

Article

Heterogeneity of Ecosystem Service Interactions Through Scale Effects and Time Effects and Their Social-Ecological Determinants in the Tuo River Basin

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Abstract: Ecosystem services (ESs) assessment plays a significant role in managing ecological resources. Uncovering the complex interdependencies between ESs and their key drivers is an essential preliminary step toward the coordinated management of ESs. Currently, a major challenge lies in precisely evaluating trade-offs and synergies among ESs across different spatial and temporal scales, particularly in capturing their dynamic evolution and determinants. This study focuses on the Tuo River Basin in China, quantifying four key ESs, namely, habitat quality (HQ), nitrogen export (NE), soil conservation (SC), and water yield (WY), and assessing their interactions from 2000 to 2020 at both grid and county scales. Moreover, this study explored the social-ecological driving factors influencing these ESs. The results showed that (1) SC and WY in the region exhibited an increasing trend, HQ and NE declined, and ESs at the county scale showed a central collapse feature; (2) synergies between HQ–NE, HQ–WY, and SC–WY pairs generally increased, the relationships between NE–SC and NE–WY pairs showed slight fluctuations, and there was a decline in the synergies within the HQ–SC pair; and (3) the interplay of all drivers positively affected ESs, with land use/land cover being the most significant and GDP exerting a lower influence. ES assessment results exhibited distinctive characteristics at two scales. Based on these findings, management strategies that incorporate both scales and cross policy boundaries are proposed to effectively meet management objectives. These results can facilitate improved synergy between regional ecological protection and economic development.

Keywords: ecosystem services; scale effect; social–ecological driver; tradeoffs/synergies



Academic Editor: Alejandro Javier Rescia Perazzo

Received: 23 September 2024

Revised: 28 December 2024

Accepted: 2 January 2025

Published: 7 January 2025

Citation: He, S.; Xie, Y.; Zhang, J.; Luo, Y.; Wang, Q. Heterogeneity of Ecosystem Service Interactions Through Scale Effects and Time Effects and Their Social-Ecological Determinants in the Tuo River Basin. *Land* **2025**, *14*, 103.

<https://doi.org/10.3390/land14010103>

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1. Introduction

As the social economy progresses and the pace of urbanization rapidly increases, the use of ecological resources by humans is increasing. Concurrently, global warming, water shortages, and other environmental issues have become increasingly prevalent, placing the ecological environment under serious threat [1–3]. Nowadays, the contradiction between limited ecological resources and economic development has become one of the most pressing global challenges. Ecosystem services (ESs), which provide various benefits that humans derive, both directly and indirectly, from the structures, functions, and processes of ecosystems, play a significant role in addressing this challenge. ESs serve as a major link between social systems and natural ecosystems [4–6]. Optimizing the use of ESs can

foster synergy between ecological conservation and economic growth. However, nearly 60% of global ESs are continuously deteriorating and weakening through land degradation and biodiversity loss [7], mainly caused by deforestation, urban expansion, and industrial development. The management of ESs is a substantial determinant of the status of these services, significantly influenced by a confluence of intrinsic characteristics and extrinsic environmental factors. Therefore, grasping the interactions between ESs and their social–ecological driving factors is a prerequisite for enhancing the scientific management of ESs to achieve the most beneficial use of ESs [8–11].

Understanding and exploring the interrelationships among ESs is fundamental to their effective management. These relationships, however, are inherently complex, influenced by various factors including the diversity and spatio-temporal heterogeneity of ESs, environmental changes, and policy interventions [12]. These relationships are primarily expressed as trade-offs and synergies [13]. Trade-offs occur when increasing one ES leads to a decrease in another, showing competition, whereas synergies happen when multiple ESs improve together, showing cooperation [14]. Synergistic relationships are usually considered positive, indicating a relatively balanced and healthy state with higher overall benefits from the ES [15,16]. Correlation analysis currently stands as a prevalent method for quantifying the general trade-offs and synergies among ESs [17,18]. Geographically weighted regression (GWR), which accounts for the local effects of spatial entities, is commonly used to capture the spatially explicit dynamics of interactions among ESs [19]. Numerous studies have focused on analyzing these interactions. Li et al. investigated the interrelationships between ESs in the Yinchuan Basin from 1993 to 2014 for land use planning [20]. Shao et al. assessed the trade-offs and synergies between ESs and their driving mechanisms in the Yellow River Basin [21]. Unfortunately, these prior studies have been constrained to a single spatial scale [22,23]. They cannot elucidate the complexity of the interactions between ESs, because they change their direction and strength with the joint changes in different temporal and spatial scales [24].

The Tuo River Basin (TRB) acts as a significant ecological buffer in the Yangtze River and connects the most important economic core cities—Chengdu City and Chongqing City within the Chengdu–Chongqing Urban Agglomeration, regarded as the fourth pillar of economic development in China. The region is prominent for advancing high-level ecological conservation and high-quality economic growth in the upper reaches of the Yangtze River. However, it faces significant challenges, including an exceptionally high environmental load and a significant deficit of ecological resources [25]. Its per capita water resources are only one quarter of the average in the Yangtze River basin. Despite having only 3.5% of Sichuan Province’s water resources, the region supports approximately a quarter of the population and contributes a third of the GDP [26]. Furthermore, it is afflicted with a considerable degree of pollution, largely attributable to the application of manure, pesticides, and fertilizers [27]. Although it has introduced a variety of environmental protection measures, the implementation among counties is not sufficiently coordinated. ESs have significant differences in different counties, and the relationship between ESs here is very complex. In 2020, the Chengdu–Chongqing Twin Cities Economic Circle Strategy rose to the National Strategy, and the development of TRB was on a new upswing; however, the discrepancy between ecological conservation and economic growth is growing more pronounced.

This study considers the research background and addresses the distinctive topographical features and critical ecological challenges of the TRB. It conducted a dynamic evaluation of four representative ESs over the period from 2000 to 2020. Furthermore, it systematically analyzed the spatial heterogeneity of social–ecological driving factors influencing the distribution of ESs, comparing their driving intensities across grid and county

scales. The primary research objectives are as follows: (1) to reveal the shifts in ESs within the TRB and the trade-offs/synergies among them; (2) to identify the principal drivers of spatio-temporal heterogeneity of ESs; (3) to evaluate the effects of different counties' policies on ESs; and (4) to provide reference suggestions for regional management policies and enhance synergies among ESs to achieve the most beneficial use of ESs. This study contributes to promoting high-level ecological conservation and high-quality economic growth in the Upper Yangtze River Economic Zone, while also providing insights for managing other watersheds.

2. Materials and Methods

2.1. Study Area

The Tuo River, located in the east-central Sichuan Province of China, has its source in Qingping Town, Mianzhu City. It flows in southeast for about 638 km through an area of approximately 32,900 km². The geographical coordinates of the area are 103°38'~105°50' E and 27°50'~31°41' N. The river flows through seven large and medium-sized cities, including Deyang, Chengdu, Ziyang, Meishan, Neijiang, Zigong, and Luzhou City. In accordance with the Overall Program in TRB [28] and based on the principle that the watershed area exceeds 70% of the total administrative area, 27 counties from seven large and medium-sized cities were selected for this study (Figure 1).

