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Evolution and Driving Forces of Ecological Service Value in Response to Land Use Change in Tarim Basin, Northwest China

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Abstract: The main objective of protecting ecosystems and enhancing the supply of ecosystem services (ESs) is to quantify the value of ecological services. This article calculates the ecological service value (ESV) of the Tarim Basin over the past 40 years using the improved benefits transfer method of satellite remote sensing data, such as Landsat, analyzes the spatiotemporal evolution characteristics of ESV, and studies the driving mechanism of ESV changes using GeoDetector. Finally, the FLUS model was selected to predict the ecosystem service value until 2030, setting up three scenarios: the Baseline Scenario (BLS), the Cultivated Land Protection Scenario (CPS), and the Ecological Protection Scenario (EPS). The results indicate that (1) the ESV in the Tarim Basin decreased by USD 1248.21 million (−2.29%) from 1980 to 2020. The top three contributors are water bodies, wetlands, and grassland. (2) Waste treatment and water supply functions had the highest service value, accounting for 44.53% of the total contribution. The rank order of ecosystem functions in terms of their contribution to the total value of ESV was as follows, refining from high to low importance: water supply, waste treatment, biodiversity protection, climate regulation, soil formation, recreation and culture, gas regulation, food production, raw material. (3) The spatial differentiation driving factors of ESV were detected, with the following Q-values in descending order: net primary productivity (NPP) > normalized difference vegetation index (NDVI) > precipitation > aspect > temperature > slope > soil erosion > GDP > land use intensity > per capita GDP > population > human activity index. (4) The ESVs simulated under the three scenarios (BLS, CPS, and EPS) for 2030 were USD 51,133.9 million, USD 53,624.99 million, and USD 54,561.26 million, respectively. Compared with 2020, the ESVs of the three scenarios decreased as follows: BLS (USD 4209.33 million), CPS (USD 1718.24 million), and EPS USD (−781.97 million). These findings are significant for maintaining the integrity and sustainability of the large-scale ecosystem, where socioeconomic development and the fragile features of the natural ecosystem interact. Additionally, the study results provide a crucial foundation for governmental decision-makers, local residents, and environmental researchers in northwest China to promote sustainable development.

Keywords: land use land cover; Tarim Basin; ecosystem service value; Geo-Detector; FLUS model

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1. Introduction

Ecological services encompass the diverse benefits, including provisioning, supporting, regulating, and cultural services, that humans derive from natural ecosystems [1]. Ecosystems not only offer tangible ecological products but also provide a wide array of intangible ESs, which hold irreplaceable and invaluable value for humanity [2]. However, the escalating global and regional ecological problems resulting from population growth, rapid urbanization, and the rapid pace of economic and social development have intensified [3,4]. These challenges have had a profound impact on the stability of ecosystems and their ability to provide essential ESs [5,6]. ESV serves as a fundamental indicator for identifying regional ecological environmental issues, evaluating the supply and demand of ESs, formulating ecological environmental protection plans [7], and designing ecological functional zoning [8,9]. It offers a direct basis for understanding the supply–demand imbalances within ecosystems [10].

The assessment of ESV serves as a scientific foundation for regional ecological zoning, spatial planning of land resources, and the development of ecological compensation policies [11]. However, ecosystems are dynamic systems undergoing continuous change, and it is widely recognized that the combined and interactive effects of natural and human factors influence the spatial distribution of ESVs [12,13]. Numerous scholars have employed various methods to explore the evolutionary characteristics of ESVs at various spatial and temporal scales and to analyze the driving forces behind their changes [14]. However, due to the diversity of approaches used, different studies have produced varying findings regarding the driving factors in different spatiotemporal dimensions. One significant factor contributing to the variation in ESs is land use change [15]. Distinct development patterns lead to diverse land use scenarios, resulting in differences in the structure, function, and value of regional ecosystems. Changes in land use directly alter the structure and functioning of ecosystems, thereby affecting the provision of various services [16]. The assessment outcomes of ESV can provide a theoretical basis for formulating policies related to land use [17,18]. Therefore, it holds great significance to scientifically and reasonably evaluate and predict future ESVs using models that incorporate land use change [19].

The impact of human activities on ecosystems can be manifested through land use and land cover changes (LULCCs). LULCCs alter ecosystems' functions and performance and affect their ESV [20]. The causes of LULCCs include weathering and vegetation succession, earthquakes, floods, urbanization, reclamation, etc. [21]. Costanza et al. [22] evaluated ESV in the form of currency, allowing different ecosystem services to be aggregated [23] and to adapt to horizontal or vertical comparisons in different periods [24], areas, or LULCCs [25,26].

There are different models for calculating ESVs. Xie et al. [27,28] developed the Chinese equivalent of the ESV scale based on the actual situation in China, which provided great convenience to Chinese scholars. The expression of the first law of geography is the observed data of variables in the region, which have certain interdependence. Spatial dependence becomes stronger with closer distance [29,30]. Currently, studying ESV has shifted from ecological service assessment to analyzing the intrinsic causes of ESV change [31]. Pan et al. [32] studied the changing trends and driving factors of ecosystem service value (ESV) in karst areas for the first time. However, the scale for spatial autocorrelation analysis of ESV is limited and the driving mechanism of ESV changes is not clear. Simulating the future ESV of cities can provide valuable references for the strategic deployment of agricultural development, urban planning, and ecological security patterns. Currently, there are many methods used in land use simulation: CA-Markov [33], CLUE-S [34], and PLUS [35]. The GeoSOS-FLUS model has higher simulation accuracy and is well known [36,37].

The Tarim Basin, situated in the northwest region of China, exhibits distinct attributes of inland river ecosystems. It faces multiple environmental challenges and significant anthropocentric disturbances [38]. This area is considered an ecologically fragile zone within arid basins, representing a transitional landscape between tall mountains and plains. The landscape of the Tarim Basin comprises a unique combination of mountain, oases, and desert ecosystems, as well as the coexistence of agricultural and animal husbandry practices [39]. In recent decades, the rapid socioeconomic development in the Tarim Basin has undeniably enhanced the living standards of its residents. However, it has also led to increasingly prominent ecological issues resulting from the combined impacts of natural processes and human activities.

Various natural and socioeconomic factors have likely caused significant land use and land cover changes (LULCCs) in the Tarim Basin, leading to a dramatic alteration in ecosystem services functions (ESFs). In this study, Landsat TM data and remote sensing and GIS technology were employed to analyze the fundamental characteristics of ESV in the Tarim Basin in northwest China during the periods of 1980, 1990, 2000, 2010, and 2020. The primary objectives of this research are as follows: (1) Examine temporal and spatial variations in ESV. (2) Identify the natural and social factors that impact the ESV of the Tarim Basin in northwest China. (3) Simulate the future development of ecological services in the Tarim Basin using the FLUS model. These quantitative analyses are of utmost importance and will be valuable for land use planning in arid river basins. They will also offer scientific guidance for eco-environmental conservation and the sustainable development of arid lands in the Tarim Basin in northwest China.

2. Materials and Methods

2.1. Study Site

The Tarim Basin is situated in the southern part of Xinjiang, China, bounded by the Tianshan Mountains and the Kunlun Mountains (73°24′–93°38′E, 34°48′–43°21′N) [40]. It holds the distinction of being the largest inland basin in China, covering a total land area of approximately 102.34 $\times$ 10^4 km^2, as illustrated in Figure 1 below. The basin encompasses several administrative divisions, including the Kizilsu Kyrgyz Autonomous Prefecture (Kizilsu), the Bayingolin Mongol Autonomous Prefecture (Bayingol), the Aksu Region, the Hotan Region, and the Kashi Region, comprising a total of 37 counties or autonomous counties.

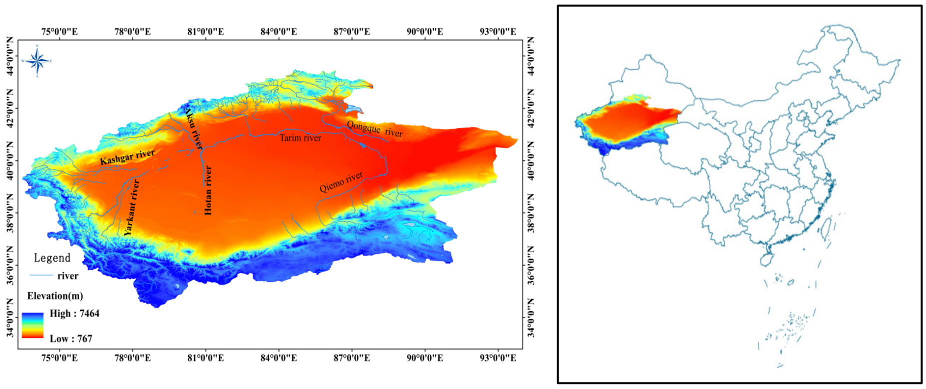

Figure 1. The location of the Tarim Basin.

