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Spatiotemporal Changes in Ecosystem Services Value and Its Driving Factors in the Karst Region of China

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Abstract: Over the last few decades, most regional ecosystem services (ESs) have significantly deteriorated, primarily driven by an increase in human dominance over the natural environment. Creating an assessment framework of ESs and identifying its driving factors at the regional scale is challenging for researchers, administrators, and policy-makers. In this study, we attempt to quantify the economic value of ESs (ESV) in Guizhou Province from 2000 to 2018, one of the most prominent areas of karst landforms in China. We identified the major factors affecting ESs using the geographical detector (GD) model. Then, we conducted a multiscale geographically weighted regression (MGWR) analysis to examine the spatial differentiation of the causal effects of both natural and anthropogenic factors on ESs. Our results demonstrate the following: (1) the total ESV of Guizhou Province was approximately USD 81,764.32 million in 2000, USD 82,411.06 million in 2010, and USD 82,065.31 million in 2018, and the increase of USD 300.99 million from 2000 to 2018 was the result of the remarkable conversion from cultivated land to forestland; (2) significantly considerable differentiation existed in the spatial distribution of ESV at the county level, with a higher value in the eastern region and a lower value in the western region; (3) among the driving factors, population density had a more significant effect on the spatial differentiation of ESV than did natural factors; and (4) agricultural output value was the dominant factor influencing the ESV during the study period, with a significantly positive correlation, whereas per capita GDP and population density had significantly negative impacts on ESV, according to the effective performance of the MGWR model that evaluated the spatial heterogeneity in geospatial relationships between the driving factors of ESV. Our findings can provide notable guidance to land administrators and policy-makers for effective land resource conservation and management plans, thereby improving regional sustainability.

Keywords: ecosystem services value; driving factors; geographical detector model; multiscale geographically weighted regression; karst areas

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1. Introduction

ESs refer to life-supporting products and services obtained directly or indirectly through the structures, processes, and functions of an ecosystem [1,2]. Since the 1990s, severe environmental issues have created impediments for future food security and national development strategies, and thus ESs have attracted the attention of researchers and governments. The scientific community has revealed that intensive human activity has both a direct and indirect impact on numerous environmental factors (e.g., climate, landscapes, socioeconomic factors) and is responsible for altering the structures, processes, and functions of ESs [3,4]. A multiscale assessment framework at the local, regional, and global levels is crucial to more deeply understanding the benefits or damages that result from the alteration of Ess [5]. Since Costanza et al. (1997) first mapped the global values of ESs and put forth the concept of ESV, defined as a range of goods and services important for human well-being from a monetary-unit perspective [6], ESV has been applied in numerous studies that assess the changes to ecological services occurring across regions [7–10]. Subsequently, various classifications have been developed and adjusted for scientific assessment of ESV over the last decades, e.g., the Millennium Ecosystem Assessment (MA) [11,12], the Economics of Ecosystems and Biodiversity (TEEB) [13,14], the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) [15], the Common International Classification of Ecosystem Services (CICES) [16,17], and the National Ecosystem Services Classification System (NESCS) [18]. It is concluded that there are differences in the details among these classification systems, that is, Costanza's method includes seventeen services, while MA includes twenty-three and the TEEB includes twenty-two while the CICES was developed to provide a hierarchically consistent and science-based classification to be used for natural capital accounting purposes [19].

Since then, a growing number of studies on ecosystem service values (ESV) and the impact of land use land cover (LULC) on ESV have been performed at different levels all over the world [20,21]. However, the methods of valuation have been challenged due to their limited use and regional characteristics, such as, regional area, changes of ecological protection, observation and survey of the environment, which have affected the data that were required in many classification systems (e.g., MA, or TEEB) and have made data acquisition extraordinarily difficult [5,22]. Therefore, Costanza's method is considered a relatively simple approach to quantifying the spatial distribution of ESV and rapidly obtaining sustained momentum as a framework to communicate values and benefits to scientists, stakeholders, policy-makers, and the public [23–27]. In China, a series of coefficients for Chinese ESV, namely China's ESV system, at the national scale were developed from Costanza's research according to China's characteristics by Xie et al. [28,29]. Owing to more flexibility and less requirement for basic data, many scholars have widely utilized the China's ESV system to quantitatively estimate ecological functions and the benefits that land use transition may provide [10,30–34].

