SPATIO-TEMPORAL DYNAMICS AND DRIVING MECHANISMS OF ECOSYSTEM SERVICE FUNCTION VALUE: AN INTEGRATED EXPLAINABLE MACHINE LEARNING APPROACH IN THE GANJIANG RIVER BASIN, CHINA

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Abstract. It is imperative to comprehend the variation and identify the driving factors of ecosystem service value (ESV) to enhance regional ecological security of the Ganjiang River Basin (GRB), China. However, existing research methods face the challenge of multiple covariates and nonlinear effects among variables, as well as the "black box" problem inherent in machine learning methods. This study proposed a novel approach by integrating the explainable machine learning approach to identify the driving factors of the four ecosystem service function value (ESFV): provisioning services, regulating services, supporting services, and cultural services. The findings of the study suggest the following: (1) The forestland constituted the primary land use in the study area, and the ESV exhibited a net decline of 3.74 billion yuan from 1990 to 2020. (2) With regard to vertical spatial evolution, the unit ESV was found to be highest in the 0-3° slope segments, while it was relatively high in the 500-1200 m elevation range. (3) The spatial distribution of ESV demonstrated lower values in the northern regions and higher values in the southern and central regions. (4) The Human Activity Index (HAI) showed the largest substantial impact among the four ecosystem services, with its contribution to the model being predominantly negative.
Keywords: *equivalent factor, human activity index, XGBoost, SHAP, vertical change*

Introduction

The term "ecosystem services" is employed to denote the life-supporting products and services that are obtained, either directly or indirectly, through the structure, processes, and functions of ecosystems. The valuation of ecosystem services provides a fundamental basis for environmental protection, ecological zoning, environmental economic accounting, and decision-making regarding ecological compensation (Daily et al., 2000). A foundational study in this area was Daily's seminal definition of the concept, which prompted a substantial body of research by numerous scholars into the valuation of ecosystem services (Daily, 1997). Currently, two principal methodologies are employed for the assessment of ESV: the functional value method and the equivalent factor method (Li et al., 2023; Zhao et al., 2023). The latter, initially proposed by Costanza, has garnered significant recognition and application among scholars (Costanza et al., 1997). During the 1990s, Chinese scholars initiated comprehensive investigations into the subject of ecosystem services. The initial work on ecosystem service valuation in China was conducted by Ouyang Zhiyun, who provided a comprehensive account of the methods for evaluating and assessing the value of ecosystems (Ouyang et al., 1999). Research encompasses not only the impact of past and present land use changes on ecosystem value but also the prediction of the value of ecosystem services in future scenarios (Xie et al., 2015; Xiao et al., 2019; Wei et al., 2023). This prediction is made using models such as CA-Markov, FLUS, and PLUS (Wang et al.,

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2025; Song et al., 2025). The research on natural resource accounting based on ecosystem services in China carries profound implications for the construction of an ecological civilization, the development of ecological security frameworks, and the enhancement of human well-being (Lin et al., 2025; Li et al., 2025a).

The scale at which an ecosystem is observed is crucial for understanding the patterns and processes that occur within it. Furthermore, the scale plays a pivotal role in the spatio-temporal evolution of ecosystem services and their application in ecological regulation (Lü and Fu, 2001). At larger scales, the assessment of ESV may be influenced by the dominant land ecosystem elements within the unit, with the result that the differences between various ecological subsystems may be overlooked. As a result, the generalizability of smaller-scale assessments to larger-scale ecological regulatory applications is often challenging (Zhang et al., 2007). The majority of extant studies on ESV assessments concentrate on single-scale, static analyses, with scant consideration of the spatio-temporal disparities in ecosystem types and quality. Consequently, the assessment outcomes may not accurately reflect the dynamic evolution of ecological service functions, which limits the applicability of these evaluations in ecological planning and management (Zhang et al., 2010; Wang and Lu, 2009). This study aims to analyze the dynamic evolution of the ESV based on two scales.

The extant methodologies employed for the study of the driving mechanisms of ESV have traditionally encompassed both qualitative and quantitative approaches. Qualitative research involves the description of collected data in the form of words following a simple trend analysis (Yan et al., 2014). Conversely, quantitative research employs mathematical analysis methods to identify the reasons for the evolution of ESV and its relationship with related factors (Luo and Yan, 2018; Tang et al., 2025). However, conventional statistical models exhibit the following limitations when employed in the analysis of driving factors: Initially, the data distribution, linear relationships, and independence assumptions are of paramount importance. However, it is crucial to acknowledge that real data may not always align with these assumptions, thereby introducing potential challenges in data analysis and interpretation. Secondly, the management of large-scale data sets and the navigation of complex nonlinear relationships pose significant challenges. Thirdly, they exhibit sensitivity to data alterations and outliers, and they are challenging to adapt to dynamically changing environments (Shi et al., 2022; Gao et al., 2021; Zhang et al., 2023; Deng et al., 2025; Liu et al., 2025). The evolution of ecosystem structure and function services is a complex formation process driven by both natural and anthropogenic factors (Yang et al., 2025). In contrast to traditional statistical approaches, machine learning (ML) models demonstrate superior predictive power and generalization capabilities. They are particularly proficient at identifying and modeling complex nonlinear relationships inherent in data. The eXtreme Gradient Boosting (XGBoost) is a tree-based ensemble method that has demonstrated particular aptitude for modeling non-linear relationships. It has the capacity to capture the interactions between variables and their combined effects on ESV, thereby providing a more accurate representation of the underlying dynamics (Li et al., 2025b; Liu et al., 2021; Guo et al., 2021; Wang et al., 2022). However, the "black box" nature of conventional machine learning models poses significant challenges to their application in ecological management decision - making. The lack of interpretability in prediction results has been shown to undermine decision- makers' confidence in and willingness to accept model outputs (Lee et al., 2022). The integration of the Shapley Additive Explanations (SHAP) with XGBoost enhances interpretability by explaining how each factor influences the predictions (Zhao et al., 2022). The SHAP model offers interpretability for machine

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learning model predictions through the utilization of Shapley values. The model under discussion has a solid theoretical foundation, is model-agnostic, can provide global and local explanations, and supports a wide range of visualization tools. This approach facilitates a more comprehensive understanding of the confidence in the identified driving factors (Ling et al., 2022).

The preservation of the ecological environment in the GRB is of paramount importance to the ecological and economic development of both the Poyang Lake Ecological Economic Zone and the Yangtze River Economic Belt. However, there is a dearth of studies that have examined the evolution of ecosystem structure and function in the GRB, China (Wang et al., 2024, 2016). The relationship between driving factors and ESFV remains unclear. Consequently, the assessment of ESV in the GRB, coupled with a thorough investigation into its evolution and driving forces, is imperative to foster ecological construction and sustainable development. This paper utilizes Landsat data to generate land use distribution maps for the GRB in 1990, 2000, 2010, and 2020. The spatial and temporal evolution of ESV, as well as the importance of the factors, is also conducted using XGBoost and SHAP model. The objectives of the present study are as follows: first, to reveal the multi-dimensional characteristics of the ESV; and second, to identify the driving factors of the four ESFV. The findings of this study provide a scientific basis for the rational allocation of land resources, ecological environmental protection, and resource development and utilization in the GRB, China.

Materials and methods

General situation of the study area

The Ganjiang River constitutes the most substantial water system within the Poyang Lake Basin, thereby serving as a considerable tributary of the lower Yangtze River. It is situated in the south-central part of Jiangxi Province, China, between 113° 42’ and 116° 38’ east longitude and 24° 30’ and 28° 42’ north latitude. The GRB encompasses an area of 80,948 km^2, constituting 50% of the total area of the Poyang Lake Basin. The average annual runoff is estimated at 68.7 billion m^3, constituting approximately 50% of the total runoff in the Poyang Lake region. The climatic characteristics are defined by a subtropical humid monsoon climate, with an average annual precipitation of 1590 mm. The region is characterized by a plentiful supply of water resources, though there is significant variability in annual rainfall, resulting in an uneven distribution of precipitation throughout the year. The mean annual temperature of the basin is approximately 18°C, with notable climatic variations between the northern and southern regions. The topography of the basin is predominantly mountainous and hilly, exhibiting a step-like elevation pattern that gradually decreases from south to north (Wang et al., 2024). The geographical location of the study area is delineated in *Figure 1*.

Data sources

The data utilized in this study encompass a digital elevation model (DEM), monthly mean temperature and precipitation, normalized difference vegetation index (NDVI), land use data, and grain output. The grain output data was derived from the statistical yearbooks of Jiangxi province (2021), while the product price data was sourced from the China Agricultural Products Price Survey Yearbook (2021). The detailed data is presented in *Table 1*.

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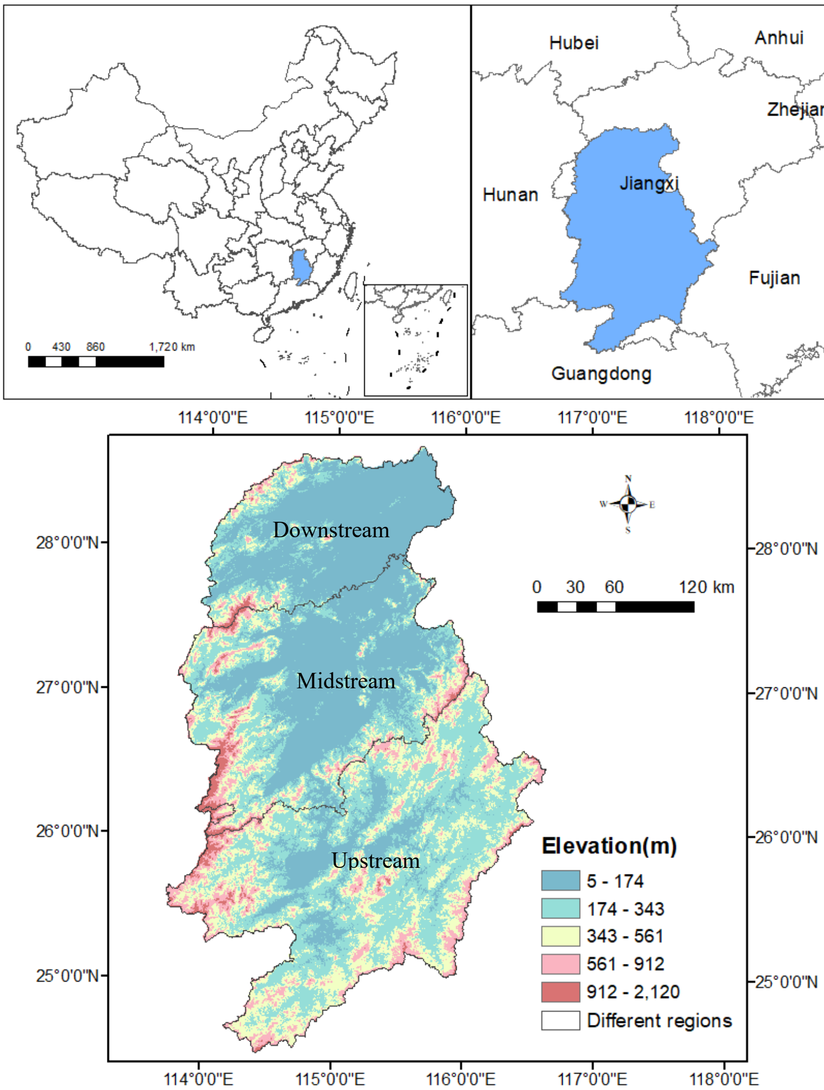