The Tarim Basin exhibits a diverse topography, including mountains, basins, unused land, deserts, and plain oases. Notably, the oasis area comprises only 3.76% of the total area [41]. The terrain gradually rises towards the west and descends towards the east, resulting in an average altitude of approximately 1000 m. The Tarim Basin falls under the category of a temperate continental arid climate, characterized by aridity and limited rainfall. Due to its distinct topography, the region experiences a hot and dry climate year-round, with scarce precipitation and abundant sunshine. The average annual rainfall amounts to around 50 mm, while the average annual evaporation surpasses 2000 mm. Consequently, the Tarim Basin is classified as a typical, continental warm temperate arid climate.

At the end of 2020, the population of the Tarim Basin reached 13.5926 million, constituting approximately 47.62 percent of the total population of Xinjiang [42].

2.2. Data Collection

In this study, land use data played a crucial role in our analysis. We obtained multi-period and deferential resolution remote sensing data, including Landsat TM/ETM and OLI images, from the United States Geological Survey (USGS) website. According to China's land use classification method and Xinjiang Province's land use characteristics, the classification includes cultivated land, woodland, grassland, water body, construction land, unused land, and wetland. Using the maximum likelihood classification method in the software ENVI5.3, the land use data of TRB every ten years from 1980 to 2020 were obtained. After analyzing detailed land use survey data and field sampling surveys in typical areas during the same period, the overall accuracy was verified to be around 85%. In addition, the Kappa coefficients all reach above 0.89, which meets the basic conditions of the research.

We checked the Xinjiang Provincial Statistical Yearbook to obtain data on the planting range, output, and price of food. The, we selected 12 influencing factors from two aspects: natural and socioeconomic, as shown in Table 1 below. The elevation, slope, and aspect are calculated using SRTM 30 m obtained from the GEE platform and processed in Arcgis10.8 (https://www.webmap.cn, accessed on 1 May 2024). Precipitation, NPP, NDVI, population, GDP, soil erosion, temperature, per capita GDP, land use intensity (LUI), and human activity index (HAI) factors were downloaded from the Data Box (https://www.databox.store, accessed on 1 May 2024).

Table 1. Selected driving factors for ESV.

Main Factors	Driving Factors	Units	Signs
Natural factors	Slope	degree (°)	E1
	Aspect	degree (°)	E2
	Precipitation	(mm)	E3
	Temperature	(°C)	E4
	Soil erosion	Multi-class	E5
	NDVI	/	E6
	NPP	/	E7
Socioeconomic factors	GDP	10,000 yuan/km^2	E8
	Population	people/km^2	E9
	Per capita GDP	Yuan/people	E10
	Land use intensity (LUI)	/	E11
	Human activity index (HAI)	/	E12

In this study, the assessment of the impact of these factors is divided into two main categories: natural factors and socioeconomic factors. Table 1 provides an overview of the selected influences. To analyze the natural factors, temperature, precipitation, NPP, soil erosion, and the NDVI were obtained from the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (http://www.resdc.cn, accessed on 1 May 2024). Meanwhile, we utilized SRTM 30 m data obtained from the Google Earth Engine (GEE) platform to calculate slope and aspect. These variables are essential in understanding the natural characteristics of the study area. By incorporating these diverse datasets, we aimed to capture the interplay between natural and socioeconomic factors in driving changes in the value of ecological services. This comprehensive approach allows us to gain insights into the intricate dynamics of ESs and their relationship with the environment and human activities.

2.3. Methods

2.3.1. Technical Process

This paper conducts research through four key steps:

(1) Acquisition of LULC data: Multiperiod and deferential resolution remote sensing images from the years 1980, 1990, 2000, 2010, and 2020 were obtained. These images undergo atmospheric correction and topographic correction using the GEE platform. The maximum likelihood classification (MLC) method in ENVI 5.3 is employed to generate land use data for the Tarim Basin based on these images.

(2) Evaluation of ESV distribution: The ESV distribution in the Tarim Basin is calculated for each of the five periods. This assessment is based on the unique characteristics of the Tarim Basin and utilizes the ESV benefit transfer methods. Additionally, an

analysis of the spatiotemporal changes in nine ecosystem functions and the ecological sensitivity of ESV is conducted.

(3) Analysis of driving factors: The driving factors influencing ESV are identified and analyzed using the Geo-Detector tool. This analysis helps to understand the interactions and relationships between different factors that contribute to changes in ESV over time.

(4) Future ESV prediction: The FLUS simulation model is utilized to forecast ESVs for the year 2030. Three different scenarios are set up to account for different future conditions and potential changes in the Tarim Basin's ESs.

By following these steps, the research aims to provide a comprehensive understanding of the changes in ESV in the Tarim Basin, including their spatiotemporal dynamics, driving factors, and future projections.

2.3.2. LULC Analyzing

(1) The absolute dynamic index: The Absolute Dynamic Index (ADI) is utilized to directly quantify the rate and extent of change for a specific land use type. It serves as an indicator of variations among different land classes within a particular study period in a given region [43]. The general formula for ADI is

$$ADI = (R_b - R_a) \times \frac{1}{T} \times 100\% \tag{1}$$

where R_b and R_a denote the areas of a specific LULCC class at the initial and final dates, respectively, while T represents the duration of the study period.

(2) Land use transfer matrix (W_{ij}): It is utilized to depict the dynamic changes in each LULCC type during the monitoring period [44]. It can be calculated as

$$W_{ij} = \begin{bmatrix} W_{11} W_{12} W_{13} \ldots\ldots\ldots W_{1n} \\ W_{21} \ldots\ldots\ldots\ldots\ldots\ldots\ldots W_{21} \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ W_{n1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots W_{nn} \end{bmatrix} \tag{2}$$

2.3.3. The ESV Assignment

In this study, to assess the ESV for each of the seven land use categories, a comparison was made between each category and various biomes identified worldwide [45]; then, this study drew on the research results of Xie Gaodi et al. [46] and adopted benefit transfer methods to build an ESV estimation model for the Tarim Basin and to calculate the ESV in the study area. Based on the specific conditions of the study area and relevant research conducted in similar regions, the ESFs in this study are classified into 9 categories [47]. Based on the actual situation of the study area, the cultivated land equivalent in this study was taken as the value of dry land. The woodland equivalent and grassland equivalent were averaged. The water body and glacier equivalent is the average of the water system. Wetland equivalents were averaged. As for construction land, except for recreation and culture services, other ecological services were considered to be zero [48]. The unused land equivalent takes the value of the bare land. The ESV coefficient of unit area in the Tarim Basin can be calculated as shown in Table 2.

(1) Calculation of ESV

In this study, the ESV and the value of the ESFs for each land use type in the Tarim Basin were calculated using the following methodology [49,50]:

$$ESV_k = \sum_f A_k \times VC_{kf} \tag{3}$$

$$ESV_f = \sum_k A_k \times VC_{kf} \quad (4)$$

$$ESV = \sum_k \sum_f A_k \times VC_{kf} \quad (5)$$

where ESV_k, ESV_f, and ESV are represented by the ESVs of land use types "k", the value of ESF type "f", and the total ESV, respectively. A_k denotes the area (ha) for land use type "k", VC_{kf} denotes the value coefficient ($USD^{\cdot ha-1\cdot a-1}$) for land use type "k", and "f" denotes ESF type. The variation in ESV was estimated by calculating the estimated values for each land use type in 1980, 1990, 2000, 2010, and 2020.

Table 2. ESV of unit area of different land use categories ($USD^{\cdot ha-1\cdot a-1}$).

