land

Article

Interactive Effects of Ecological Land Agglomeration and Habitat Quality on Soil Erosion in the Jinsha River Basin, China

Bo Wen [1], Chenxi Liu [1], Xu Tian [2], Qi Zhang [2], Shaolie Huang [2] and Yanyuan Zhang [3,*]

[1] College of Landscape Architecture, Nanjing Forestry University, Nanjing 210037, China; wenbo2019@njfu.edu.cn (B.W.); liuchenxi@njfu.edu.cn (C.L.)
[2] China Construction First Group the Fifth Construction Co., Ltd., Beijing 100024, China; tianxu@cscec.com (X.T.); zhangqi_wgs@cscec.com (Q.Z.); huangshaolie@cscec.com (S.H.)
[3] College of Economics and Management, Nanjing Forestry University, Nanjing 210037, China
* Correspondence: yyzhang@njfu.edu.cn

Abstract: Soil erosion is a significant global environmental issue and a crucial aspect of global change. Exploring the interactive effect of ecological land agglomeration and habitat quality on soil erosion can effectively guide the positive intervention of ecological restoration activities. The study calculated the comprehensive ecological land agglomeration with Fragstats 4.2 and the habitat quality with InVEST 3.7.0 for the years 2000, 2010, and 2020 within the Jinsha River Basin in Yunnan, China. In addition, the RUSLE model was utilized to calculate soil erosion in the study area. The Geographic and Temporally Weighted Regression (GTWR) model was employed to obtain the regression coefficients and their spatial and temporal variations. The findings of this study revealed the following: (1) During the study period, there was an overall 29.06% reduction in the soil erosion modulus with an annual rate of 1.70% reduction on average, accompanied by an increase in both the comprehensive ecological land agglomeration and habitat quality. Soil erosion was more severe in the eastern regions than in the western ones and the other two indicators were higher in the northeast and southwest. (2) The GTWR results demonstrate that comprehensive ecological land agglomeration and habitat quality were negatively correlated with soil erosion, with results of −0.1383 and 0.0021, respectively. However, in northwest regions, there was a significant positive correlation between habitat quality and soil erosion. (3) The interaction term between comprehensive ecological land agglomeration and habitat quality was significantly negatively correlated with soil erosion with a result of −0.0299, and the interaction coefficients have regional variations. This study offers valuable guidance for land-use development and soil and water conservation in the Jinsha River Basin.

Keywords: soil erosion; ecological land agglomeration; quality habitat; GTWR; interaction effect

check for updates

Citation: Wen, B.; Liu, C.; Tian, X.; Zhang, Q.; Huang, S.; Zhang, Y. Interactive Effects of Ecological Land Agglomeration and Habitat Quality on Soil Erosion in the Jinsha River Basin, China. *Land* **2024**, *13*, 229. https://doi.org/10.3390/land13020229

Academic Editors: Guanghui Dong, Shanjia Zhang and Zhiping Zhang

Received: 17 January 2024
Revised: 1 February 2024
Accepted: 9 February 2024
Published: 12 February 2024

1. Introduction

As the main ecological issue in hilly and mountain areas, soil erosion removes the nutrients and destroys the vegetation cover on the surface [1,2], resulting in the supply capacity of ecosystem services, such as land productivity, water conservation, and environment purification retrograde [3,4]. The controlling of soil erosion has been paid extensive attention all over the world [5–7]. The expansion of human activities exacerbates ecological land fragmentation [8]. The reduction in area and spatial continuity disruption of ecological land may cause a series of ecological problems such as a decline in vegetation cover, reduction in biodiversity, and a decrease in habitat quality, which could result in soil erosion in hilly and mountain areas. Specific studies need to be conducted to improve the effects of soil erosion, which would also be helpful for guiding the control of the spatial continuity of ecological land and maintaining habitat quality through human intervention.

Nowadays, soil erosion has become a research hotspot worldwide. Studies on soil erosion are concentrated on estimating methods, the spatiotemporal evolution characteristics, influencing factors, and control techniques [6,9–12]. The Universal Soil Loss Equation

(USLE), RUSLE, and Chinese Soil Loss Equation (CSLE) models are the most common soil erosion estimation methods, and have been applied in different regions and scales. At the same time, the influence factors including land use/land cover change, terrains, and other factors have been considered to affect soil erosion. Recently, ecological land fragmentation caused by human activities has been recognized as the main reason for reducing regional ecological resilience, as extreme ecological problems emerged frequently. Ecological land agglomeration under human intervention is an important path to ecological restoration. Previous studies looked at the measurement of the spatial continuity of ecological land, spatial–temporal evolution, and their driver forces [13–15]. The landscape ecology index is often used to measure the spatial continuity of ecological land. It has been demonstrated that landscape ecological indexes like Contagion (CONTAG), the Largest Patch Index (LPI), and the Aggregation Index (AI) have a substantial adverse correlation with sand production, which is related to soil erosion. Additionally, during the process of soil erosion control and ecological land spatial continuity recovery, habitat quality needs to be valued. This is because there are some associated mechanisms between changes in habitat quality and ecological land spatial continuity, as well as the potential relationship between soil erosion and habitat quality evolution, which have been presented in previous studies [16,17]. Previous research has primarily concentrated on independently studying land agglomeration, habitat quality, and soil erosion, as well as their dynamic changes and influencing factors. However, there is a lack of clarity regarding the interaction effect of ecological land agglomeration, habitat quality, and soil erosion. There might be some comprehensive effects in preventing soil erosion. It is necessary to consider these contents as a whole in the implementation of ecological restoration. Conducting research into how soil erosion, ecological land agglomeration, and habitat quality interact can enhance the ecological landscape of erosion management in patches, corridors, and matrix pathways. This can provide a sound basis for optimizing ecological environments and, particularly, soil erosion management.

The Jinsha River Basin is a significant region for the development of southwest China, as well as for ecological restoration and the protection of the Yangtze River basin. Soil erosion significantly limits the biological productivity of the land and can trigger landslides, mudslides, and other geological disasters in mountainous regions. It has been demonstrated that the upper Yangtze basin suffered from serious soil erosion with an erosion area of approximately 352,000 km^2 from 1955 to 2010, and the average annual suspended sediment load was approximately 0.43 billion t [18]. There are major challenges to ecological restoration in this area. Quantitative research on the relationships among ecological land agglomeration, habitat quality, and soil erosion needs to be conducted before human intervention for ecological restoration is put into effect. The theoretical basis of synergistic habitat quality and ecological land agglomeration to control soil erosion can be obtained. The objective of the present study is to (1) investigate the ecological land agglomeration, habitat quality, soil erosion, and the characteristics of spatiotemporal change in the Jinsha River Basin; (2) estimate the interaction effects among ecological land agglomeration, habitat quality, and soil erosion; and (3) explore effective ways and methods to alleviate soil erosion in the study area. It is helpful to provide a theoretical and practical foundation for preventing soil erosion and restoring the ecological environment of the Jinsha River Basin.

2. Research Design

It has been proven that ecological land agglomeration has a positive effect on soil erosion control, as the vegetation cover increases and the connectivity in the ecosystem is reinforced [19]. Enhancing habitat quality is one of the important goals and pathways of ecological restoration, which is a regional systematic project that goes beyond simply raising the level of ecological land agglomeration. When the habitat quality faces a threat, the restoration of the surface vegetation is considered first, and, as a result, habitat quality has an effect on the soil erosion formed. According to previous studies, the effects of ecological land agglomeration and habitat quality on soil erosion were analyzed first. In these analyses, ecological land agglomeration and habitat quality were found to be the main explanatory variables [19,20]. In addition to ecological land agglomeration and habitat quality, soil erosion was also affected by other factors such as climate change, vegetation succession, and human activities [21]. An analysis that considered other factors was conducted sequentially. Additionally, ecological land agglomeration and habitat quality do not play an independent role in the evolution of soil erosion. There may be an interaction effect between ecological land agglomeration and habitat quality on soil erosion. The study was extended to include the interaction term of ecological land agglomeration and habitat quality. As the ecological restoration of the upper of the Yangtze River began in 1999, the soil erosion, habitat quality, and the comprehensive ecological land agglomeration of the study area from the year 2000 were analyzed. The research design is presented in Figure 1.

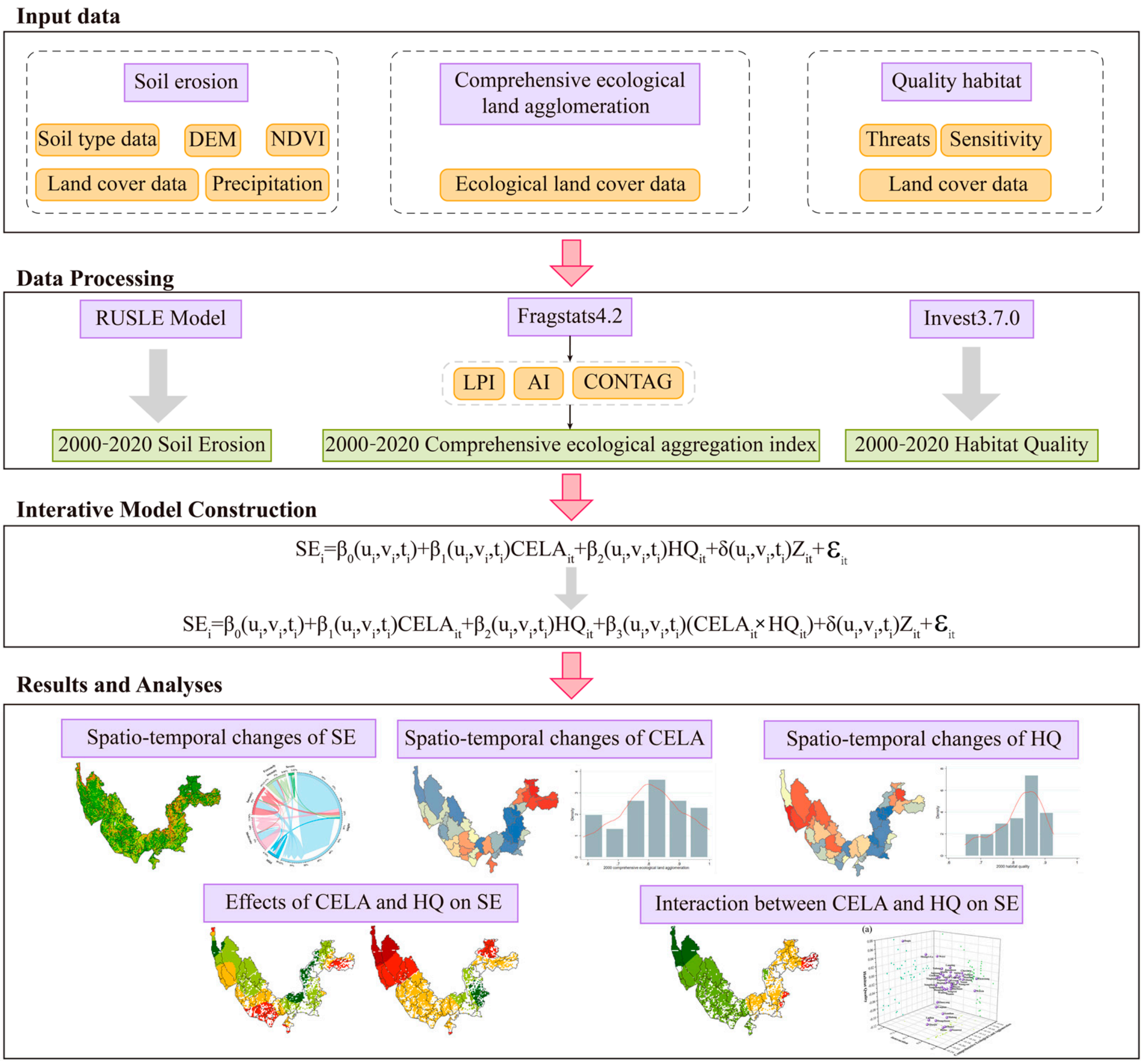

Figure 1. Research Design. *SE* is soil erosion; *CELA* is comprehensive ecological land agglomeration; *HQ* is habitat quality; *DEM* is Digital Elevation Model; *NDVI* is Normalized Difference Vegetation Index; *LPI* is Largest Patch Index; *AI* is Aggregation Index; *CONTAG* is Contagion; i is some observation point in space; Y represents the average soil erosion modulus; A represents comprehensive ecological land agglomeration; B represents habitat quality; Z denotes additional factors other than the comprehensive ecological land agglomeration and habitat quality that affect soil erosion; β is the regression coefficient; t is time; u and v are the latitude and longitude; and ε is the residual term.

