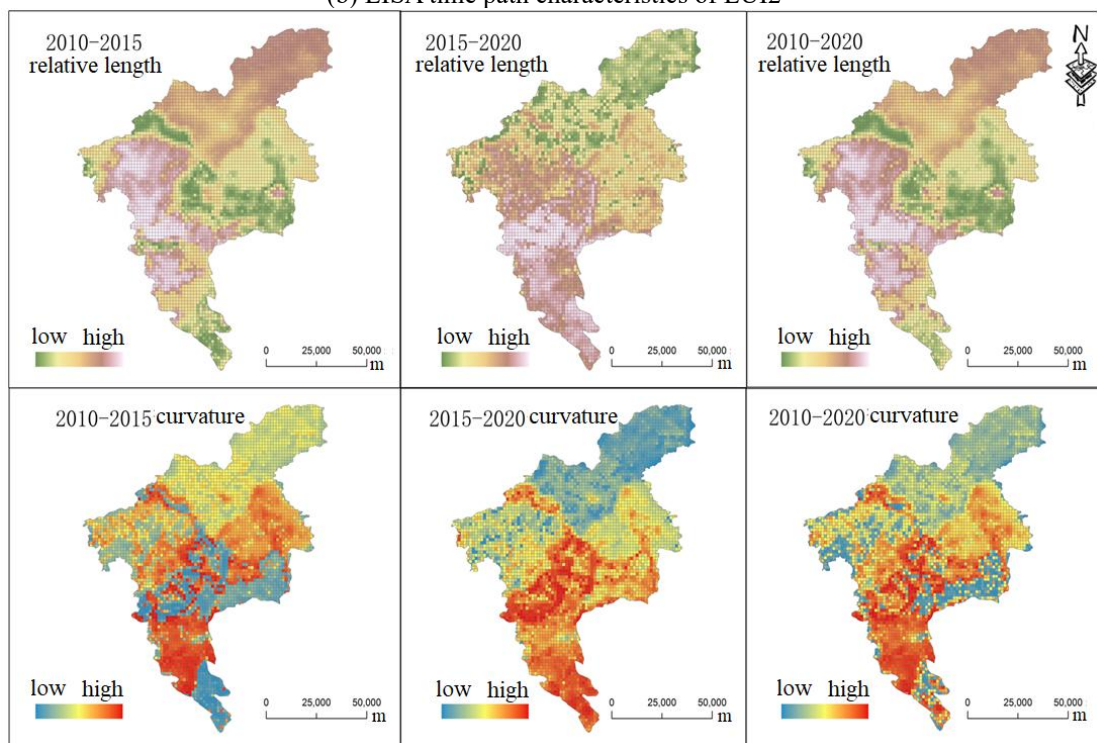
By 2015-2020, the overall length and curvature of the LUI1 path decreased slightly, while fragmentation increased, with only the fragmentation in the P4 region decreasing; showing a trend of local displacement and differentiation between high and low values. the polarization of the LUI2 path increased, along with an increase in curvature and a change rate of 0.39; the fragmentation of the LUI3 pathway significantly increased, with an overall sharp decline to an average value below 1. The increase in curvature led to a noticeable overall displacement across boundaries between P4 and P2 regions, resulting in a more pronounced aggregation of high values in P1, P3, and P2 regions, while the P4 region exhibited low-value aggregation.



(a) LISA time path characteristics of LUI1



(b) LISA time path characteristics of LUI2



(c) LISA time path characteristics of LUI3

Figure 7. LISA time path characteristics of Guangzhou LUI

Time-path coupling analysis

(1) LUI-ESV Spatial Partition Coupling Analysis of Temporal Paths. The spatiotemporal path characteristics of the relationship between ESV and LUI during the

period of 2010–2020 were analyzed using the LISA path feature correlation model, as shown in *Table 8*. Overall, the ESV path exhibited a strong positive correlation with the LUI1 path (coupling coefficient = 0.92), a moderate positive correlation with the LUI2 path (coupling coefficient = 0.54), and a significant negative correlation with the LUI3 path (coupling coefficient = −0.48). The coupling patterns also showed significant spatial partition effects.