ESV	Cultivated Land	Woodland	Grassland	Water Body	Construction Land	Unused Land	Wetland
Gas regulation (GR)	71.18	285.31		0.00	0.00	3.97	256.26
Climate regulation (CR)	126.71	268.79		65.49	0.00	8.59	2434.47
Water supply (WS)	85.43	270.12		2904.28	0.00	4.62	2206.68
Soil formation (SF)	207.85	265.50		1.43	0.00	11.24	243.44
Waste treatment (WT)	233.49	113.60		2591.07	0.00	17.18	2588.22
Biodiversity protection (BP)	101.07	297.85		354.50	0.00	26.41	355.91
Food production (FP)	142.37	21.79		14.24	0.00	1.32	42.71
Raw material (RM)	14.24	196.81		1.43	0.00	2.65	9.97
Recreation and culture (RC)	1.43	137.37		617.87	12.15	15.85	790.13
Total	983.75	1857.15		6550.29	12.15	91.82	8927.79

(2) The ESV growth rate can be formulated as follows:

$$ESV_{gr} = \frac{ESV_{r2} - ESV_{t1}}{ESV_{t1}} \times 100\% \quad (6)$$

where ESV_{gr} represents the growth rate of ESV during the observation period from t_1 to t_2, and ESV_{t1} and ESV_{t2} denote the estimated total ESV at the beginning and end of the observation period t_1 and t_2, respectively.

(3) Sensitivity analysis (CS)

In this study, a sensitivity analysis model was utilized to examine the sensitivity of ESV to changes in the *VC* for each land use type. The VC was adjusted by ±50% to assess the impact of such variations.

In this analysis, the CS was calculated using the standard economic concept of elasticity in the following manner [51]:

$$CS = \frac{(ESV_j - ESV_i)/ESV_i}{\left(VC_{jk} - VC_{ik}\right)/VC_{ik}} \quad (7)$$

where ESV denotes the estimated ESV, *VC* denotes the value coefficient, "i" and "j" denote the original and adjusted values separately, and "*k*" denotes the land use types. If the CS is greater than 1, it indicates that the estimated ecosystem value is elastic in response to changes in that coefficient. Conversely, if CS is less than 1, the estimated ecosystem value is considered to be inelastic [52].

2.4. Geographic Detector Model

The Geo-Detector model, developed by Wang Jinfeng et al., is a statistical model that utilizes spatial hierarchical heterogeneity to examine the relationship between dependent and independent variables. This model is considered more reliable than traditional regression models, as it offers a comprehensive approach to understanding the driving factors behind geographical elements. It has been widely applied in various fields, including agricultural economy [53], land use [54], and ESV [3].

In this study, the Geo-Detector model was employed to investigate the driving forces contributing to the spatial differentiation of regional ESV. By utilizing the interaction detector, this study further explored the interactive effects of different factors on the spatial patterns of regional ESV. The model expression is as follows:

$$Q = 1 - \frac{\sum_{n=1}^{M} L_h \delta_h^2}{L\delta^2} \tag{8}$$

where Q represents the explanatory power of a factor in relation to the spatial differentiation of ESV, with a value ranging from 0 to 1. A higher Q value indicates a stronger explanatory power of the factor in influencing the spatial differentiation of ESV, while a lower value indicates a weaker influence. M is the grading region; L_h is the number of samples in the grading area. δ_h^2 is the discrete variance of a hierarchical region; δ^2 is the regional discrete variance; L is the number of samples.

In this study, the Geo-Detector interaction detection method was conducted by comparing the power of Q(E1∩E2) and Q(E1, E2), where E1 and E2 represent the two factors under consideration. If the interaction between the two factors had a greater effect on the ESV than a single factor, it indicated that these factors collectively enhanced the explanatory power of ESV.

2.5. Multiscenario Simulation of ESV

The FLUS model, developed by Liang et al. [55], is a land use change simulation model that utilizes patch-based methods. It is designed to accurately simulate the evolution of different land use types under various scenarios and has been widely used for scenario prediction in different spatial and temporal dimensions. The FLUS model is built on the principle of cellular automaton (CA) and incorporates an artificial neural network (ANN) algorithm [56]. This combination allows the model to generate suitability probabilities for different types of land use changes based on the initial land use conditions and various driving factors. The flexibility and accuracy of FLUS make it suitable for a broad range of applications in land use planning, environmental management, and policymaking. Different land use management policies require different land use change scenarios. In accordance with the latest cultivated land protection policy in the Xinjiang Autonomous Region, it is crucial to prevent the reduction or encroachment of cultivated land and strive for its gradual expansion. Hence, this study aims to establish simulation analysis scenarios that focus on cultivated land protection and ecological conservation. Therefore, three distinct scenarios (BLS, CPS, and EPS) were selected.

Before predicting land use and land cover in 2030, we first specialized the LULCC drivers for 2020 and then selected the 12 drivers described above. Then, using the 2020 LUCC data as input data, the probability of occurrence of each land use type in the Tarim Basin was calculated. The three-scenario probability matrix of LUCC shifts for 2010–2020 was then calculated. In the end, the spatial distribution data of land use and land cover and their ESV in 2030 under BLS, CPS, and EPS scenarios were obtained through simulations.

3. Results

3.1. The Dynamics of Land Use Changes

Figures 2 and 3 present the classification results of land use changes in the Tarim Basin from 1980 to 2020. The analysis of land use and land cover changes over the past 41 years reveals that unused land has remained the dominant land cover in the Tarim Basin. However, its proportion has slightly decreased from 65.71% of the total area in 1980 to 65.28% in 2020. Grassland, on the other hand, is the second most prevalent land cover category, but its coverage has experienced a decline from 27.91% in 1980 to 26.08% in 2020. From Figures 2 and 3, it is evident that there have been notable changes in land use and land cover in the Tarim Basin over time. Cultivated land has experienced an increase from 2.6% of the total land area in 1980 to 4.16% in 2020. The proportion of woodland has exhibited a fluctuating pattern over time: it experienced a gradual rise, starting from 1.22 percent in 1980 and reaching 1.30 percent in 2000. However, it subsequently declined, settling at 1.25 percent by the year 2020. On the other hand, the water body has undergone a slight reduction from 2.23% of the total land area in 1980 to 2.2% in 2020. However, the construction land category has shown an upward trend, expanding from 0.17% of the total land area in 1980 to 0.29% in 2020. Wetlands display a mixed trend with periods of growth and decline. They initially experienced an upward trajectory, expanding from 0.82 percent in 1980 to 0.84 percent in 2000. However, between 2000 and 2020, there was a slight decrease, with wetland coverage settling at 0.77 percent. Despite these fluctuations, the overall long-term trend indicates a decrease in wetland area. Therefore, wetlands can be classified as a decreasing land type. In the Tarim Basin, despite the relatively small size of wetlands and water bodies, these land types play a crucial role in *ES*s and possess noticeably high service value. Although wetlands and water bodies account for only approximately 3% of the total area in the Tarim Basin, they have a substantial influence on the overall ESV in the region.