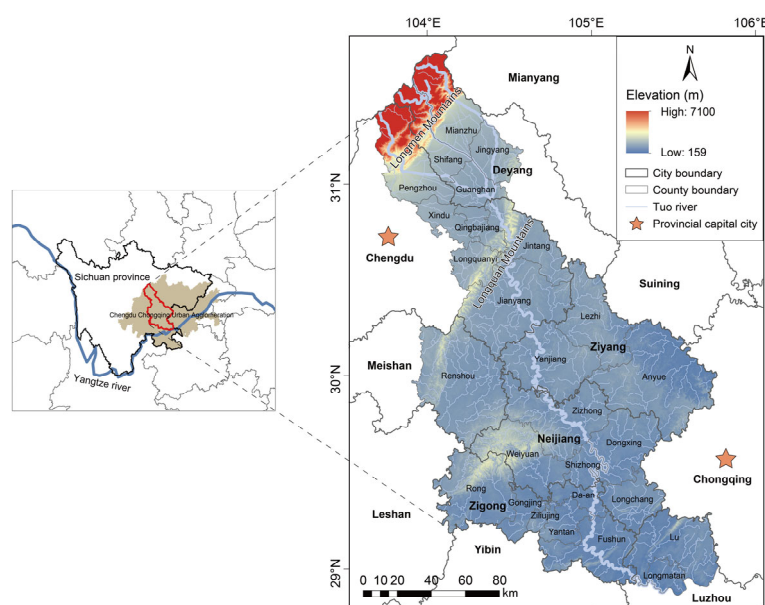


Figure 1. Study area.

The region features a well-developed hydrological network, with the upper reaches connected to the neighboring Min River system, while the middle and lower reaches exhibit a symmetrical dendritic pattern of tributaries and the main watercourse, reflecting a well-organized fluvial system. The terrain is diverse and complex, transitioning from mountainous regions in the northwest to plains and hilly landscapes in the southeast, with significant variations in topographic relief. The region is also home to several mountain ranges, including the Minshan Mountains, Longmen Mountains, and Longquan Mountains. The region's vegetation is predominantly subtropical evergreen broad-leaved forests, though the forest cover is relatively low at 6.1%. The regional climate transitions from a plateau monsoon type in the northern areas to a subtropical monsoon climate in the south. Precipitation within the region averages 1010 mm annually, with a gradual increase from the northern to the southern parts.

In 2020, the TRB had a total population of 21,008,900, of whom 18,686,600 are residents. It is an important industrial agglomeration and agricultural products security base. The GDP was 1.11 trillion CNY, with primary production accounting for only 11.85% and tertiary industries accounting for 46.74% [26]. However, it faces significant environmental challenges, and the ostensible discrepancy between ecological preservation and economic advancement necessitates our attention.

2.2. Data Sources and Processing

This study employed a multi-source dataset to assess the spatial distribution of ESs (Table 1), and all raster datasets, which varied in their original spatial resolutions, were uniformly resampled to a standard resolution of 30 m × 30 m. The land use/land cover (LULC) data were stratified into six distinct thematic classes: crop land, forest, grassland, water body, barren land, and built-up area. Furthermore, the spatial analysis in this study utilized the WGS_1984_UTM_Zone_48N projection coordinate system for all data to ensure consistency and accuracy in the evaluation.

Table 1. Summary of the primary data.

Category	Data	Year	Spatial Resolution	Data Source
Basic data	Administrative boundary	2020	-	National Earth System Science Data Center (http://www.geodata.cn , accessed on 27 February 2024)
Hydrological data	Water data	2017	-	National Platform for Common GeoSpatial Information Services (https://www.tianditu.gov.cn/ , accessed on 27 February 2024)
Land dataset	Land use/land cover	2000, 2010, 2020	30 m	Annual China Land Cover Dataset from Wuhan University [29]
Road data	Road	2000, 2010, 2020	-	National Earth System Science Data Center (http://www.geodata.cn , accessed on 1 March 2024)
Topographic data	Digital elevation model	2020	30 m	Geospatial Data Cloud (https://www.gscloud.cn/ , accessed on 27 February 2024)
Soil characteristics	China Soil Database	1995	1 km	National Tibetan Plateau Data Center. (https://data.tpdc.ac.cn/ , accessed on 26 March 2024)
Climate data	Annual average temperature	2000, 2010, 2020	1 km	National Tibetan Plateau Data Center. (https://data.tpdc.ac.cn/ , accessed on 26 March 2024)
	Annual average precipitation			
	Annual average potential evapotranspiration			
	Annual sunshine hours	2000, 2010, 2020	1 km	Resource and Environmental Science Data Platform
Socio-economic data	GDP	2000, 2010, 2020	1 km	(https://www.resdc.cn/ , accessed on 8 June 2024)
	Population density	2000, 2010, 2020	1 km	Oak Ridge National Laboratory (https://landscan.ornl.gov/ , accessed on 8 June 2024)

2.3. Method

2.3.1. ESs Assessment

In this study, the criteria for the ESs were primarily informed by three key considerations: (1) alignment with the Millennium Ecosystem Assessment and previous studies [30,31]; (2) representativeness of ESs with watershed characteristics and concern for ecological protection and economic development conditions of the region [25]; (3) availability and practicality of data. We selected four typical ESs, namely, habitat quality (HQ), nitrogen export (NE), soil conservation (SC), and water yield (WY). Among them, HQ (Tables A1 and A2) is used to assess the suitability of the living environment [32], and it can visually encapsulate the ecological environment's present condition. NE (Table A3) is indicative of regional water quality [33], and lower NE indicates a stronger water purification capacity and a higher quality of water environment [34]. It is significantly influenced by pollutant emissions and the use of fertilizers and pesticides, which can reflect the current situation of agriculture and industry. SC (Table A4) plays a significant role in maintaining a healthy agricultural ecosystem [35] and is associated with regional vegetation cover. WY (Table A5) is an important indicator of ecological water use and can be used for irrigation supply [36]. It is also associated with man-made land surface and vegetation. ESs were initially quantified at the grid scale for the years 2000, 2010, and 2020. Subsequently, the mean values of these services were aggregated to the county scale using the Zonal Statistics toolbox within the ArcGIS 10.5 platform. All the ESs were calculated using the InVEST 3.14.0 model, and detailed ES assessment parameter settings are presented in Appendix A Tables A1–A5.

2.3.2. Quantification of Trade-Offs/Synergies Among ESs

Correlation analysis is a key tool for quantifying the intricate dynamics between ESs [37]. Negative correlations between ESs often signify trade-offs, whereas positive correlations suggest synergistic relationships. We employed Pearson correlation analysis at two scales across three key years, namely, 2000, 2010, and 2020, using the “corrplot” package in R 4.4.0 software [38].

Beyond the insights gleaned from correlation analysis regarding the general trade-offs and synergies, we deployed the GWR model to delve into the spatial heterogeneity within these interactions. The concurrent influence of a single driving factor on various ESs is a key determinant of the trade-offs or synergies observed among them. Accordingly, the spatial variability among the driving factors leads to a corresponding spatial variability in the trade-offs and synergies of these services [39]. The GWR model adapts the conventional regression framework to test for spatial non-stationarity [10]. In the model configuration, we strategically employed ES variables exclusively as either independent variables or dependent variables, thereby avoiding potential multicollinearity issues among the explanatory factors. This study used the ‘GW model’ package [40] within the R 4.4.0 software environment to perform the GWR analyses at both grid and county scales for the years 2000, 2010, and 2020. The GWR model's calculation formula is as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^p \beta_k(u_i, v_i) x_{jk} + \varepsilon_i \quad (1)$$

In Equation (1), y_i is the ES at position i . p indicates the total count of independent variables considered in the model. x_{jk} refers to the remaining ESs at position i . (u_i, v_i) signifies the geographic coordinates of the sampling point i . $\beta_0(u_i, v_i)$ is the local intercept term. $\beta_k(u_i, v_i)$ corresponds to the regression coefficient associated with each independent variable. ε_i represents the error term.

2.3.3. Critical Driver Analysis of ESs

To delve into the influence of driving factors on the spatial distribution of ESs, we employed GeoDetector (GD) analysis to assess the relative importance of potential social–ecological determinants. Our selection of indicators was guided by the following criteria: (1) based on previous research [38,41]; (2) considers the current ecological and economic conditions of the area; and (3) the widespread use and interpretability of the indicators for both researchers and planners [42]. Consequently, we identified eight representative driving factors as variables: LULC, GDP, population density (PD), precipitation (PRE), temperature (TEM), evapotranspiration (EVP), sunlight (SUN), and the digital elevation model (DEM). ESs were used as dependent variables, and the ‘GD’ package in R 4.4.0 software was utilized for the geographical detector analysis.

