

Article

Scenario Simulation and Driving Force Analysis of Ecosystem Service Values Based on Land Use/Cover in the Tumen River Basin, China

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Abstract: Key ecological function areas play a crucial role in safeguarding and rehabilitating ecosystems and mitigating regional ecological degradation. Unraveling the interconnectedness between land use/cover (LULC) transformation and the ecosystem service value (ESV) in these regions is of profound importance for sustainable development. In this paper, the LULC response in the Tumen River Basin (TRB) to an assessment of ESV from 2000 to 2020 was explored. An advanced equivalent factor that incorporates both biomass and socioeconomic factors was used to evaluate the ESV of the TRB. Taking the potential impact of factors such as temperature (TEM), precipitation (PRE), normalized difference vegetation index (NDVI), digital elevation model (DEM), soil organic matter content (SOMC), and human activity intensity of land surface (HAILS) into account, the patch-generating land use simulation model (PLUS) was used to simulate and predict the spatial evolution of the ESV under different land resource management strategies in 2030. The results indicate an increasing trend in the total ESV in the study area from 2000 to 2020, with forested land accounting for nearly 94% of the total ESV for the TRB. HAILS, DEM, and NDVI were identified as the main factors affecting the spatial differentiation of ESV. A negative correlation (-0.65) was found between ESV and the landscape shape index (LSI), indicating that more irregularly shaped landscapes have a lower ESV. Positive correlations were observed between the Shannon's Diversity Index (SHDI) (0.72) and the Aggregation Index (AI) (0.60), suggesting that more diverse and interconnected landscapes have a higher ESV. The PLUS simulation results provide valuable data-based support for achieving planning objectives under different land resource management strategies. Specifically, these findings can serve as a reference for the integrated planning of land resources and environmental protection, promoting the sustainable development of ecological functional areas along the northeast border of China.

Keywords: ESV; driving factors; patch-generating land use simulation (PLUS) model; Tumen River Basin



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1. Introduction

Ecosystem services (ES) are the benefits that humans derive from the natural world. These benefits are generated by the ecological functions of ecosystems, which can provide products and services directly or indirectly through their processes, structures, and functions. There are four types of ecosystem services: provisioning, regulation, support, and cultural services [1,2]. The study of ecosystem services was propelled to the forefront of ecological economics research by the publication of Costanza et al.'s paper "Estimation of the value of global ecosystem services" in the journal *Nature* (1997) [3]. This research provides the foundation for ecological conservation, function zoning, asset accounting, and compensation decisions [4–6]. Assessments of ecosystem services have increasingly been used worldwide as a framework for ecological restoration and conservation, watershed

management, and sustainable development policy making [7]. Such assessments also provide recommendations for decision making on the balance and sustainable development of regional ecosystems [8,9]. Given the impact of natural environmental changes and human activities on ecosystem services, it is urgent to investigate the internal causes of changes in these services, particularly in inland river basins located in ecological function areas [10]. Such research will aid in developing effective strategies for ecological restoration and conservation in these areas.

Land use/cover (LULC) represents the closest connection between humans and nature, and it significantly impacts ecosystem structures and functions through biogeochemical cycle processes [11]. As such, LULC is a major driver of ecosystem service value (ESV) change and is decisive in maintaining ecosystem service functions [12,13]. Understanding the spatial relationship between LULC and ecosystem services is essential for effective regional ecosystem management and sustainable development. Most current studies in this area focus on estimating and changing the value of ecosystem services, which serves as an important benchmark for sustainable environmental development [14]. Extensive research on ecosystem services has been conducted by Chinese scholars [10]. In 2001, Xie Gaodi and other scholars revised the “Table of Equivalent Factors for Ecosystem Service Value” to align it with the Chinese context, using Costanza’s estimation method. This table was further updated and corrected by Xie et al. in 2007 and 2015 [6,15]. Numerous scholars have widely utilized this equivalent factor table to investigate the connection between land use and the value of ecosystem services [16–18]. However, despite its nonreliance on a model or redundant calculations, this equivalent method can lead to erroneous evaluation results due to its dependence on predetermined value coefficients [10]. Therefore, it becomes essential to adjust the coefficient values based on the specific conditions of the research area.

In contemporary research, various aggregation models, such as CLUE-S, ANN, CA, and FLUS, are frequently employed to analyze the spatial–temporal dynamic evolution of the ESV based on land use changes [10,19–22]. However, these models encounter limitations in identifying factors influencing land use changes, impeding the implementation of dynamic spatiotemporal simulations for multiple land use patches [10,20,22]. The recently introduced advanced patch-generating land use simulation model (PLUS) builds upon and enhances the effective adaptive inertia competition and roulette competition mechanisms present in existing models for simulating future land use [23]. This model integrates the random forest (RF) algorithm to ascertain the developmental potential of each land use type, yielding a more precise simulation of changes in the spatial distribution of land use [24]. In comparison to commonly used models in the past, this model demonstrates higher simulation accuracy, and its outcomes can better support planning policies aimed at achieving sustainable development. The PLUS model has been applied in several studies for simulating the ESV based on LULC [10,22,25], revealing that PLUS simulations achieve greater accuracy and computational efficiency. Furthermore, LULC-based ESV simulations play a pivotal role in decision making regarding sustainable regional ecological management.

The temporal and spatial dynamics of ESV are undoubtedly crucial, yet it is equally imperative to consider the potential factors influencing the ESV. To adeptly design, implement, and adjust management strategies for achieving sustainable development, a nuanced understanding of the interplay between ESV and landscape patterns is essential [15]. Moreover, further exploration is warranted to comprehend how natural conditions, climate change, and human activities collectively drive changes in the ESV. Climate factors, vegetation cover, and human disturbance emerge as pivotal drivers of the ESV changes in key ecologically functional areas, necessitating their inclusion in the ESV estimation [10,26,27]. However, existing research based on land-use data often overlooks the spatiotemporal simulation of ESV with co-influencing factors. Hence, there is a pressing need to enhance our understanding of the impact of ecological changes induced by potential factors on the ESV [10]. In the key ecological functional area of Changbai Mountain, the relationship between ESV and the aforementioned potential factors remains unclear. Simultaneously, the exploration of potential influencing factors of the ESV in ecological functional areas

contributes to global ESV assessment, offering research insights and case support for the broader assessment of global ESV. Through the study of these potential influencing factors, a more profound comprehension and safeguarding of ecosystem services can be achieved, thereby making a substantial contribution to sustainable development.

The Changbai Mountain Ecological Function Zone is an extremely important ecological barrier in Northeast China, undertaking critical functions such as soil and water conservation, biodiversity maintenance, and strategically implementing the concept of ecivilization construction to achieve harmonious coexistence between humans and nature. This study focuses on the representative Tumenn River Basin, a typical watershed within the Changbai Mountain Ecological Function Zone. Guided by principles of ecological protection and sustainable development, it integrates regional development goals with implementation methods, utilizing the coupled PLUS model to optimize land use structure. This approach aims to coordinate economic and social development with ecological protection. This research delves into the transformation patterns of land use from 2000 to 2020, identifying potential driving factors influencing changes in the ESV. Additionally, it examines the correlation between ESV and landscape pattern indices to analyze the spatial-temporal trends of ESV changes in the study area. Moreover, drawing on “Jilin Province’s Land and Space Planning (2021–2035)” and “Yanbian Korean Autonomous Prefecture’s Land and Space Master Plan (2021–2035)” (hereinafter referred to as “the Plan”), the PLUS model is employed to establish multiple scenarios for spatial constraints on land use in 2030. This study explores the changes in spatial cold and hot spots of ESV in the Tumen River Basin in 2030 under the natural development scenario (S1) and target-oriented scenario (S2). This comprehensive analysis offers decision-making support for land and space planning and management, particularly in ecological protection or functional areas.

2. Study Area and Data Resources

2.1. Study Area

The Tumen River, originating from the main peak of the Changbai Mountain Range, spans 525 km with a total drop of 1297 m. The river basin covers approximately 22,860 km², constituting 11.9% of Jilin Province’s total area. Positioned at the confluence of China, Russia, and North Korea, it includes a 510 km-long China–DPRK border river segment and a 15 km-long Russia–DPRK border river east of the Sea of Japan. The region experiences a temperate continental monsoon climate, with prevailing northwest winds in winter and dominant southeast winds in summer. The average annual temperature is 5.3 °C, with a total annual radiation of 468.6 kJ/m². The frost-free period extends for 141 days, and the average annual precipitation is 538 mm. The landscape is characterized by low mountains and hills, featuring flat river valley basins on both sides with fertile soil, a mild climate, and abundant water—rendering them primary agricultural production areas [28].