The relationships between ESs and their driving factors, particularly human activity, have gained increased attention over the last several years, and several studies have found that a multitude of factors influence ESs and ESV [35–38]. For instance, Cai et al. demonstrated that the rapid expansion of urban areas has resulted in a dramatic decline in ecosystem services and that the ESV of cultivated lands and wetlands has had a significant negative correlation with total GDP [39]. Zhu et al. explored global and local factors impacting ESV in the Beijing–Tianjin–Hebei region and found that the primary industry-related factors were socioeconomic factors [40]. The extensive land use transition from rural to urban areas, accompanied by rapid industrialization and the intensification of human activities, is the dominant factor leading to changes in ESs. Pilogallo et al. revealed that the greatest loss in ESV in the Basilicata region occurred within wooded areas and agricultural mosaics, whereas bare and arable lands increased in ESV [41]. Berihun et al. evaluated the impact of human-driven LULC changes on ESV and concluded that the population growth leading to the expansion of cultivated land had a negative impact on ESV in the Upper Blue Nile basin area of Ethiopia [42]. Given that different sets of environmental characteristics will generate different ESs, it is necessary to understand how these climatic and natural and human-induced socioeconomic factors ultimately decide which ESs will be sustainable.

The relationship between ES and its driving factors is not linear but rather has significant spatial heterogeneity [34,43]. To understand the spatial variation in ES and ESV, due to the spatial heterogeneity of driving factors such as topography, soil, vegetation, climate, and landscape structures, an increasing number of studies have concentrated on spatial autoregressive and multivariate regression methods [44–46]. Among them, the ordinary least square (OLS) model has been utilized to identify the interactions between ESV and its driving factors and ESV [47–49] but does not reflect the essential autocorrelation or homogeneity in space [50]. Compared with this model, the geographically weighted regression (GWR) model, developed from a linear regression with the weighted least squares (WLS) method, is a simple yet beneficial approach for identifying the spatial characteristics of relationships by measuring spatial variations in spatial association for each unit in the study area [51–56]. Therefore, we implemented the GWR model in this study to produce varying local attributes throughout the feature space by establishing local regression equations for ESV and its driving factors.

Over the last few decades, the karst area in southwestern China has suffered from a sequence of anthropogenic and natural adversities, including rocky desertification and soil erosion, which have resulted in a rapid decrease in ESs. Guizhou Province, located in Southwest China and known as one of the most prominent karst landform areas, has confronted notable pressure to balance its ecological protection and economic growth. Its vulnerable ecosystem provides a distinctive landscape and necessary habitat for rare plants and animals, which can contribute to the ecotourism industry, one of the province's predominant economic services [57–59]. Despite its profound ecological significance, researches on ESs changes and their driving mechanisms in karst areas have been explored in only a few studies, among which, the assessments and development trends of ESV based on MA, TEEB, IPBES, were so rarely involved that it was difficult to gain approximate parameters from the literature. Therefore, we attempted to investigate the spatial and temporal variability of the ESV and identify the primary driving factors for ESV in Guizhou Province via the following: (1) assessing the spatial and temporal variability of the ESV by using China's ESV system; (2) identifying potential driving factors by adopting GD; and (3) exploring the spatially heterogeneous relationship between the ESV and its driving factors based on MGWR. The outcomes of this study may not only enrich the current existing research on ESV in ecologically fragile areas and easily compare with other regions of China, but they may also provide suggestions for safeguarding both ecology and development.

2. Materials and Methods

2.1. Study Area

Guizhou, which lies at the eastern end of the Yungui Plateau in Southwest China (103°36′–109°35′ E, 24°37′–29°13′ N), is a crucial ecologically protected area in the upper reaches of the Yangtze and Pearl rivers and is an important part of the Yangtze River Economic Belt. Covering approximately 176,000 km^2 (Figure 1), Guizhou's orography is high in the west and low in the east. There are four major mountains in the province—Wumeng, Dalou, Miaoling, and Wuling—altogether accounting for 92.5% of the total area. Known as one of the most prominent karst areas in the world, 61.9% of the total area comprises karst landscapes and holds abundant resources, including water resources and coal mines. Guizhou Province currently governs six county-level cities—Guiyang, Zunyi, Liupanshui, Anshun, Bijie, and Tongren—and three autonomous prefectures—Qiandongnan, Qiannan, and Qianxinan)—encompassing 88 counties in total.

With the implementation of various national strategies (e.g., the development of the western region in China, the National Big Data Strategy, and the rise of the Yangtze River Economic Zone), Guizhou has undergone rapid economic development, with an average annual 8.32% increase in GDP from 2000 to 2019. However, as one of the nation's ecological civilization pilot zones, as well as the first of these zones in western China, Guizhou faces significant disturbances to its fragile ecosystems that occur as a result of rapid urbanization, economic growth, and drastic increases in land use. An assessment of the spatiotemporal status of ESs in this region can provide a scientific reference for ecological management; furthermore, it has important guiding implications for territorial spatial planning.