The GD is an analytical instrument specifically designed to identify spatial heterogeneity and to expose the key factors that drive it. The fundamental postulate of this approach is that there should be a congruence in the spatial distributions of an independent variable and a dependent variable if the former significantly influences the latter [43]. The factor detector component of the GD employs the q value to gauge the degree to which a specific driving factor accounts for the spatial heterogeneity of ESs. This is achieved by comparing the variance in the factor within a localized subregion against its variance when considered over the entire region, thereby quantifying the factor’s influence on the spatial heterogeneity of ESs [44]. The calculation formula is as follows:

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

In Equation (2), the q value quantifies the explanatory power of driving factors, where q ranges from 0 to 1. An increased q value signifies a greater impact of the factor. L refers to the total count of administrative units within the study area. h signifies the stratum of the driving factor. N is the total number of sample units, and N_h represents the size of layer h . Similarly, σ^2 is the total variance in the region, while σ_h^2 represents the variance in layer h .

3. Results

3.1. Spatio-Temporal Variations of LULC

LULC types in this region include crop land, forest, grassland, water body, barren land, and built-up area (Figure 2). Cropland is the predominant LULC type, covering approximately 80% of the region, while barren land has the smallest area, primarily found in the high-altitude northern regions. In the northern mountainous regions and the southwestern hilly areas, forests and grasslands are predominantly found, with notable concentrations in the Longmen and Longquan Mountains. The main water body is the Tuo River, which traverses the area from north to south. Built-up areas are primarily located along the Tuo River, with a significant concentration observed in the northern region near Chengdu City (Figure 2).

Regarding LULC changes, the TRB has experienced shifts in various LULC types. The area of crop land demonstrated a decreasing trend; conversely, other LULC types, especially the built-up area, experienced a rise (Figure 2). Between the years 2000 and 2020 the built-up area notably expanded by 757.99 km², almost tripling in size and mainly replacing crop land. There was significant conversion between forest and crop land, and then more crop land was converted to forest in the period from 2010–2020. The total forest area increased by 564.53 km², representing a growth of 20.67%. While the total crop land area decreased by 1364.09 km², the overall reduction was 4.33%. The reduction in crop land was more pronounced in the north than in the south. Other LULC types exhibited relatively minor fluctuations. Overall, the TRB showed more significant changes in the latter decade compared to the former decade (Figure A1).

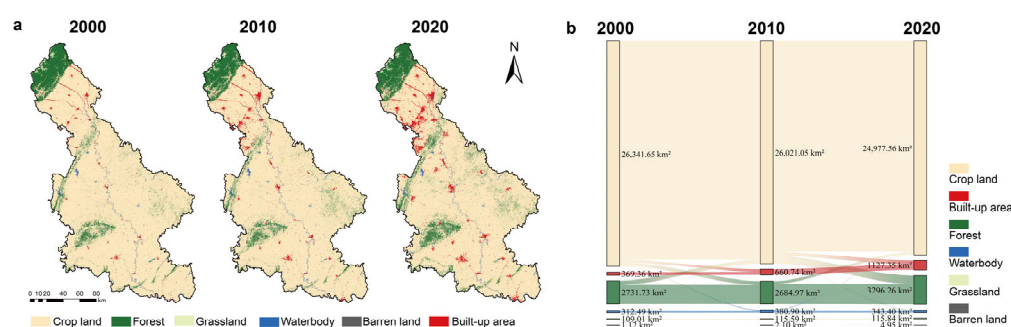


Figure 2. Land use/land cover in the TRB: (a) Land use/land cover in 2000, 2010, and 2020; (b) Land use/land cover conversion from 2000 to 2020.

3.2. Spatio-Temporal Variations in ESs

The findings revealed that ESs within the TRB exhibited spatio-temporal heterogeneity, yet their spatial configurations were relatively consistent over time (Figure 3). Regions with high ES provision were chiefly located in the northern mountainous areas and the southwestern hilly regions, which are characterized by high vegetation cover dominated by forest and grassland. HQ and SC values were generally high, while the low NE values indicated better water purification capacity in these regions. However, WY values were very low. HQ and NE showed notably lower values in specific northern and central areas subjected to significant human disturbance. Additionally, at the county level, there was an observable trend of declining ESs from the peripheral counties toward the central counties (Figure 3).

From 2000 to 2020, the ESs in the TRB showed an improving trend. There was a significant surge in SC and WY, with the most substantial increase occurring in SC, where the average value rose from 3870.07 t/km² to 5286.49 t/km², representing a growth of 36.59%. At the same time, the growth of WY was 27.38%, with the average value increasing from 710.90 mm to 905.53 mm. Additionally, the water purification capacity also increased, with the average NE value decreasing from 625.06 kg/km² to 597.95 kg/km². However, this could also be a temporary effect of rainy years. From 2000 to 2020, the annual average precipitation in the region increased, meaning that the NE decrease might be an effect of dilution, as more water usually also means clearer water. There was a slight decrease in HQ, with the average value decreasing from 0.3739 to 0.3558. Spatially, the changes in ESs in the TRB were found to be relatively consistent across both spatial scales examined (Figure 4). At the grid scale, all ESs exhibited significant changes in areas characterized by forest and grassland, such as the northern Longmen Mountains, Longquan Mountains, and southwestern hilly regions. In the regions dominated by built-up areas, particularly in the north and central parts, there was a notable decrease in the values of HQ, NE, and WY. Additionally, HQ values showed a linear decrease in some central areas where road

networks are concentrated. At the county scale, the reduction in ESs was more pronounced in the northern counties, particularly those in close proximity to the city of Chengdu, such as Xindu County, Longquanyi County, and Pengzhou County (Figure 4). Furthermore, the HQ of Jianyang County also showed a considerable reduction from 2010 to 2020 in comparison to the preceding decade. Conversely, the HQ and water purification capacity of several counties in Zigong City have demonstrated an upward trajectory. Moreover, the overall NE values increased in the downstream counties, while a decrease was observed in the northern counties. In general, the ESs in the TRB demonstrated an upward trajectory over the past two decades (Figure 4). However, there was a notable decline in the ESs from 2010 to 2020, particularly in the northern region.