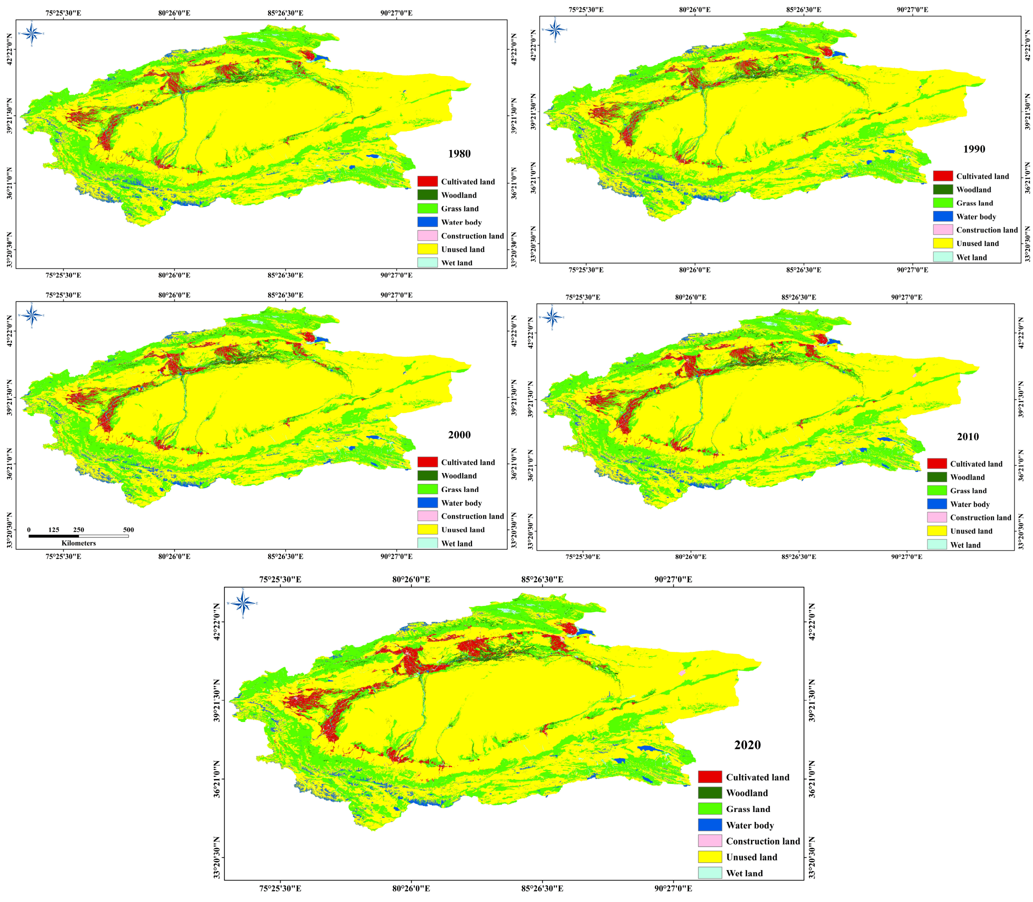

Figure 2. Land use maps of Tarim Basin in 1980, 1990, 2000, 2010, and 2020.

The considerable changes observed in wetlands, water bodies, and the simultaneous expansion of cultivated land can be attributed to rapid agricultural progress, inadequate regulations for wetland preservation, and unsustainable practices in water resource management. These factors have contributed to the alterations in land use and land cover patterns in the Tarim Basin. Understanding these dynamics is crucial for implementing effective land management practices, protecting wetland ecosystems, and promoting sustainable water resource utilization in the Tarim Basin.

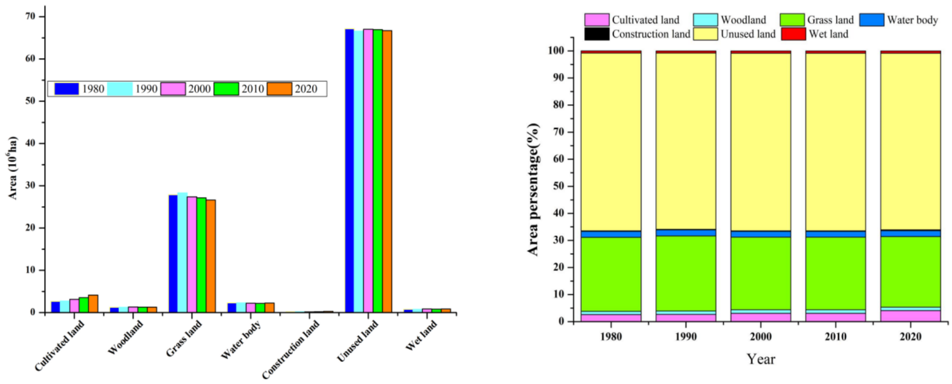

Figure 3. Land use change patterns of Tarim Basin in1980, 1990, 2000, 2010, and 2020.

3.2. Land Use Conversion

The land use/cover classification maps vividly demonstrate notable shifts in land use patterns within the Tarim Basin during the past 41 years, as shown in Figure 4. One prominent change is the dramatic reduction in grasslands in the northwest and southwest areas since 1980. This decline can be attributed to the conversion of a substantial amount of grasslands into cultivated lands, resulting in a noticeable increase in cultivated land coverage. Figure 3 presents a comprehensive overview of the dynamics of the seven land use/cover types in relation to their total areas and corresponding percentages. Among these land covers, including cultivated land, woodlands, and construction land, there has been an increasing trend. These land use types have expanded over time. Conversely, grasslands, water bodies, unused land, and wetlands have experienced a decrease in coverage, indicating a declining trend in these land use types. These changes in land use and cover signify the evolving human activities and land management practices taking place in the Tarim Basin.

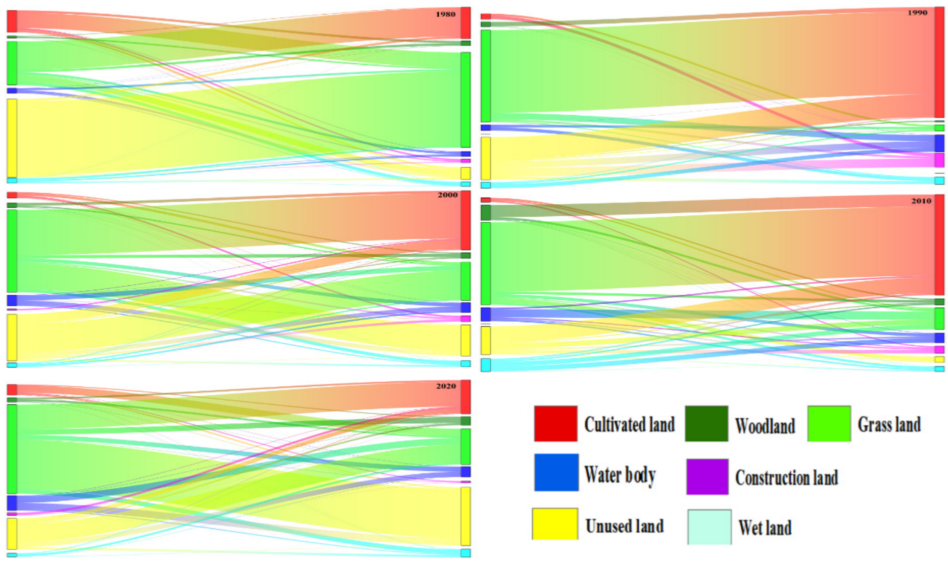

Figure 4. Transition matrix figure of LUCC from 1980 to 2020 in the Tarim Basin (10^6 ha).

The conversion of grasslands into cultivated lands suggests the expansion of agricultural activities, while the increasing coverage of construction land indicates urbanization and infrastructure development. It is important to consider the implications of these changes for ESs, biodiversity, and sustainable land management. Understanding these dynamics and the underlying drivers of land use change is crucial for informed decision making and policy development to ensure the conservation of valuable ecosystems and the sustainable utilization of land resources in the Tarim Basin.

3.3. The ESV Changes

We conducted an estimation of the total ESV for the Tarim Basin from 1980 to 2020 based on the ESV per unit area of different land use types and the total areas of these land use types in the study area. According to the data in Table 3, The results are presented in Table 4, the total ESV of the Tarim Basin increased from approximately USD 54,551.15 million in 1980 to USD 54,950.48 million in 2000. However, it then decreased to USD 53,302.94 million in 2020, indicating a fluctuating pattern over the entire study period. Specifically, there was a cumulative profit of ecosystem value of about USD 399.33 million in the first 20 years (1980–2000), followed by a cumulative loss of ecosystem value of about USD 1648.54 million in the second 20 years (2000–2020). Overall, there was a cumulative loss of ESV of approximately USD 1248.21 million over the entire 40-year period (1980–2020), indicating a decreasing trend in ESV. These findings highlight the changes in the economic value of ESs in the Tarim Basin over time. The initial period saw a net gain in ESV, possibly reflecting positive impacts from land use practices and management. However, in the subsequent years, there was a decline in ESV, suggesting potential negative consequences of land use changes, such as loss of biodiversity, degradation of ecosystems, or unsustainable land management practices.

Table 3. Description of BLS, CPS, and EPS.

Scenarios	Scenario Description
BLS	Without taking into account the restrictive effects or planning policies on *LUCCs*, simulates the future scenarios based on land use and land cover conversion patterns in the Tarim Basin from 2010 to 2020.
CPS	Probability of conversion of arable land to construction land reduced by 80–90%. Except for unused land, the other land types experienced a 40% reduction.
EPS	Taking into account the ecological, agricultural, urban, and other land use patterns, the probability of forest and grassland transitioning to built-up areas reduces by 50%, the likelihood of cropland shifting to built-up areas decreases by 30%, and the likelihood of cropland and grassland shifting to forested land increases by 30%.