The ecosystem services of the TRB underwent a significant transition, shifting focus from a forest resources value assessment in the 1980s to a period of quantitative value assessment in the 1990s [29]. In 2017, Jin Xuemei and collaborators conducted a comparative analysis, evaluating the ecological security of the TRB wetlands in both China and North Korea. Results indicated a decrease in the ecological safety evaluation value on the North Korean side from 0.708 to 0.4187, and on the Chinese side from 0.7197 to 0.4868. Utilizing a grey prediction model, they forecasted a moderate warning state for the North Korean region and a shift from a moderate to a severe warning state for the Chinese wetland ecosystem over the next 20 years [30]. The TRB includes five national and eight provincial nature reserves, housing critically endangered species such as the Siberian tiger and *Grus japonensis*, establishing it as a significant ecological function area in China and a pilot area for the national park system. Furthermore, it serves as a core area in the ecological network of Northeast Asia. This study exclusively focuses on the Chinese side of the TRB, falling under the jurisdiction of the Yanbian Prefecture (see Figure 1).

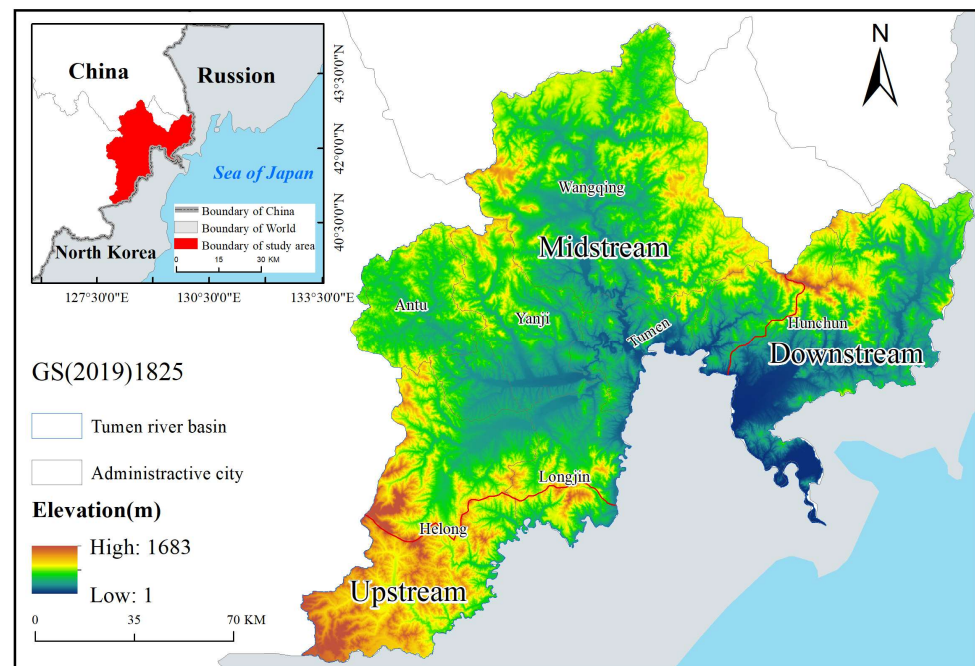


Figure 1. The location of the study area.

2.2. Data Sources

In this study, land use data were acquired from publicly available land use raster datasets produced by J. Yang et al. [31] of Wuhan University, covering the period of 2000–2020. The spatial resolution of the data was up to 30 m, and the detection accuracy was >94.3%. Annual precipitation, annual mean temperature, and NDVI data were obtained from the Resource Environment Data Center (<https://www.resdc.cn/>) (accessed on 13 June 2022) (Table 1). Ecosystems used for construction purposes were excluded from this study and assigned a value of 0. Statistical data on food crop production, food crop unit price, and food crop cultivation area were derived from the Statistical Yearbook of Jilin Province and Yanbian Korean Autonomous Prefecture, as well as the Statistical Bulletin of National Economic and Social Development of Yanbian Korean Autonomous Prefecture for the period of 2000–2020. Soil data were obtained from the National Earth System Data Center (<https://soil.geodata.cn/ztsj.html>) (accessed on 13 June 2022).

Table 1. Data sources for the study period (2000–2020).

Data Type	Year	Data Source and Resolution
Land use	2000–2020	J. Yang et al. of Wuhan University [24] (https://doi.org/10.1016/j.isprsjprs.2021.03.007 (accessed on 6 March 2022)) 30 m
Climate data (annual precipitation, annual mean temperature); NDVI	2000–2020	Resource Environment Data Center (https://www.resdc.cn/ (accessed on 6 March 2022)), 0.1 degree or 1 km
Food crop production, food crop unit price, food crop cultivation area	2000–2020	Statistical Yearbook of Jilin Province and Yanbian Korean Autonomous Prefecture (http://tjj.jl.gov.cn/ (accessed on 6 March 2022)); http://www.ybstats.gov.cn/ (accessed on 6 March 2022)); Statistical Bulletin of National Economic and Social Development of Yanbian Korean Autonomous Prefecture (http://www.ybstats.gov.cn/ (accessed on 6 March 2022))
Soil	2000–2020	National Earth System Data Center (https://soil.geodata.cn/ztsj.html (accessed on 6 March 2022)), 1:1,000,000

3. Method

3.1. Methodological Framework

In this investigation, we conducted an assessment of the ESV of the TRB by employing LULC data as the foundational elements. Equivalence factors were adapted with the inclusion of biomass and socioeconomic factors to refine the assessment. Landscape pattern indices (LPis), specifically the Shape Index (SI), Aggregation Index (AI), and Shannon's Diversity Index (SHDI), were incorporated to delineate and characterize landscape patterns. The evaluation of ecosystem service values (ESVs) was carried out with a focus on provisioning, regulating, supporting, and cultural services. The SI, AI, SHDI, and ESVs for the years 2000, 2005, 2010, 2015, and 2020 were computed, and the Mann–Kendall trend test was applied to discern temporal trends within the data. Pearson correlation coefficients and linear regression analyses were employed to scrutinize the association between ESVs and the dynamic evolution of landscape patterns. To assess the explanatory efficacy of driving factors on the spatially stratified heterogeneity of ESV, we utilized a geographic detector, calculating and comparing the q-values associated with each driving factor. Ultimately, the PLUS model was deployed to simulate the spatial distribution patterns of land use under diverse scenarios. This facilitated an in-depth analysis of the spatiotemporal evolution characteristics of the ESV under varying scenarios (Figure 2).

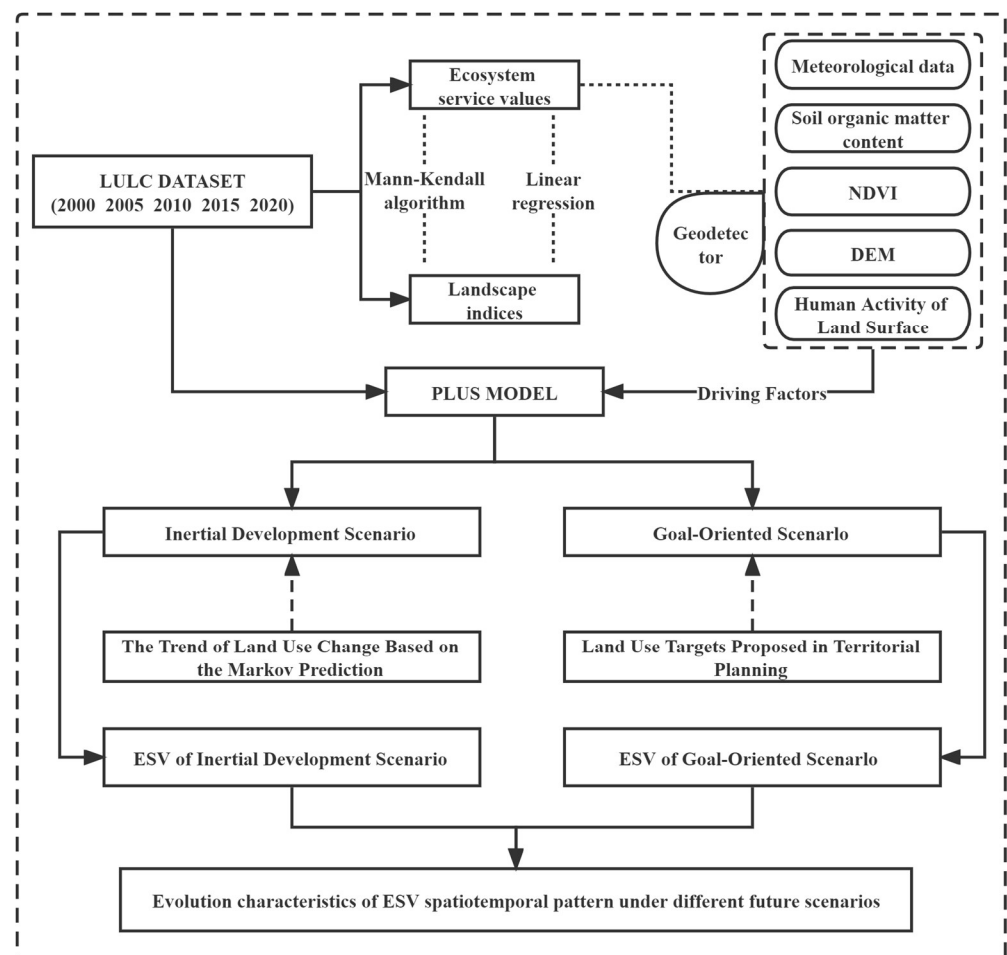


Figure 2. Schematic analysis of the methodology.