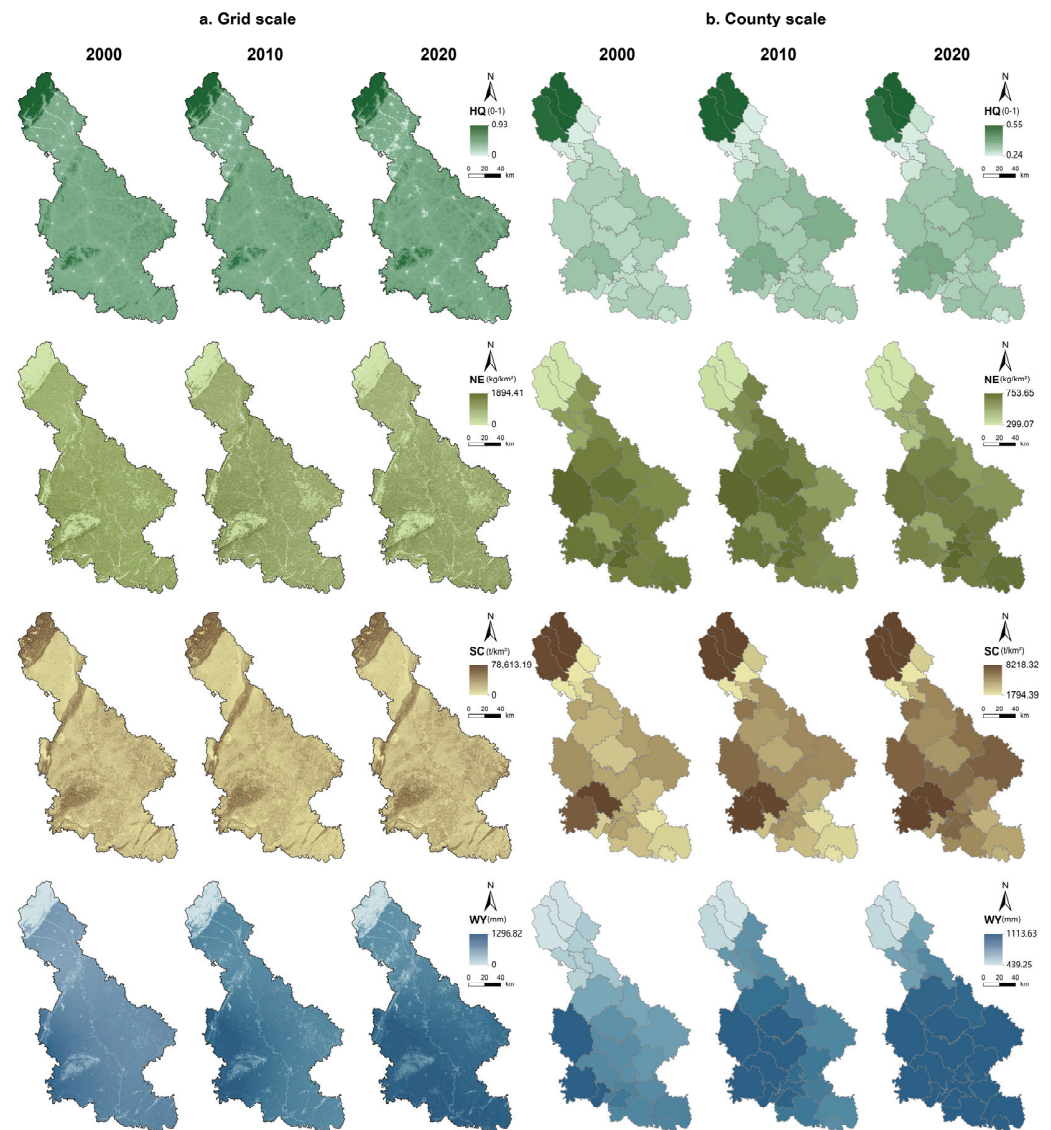


Figure 3. The spatio-temporal distribution of ESs at different scales in 2000, 2010, and 2020: (a) at the grid scale; (b) at the county scale.

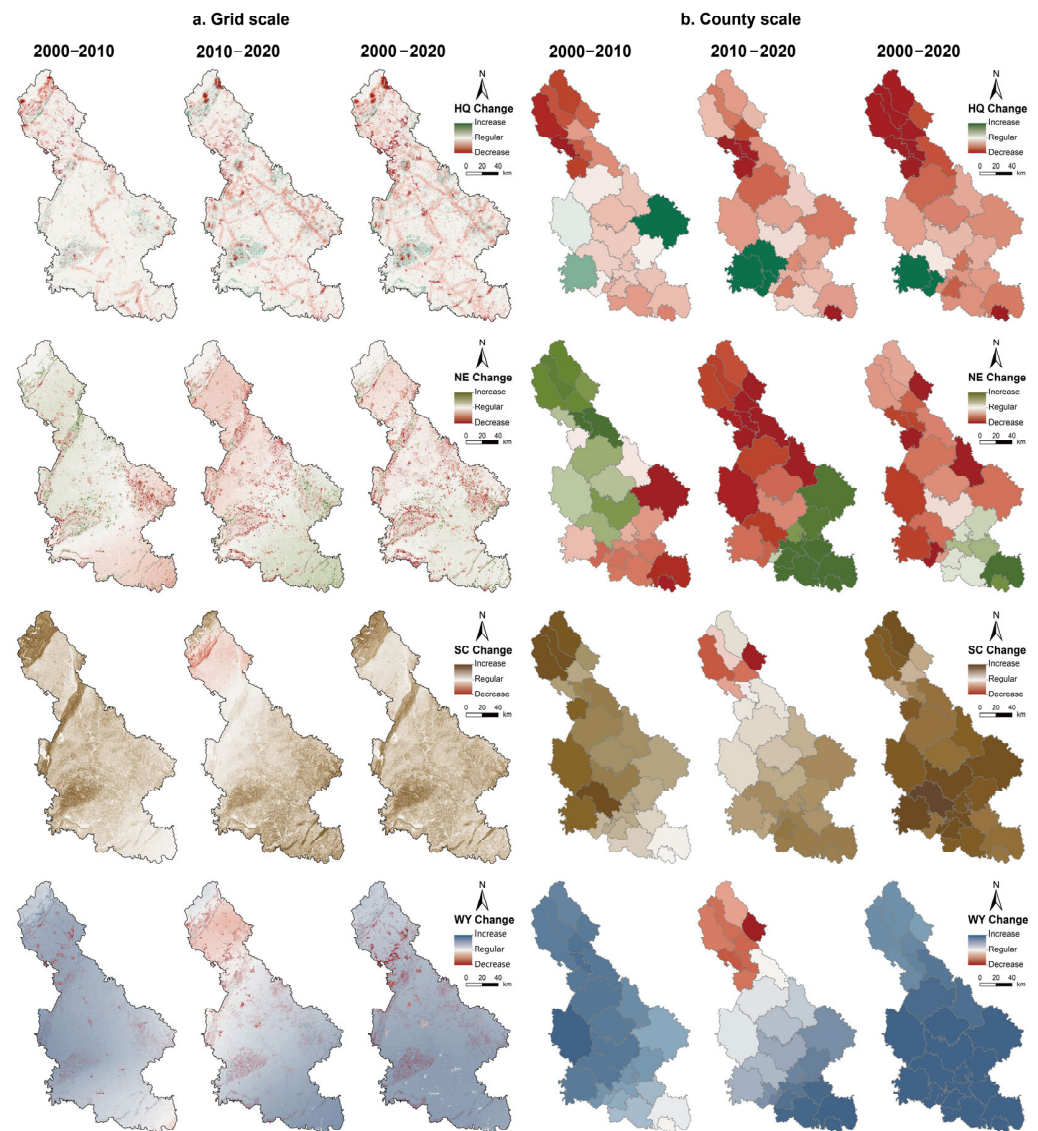


Figure 4. The variability in ESs at different scales from 2000 to 2020: (a) at the grid scale; (b) at the county scale.

3.3. Trade-Offs/Synergies Between ESs

3.3.1. Correlation Analysis

Overall, ES pairs generally exhibited statistically significant correlations (Figure 5). At the grid scale, a total of six correlations showed significant indices with p -values less than 0.05. At the county scale, most ES pairs had p -values less than 0.05. In general, a significant proportion of the ES pairs successfully met the criteria of the significance test.

Consistent correlations were observed across the two spatial scales throughout the 20-year period. It was determined that only the HQ–SC and NE–WY pairs exhibited a positive correlation, whereas the other four ES pairs were negatively correlated. It may be posited that a high-quality ecological environment is enhanced by healthy vegetation and soil structure, where plant roots effectively fix soil and reduce erosion. However, the observed synergistic relationship between NE and WY may be attributed to the increased water production accompanied by surface runoff, which brings out more nitrogen fertilizer.