2.2. Data Sources and Descriptions

In this study, we utilized three types of data: land-use remote image data, ESV coefficient data, and social and economic development data for Guizhou Province. These included the following: (1) land-use maps (Shapefile data) from 2000, 2010, and 2018 (Figure A1, Appendix A) provided by the Resource and Environment Science and Data Central (http://www.resdc.cn, accessed on 19 September 2020); using the ESV coefficient established by the Chinese Academy of Sciences, we converted original land-use maps to TIFF images with 30 m × 30 m spatial resolution, extracted and generalized seven land classification types (cultivated land, forestland, grassland, water bodies, construction land, and unused land) in Guizhou Province; (2) a digital elevation model (DEM) (30 m × 30 m spatial resolution), the average annual temperature (30 m × 30 m spatial resolution), and the average annual precipitation (30 m × 30 m spatial resolution) obtained from the Resource and Environment Science and Data Central (http://www.resdc.cn, accessed on 19 September 2020); and (3) statistical data, including grain yield, grain price, GDP data primarily collected from the Statistical Yearbooks of Guizhou Province (http://data.cnki.net, accessed on 29 September 2020), and the statistical bulletin of national economic and social development of Guizhou Province (http://stjj.guizhou.gov.cn, accessed on 29 September 2020).

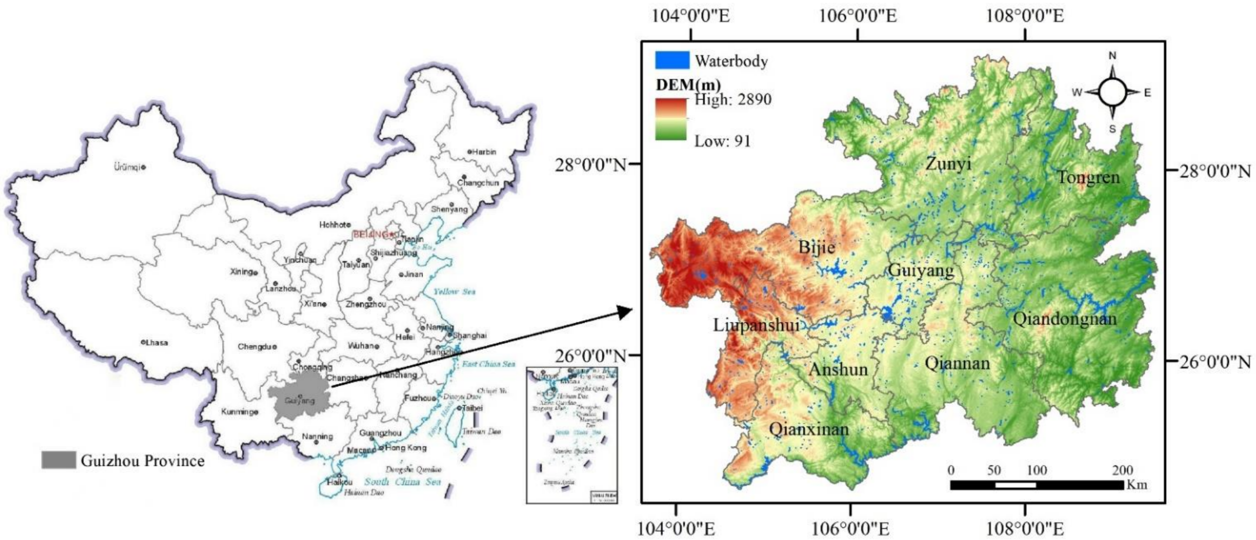

Figure 1. Location of the study area.

2.3. Assessment of Ecosystem Services Value

We adopted the China's ESV system which was based on the equivalent value factor per unit ecosystem area originated from Costanza et al. [6] and developed by Xie et al. [28,29] to quantify the ESV in China. Integrating Costanza's research and China's characteristics, Xie et al. divided the country's ESs into nine functions and adjusted the ESV coefficient; here, the function of food production from farmland represented the net profit of grain production per unit area of farmland and defined it as the standard ESV coefficient of China, with its equivalent value deemed as 1; meanwhile, the other function coefficients were all equivalent values based on the standard value of 1 (Table 1) [16]. Moreover, it should be noted that we evaluated the ESV coefficient framework at the national level and provincial or local ESV coefficients should be therefore revised to comply with local characteristic factors. Accordingly, Xie et al. proposed various biomass factors for different provinces in China to revise the national ESV coefficients; the biomass factor for Guizhou Province was 0.63 (Table 1) [17]. The economic value of the standard ESV coefficient is the average natural food production of farmland per unit area per year, which was assumed to be one seventh of the actual food production without any labor input. In Guizhou Province, the average actual food production of farmland was 3704.91 kg/ha between 2000 and 2018, and the average market price for grain in 2018 was USD 0.72/kg (CNY4.77/kg) (Note: the average exchange rate between USD and CNY in 2018 was 6.6174 (http://www.gov.cn, accessed on 28 April 2022). Hence, the economic value of the standard ESV coefficient is USD 381.53 /ha (CNY 2524.76/ha). We calculated the ESV for each land-use type per hectare using Equation (1). Table 2 (or CNY see Table A1) displays the results.

$$VC_{kf} = EC_{kf} \times 381.53 \quad (1)$$

where VC_{kf} is the ESV per hectare for land-use type k and service function f, and EC_{kf} is the equivalent ESV coefficient for land-use type k and service function f in Table 1.