3.2. ESV Assessment Based on LULC

According to Xie Gaodi's [6] improved table on ecological services equivalence per unit area for Chinese ecosystems (Table 2/Supplementary Materials), this study utilized this method to comprehensively evaluate the value of ecosystem services [32]. To account

for the actual natural geographical conditions of the study area, we considered the average ecological services value of paddy and dry fields as the equivalent value of cultivated land. As no shrubs were present in the study area, the average values of the remaining three categories were used instead. The value of construction land was excluded from the calculation and represented by 0.

Table 2. Ecosystem service equivalent value per unit area.

	Type	Cropland	Forest	Grassland	Water	Barren	Impervious	Wetland
Provisioning	Food production	1.11	0.27	0.23	0.80	0.01	0.00	0.51
	Raw materials	0.25	0.63	0.34	0.23	0.02	0.00	0.50
	Water supply	−1.31	0.33	0.19	8.29	0.01	0.00	2.59
Regulating	Gas regulation	0.89	2.07	1.21	0.77	0.07	0.00	1.90
	Climate regulation	0.47	6.20	3.19	2.29	0.05	0.00	3.60
	Purifying the environment	0.14	1.80	1.05	5.55	0.21	0.00	3.60
	Water conservation	1.50	3.86	2.34	102.24	0.12	0.00	24.23
Supporting	Soil formation and retention	0.52	2.52	1.47	0.93	0.08	0.00	2.31
	Maintaining nutrient circulation	0.16	0.19	0.11	0.07	0.01	0.00	0.18
	Biodiversity conservation	0.17	2.30	1.34	2.55	0.07	0.00	7.87
Culture	Recreation and cultural	0.08	1.01	0.59	1.89	0.03	0.00	4.73

3.2.1. Economic Value Assessment of Unit Grain Yield

Xie Gaodi et al. [6] contend that the economic value of natural grains produced on one hectare of arable land is comparable to the ecosystem's equivalent value. However, considering the socioeconomic development situation in the research area, it is necessary to modify the economic value generated by the unit area of food production. This adjustment involves utilizing a standard ecological system value coefficient, which is 1/7 of the economic value of food production per unit area of farmland (referred to as the "1/7 formula"). By implementing this adjustment method, the standard calculation for the ecosystem service value (ESV) in the research area can be determined.

$$E_a = \frac{1}{7} \sum_{i=1}^n \frac{m_i p_i q_i}{M}, \quad (1)$$

where E_a is the standard equivalent factor value; n is the number of kinds of grain crops in the TRB, m_i is the sown area of i grain crops, p_i is the unit price of i grain crops, q_i is the unit yield of i grain crops, and M is the sum of the area of all kinds of grain crops planted in the TRB.

3.2.2. Regional Differences and Socioeconomic Adjustment Factor Correction

Xie et al. primarily investigated the mean of ecosystem service values in China [33]. However, differences in location, ecological environment, and biodiversity across different regions can impact the magnitude of ecosystem service values. To ensure accuracy in ecosystem service valuation results, it is crucial to consider a combination of factors [34,35]. One approach to address regional variation involves incorporating the true situation of the study area and data collection convenience in the evaluation process. Specifically, the correction factor based on differences in biomass across the region can help adjust the value of ecosystem services [36]. This study uses a biomass correction factor of 0.88 for the Jilin

region [37]. To calculate the socioeconomic adjustment coefficients, we refer to previous research findings [10,38]. The coefficients are calculated as follows:

$$PI = Wt \times At, \quad (2)$$

where PI is the adjustment coefficient for socioeconomic factors, and Wt denotes people's willingness to pay for ecological values, which can be computed using a logistic regression model. The larger the value, the higher the willingness to pay. It denotes the ability to pay ecological values, which can be calculated as a function of GDP per capita. The higher the value, the more people are able to pay [12,38].

$$At = \frac{GDP_{ms}}{GDP_m}, \quad (3)$$

where GDP_{ms} and GDP_m refer to GDP per capita in the study area and GDP per capita at the national level in year t , respectively.

$$Wt = \frac{Ws}{Wg}, \quad (4)$$

where Ws and Wg are the willingness-to-pay parameters within the study region and nationally.

$$W = \frac{2}{(1 + e^{-m})}, \quad (5)$$

$$m = \frac{1}{En} - 2.5, \quad (6)$$

$$En = En_r \times (1 - Pu) + En_u \times Pu, \quad (7)$$

where W is the willingness-to-pay parameter of Wt , m is the coefficient of the social development stage, and En is the Engel coefficient in year t . En_r and En_u are the Engel coefficients for the urban and rural areas in year t , respectively, and Pu is the proportion of the population living in the urban area in year t [38].

The values of the standard equivalence factors corrected according to Equations (1) and (2) are as follows:

$$Ea' = Ea \times 0.88 \times PI, \quad (8)$$

The ESV factors for different land use types are calculated as follows:

$$ESV = \sum_{k=1}^n (Ea' \times ECKi \times Ak), \quad (9)$$

where $ECKi$ is the ES equivalent factor of type k for land use type i , and Ak is the area of land use type i . Using the equation above and the area of seven land use types in the Tumen River Basin in the years 2000, 2005, 2010, 2015, and 2020, the ESV can be computed in Table 3.

Table 3. The unit equivalent value of ecosystem service in the TRB from 2000 to 2020.

	2000	2005	2010	2015	2020
Ea'	837.31	670.45	872.18	951.93	723.16

3.2.3. The Coefficient of Sensitivity (CS)

In order to identify the dependency of changes in ecosystem service values on changes in value coefficients and to check the rationality of ESV evaluation, in this article, we introduce CS [10]. CS refers to the ESV change caused by a 1% VC change. ESV is elastic

relative to VC if $CS > 1$. ESV is said to be inelastic if $CS < 1$. The lower the CS, the more reliable the ESV-adjusted coefficient [10].

$$CS = \left| \frac{(ESV_j - ESV_i)/ESV_i}{(VC_{jk} - VC_{ik})/VC_{ik}} \right|, \quad (10)$$

where ESV_i and ESV_j are the pre- and post-fit *ESV*, respectively, and VC_{ik} and VC_{jk} are the *ESV* coefficients before and after adjusting for the *k*th land use type, respectively.

3.3. Human Activity Intensity of Land Surface (HAILS)

The HAILS indicator measures the degree of ecological disturbance caused by human activities based on the type of land use [10]. HAILS uses construction land, which has the greatest impact on the land surface, as the basic unit of measurement. The indicator calculates the intensity of human activities through an integrated and comprehensive approach that considers the degree of change in natural land cover across different regions and the depth of artificial compartments that block material energy. This method is more comprehensive and extensive than traditional human activity intensity calculation methods [39]. HAILS is an innovative approach to quantitatively measure the intensity of human activities. It provides a more comprehensive and exhaustive means of measuring the ecological impact of human activities on land use compared to previous methods. Providing additional details about construction land and LULC would further enhance readers' understanding of the methodology employed. The formula used to calculate HAILS is as follows:

$$HAILS = \frac{S_{CLE}}{S} \times 100\% \quad (11)$$

$$S_{CLE} = \sum_{i=1}^n (SL_i \times CL_i) \quad '$$

where HAILS is human activity intensity on the land surface; S_{CLE} is the area of the construction land equivalent; S is the total land area; SL_i is the area of LULC type i ; CL_i is the conversion coefficient of type i for the construction land equivalent; and n is the number of LULC types.