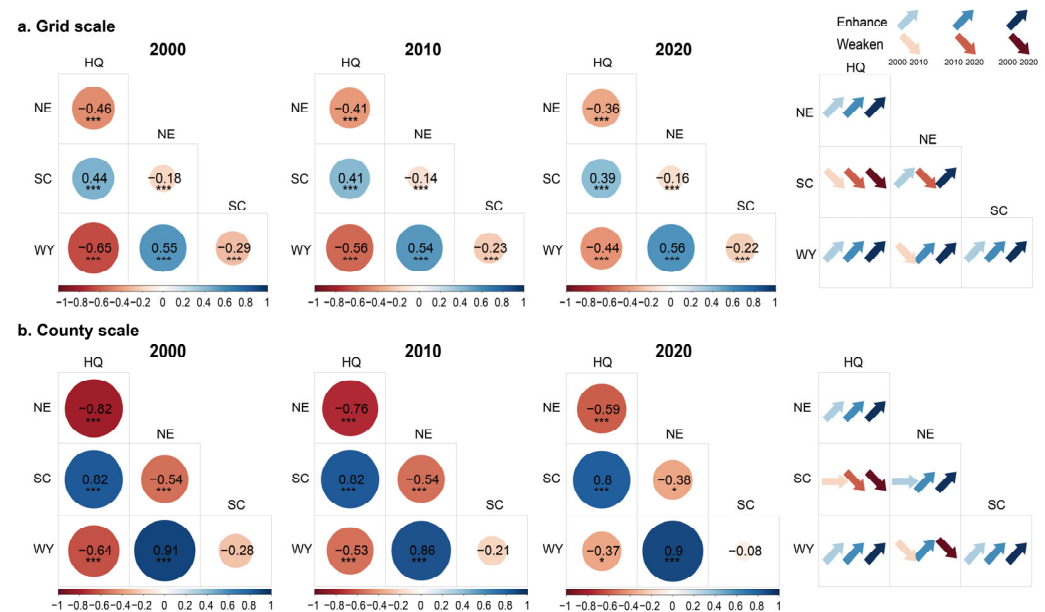


Figure 5. Correlations among ES pairs and correlation changes at both scales: (a) grid scale from 2000 to 2020; (b) county scale from 2000 to 2020. (* means $p < 0.1$; *** means $p < 0.01$).

Between 2000 and 2020, most ES pairs exhibited a rising trend in synergy, but the synergy of the SC–HQ pair, which was originally synergistic, decreased. At the grid scale, the increase in synergy was more moderate. The largest decrease in the trade-off relationship was observed in the HQ–WY pair, with a decrease of 32%, and the smallest decrease was seen in the NE–SC pair, with a decrease of only 11%. At the county scale, the SC–WY pair exhibited the greatest decline in the trade-off relationship, with a decrease of 71%. Even the smallest drop in the HQ–NE pair represented a decrease of 28%. Notably, the increase in synergies became particularly evident when comparing the period from 2010 to 2020 with the period from 2000 to 2010.

3.3.2. Spatio-Temporal Patterns of Trade-Offs/Synergies Between ES Pairs

The GWR disclosed that the spatial dynamics of trade-offs and synergies among ES pairs demonstrated variability across spatial scales (Figure 6). The spatial relationships for the majority of ES pairs were consistent between the two scales, except for the NE–SC and SC–WY pairs, exhibiting distinct patterns of spatial interactions.

At the grid scale, the spatial synergy was more pronounced than the spatial trade-off for HQ–SC, NE–SC, and NE–WY pairs. The NE–WY pair exhibited the greatest spatial synergy proportion, approaching 100%. At the same time, the average spatial synergy proportions of the HQ–SC and NE–SC pairs were 62.58% and 68.02%, respectively. Conversely, the HQ–NE, HQ–WY, and SC–WY pairs had lower spatial synergy ratios than spatial trade-off proportions, with average spatial synergy ratios of 33.23%, 24.20%, and 34.13%, exhibiting spatial trade-off characteristics. Contrasting with the findings observed at the grid scale, ES pairs including HQ–SC, NE–WY, and SC–WY predominantly showed spatial synergies, except for the SC–WY pair, while the spatial synergy ratios of the other two ES pairs approached 100%. In contrast, the HQ–NE, HQ–WY, and NE–WY pairs exhibited characteristics of spatial trade-offs, with average spatial synergy ratios amounting to 12.69%, 42.21%, and 18.45%, respectively. From 2000 to 2020, the majority of ES pairs exhibited an overall increasing trend in synergy areas at both scales.

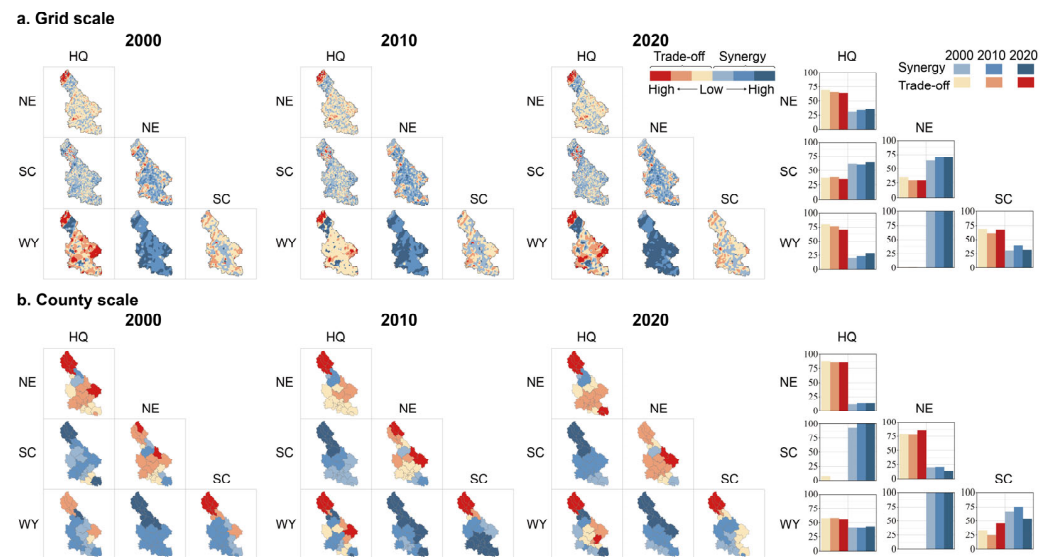


Figure 6. Spatial trade-offs/synergies for ES pairs and changes based on GWR at both scales: (a) grid scale from 2000 to 2020; (b) county scale from 2000 to 2020.

Spatially, there were high spatial synergies (e.g., HQ–SC, NE–WY) and high spatial trade-offs (e.g., HQ–NE, HQ–WY) in the northern Longquan Mountains, the Longmen Mountains, and the southwestern hilly regions characterized by a particularly high level of vegetation cover. Conversely, the northern areas, marked by significant built-up areas and high anthropogenic interference, exhibited high spatial synergies (e.g., HQ–NE, HQ–WY). At the county scale, high spatial trade-offs (e.g., HQ–NE, SC–WY) and high spatial synergies (e.g., HQ–SC, NE–WY) were more prevalent in the upstream counties, particularly in Chengdu and Deyang City.

3.4. Drivers of ESs

All eight selected driving factors exerted a significant impact on ESs in the TRB, with all p -values < 0.01 for each factor.

The single-factor detector results (Figure 7) indicated that the driving factors had a larger influence on HQ and WY, with an explanatory power of more than 40%, except for the GDP, and a relatively small effect on NE and SC, with an explanatory power of less than 20%, except for the LULC. Overall, the LULC exerted the most significant influence on ESs, whereas GDP had the least impact. The LULC was the main driving factor for all ESs, demonstrating its most substantial explanatory power on HQ, with average q -values of 0.76. DEM was the second driver for all ESs except WY. TEM and SUN were identified as the primary drivers of HQ, each exhibiting average q -values of 0.56 and 0.51, respectively. Additionally, PRE exerts a direct influence on WY. The average q -value was 0.53 for WY, ranked the second highest. In addition, PD ranked in the middle in terms of explanatory power for all ESs. However, the role of GDP was relatively minor, with an explanatory power of less than 10%.

According to the interaction detector results (Figure 8), the interaction between driving factors generally exhibited an enhancement effect, primarily as a two-factor enhancement. This indicates that factor interactions are crucial for understanding the spatial variance in ESs within the study area. The interplay between LULC and other variables, particularly ecological factors, was substantial. For HQ, the combined explanatory power derived from the interaction of the LULC with other factors is above 80%. Furthermore, the interaction influences of the LULC and PRE were particularly prominent for WY, with an explanatory power of around 90%.