***Figure 1.** Geographical location of the study area*

***Table 1.** Data source*

Data type	Data sources	Data accuracy	Year
Digital Elevation Model	Geospatial Data Cloud (https://www.gscloud.cn/)	30 m	2024
Monthly mean temperature	National Meteorological Science Data Centre (http://data.cma.cn/)	1 km	1990-2020
Monthly mean precipitation	National Meteorological Science Data Centre (http://data.cma.cn/)	1 km	1990-2020
Normalized Difference Vegetation Index	Resource and Environmental Science Data Platform, Chinese Academy of Sciences (https://www.resdc.cn/)	1 km	1990, 2000, 2010, 2020
Land use	Resource and Environmental Science Data Platform, Chinese Academy of Sciences (https://www.resdc.cn/)	30 m	1990, 2000, 2010, 2020
Population and GDP	Jiangxi Statistical Yearbooks	County	2021

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The research framework

This study employed the per unit area equivalent method to estimate the value of ecosystem services. The analysis of the spatial and temporal evolution of ESV, as well as the revelation of the main driving factors of the four ESFV, were conducted. The research framework is shown in *Figure 2*.

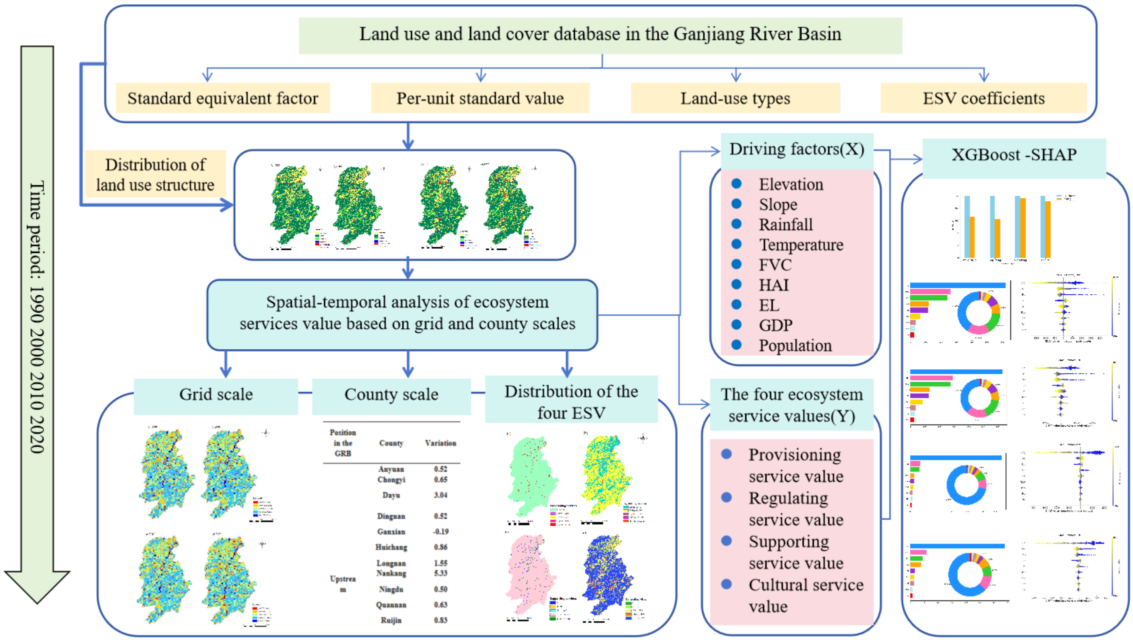

Figure 2. *The research framework*

ESV assessment and measurement

The total ESV is comprised of four distinct ESFV based on the first category: provisioning services, regulating services, supporting services, and cultural services. The four ESFV are classified into three, four, three, and one types, respectively, in the second category (*Table 2*). In consideration of the prevailing socio-economic development conditions in China, Gaodi Xie and colleagues derived dynamic equivalent factors that are particularly suitable for China's terrestrial ecosystems (Xie et al., 2003). In this study, the equivalent factor method was employed to ascertain the value of individual ecosystem service equivalent factors and to estimate the unit area value coefficients for different landscape types. The equivalent factor of ESV is defined as the relative contribution rate of the ecosystem's potential service value. This factor is equivalent to one-seventh of the annual per-hectare value of grain production (Hu et al., 2023; Shi et al., 2012). It has been observed that the built-up land has a significant negative impact on the ability to regulate hydrology and purify the environment. Consequently, the equivalent factors for these two services were assigned values of -7.55 and -2.46, respectively (Hasan et al., 2020).

In consideration of the particulars of agricultural crop production within the GRB, the grain crops selected for examination in this study included cereals, legumes, and tubers. The mean grain yield in the GRB is 5736.11 kg/hm^2. Considering that the research duration extended over three decades, a fixed price level was utilized to correlate the ESV of each period, hence improving result comparability and alleviating the effects of inflation. The aim of this study is to recalibrate the ESV for the years 1990, 2000, and

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2010 to the price level of 2020. This methodological technique will eliminate price variations from the analysis, ensuring a more precise and objective assessment of value changes (Guo et al., 2021). In 2020, the market prices of cereals, legumes, and tubers were recorded at 2.77 yuan/kg, 2.68 yuan/kg, and 6.56 yuan/kg, respectively. Consequently, the ESV equivalent factor of the GRB was 2306.47 yuan/hm^2 in 2020 (*Table 2*). The formulas are shown in *Equations 1* and *2* (Dai et al., 2020):

$$ESV = \sum(A_k \times VC_k) \quad \text{(Eq.1)}$$

$$ESV_k = \sum(A_k \times VC_{fk}) \quad \text{(Eq.2)}$$

where ESV represents the total value of ecosystem services, VC_k is the ecosystem value coefficient, A_k is the area of land use type k, ESV_k is the value of the f-th ecosystem service function, and VC_{fk} is the value coefficient of the f-th service function for land use type k.

Table 2. *ESV coefficients for a variety of land types in the Ganjiang River Basin, China, 2020 (yuan/hm^2)*

Ecosystem type		**Farmland**	**Forest**	**Grassland**	**Wetland**	**Urban**	**Desert**
Land-use type		**Cultivated land**	**Forestland**	**Grassland**	**Water**	**Built-up land**	**Bare land**
Provisioning services	Food production	2548.65	538.56	701.17	1677.95	0.00	0.00
	Raw material production	565.08	1230.50	1033.30	686.17	0.00	0.00
	Water supply	-3009.94	638.89	572.00	15833.90	0.00	0.00
Regulating services	Gas regulation	2052.76	4065.15	3634.99	2427.56	0.00	46.13
	Climate regulation	1072.51	12167.77	9613.35	6037.18	0.00	0.00
	Environmental purification	311.37	3491.99	3173.70	11676.49	-5673.91	230.65
Supporting services	Hydrological regulation	3448.17	6789.09	7048.56	190831.31	-17413.83	69.19
	Soil retention	1199.36	4949.68	4428.42	2940.75	0.00	46.13
	Nutrient cycling	357.50	379.41	332.13	224.88	0.00	0.00
	Biodiversity conservation	392.10	4503.38	4022.48	8949.09	0.00	46.13
Cultural services	Aesthetic landscape	172.99	1975.49	1771.37	5996.81	0.00	23.06
---	Total	9110.54	40729.90	36331.47	247282.09	-23087.73	461.29

Grid-based spatial expression of ESV

The grid method is a significant approach for the expression of spatial distribution patterns and serves as an effective evaluation unit when quantifying the spatio-temporal evolution of land use at a micro scale (Syrbe and Walz, 2012). In light of the findings of previous research, four grid sizes were initially identified as potential evaluation units: 3 km × 3 km, 6 km × 6 km, 8 km × 8 km, and 10 km × 10 km. The final grid size was determined through the utilization of analytical tools, specifically Create Fishnet, Clip, and Dissolve in ArcGIS 10.8. This process yielded a grid size of 6 km × 6 km, comprising a total of 2432 grid cells. The ESV of each land use type within each grid cell was calculated based on the land use data. The total ESV for each grid cell was obtained by aggregating the values for each land use type. The specific formulas employed are shown in *Equations 3* and *4* (Li et al., 2018; Yang et al., 2022):

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$$ESV_n = \sum s_{mn} \times LU_m \qquad \text{(Eq.3)}$$

$$ESV = \sum_{n=1}^{k} ESV_n \qquad \text{(Eq.4)}$$

ESV_n represents the ESV of the n-th land use type within each grid cell; S_{mn} denotes the area (in hectares) of the n-th land use type in the m-th grid cell; LU_m is the ESV coefficient for the m-th land use type; and k is the total number of land use types.