3.4. Geodetector

Geodetector methods comprise a set of statistical techniques that enable the detection of spatial differentiation and elucidate the drivers of such differentiation [40]. These methods are capable of analyzing both numeric and qualitative data and of detecting two-factor interactions that affect the dependent variable. In this study, we employed a factor interaction detector to examine the relationship between various factors, such as *ESV*, temperature (TEM), precipitation (PRE), NDVI, DEM, soil organic matter content (SOMC), and HAILS, and quantify the spatial heterogeneity of these factors. We evaluated the results using the *q*-value approach, which is widely used to control the false discovery rate in multiple hypothesis testing.

$$q = 1 - \frac{1}{N\sigma^2} \sum_{h=1}^L N_h \sigma_h^2, \quad (12)$$

where q denotes the explanatory power of the factor, $h = 1, \dots, L$ is the stratification of variable Y or factor X ; N_h and N are the number of cells in stratum h and the whole area, respectively; and σ_h^2 and σ^2 are the variances of Y values in stratum h and the whole area, respectively. q is between 0 and 1, and a larger q indicates a stronger explanatory power of the factor.

3.5. Landscape Pattern Indices (LPIs)

LPIs have diverse applications in landscape ecology. They serve as useful tools for describing landscape patterns and changes, establishing links between patterns and landscape processes, and quantifying changes in landscape patterns over time at different

scales (Table 4). LPIs provide highly concentrated landscape pattern information and are considered quantitative indicators that reflect the structural composition and spatial configuration characteristics of the landscape. Therefore, they are crucial indicators in landscape pattern research and have been widely utilized to measure the relationships between landscape patterns and land use, biodiversity distribution, ecological processes, and ecosystem services [10,41].

Table 4. LPIs and the associated ecological meaning.

Index	Ecological Significance	Unit	Level
Shape Index (SI)	Shape complexity is measured by computing the degree to which the shape of a patch in the region deviates from a circle or square of the same area, and the larger the value, the more irregular the landscape shape and the greater the mutual interference between the landscape classes.	None	Landscape
Aggregation Index (AI)	If a landscape is made up of many small discrete patches, then the value of aggregation is small, and is largest when the landscape is dominated by a few large patches or when patches of the same type are strongly connected. Its value is taken to be between 0 and 100.	%	Landscape
Shannon's Diversity Index (SHDI)	This scale measures landscape richness and complexity. This approach reflects landscape heterogeneity and is particularly sensitive to the nonequilibrium distributional state of patchwork types across the landscape; this index focuses on the contribution of rare mosaic types to the information, which is different from other diversity indices. SHDI is also a sensitive indicator when comparing and analyzing changes in diversity and heterogeneity between landscapes or over time within the same landscape. In a landscape system, as land use becomes richer and the degree of fragmentation increases, the information content of its uncertainty increases, and the calculated SHDI increases.	None	Landscape

3.6. Mann–Kendall (M–K) Trend Detection

The MK nonparametric test, originally developed by Mann et al. (1945) and Kendall et al. (1948), is a widely utilized statistical method for analyzing trends in time series data pertaining to various natural processes such as precipitation, runoff, and temperature [42,43]. The MK test offers several advantages over other statistical methods, including its robustness to non-normal distributions, insensitivity to missing data, resistance to outliers, and ease of calculation. Moreover, the MK test can be applied to both discrete and continuous variables. In this study, we employed the MK trend-detection technique to analyze the temporal trends and abrupt changes in landscape pattern indices and ESV. We evaluated the significance of trends using the Z-statistic, whereby positive values indicate increasing trends and negative values indicate decreasing trends. Z-values exceeding 1.28, 1.64, and 2.32 indicate passing significance tests at 90%, 95%, and 99% confidence levels, respectively.

3.7. PLUS Model

The PLUS model, developed by the HMSCIL@CUG laboratory of China University of Geosciences [44], simulates land use changes at the patch scale [23]. In this study, we applied the PLUS model to simulate the spatial pattern of the ESV in the TRB in 2020, using six drivers, including NDVI, TEM, PRE, DEM, SOMC, and HAILS. We adjusted the neighborhood weight parameters by calculating the expansion intensity of each land class to simulate the spatial pattern of the ESV. The predicted ESV per unit area of each land class for 2030 was determined using the GM model (1, 1) and the values are shown in Table 4. To evaluate the model's accuracy, we used the figure of merit (FoM) provided with the PLUS model, which characterizes the agreement between simulated and observed land use patterns. Additionally, we used the kappa coefficient, which measures the agreement between observed and simulated land use changes at the patch level. These metrics provide

a comprehensive assessment of the model's accuracy, both in terms of unit-level consistency and model-level similarity [24,34,45].

4. Results

4.1. Spatiotemporal Change in Land Use

The dominant land use in the TRB is forest, followed by cropland. Over the time scale from 2000 to 2020, there have been fluctuations in forest area with an overall increasing trend, while cultivated land area has decreased year by year at a decreasing rate. Table 3 shows that cultivated land area decreased most significantly, with a reduction of 442.65 km². Especially in the period of 2000–2005, the total area of cultivated land decreased by 278.50 km² in just five years. In addition, unused land and wetland also showed a decreasing trend. During the period from 2000 to 2020, construction land increased significantly at an increasing rate year by year, with an increase of 180.79 km² over the past 20 years (Table 5). Spatially, the reduction in cultivated land from 2000 to 2005 primarily concentrated around the central cities of Helong, Yanji, and Hunchun in the mid-to-lower reaches. In contrast, cultivated land in the upper reaches continued to expand. The converted land was predominantly composed of forest and grassland. The ongoing acceleration of urbanization is notably reflected in the continuous encroachment of construction land in areas characterized by dense urban distribution in the mid-to-lower reaches, encroaching upon surrounding farmland for expansion (Figure 3).

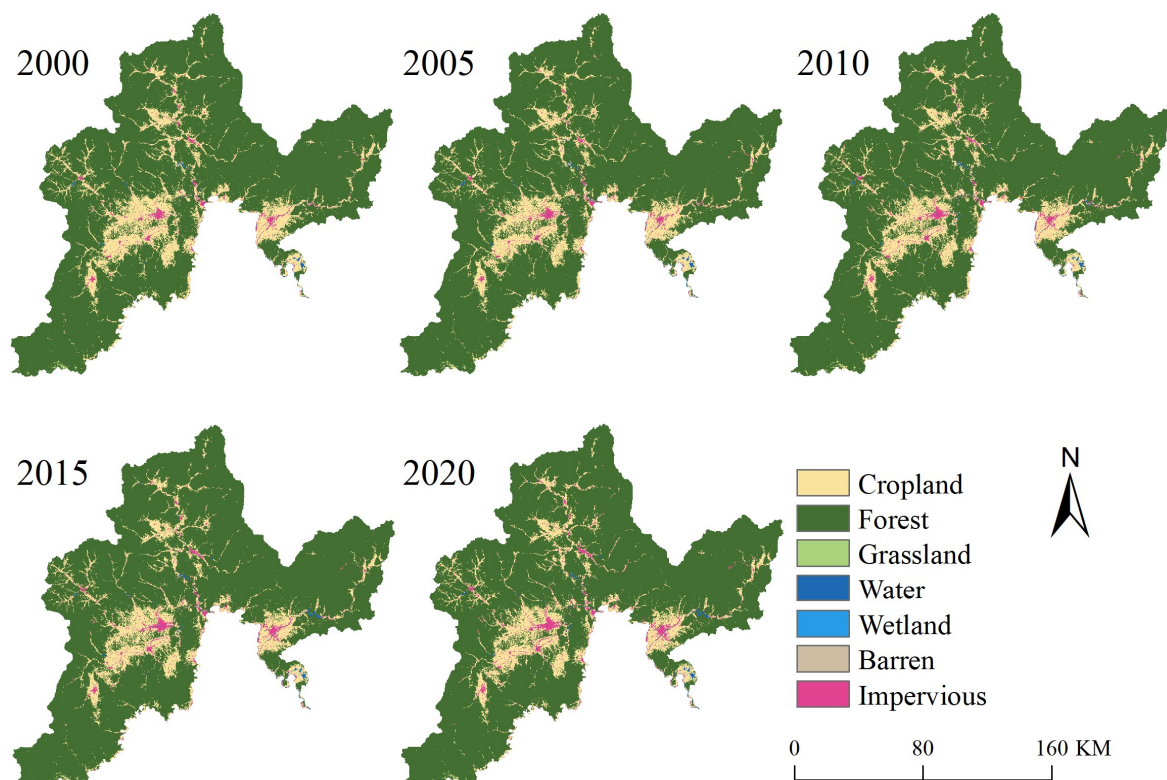


Figure 3. Spatial distribution of LULC from 2000 to 2020.

Table 5. Land use area of the study area from 2000 to 2020 (unit: km²).