Table 8. LISA time path coupling relationship of LUI-ESV

Region	coupling coefficient		
	ESV and LUI1	ESV and LUI2	ESV and LUI3
P1	0.96	0.03	-0.26
P2	0.92	0.25	0.01
P3	0.72	0.63	0.01
P4	0.89	0.89	-0.46
P0	0.92	0.54	-0.48

(2) The time path of LUI-ESV is divided into stages and features for coupled analysis. Plot the scatter diagrams of the path characteristics of ESV and LUI in 11 districts of Guangzhou City from 2010 to 2020 to identify the changing patterns of the impact of LUI changes on ESV.

From *Figure 8*, it can be observed that the LISA path characteristics of LUI shift from distinct differentiation to similar fusion, where LUI1 and LUI2 both exhibit a transition from short-distance discrete bends to short-distance co-directional bends, while LUI3 transitions from long-distance discrete bends to short-distance co-directional bends. Overall, the migration distance decreases, and the fragmentation degree increases.

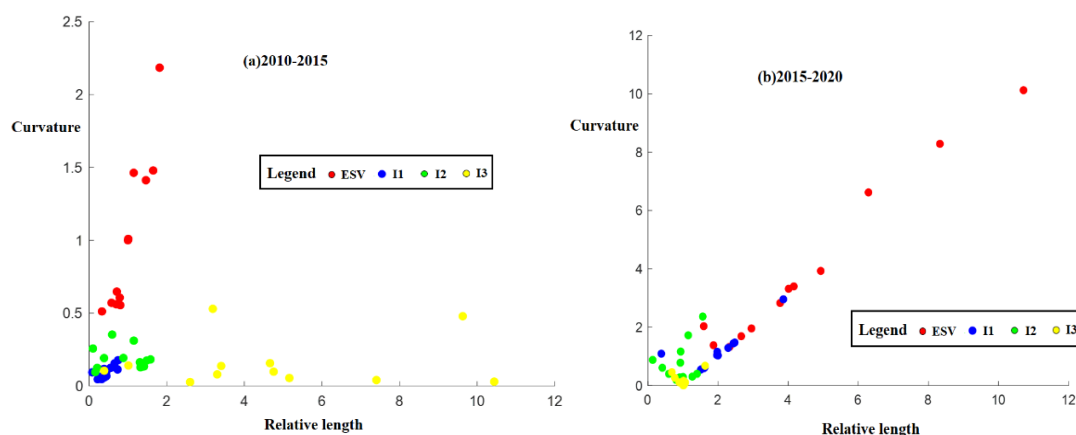


Figure 8. Time path characteristics relationship between ESV and LUI in Guangzhou

Time-path migration reognition

The time-path migration patterns of ESV and LUI are statistically analyzed, and the results are shown in the *Table 9*. It can be observed that from 2010 to 2020, the spatiotemporal migration patterns of ESV and LUI are mainly characterized by Type IV, further indicating that the overall coupling pattern is neighborhood-related; only the

Baiyun area of P2 and the Panyu District of P3 show Type I in both periods, while the Nansha District of P3 shows Type III; LUI2 exhibits Type II in Huadu of P2 from 2015 to 2020, and LUI3 shows Type II in Panyu District of P3 from 2010 to 2015, showing a cross-boundary displacement phenomenon, with the displacement direction increasingly resembling the “northeast-southwest” direction.

Table 9. Spatiotemporal migration pattern of LUI-ESV in different regions

Region	ESV		LUI1		LUI2		LUI3	
	2010-2015	2015-2020	2010-2015	2015-2020	2010-2015	2015-2020	2010-2015	2015-2020
P1	IV	IV	IV	IV	IV	IV	IV	IV
P2	IV	I, IV	IV	IV	IV	II, IV	IV	IV
P3	I, III	I, III	IV	IV	IV	IV	II, IV	IV
P4	IV	IV	IV	IV	IV	IV	IV	IV

It can be found that, the spatiotemporal migration and development patterns of LUI-ESV are closely related to the context of Guangzhou’s rapid urbanization. The comprehensive value of Guangzhou’s urbanization level has been continuously increasing, representing the three stages of population urbanization, spatial urbanization and economic urbanization in the urbanization process, which corresponds to the three stages of the ESV-LUI coupling model.