3. Materials and Methods

3.1. Study Area

The study was carried out in the Jinsha River Basin in Yunnan Province (Figure 2), China, which extends from 29°22′ to 24°53′ N latitudes and from 98°91′ to 105°31′ E longitudes, covering an area of 133,754.1 km^2. The Jinsha River is located in the upper reaches of the Yangtze River in China, originating in Dasngqu, Qinghai Province. It then flows through the Qinghai–Tibet Plateau, the western Sichuan Plateau, the Hengduan Mountain area, the Yunnan–Guizhou Plateau, and the southwest Sichuan Mountains before joining the Minjiang River in Yibin, Sichuan Province. The annual average discharge of the upper reaches of the Yangtze River reaches 428 billion m^3. The topography of the Jinsha River Basin is complex, and numerous mountains and deep valleys are juxtaposed. The gradients range from 0 to 81.4 degrees and the altitudes are between 300 and 4800 m above sea level [22]. It receives an average of 867 mm of annual rainfall with an annual average temperature of 15.19 °C. However, the water and soil conservation capacity of this area has recently been influenced by the land use and urban growth of the nearby cities and towns [23]. Simultaneously, ecologically friendly communities and economic development in this area have driven soil erosion control in recent years. Therefore, studying soil erosion and the interactive effect of its influencing factors is of great importance.

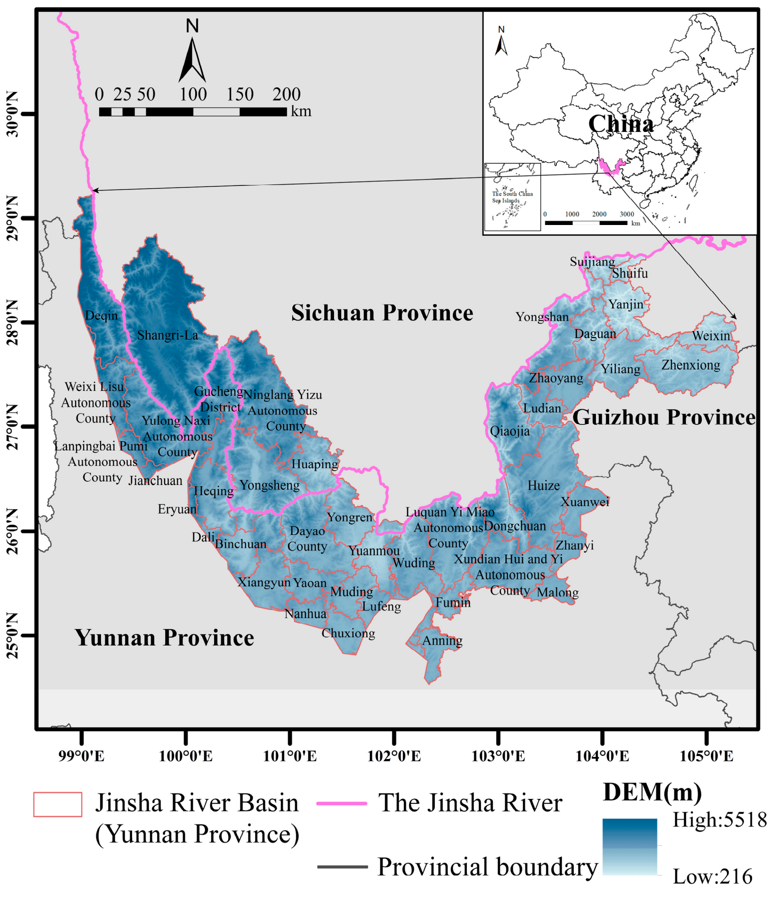

Figure 2. Location and extent of the research area.

3.2. Data Collection

The 2000, 2010, and 2020 land-use data used in this study were extracted from Landsat-TM/ETM and Landsat 8 images (Landsat Collection 2 Level-1 products) with a resolution of 30 m. To improve accuracy and comparability, the images were selected from June to September each year due to the lesser cloud and rich vegetation cover [24]. With the use of ENVI 5.3, geometric, topographic, and radiometric corrections were conducted [25]. Based on previous studies, Maximum Likelihood (ML) was used for supervised classification. Land use was classified into cultivated land, forest land, grassland, waters, construction land, and unused land [26,27]. A series of random precision evaluation points were created, 2000 verification grids were selected for the high-resolution remote-sensing image test. The Kappa index was used to evaluate the accuracy. The accuracy of the data interpretation for each year was more than 85%, which met the precision requirement of the study.

The DEM data, obtained from the geospatial data cloud with a spatial resolution of 30 m, is an ASTER GDEM image, which was obtained from the Geospatial Data Cloud of the Computer Network Information Center, Chinese Academy of Sciences (http://www.gscloud.cn/ (accessed on 6 September 2023)). The soil type data came from the Harmonized World Soil Database v 1.2 (https://www.fao.org/soils-portal, accessed on 20 September 2023), which was built by the Resources and Environmental Science and Data Center, the Food and Agriculture Organization of the United Nations (FAO, Rome, Italy), and the International Institute for Applied Systems (IIASA) in Vienna, with a spatial resolution of 1 km^2. The precipitation data, with a spatial resolution of 30 m, was downloaded from the Resources and Environmental Science and Data Center and the National Science and Technology Basic Conditions platform—National Earth System Science Data Center. The NDVI, derived from the Source Environmental Science and Data Center (http://www.resdc.cn (accessed on 6 September 2023)), has a spatial resolution of 250 m^2. In addition, fishing nets were created. Comprehensive ecological land agglomeration, habitat quality, and soil erosion were estimated with the fishing nets. After comparing efficiency and the accuracy, a 5 km $\times$ 5 km fishing net with a total of 5397 grids was selected to estimate.

3.3. Methods

3.3.1. RUSLE Model

The RUSLE model is a common method for quantitatively evaluating soil loss in this region. According to the previous studies [28,29], the basic form of the RUSLE formula is as follows:

$$A = R \times K \times LS \times C \times P$$

where A (t/(hm^2·a)) is the annual soil erosion modulus; R ((MJ·mm)/(hm^2·h·a)) is the rainfall erosivity factor, which is calculated by the method of Arnoldus et al. [30]; K (t·hm^2·h/(hm^2·MJ·mm)) is the soil erodibility factor, and the calculation method is taken from Williams et al. [31]; LS (dimensionless) is the slope factor S and slope length factor L. This paper used a modified LS algorithm according to Zhang et al. [32]; C (dimensionless) is the land cover and management factor, and the calculation method is taken from Zhang et al. [32]. P (dimensionless) is the soil and water conservation measures factor, which has a certain relationship with slope and surface shape, and the p value varies between 0 and 1. According to a previous study [33,34], the value of farmland was assigned a value of 0.25, the p-value of woodland, shrub, and grassland was assigned a value of 0.1, the value of wetland was assigned a value of 0.18, and the value of other land use types was assigned a value of 0.

3.3.2. Comprehensive Ecological Land Agglomeration

There is a lack of unified standards for the classification of ecological land. Referring to a previous study, forests, grassland, water, and unused land were included in the ecological land [35]. The moving window method in Fragstats 4.2 was used to calculate the ecological land agglomeration (Table 1). The Largest Patch Index (LPI), the Aggregation Index (AI), and contagion (CONTAG) methods were used to investigate the overall evolution characteristics of the comprehensive aggregated landscape pattern. The original data were normalized using the z-score standardization method and all the indicators were added with equal weight for the comprehensive ecological land agglomeration [36].

Table 1. Statistical characteristics of ecological land agglomeration.

Agglomeration Index	Min	Max	Mean	SD
LPI	22.22	100	86.29	27.67
AI	0	100	86.98	28.62
CONTAG	0	55.30	17.65	36.36

3.3.3. Habitat Quality Assessment Model

Habitat quality refers to the ability of an ecosystem to provide suitable conditions for the sustainability of individuals and populations, and is reflected in the status of regional biodiversity to a certain extent [37]. In the Habitat Quality module of InVEST 3.7.0, the relationship between land use and threat sources was established to evaluate the habitat quality, and the weight of threat factors and sensitivity data of each land use type was input.

Based on the InVEST modeling manual, the characteristics of the study area, and related studies [38,39], a threat factor data table was developed in Table 2, with habitat types and their sensitivity to threats displayed in Table 3. The habitat quality map of the study area was obtained by inputting the parameters into InVEST 3.7.0. Habitat quality values range from 0 to 1, with higher values indicating better habitat quality.

Table 2. Threat factor parameter setting.

Threat	Max Distance	Weight	DECAY
Cropland	6	0.7	linear
Unused	3	0.5	linear
Impervious	10	1	exponential

Table 3. Sensitivity of land-cover types to each threat.

Land Use Types	Habitat	Cropland	Unused	Impervious
Cropland	0.5	0.5	0	0.4
Forest	1	1	0.6	0.5
Shrub	0.8	0.8	0.6	0.5
Grassland	0.6	0.6	0.5	0.6
Water	0.8	0.8	0.4	0.4
Unused	0.3	0.3	0.3	0
Impervious	0	0	0	0

3.3.4. Spatial Autocorrelation Analysis

Spatial Autocorrelation refers to the calculation of the spatial autocorrelation degree between a spatial unit and its surrounding units in terms of some characteristic values through statistical methods, so as to analyze the characteristics of the spatial distribution phenomenon of these spatial units [40]. Global Moran's I was utilized to calculate spatial autocorrelation in this study. The Moran's I ranged from -1 to 1. When the value is greater than 0, it indicates that there is a positive spatial correlation in the study area, and the closer the value is to 1, the stronger the positive spatial autocorrelation is, and the value of the research object is clustered [40]. When the value is less than 0, it indicates that there is a negative spatial correlation in the study area. The closer the value is to -1, the stronger the negative spatial autocorrelation is. When its value is close to 0, the value of the research object is randomly distributed and there is no autocorrelation.