LULC Type	Cropland	Forest	Grassland	Water	Barren	Impervious	Wetland
2000	336,356.91	1,886,073.93	4176.36	6969.96	138.69	28,603.80	107.28
2005	308,506.94	1,911,733.86	4337.65	7349.79	114.37	31,718.06	97.63
2010	302,980.86	1,912,014.63	3692.88	8299.44	82.98	35,273.97	82.17
2015	296,799.52	1,911,827.98	4793.14	8859.95	57.59	41,445.07	75.04
2020	292,091.67	1,907,610.84	6908.76	8975.97	86.58	46,682.01	71.10

4.2. Spatiotemporal Change in ESV

This study estimates the ESV of the TRB using a modified ecosystem service value equivalent per unit area. The four components of ecosystem services (PSV, RSV, SSV, and CSV) affect the total ESV of the basin (Figure 4a). Over the time scale from 2000 to 2020, the ESV in the TRB generally showed an upward trend, with the most significant increase occurring from 2005 to 2010. However, after 2015, the ESV of the TRB began to decline rapidly, with a year-on-year decrease of CNY 0.98×10^{10} in 2020. At a spatial scale, the ESV was categorized into six levels for a comprehensive spatial distribution assessment (Figure 5). Results demonstrate a stable overall distribution pattern with evident spatial heterogeneity from 2000 to 2020. The regional ESV distribution closely correlates with the type of LULC. Low-value areas were predominantly situated in downstream regions of central cities such as Hegang and Yanji, while high-value areas were primarily distributed in relatively pristine natural ecosystems featuring dense forests and wetlands in both upstream and downstream areas. RSV and SSV emerged as the dominant ecosystem functions, constituting 66% and 23%, respectively, of the total ESV in 2020. In contrast, CSV and PSV combined accounted for merely 11% of the total ESV. Climate and hydrological regulation played a pivotal role in RSV. Over the past two decades, while PSV and CSV remained relatively stable, RSV and SSV underwent significant changes. Their trajectories closely mirrored each other, reaching their nadir in 2005, followed by an ascending phase until 2015 before declining again. By 2020, RSV and SSV had decreased by CNY 0.29×10^{10} and CNY 0.11×10^{10} compared to 2000. Changes in ESV primarily hinge on alterations in LULC, with different land use patterns carrying distinct unit values. Examining changes in the ESV per unit area for the six land use types from 2000 to 2020 (Figure 4b), forests emerged as the primary contributors, followed by farmland and water areas. Their patterns of change align with the overarching ESV trends. Analyzing the total ESV of the different land use types (Table 6), farmland, unused land, and wetland ESV experienced gradual declines, reducing by CNY 278.11×10^6 , CNY 0.03×10^6 , and CNY 2.00×10^6 , respectively, by 2020 compared to 2000. While there were fluctuations in the ESV of the remaining three land use types, they generally exhibited an increasing trend.

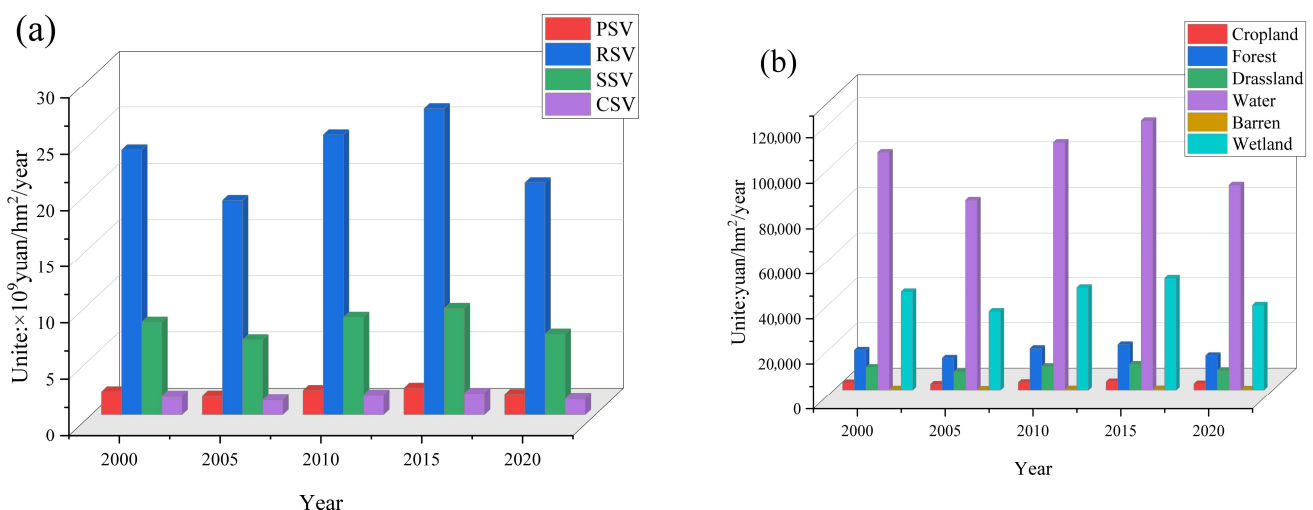


Figure 4. ESV per unit area in the TRB from 2000 to 2020 ((a) The 4 types of ESV from 2000 to 2020 and (b) the ESV of 6 types of land use, 2000–2020).

The ESV analysis of the TRB revealed that the sensitivity index of the ESV to VC was less than 1 for all land uses in the basin, with the forested area having the highest sensitivity index, followed by farmland, water, grassland, wetland, and desert (Table 7). These findings suggest that the ESV estimates are inelastic with respect to VC, supporting the validity of the results. Notably, the gradual increase in VC of the water and grassland over the past two decades has contributed to amplifying the total ecosystem service value,

while the consistently high VC of the forest has had a decisive influence on the total ESV of the TRB. Overall, the modified equivalence factors applied in this study have effectively captured ESV fluctuations in the TRB.

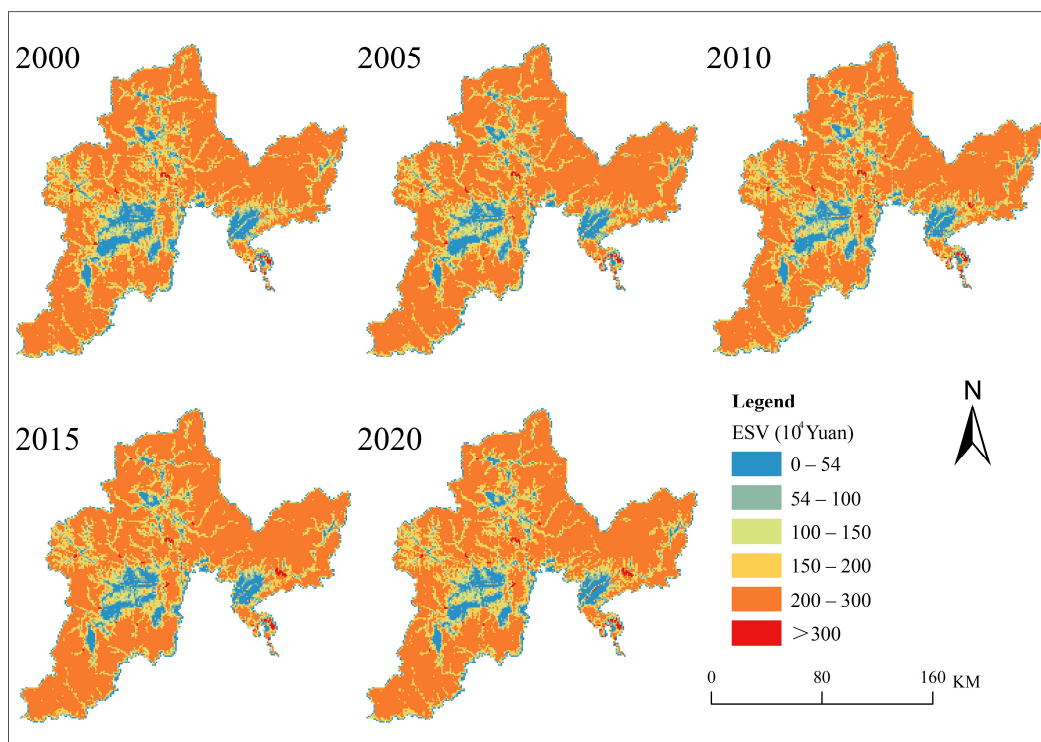


Figure 5. Spatial distribution of ecosystem service value (ESV) during 2000–2020.

Table 6. ESV of 6 types of land use in the TRB from 2000 to 2020 (unit: 10^6 CNY).

	Cropland	Forest	Grassland	Water	Barren	Wetland
2000	1112.46	33,463.89	42.18	733.06	0.08	4.67
2005	817.01	27,159.50	35.08	618.96	0.05	3.40
2010	1043.80	35,336.91	38.85	909.24	0.05	3.73
2015	1116.00	38,564.12	55.04	1059.40	0.04	3.72
2020	834.35	29,231.66	60.27	815.34	0.04	2.67

Table 7. The results of the coefficient of sensitivity (CS) analysis for ESV in the TRB.