Table 4. ESV*s* of Tarim Basin in 1980, 1990, 2000, 2010, and 2020 (10^6 USD).

Land Use Types	1980	1990	2000	2010	2020	1980–1990 (%)	1990–2000 (%)	2000–2010 (%)	2010–2020 (%)	1980–2020 (%)
Cultivated land	2609.58	2689.39	3084.34	3483.73	4096.86	3.06	14.69	12.95	14.97	56.99
Woodland	2307.49	2349.42	2479.79	2409.82	2369.69	1.82	5.55	−2.82	−1.69	2.70
Grassland	21,510.51	21,848.70	21,135.56	20,937.49	20,699.94	1.57	−3.26	−0.94	−1.15	−3.77
Water Body	14,944.57	14,926.63	14,405.71	14,306.49	13,431.58	−0.12	−3.49	−0.69	−6.51	−10.12
Construction land	2.10	2.47	2.26	2.63	3.65	17.74	−8.39	16.22	27.92	73.91
Unused land	6165.74	6113.78	6156.95	6148.38	6134.47	−0.84	0.71	−0.14	−0.23	−0.51
Wetland	7011.16	6970.77	7685.86	7390.19	6566.74	−0.58	10.26	−3.85	−12.54	−6.34
Total	54,551.15	54,901.16	54,950.48	54,678.73	53,302.94	0.64	0.09	−0.49	−2.58	−2.29

The volatility in ESV in the Tarim Basin can be largely attributed to changes in the areas of grassland, water bodies, and wetlands, which have substantial service value. Grassland, in particular, covers a large area and possesses high service value. The overall changes in ESV, driven primarily by the fluctuations in the areas of water bodies and wetlands, amounted to losses of USD 58.33 million, gains of USD 194.17 million, and losses of USD 2093.25 million during the periods of 1980–1990, 1990–2000, and 2000–2020, respectively.

Furthermore, the ESV of each land use type corresponded to the land use and land cover change trends observed from 1980 to 2020. While cultivated land, woodlands, and construction land belong to the types with increasing ESV, their contributions to the total ESV were smaller compared with grasslands (which had a large area and high coefficient value), water bodies, and wetlands (which had high coefficient values). Among the seven land use types, grassland, due to its substantial size and significant coefficient value, accounted for the highest ESV, representing approximately 39% of the total value. Water bodies, with their high service value, contributed significantly to ESV as well, comprising around 26.4% of the overall value. Wetlands, with the highest coefficient value, ranked as the third-highest contributor among the land use types, constituting approximately 13.1% of the total value. The combined ESVs of grassland, water bodies, and wetlands amounted to approximately 78.5% of the total value, underscoring the substantial roles these land use types play in the overall ESV of the Tarim Basin.

3.4. Impacts of Land Use Changes on Ecosystem Functions (EFs)

To assess the impact of EFs within the Tarim Basin over the past 41 years, we calculated the ESV provided by each individual EF (as shown in Table 5). The contribution rates of individual EFs to the total value of ESs were ranked based on their calculated ESVs in 1980, 1990, 2000, 2010, and 2020. The trend in the contribution rate of each ecosystem function to the total value of ESs is illustrated in Table 5 using symbols: an upward arrow "↑" signifies an increasing contribution, a downward arrow "↓" suggests a decreasing contribution, and a dash "-" indicates no significant change. The variations in the contribution of each ecosystem function to the total value of ESs were evident, while the rank order remained relatively consistent over time. The rank order of ecosystem functions based on their contribution rates to the total value of ESs is as follows, from high to low: water supply, waste treatment, climate regulation, biodiversity protection, recreation and culture, soil formation, gas regulation, food production, and raw material. The analysis of the composition of the ESFs reveals that water supply and waste treatment functions are the two predominant ecosystem functions with high service value, constituting a contribution rate of 45.4%. On the other hand, food production and raw material functions have lower service values, with a contribution rate of only about 4.67%. This study highlights the regulating service functions (referring to the natural processes and functions provided by ecosystems that help regulate and stabilize the environment) of the Tarim Basin ecosystem hold far greater value than the provision service functions (refer to the range of services provided by ecosystems that directly support and supply resources necessary for human life and well-being).

Table 5. Values of *ES* functions in 1980, 1990, 2000, 2010, and 2020 (10^6 USD).

	1980		1990		2000		2010		2020		Average	Rank	Tend
	ESV_f	%	ESV_f	%	ESV_f	%	ESV_f	%	ESV_f	%	%		
GR	3776.08	6.9	3828.36	6.97	3807.69	6.93	3791.53	6.93	3780.37	6.83	6.91	7	↓
CR	6183.62	11.3	6229.12	11.35	6397.35	11.64	6329.77	11.58	6371.67	11.51	11.48	4	↑
WS	12,033.07	26.9	12,069.59	21.98	11,977.93	21.80	11,859.13	21.69	12,064.44	21.80	22.83	1	↓
SF	5959.30	10.9	6039.60	11.00	6029.47	10.97	6056.70	11.08	6104.48	11.03	11.00	5	↑
WT	12,291.40	22.5	12,322.63	22.44	12,353.01	22.48	12,294.55	22.48	12,581.23	22.73	22.53	2	↑
BP	6946.67	12.7	6998.26	12.75	6958.21	12.66	6936.66	12.69	6950.12	12.56	12.67	3	↓
FP	1352.02	2.5	1375.54	2.51	1410.86	2.57	1458.79	2.67	1533.56	2.77	2.60	8	↑
RM	1135.02	2.1	1149.51	2.09	1148.97	2.09	1140.62	2.09	1132.67	2.05	2.08	9	↓
RC	4874.73	8.9	4889.30	8.91	4867.75	8.86	4811.75	8.80	4824.68	8.72	8.84	6	↓
Total	54,551.90	100.00	54,901.91	100.00	54,951.25	100.00	54,679.50	100.00	55,343.23	100.00	100.00		↓

3.5. ES Sensitivity Analysis

The results of the sensitivity analyses are presented in Table 6. The sensitivity index for all seven land types in the Tarim Basin was generally less than 1 and often close to 0. This indicates that the calculated total ESV in the Tarim Basin is relatively inelastic and not highly responsive to changes in the value coefficients. Among the land types, grassland, water bodies, and wetlands showed relatively larger sensitivity indices. This is primarily due to their large areas and high service value coefficients. Grassland had the highest sensitivity index, consistently above 0.497 during the 1980–2020 period. This means that a 1% increase in the ESV coefficient per unit area of grassland would result in a 0.497% increase in the total value of ESs in the Tarim Basin. Water bodies had the second-largest sensitivity index, with an average sensitivity index for grassland of 0.233. Wetlands ranked third in terms of sensitivity index, with an average sensitivity index for wetlands of 0.22. On the other hand, cultivated land, woodland, construction land, and unused land exhibited comparatively smaller sensitivity indices. This implies that the value coefficients of these land use types have little impact on the overall value of ESs in the Tarim Basin. In 2020, the sensitivity indices for cultivated land, woodland, grassland, water bodies, wetlands, and unused land were 0.052, 0.018, 0.497, 0.228, 0.163, and 0.04, respectively. When compared with 1980, the sensitivity indices for grassland and water bodies decreased, indicating a reduced influence of these land use categories on the ESV. Conversely, the influence of cultivated land and woodland increased during the same period. In conclusion, the impact of the ESV coefficient per unit area of water bodies and grassland on the total ESV in the Tarim Basin declined from 1980 to 2020. These findings highlight the changing dynamics of land use types and their effects on the ESV in the Tarim Basin over time.

Table 6. Percentage variation in total ESV and coefficient sensitivity.

Variation in Value Coefficient	**1980**		**1990**		**2000**		**2010**		**2020**	
	%	*CS*	%	*CS*	%	*CS*	%	*CS*	%	*CS*
Cultivated land value coefficient ±50%	1.51	0.030	1.75	0.035	1.8	0.04	2.22	0.04	2.62	0.052
Woodland value coefficient ±50%	0.62	0.012	0.71	0.014	0.78	0.017	0.88	0.018	0.94	0.018
Grassland value coefficient ±50%	27.90	0.544	26.74	0.530	26.27	0.520	25.10	0.50	24.86	0.497
Water body value coefficient ±50%	12.04	0.241	11.96	0.239	11.38	0.228	11.38	0.23	11.40	0.228
Construction land value coefficient ±50%	0.00	0.000	0.00	0.000	0.00	0.000	0.00	0.00	0.00	0.000
Unused land value coefficient ±50%	2.02	0.040	2.05	0.041	1.97	0.039	2.00	0.04	2.01	0.040
Wetland value coefficient ±50%	8.71	0.174	10.52	0.222	9.77	0.195	8.45	0.17	8.19	0.164

3.6. Geographic Detection of Spatial Differentiation of ESV

The distribution differences in ESV in the Tarim Basin are influenced by both natural and socioeconomic factors, as shown in Figure 5. Among these factors, the influence of each factor, from largest to smallest, is as follows: NPP > NDVI > precipitation > aspect > temperature > slope > soil erosion > GDP > LUI (Land Use Intensity) > Per capita GDP > population > human activity index.