3.3.5. Geographic and Temporally Weighted Regression (GTWR)

GTWR, a model for studying spatial heterogeneity, incorporates geographical location and time factors in regression to analyze the influence of the geographical location heterogeneity and time heterogeneity of soil erosion [41]. By establishing the spatiotemporal weight matrix, GTWR increases the sample size of the model and makes it applicable to situations with fewer cross-section area samples. Additionally, GTWR utilizes the information of adjacent sample areas in the study area and the sample information of the time series in the local regression of a sample area, leading to more scientifically reliable estimation results [41].

The formula of the GTWR model is as follows:

$$Y_i = \beta_0(u_i, v_i, t_i) + \beta_1(u_i, v_i, t_i)A_{it} + \beta_2(u_i, v_i, t_i)B_{it} + \delta(u_i, v_i, t_i)Z_{it} + \varepsilon_{it}$$

where i is an observation point in space. Y represents the average soil erosion modulus. A represents comprehensive ecological land agglomeration, and B represents habitat quality. Z denotes additional factors other than the comprehensive ecological land agglomeration and habitat quality that affect soil erosion, including NDVI, precipitation, and population. β is the regression coefficient. t is time. u and v are the latitude and longitude. ε is the residual term.

The estimation process of the GTWR model depends on its spatio-temporal weight matrix. In this paper, the spatiotemporal weight function of the Gaussian distance decay function method proposed by Huang et al. is used to construct W as follows:

$$W_{ij} = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{d_{ij}^2}{h^2}\right)$$

$$W_{ij}^{ST} = \exp\left(-\frac{\left(d_{ij}^{ST}\right)^2}{b_{ST}^2}\right)$$

where d is the spatiotemporal distance, W is the spatiotemporal weight matrix; h and b represent the bandwidth (the optimal bandwidth is estimated by the AICc method), i and j represent different section individuals, and S and T represent space and time, respectively.

The impact of comprehensive ecological land agglomeration on soil erosion is also affected by habitat quality, with the marginal effect varying depending on the value of habitat quality. Therefore, it is recommended to introduce a comprehensive ecological land agglomeration $\times$ habitat quality interaction term into the model as follows:

$$\begin{aligned} Y_{it} = \; & \beta_0(u_i, v_i, t_i) + \beta_1(u_i, v_i, t_i)A_{it} + \beta_2(u_i, v_i, t_i)B_{it} \\ & + \beta_3(u_i, v_i, t_i)(A_{it} \times B_{it}) + \delta(u_i, v_i, t_i)Z_{it} + \varepsilon_{it} \end{aligned}$$

Before applying the GTWR model, it is necessary to conduct a Variance Inflation Factor (VIF) test on the dependent variables to ensure the absence of multicollinearity problems between explanatory variables [42]. The results showed that the Variance Inflation Factors (VIFs) of all explanatory variables was less than 10, and the mean variance inflation factor was also less than 10, indicating that there was no multi-collinearity between explanatory variables, which met the requirements of the GTWR model estimation.

4. Results

4.1. Spatio-Temporal Changes of Soil Erosion

According to the Classification and Grading Standard of Soil Erosion in the water conservancy industry (SL 190-2007) [43], the soil erosion modulus in the region was divided into six intensity levels: slight, mild, moderate, intensity, extreme intensity, and severe. The average soil erosion modulus in 2000, 2010, and 2020 were 31.01 t/(hm^2·a), 22.71 t/(hm^2·a) and 22.00 t/(hm^2·a), respectively. During the study period, there was an overall 29.06% reduction in the soil erosion modulus with an annual rate of 1.70% reduction on average. Soil erosion was 418.59 $\times$ 10^6 t/a, 306.53 $\times$ 10^6 t/a, and 296.88 $\times$ 10^6 t/a, respectively. During the study period, the areas without erosion accounted for 53.60%, 64.27%, and 71.27% of the total area, respectively (Figure 3). It is evident that slight and mild erosions dominated, comprising approximately 59.21% in 2000, 69.12% in 2010, and 74.31% in 2020. Areas with moderate or higher levels of erosion accounted for about 40.79% in 2000, 30.88% in 2010, and 25.69% in 2020, while areas of severe erosion were minimal, accounting for 2.83%, 1.79%, and 2.70%, respectively. Overall, the area of soil erosion decreased from 95,364.62 km^2 to 71,730.98 km^2 throughout the study period. The areas of slight and mild erosion increased from 79,190.94 km^2 to 99,429.99 km^2, while the areas with more than moderate erosion decreased from 54,563.15 km^2 to 34,324.07 km^2 (Table 4). From the perspective of spatial distribution, the soil erosion modulus in the study area was observed to be higher in the northwest and lower in the northeastern and central regions (Figure 4). Dongchuan District displayed the highest soil erosion modulus in 2000, 2010, and 2020, with respective values of 61.82 t/(hm^2·a), 55.55 t/(hm^2·a), and 55.16 (hm^2·a).

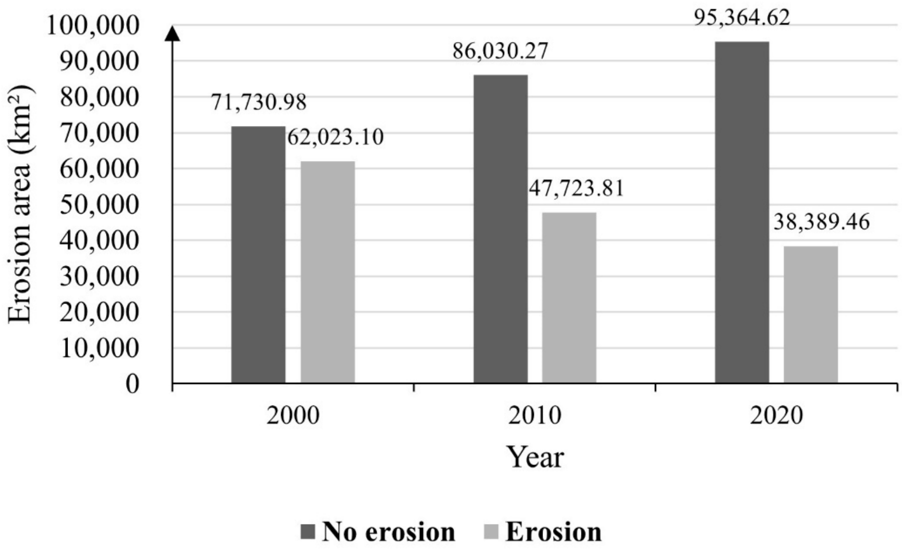

Figure 3. Comparison of soil erosion area and no erosion area.

Table 4. Soil erosion intensity classification and the proportion of soil erosion area in different levels of soil erosion.

Level	Soil Erosion Modulus/(t·hm^{-2}a^{-1})	2000 Area (km^2)	2000 Proportion	2010 Area (km^2)	2010 Proportion	2020 Area (km^2)
Slight	0–10	72,349.67	54.09%	86,609.38	64.75%	95,797.02
Mild	10–25	6841.27	5.11%	5896.34	4.41%	3632.97
Moderate	25–50	20,249.68	15.14%	16,016.36	11.97%	10,597.78
Intensity	50–80	17,320.33	12.95%	13,375.6	10.00%	10,844.87
Extremely intensity	80–150	13,179.67	9.85%	9457.9	7.07%	9260.03
Severe	>150	3813.47	2.85%	2398.5	1.79%	3621.39
Total	-	133,754.08	100.00%	133,754.1	100.00%	133,754.1

The soil erosion intensity transfer from 2000 to 2020 is shown in Table 5 and Figure 4. During the study period, there was an alteration in the soil erosion modulus level over an area of approximately 52,812.29 km^2, which accounted for 39.48% of the total area. Some of the mild, moderate, intense, extremely intense, and severe erosion transferred to slight erosion, and the transfer areas were 3173.54 km^2, 11,273.42 km^2, 9533.18 km^2, 6798.80 km^2, and 2127.28 km^2, respectively. The transfer areas from mild, moderate, intense, and extremely intense erosions to slight erosions were 3173.54 km^2, 11,273.42 km^2, 9533.18 km^2, 6798.80 km^2, and 2127.28 km^2, respectively, accounting for 3.31%, 11.77%, 9.95%, 7.10% and 2.22%, respectively, of the slight erosion. However, the transition from slight erosion to other erosion intensity levels was relatively small at 9458.86 km^2. Severe erosion was mainly transformed to extreme intensity erosion, slight erosion, and intensity erosion, and the transition areas were 983.53 km^2, 940.09 km^2, and 409.24 km^2, respectively. They accounted for 27.16%, 25.96%, and 11.30% of severe erosion, respectively. The slight erosion category changed most significantly, increasing by 23,447.35 km^2, accounting for 24.48% of the slight erosion in 2020. This was followed by intensity of erosion, which decreased by 6475.46 km^2, accounting for 59.71% of the slight erosion in 2020.

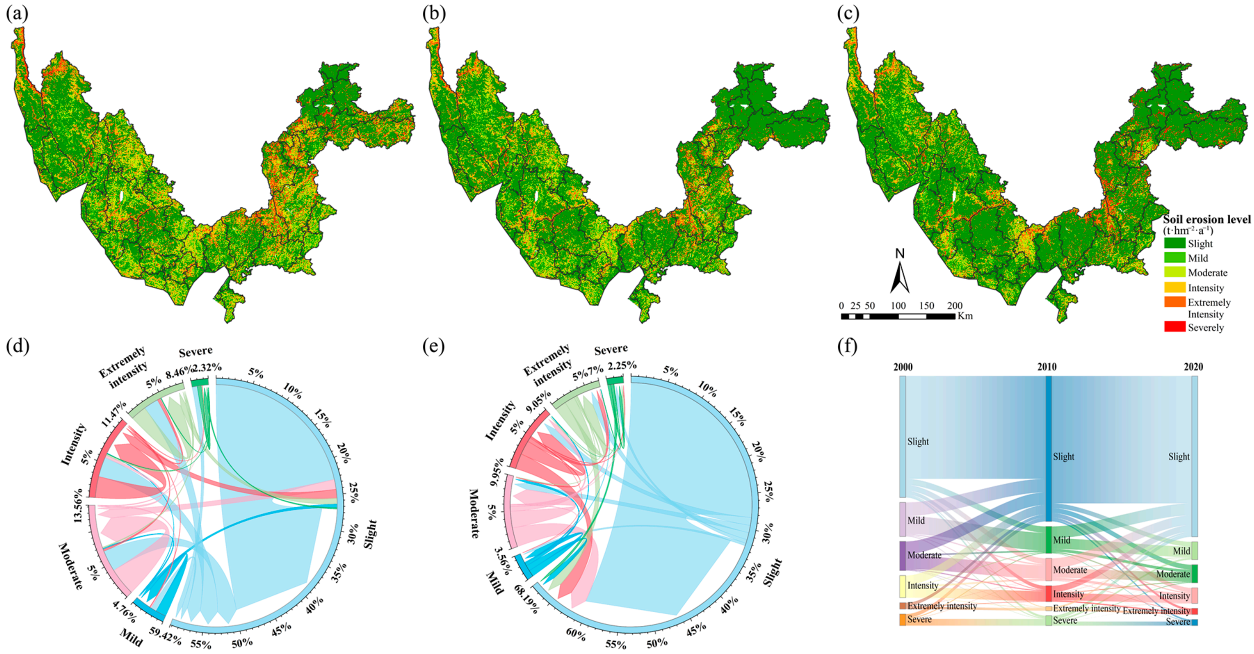

Figure 4. Spatial distribution of soil erosion intensities for (**a**) 2000, (**b**) 2010, and (**c**) 2020. Soil erosion conversion statistics for (**d**) 2000–2010, (**e**) 2010–2020, and (**f**) 2000–2020.