	Cropland	Forest	Grassland	Water	Barren	Wetland
2000	0.031464	0.946475	0.001193	0.020734	0.0000021	0.000132
2005	0.028533	0.948505	0.001225	0.021616	0.0000017	0.000119
2010	0.027960	0.946543	0.001041	0.024355	0.0000013	0.000100
2015	0.027354	0.945238	0.001349	0.025967	0.0000009	0.000091
2020	0.026963	0.944653	0.001948	0.026349	0.0000013	0.000086

4.3. The Effect of LPI Change on ESV

The LPI is a comprehensive measure used to quantify the landscape pattern of the TRB, considering the impact of changing land use on the fragmentation or clustering of landscape patches. The z-values of the MK trend tests for SI, SHDI, AI, and ESV were -1.90 , 1.04 , 1.60 , and 1.80 , respectively, indicating a monotonic trend for each. Both SI and ESV passed the significance test with a 95% confidence level, while AI passed the significance test with a 90% confidence level. The results indicate a decreasing trend in SI, suggesting a trend toward a more regularized landscape pattern in the watershed. SHDI and AI showed an overall increasing trend, indicating a more uniform and concentrated

distribution of various land use types within the watershed (Table 8). Correlation tests revealed Pearson correlation coefficients of -0.65 , 0.72 , and 0.60 between ESV and SI, SHDI, and AI, respectively, as well as a correlation between ESV and LPI.

Table 8. Results of the M–K trend test of the landscape index from 2000 to 2020 (ESV unit: $\times 10^{10}$ CNY).

	SI	SHDI	AI	ESV
2000	1.275	0.521	96.979	3.536
2005	1.274	0.506	97.159	2.863
2010	1.265	0.508	97.130	3.733
2015	1.260	0.518	97.184	4.080
2020	1.262	0.529	97.122	3.050

4.4. Analysis of the Driving Factors of ESV Change

Based on the results, all variables passed the 0.005 significance test. The q-values were ranked as follows: HAILS (0.678) > TEM (0.470) > NDVI (0.435) > DEM (0.348) > SOMC (0.305) > PRE (0.148). Regarding interaction detection, the findings indicated that the interplay of any two factors had a more significant explanatory power than individual factors alone. The type of interaction mainly manifested as bilateral enhancement of the two factors, with human activity intensity and NDVI exerting a strong influence on the interaction (Table 9).

Table 9. The result of factor detection and interactive detection.

Factor Detection	SOMC	TEM	PRE	DEM	HAILS	NDVI
q	0.305	0.470	0.148	0.348	0.678	0.435
p	0.000	0.000	0.000	0.000	0.000	0.000
Interaction detection	SOMC	TEM	PRE	DEM	HAILS	NDVI
SOMC	0.305					
TEM	0.610	0.470				
PRE	0.458	0.572	0.148			
DEM	0.525	0.620	0.506	0.348		
HAILS	0.743	0.754	0.740	0.715	0.678	
NDVI	0.600	0.652	0.563	0.601	0.765	0.435

4.5. Spatiotemporal Simulation of ESV

In this study, we utilized the PLUS model to generate simulation maps for the natural development scenario (S1) and the goal-oriented scenario (S2) in 2020 and 2030, respectively, based on the land use data from 2000 to 2020 (Figure 6). The accuracy validation analysis revealed an overall simulation accuracy of 96.2%, a Kappa coefficient of 91.6%, and an FOM value of 0.23, indicating the reliability of the simulation results.

This paper presents two scenarios, the natural development scenario (Figure 7—S1) and the goal-oriented scenario (Figure 7—S2), based on the objectives of the Plan. The natural development scenario utilizes the Markov model to project land use in 2030, using data from 2010 to 2020. The goal-oriented scenario considers the overall land use planning proposed in the Plan, along with the Yanlongtu Core Development Area, Northeast Tiger and Leopard National Park, and future transportation planning, and employs PLUS for spatial constraint simulation. The CARS simulation weights are set to 70% by 2030 based on the Yanlongtu Core Development Area's urbanization level in the Plan. The simulation results indicate that the ESV in 2030 aligns with the overall upward trend of ESV in the TRB from 2000 to 2020, with an increase of 0.58×10^{10} compared to 2020. Forest land has the highest ESV, accounting for 94% of the total ESV in 2030. In terms of the unit ESV, cropland, grassland, watershed, and unused land with wetlands have values of 3394.79 CNY/hm², 10,367.71 CNY/hm², 107,954.261 CNY/hm², 558.64 CNY/hm², and 44,708.07 CNY/hm² (Figure 7), respectively.

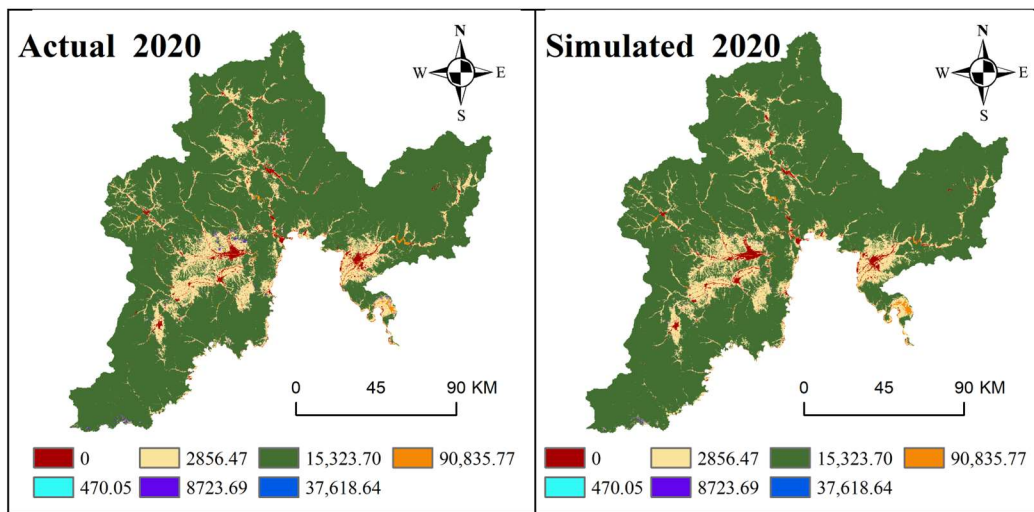


Figure 6. Comparison of the actual and simulated ESV in 2020.

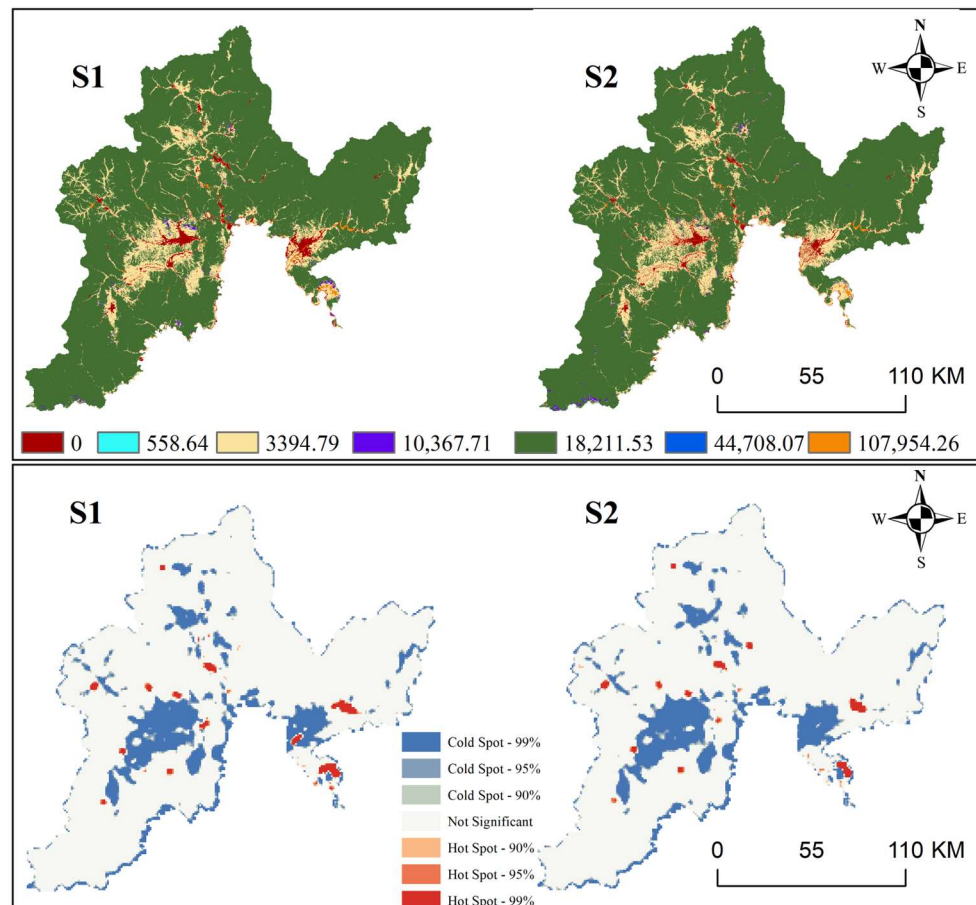


Figure 7. Spatial distribution of ESV hot/cold spots under different scenarios in 2030 (S1: natural development scenario, S2: goal-oriented scenario).