Table 1. Equivalent value per unit area of ecosystem services in China and Guizhou Province.

Ecosystem Service and Functions	Cultivated Land		Forestland		Grassland		Water Body		Barren Land	
	China	Guizhou	China	Guizhou	China	Guizhou	China	Guizhou	China	Guizhou
Food production	1	0.63	0.33	0.21	0.43	0.27	0.53	0.33	0.02	0.01
Raw material	0.39	0.25	2.98	1.88	0.36	0.23	0.35	0.22	0.04	0.03
Gas regulation	0.72	0.45	4.32	2.72	1.5	0.95	0.51	0.32	0.06	0.04
Climate regulation	0.97	0.61	4.07	2.56	1.56	0.98	2.06	1.30	0.13	0.08
Water supply	0.77	0.49	4.09	2.58	1.52	0.96	18.77	11.83	0.07	0.04
Waste treatment	1.39	0.88	1.72	1.08	1.32	0.83	14.85	9.36	0.26	0.16
Soil formation and retention	1.47	0.93	4.02	2.53	2.24	1.41	0.41	0.26	0.17	0.11
Biodiversity protection	1.02	0.64	4.51	2.84	1.87	1.18	3.43	2.16	0.4	0.25
Recreation and culture	0.17	0.11	2.08	1.31	0.87	0.55	4.44	2.80	0.24	0.15
Total	7.9	4.98	28.12	17.72	11.67	7.35	45.35	28.57	1.39	0.88

Table 2. The annual ESV for each land use type per hectare in Guizhou Province (USD/ha yr).

Ecosystem Service and Functions	Cultivated Land	Forestland	Grassland	Water Body	Construction Land	Unused Land
Food production	240.37	80.12	103.01	125.91	0	3.82
Raw material	95.38	717.28	87.75	83.94	0	11.45
Gas regulation	171.69	1037.77	362.46	122.09	0	15.26
Climate regulation	232.73	976.73	373.90	495.99	0	30.52
Water supply	186.95	984.36	366.27	4513.54	0	15.26
Waste treatment	335.75	412.06	316.67	3571.15	0	61.05
Soil formation and retention	354.83	965.28	537.96	99.20	0	41.97
Biodiversity protection	244.18	1083.56	450.21	824.11	0	95.38
Recreation and culture	41.97	499.81	209.84	1068.29	0	57.23
Total	1903.85	6756.96	2808.09	10,904.23	0	331.93

Table 2 exhibits the ESV of one unit area of each land use type in Guizhou Province assigned based on the nearest equivalent ecosystems. For instance, cultivated land falls under the category of "farmland," forestland falls under "forest," and unused land falls under "barren land." We suppose that the ESV for construction land is 0 as a result of the transformation to construction land. The service value for each land use type and service function are provided in Equation (2):

$$ESV = \sum_{k} \sum_{f} A_k \times VC_{kf} \tag{2}$$

where ESV refers to the total ecosystem service value. A_K is the area for land-use type k, and VC_{kf} is the ESV per hectare for land-use type k and service function f in Table 2.

We analyzed the spatial changes in ESV in each county by using the ESV per unit area, which can be calculated as follows:

$$ESVA_i = ESV_i / Area_i \tag{3}$$

where $ESVA_i$ is the ESV per unit area of county i. ESV_i is the total ESV of county i, and Areai is the total area of county i.

2.4. Potential Driving Factor System of ESV

The potential driving factor system of ESV reveals the degree to which natural, economic, and social factors have potential impacts on ecosystems. Because no factor system is universal and the relevant criteria of ESV vary, depending on local conditions, we established a potential driving factor system of ESV for Guizhou Province, with four natural factor variables, five economic factor variables, and three social factor variables (Table 3).

Each factor, based on counties or administrative districts, has unique attributes, which allows for more area-specific results.

Table 3. Factors and their data sources in the primary driving factor system of ESV.