Table 5. Soil erosion intensity transfer matrix km^2.

Year		2020						
	Level	**Slight**	**Mild**	**Moderate**	**Intensity**	**Extremely Intensity**	**Severe**	**Total**
2000	Slight	62,890.81	1064.60	2630.14	2659.10	2164.92	940.09	72,349.67
	Mild	3173.54	2153.34	1031.79	462.33	20.27	0.00	6841.27
	Moderate	11,273.42	368.70	5859.67	1816.49	887.01	44.40	20,249.68
	Intensity	9533.18	46.33	888.94	4724.60	1718.04	409.24	17,320.33
	Extremely intensity	6798.80	0.00	187.25	1140.85	4069.24	983.53	13,179.67
	Severe	2127.28	0.00	0.00	41.50	400.55	1244.13	3813.47
	Total	95,797.02	3632.97	10,597.78	10,844.87	9260.03	3621.39	133,754.08

4.2. Spatio–Temporal Changes of the Comprehensive Ecological Land Agglomeration and Habitat Quality

The Comprehensive Ecological Land Agglomeration Index of the years 2000, 2010, and 2020 was calculated after weighting. In general, the comprehensive ecological land agglomeration in the study area showed an upward trend with a significant spatial difference from 2000 to 2020 (Figure 5d–f). This study found that low agglomeration and light agglomeration were predominantly distributed in the northwest and southeast (Figure 5a–c), while medium agglomeration and high agglomeration were widely distributed in the northeast and southwest. Specifically, Xundian Hui and Yi Autonomous County, Yuanmou County, and Huize County comprehensive ecological land agglomeration increased obviously. On the other hand, the comprehensive ecological land agglomeration for Yimen County and Yongshan County showed an obvious decrease. Shuifu exhibited relatively stable agglomeration patterns, with no significant changes observed.

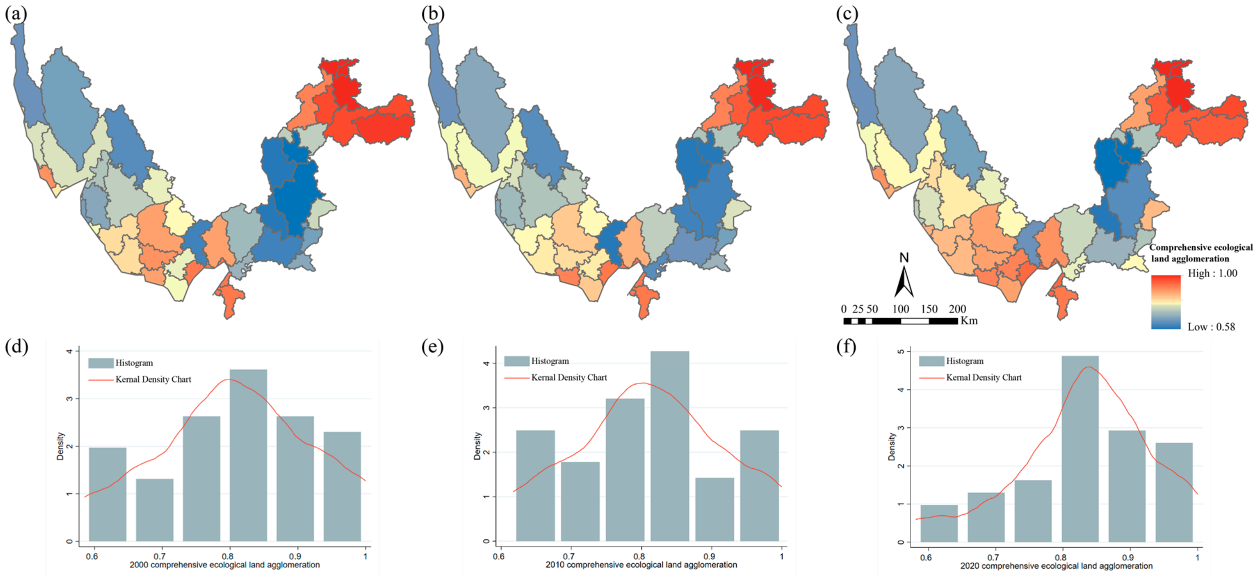

Figure 5. Spatial distribution of comprehensive ecological land agglomeration for: (**a**) 2000, (**b**) 2010, and (**c**) 2020. Histogram distribution and fitted kernel density curves of comprehensive ecological land agglomeration for (**d**) 2000, (**e**) 2010, and (**f**) 2020.

The average habitat quality in 2000, 2010, and 2020 were 0.8244, 0.8286, and 0.8297, respectively. There was an average increase of 0.64% in habitat quality. The habitat quality ranging from 0.8 to 1 accounted for a proportion of 62.27% in 2000, 62.90% in 2010, and 63.74% in 2000, while the habitat quality ranging from 0 to 0.3 accounted for a proportion of 0.57% in 2000, 0.53% in 2010, and 0.59% in 2000. It indicates that the overall habitat quality of the research area was high. In addition, the observed rightward shift in the highest proportion of the habitat quality range indicates a melioration in the overall ecological environment (Figure 6d–f). In terms of spatial distribution, the study area exhibited high levels of habitat quality in the northwest and northeast regions, but low habitat quality in the southeast and southwest (Figure 6a–c).

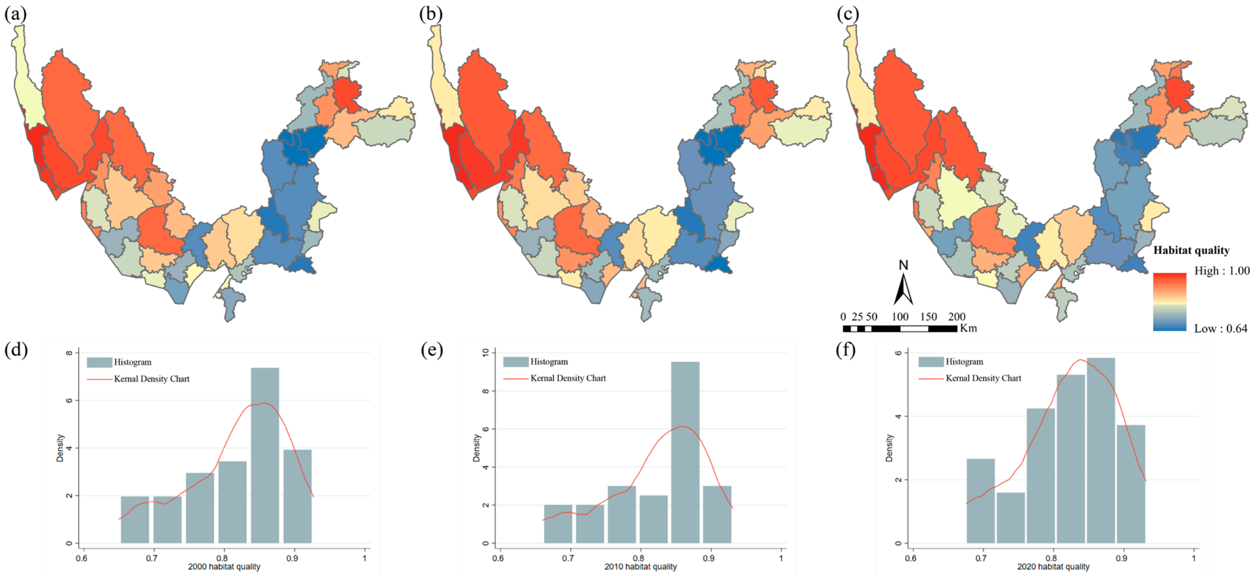

Figure 6. Spatial distribution of habitat quality levels for (**a**) 2000, (**b**) 2010, and (**c**) 2020. Histogram distribution and fitted kernel density curves of habitat quality for (**d**) 2000, (**e**) 2010, and (**f**) 2020.

4.3. Effects of Comprehensive Ecological Land Agglomeration and Habitat Quality on Soil Erosion

The results of the variables in this study after Global autocorrelation analysis are shown in Table 6. It can be seen from the table that the p values of the variables from 2000 to 2020 are less than 0.05, and the I values are greater than 0, indicating that the null hypothesis is rejected. The degree of "high-high" (H-H) and "low-low" (L-L) clustered distributions are higher than expected.

Table 6. Results of global spatial autocorrelation analysis of soil erosion for 2000, 2010, and 2020.

Year	Moran's	Z Score	*p* Score
2000	0.52	67.94	0.00
2010	0.53	68.82	0.00
2020	0.51	66.33	0.00

The GWR model was used first, before using the GTWR model to ensure the validity of the regression results. It can be observed that the R^2, Sigma, and Akaike information criterion (AICc) of the GTWR model were 0.625, 0.612, and 20,945.6, respectively, which are better than those of the GWR model (Table 7). This suggests that the GTWR model provides a more explanatory analysis of the spatial and temporal heterogeneity of the coefficients of the influencing factors. The cointegration diagnosis ensured that the Variance Inflation Factor (VIF) was <10 for each explanatory variable, eliminating multi-collinearity as much as possible. After performing the GTWR, results with p values greater than 0.05 were removed to obtain regression results for the localized samples.

Table 7. Comparison of GWR and GTWR model.

Models	R^2 Adjusted	Sigma	AICc
GWR	0.616	0.620	21,148.6
GTWR	0.625	0.612	20,945.6

The regression coefficients of the local samples are visualized in Figures 7 and 8. For the comprehensive ecological land agglomeration, the regression coefficients mostly had negative values, indicating that comprehensive ecological land agglomeration had a significant negative effect on soil erosion. As the comprehensive ecological land agglomeration increased, the soil erosion in the study area decreased. The values of the regression coefficients showed a high distribution in the northeast and southwest. On the other hand, regions with high negative values are mainly distributed in the north. Overall, the absolute values of the regression coefficients had an increasing spatial trend from south to north.

The absolute values of the average of the regression coefficients overall decreased from 2000 to 2020. The number of regions with high negative values decreased from 2000 to 2010, and was mainly concentrated in the northeast marginal regions. The spatial pattern of regression coefficients in other regions remained stable from 2000–2010. However, from 2010 to 2020, the absolute values of regression coefficients decreased in the east and northwest, resulting in an overall higher distribution trend of in the west-central and lower in other regions for the absolute values of the regression coefficients. In addition, the maximum value of the regression coefficient in the northwest of the study area was greater than 0 in 2020.

For habitat quality, the regression coefficient values were both positive and negative. In terms of spatial distribution, the regression coefficients in the northeast and northwest of the study area were greater than 0. The regions with larger absolute values of regression coefficients were mainly located in the southeast and northwest. Overall, the regression coefficients were large in the northeast and northwest, decreasing successively in the southwest and southeast.