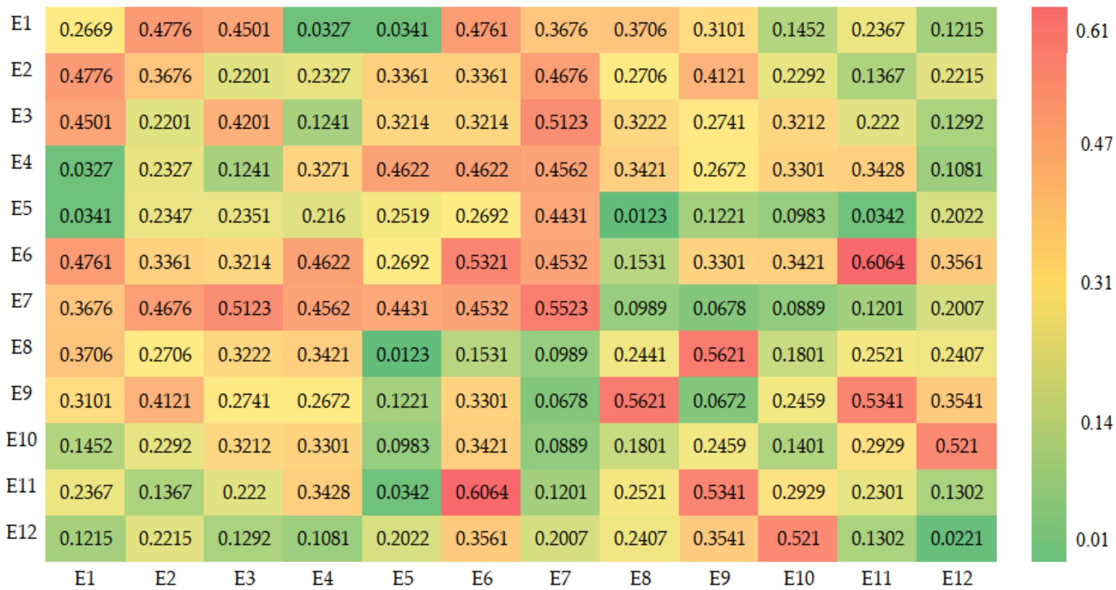

Figure 5. The results of single-element detection and two elements' interaction detection.

Among the twelve influencing factors, E7 (NPP) has the highest value of 0.5523, signifying the most substantial contribution to the spatial differentiation of ESV. Among the natural and socioeconomic factors, E7 (NPP), E6 (NDVI), and E3 (Precipitation) have the highest contribution rates, respectively. Figure 5 illustrates that the interaction between factors exerts a more pronounced influence than the independent effect of individual factors. This confirms that the spatial differentiation of ESV in the Tarim Basin arises from the combined effects of multiple driving factors. After performing interaction detection, the highest interaction value is observed between E6 and E11, with a value of 0.6064. This interaction effect is more than double the impact of a single factor. There are also cases where the degree of interaction reaches 0.4 or higher, including E1 and E6 (Q = 0.4761), E2 and E7 (Q = 0.4676), E3 and E7 (Q = 0.5123), E4 and E6 (Q = 0.4622), E5 and E7 (Q = 0.4431), E6 and E11 (Q = 0.6064), E8 and E9 (Q = 0.5621), E9 and E11 (Q = 0.5341), and E10 and E11 (Q = 0.5210). These findings highlight the complex interactions between natural and socioeconomic influences that shape the distribution of ESV in the Tarim Basin. Understanding these interactions is crucial for effective land management and policymaking to ensure the long-term provision of ESs in the region.

3.7. Trends in Future ESV Changes

The predicted values for ESV in 2030 under different scenarios are presented in Table 7. According to the predictions, under the BLS scenario, the ESV is projected to be 51,133.90 million dollars, while under the CPS scenario, it is expected to be 53,624.99 million dollars, and under the EPS scenario, it is estimated to be 54,561.26 million dollars. Compared with the ESV in 2020, these predictions indicate a decrease in ESV for all scenarios. Specifically, under the BLS scenario, the ESV is predicted to decrease by 4209.33 million dollars (−4.27%). Under the CPS scenario, the decrease is projected to be 1718.24 million dollars (−3.58%), and under the EPS scenario, the decrease is estimated to be 781.97 million dollars (−0.78%). Among the scenarios, the BLS scenario shows the highest loss of ESV for the Tarim Basin, while the EPS scenario demonstrates the least loss of ESV. Figure 6 illustrates that the expansion of construction land in cities such as Kashi, Hotan, Korla, Aksu, and Atux has significantly slowed down in both the BLS and CPS scenarios. In the BLS scenario, the increased construction land is primarily distributed in cultivated land, while in the CPS scenario, it is mainly observed in grassland. Under the EPS scenario, the increased construction land is predominantly found in woodlands and grasslands. These findings highlight the potential impacts of different scenarios on ESV and land use changes in the Tarim Basin.

Table 7. ESV under Different Scenario Simulations (10^6 USD).

	2020	2030 (*BLS*)	2030 (*CPS*)	2030 (*EPS*)
Total	55,343.23	51,133.90	53,624.99	54,561.26
difference	0	4209.33	1718.24	781.97

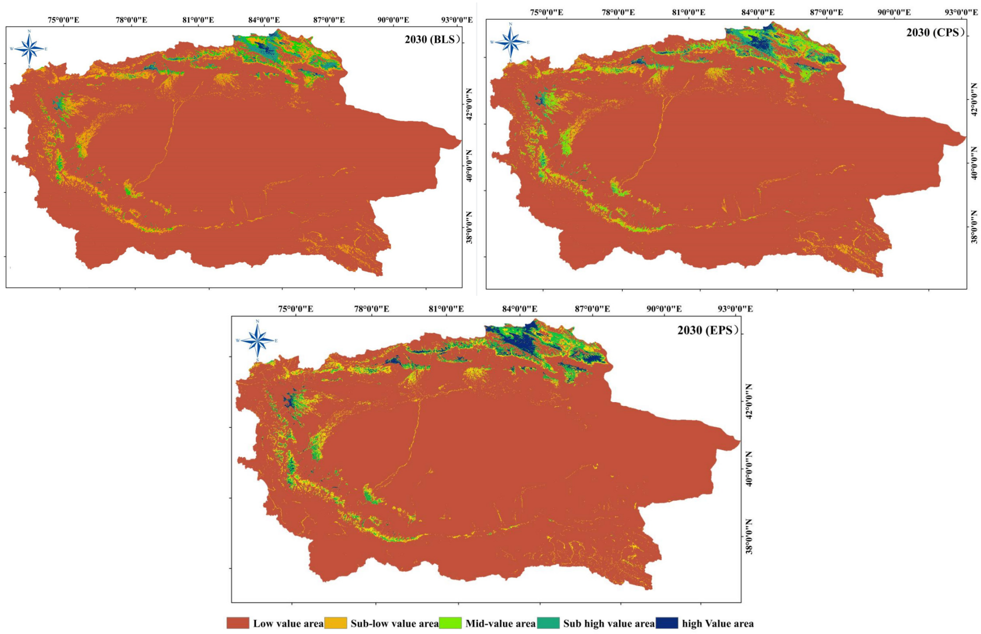

Figure 6. Land use and cover changes under the in BLS, CPS, and EPS scenarios.

4. Discussion

This study aims to analyze and quantify the spatial and temporal fluctuations of ESV in the Tarim Basin from 1980 to 2020 using LULC data. It also investigates the driving forces behind the divergence in ESV and provides predictions for changes in LULC and its associated ecological service value in 2030.