The Getis–Ord GI^* hot spot analysis reveals that both scenarios have cold hot spots, concentrated primarily in the middle and lower reaches of the basin. The core development areas of Yanlongtu and Hunchun City have more cold spots than hot spots. The hot spots are sparsely distributed in the eastern and central parts of the study area, with rivers, ecological reserves, lakes, and reservoirs concentrated along the route. Notably, the S2 scenario exhibits more concentrated cold spots than S1, particularly in the Hunchun area,

while hot spots within the ecological zone, such as Tiger Balm Park, show a growing trend under the S2 scenario compared to S1.

5. Discussion

5.1. *ESV Evolution Driven by LULC*

In recent years, there has been abundant research on land-use modeling and ESV. Among these, the study of land-use effects on ESV has become a research hot spot [25], and many researchers have demonstrated that LUCC is a direct driver of ESV changes through quantitative methods [22,46,47]. This study explores the spatial and temporal changes in ESV driven by LUCC in the watershed based on transitions in and out of seven land use types for four phases: 2000–2005, 2005–2010, 2010–2015, and 2015–2020. The primary land use change pattern observed from 2000 to 2020 involves the reciprocal transformation between farmland, forest, and built-up land. The growth in central cities such as Helong, Yanji, and Hunchun in the downstream region of the TRB is primarily attributed to farmland conversion. Furthermore, during the period from 2015 to 2020, a rapid shift of high-value areas (cultivated land and wetland) in the midstream and downstream regions to low-value areas (built-up land and grassland) resulted in a year-on-year decrease of $\text{CNY } 0.98 \times 10^{10}$ in the total ESV of the watershed in 2020. This decline is indicative of the substantial impact of human activities on natural landscapes, particularly the conversion of cultivated land to built-up land, which is more pronounced in areas experiencing rapid population growth and urban expansion [21].

In general, impervious occupying natural ecosystems (forest, grassland, and water) in the study area has been increasing year by year, and the ESV should have been decreasing, but actually showed a trend of reducing increase. This phenomenon can be attributed to two main factors. Firstly, this study differs from previous studies that calculated ESV with fixed unit equivalence values by correcting the unit equivalence values for ecosystem services for each year [25,46,48], and Table 9 shows the corrected standard equivalence factors (Ea'). Since ESV is closely related to social and economic development, people's willingness to pay for ESV is usually influenced by both their willingness and ability to pay, and fixing the unit equivalent value would result in low ESV calculations [10]. On the other hand, although there is also a decrease in the ESV due to the conversion of some forest land and cropland to built-up land, more cropland with lower unit value has been diverted to forest land with higher value during the last 20 years, and the watershed has increased by 82.28 km^2 during this period, mainly from the conversion of cropland and built-up land with lower value. Additionally, because the NDVI has a strong explanatory power for the ESV [10], a good indication of the increasing trend in the total ESV in the study area can be seen by comparing the NDVI in the study area. At the same time, the trends in ESV in the TRB are consistent with the conclusions of previous studies in the study area [28,49,50].

From 2000 to 2020, forest land and cropland underwent significant changes in PSV, SRV, SSV, and CSV among the six land use types. Forest land had the highest values for PSV, RSV, SSV, and CSV, which can be attributed to its dominant coverage in the TRB. The total ESV of forest land peaked in 2015 at 2.24×10^9 CNY, after which it declined due to a reduction in forest land area by 4217.14 km^2 from 2015 to 2020. However, establishing the Northeast Tiger and Leopard National Park and other ecological reserves led to converting arable land to forest and grassland, which, along with urban development, resulted in no net increase in arable land. The reduction in arable land led to decreased water use for agriculture, which hindered the development and utilization of rivers and groundwater. This is the primary reason for the increasing watershed area trend. The LULC in the TRB promoted a progressive increase in the ESV, as previously shown by studies in the TRB or Jilin [28,49–52].

In the study area, the proportion of forest land remains highest among the top ten ecological services. However, the continuous reduction in farmland over the entire study period has led to a gradual decline in its food production function (Figure 8). The annual expansion of water area has contributed to the increase in two major service components:

water regulation and environmental purification. Being a crucial ecological barrier in the east of Jilin Province, the study area emphasizes soil and water conservation, with water regulation and climate regulation emerging as the most vital ecological services [46]. To address the conflict between farmland protection and ecological conservation, a stringent forest protection policy is imperative to prevent the excessive development and utilization of forest land. Simultaneously, strategic investments should be directed towards enhancing the construction of farmland water conservancy facilities. This approach ensures the irrigation needs of farmland are met while promoting the functions of water regulation and environmental purification. By implementing these measures, the ecological service function of the study area can be effectively protected and enhanced. This concerted effort contributes to achieving the dual goals of sustainable ecology and economic development.

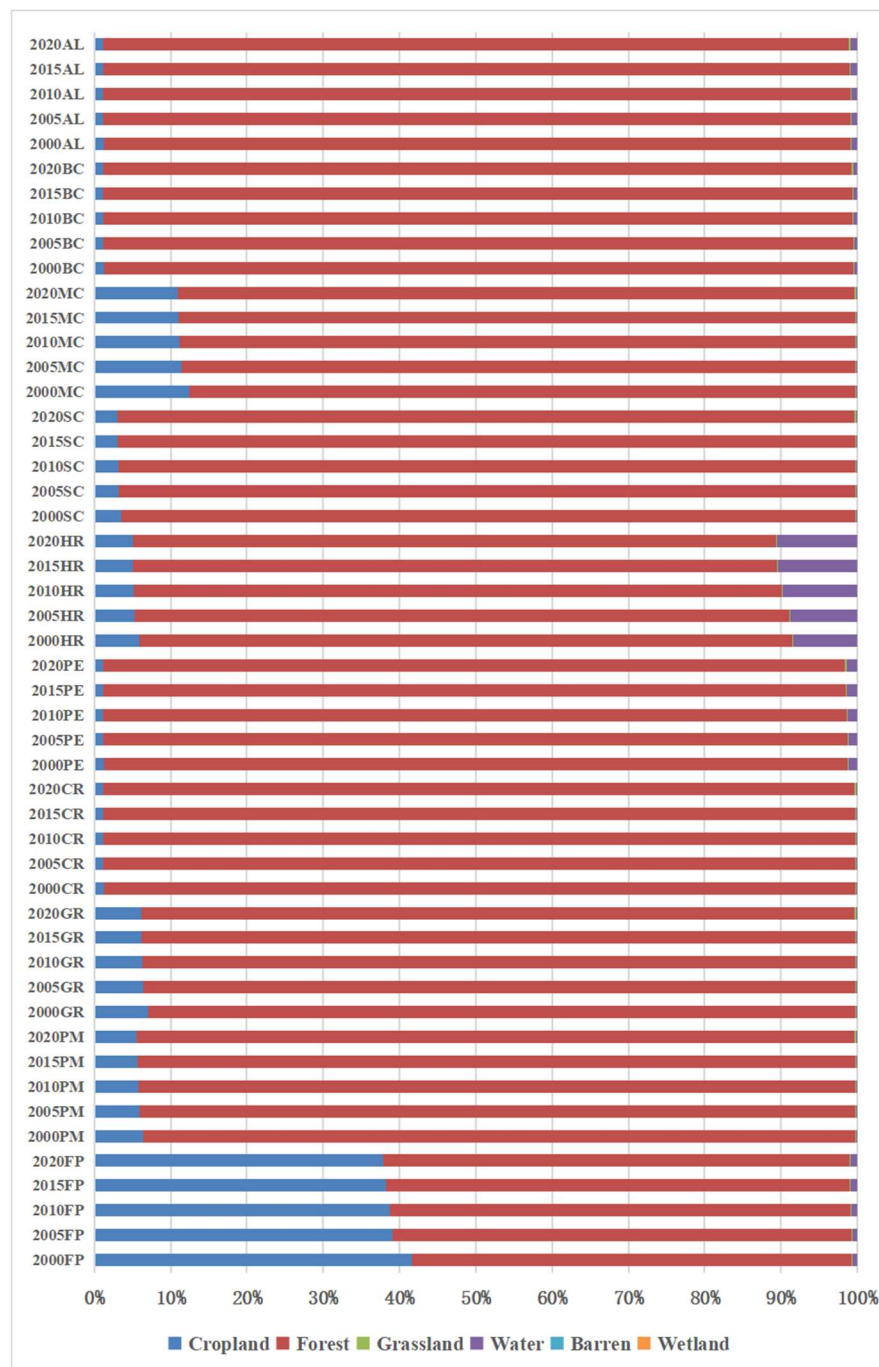


Figure 8. Changes in 10 ESs in the TRB from 2000 to 2020.