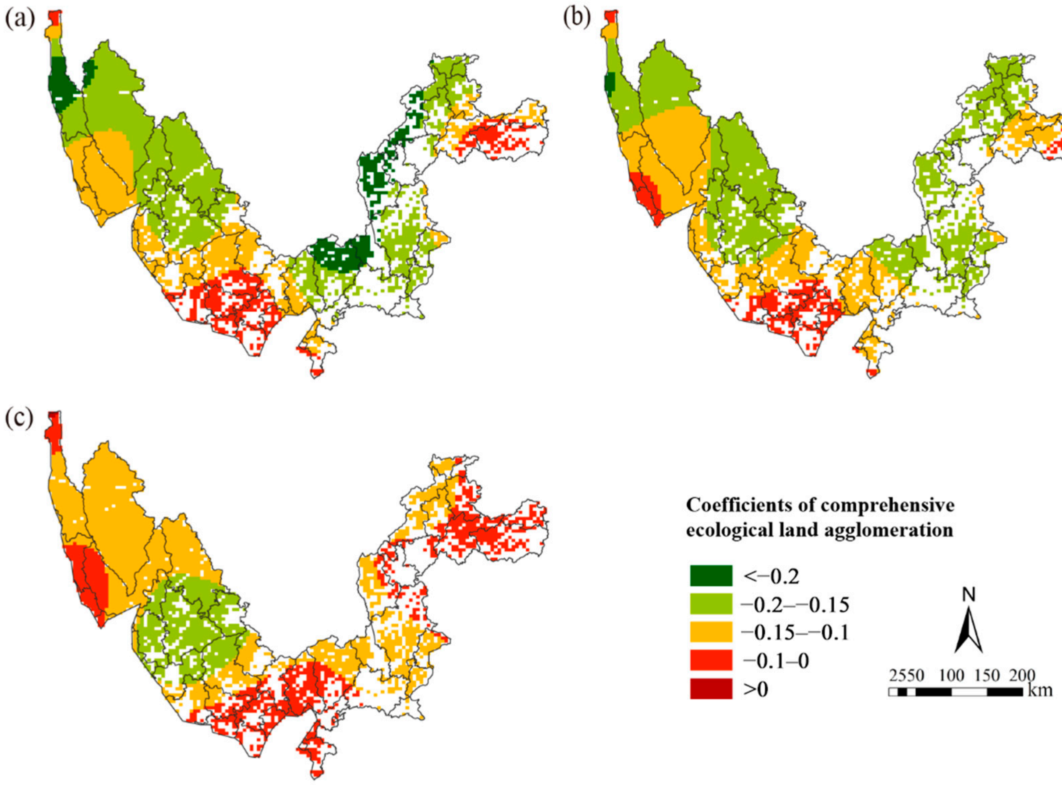

Figure 7. GTWR coefficients of comprehensive ecological land agglomeration for (**a**) 2000, (**b**) 2010, and (**c**) 2020. Coefficients of comprehensive ecological land agglomeration are the GTWR influence coefficients of comprehensive ecological land agglomeration on soil erosion.

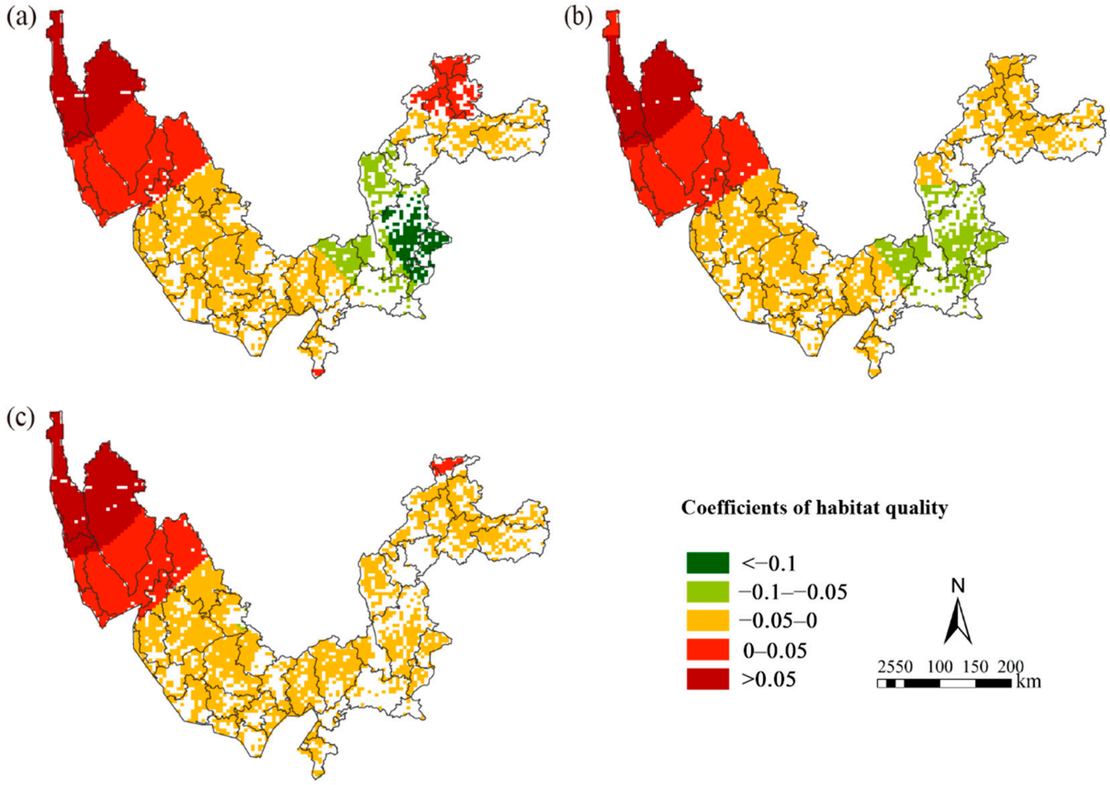

Figure 8. GTWR coefficients of habitat quality for (**a**) 2000, (**b**) 2010, and (**c**) 2020. Coefficients of habitat quality are the GTWR influence coefficients of habitat quality on soil erosion.

The absolute values of the average of the regression coefficients overall decreased from 2000 to 2020. The spatial pattern of the regression coefficient remained relatively stable from 2000–2010. From 2010 to 2020, the regions with high negative values decreased and were mainly concentrated in the southeast.

4.4. Interaction between Comprehensive Ecological Land Agglomeration and Habitat Quality on Soil Erosion

The mean regression coefficient for comprehensive ecological land agglomeration was −0.4026, while for habitat quality it was −0.9047 (Table 8). It is suggested that both comprehensive ecological land agglomeration and habitat quality have a significant negative effect on soil erosion, making them significant contributors to soil erosion. And the R^2 was 0.370.

Table 8. Estimation results and statistical characteristics based on the GTWR model (without interaction and control variables).

Variable	Average Value	Standard Deviation	Minimum Value	Maximum Values
intercept	0.7906	0.4208	−0.2335	3.3109
Comprehensive ecological land agglomeration	−0.4026	0.0861	−0.6850	−0.0344
Habitat quality	−0.9047	0.3456	−2.9933	−0.4106
R^2	0.370			

Since soil erosion is affected by more than just comprehensive ecological land agglomeration and habitat quality, it is necessary to include key factors affecting soil erosion as control variables in the model. Further parameter estimation of the model with control variables using the GTWR model not only makes the analytical framework more comprehensive, but also ensures the robustness of the analytical results of the key variables in the process of adding variables.

The estimated average regression coefficients for comprehensive ecological land agglomeration and habitat quality remained significantly negative after the introduction of control variables, which demonstrates the good robustness of the above estimation results (Table 9). In terms of the control variables, the average regression coefficients of precipitation and population factors were basically as expected at 0.0696 and 0.0466, respectively, and have positive effects on soil erosion. In addition, the average regression coefficient of DNVI was negative at −0.7912, and its absolute value was the largest among the average regression coefficients. The R^2 was 0.625. Compared to before the control variables were introduced, the fit of the model was improved and could better explain the effects of the above variables on soil erosion.

Table 9. Estimation results and statistical characteristics based on the GTWR model (with control variables).

Variable	Mean	Standard Deviation	Minimum Value	Maximum Values
Intercept	0.0283	0.1620	−0.1491	0.5699
comprehensive ecological land agglomeration	−0.1383	0.0381	−0.2538	0.0246
Habitat quality	−0.0021	0.0430	−0.1190	0.1130
NDVI	−0.7912	0.2935	−1.6782	−0.5024
Precipitation	0.0696	0.0822	−0.1633	0.3154
Population	0.0466	0.0859	−0.2211	0.3599
R^2	0.625			

After introducing the interaction terms of comprehensive ecological land agglomeration and habitat quality into the model, the average regression coefficients of comprehensive ecological land agglomeration and habitat quality on soil erosion remained less than 0

(Table 10). The average regression coefficients of the interaction terms were significantly negative.

Table 10. Estimation results and statistical characteristics based on the GTWR model (with control variables interaction terms).

Variable	Mean	Standard Deviation	Minimum Value	Maximum Values
Intercept	0.0390	0.1552	−0.1392	0.5660
Comprehensive ecological land agglomeration	−0.1337	0.0369	−0.2573	−0.0063
Habitat quality	−0.0321	0.0478	−0.4705	0.0261
Interaction term	−0.0299	0.0886	−0.5966	0.1677
NDVI	−0.7958	0.2936	−1.6856	−0.5021
Precipitation	0.0696	0.0831	−0.1630	0.3179
Population	0.0476	0.0851	−0.1452	0.3594
R^2	0.639			

The absolute value of the mean of the interaction term between 2000 and 2020 displays a decreasing trend. Figure 9 illustrates the distribution of the coefficients of the interaction terms. Furthermore, the larger absolute values of the interaction term coefficients are mainly situated in the northwest regions. The northwest regions were characterized by regression coefficients below 0, and the regions of negative values displayed a reduction trend from 2000 to 2020. Conversely, from 2000 to 2020, regression coefficients in the eastern regions were greater than 0 and the regions exhibited a gradual enlargement. Overall, the regression coefficients of the interaction terms exhibited greater stability in the northwest regions, whereas significant changes were observed in the other regions.