4.1. The LULC Effect to the ESV

Over the course of the study period, this study observed intricate dynamics in land use changes, with significant transformations occurring in the oasis irrigation areas that are characterized by concentrated human activities. These findings align with previous research conducted in arid regions [57]. One noteworthy transformation observed was the substantial conversion of grassland into unused land and cultivated land throughout the study period from 1980 to 2020. This conversion led to a significant decline of 14.39% in the ESV associated with grassland (Figure 7).

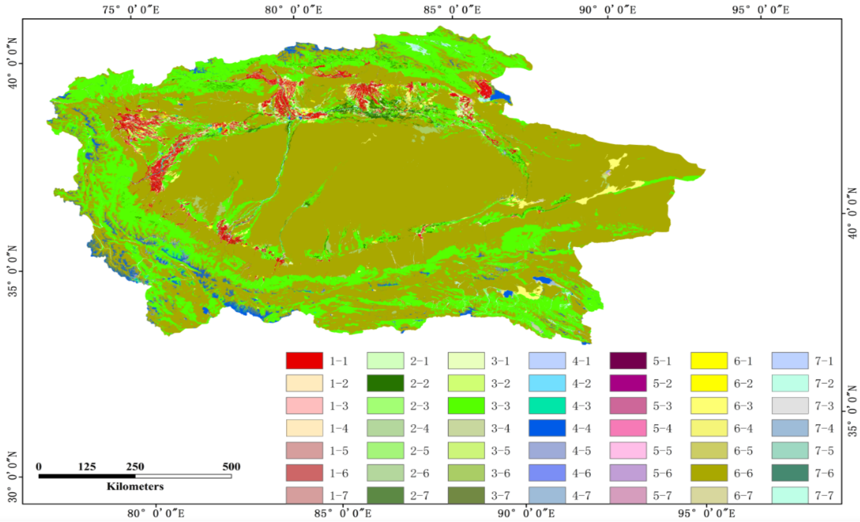

Figure 7. Land use transfer map of Tarim Basin in 1980–2020. Note: In this map, 1, 2, 3, 4, 5, 6, 7, and 8 denote cultivated land, woodland, grassland, water body, construction land, wetland, and unused land, respectively. The "1–2" denotes the land use change from cultivated land to woodland, and the same for other expressions.

From 1980 to 2020, the Tarim Basin experienced significant population growth and rapid economic development, leading to a surge in cultivated land and construction land expansion. This expansion, in turn, accelerated deforestation and the conversion of grasslands and wetlands into other land use types. As a result, the landscape structure underwent notable changes, leading to the degradation of ecosystem functions.

Throughout this period, the areas of different land use categories in the Tarim Basin exhibited continuous changes. Cultivated land, woodland, and construction land areas increased, while grasslands, water bodies, wetlands, and unused land decreased. This finding emphasizes that the reduction in grassland area has been the primary driver behind the decrease in ESV in the study area. Moreover, although water bodies occupy a relatively small portion of the study area, they still make a notable contribution to ESV and play an indispensable role in enhancing the regional ecosystem.

From Figure 7, it is evident that the ecological services in the central area of the suboasis region (including Korla City, Aksu City, Atux City, Kashi City, and Hotan City) have experienced a continuous decline. This decline can be attributed to urban planning and urbanization activities that occurred in the Tarim Basin from 1980 to 2020. Moreover, the ESV in the mountainous regions in the northwest of the Tarim Basin has experienced a relative decline, while the ESV in the desert areas in the southeast has shown a consistent increase. This increase is particularly prominent in areas where unused land has been converted to cultivated land. The higher value of cultivated land compared with unused land explains this change. However, it is important to note that the conversion of land use from grassland to cultivated land and from cultivated to construction land, which has a value coefficient close to zero, can harm the ESV of the Tarim Basin and cause ecological degradation.

This study's results indicate that the total ESV in the Tarim Basin experienced a decrease of −2.29% from 1980 to 2020, primarily due to a decline in grassland (−3.77%), water bodies (−10.12%), and wetland (−6.34%), as well as an increase in construction land (73.91%). The substantial expansion of construction land has had a detrimental effect on the ecology of the study area over the entire duration of the study. In conclusion, this study highlights the significant impact of land use and land cover changes on ESV, emphasizing the need for orderly and sustainable land resource management in the Tarim Basin. Priority should be given to the protection of land resources such as grasslands, water bodies, and wetlands to enhance ESs and ecological security. It is recommended to enhance land resource management in the study area in order to accomplish these objectives.

The analysis of ESF composition revealed that water supply and waste treatment were the top two EFs with high service value, contributing to approximately 45.4% of the total value. In contrast, food production and raw material functions had lower service value, contributing only about 4.67%. This study also found that the value of regulating service functions in the Tarim Basin ecosystem was significantly higher than that of provision service functions, indicating that the ESF of the Tarim Basin primarily falls under the regulating category.

Among the top-ranked nine EFs, the contribution rates of soil formation, waste treatment, food production, biodiversity protection, and raw material functions increased during the period of 1980–2020. Conversely, the contribution rates of gas regulation, climate regulation, water supply, and recreation and culture functions decreased over the same study period. Due to the predominance of regulating functions in the Tarim Basin's ES, the total ecological service value of the study area decreased with the reduction in regulating functions. This implies that the *ES* functions provided by the Tarim Basin primarily fall under the category of regulating functions.

4.2. Driving Factors Analysis of ESV

Understanding the driving mechanisms behind ESV in the Tarim Basin is crucial for effective ecological management and modeling, as it can shed light on the causes of ecological issues. Figures 5 and 8 demonstrate the primary factors that impact the spatial variation in ESVs in the Tarim Basin (with Q-values greater than 0.4) are NPP (E7), NDVI (E6), and precipitation (E3). These findings are consistent with previous studies: net primary productivity directly affects ESV by representing the status of plant growth. Precipitation (E3) provides energy and water for plant growth, and within a certain range, the higher the precipitation, the greater the ESV.

NDVI (E6): Reflecting the impact of urbanization and agricultural activities on ecology, these three factors mainly affect land use. Through this article, we can understand the changing characteristics and influencing mechanisms of the ESV in the study area. In the optimization and protection of the ecosystem, we should consider the characteristics of different factors and the interactive and synergistic enhancement effect of the two factors, adopt a differentiated multiregulatory strategy, and choose a method that is consistent with the regional natural environment, such as land use and development models that are suitable for conditions and socioeconomic development levels and avoid unreasonable or strong human interference and other factors that synergistically increase pressure on regional ecosystems [58].

Therefore, for future ecosystem optimization and protection, it is essential to consider the distinct characteristics of various factors and examine their interactions and synergistic effects. Adopting differentiated multiregulatory strategies and selecting methods that align with a study area's natural environment are recommended. Land use and development patterns should be appropriate for the level of economic and socioeconomic development, avoiding unreasonable or excessive anthropocentric disturbances and pressures on the ecosystem.

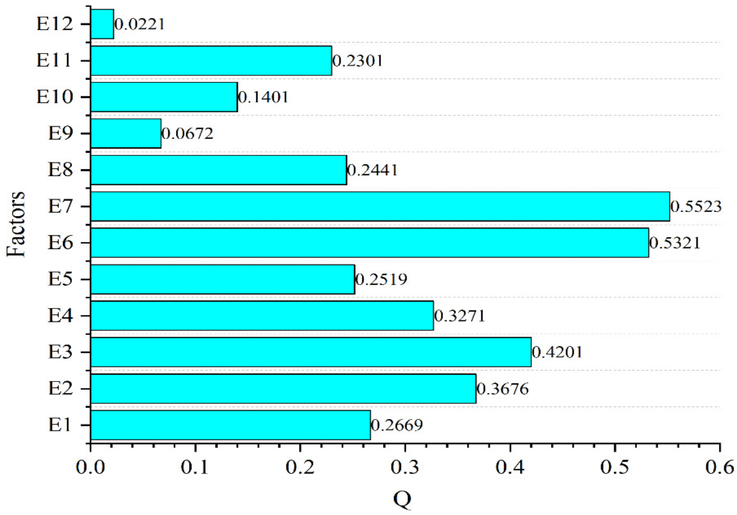

Figure 8. Contribution of ESV drivers in the Tarim Basin.