Discussion

The connection analysis between land use system and ecosystem service value

Analysis for the methods of assessment of LUC-ESV

From 2010-2020 years, ESV value based on LUC value equivalent assessment methods showed reasonable and scientific, with spatial autocorrelation of Phase 3 ESV exhibiting stable fluctuations.

According to the ESV evaluation results, we can found that: By 2020, the total ESV in Guangzhou City was 34.816 billion yuan. Among them, the ESV of forest land was the highest, accounting for 43.35%; apart from the artificial surface, the ESV contributed by bare land and meadow are relatively low, accounting for 0.00013%, 0.07% and 3.07% respectively. Meanwhile, the value per unit area of water bodies is the highest, reaching 326,430.05 yuan, followed by forest land, with values of 135,188.59 yuan and 59,641.50 yuan per unit area. This is reflected in the sharp decline of ESV during the urban spatial expansion period, and an increase in the total ESV during the urban spatial displacement period. This is in line with the actual situation.

In addition, from 2010 to 2015, the eastern part of P4 and P2 in Guangzhou was in the development stage, while the western part of P1 and P2, the southern part of P3, and the eastern part of P4 were in the adjustment or decline stage. From 2015 to 2020, the western part of P2 and P3 were in the development stage, while parts of P4 and P2 showed signs of decline or adjustment. In whole, the trend of continuously decreasing per capita ESV is quite obvious, indicating that the population density in each area is growing faster than the growth rates of ecological land and ESV. The P3 and P4 areas have shown particularly significant differences in this regard.

Analysis for the reason of time-path changes in LUI-ESV

According to the results of time path coupling analysis and pattern recognition for LUI-ESV time path, we explore the reasons as following:

(1) At the beginning of 2010, the ESV and LUI1 pathways were highly similar, indicating that the LUI1 has a long-term dominant effect, guiding the adjacent and similar evolution of the ESV pathways, suggesting that local fluctuations in ESV are more derived from spatial planning, spontaneous population input dynamics, and macroeconomic orientation; the border towns and streets between the four regions are influenced by the radiation effect of the multi-center development zones, exhibiting characteristics of significant local spatial changes and high dependence on neighboring spaces, with evident administrative boundary effects.

(2) In mid-2015, the ESV maintained a slightly declining trend with positive strong coupling to LUI1; it gradually shifted from negative weak coupling to negative strong coupling to LUI2. Among these, the spatial pattern fluctuations in the P3 zone were the greatest, followed by the zone P4. The main reason for this is that these zones were designated as key development zones during this period, causing fragmentation of the local spatial pattern of ESV and localized cross-boundary displacement phenomena; the land carrying capacity shifted from frequent migration to a directional polarization trend, enhancing the directionality dependence on the ESV path.

(3) In 2020 later adjustment phase, with the LUI3 shifting from macro-oriented to multi-point localized development, leading to a more fragmented ESV path. The dynamic and evolutionary characteristics of the ESV spatial pattern are coupled to varying degrees with the changes in jointly of LUI1, LUI2, and LUI3 spatial patterns.

Suggestions of harmonious development for land use system and ecosystem service value

In view of the partition effect and stage effect of the LUI path on the impact of the ESV path, optimization strategies and suggestions are proposed:

(1) The P1 zone's ESV pathway shows a high spatial positive correlation with the LUI1 pathway and a negative correlation with the LUI3 pathway. The transformation of land ecological regulation from stable development to partial orderly dynamic increase indicates that urban renewal strategies in the later stages of urbanization have supported a certain degree of ESV structural optimization. In the future, efforts should be intensified to enhance urban renewal and continue the strategy of partial greening.