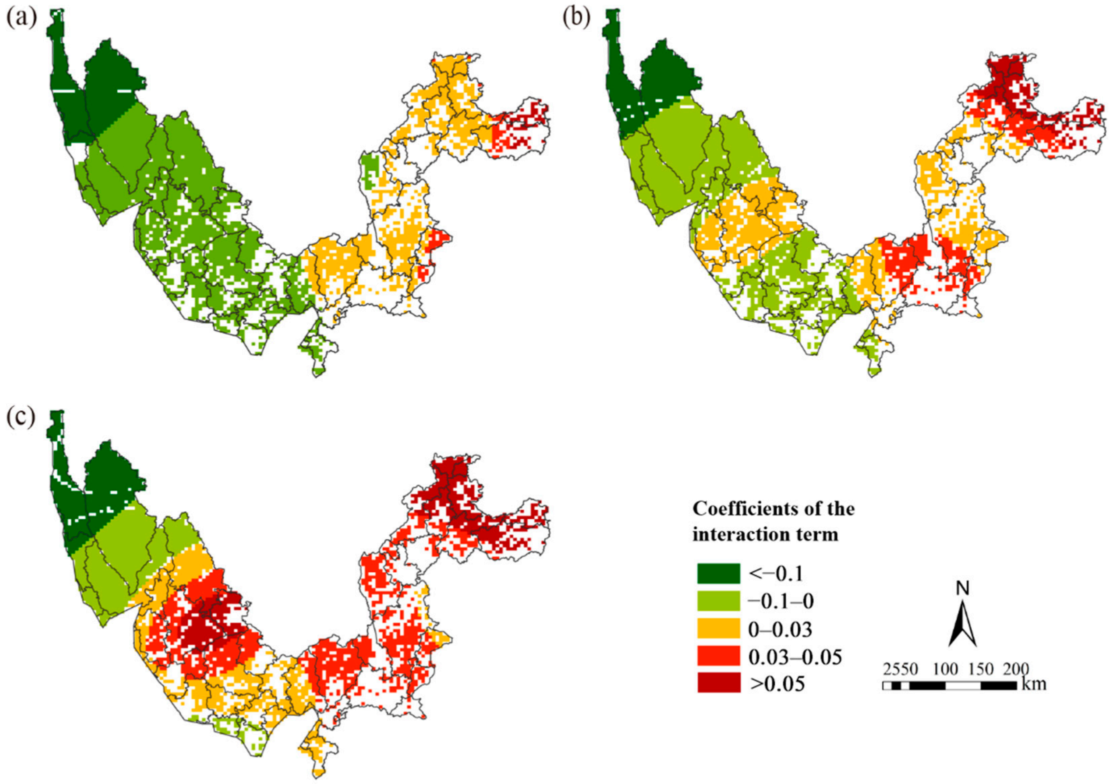

Figure 9. GTWR coefficients of the interaction term of comprehensive ecological land agglomeration and habitat quality for (**a**) 2000, (**b**) 2010, and (**c**) 2020. Coefficients of the interaction term are the GTWR influence coefficients of comprehensive ecological land agglomeration and habitat quality on soil erosion.

The results of the regression above indicate that comprehensive ecological land agglomeration has a negative effect on soil erosion. Additionally, the negative coefficient of the interaction term demonstrates that the negative effect of comprehensive ecological land agglomeration on soil erosion is strengthened with the optimization of habitat quality in the western regions. Conversely, in the eastern regions, the positive coefficient of the interaction term demonstrates that the negative effect of comprehensive ecological land agglomeration on soil erosion is weakened with the optimization of habitat quality.

The average regression coefficients of other control variables such as NDVI, precipitation, and population were −0.7958, 0.0696, and 0.0476, respectively, which emphasizes that vegetation cover is the major factor affecting soil erosion. The R^2 was 0.639. Compared to the previous two results, the model had the best fit and best explained the effect of the above variables on soil erosion.

The results regarding coefficients of comprehensive ecological land agglomeration on soil erosion, coefficient of habitat quality on soil erosion, and interaction coefficient on soil erosion of study countries are presented in Figure 10. The three coefficients generally moved forward and downward, with the habitat quality coefficients concentrating on negative values, the interaction term coefficients concentrating on positive values, and the ecological land agglomeration coefficients increasing in absolute value. This indicates that soil erosion in the studied counties decreased with the optimization of habitat quality. The negative effect of ecological agglomeration on soil erosion increased. The effect of ecological land agglomeration on soil erosion increased with the enhancement of habitat quality. Among study counties, habitat quality in Deqin County had the greatest effect on soil erosion. The ecological land agglomeration in Gucheng District had the greatest effect on soil erosion, and habitat quality in Suijiang County and Zhenxiong County had the greatest moderating effect on habitat quality.

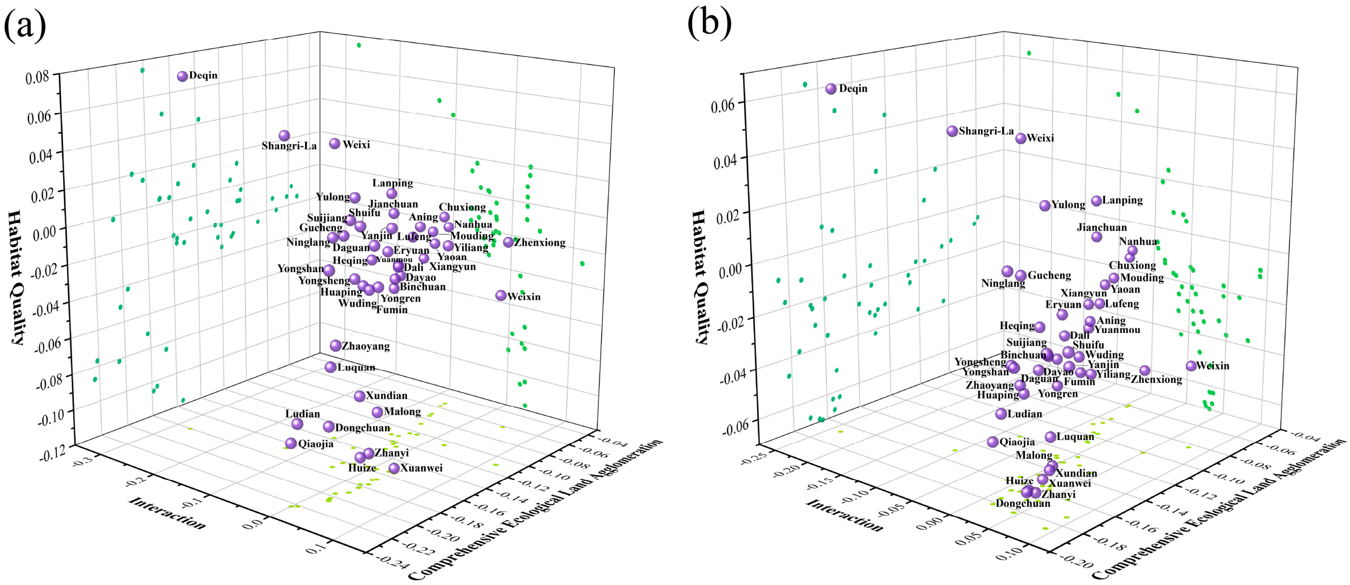

Figure 10. *Cont.*

(c)

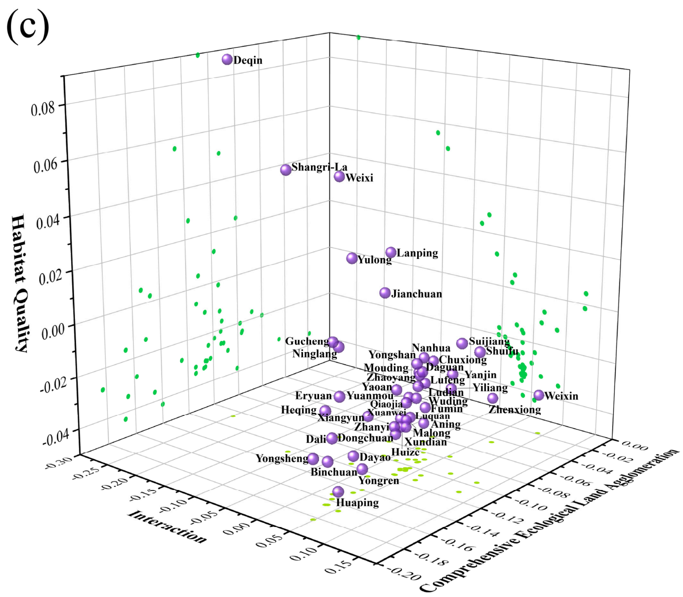

Figure 10. Scatter chart of coefficients of comprehensive ecological land agglomeration on soil erosion, coefficient of habitat quality on soil erosion, and interaction coefficient on soil erosion for: (**a**) 2000; (**b**) 2010; and (**c**) 2020. The pots are the projection of the corresponding indicators.

5. Discussion

5.1. Feasibility and Rationality of Methods

Soil conservation service refers to the ability of ecosystems to prevent soil erosion, limit soil loss, and store and retain sediment. Soil conservation service is crucial for preventing regional land degradation and reducing the risk of flooding. The Sediment Delivery Ratio of the InVEST model serves as an effective indicator for assessing soil erosion and has been widely utilized in ecological assessments across various scales. The InVEST Model has been employed to calculate soil conservation using DEM, erosivity, soil erodibility, land use biophysical table, watersheds, and threshold flow accumulation datasets [28,44,45]. An evaluation of the similarities and differences between RUSLE and the InVEST Model concerning spatial distribution and spatiotemporal changes was conducted in the study area. The overall spatiotemporal distribution of RUSLE closely resembles that of the InVEST Model.

In addition, many studies have researched the response or correlation of soil erosion to specific influencing factors at different scales [9–11,46], but few studies have analyzed the interaction effect of comprehensive ecological land agglomeration and habitat quality on soil erosion at watershed scales. The small grid will improve the accuracy of the results but may also increase the computational cost. A larger grid may reduce the computational time but may ignore some local details. Taking into account the complexity of the model, the limitation of computational resources, and other aspects, and in combination with the relevant literature [42,47], the grid partitioning result of a 5 km × 5 km fishing net has a better fitting effect. Compared with previous studies [42,47], the estimation results of this paper are within the reliable range, further indicating their high degree of accuracy.

The soil-type data used in the present study were in the solution of 1 km × 1 km, and land use data were in the solution of 30 m × 30 m. This inconsistent precision could bring a bias in the results. The results were compared with the relevant studies in the study area, and the overall scope and distribution trends of the results were consistent [42,47]. As more precise data can be collected, the results could be accurate. It could be improved in our further studies. Additionally, the parameters of the RUSLE Model and habitat quality varied, and only one type was selected for each calculation. The effects of the different parameters on the results can be conducted in subsequent studies.

5.2. Interaction among Comprehensive Ecological Land Agglomeration, Habitat Quality, and Soil Erosion in the Jinsha River Catchment in Yunnan Province

The results revealed a significant correlation between comprehensive ecological land agglomeration, habitat quality, and soil erosion. The study area demonstrated a significant negative correlation between comprehensive ecological land agglomeration and soil erosion. It is possibly due to the impact of vegetation patches and agricultural land on hydrological and soil connectivity, which ultimately affects soil erosion [12]. Nevertheless, a small portion of the study area displayed a significant positive correlation due to the dominant influence of slope factors on soil erosion. In the study area, habitat quality exhibited a significant negative correlation with soil erosion as expected for areas with poor habitat quality have low vegetation coverage, making the soil vulnerable to erosion by wind and water [48]. Studies have shown that in areas with high slopes, the slope is a dominant effect factor on soil erosion [9,49]. Accordingly, habitat quality has a positive effect on soil erosion in the high-altitude northwestern region.

Previous research indicates that increased agglomeration adversely affects low habitat quality by disrupting natural habitats, and vice versa [42]. The impact of comprehensive ecological land agglomeration on soil erosion is regulated by habitat quality. Specifically, the western regions encompass a vast ecological land area characterized by high vegetation coverage and excellent habitat quality. In these regions, soil erosion is primarily influenced by natural environmental factors. Comprehensive ecological land agglomeration plays a crucial role in enhancing soil connectivity and improving soil and water conservation, subsequently reducing soil erosion. However, in the eastern regions with high habitat quality, the impact of comprehensive ecological land agglomeration on soil erosion was weakened. This is mainly due to the high intensity of human activities and large-scale urban construction in the regions, which made soil erosion more sensitive to human activity. Therefore, habitat quality has varying regulatory effects depending on the natural conditions and human activities [50].