Factors	Variables	Data Resources	Variable Number
Natural factors	Elevation	DEM	X_1
	Terrain slope	DEM	X_2
	Average annual temperature	Meteorological map	X_3
	Average annual precipitation	Meteorological map	X_4
Economic factors	Gross domestic product (GDP)	Statistical annual	X_5
	Per capita GDP	Statistical annual	X_6
	Per capita disposable income of rural residents	Statistical annual	X_7
	Agricultural output value	Statistical annual	X_8
	Forestry output value	Statistical annual	X_9
Social factors	Resident population	Statistical annual	X_{10}
	Population density	Statistical annual	X_{11}
	Rural employment	Statistical annual	X_{12}

2.5. Exploring the Driving Factors of ESV Using GD and GWR

2.5.1. Geographical Detector Model

The geographical detector (GD) model is a relatively novel statistical technique for detecting spatial heterogeneity and revealing the driving force behind it. Its core hypothesis is that if independent variable X has an important impact on dependent variable Y, then a similar spatial distribution exists between them [60,61]. The GD model has unique advantages for dealing with both numerical and quantitative data and has been gradually used over the last several years in various research fields, such as environmental [62], social, and health sciences. The GD model includes four detectors: the factor detector, interaction detector, risk detector, and ecological detector. In this study, we used the factor detector to quantify the degree of impact of each explanatory variable X (the potential driving factors in Table 3) on dependent variable Y (ESV) for each year by calculating the q-statistic. In a range from 0 to 1, the higher its value, the greater the explanatory variable contributes to the dependent variable. The q-statistic is calculated by Equation (4):

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} \tag{4}$$

where h = 1, 2, ... , L is a certain stratum of each explanatory variable X (potential driving factor) and, of the dependent variable Y (ESV), L is the number of strata, N_h and N are the number of samples in stratum h and the entire study area, respectively, and σ^2 is the variance of dependent variable Y in stratum h and the entire study area. A *p* value, as the significance indicator of each explanatory variable, is also calculated through the noncentral F-distribution.

2.5.2. MGWR

Multiscale geographically weighted regression (MGWR) has become a popular approach for local spatial statistical analysis since it was first proposed by Brunsdon et al. [51]. This method can obtain spatially nonstationary relationships between dependent and independent variables by incorporating geographical information. Based on the Tobler Law [63], which states that "everything is related to everything else, but near things are more related than distant things", the GWR model predicts different weights for each location. The model is mathematically expressed as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_m \beta_m(u_i, v_i)x_{im} + \varepsilon_i \tag{5}$$

where v_i is the dependent variable at location i (ESV), x_{im} is the m-th potential driving factor at location i, (u_i, v_i) are the geographical coordinates at location i, $\beta_0(u_i, v_i)$ is the intercept coefficient at location i, $\beta_m(u_i, v_i)$ is the m-th local regression coefficient for x_{im} and ε_i represents the random error term associated with location i.

MGWR is an improved version of GWR that considers spatial multiscale effects and heterogeneity and reflects those differences in ESV [64]. The MGWR model expression is Equation (6) as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_m \beta_{bwm}(u_i, v_i) x_{im} + \varepsilon_i \quad (6)$$

where bwm in β_{bwm} indicates the bandwidth used for the calibration of the m-th conditional relationship. MGWR allows for the estimation of local regression coefficients of dependent and independent variables on different spatial scales [64–66].

In this study, both the MGWR and GWR models used a fixed Gaussian kernel function and were calibrated using a golden section search bandwidth selection routine [66]. All model calibrations were undertaken using MGWR 2.2 software [64].

3. Results

3.1. Historical Changes in Land Use and ESV

To explore the substantial magnitude of land use transitions that significantly affected the total ESV in Guizhou Province, we produced statistics of land use changes by using "Analysis Tools" in ArcGIS 10.2 software (Figure A2) and ESV changes between 2000 and 2018 (Table 4), which combine the data in Table 2 with Equation (2). Cultivated land and forestland comprised the largest portions of the total area (over 80%). The area of cultivated land was 493.73×10^4 ha in 2000 and 484.46×10^4 ha in 2018, decreasing by 1.88% to an average annual decrease of 5.15×10^3 ha. In contrast, forestland dramatically increased to 1.49×10^5 ha before 2010, owing to the policy mandating the conversion of farmland to forests, but it slightly dropped to 2.87×10^4 ha from 2010 to 2018; however, the increased area was higher than the decreased area during the period from 2000 to 2018. Grassland experienced the most conspicuous change from 2000 to 2018: with a continuous decline, the area decreased by 5.06% to 16.70×10^4 ha. The water area increased marginally, experiencing a continuous rise from 2000 to 2010 of 0.76×10^4 ha and 0.48×10^4 ha from 2010 to 2018. Construction land saw a dramatic ascension as a result of urban development—from 8.80×10^4 ha in 2000 to 21.61×10^4 ha in 2018, increasing by 145.71%. From 2000 to 2010, unused land decreased by 25.45%, nearly 0.10×10^4 ha, whereas from 2010 to 2018, the area increased by 2.61%, equal to 0.01×10^4 ha.