(2) The P2 zone's ESV pathway is significantly influenced by the planning of LUI1, initially showing sporadic directional neighborhood correlation with the LUI2 pathway, and later exhibiting directional neighborhood correlation with the LUI2 pathway, indicating that the direction of population migration and the direction of ESV changes have shifted from random to directed. In the future, it is necessary to expand the scale of the ecological tourism system, establishing a new pattern of coordinated development between the ecological environment and economic construction.

(3) As a new development zone, the ESV path of the P3 zone is affected by both LUI1 and LUI2 paths. In the later stage, the influence of the LUI3 path will gradually strengthen. In the future, we should pay attention to improving the utilization rate of urban land space to support higher level and better quality economic growth with less resource consumption.

(4) The ESV pathways in P4 zone show significant neighborhood correlation with the LUI1 and LUI2 pathways, and significant cross-boundary displacement correlation with

the LUI3 pathway, indicating a continuous increase in population density and tight constraints on resource and environmental resources. In the future, it is necessary to optimize the long-term orientation mechanism of LUC, strictly implement the arable land protection red line and ecological protection red line, and prevent the “non-agriculturalization” and “non-grainization” of arable land. At the same time, attention should be paid to the micro-ecological protection and micro-renewal development of marginal zones and boundary zones between different areas.

Conclusion

This study considers the comprehensive impact of LUC and LUI on the spatiotemporal pattern evolution of ESV simultaneously. The main conclusions in Guangzhou from 2010 to 2020 are as follows:

(1) The rate of change in LUC in Guangzhou reached 14.53% in Phase I and increased to 19.71% in Phase II, showing an accelerating trend of change. The LUC exhibited multidimensional changes. Specifically, the change rate of LUI1 and LUI2 increased significantly; and the change rate of LUI3 decreased in major areas, indicating a significant enhancement and polarization trend in the effects of the four zones.

(2) The total ESV and per capita ESV in Guangzhou City are showing a yearly decreasing trend, with more deficit areas than surplus areas, and this trend is more pronounced in per capita ESV. The total ESV and per capita ESV values show a trend of $P4 > P2 > P3 > P1$, while the P1, P2, and P3 zones show a “positive U-shaped” change, and the P4 zone shows an “inverted U-shaped” change.

(3) The bivariate LISA analysis of LUI-ESV indicates that the utility rate of ESV in Guangzhou is significantly influenced by negative LUI pressure, following a pattern of $LUI1 > LUI3 > LUI2$, demonstrating that the current intensity of land allocation has a long-term inhibitory effect on ESV, the intensity of land carrying capacity has a direction-dependent influence on population mobility, and the intensity of land output has a phased overall impact on economic development.

(4) The LISA time path measurement and coupling analysis of LUI-ESV shows that: The overall ESV path change rate shows a significantly positive correlation with the combined change rates of LUI1 and LUI2 paths, indicating significant spatial proximity effects and boundary effects indicating significant spatial proximity effects and boundary effects; it also shows a significantly negative correlation with the change rate of the LUI3 path, indicating significant cross-boundary displacement effects, leading to alternating and unbalanced impacts.

(5) From 2010 to 2015, due to the large-scale expansion of Artificial surface in the northeastern part of P4, frequent population migration, and economic polarization development, ESV suffered significant and widespread destruction. During the period from 2015 to 2020, the localized expansion of Artificial surface in the central part of P2 and the southern part of P3, directional population migration, and diversified economic development led to a trend of more fragmented and mitigated damage to ESV. The values of ESV in the Pearl River Basin showed a trend of recovery and increase. The protection and renewal of micro-environments in areas P2, P3 and the border areas represent the main task of achieving coordinated urbanization and ecological development.