5.3. The Management of Ecological Land Agglomeration and Restoration of Habitat Quality Are Effective Tools for Soil Erosion Management

It was found by Li et al. and Mirghaed et al. that a strong correlation between the landscape pattern index and soil conservation under land use change [11]. Changes in landscape composition and spatial arrangements within landscape patterns can significantly impact surface interception and nutrient storage, leading to reduced soil water conservation and sand conservation as well as decreased productivity. During the study period, soil erosion in the study area reduced, which was due to the implementation of ecological projects such as returning farmland to forests and afforestation in the area [51]. Areas with low soil erosion in the study area have a high percentage of woodland, grassland, and shrub cover, and low urbanization impact. These areas also exhibit a high degree of comprehensive ecological land agglomeration. The woodland ecosystem, which plays a crucial role in water conservation and regulation of surface water and soil, can effectively inhibit soil erosion through its aggregated distribution and high coverage. Furthermore, the northwest of the study area is characterized by a diverse range of forest plant species. This abundance of species has a significant impact on the organic carbon content of soil macroaggregates [46]. Additionally, it acts to enhance the cohesiveness and adhesiveness of the soil, thereby strengthening its overall structure and stability [46]. Consequently, this leads to a reduction in the infiltration performance and overall quality of the soil. Ultimately, these factors contribute to the enhancement of the natural resistance ability of soil erosion and the mitigation of soil erosion and desertification phenomena.

This study preliminarily explores the specific influence mechanisms of comprehensive ecological land agglomeration and habitat quality on soil erosion, based on which planners can propose strategies for mitigating soil erosion by calculating agglomeration indicators and optimizing the current land use status from the perspectives of comprehensive ecological land agglomeration and habitat quality. In addition, The findings suggest that comprehensive ecological land agglomeration is regulated by habitat quality, which affects soil erosion. To address soil erosion, relevant planners can prioritize enhancing e comprehensive ecological land agglomeration by incorporating high-habitat patches like woodlands and improving their connectivity [10]. This approach will optimize habitat quality, enhancing the effect of both on soil erosion reduction.

5.4. Strategies for Ecological Land Agglomeration Management and Habitat Quality Restoration

It has been demonstrated that at the macro level, green infrastructure (GI) refers to the network of natural areas and open spaces with internal connectivity [52]. It is composed of interconnected green spaces, including natural spaces or artificial and semi-artificial green vegetation, water bodies, etc., and can provide various types of ecological services. Habitat quality based on the GI perspective is of great value in minimizing the impacts of reduced ecological land agglomeration on regional soil erosion.

This study preliminarily explores the specific influence mechanisms of comprehensive ecological land agglomeration and habitat quality on soil erosion. Based on this exploration, planners can mitigate the regional soil erosion phenomenon by calculating several indicators of ecological land agglomeration and proposing habitat quality optimization strategies from the perspective of landscape patterns [53]. The composition and distribution of GI should be enhanced as much as possible to ensure their integrity and provision of comprehensive ecosystem services. Specifically, the GI network of the district can be optimized by supplementing the center of the GI network, installing additional small sites, and identifying potential ecological corridors to improve the integrity, so that it covers the entire district and ensures that the regional ecosystem service function is performed [53].

In terms of land use, for cultivated land, improved farming methods need to be adapted to local conditions and scientific planting. At the same time, it is necessary to strictly control the increase in agricultural land at the expense of forest land. Strengthening the protection of woodlands, grasslands, and scrublands and implementing mechanisms for the management of deforestation are also essential [54]. Policies such as returning farmland to forests should be implemented as well. In future urban construction or planning for the expansion of construction land, reducing the occupation of forest land and other ecological lands should be a priority. Instead, the focus should be on the protection and restoration of ecological land and the addition of urban green space to harmonize the relationship between urban development and ecological protection. Increasing the connectivity of woodlands and grasslands and aggregating small pieces of cultivated land into larger patches can improve soil erosion in specific management practices [53]. Local planning can integrate the goals, policies, and recommendations of regional planning with local land use planning. The results of this study are expected to serve as evidence that can be used to update regional green infrastructure planning.

In the Yunnan section of the Jinsha River Basin, ecological protection and high-quality development should be prioritized [55,56]. This involves strengthening the protection of existing ecological land and carrying out restoration and construction of fragmented green development space. It is important to formulate relevant land use policies and measures to optimize the green infrastructure network in the Jinsha River Basin and explore the balance between regional development and ecological protection.

6. Conclusions

In this study, the Yunnan section of the Jinsha River Basin was used as the research object. Based on land-use data, meteorological data, and soil type data, the RUSLE model, Fragstats, and the InVEST model's Habitat Quality Module were used to quantify soil erosion, comprehensive ecological land agglomeration, and habitat quality. GTWR was also used to explore the interactive effects of ecological land agglomeration and habitat quality on soil erosion in time and space.

The study showed that, during the study period, the soil erosion modulus in the study area gradually decreased and soil erosion was alleviated. In terms of spatial distribution, soil erosion was more severe in the eastern regions than in the western ones, mainly due to high-intensity human activity and low vegetation cover. Both comprehensive ecological land agglomeration and habitat quality showed an increasing trend during the study period, indicating that the ecological capacity and ecological environment of the study area are being optimized. In terms of driving mechanisms, both comprehensive ecological land agglomeration and habitat quality had significant negative effects on soil erosion. However, comprehensive ecological land agglomeration had a greater impact on soil erosion. The magnitude of the negative effects of comprehensive ecological land agglomeration and habitat quality on soil erosion decreased. The interactive effect of comprehensive ecological land agglomeration and habitat quality has a significant negative impact on soil erosion, indicating that comprehensive ecological land agglomeration affects soil erosion through the regulation of habitat quality and the negative effect of comprehensive ecological land agglomeration on soil erosion is strengthened with the optimization of habitat quality. In addition, habitat quality has varying regulatory effects depending on the natural conditions and human activities.

Based on the results of the study, the following recommendations are made. At the macro level, building large-scale core ecological sources and first-level connecting corridors will optimize the urban ecological network and improve the connectivity of the habitat areas. At the micro level, the current land use in the region should be optimized, and policies such as returning farmland to forests should be implemented. Small pieces of cultivated land can be clustered into larger patches to enhance regional habitats. These practices help mitigate soil erosion, leading to an increase in biodiversity and an overall improvement in the regional ecological environment.

Author Contributions: Conceptualization, Y.Z.; methodology, C.L.; software, B.W.; formal analysis, C.L.; data curation, X.T., Q.Z. and S.H.; writing—original draft preparation, B.W.; writing—review and editing, Y.Z.; funding acquisition, Y.Z. 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 72003090); General Project of Philosophy and Social Science Research in Universities of Jiangsu Province (grant number 2023SJYB0149).

Data Availability Statement: The data that support the findings of this study is available upon request.

Conflicts of Interest: Authors Xu Tian, Qi Zhang, and Shaolie Huang are employed by the China Construction First Group the Fifth Construction Co., 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. In addition, all the authors declare no conflicts of interest.

References

1. Li, Z.W.; Ning, K.; Chen, J.; Liu, C.; Wang, D.Y.; Nie, X.D.; Hu, X.Q.; Wang, L.X.; Wang, T.W. Soil and water conservation effects driven by the implementation of ecological restoration projects: Evidence from the red soil hilly region of China in the last three decades. *J. Clean. Prod.* **2020**, *260*, 121109. [CrossRef]
2. Xu, F.J.; Zhao, W.J.; Yan, T.T.; Qin, W.; Chen, H.A. Can slope spectrum information entropy replace slope length and steepness factor: A case study of the rocky mountain area in northern China. *Catena* **2022**, *212*, 106047. [CrossRef]
3. Li, Y.; Li, Y.R.; Fang, B.; Wang, Q.Y.; Chen, Z.F. Impacts of ecological programs on land use and ecosystem services since the 1980s: A case-study of a typical catchment on the Loess Plateau, China. *Land Degrad. Dev.* **2022**, *33*, 3271–3282. [CrossRef]
4. van Zelm, R.; van der Velde, M.; Balkovic, J.; Cengic, M.; Elshout, P.M.F.; Koellner, T.; Núñez, M.; Obersteiner, M.; Schmid, E.; Huijbregts, M.A.J. Spatially explicit life cycle impact assessment for soil erosion from global crop production. *Ecosyst. Serv.* **2018**, *30*, 220–227. [CrossRef]
5. Abdulkareem, J.H.; Pradhan, B.; Sulaiman, W.N.A.; Jamil, N.R. Prediction of spatial soil loss impacted by long-term land-use/land-cover change in a tropical watershed. *Geosci. Front.* **2019**, *10*, 389–403. [CrossRef]
6. Ochoa, P.A.; Fries, A.; Mejía, D.; Burneo, J.I.; Ruíz-Sinoga, J.D.; Cerdà, A. Effects of climate, land cover and topography on soil erosion risk in a semiarid basin of the Andes. *Catena* **2016**, *140*, 31–42. [CrossRef]
7. Wang, L.; Yan, H.; Wang, X.W.; Wang, Z.; Yu, S.X.; Wang, T.W.; Shi, Z.H. The potential for soil erosion control associated with socio-economic development in the hilly red soil region, southern China. *Catena* **2020**, *194*, 104678. [CrossRef]