The total ESV of Guizhou Province was approximately USD 81,764.32 million in 2000, USD 82,411.06 million in 2010, and USD 82,065.31 million in 2018 (Table 4, or CNY see Table A2). Because of its larger equivalent ESV coefficient value and larger area, forestland ESV was the highest, representing approximately 77% of the total value. Although the equivalent ESV coefficient value of the water body areas was the highest among the six land use types, these areas were small and thus generated low ESV. Therefore, forestland played the most important role in Guizhou Province ESs. From 2000 to 2010, the ESV increment due to the increase in forestland was offset by a value decline in grassland and cultivated land. As a result, the total ESV increased by USD 646.74 million in last decade; however, the total ESV of Guizhou Province from 2010 to 2018 shrank by USD 345.76 million, primarily as a result of the decrease in forestland and the continuous decline in grassland and cultivated land. Overall, the net growth of the province's ESV was approximately USD 300.99 million from 2000 to 2018, primarily because of the significant conversion from cultivated land to forestland over the past 18 years.

Our value calculation results of different ES functions in Guizhou Province (Table 5, CNY see Table A3) revealed that the ESV of food production exhibited a downwards trend during the study period, whereas changes in other functions were overall consistent, increasing from 2000 to 2010 and declining from 2010 to 2018. The total values of each ES function from 2000 to 2018 from largest to smallest were as follows: biodiversity protection, soil formation and retention, water supply, gas regulation, climate regulation, raw material, waste treatment, recreation and culture, and food production. Due to the large area of forestland in Guizhou Province, changes in biodiversity protection and soil formation and retention were similar to those of forestland. Meanwhile, widely distributed water bodies throughout the area—namely, the Wujiang River, Nanpan River, and Beipan River—play crucial roles in microclimate improvements and ecosystem regulation services; however, the influence of the forestland to built-up land conversion on gas regulation, climate regulation, and water supply was heightened. These results reflect that, although human socioeconomic activities negatively affected the ESV of the Guizhou Province, the changes and structural distributions of the ESV for single functions, which came with changes in land use patterns, were relatively stable. Obviously, biodiversity protection has been the dominant ES function of the Guizhou Province over the last few decades, which has been closely related to the protection of forestland and the ecological civilization policy.

Table 4. Land use and ESV changes in Guizhou Province in 2000, 2010, 2018, 2000–2010, and 2010–2018.

Land Use Types		**Cultivated Land**	**Forestland**	**Grassland**	**Water Body**	**Construction Land**	**Unused Land**	**Total**
2000	Land area (10^4 ha)	493.73	918.99	329.99	9.18	8.8	0.4	1761.09
	ESV (Million USD)	9399.94	62,095.74	9266.50	1000.82	0.00	1.33	81,764.32
2010	Land area (10^4 ha)	491.82	933.88	315.55	9.94	9.6	0.3	1761.09
	ESV (Million USD)	9363.57	63,102.07	8861.00	1083.44	0.00	0.99	82,411.06
2018	Land area (10^4 ha)	484.46	931.01	313.29	10.41	21.61	0.31	1761.09
	ESV (Million USD)	9223.35	62,908.15	8797.45	1135.34	0.00	1.01	82,065.31
2000–2010	Land area (10^4 ha)	−1.91	14.89	−14.44	0.76	0.8	−0.1	0
	ESV (Million USD)	−36.37	1006.33	−405.50	82.62	0.00	−0.34	646.74
2010–2018	Land area (10^4 ha)	−7.36	−2.87	−2.26	0.48	12.01	0.01	0
	ESV (Million USD)	−140.22	−193.92	−63.55	51.90	0.00	0.03	−345.76
2000–2018	Land area (10^4 ha)	−9.28	12.02	−16.7	1.23	12.82	−0.09	0
	ESV (Million USD)	−176.58	812.41	−469.05	134.52	0.00	−0.31	300.99

Table 5. Value changes of different ecosystem service functions in Guizhou Province in 2000, 2010, and 2018.

Ecosystem Service Functions	**ESV (Million USD)**			**Changes of ESV (Million USD)**		
	2000	**2010**	**2018**	**2000–2010**	**2010–2018**	**2000–2018**
Food production	2274.59	2268.01	2246.27	−6.58	−21.73	−28.32
Raw material	7360.02	7452.98	7423.78	92.96	−29.20	63.76
Gas regulation	11,592.05	11,691.90	11,641.85	99.85	−50.05	49.80
Climate regulation	11,404.60	11,495.35	11,444.08	90.75	−51.27	39.48
Water supply	11,592.17	11,716.49	11,687.67	124.32	−28.82	95.50
Waste treatment	6817.47	6853.69	6826.98	36.22	−26.72	9.51
Soil formation and retention	12,407.22	12,467.23	12,401.70	60.01	−65.53	−5.53
Biodiversity protection	12,725.04	12,822.89	12,767.55	97.85	−55.34	42.51
Recreation and culture	5591.15	5642.52	5625.43	51.37	−17.09	34.27
Total ESV	81,764.32	82,411.07	82,065.31	646.74	−345.76	300.99