Regional variation analysis based on administrative units

The GRB encompasses 69 counties and districts across Jiangxi, Fujian, Guangdong, and Hunan provinces. However, given the limited area within certain counties and districts, which compromises the comparability of the data, this study has identified 43 counties and districts with an ESV exceeding 1 billion yuan as the primary objects of study. The regional variation in ESV at the county scale can be reflected using the relative change rate, the formulas are shown in *Equation 5* (Liu et al., 2014):

$$R = \frac{R_L}{R_C} = \frac{(L_b - L_a)/L_a}{(C_b - C_a)/C_a} \qquad \text{(Eq.5)}$$

R represents the relative change rate, where R_L and R_C are the regional and overall change rates, respectively; L_a and L_b denote the initial and final ESV values at the local level; and C_a and C_b represent the initial and final ESV values at the global level. The relative change rate exhibits the following characteristics:

(1) When the absolute value of the relative change rate $|R| \geq 1$, it indicates that the magnitude of change in regional ESV is greater than that of the entire study area. A value of $R \geq 1$ indicates that the trend and direction of change in regional ESV are consistent with those of the global ESV. Conversely, if R is less than or equal to -1, this indicates that the trend and direction of change in regional ESV are opposite to those of the global ESV.

(2) Conversely, when the absolute value of the relative change rate $|R| < 1$, it indicates that the magnitude of change in regional ESV is smaller than that of the entire study area. Should the absolute value of the relative change rate fall between -1 and 0, it would indicate that the trend and direction of change in regional ESV are in opposition to those observed at the global level. Conversely, if $0 < R < 1$, this indicates that the trend and direction of change in regional ESV are consistent with those of the global ESV.

The driving factors of ESV

The selection of driving factor indicators in this paper is primarily based on natural geographic and humanistic socioeconomic factors that may affect the change of ecosystem function. Specifically, nine indicators from two categories were selected based on the actual situation of the study area, natural factors: Elevation (Ele), Slope (Slo), Rainfall (Rai), Temperature (Tem), and Fractional Vegetation Cover (FVC); human socioeconomic factors: Human Activity Index (HAI), Ecological Land Area Proportion (EL), Population (Pop), and Gross Domestic Product (GDP). The extraction of elevation and slope data was conducted using DEM, while the calculation of the FVC, EL, and HAI indicators was informed by relevant literature.

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FVC is defined as the percentage of the vertical projection area of vegetation in a given unit area. These calculations are shown in *Equation 6* (Li et al., 2021):

$$FVC = \frac{NDVI - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}} \tag{Eq.6}$$

In the formula, FVC represents the vegetation cover (%), NDVI is the normalized difference vegetation index, with the multi-year monthly average used in this study. $NDVI_{max}$ refers to the NDVI value of pixels completely covered by vegetation, and $NDVI_{min}$ refers to the NDVI value of bare soil or areas without vegetation cover.

The EL is a metric used to assess the proportion of land within an evaluation area that is characterized by ecological attributes. The indices are shown in *Equation 7* (Ministry of Ecology and Environment, 2021):

EL = A_{el} × (area of forest land + area of shrub forest + area of open forest land + area of grassland + area of river + area of lake + area of mudflat + area of permanent glacier snow area + area of swamp + area of sand + area of other forest land × 0.7 + area of reservoir × 0.7 + area of paddy field × 0.7 + area of dry land × 0.5) / LA (Eq.7)

where, EL is the ecological land area ratio index, A_{el} is the normalization coefficient of the ecological land area ratio index with a reference value of 100.5022, and LA is the regional land area.

The HAI was employed to quantify the intensity of human interference in a specific region's landscape. The HAI value ranged from 0 to 1, with higher values indicating greater human activity impact on the landscape components. The formulas are shown in *Equation 8* (Yan et al., 2014):

$$HAI = \sum_{i=1}^{N} A_i P_i / TA \tag{Eq.8}$$

where HAI is the comprehensive index of anthropogenic impacts, N is the number of landscape types, A_i is the area of the ith type of landscape, P_i is the intensity coefficient of anthropogenic impacts of the ith type of landscape, TA is the total area of the landscape.

Driving factors of ESFV based on XGBoost plus SHAP model

A 6 km × 6 km grid was generated in the designated study area, yielding a total of 2432 grid cells. The mean value of each grid was extracted, and the corresponding data of natural and humanistic drivers were obtained. This preliminary step provided fundamental support for the subsequent analysis. The total ESV is comprised of four distinct ESFV: provisioning services, regulating services, supporting services, and cultural services.

XGBoost is a highly efficient implementation of the Gradient Boosting Tree algorithm, widely utilized in both classification and regression tasks. Its primary strengths lie in its ability to handle high-dimensional data, its robust mechanisms for preventing overfitting, and its capacity to achieve high accuracy across a diverse range

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of machine learning tasks. The XGBoost model was employed to detect the driving factors of the four ESFV of the GRB, primarily to establish a large data-set. The four ESFV constitute the target variables, and nine indicators constitute the feature variables. The dataset was randomly partitioned into two subsets: training, consisting of 70% of the data, and testing, containing 30% of the data. The XGBoost regression model was constructed using the following parameters: (n_estimators = 200, max_depth = 5, learning_rate = 0.1, subsample = 0.8, colsample_bytree = 0.8). The model was trained using the training set, and its performance was evaluated by predicting and calculating the coefficient of determination (R^2) on the training set and test set, respectively. To facilitate interpretation, SHAP analysis was employed, yielding feature importance bar charts, pie charts, and SHAP value hive charts (Dandolo et al., 2023; Chen and Guestrin, 2016).

Results and analysis

Land use change in the GRB, China

Figure 3 presents a visual representation of the land use types present in the GRB from 1990 to 2000, while *Table 3* offers a quantitative analysis of the area change in land use types. The results demonstrated that forestland remained the predominant land use in the GRB, comprising over 66% of the total area. From 1990 to 2020, the area of forestland demonstrated an initial increase, followed by a subsequent decline, resulting in a net reduction of 589.22 km^2, which corresponds to an 1.10% reduction rate. Cultivated land, the second most prevalent land cover type in the basin, constituted approximately 25% of the total area. Despite the relatively minor proportion of built-up land within the total area, it has exhibited a notable increase, with a net expansion of 1020.74 km^2, representing an 80.08% growth rate. The area of water bodies had a net increase of 58.08 km^2. Conversely, the proportion of bare land, constituting 0.01% of the total area, exhibited a net reduction of 1.22 km^2.

Temporal changes of the ESV in the GRB, China

During the study period, the ESV of the GRB demonstrated an initial increase, subsequently followed by a decrease. The ESV increased from 283.588 billion yuan in 1990 to 284.286 billion yuan in 2000, before declining to 279.847 billion yuan by 2020. This represented a net reduction of 3.741 billion yuan, or a decrease of 1.32% (*Table 4*).

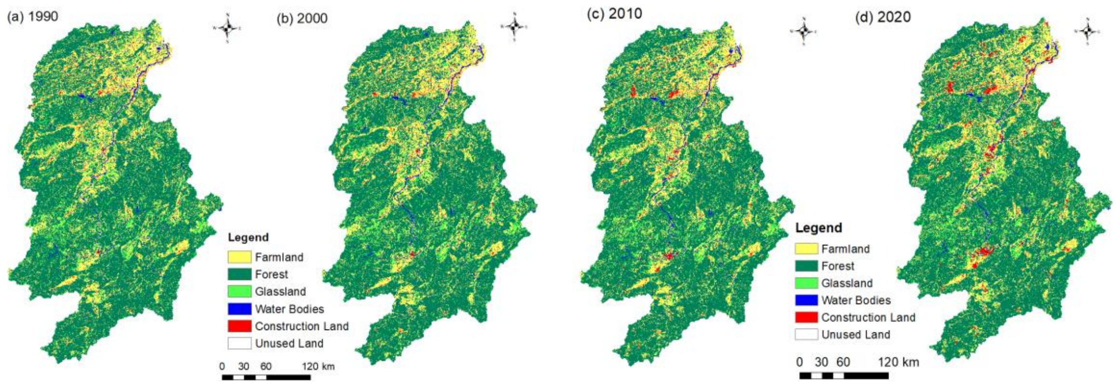

Figure 3. *Map of land use types in the Ganjiang River Basin, China, 1990-2020*

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***Table 3.** Area change of land use types in the Ganjiang River Basin, China, 1990-2020*

Year	Statistics	Cultivated land	Forestland	Grassland	Water	Built-up land	Bare land
1990	Area (km^2)	20272.11	53482.95	4432.23	1379.93	1274.72	11.25
	Area (%)	25.07%	66.15%	5.48%	1.71%	1.58%	0.01%
2000	Area (km^2)	20186.8	53611.43	4302.44	1414.18	1328.13	11.52
	Area (%)	24.97%	66.31%	5.32%	1.75%	1.64%	0.01%
2010	Area (km^2)	20091.13	53469.92	4173.65	1421.83	1692.2	10.5
	Area (%)	24.85%	66.13%	5.16%	1.76%	2.09%	0.01%
2020	Area (km^2)	19781.71	52893.73	4439.33	1438.01	2295.46	10.03
	Area (%)	24.46%	65.42%	5.49%	1.78%	2.84%	0.01%
1990-2020	Change (km^2)	-490.4	-589.22	7.1	58.08	1020.74	-1.22
	Change (%)	-2.42%	-1.10%	0.16%	4.21%	80.08%	-10.84%

***Table 4.** Temporal changes of the ESV in the Ganjiang River Basin, China, 1990-2020*

Year	Statistics	Cultivated land	Forestland	Grassland	Water	Built-up land	Bare land	Total
1990	Value (10^8/year)	184.69	2178.36	161.03	341.23	-29.43	0.01	2835.88
	Ratio (%)	6.51%	76.81%	5.68%	12.03%	-1.04%	0.00%	100.00%
2000	Value (10^8/year)	183.91	2183.59	156.31	349.70	-30.66	0.01	2842.86
	Ratio (%)	6.47%	76.81%	5.50%	12.30%	-1.08%	0.00%	100.00%
2010	Value (10^8/year)	183.04	2177.82	151.63	351.59	-39.07	0.00	2825.03
	Ratio (%)	6.48%	77.09%	5.37%	12.45%	-1.38%	0.00%	100.00%
2020	Value (10^8/year)	180.22	2154.36	161.29	355.59	-53.00	0.00	2798.47
	Ratio (%)	6.44%	76.98%	5.76%	12.71%	-1.89%	0.00%	100.00%
1990-2020	Value (10^8/year)	-4.47	-24.00	0.26	14.36	-23.57	0.00	-37.41
	Ratio (%)	-2.42%	-1.10%	0.16%	4.21%	80.08%	-10.84%	-1.32%

Among the various land use categories, forestland contributed the most to the overall ESV, representing over 76% of the total, which is significantly higher than the proportion contributed by other land use types. Water bodies constituted the second-largest contributor to the ESV, accounting for over 12% of the total and exhibiting an increasing trend. The trend for grassland exhibited an initial decline, followed by an increase. Conversely, the trend exhibited by cultivated land was characterized by fluctuations, with an initial decline, a subsequent increase, and then another decline. The contribution of bare land was minimal, accounting for less than 0.01% of the total ESV, and can be considered negligible. The ESV of built-up land exhibited a downward trajectory.