4.3. Policy Recommendations for Different Land Use Scenarios

Predicting future land use patterns under different development scenarios in the Tarim Basin is of great importance. Multiscenario simulations can provide valuable insights and recommendations for future land use management and planning (Figure 9). The land management authorities in the Tarim Basin should prioritize the preservation and security of cultivated land, wetlands, grasslands, and overall ecological safety. During the forthcoming spatial planning for land resources, it is crucial to analyze the influence of cultivated land changes and internal factors on ecological services. Based on this analysis, it becomes possible to scientifically designate ecological protection zones, basic cultivated land protection zones, and urban development zones, while effectively coordinating the relationship between these three zones. This approach ensures a balanced and harmonious utilization of land resources, taking into account human activities, socioeconomic development, and other relevant factors. The protection of cultivated land holds paramount importance as it serves as the foundation for food production. Therefore, it is imperative to implement strict measures for the preservation and safeguarding of cultivated land resources. By doing so, we can guarantee long-term sustainability development and environmental protection.

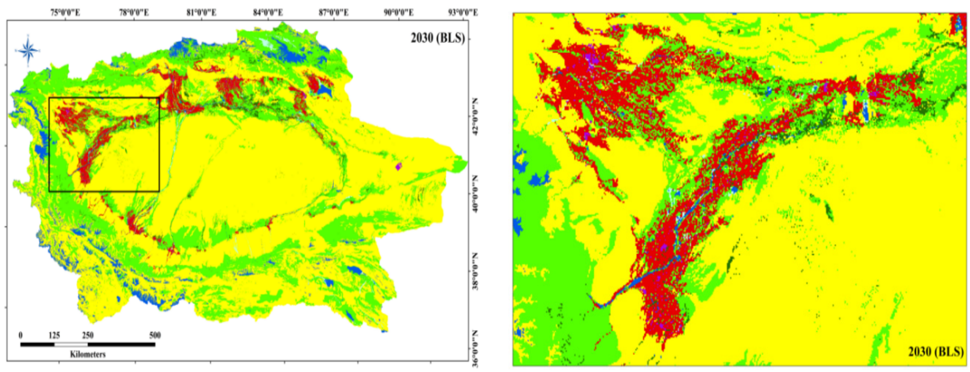

Figure 9. *Cont.*

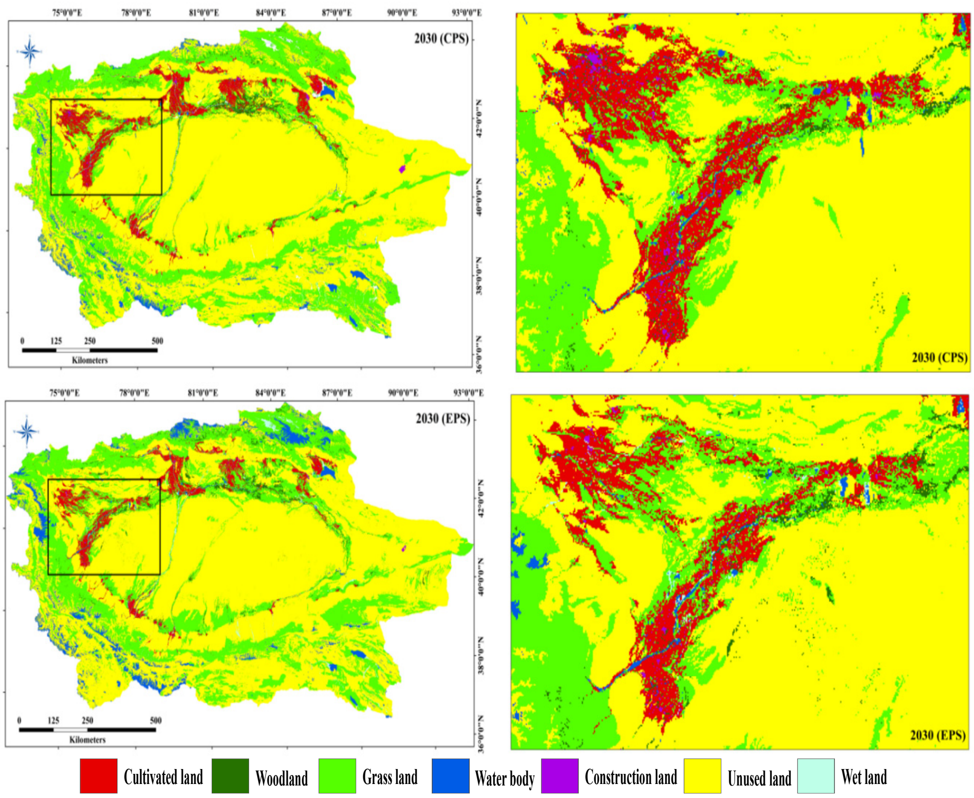

Figure 9. Spatial distribution of predicted ESV in the Tarim Basin region in 2030 under *BLS*, *CPS*, and *EPS*.

4.4. Research Limitations and Prospects

The main focus and innovation of this study lie in enhancing the comprehensiveness of ESV research through the coupling of land use models, causal analysis models, and the FLUS model. However, there are several limitations that need to be addressed.

Firstly, the measurement of ESV in the region relies on the benefits transfer method, which assesses the total amount of ESV but lacks reflection on the provision of ESs that are most urgently needed by the region and most representative of local characteristics.

Secondly, while geographic detectors have advantages in measuring spatial specificity, interpreting factors, and analyzing variables, there are limitations when exploring the complex causal chain between drivers.

Third, while the FLUS model exhibits high precision in simulating the evolution of different land use types under various scenarios, it can only simulate the future based on the changing rules of existing land use types. It fails to account for many future policy and environmental factors, thereby limiting its ability to capture the full complexity of land use dynamics.

Additionally, to address these shortcomings in future studies, several improvements can be made. Firstly, modeling predictions should be based on more accurate land use data, while also incorporating policy factors to enhance simulation accuracy. Secondly, future research should employ various ES measurement models to simulate and examine specific services, thereby shedding light on the driving mechanisms behind them. Lastly, different causal analysis models should be selected to better align with regional characteristics and the evolution of specific ESs.

By addressing these points, future studies can overcome these limitations and provide more robust and comprehensive insights into the dynamics of ESV and its driving factors.

5. Conclusions

This study examines the spatial and temporal changes, sensitivity, and driving mechanisms of ESV in the Tarim Basin from 1980 to 2020. Additionally, using the *FLUS* model, this research also simulates the ecological service value and its distribution characteristics in the Tarim Basin in Xinjiang for the year 2030. The key findings of this study can be summarized as follows:

The total ESV*s* of the Tarim Basin were about 54,551.15 million dollars, 54,901.16 million dollars, 54,950.48 million dollars, 54,678.73 million dollars, and 53,302.94 million dollars in the years 1980, 1990, 2000, 2010, and 2020, respectively. The net profit of ESV was about USD 399.33 million from 1980 to 2000, with a net loss of USD 1647.54 million from 2000 to 2020. During the 1980–2020 time period, grasslands produced about 38.96% of the total ESV, and water bodies produced about 26.43% of the total ESV, while wetlands produced about 13.07% of the total ESV. The sum ESV of water bodies, grasslands, and wetlands was about 78.5% of the total value, implying that these land use types play significant roles in the ES of the study area.

(1) The waste treatment and water supply functions were the top two ecological functions with high service value; and the contribution rate was 44.53%, whereas food production and raw material were the lowest ecological functions, with little service value; therefore, the ESF*s* of the Tarim Basin belong to the regulating service function. The rank order of ecosystem functions based on their contribution rates to the total value of *ES* was as follows, listed from highest to lowest: WS > WT > BP> CR > SF >RC > GR > FP > RM.

(2) The detection results of the spatial differentiation driving factors of ESV, sorted according to *Q* values, are as follows: NPP (E7) > NDVI (E6) > precipitation (E3) > aspect (E2) > temperature (E4) > slope (E1) > soil erosion (E5) > GDP (E8) > land use intensity (E11) > per capita GDP (E10) > population (E9) > human activity index (E12).

(3) The ESV*s* simulated in the three scenarios of BLS, CPS, and EPS in 2030 were 51,133.9 million dollars, 53,624.99 million dollars, and 54,561.26 million dollars. The ESVs of the three scenarios decreased in order compared with 2020: BLS (4209.33 million dollars), CPS (1718.24 million dollars), and EPS (−781.97 million dollars).

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