3.2. Historical Transitions of Land Use and ESV

As shown in Table 6, we found that between 2000 and 2018, 2.49% of the total land area had been transformed, whereas the ESV increased by USD 300.99 million. The most notable land use change in Guizhou Province was the transition from grassland to forestland, during which forestland increased by approximately 136,522.14 ha over 18 years, leading to an ESV increase of USD 539.11 million. The conversion of cultivated land (74,856.53 ha) to built-up land caused an ESV loss of USD 142.52 million. Meanwhile, the water body areas displayed a significant increase in both area and ESV, mostly due to the conversion of cultivated land (4880.96 ha), which was primarily the result of the implementation of an ecological protection policy that mandated the return of farmland to lakes and wetlands. However, both the cultivated land and grassland showed declining trends—specifically, the grassland area decreased as a result of forestland and cultivated land encroachment. The transformation of 48,589.04 ha from grassland to cultivated land resulted in an ESV decrease of USD 43.94 million; however, the transition from grassland to forestland subsequently increased the ESV to USD 539.11 million. The area of cultivated land shrank due to the increase in built-up land (74,856.53 ha), representing an ESV decline of USD 142.52 million. The transition from cultivated land to forestland, equal to 43,461.11 ha, gave rise to an increase in ESV of USD 210.92 million.

Table 6. Transition of land use and ecosystem service value from 2000 to 2018 in Guizhou Province.

2000–2018	Cultivated Land	Forestland	Grassland	Water Body	Construction Land	Unused Land	Total
			Land use transition (ha)				
Cultivated land	4,776,695.05	43,461.11	37,411.82	4880.96	74,856.53	19.30	4,937,324.77
Forestland	18,926.50	9,129,075.19	10,148.60	3243.34	28,389.13	111.67	9,189,894.43
Grassland	48,589.04	136,522.14	3,084,531.42	4188.45	26,047.77	55.95	3,299,934.76
Water body	55.25	2.19	27.57	91,654.94	42.59	0.00	91,782.53
Construction land	117.75	289.83	736.85	135.07	86,675.00	0.00	87,954.50
Unused land	190.16	777.30	42.39	16.64	99.39	2868.79	3994.67
Total	4,844,573.74	9,310,127.74	3,132,898.65	104,119.40	216,110.42	3055.70	17,610,885.66
			ESV transition (Million USD)				
Cultivated land	0.00	210.92	33.83	43.93	−142.52	−0.03	146.13
Forestland	−91.85	0.00	−40.08	13.45	−191.82	−0.72	−311.02
Grassland	−43.94	539.11	0.00	33.91	−73.15	−0.14	455.80
Water body	−0.50	−0.01	−0.22	0.00	−0.46	0.00	−1.19
Construction land	0.22	1.96	2.07	1.47	0.00	0.00	5.72
Unused land	0.30	4.99	0.10	0.18	−0.03	0.00	5.54
Total	−135.76	756.97	−4.30	92.94	−407.98	−0.89	300.99

3.3. Spatial Distribution of Land Use Changes and ESV Changes at the County Level

As shown in Figure 2, calculated with Equation (3), from 2000 to 2018, the maximum value of ESVA at the county level increased by 5.57%, totaling USD 327.89/ha, whereas the minimum value was raised by 9.73% (USD 69.71/ha). Lower ESV was primarily located in the western regions (Bijie and Liupanshui) and the south and east of Zunyi where vegetation coverage was low. The capital of Guizhou Province, Guiyang city, had the lowest ESVA owing to the rapid urban expansion in the area. In contrast, the eastern and southern areas with higher vegetation mountains, including Tongren, Qiandongnan, and Qiannan, had higher ESV due to the extensive forest areas within them.

In terms of spatial variation, the ESVA in most counties experienced a significant increase from 2000 to 2010 as a result of the conversion of grassland to forestland. Moreover, the growth of ESVA (with an increase of less than 10%) distinctly emerged in seven counties (Chishui, Shuicheng, Guanshanhu, Longli, Fuquan, and Jianhe) while the growth of more than 10% was only located in Xingyi. For instance, the increased ESVA in southwestern Qianxinan, was the result of an increase in grassland transitioning to waterbodies and forestland. In contrast, areas with a marked decline in ESVA were largely found in the western and central regions as a result of the rapid increase in built-up land and notable losses of forestland and grassland; however, from 2010 to 2018, ESVA throughout the study region dropped to less than 10% due to urban expansion and cultivated land conservation, particularly in Tongren and Qiannan. Of note, the ESVA in southern Guiyang and southern Zunyi (Bozhou) was reduced to more than 10% because of the urbanized regions in Guizhou Province. Nevertheless, the areas with specific increases in ESVA were mainly scattered in 18 counties along rivers (e.g., the Nanpan River and Beipan River in Qianxinan and the Sancha River in Liupanshui) as a result of lowered human activity and the implementation of protection policies for water resources.