Vertical spatial variation of ESV based on DEM

From 1990 to 2020, the per-unit ESV across all slope gradients in the GRB initially demonstrated a decline, followed by an increase. It is noteworthy that the 0-3° and 15-25° slope gradients exhibited a significant increase, while the 8-15° and > 25° slope gradients demonstrated a more gradual increase. A significant decrease was observed in the 3-8° slope gradient. The 0-3° slope gradient exhibited the highest per-unit ESV among the various slope gradients (*Table 5*).

With regard to the total ESV, the > 25° slope gradient exhibited the highest value. The 8-15° and 15-25° slope gradients also exhibited relatively high ESV, representing more

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than 27% and 24% of the total value, respectively. The 0-3° slope gradient exhibited an initial increase, followed by a subsequent decline. The 3-8° slope gradient exhibited the lowest total ESV and demonstrated a declining trend.

Table 5. *Value of ecosystem services by slope section in the Ganjiang River Basin, China, 1990-2020*

Slope	Value per unit area (yuan/hm^2)				Total value (10^8 yuan/year)			
	1990	2000	2010	2020	1990	2000	2010	2020
0-3°	61080.90	51409.78	51443.31	50708.98	255.72	270.80	270.99	267.12
3-8°	25392.72	25352.77	24540.91	23981.37	149.53	149.30	144.53	141.23
8-15°	29716.70	30683.97	29171.30	28702.98	793.20	782.13	779.28	766.18
15-25°	36553.62	36608.10	36530.85	36329.94	702.37	703.43	702.00	698.12
> 25°	38892.52	38934.65	38998.06	38916.07	923.18	924.21	925.75	923.79

From 1990 to 2020, the per-unit ESV in the GRB exhibited an initial increase followed by a subsequent decline with increasing altitude. The 200-500 m altitude range exhibited a significant increase, while the 500-800-m and 800-1200 m ranges demonstrated a more gradual increase. Conversely, the altitude range exceeding 1200 m exhibited a slight decrease. The 500-800 m and 800-1200 m ranges exhibited relatively high per-unit ESV, while the 0-200 m range demonstrated the lowest per-unit ESV (*Table 6*). During the study period, higher altitudes exhibited higher per-unit ESV, which is consistent with the distribution of landscape types across different altitudes. In the GRB, water bodies, agricultural land, and built-up areas are predominantly situated at lower altitudes, whereas grasslands and forests are distributed at higher altitudes.

With respect to the total ESV, the altitude range of 200-500 m exhibited the highest total ESV. The altitude range of 0-200 m exhibited the second highest total ESV. The ESV for altitudes between 0 and 500 m accounted for over 83% of the total ESV.

Table 6. *Value of ecosystem services by altitude zone in the Ganjiang River Basin, China, 1990-2020*

Altitude	Value per unit area (yuan/hm^2)				Total value (10^8 yuan/year)			
	1990	2000	2010	2020	1990	2000	2010	2020
0-200 m	32228.20	32199.18	31911.71	31298.45	1123.31	1132.32	1112.74	1091.34
200-500 m	36731.33	36756.56	36653.76	36521.72	1264.34	1264.89	1261.41	1256.84
500-800 m	38818.73	38840.90	38907.42	38858.25	344.34	344.52	345.13	344.69
800-1200 m	38600.15	38600.03	39187.92	39121.08	85.70	85.68	86.99	86.84
>1200 m	37379.31	37387.37	38684.40	38648.57	17.64	17.68	18.25	18.23

Spatial variation of ESV based on gridded analysis

The 6 km × 6 km grid was utilized for the purpose of equidistant sampling, resulting in the creation of 2432 grid cells. The ecosystem service value index (ESVI) was classified into five levels, ranging from low to high, according to the following criteria: low (ESVI ≤ 13,000 yuan/hm^2), moderately low (13,000 yuan/hm^2 < ESVI ≤ 26,472 yuan/hm^2), medium (26,472 yuan/hm^2 < ESVI ≤ 35,422 yuan/hm^2), moderately high (35,422 yuan/hm^2 < ESVI ≤ 55,638 yuan/hm^2), and high (ESVI > 55,638 yuan/hm^2).

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The classification described above resulted in the generation of spatial variation maps of ESV within the GRB (*Fig. 4*). The findings indicate that there have been substantial alterations in the levels of ESV between 1990 and 2020, with discernible spatial variations. The northern part of the basin exhibited lower per-unit ESV, while the southern part demonstrated higher values. The counties and cities exhibited a concentration of low ESV areas, while higher values were observed in the surrounding regions.

A comparison of the ESV levels at two distinct points in time reveals that if the two ESV levels are identical, this is referred to as a "grade stability zone". Conversely, if the ESV level of the latter demonstrates an improvement, this is designated as a "grade up zone". Finally, if the level of the following ESV experiences a decline, this is termed a "grade drop zone". *Figure 5* illustrates the changes in ESV classes in the GRB over four periods: 1990–2000, 2000–2010, 2010–2020, and 1990–2020. The analysis revealed that from 1990 to 2000, 97.98% of the area exhibited no alteration in the level of regional ecosystem services. An increase was documented in 1.39% of the area, with the majority of these changes occurring at county boundaries and along county edges. Conversely, a decrease was observed in 0.63% of the area. From 2000 to 2010, 1.53% of the area exhibited an increase, while 2.74% demonstrated a decrease. The interval spanning from 2010 to 2020 witnessed minor and sporadic increases in 0.12% of the area, while 5.57% of the area underwent a decrease. Finally, between 1990 and 2020, an increase was observed in 1.3% of the area, while a decrease was evident in 6.92%.

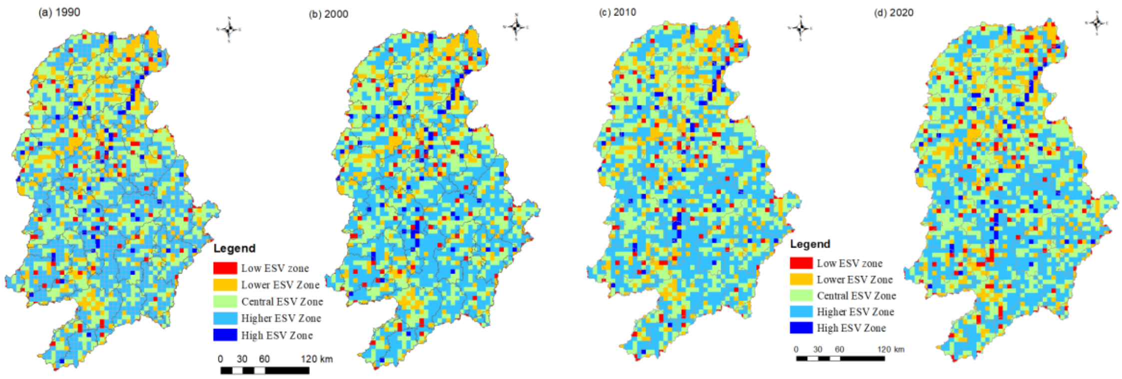

***Figure 4.** Distribution of ESV based on grid in the Ganjiang River Basin, China, 1990-2020*

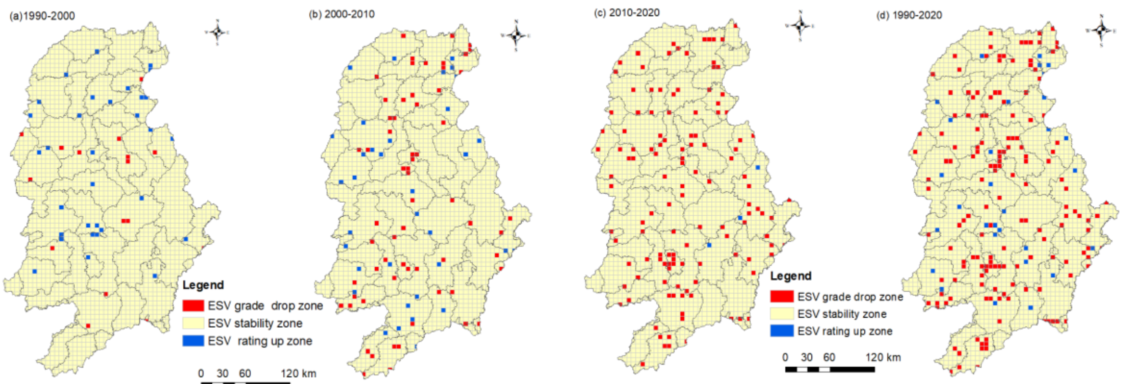

***Figure 5.** Changes in ESV classes based on grid in the Ganjiang River Basin, China, 1990–2000 (a), 2000–2010 (b), 2010–2020 (c), and 1990–2020 (d).*

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Regional discrepancies based on administrative scales

The ESV of Ganxian, Jishui, Taihe, Wan'an, and Luxi exhibited an increase of 0.25%, 0.53%, 0.16%, 6.89%, and 0.13%, respectively. Conversely, the ESVs of the remaining 38 counties demonstrated a decline.

As illustrated in *Table 7,* the ESV of the GRB demonstrated a decline of 1.32% from 1990 to 2020, with 20 counties and districts (46.51%) exhibiting an R value of at least 1. Of these, 19 counties and districts exhibited R values greater than 1, indicating that the changes in ESV in these areas were more pronounced than in the overall region and followed the same trend. A single county, Wan'an, exhibited an R value greater than -1, indicating a notable increase in its ESV over the specified period.

With regard to the spatial distribution, the proportions of ESV for the upper, middle, and lower reaches of the GRB in 2020 were 46.12%, 35.13%, and 18.75%, respectively. In comparison to the data from 1990, the ESV for the upper, middle, and lower reaches demonstrated a decrease of 2.39%, 1.17%, and 3.27%, respectively.