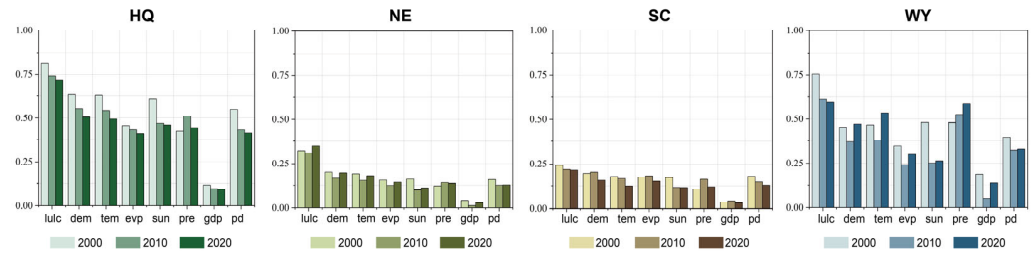


Figure 7. Single-factor explanatory power histogram.

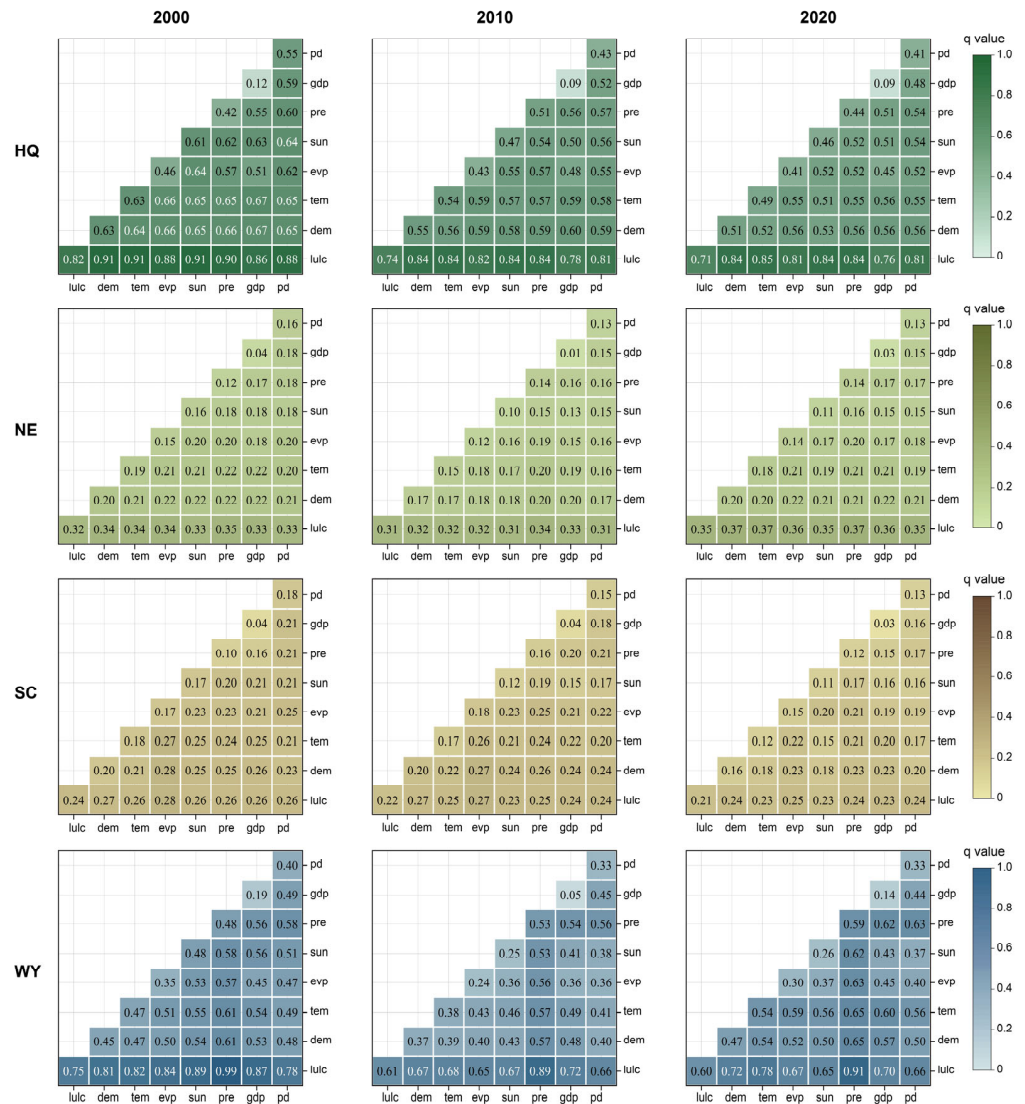


Figure 8. Interaction heat map.

Despite some annual variations, the stability of the driving factors remained largely unchanged, with no significant changes in the ranking based on q -values. In general, the explanatory power of all driving factors tended to decrease over time, with the exception of the PRE factor.

4. Discussion

4.1. Characteristics of ESs

The ESs exhibited spatio-temporal heterogeneity, with the four ESs displaying analogous spatial distribution patterns. This finding aligns with the outcomes of preceding

studies [45,46]. Regions with superior ESs were predominantly situated in mountainous and hilly areas, which have a richer ecological environment and stronger soil retention capacity, minimal pollution in the water environment, and reduced surface runoff resulting from the robust water storage capacity of plants. However, it is also important to note that these regions, despite their high SC values, are also at a higher risk of soil erosion, particularly in sloped areas [47]. This highlights the complex interplay between soil conservation and erosion dynamics in these areas. In contrast, areas with lower ESs were mainly found in places of high anthropogenic interference, which demonstrated particularly high habitat fragmentation, high pollutant emissions from fertilizer and pesticide use [48], and reduced surface water due to limited infiltration caused by buildings and roads. At the county level, the ESs in the central region of the TRB are noticeably lower compared to the peripheral areas, showing a characteristic central collapse. This phenomenon aligns with the regional economic pattern, where central areas exhibit lower values while the peripheries show higher values. The TRB connects the most crucial economic cores of Chengdu and Chongqing City yet experiences lagging economic development. This situation may be because the LULC in these areas is dominated by the built-up area and the vegetation cover is notably lower than that in marginal counties.

In terms of correlation analyses, within the TRB, the trade-off relationship dominated among the ESs, with only synergistic relationships between HQ and SC and between NE and WY. This phenomenon exhibits some differences from the findings of previous studies [39,41], where the relationships between HQ–WY and SC–WY pairs were generally synergistic. The phenomenon in which the improvement of one ES may come at the cost of the degradation of others is particularly pronounced in the TRB region, which reveals that the TRB has more prominent regional ecological resource utilization issues. In addition, at the county scale, northern counties showed a prominent high spatial correlation, which may be due to the fact that northern counties, such as Xindu County, Longquanyi County, and Jianyang County, generally have significantly denser built-up. Some counties in the north also have superior ecological system quality, such as Pengzhou County, Shifang County, and Mianzhu County.

The spatial patterns of ESs are significantly determined by factors such as LULC, PD, and ecological factors, a finding that corroborates the outcomes of several studies in the field [49,50]. This is because LULC dictates patterns of land utilization, exerting a profound and direct influence on ESs, while a higher PD is accompanied by a greater number of human activities, which indirectly affect the supply and quality of ESs. Regarding ecological factors, DEM significantly impacts hydrological processes and vegetation distribution. TEM and SUN exert a considerable influence on plant growth and biodiversity. However, the impact of low GDP on ESs is particularly pronounced, which differs from previous studies that mostly indicate a significant influence of GDP on ESs [38,41]. This may be attributed to the relatively minor contribution of built-up areas within the watershed and the concentration of economic activities at the local level. Furthermore, from 2000 to 2020, the regional economy remained underdeveloped, thereby limiting the influence of GDP. As the regional economy develops, it is important to continue to emphasize the influence of GDP on ESs.

4.2. Analysis of Policy Influence on ESs

From 2000 to 2020, the TRB has taken a large number of policies and initiatives on both ecological conservation and economic growth. The implementation of policies has a large effect on LULC, which is the most critical driver of ESs. The results of the comparison between the two scales clearly shows that ESs are characterized by significant differences between the counties. This is because counties possess disparate administrative units,

which are governed by distinct management structures and adhere to varying policies and action priorities.