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REFERENCES

- [1] Chen, R., Yang, C., Tong, J., Jiang, X., Lin, X., Wu, O. (2023): Effects of new urbanization in Changsha-Zhuzhou-Zhuzhou-Zhuhai-Tan urban agglomeration on the spatial differentiation of ecosystem service value. – *Journal of Central South University of Forestry & Technology* 6: 158-167.
- [2] Chen, X., Li, H., Zhang, W., Ge, X. (2025): The impact of land use transition on ecosystem service value in Lixiahe area: a multi-scenario simulation analysis based on Markov-FLUS model. – *Resources Science* 1: 182-195.
- [3] Costanza, R., d'Arge, R., de Groot, R., Farber, S., Grasso, M., Hannon, B., et al. (1997): The value of the world's ecosystem services and natural capital. – *Nature* 387(15): 253-260.
- [4] Duan, R., Hao, J., Wang, J. (2005): A study on the change of land use structure and ecosystem service function value: a case study of Datong City, Shanxi Province. – *Ecological Economy* 3: 60-62+64.
- [5] Guo, L., Zhao, D., Yang, S., You, Q., Sun, T. (2024): Ecosystem service value assessment and multi-scenario simulation in Zhengzhou City. – *Environmental Science and Technology* 6: 191-199.
- [6] He, Y., Jing, X., Sun, Y. (2024): Multi-scenario simulation of land use and ecosystem service value change in Changzhou City based on FLUS model. – *Hubei Agricultural Sciences* 11: 47-56+78.
- [7] Jun, C., Lijun, C., Ran, L., Anping, L., Shu, P., Nan, L., Yushuo, Z. (2015): Statistical analysis of the spatial distribution and change of global urban and rural construction land based on GlobeLand30. – *Journal of Surveying and Mapping* 11: 1181-1188.
- [8] Lai, M., Wu, S. H., Yin, Y., Pan, T. (2015): Ecological compensation based on ecosystem service value in Sanjiangyuan area. – *Acta Ecologica Sinica* 2: 227-236.
- [9] Lei, J., Chen, Z., Wu, T., Li, Y., Yang, Q., Chen, X. (2019): Spatial autocorrelation pattern analysis of land use and ecosystem service value in northeastern Hainan Island. – *Acta Ecologica Sinica* 7: 2366-2377.
- [10] Li, C., Niu, W., Huang, H., Yao, S., Gong, Z. (2024): Spatiotemporal evolution of ecological risk and identification of ecological zoning in the Guangdong-Hong Kong-Macao Greater Bay Area under the background of urbanization. – *Journal of Environmental Engineering Technology* 2: 562-573.
- [11] Li, J., Wang, W., Hu, G., Wei, Z. (2011): Impacts of land use change on ecosystem service value in the Zoige Plateau. – *Acta Ecologica Sinica* 31(12): 3451-3459.
- [12] Li, P., Zhang, R., Xu, L. (2021): Three-dimensional ecological footprint based on ecosystem service value and their drivers: a case study of Urumqi. – *Ecological Indicators* 131.
- [13] Li, W. (2011): Ecological research in China and its contribution to social development. – *Acta Ecologica Sinica* 19: 5421-5428.
- [14] Liu, F., Yang, R., Yang, L., Peng, H. (2024): Changes and predictions of ecosystem service value in Wuhan under the background of rapid urbanization. – *Ecological Science* 3: 124-134.
- [15] Luan, S., Ma, S. (2024): Research on the impact of land use change on ecological service value based on GEE: a case study of Dalian City. – *Journal of Environmental Science* 8: 446-458.
- [16] Ma, R., Hou, B., Jin, Y., Zhang, Y. (2019): Measurement of the spatial relationship between land use non-agricultural and urbanization in Zhejiang Province. – *Resources and Environment in the Yangtze River Basin* 9: 2059-2069.
- [17] Pan, N., Guan, Q., Wang, Q., Sun, Y., Li, H., Ma, Y. (2021): Spatial differentiation and driving mechanisms in ecosystem service value of arid region: a case study in the middle and lower reaches of Shule River Basin, NW China. – *Journal of Cleaner Production* 319.