Table 7. *Variation rate of ESV based on county scale in the Ganjiang River Basin, China, 1990-2020*

Position in the GRB	County	Variation	Position in the GRB	County	Variation	Position in the GRB	County	Variation
Upstream	Anyuan	0.52	Midstream	Anfu	0.26	Downstream	Fenyi	0.34
	Chongyi	0.65		Ji'an	2.36		Gaoan	2.72
	Dayu	3.04		Jinggangshan	0.77		Luxi	-0.10
	Dingnan	0.52		Jishui	-0.40		Shanggao	2.31
	Ganxian	-0.19		Jizhou	7.14		Wanzai	1.23
	Huichang	0.86		Le'an	0.65		Fengcheng	3.10
	Longnan	1.55		Lianhua	1.45		Xinjian	5.92
	Nankang	5.33		Qingyuan	1.33		Yifeng	1.19
	Ningdu	0.50		Suichuan	0.53		Yuanzhou	4.47
	Quannan	0.63		Taihe	-0.12		Yushui	5.32
	Ruijin	0.83		Wan'an	-5.22		Zhangshu	0.75
	Shangyou	0.01		Xiajiang	0.55			
	Shicheng	0.53		Yongfeng	0.64			
	Xinfeng	1.02		Yongxin	0.25			
	Xingguo	0.27		Xin'gan	3.08			
	Yudu	1.02						
	Zhanggong	13.69						

The spatial distribution of driving factors and the four ESFV

Due to the substantial computational demands of this approach, only the year 2020 data were used to identify the driving factors for the four ESFV. The spatial variation of the four ESFV of 2020 was observed, as illustrated in *Figure 6*. The provisioning services value was predominantly low grade (ESVI $\leq$ 3640 yuan/hm^2). Conversely, the regulation service values were predominant in moderately low and low grades, with higher values observed in the southern region compared to the northern regions. The regulation service values accounted for nearly 50% of the total ESV. The supporting service values were predominant by moderately high grade. The cultural service values were predominant by high and moderately high grades, with higher values observed in the south.

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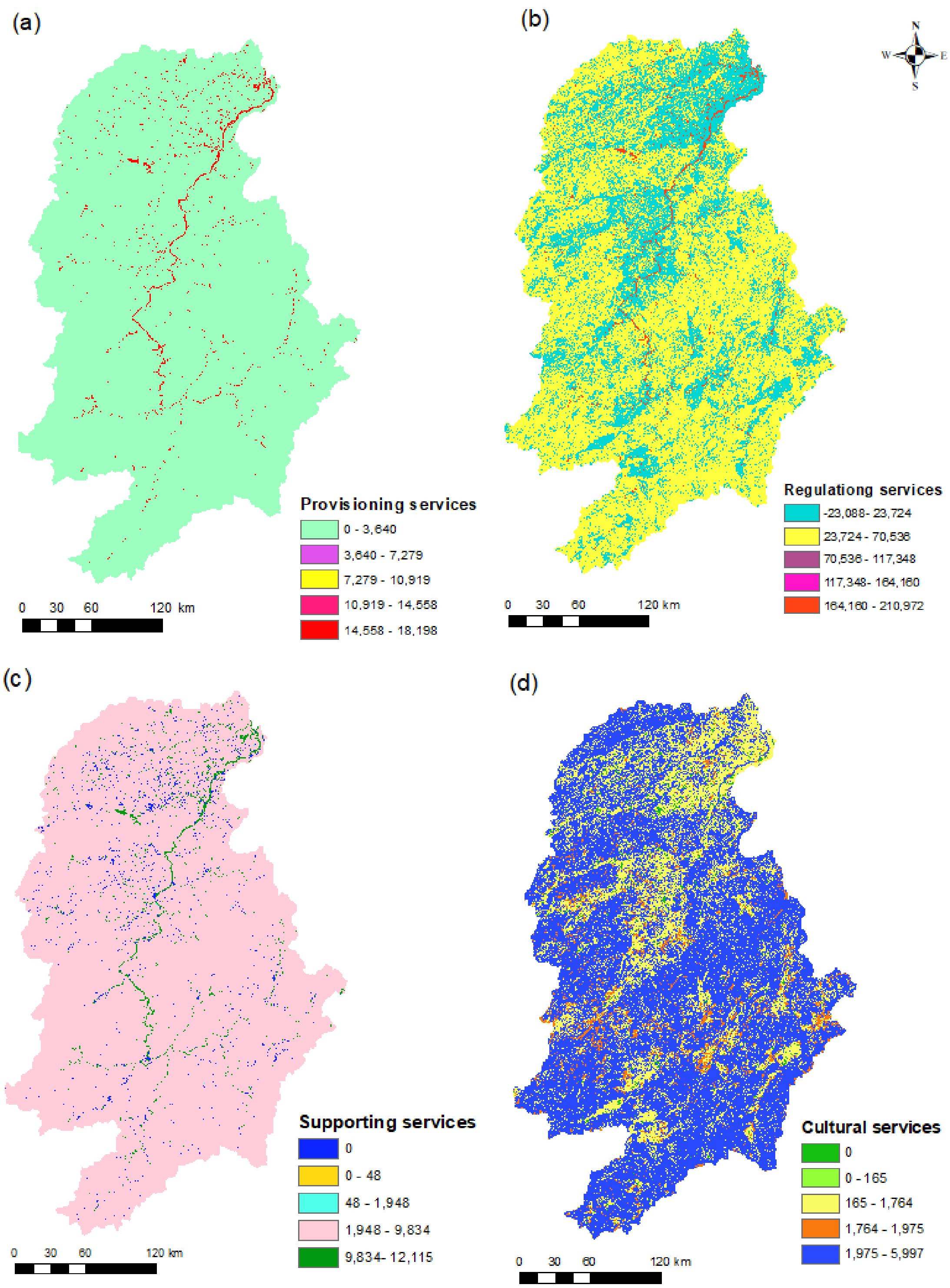

***Figure 6.** Distribution of the four ESFV in the Ganjiang River Basin, China, 2020. (a) Provisioning services, (b) Regulation service, (c) Supporting services, (d) Cultural services*

The spatial distribution of driving factors was illustrated in *Figure 7*. The northern part of the basin exhibited lower elevation and slope, while the southern part demonstrated higher values. The distribution of low-temperature areas was found to be concentrated in the western regions, while higher values were observed in the southern areas. The

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precipitation exhibited a contrasting pattern, with higher rainfall areas concentrated in the surrounding regions of the GRB. The northern part of the basin exhibited lower FVC, while the southern part demonstrated higher values. The high GDP and population density were concentrated in urban areas. The northern part of the basin exhibited higher HAI values, while the southern part demonstrated lower values. The EL exhibited a contrasting pattern, with higher values observed in the southern regions.

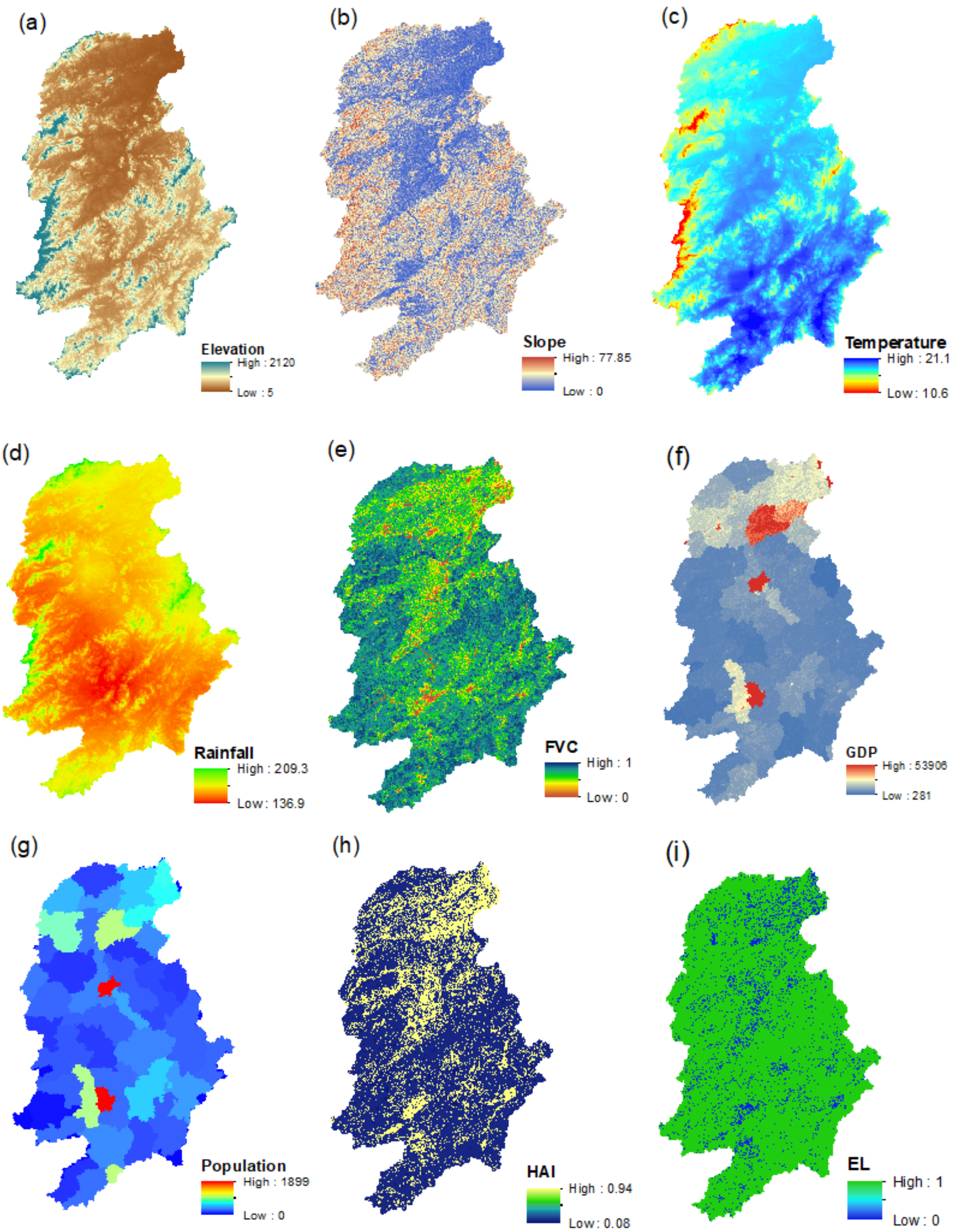

Figure 7. *The spatial distribution of driving factors in the Ganjiang River Basin, China, 2020. Fractional Vegetation Cover (FVC), Human Activity Index (HAI), Ecological Land Area Proportion (EL)*

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Exploration of drivers based on XGBoost + SHAP model

As demonstrated in *Figure 8,* the model attained an R^2 of 0.9923 and 0.6580 for the provisioning service value driver detection model during the training and testing phases, respectively. Analogously, the R^2 values for the regulating service value driver detection model were 0.9919 and 0.6281 during these phases. Meanwhile, the R^2 values for the supporting service value model were 0.9991 and 0.9626. The cultural service value model demonstrated an R^2 of 0.9974 and 0.9046 during these phases. In summary, the XGBoost model exhibited a high degree of efficacy in detecting the drivers of these four ESFV. The model's capacity to discern these drivers with a high degree of confidence is particularly noteworthy.