In terms of ecological protection, the TRB has adopted a series of policies on water pollution control, such as the implementation of zero-growth action regarding fertilizers, pesticide reduction, and sea control action. In 2017, it made a prevention planning program aimed at constructing several high-quality water sources. By 2020, the region had achieved a water quality compliance of 92.3%, up from 52% in 2016. The improvement in water environmental quality is also reflected in the ESs assessment result, where NE shows a significant reflection. In terms of soil conservation, in 2012, Sichuan Province established measures for soil and water conservation. Since 2016, it has completed the comprehensive treatment of soil and water erosion in an area of 19,000 km². The effectiveness of the action can also be reflected in the rising trend of SC. Additionally, the initiative to convert crop land back to forest may be a primary driver for the improvement of regional ESs [51], because it hugely increased the forest coverage. This policy was initially put into effect in 1999 and strengthened in 2007, and it slowed down the loss of forests in northern counties that are predominantly forested, such as Pengzhou County, Shifang County, and Mianzhu County. As a result, the decline in HQ in these counties slowed down after 2010, and there was a significant increase in SC. In addition, the southern counties, such as Zigong City, carried out provincial forest city construction action in 2014 and took large-scale greening action in 2017. These actions continued to increase the HQ in some counties of the city and were promoted more significantly from 2010 to 2020.

Meanwhile, the TRB has also experienced economic expansion, especially in counties near Chengdu City and Chongqing City. In 2011 the Chengdu–Chongqing Twin Cities Economic Circle Strategy was gradually implemented. In the same period, Chengdu City planned to renovate 61,500 km² land and increase the 91.6 km road network in the northern area, with Xindu County and Qingbaijiang County as the key targets. In 2012, Longmatan County also continued to increase the construction of its transport infrastructure. In 2016, Jianyang County was formally assigned to Chengdu City, and later in 2017, Xindu County and Longquanyi County were assigned to the Chengdu City center county. These policies increased the built-up area and affected population distribution, impacting ES results. Their HQ declined significantly, and Ziyang City, Jianyang County, and Longmaitan County had a more significant decrease from 2010 to 2020 compared to the previous 10 years.

Overall, the supply of ESs in the TRB has improved, as well as the synergy between ESs, which reflects the effectiveness of regional ecological protection work. However, the HQ of the region has slightly declined, the trade-off relationships are dominant, and some of the synergistic relationships have been weakened. In addition, the different changes in the ESs in various counties are notable. This shows that the problem of irrational use of resources in the TRB is prominent, the efforts of counties are uneven, and there is still a gap in the overall integration of the region [52]. However, it is also important to recognize that, under certain circumstances, the divergence among counties, if properly managed and leveraged, can be a resource and advantage, contributing positively to regional coordinated development and spatial sustainability [53]. Therefore, it needs more targeted management measures and policies.

4.3. Management Insights and Policy Implications

In light of the considerable scale variability observed in ESs, it is imperative to implement targeted strategies at varying spatial scales. The grid-scale breaks through the limitations of policy boundaries, treats the watershed as a whole, and emphasizes the protection of patches in the wide-area scale, which is important for the preservation of forest lands. The county scale emphasizes the role of policy formulation and puts forward-focused

strategies to address the ecological background, ecology, and developmental status of different regions. We proposed management strategies for both grid and county scales, linking the two scales, and considered the potential use of ES-related research in policy-making and regional refinement.

At the grid scale, areas dominated by forest and grassland, especially in the northern and southwestern regions characterized by mountainous and hilly terrain with intricate topography, should mainly enhance vegetation cover and richness, increase green patches, and connect dispersed high-quality habitats to establish ecological corridors and form green networks, protect rare and endangered species and minimize human interference, and promote the regulation of the water cycle and the stability of ecosystems. These activities will improve the microclimate and thus further enhance habitat amenities and increase biodiversity. There will be an enhancement of HQ and SC and a reduction in NE, promoting synergies between HQ, SC, and water quality purification. In areas dominated by crop land, it is important to enhance soil fertility and health while ensuring food security. In addition, sustainable agriculture and efficient water-saving irrigation systems should be promoted to reduce water wastage and curtail the reliance on chemical fertilizers and pesticides, especially in the crop land along the river. This can reduce NE and protect soil quality and the water environment, thus increasing the synergy between WY and water purification. In areas with a concentration of built-up areas, the PD has a greater impact on ESs. As the heat island effect makes the microclimate unfavorable, it may also have some effect on ESs. These areas should build urban ecological corridors and increase urban green space to improve the microclimate. Moreover, they can reduce urban surface runoff and promote rainwater infiltration by promoting green building and permeable surface technology. In addition, strict control of industrial and domestic pollutant discharges is also needed. These measures will help to enhance HQ and SC and reduce NE. In areas dominated by water bodies, especially along the mainstream and tributaries of the Tuo River, the integrity of the water environment must be ensured. The establishment and protection of water source conservation areas are essential. The preservation of existing wetlands is imperative for maintaining ecological balance. Moreover, strengthening the surveillance of water quality is crucial for the timely detection and treatment of pollution sources. Furthermore, the riparian zones should be rehabilitated and protected with vegetation to reduce riverbank erosion.

At the county scale, counties with good ecological backgrounds in the north, such as Pengzhou County, Shifang County, and Mianzhu County, can consider developing eco-tourism, developing the level of the economy based on the protection of the existing ecological background. Central counties with faster economic development, such as counties in Chengdu City, should focus on ecological protection while enhancing GDP as well. The northern upstream counties should strictly control the water quality and promote soil and water conservation. The economic and ecological environment in the middle of the collapse features is more significant in central areas such as Neijiang City, a generally agricultural aggregation; they should abate farmland surface pollution and explore ecological governance and industrial development combined with a sustainable development model. They can consider the development of agricultural tourism. Moreover, they should also improve infrastructure and promote industrial transformation to high value-added industries producing low pollution. Counties with high vegetation cover in the south, such as Zigong's Rong County and Weiyuan County, should strengthen efforts to construct forest city clusters with nearby counties. Counties with serious downstream water pollution problems should invest more in comprehensive water environment management. On the whole, counties should also strengthen collaborative governance among themselves and establish cross-regional mechanisms for ecological environmental protection and governance;

for example, they could incorporate water environmental protection into the important content of economic cooperation between them, encourage the sharing of environmental protection infrastructures among neighboring counties, and carry out joint law enforcement and cross-enforcement.

4.4. Limitations and Prospects

Although this research offers an analytical framework and theoretical insights that contribute to the management of ESs in the TRB, it is essential to acknowledge the existence of certain constraints. Firstly, different parameter settings can lead to potential variations in ES value quantification results. The parameter settings in the ES assessment model InVEST used in this study are primarily derived from the literature corresponding to regions with analogous environmental contexts. Although these parameters have been validated in prior studies, the lack of observational data still hinders comprehensive validation. A crucial step in future research will involve conducting comparative experiments that encompass a range of parameter settings and selecting typical areas for field studies to validate the model results. This will lead to an improvement in the model performance and an enhancement of the overall reliability of the model results.

Moreover, this study only considers the temporal scale effects in exploring driving factors and does not delve into the complex relationships between ES spatial distributions at different spatial scales and various driving factors. Consequently, subsequent research should expand upon the discoveries of this study to incorporate comparative spatial scale investigations into driver exploration. This approach will contribute to a more accurate understanding of dynamic changes in ES driver dynamics at the scale, thereby enhancing targeted management policy references.