5.2. Driving Analysis of ESV Evolution

According to Xie et al. (2022), anthropogenic land use change has the most profound and negative impact on ecosystems, followed by temperature, NDVI, and precipitation [10]. Han (2021) adds that the NDVI is highly explanatory for the ESV, and that climate change is critical to driving the evolution of LULC and ESV dynamics [53]. Our study confirms these findings and further reveals that an increase in precipitation can help alleviate water scarcity, promote cropland conversion to woodland, and be a key factor in the transition from bare ground to grassland, all of which contribute to an increase in the ESV. However, the explanatory power of temperature and precipitation for the ESV is weaker, as shown by the DEM and SOMC analyses.

To study ecological problems and identify potential solutions, the landscape pattern index is a reliable tool [54]. In line with this, analyzing the correlation between landscape patterns and ecosystem services can shed light on the impact of the landscape composition and configuration elements on ESV [10]. In our study, we found a positive correlation between AI, SHDI, and ESV, indicating that a more uniform and clustered landscape is favorable for improving ESV. Our study also examined changes in the study area. We found that from 2000 to 2005, fragmentation increased, leading to a decrease in the value of ecosystem services. However, from 2005 to 2015, the area of dominant landscape-type patches increased, and their aggregation contributed to an increase in the regional ESV. From 2015 to 2020, the expansion of urban construction land and the emergence of a crisscrossing road network severely fragmented all types of landscapes, leading to a continuous decline in the total value of ecosystem services in the region. These findings are consistent with Yu et al.'s (2021) study on the Yanbian Prefecture [54].

5.3. ESV Evolution Driven by Political Context

The TRB region is a crucial part of China's agricultural production and ecological security system. It is located in the "One Circle, Two Screens, Three Districts, Four Axes" of the "Jilin Territorial Spatial Plan (2021–2035)" and spans the eastern mountainous agricultural zone and the eastern forest zone. Its main responsibilities are food production and ecological protection. Implementing the "return of farmland to forest" policy in 2006 has led to a significant increase in the ESV in the TRB [54]. However, it is important to note that an increase in the ESV does not guarantee sustained economic growth in the region [55].

Since 2015, accelerated urban development has resulted in a reduction in forest and arable land in the TRB, creating a conflict between agricultural production, urban expansion, and ecological protection. This conflict threatens the stability of the region's natural ecosystem. To address this challenge, local governments and policymakers must promote the scale and technology of original agriculture, strictly control land leasing or reclamation of abandoned land, and develop and utilize land resources based on ecological principles. For instance, urban and highway planning should prioritize the avoidance of woodlands and wetlands, control the occupation of high ecological services land, and focus on developing a green economy. The land use and cover models should be transformed, and a green ecological industrial system should be built. These efforts will promote diversified development of ecosystem structures and functions, strengthen the TRB's role as an ecological security barrier, and ultimately facilitate sustainable economic development [56]. In conclusion, the TRB region is of significant importance to China's agricultural production and ecological security system. However, it faces challenges in balancing agricultural production, urban development, and ecological protection. By promoting sustainable development practices and adhering to ecological principles, policymakers can reconcile these challenges and ensure the region's natural ecosystem stability.

5.4. Spatiotemporal Simulation of ESV

This study establishes different scenarios of spatial constraints based on land planning policies and potential factors affecting the ESV. By comparing the spatial cold spots and hot spots of ESV under different scenarios, the research results become more informative

and can provide decision makers with a contrasting context for promoting sustainable development [22,44]. This study finds that the area of forested and cultivated land decreases while the land for construction rapidly expands, resulting in a reduction in the ESV. However, the increase in grassland and water area due to natural and anthropogenic disturbances compensates for some of the reduced ESV. Moreover, this study overcomes the limitation of using a fixed unit equivalent value for the ESV calculation in previous studies [10] and predicts a gradual increase in people's intention to pay for ESV using the GM (1, 1) model to forecast ESV values beyond 2020. The downstream areas have more ESV hot spots, and they need to focus on protecting and restoring natural resources such as forests, water, and wetlands. The midstream areas, such as the core development area of Yanlongtu, are cold spots for ESV changes. To mitigate the decline in ESV, ecological corridors and reserves can be established between cities to promote the coordinated development of human–nature relationships. Moreover, the S2 scenario aligns more closely with research on the correlation between changes in landscape pattern indices and ESV. The trend towards a more regular and concentrated distribution of landscapes within the watershed is identified as a potential contributor to ESV growth. Consequently, it is imperative to persist in implement planning goals, enhancing the management system for ecological and food security, safeguarding forests, fortifying the construction of farmland water conservancy facilities, promoting eco-agriculture, reinforcing ecological compensation mechanisms, intensifying public education and awareness, leveraging technological innovation to enhance resource utilization efficiency, and implementing robust monitoring and management of the ecological environment. These measures collectively advance the cause of sustainable development.

5.5. Limitations and Future Research

This study utilized the GM (1, 1) method to predict future ESV coefficients and economic efficiency per unit area for each LULC type. However, it is worth noting that even though these predictions have been proven highly accurate, there is still an inherent degree of uncertainty [56]. As economies grow and living standards improve, the willingness and ability to pay for ecosystem services should also increase. Consequently, projected ESV can offer more precise information and better reflect the trade-offs between ESV and economic benefits [22]. The future simulation adopted spatially-constrained–multi-scenario settings, resulting in ESV values that were constant, but their spatial distribution varied. However, this approach can lead to inaccurate results when applied to larger regional scales. As such, future studies covering wider regions should consider incorporating quantitative constraints to ensure the accuracy of the results.

6. Conclusions

In this comprehensive study, we conducted an assessment of the ESV of the TRB by leveraging LULC data. Equivalence factors were modified with consideration for biomass and socioeconomic factors, leading to insights into the intricate relationships between the ESV and natural conditions, climate change, human activity, and LPIs. Finally, the PLUS model was subsequently employed to simulate the spatiotemporal evolution of the TRB's ESV under two scenarios: the natural development scenario and the goal-oriented scenario for 2030. The key findings are outlined below:

(1) The ESV of the TRB demonstrated a consistent increase from CNY 3.54×10^{10} in 2000 to CNY 4.08×10^{10} in 2015, followed by gradual fluctuations but an overall upward trajectory. This rise was attributed to the corrected standard equivalent factor (Ea'), emphasizing the developmental progress of the ecological environment and society;

(2) Regulating service value (RSV) and supporting service value (SSV) emerged as pivotal ecosystem functions within the watershed, displaying temporal consistency. The changes in provisioning service value (PSV) and cultural service value (CSV) remained relatively modest across the four stages. Notably, forest land held the highest proportion

of the ESV, constituting 94% of the total value, while water areas and wetlands exhibited higher unit area ESV compared to other land types;

(3) Pearson correlation coefficients between the ESV and landscape pattern indices (SI, SHDI, and AI) revealed values of -0.65 , 0.72 , and 0.60 , respectively. Factor exploration indicated the significance of all variables, with the q-value ranking as follows: HAILS (0.678) > TEM (0.470) > NDVI (0.435) > DEM (0.348) > SOMC (0.305) > PRE (0.148);

(4) The PLUS simulation forecasted that forest land would continue to have the highest ESV in 2030. Utilizing the GM (1, 1) model for prediction, unit ESV values for different land types were estimated: cultivated land (3394.79 CNY/ha), grassland (10,367.71 CNY/ha), water area (107,954.26 CNY/ha), unused land (558.64 CNY/ha), and wetland (44,708.07 CNY/ha). The exploration of ESV spatial cold spots and hot spots under different conditions validated the scientific basis and necessity for implementing the Plan.

In summary, our research underscores the imperative and scientific foundation for implementing sustainable development and ecological conservation plans in the TRB region. This study provides valuable insights and recommendations for future implementation efforts.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su16010399/s1>.

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