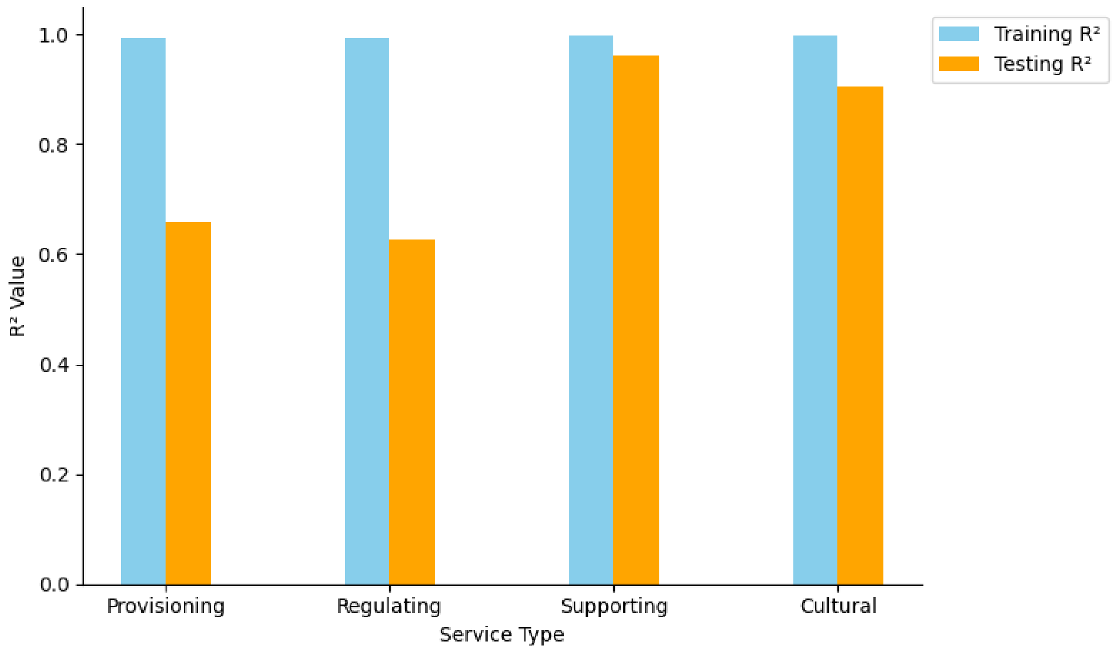

***Figure 8.** The training and testing R^2 of the driver detection model*

As illustrated in *Figure 9A1-A4*, the findings of the importance analysis of each driver factor to the model output are presented through bar charts and pie charts. The bar chart represents the mean absolute SHAP value (|SHAP|) of the eigenvalues of each driver, that is, the average absolute SHAP value of each factor across all samples. This reflects the average contribution of the factor to the model's prediction results. The pie chart, on the other hand, signifies the percentage contribution of each factor to the model predictive value, thereby illustrating the relative proportion of each factor's contribution to the model predictive outcome. It is noteworthy that the larger the value, the more significant the overall impact of the factor on the model's predicted results.

Figure 9B1-B4 employs the SHAP model to illustrate the direction of influence of each characteristic factor on the model prediction results. The horizontal axis denotes the SHAP value, with positive values indicating a favorable contribution of the factor to the prediction outcome. The vertical axis represents the eigenfactors, which have been meticulously sorted from top to bottom according to their relative importance. The color of the dots undergoes a gradual transition from blue to yellow, signifying the magnitude of different eigenvalues and their corresponding SHAP values.

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Figure 9. *(A1) Bar plots of average absolute SHAP values and pie charts of contribution percentages of factors and (B1) SHAP summary plot of provisioning service values. (A2) Bar plots of average absolute SHAP values and pie charts of contribution percentages of factors and (B2) SHAP summary plot of regulating service values. (A3) Bar plots of average absolute SHAP values and pie charts of contribution percentages of factors and (B3) SHAP summary plot of supporting service values. (A4) Bar plots of average absolute SHAP values and pie charts of contribution percentages of factors and (B4) SHAP summary plot of cultural service values. Elevation (Ele), Slope (Slo), Rainfall (Rai), Temperature (Tem), and Fractional Vegetation Cover (FVC), Human Activity Index (HAI), Ecological Land Area Proportion (EL), Population (Pop), and Gross Domestic Product (GDP)*

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As illustrated in *Figure 9A3* and *B3*, an analysis of the factors influencing supporting service values indicates that the |SHAP| Value of HAI is 1275.68, contributing 71.88% to the prediction results. EL and Slo emerge as more significant secondary factors, with the contribution of other factors amounting to less than 15% in total. The findings indicate that elevated HAI levels exert a deleterious influence on model predictions, signifying that human activities substantially diminish supporting service values as HAI escalates.

As illustrated in *Figure 9A1* and *B1*, an analysis of the impact of factors influencing provisioning service value reveals that the |SHAP| Value of HAI is 620.88, contributing 41.09% to the prediction results. This feature factor is the most significant, and it has the greatest impact on the prediction results. The |SHAP| Value of FVC is 260.63, contributing 17.25% and ranking as the second most important feature factor. The EL is the third most significant eigenfactor. Slo and EL are the other two important eigenfactors, followed by Pop, Tem, Rai, and GDP, in that order. A high HAI value has been shown to exert a negative effect on the model prediction results. As the HAI increases, the sustainability of land resources and natural systems decreases, leading to a decrease in the value of provisioning services. Conversely, low FVC and Ele values have been observed to have a positive effect on the model prediction results.

As illustrated in *Figure 9A2* and *B2*, the examination of the impact of regulatory factors on regulating service value indicates that the |SHAP| Value of HAI is 6318.20, contributing 38.36% to the prediction results. This is the most significant characterization factor, contributing the most to the prediction results. The XGBoost model displays a |SHAP| Value of Ele of 2937.13, contributing 17.83%, and a |SHAP| Value of FVC of 2779.86, contributing 16.88%. Slo and EL emerge as less significant secondary factors. The findings indicate that a high HAI had a negative effect on the model predictions, suggesting that human activities would reduce the regulating service values with the increase of HAI.

As illustrated in *Figure 9A4* and *B4*, the investigation of the factors influencing cultural service values indicates that the |SHAP| Value of HAI is 337.78, accounting for 62.60%. This is the most significant characteristic factor and contributes the most to the prediction results. The |SHAP| Value of FVC is 59.16, accounting for 10.96%, which is the second most significant characteristic factor. Ele, Slo, and EL emerge as additional salient feature factors. The high HAI exerts a negative influence on the model predictions. Conversely, the low FVC and Ele exert a favorable influence on the model predictions. The SHAP values for other factors were concentrated around 0, indicating that the direction of their effect was not clear.

Discussion

Impacts of natural and anthropogenic factors on ESFV in the GRB, China

This study revealed a net reduction of 3.741 billion yuan in total ESV in the GRB from 1990 to 2020. The investigation of the impact of natural and socioeconomic factors on the ESV was crucial for effective environmental management. The utilization of XGBoost and SHAP analysis to identify the drivers of ESFV revealed that the functional value of each service was influenced by different primary factors. Human activities were found to be a dominant influence on the four ESFV. Among the four ESFV, HAI exhibited the most significant impact, contributing to the model primarily through negative values. The expansion of urban areas had a discernibly detrimental effect on hydrological regulation and environmental purification, with these two analogous factors yielding negative values (Wei et al., 2023; Dai et al., 2020). China issued “National New-Type Urbanization Plan

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(2014-2020)" in 2014, which clearly stated that by 2020, the urbanization rate of the permanent population should reach approximately 60%. The implementation of this plan signaled China's official entry into a new stage of rapid urbanization, which subsequently led to a rapid expansion in urban land use (Liu et al., 2021; Yao et al., 2015). The rapid urbanization that occurred during the period under review resulted in a dramatic increase in the amount of built-up land, with the consequence that there was a net decrease of 23.57 billion yuan in the GRB. Over the 30-year period, all ESFV, with the exception of water supply, demonstrated a downward trajectory in this study. It was therefore evident that alterations in land use within the GRB directly impact the composition of individual ecosystem service functions. The influence of anthropogenic activities on land use patterns had resulted in a reduction of the ESV (Guo et al., 2022).

Natural factors also exerted notable influences (Zhang et al., 2023; Song et al., 2021). In the study, FVC and Ele represent the other two significant drivers, which are prominent in the functional values of resource provisioning, regulation, and cultural services. Lower FVC values are often associated with a higher proportion of agricultural land, which contributes to the value of resource provisioning services. Conversely, lower Ele values are usually associated with low-elevation areas suitable for farming, which enhances the related ecological functions. Slo and EL also contribute to some service functions. The explainable machine learning model employed in this study effectively addresses the multiple covariates and non-linear effects among variables that are commonly encountered in other approaches, as well as the "black box" problem that is inherent to machine learning (ML) methods in general.