5. Conclusions

This study compared the ESs in the TRB and the interrelationships among these services at the grid and county scales. Additionally, it identified the critical social–ecological driving factors of ESs. It aims to guide the management of these services in the TRB. (1) Firstly, a general upward trend was observed in most ESs across the region, although the HQ slightly deteriorated. The ESs were more prominent in the northern mountainous and southwestern hilly regions, while the county scales displayed central collapse characteristics. (2) Secondly, trade-offs predominated between ESs in the TRB; synergistic relationships only existed in the HQ–SC and NE–WY pairs. Generally, an upward trend in synergies was observed. High trade-offs and synergies existed mainly in forest, grassland, and built-up areas, as well as at county scales mainly in the northern counties. (3) The interaction of all the social–ecological driving factors exerted an enhancement effect. LULC was the most dominant driver, while only the GDP had a relatively small driver effect for ESs. Additionally, notable discrepancies were identified in the ES assessment outcomes at two scales. Based on these findings, management strategies for these two scales are proposed in this study.

Author Contributions: S.H.: Conceptualization; methodology; formal analysis; software; visualization; writing—original draft preparation. Y.X.: Conceptualization; writing—original draft preparation; writing—review and editing. J.Z.: Writing—review and editing. Y.L.: Writing—review and editing. Q.W.: Conceptualization; project administration; supervision; writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China, grant number 32371942.

Data Availability Statement: The original contributions presented in the study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: Author Jing Zhang was employed by the company China Southwest Architectural Design and Research Institute Corp. Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A

Appendix A.1. Land Use/Land Cover Conversion

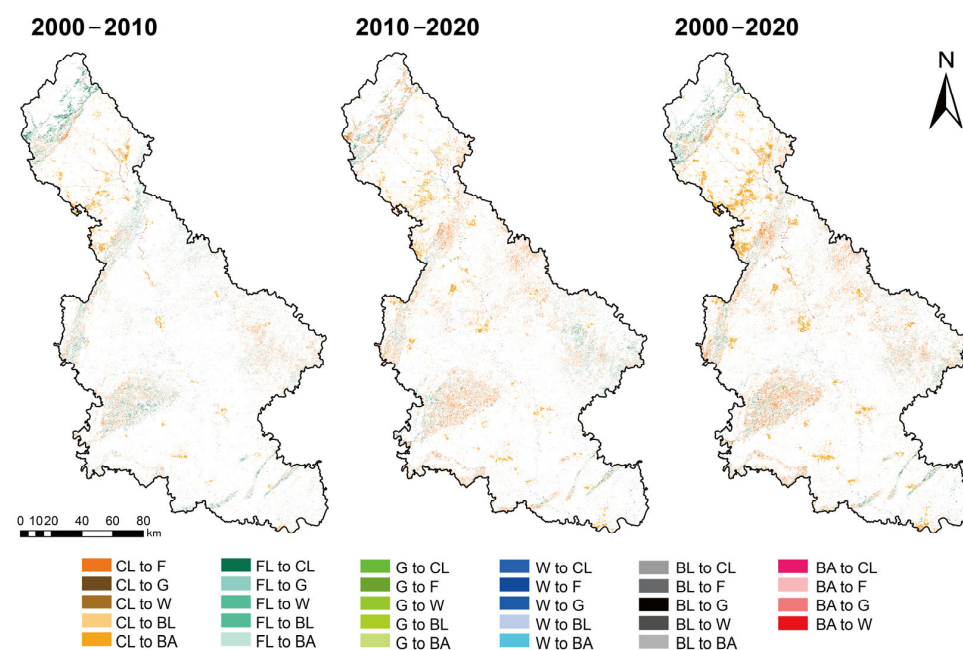


Figure A1. Land use/land cover conversion from 2000 to 2020 in TRB. (CL: crop land; F: forest; G: grassland; W: water body; BL: barren land; BA: built-up area).

Appendix A.2. Ecosystem Service (ES) Assessments

We used the Habitat Quality module of the InVEST model to calculate by combining the sensitivity of land use types and the intensity of external threats, and the model parameters were set with reference to existing research results [54]. Table A1 presents the threat source data, while Table A2 demonstrates the habitat types and their sensitivity to threat sources. HQ was calculated using the following formula:

$$Q_{xj} = H_j \left(1 - \frac{D_{xj}^z}{D_{xj}^z + k^2} \right) \quad (A1)$$

where Q_{xj} is HQ value of grid x ; H_j is the habitat suitability of LULC type j ; D_{xj} signifies the distance to threats to land use type j ; z is a scaling parameter which was set at 2.5; and k is the half-saturation constant, which was set at 0.5.

Table A1. The sensitivity of habitat types to each threat factor.

Threat Factors	Maximum Distance of Influence	Weights	Spatial Decay Types
Crop land	2.6	0.26	exponential
Built-up area	5.8	0.73	linear
Barren land	2	0.25	exponential
Road	4	0.4	linear

Table A2. Habitat suitability and sensitivity of habitat types to each threat factor.

Habitat Type	Habitat Suitability Score	Sensitivity to Threats			
		Crop Land	Built-Up Land	Barren Land	Road
Crop land	0.4	0.3	0.5	0.2	0.2
Forest	0.91	0.56	0.84	0.3	0.8
Grassland	0.7	0.46	0.8	0.15	0.2
Water body	0.93	0.63	0.86	0.33	0.5
Barren land	0	0	0	0	0
Built-up area	0	0	0	0	0

NE was calculated using the Nutrient Delivery Ratio (NDR) module of the InVEST model, with model parameters referenced to existing similar research results [55] and the InVEST user guide. The biophysical attributes of various land use/cover types are presented in Table A3. NE was calculated using the following formula:

$$X_{export_i} = load_{surf,i} \times NDR_{surf,i} + load_{subs,i} \times NDR_{subs,i} \quad (A2)$$

$$X_{export_{tot}} = \sum_i X_{export_i} \quad (A3)$$

where, X_{export_i} is the annual nitrogen export of per unit grid; $load_{surf,i}$ and $NDR_{surf,i}$ are the surface nitrogen load and nitrogen export load factor on the unit grid; $load_{subs,i}$ and $NDR_{subs,i}$ are the subsurface nitrogen load and nitrogen export load factor; and $X_{export_{tot}}$ denotes the total amount of nitrogen exported from a certain plot.

Table A3. Biophysical parameters in the NDR module.

LULC Name	Load_n	Eff_n	Crit_len_n	Proportion_Subsurface_n
Crop land	24.2	0.25	25	5.75
Forest	3.68	0.8	150	0.28
Grassland	8.5	0.4	100	0.55
Water body	0.01	0.05	15	0.01
Barren land	6	6.25	0.05	5
Built-up area	7	14.5	0.05	10

SC was calculated using the Sediment Delivery Ratio module (SDR) in the InVEST model, and the model parameters were set according to the research results [56] and the InVEST model user guide. The biophysical attributes of various land use/cover types are presented in Table A4. SC was calculated using the following formula:

$$SD = R \times K \times LS \times (1 - C \times P) \quad (A4)$$

where SD represents soil retention, R denotes rainfall erosion, K signifies soil erodibility, LS represents slope length and steepness, C represents vegetation cover and management, and P represents soil retention practices.

Table A4. P value and C value of different land use types.

LULC Name	usle_c	usle_p
Crop land	0.22	0.35
Forest	0.05	1
Grassland	0.25	1
Water body	0	0
Barren land	1	1
Build-up area	1	0

WY was calculated based on the water balance equation using the Water Production module in the InVEST model, and the model parameters were set with reference to the results of the study [57] and the InVEST model user guide. The biophysical table required for the module can be found in Table A5. WY was calculated using the following formula:

$$Y_{(x)} = \left(1 - \frac{AET_{(x)}}{P_{(x)}}\right) \times P_{(x)} \quad (A5)$$

where $Y_{(x)}$ is the annual water yield of regional cell x and $P_{(x)}$ and $AET_{(x)}$ are the annual rainfall and actual evapotranspiration of grid x .

Table A5. Biophysical parameters in the water yield module.

LULC Name	root_Depth	Kc	LULC_veg
Crop land	500	0.6	1
Forest	5000	1	1
Grassland	300	0.7	1
Water body	5000	0.95	1
Barren land	1	1	0
Build-up area	100	0.2	0

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