8. Pili, S.; Serra, P.; Salvati, L. Landscape and the city: Agro-forest systems, land fragmentation and the ecological network in Rome, Italy. *Urban For. Urban Green.* **2019**, *41*, 230–237. [CrossRef]
9. Liu, Q.-Q.; Chen, L.; Li, J.-C. Influences of slope gradient on soil erosion. *Appl. Math. Mech.* **2001**, *22*, 510–519. [CrossRef]
10. Shi, P.; Li, P.; Li, Z.; Sun, J.; Wang, D.; Min, Z. Effects of grass vegetation coverage and position on runoff and sediment yields on the slope of Loess Plateau, China. *Agric. Water Manag.* **2022**, *259*, 107231. [CrossRef]
11. Yang, M.; Li, X.; Hu, Y.; He, X. Assessing effects of landscape pattern on sediment yield using sediment delivery distributed model and a landscape indicator. *Ecol. Indic.* **2012**, *22*, 38–52. [CrossRef]
12. Zhao, G.; Gao, P.; Tian, P.; Sun, W.; Hu, J.; Mu, X. Assessing sediment connectivity and soil erosion by water in a representative catchment on the Loess Plateau, China. *Catena* **2020**, *185*, 104284. [CrossRef]
13. Ferretti, V.; Pomarico, S. Ecological land suitability analysis through spatial indicators: An application of the Analytic Network Process technique and Ordered Weighted Average approach. *Ecol. Indic.* **2013**, *34*, 507–519. [CrossRef]
14. Kemp, K.K. *Environmental Modeling with GIS: A Strategy for Dealing with Spatial Continuity*; University of California: Santa Barbara, CA, USA, 1992.
15. Xia, N.; Hai, W.; Tang, M.; Song, J.; Quan, W.; Zhang, B.; Ma, Y. Spatiotemporal evolution law and driving mechanism of production–living–ecological space from 2000 to 2020 in Xinjiang, China. *Ecol. Indic.* **2023**, *154*, 110807. [CrossRef]
16. Shi, M.; Wu, H.; Fan, X.; Jia, H.; Dong, T.; He, P.; Baqa, M.F.; Jiang, P. Trade-offs and synergies of multiple ecosystem services for different land use scenarios in the yili river valley, China. *Sustainability* **2021**, *13*, 1577. [CrossRef]
17. Yohannes, H.; Soromessa, T.; Argaw, M.; Dewan, A. Spatio-temporal changes in habitat quality and linkage with landscape characteristics in the Beressa watershed, Blue Nile basin of Ethiopian highlands. *J. Environ. Manag.* **2021**, *281*, 111885. [CrossRef]
18. Wei, J.; Hou, L.; He, X. An assessment of human versus climatic impacts on large-sized basin erosion: The case of the upper Yangtze River. *Nat. Hazards* **2014**, *74*, 405–420. [CrossRef]
19. Li, J.; Zhou, Z.X. Coupled analysis on landscape pattern and hydrological processes in Yanhe watershed of China. *Sci. Total Environ.* **2015**, *505*, 927–938. [CrossRef]
20. Liu, Y.; Zhang, C.; Zeng, H. Constraint effects among several key ecosystem service types and their influencing factors: A case study of the Pearl River Delta, China. *Ecol. Indic.* **2023**, *146*, 109883. [CrossRef]
21. Guo, L.; Liu, R.; Men, C.; Wang, Q.; Miao, Y.; Shoaib, M.; Wang, Y.; Jiao, L.; Zhang, Y. Multiscale spatiotemporal characteristics of landscape patterns, hotspots, and influencing factors for soil erosion. *Sci. Total Environ.* **2021**, *779*, 146474. [CrossRef]
22. Shen, G.; Chen, N.; Wang, W.; Chen, Z. WHU-SGCC: A novel approach for blending daily satellite (CHIRP) and precipitation observations over the Jinsha River basin. *Earth Syst. Sci. Data* **2019**, *11*, 1711–1744. [CrossRef]
23. Liu, S.; Wang, D.; Miao, W.; Wang, Z.; Zhang, P.; Li, D. Characteristics of runoff and sediment load during flood events in the Upper Yangtze River, China. *J. Hydrol.* **2023**, *620*, 129433. [CrossRef]
24. Zhu, Z.; Fu, Y.; Woodcock, C.E.; Olofsson, P.; Vogelmann, J.E.; Holden, C.; Wang, M.; Dai, S.; Yu, Y. Including land cover change in analysis of greenness trends using all available Landsat 5, 7, and 8 images: A case study from Guangzhou, China (2000–2014). *Remote Sens. Environ.* **2016**, *185*, 243–257. [CrossRef]
25. Zhang, F.; Tiyip, T.; Feng, Z.D.; Kung, H.T.; Johnson, V.C.; Ding, J.L.; Tashpolat, N.; Sawut, M.; Gui, D.W. Spatio-Temporal Patterns of Land Use/Cover Changes Over the Past 20 Years in the Middle Reaches of the Tarim River, Xinjiang, China. *Land Degrad. Dev.* **2015**, *26*, 284–299. [CrossRef]
26. Gao, J.; Wang, H. Temporal analysis on quantitative attribution of karst soil erosion: A case study of a peak-cluster depression basin in Southwest China. *Catena* **2019**, *172*, 369–377. [CrossRef]
27. Yonaba, R.; Koïta, M.; Mounirou, L.A.; Tazen, F.; Queloz, P.; Biaou, A.C.; Niang, D.; Zouré, C.; Karambiri, H.; Yacouba, H. Spatial and transient modelling of land use/land cover (LULC) dynamics in a Sahelian landscape under semi-arid climate in northern Burkina Faso. *Land Use Policy* **2021**, *103*, 105305. [CrossRef]
28. Aneseyee, A.B.; Elias, E.; Soromessa, T.; Feyisa, G.L. Land use/land cover change effect on soil erosion and sediment delivery in the Winike watershed, Omo Gibe Basin, Ethiopia. *Sci. Total Environ.* **2020**, *728*, 138776. [CrossRef]
29. Fu, B.J.; Zhao, W.W.; Chen, L.D.; Zhang, Q.J.; Lü, Y.H.; Gulinck, H.; Poesen, J. Assessment of soil erosion at large watershed scale using RUSLE and GIS: A case study in the Loess Plateau of China. *Land Degrad. Dev.* **2005**, *16*, 73–85. [CrossRef]
30. Arnoldus, H. Methodology used to determine the maximum potential average annual soil loss due to sheet and rill erosion in Morocco. *Environ. Sci.* **1977**, *34*, 39–51. Available online: http://www.oalib.com/references/9333552 (accessed on 6 September 2023).
31. Williams, J.R.; Greenwood, D.J.; Nye, P.H.; Walker, A. The erosion-productivity impact calculator (EPIC) model: A case history. *Philos. Trans. R. Soc. Lond. Ser. B Biol. Sci.* **1997**, *329*, 421–428. [CrossRef]
32. Zhang, J.; Wang, N.; Wang, Y.; Wang, L.; Hu, A.; Zhang, D.; Su, X.; Chen, J. Responses of soil erosion to land-use changes in the largest tableland of the Loess Plateau. *Land Degrad. Dev.* **2021**, *32*, 3598–3613. [CrossRef]
33. Yu, Y.; Shen, Y.; Wang, J.; Wei, Y.; Liu, Z. Simulation and mapping of drought and soil erosion in Central Yunnan Province, China. *Adv. Space Res.* **2021**, *68*, 4556–4572. [CrossRef]
34. Rao, W.; Shen, Z.; Duan, X. Spatiotemporal patterns and drivers of soil erosion in Yunnan, Southwest China: RULSE assessments for recent 30 years and future predictions based on CMIP6. *Catena* **2023**, *220*, 106703. [CrossRef]
35. Guo, X.; Chang, Q.; Liu, X.; Bao, H.; Zhang, Y.; Tu, X.; Zhu, C.; Lv, C.; Zhang, Y. Multi-dimensional eco-land classification and management for implementing the ecological redline policy in China. *Land Use Policy* **2018**, *74*, 15–31. [CrossRef]

36. Li, J.; Zhou, K.; Xie, B.; Xiao, J. Impact of landscape pattern change on water-related ecosystem services: Comprehensive analysis based on heterogeneity perspective. *Ecol. Indic.* **2021**, *133*, 108372. [CrossRef]
37. Dale, V.H.; Polasky, S. Measures of the effects of agricultural practices on ecosystem services. *Ecol Econ.* **2007**, *64*, 286–296. [CrossRef]
38. Sun, X.; Yu, Y.; Wang, J.; Liu, W. Analysis of the Spatiotemporal Variation in Habitat Quality Based on the InVEST Model- A Case Study of Shangri-La City, Northwest Yunnan, China. *J. Phys. Conf. Ser.* **2021**, *1961*, 012016. [CrossRef]
39. Lei, J.; Chen, Y.; Li, L.; Chen, Z.; Chen, X.; Wu, T.; Li, Y. Spatiotemporal change of habitat quality in Hainan Island of China based on changes in land use. *Ecol. Indic.* **2022**, *145*, 109707. [CrossRef]
40. Zhao, X.; Deng, C.; Huang, X.; Kwan, M.-P. Driving forces and the spatial patterns of industrial sulfur dioxide discharge in China. *Sci. Total Environ.* **2017**, *577*, 279–288. [CrossRef]
41. Huang, B.; Wu, B.; Barry, M. Geographically and temporally weighted regression for modeling spatio-temporal variation in house prices. *Int. J. Geogr. Inf. Sci.* **2010**, *24*, 383–401. [CrossRef]
42. Hu, J.; Zhang, J.; Li, Y. Exploring the spatial and temporal driving mechanisms of landscape patterns on habitat quality in a city undergoing rapid urbanization based on GTWR and MGWR: The case of Nanjing, China. *Ecol. Indic.* **2022**, *143*, 109333. [CrossRef]
43. Li, Y.; Bai, X.; Zhou, Y.; Qin, L.; Tian, X.; Tian, Y.; Li, P. Spatial–Temporal Evolution of Soil Erosion in a Typical Mountainous Karst Basin in SW China, Based on GIS and RUSLE. *Arab. J. Sci. Eng.* **2016**, *41*, 209–221. [CrossRef]
44. Ran, C.; Wang, S.; Bai, X.; Tan, Q.; Zhao, C.; Luo, X.; Chen, H.; Xi, H. Trade-offs and synergies of ecosystem services in southwestern China. *Environ. Eng. Sci.* **2020**, *37*, 669–678. [CrossRef]
45. Sun, L.; Yu, H.; Sun, M.; Wang, Y. Coupled impacts of climate and land use changes on regional ecosystem services. *J. Environ. Manag.* **2023**, *326*, 116753. [CrossRef]
46. Quinton, J.N.; Govers, G.; Van Oost, K.; Bardgett, R.D. The impact of agricultural soil erosion on biogeochemical cycling. *Nat. Geosci.* **2010**, *3*, 311–314. [CrossRef]
47. Singh, G.; Panda, R.K. Grid-cell based assessment of soil erosion potential for identification of critical erosion prone areas using USLE, GIS and remote sensing: A case study in the Kapgari watershed, India. *Int. Soil Water Conserv. Res.* **2017**, *5*, 202–211. [CrossRef]
48. Yan, Y.; Dai, Q.; Wang, X.; Jin, L.; Mei, L. Response of shallow karst fissure soil quality to secondary succession in a degraded karst area of southwestern China. *Geoderma* **2019**, *348*, 76–85. [CrossRef]
49. Koulouri, M.; Giourga, C. Land abandonment and slope gradient as key factors of soil erosion in Mediterranean terraced lands. *Catena* **2007**, *69*, 274–281. [CrossRef]
50. Li, P.; Zuo, D.; Xu, Z.; Zhang, R.; Han, Y.; Sun, W.; Pang, B.; Ban, C.; Kan, G.; Yang, H. Dynamic changes of land use/cover and landscape pattern in a typical alpine river basin of the Qinghai-Tibet Plateau, China. *Land Degrad. Dev.* **2021**, *32*, 4327–4339. [CrossRef]
51. Li, W.; Zinda, J.A.; Zhang, Z. Does the "Returning Farmland to Forest Program" Drive Community-Level Changes in Landscape Patterns in China? *Forests* **2019**, *10*, 933. [CrossRef]
52. Dong, J.; Guo, F.; Lin, M.; Zhang, H.; Zhu, P. Optimization of green infrastructure networks based on potential green roof integration in a high-density urban area—A case study of Beijing, China. *Sci. Total Environ.* **2022**, *834*, 155307. [CrossRef] [PubMed]
53. Valeri, S.; Zavattero, L.; Capotorti, G. Ecological Connectivity in Agricultural Green Infrastructure: Suggested Criteria for Fine Scale Assessment and Planning. *Land* **2021**, *10*, 807. [CrossRef]
54. Wang, F.; Yu, Q.; Qiu, S.; Xu, C.; Ma, J.; Liu, H. Study on the relationship between topological characteristics of ecological spatial network and soil conservation function in southeastern Tibet, China. *Ecol. Indic.* **2023**, *146*, 109791. [CrossRef]
55. Wang, D.L.; Ding, W.L. Spatial pattern of the ecological environment in Yunnan Province. *PLoS ONE* **2021**, *16*, e0248090. [CrossRef]
56. Zhang, Z.; Hu, Z.; Zhong, F.; Cheng, Q.; Wu, M. Spatio-Temporal Evolution and Influencing Factors of High Quality Development in the Yunnan–Guizhou, Region Based on the Perspective of a Beautiful China and SDGs. *Land* **2022**, *11*, 821. [CrossRef]