Assessment of ESV based on muti-scales

The definition of ecosystems can be performed across a range of spatial scales, and thus the evaluation of their services can also be conducted at varying scales. Gao et al. (2021) calculated the reclassified land area at a grid scale to investigate the spatial-temporal dynamics of ESV and ecological compensation in the Taihu Lake Basin. However, this study did not take into account the self-consumption and spillover effects of regions on ESV. The incorporation of self-consumption and spillover effects based on administrative units represents an intriguing topic of further research. In a related study, Zhang et al. (2022) conducted an analysis of the temporal and spatial changes in economic and ecological service values across provinces in the Yangtze River Economic Belt over an extended period, utilizing a provincial scale. However, their study did not investigate the coupling and coordination relationships between socio-economic and ecological subsystems from a multi-scale perspective, thereby leaving room for further exploration of the mechanisms affecting ecosystem services. In a comparative analysis, ESV was evaluated across four types of nine-level scales, including grid scales, township administrative units, sub-basin units, and county administrative units. The researchers calculated and compared ESV at these different scales, analyzing the spatial distribution and heterogeneity of ecosystem services (Huang et al., 2019).

This study employed a grid-based approach to analyze the spatial and temporal distribution patterns of ESV and identified changes in ESV at different levels and ranked the ESV of 43 counties and districts within the administrative boundaries. The grid-based approach offers significant benefits in terms of elucidating land cover mosaic patterns, suitability, and stability. Moreover, administrative measures offer several advantages when studying ESV. These advantages include the following: ease of data acquisition and management, spatial representativeness and comparability, high compatibility with

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policy formulation and implementation, and adaptability to decision-making needs at different levels. This approach is more pragmatic than implementing such measures across grid-based scales that span administrative regions. ESV demonstrates both diversity and a lack of equilibrium in space and time, with different stakeholder groups making disparate choices regarding similar services at varying scales. Multi-scale research on ESV offers numerous significant advantages (Wu et al., 2025). Firstly, multi-scale research has the capacity to comprehensively consider the various functions of ecosystem services and their interactions. Complex trade-offs and synergies may exist between ecosystem services at different scales, and multi-scale research helps reveal these relationships. Secondly, research outcomes at disparate scales have the potential to address the diverse informational needs of decision-makers at various levels. For instance, local governments may prioritize the impact of ecosystem services on residents' quality of life, while national-level decision-makers may prioritize the contributions of ecosystem services to national ecological security and sustainable development. Consequently, multi-scale research has the potential to elucidate the value discrepancies between disparate regions and ecosystem types, thereby providing precise guidance for regional ecological planning and ecological conservation (Cui and Huang, 2023). In summary, multi-scale research on ecosystem service values can comprehensively and systematically reveal the characteristics and values of ecosystem services. This provides a scientific basis and decision-making support for ecological conservation and sustainable development (Peng et al., 2017).

Conclusions

The study's primary conclusions are as follows:

(1) From 1990 to 2020, forestland has remained the dominant land use type in the GRB. Concurrently, there has been an augmentation in the areas of grassland, water bodies, and built-up land; nevertheless, the most substantial increase was observed in the built-up land category, which exhibited an increase of 80.08%. The total ESV exhibited an initial upward trajectory, followed by a decline, resulting in a net reduction of 3.741 billion yuan. Among the various land use types, forestland exhibited the most substantial contribution to ESV. Conversely, the ESV of built-up land experienced a net reduction of 2.357 billion yuan. (2) The per-unit ESV was highest in the 0-3° slope range, while the ESV in the > 25° slope range constituted the largest proportion of the total ESV, reaching 33.03% in 2020. Higher values of per-unit ESV were observed at elevations between 500 and 1200 m. The ESV in the 0-500 m elevation range constituted a greater proportion of the total ESV, reaching 83% in 2020. (3) A grid-based analysis of the GRB revealed a distinct spatial pattern, with lower values in the northern region, higher values in the southern and central regions, and lower values in the centers of counties and cities, with higher values in surrounding suburbs. Administratively speaking, the ESV in the GRB demonstrated a decline of 1.32%. Among the 20 counties and districts with an absolute value of $|R| \geq 1$ (46.51%), 19 exhibited $R > 1$, indicating that these areas experienced greater ESV changes compared to the overall region, with trends aligned with the region. (4) The explainable machine learning model indicated that the predominant drivers of the four ESFV under scrutiny differed. Human activities exerted a dominant influence on each service, whilst natural environmental factors also played a non-negligible role. The HAI had the greatest impact among the four ecosystem services, and its contribution to the model was mainly negative.

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REFERENCES

[1] Chen, T., Guestrin, C. (2016): XGBoost: a scalable tree boosting system. – Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, 785-794. https://doi.org/10.1145/2939672.2939785.

[2] Costanza, R., d'Arge, R., Groot, R. D., Farber, S., Grasso, M., Hannon, B., Limburg, K., Naeem, S., O'Neill, R. V., Paruelo, J. (1997): The value of the world's ecosystem services and natural capital. – Nature 387: 253-260. https://doi.org/10.1038/387253a0.

[3] Cui, X., Huang, L. (2023): Integrating ecosystem services and ecological risks for urban ecological zoning: a case study of Wuhan City, China. – Human and Ecological Risk Assessment 29: 1299-1317. https://doi.org/10.1080/10807039.2023.2265990.

[4] Dai, X., Wang, L., Huang, C., Fang, L., Wang, S., Wang, L. (2020): Spatio-temporal variations of ecosystem services in the urban agglomerations in the middle reaches of the Yangtze River, China. – Ecol. Indic. 115: 106394. https://doi.org/10.1016/j.ecolind.2020.106394.

[5] Daily, G. C. (1997): Nature's Service: Societal Dependence on Natural Ecosystems. – Island Press, Washington, DC. https://doi.org/10.12987/9780300188479-039.

[6] Daily, G. C., Söderqvist, T., Aniyar, S., Arrow, K., Dasgupta, P., Ehrlich, P. R., Folke, C., Jansson, A. M., Jansson, B., Kautsky, N., Levin, S., Lubchenco, J., Mäler, K.-G., Starrett, D., Tilman, D., Walker, B. et al. (2000): The value of nature and the nature of value. – Science 289: 395-396. https://doi.org/10.1126/science.289.5478.395.

[7] Dandolo, D., Masiero, C., Carletti, M., Pezze, D. D., Susto, G. A. (2023): AcME-Accelerated model-agnostic explanations: fast whitening of the machine-learning black box. – Expert Systems with Applications 214: 119115. http://dx.doi.org/10.1016/j.eswa.2022.119115.

[8] Deng, F., Zhu, S., Guo, J., Sun, X. (2025): Exploring the quality of ecosystem services and the segmental impact of influencing factors in resource-based cities. – Journal of Environmental Management 375: 124411. https://doi.org/10.1016/j.jenvman.2025.124411.

[9] Gao, X., Shen, J., He, W., Zhao, X., Li, Z., Hu, W., Wang, J., Ren, Y., Zhang, X. (2021): Spatial-temporal analysis of ecosystem services value and research on ecological compensation in Taihu Lake Basin of Jiangsu Province in China from 2005 to 2018. – J. Clean. Prod. 317: 128241. https://doi.org/10.1016/j.jclepro.2021.128241.

[10] Guo, C., Gao, J., Zhou, B., Yang, J. (2021): Factors of the ecosystem service value in water conservation areas considering the natural environment and human activities: a case study of Funiu Mountain, China. – Int. J. Environ. Res. Public Health 18: 11074. https://doi.org/10.3390/ijerph182111074.

[11] Guo, S., Wu, C., Wang, Y., Qiu, G., Zhu, D., Niu, Q., Qin, L. (2022): Threshold effect of ecosystem services in response to climate change, human activity and landscape pattern in the upper and middle Yellow River of China. – Ecol. Indic. 136: 108603. https://doi.org/10.1016/j.ecolind.2022.108603.

[12] Hasan, S. S., Zhen, L., Miah, M. G., Ahamed, T., Samie, A. (2020): Impact of land use change on ecosystem services: a review. – Environ. Dev. 34: 100527. https://doi.org/10.1016/j.envdev.2020.100527.

[13] Hu, J., Qiu, S., Luo, N., Qing, G., Huang, C. (2023): Multi-dimensional spatial and temporal variations of ecosystem service values in the Li River Basin 1990–2020. – Remote Sensing 15: 2996. https://doi.org/10.3390/rs15122996.

© 2025, ALÖKI Kft., Budapest, Hungary

[14] Huang, M., Yue, W., Fang, B., Feng, S. (2019): Scale response characteristics and geographic exploration mechanism of spatial differentiation of ecosystem service values in Dabie Mountain area, central China from 1970 to 2015. – Acta Geographica Sinica 74: 1904-1920. https://doi.org/10.11821/dlxb201909015.

[15] Lee, C. Y., Hasegawa, H., Gao, S. C. (2022): Complex-valued neural networks: a comprehensive survey. – IEEE/CAA J. Autom. Sinica 9: 1406-1426. https://doi.org/10.1109/JAS.2022.105743.

[16] Li, B., Chen, N., Wang, Y., Wang, W. (2018): Spatio-temporal quantification of the trade-offs and synergies among ecosystem services based on grid-cells: a case study of Guanzhong Basin, NW China. – Ecol. Indic. 94: 246-253. https://doi.org/10.1016/j.ecolind.2018.06.069.

[17] Li, F., Wang, F., Liu, H., Huang, K., Yu, Y., Huang, B. (2023): A comparative analysis of ecosystem service valuation methods: taking Beijing, China as a case. – Ecol. Indic. 154: 110872. https://doi.org/10.1016/j.ecolind.2023.110872.

[18] Li, M., Yin, L., Zhang, Y., Su, X., Liu, G., Wang, X., Au, Y., Wu, X. (2021): Spatio-temporal dynamics of fractional vegetation coverage based on MODIS-EVI and its driving factors in Southwest China. – Acta Ecologica Sinica 41: 1138-1147. http://dx.doi.org/10.5846/stxb201907101451.

[19] Li, W., Chen, X., Zheng, J., Zhang, F., Yan, Y., Hai, W., Yang, J., Han, C., Liu, L. (2025b): Effectiveness and driving mechanisms of ecological conservation and restoration in Sichuan Province, China. – Ecol. Indic. 172: 113238. https://doi.org/10.1016/j.ecolind.2025.113238.