- [18] Peng, J., Wang, X. Y., Liu, Y. X., Zhao, Y., Xu, Z. H., Zhao, M. Y., Qiu, S. J., Wu, J. S. (2020): Urbanization impact on the supply-demand budget of ecosystem services: decoupling analysis. – *Ecosystem Services* 44: 101139.
- [19] Qi, Q., Wang, L., Chen, J., Wang, B., He, S., Han, J., et al. (2024): Interaction between rapid urban expansion and ecosystem service value trade-off/synergy in Wuhan. – *Scientia Geographica Sinica* 6: 953-963.
- [20] Ran, Y., Lei, D., Liu, L., Gao, L. (2021): Impacts of land use change on ecosystem service value in central Yunnan urban agglomeration from 2000 to 2020. – *Bulletin of Soil and Water Conservation* 4: 310-322+2.
- [21] Sun, F., Zhang, Z., Zuo, L., Zhao, X., Pan, T., Zhu, Z., et al. (2020): Research progress, bottleneck and prospect of land use intensity. – *Pratacultural Science* 7: 1259-1271.
- [22] Wang, Y., Ding, J., Li, X., Zhang, J., Ma, G. (2022): Impact of land use/cover change on ecosystem service value in the Ili River Basin: based on intensity analysis model. – *Acta Ecologica Sinica* 42(8): 3106-3118.)
- [23] Wang, Z., Feng, H., Wang, S., Zou, B., Li, S., Wang, S. (2024): Spatiotemporal response characteristics of ecological service value to land use/cover change in Hunan Province. – *Environmental Monitoring Management and Technology* 36(3): 7-14.
- [24] Wu, X., Yuan, J., Zhao, F., Wang, H., Jin, J. (2025): Spatiotemporal relationship between carbon emissions and ecosystem service value in the Hutuo River Basin. – *Environmental Science* 1-15.
- [25] Wu, Y. (2021): Attributes of property rights and realization paths of ecosystem service functions. – *Journal of Nanjing University of Technology (Social Sciences)* 3: 53-64+110.
- [26] Xie, G., Zhang, C., Zhang, C., Xiao, Y., Lu, C. (2015a): The value of ecosystem services in China. – *Resources Science* 37(9): 1740-1746.
- [27] Xie, G., Zhang, C., Zhang, L., Chen, W., Li, S. (2015b): Improvement of ecosystem service valorization method based on unit area value equivalent factor. – *Journal of Natural Resources* 8: 1243-1254.
- [28] Xie, M., Zhou, H., Chen, Z., Wang, X. (2025): Ecosystem service value assessment and multi-scenario simulation in Yinchuan City. – *Soil and Water Conservation Research* 1: 294-304.
- [29] Xu, Y., Zhang, P., Zhou, B. (2019): Land use landscape zoning based on Shannon diversity t-test: a case study of Yongchuan District, Chongqing. – *China Agricultural Resources and Regional Planning* 1: 134-141+151.
- [30] Yu, S., Yang, B., Bin, J., Ye, B., Ding, S., Tao, Q., et al. (2019): Evaluation of land resource carrying capacity of Changsha-Zhuzhou-Zhuzhou-Tan urban agglomeration. – *Journal of Central South University of Forestry & Technology (Social Science)* 1: 37-43+63.
- [31] Zhan, S., Li, Q. (2025): Multi-scenario simulation of urban land use and ecosystem services based on PLUS model: a case study of Sanmenxia City. – *Journal of Land and Natural Resources Research* 2: 41-47.
- [32] Zhang, J., Yang, W., Li, J., Shen, S., Ma, L., Chen Liang. (2025): Spatiotemporal changes and driving forces of ecosystem service value in Beijing. – *Acta Ecologica Sinica* 1: 306-318.
- [33] Zhang, P., Jin, X. (2024): Spatiotemporal relationship between urbanization and ecosystem service value in Hangzhou Bay urban agglomeration. – *Journal of Zhejiang Normal University (Natural Science Edition)* 1-10.
- [34] Zhou, H., Wang, Z., Wang, Z., Bao, Y. (2021): Topographic gradient response of ecosystem service value in karst mountain cities: a case study of Guiyang city center. – *Research of Soil and Water Conservation* 28(6): 337-347.
- [35] Zhuang, D., Liu, J. (1997): Regional differentiation model of land use degree in China. – *Journal of Natural Resources* 2: 10-16.