[20] Li, X., Mao, D., Xue, J., Wang, S., Chang, J., Liu, X. (2025a): Integrative assessment and management implications on loss of ecosystem services value of desert-oasis ecotone due to artificial oasis expansion. – Global Ecology and Conservation 58: e03450. https://doi.org/10.1016/j.gecco.2025.e03450.

[21] Lin, Y., Liu, Y., Ouyang, Z. (2025): Integrating the valuation of water provision services into regional water management. – International Journal of Sustainable Development and World Ecology. https://doi.org/10.1080/13504509.2025.2456877.

[22] Ling, F., Luo, J., Li, Y., Tang, T., Bai, L., Ouyang, W., Yamagata, T. (2022): Multi-task machine learning improves multi-seasonal prediction of the Indian Ocean Dipole. – Nature Communications 13: 7681. https://doi.org/10.1038/s41467-022-35412-0.

[23] Liu, G., Zhang, L., Zhang, Q. (2014): Spatial and temporal dynamics of land use and its influence on ecosystem service value in Yangtze River Delta. – Acta Ecologica Sinica 34: 3311-3319. https://doi.org/10.5846/stxb201306121679.

[24] Liu, L., Shi, Y., Meng, Q. (2025): Spatiotemporal patterns and influencing factors of coupling coordination development of ecosystem services and urbanization: a case of western border counties in China. – Frontiers in Public Health 13: 1579775. https://doi.org/10.3389/fpubh.2025.1579775.

[25] Liu, Z., Wu, R., Chen, Y., Fang, C., Wang, S. (2021): Factors of ecosystem service values in a fast-developing region in China: insights from the joint impacts of human activities and natural conditions. – J. Clean. Prod. 297: 126588. https://doi.org/10.1016/j.jclepro.2021.126588.

[26] Lü, Y., Fu, B. (2001): Ecological scale and scaling. – Acta Ecologica Sinica 21: 2096-2105.

[27] Luo, S., Yan, W. (2018): Evolution and driving force analysis of ecosystem service values in Guangxi Beibu Gulf coastal areas, China. – Acta Ecologica Sinica 38: 3248-3259. http://dx.doi.org/10.5846/stxb201704050578.

[28] Ministry of Ecology and Environment (2021): Measures for Evaluating the Ecological Quality of Regions (Trial). – https://www.mee.gov.cn/.

[29] Ouyang, Z., Wang, X., Miao, H. (1999): A primary study on Chinese terrestrial ecosystem services and their ecological-economic values. – Acta Ecologica Sinica19: 607-613.

© 2025, ALÖKI Kft., Budapest, Hungary

[30] Peng, J., Hu, X., Zhao, M., Liu, Y., Tian, L. (2017): Research progress on ecosystem service trade- offs: from cognition to decision-making. – Acta Geographica Sinica 72: 960-973. https://doi.org/10.11821/dlxb201706002.

[31] Shi, J., Li, S., Song, Y., Zhou, N., Guo, K., Bai, J. (2022): How socioeconomic factors affect ecosystem service value: evidence from China. – Ecol. Indic. 145: 109589. https://doi.org/10.1016/j.ecolind.2022.109589.

[32] Shi, Y., Wang, R., Huang, J., Yang, W. (2012): An analysis of the spatial and temporal changes in Chinese terrestrial ecosystem service functions. – Chin. Sci. Bull. 57: 2120-2131. https://doi.org/10.1007/s11434-012-4978-5.

[33] Song, F., Su, F., Mi, C., Sun, D. (2021): Analysis of driving forces on wetland ecosystem services value change: a case in Northeast China. – Sci Total Environ. 751: 141778. https://doi.org/10.1016/j.scitotenv.2020.141778.

[34] Song, P., Yang, Q., Wu, W., Su, T., Jiang, Y., Lu, J., Sun, Z., Zhang, J., Yu, R., Wang, P. (2025): Assessing and predicting the value of ecosystem services in Sanya City, Hainan Island, China. – Ecol. Indic. 170: 112967. https://doi.org/10.1016/j.ecolind.2024.112967.

[35] Syrbe, R.-U., Walz, U. (2012): Spatial indicators for the assessment of ecosystem services: providing, benefiting and connecting areas and landscape metrics. – Ecol. Indic. 21: 80-88. https://doi.org/10.1016/j.ecolind.2012.02.013.

[36] Tang, R., Hou, G., Chen, Y., Liu, X., Chu, S., Li, L. (2025): Spatial and temporal characteristics and driving mechanisms of recreational ecosystem services supply-demand mismatch in rapidly urbanizing areas: evidence from the Yangtze River Delta. – Ecol. Indic. 171: 113153. https://doi.org/10.1016/j.ecolind.2025.113153.

[37] Wang, B., Lu, S. (2009): Evaluation of economic forest ecosystem services in China. – Chinese Journal of Applied Ecology 20: 417-425. https://www.cjae.net/EN/Y2009/V20/I02/417.

[38] Wang, M., Liu, S., Hu, Y., Zhao, M., Zhang, H. (2025): 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. – Applied Ecology and Environmental Research 23: 5095-5121. https://doi.org/10.15666/aeer/2303_50955121

[39] Wang, X., Dai, E., Zhu, J. (2016): Spatial patterns of forest ecosystem services and influencing factors in the Ganjiang River Basin. – Journal of Resources and Ecology 7: 439-452. http://dx.doi.org/10.5814/j.issn.1674-764x.2016.06.004.

[40] Wang, Y., Shataer, R., Zhang, Z., Zhen, H., Xia, T. (2022): Evaluation and analysis of influencing factors of ecosystem service value change in Xinjiang under different land use types. – Water 14: 1424. https://doi.org/10.3390/w14091424.

[41] Wang, Y., Zhang, Z., Chen, X. (2024): Impact of land use change on water-related ecosystem services under multiple ecological restoration scenarios in the Ganjiang River Basin, China. – Forests 15: 1225. https://doi.org/10.3390/f15071225.

[42] Wei, X., Xin, S., Zhang, Y., Long, Y., Zhang, X. (2023): Spatial difference of ecological services and its influencing factors under different scales: taking the Nanchang Urban Agglomeration as an example. – Acta Ecologica Sinica 43: 7585-7597. https://doi.org/10.20103/j.stxb.202203310811.

[43] Wu, Y., Liu, X., Zhao, Q., Liu, H., Qu, F., Zhang, M. (2025): Study on the scale dependence of the spatial distribution pattern of ecosystem service value - a case study of Gangu County, China. – Scientific Reports 15: 18671. https://doi.org/10.1038/s41598-025-03497-4.

[44] Xiao, R., Lin, M., Fei, X., Li, Y., Zhang, Z., Meng, Q. (2019): Exploring the interactive coercing relationship between urbanization and ecosystem service value in the Shanghai–Hangzhou Bay Metropolitan Region. – J. Clean. Prod. 253: 119803. https://doi.org/10.1016/j.jclepro.2019.119803.

[45] Xie, G., Lu, C., Leng, Y., Zheng, D., Li, S. (2003): Ecological assets valuation of the Tibetan Plateau. – Journal of Natural Resources 18: 189-196. https://doi.org/10.3321/j.issn:1000-3037.2003.02.010.

© 2025, ALÖKI Kft., Budapest, Hungary

[46] Xie, G., Zhang, C., Zhang, L., Chen, W., Li, S. (2015): Improvement of the evaluation method for ecosystem service value based on per unit area. – Journal of Natural Resources 30: 1243-1254. https://doi.org/10.11849/zrzyxb.2015.08.001.
[47] Yan, E., Lin, H., Wang, G., Xia, C. (2014): Analysis of evolution and driving force of ecosystem service values in the Three Gorges Reservoir region during 1990-2011. – Acta Ecologica Sinica 34: 5962-5973. http://dx.doi.org/10.5846/stxb201312263032.
[48] Yang, G., Lü, K., Li, F. (2022): Spatial and temporal correlation analysis of land use change and ecosystem service value in Nanchang City based on grid scale. – China Land Science 36: 121-130. https://doi.org/10.11994/zgtdkx.20220808.090340.
[49] Yang, Y., Qin, Y., Yuan, Z. (2025): Improving sustainable land use level with the aim of enhancing urban ecosystem service value: a case study of Xi'an in China. – Environmental Monitoring Assessment 197: 267. https://doi.org/10.1007/s10661-025-13709-z.
[50] Yao, X., Zeng, J., Li, W. (2015): Spatial correlation characteristics of urbanization and land ecosystem service value in Wuhan urban agglomeration. – Transactions of the Chinese Society of Agricultural Engineering 31: 249-256. https://doi.org/10.11975/j.issn.1002-6819.2015.09.038.
[51] Zhang, B., Li, W., Xie, G. (2010): Ecosystem services research in China: progress and perspective. – Ecological Economics 69: 1389-1395. https://doi.org/10.1016/j.ecolecon.2010.03.009.
[52] Zhang, H., Ouyang, Z., Zheng, H. (2007): Spatial scale characteristics of ecosystem services. – Chinese Journal of Ecology 26: 1432-1437. https://www.cje.net.cn/CN/10.13292/j.1000-4890.202105.029.
[53] Zhang, X., Zheng, Z., Sun, S., Wen, Y., Chen, H. (2023): Study on the driving factors of ecosystem service value under the dual influence of natural environment and human activities. – J. Clean. Prod. 420: 138408. https://doi.org/10.1016/j.jclepro.2023.138408.
[54] Zhang, Z., Nie, T., Gao, Y., Sun, S., Gao, J. (2022): Study on temporal and spatial characteristics of coupling coordination correlation between ecosystem services and economic-social development in the Yangtze River Economic Belt. – Resources and Environment in the Yangtze Basin 31: 1086-1099. https://doi.org/10.11870/cjlyzyyhj202205013.
[55] Zhao, H., Xu, X., Tang, J., Wang, Z., Miao, C. (2023): Understanding the key factors and future trends of ecosystem service value to support the decision management in the cluster cities around the Yellow River floodplain area. – Ecol. Indic. 154: 110544. https://doi.org/10.1016/j.ecolind.2023.110544.
[56] Zhao, Y., Gao, G., Ding, G., Wang, L., Chen, Y., Zhao, Y., Yu, M., Zhang, Y. (2022): Assessing the influencing factors of soil susceptibility to wind erosion: a wind tunnel experiment with a machine learning and model-agnostic interpretation approach. – Catena 215: 106324. https://doi.org/10.1016/j.catena.2022.106324.

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