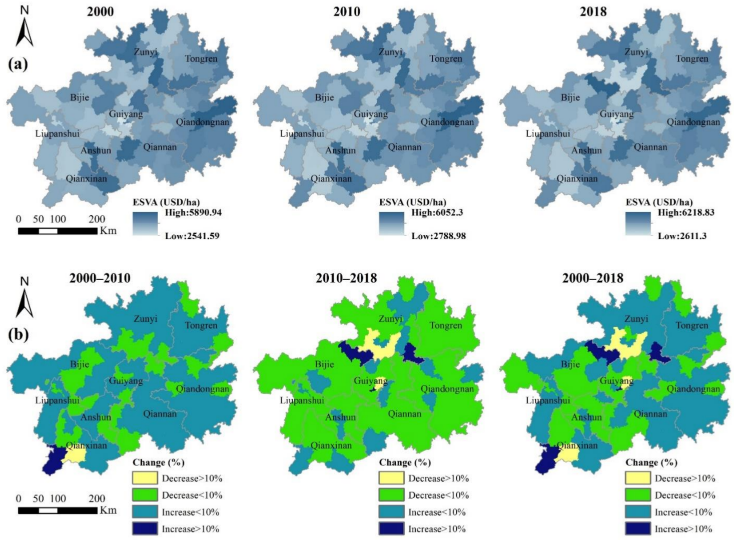

Figure 2. Spatial distribution of ESV changes at the county level from 2000 to 2018. Notes: (**a**) ESV per unit area in each county (ESVA); (**b**) ESVA changes.

3.4. Driving Factors of ESV

Using the factor detector (Table 7), we identified the impact of driving factors on ESV. In 2000, seven possible influencing factors (i.e., GDP, per capita GDP, per capita disposable income of rural residents, agricultural output value, forestry output value, population density, and rural employment) were selected and found to be statistically significant at the 99% significance level ($p < 0.01$). The q-statistic values were distributed from largest to smallest as follows: population density (0.651), per capita GDP (0.592), per capita disposable income of rural residents (0.497), agricultural output value (0.493), forestry output value (0.481), rural employment (0.427), and GDP (0.184). The results indicate that the highest q-statistic value was derived from population density, followed by per capita GDP and the per capita disposable income of rural residents. The remaining examined factors were found to be statistically insignificant at the 95% significance level. In 2010, six possible factors affected the ESV (i.e., per capita GDP, per capita disposable income of rural residents, agricultural output value, forestry output value, population density, and rural employment) with statistical significance at the 99% level. The q-statistic values were distributed from largest to smallest as follows: population density (0.600), forestry output value (0.574), per capita GDP (0.517), rural employment (0.450), per capita disposable income of rural residents (0.427), and agricultural output value (0.383). Population density still had the highest q-statistic value, followed by forestry output value and per capita GDP.

Accordingly, in 2018, six possible factors were detected with statistical significance at the 99% level, which were sequenced in q-statistic order: population density (0.572), forestry output value (0.547), agricultural output value (0.484), rural employment (0.449), per capita GDP (0.417), and per capita disposable income of rural residents (0.320). The highest q-statistic value was found in population density, followed by forestry output value and agricultural output value. From 2000 to 2018, population density as a social factor played a decisive role in ESV, and the contributions of per capita GDP and per capita disposable income of rural residents became more trivial. In contrast, the effects of forestry output value and rural employment on ESV grew more significant. The p value of GDP indicated that GDP was crucial to ESV in 2000 but insignificant in 2010 and 2018.

3.5. Spatial Variability of Driving Factors on ESV

We noticed heterogeneity in the geospatial relationships between driving factors and ESV. The results of spatial autocorrelation analysis showed that all the Moran's I values of ESV in this study were greater than 0, and the p values were all less than 0.01, indicating significant positive spatial autocorrelations in the ESV of Guizhou Province from 2000 to 2018 (Table 8).

Table 7. The q-statistic values and p values for the driving factors of ESV from the factor detector between 2000 and 2018 in Guizhou Province.

Factor Number	2000		2010		2018	
	p Value	q-Statistic Value	p Value	q-Statistic Value	p Value	q-Statistic Value
X_1	0.807	0.040	0.816	0.040	0.788	0.043
X_2	0.014	0.379	0.015	0.373	0.020	0.377
X_3	0.956	0.038	0.864	0.044	0.791	0.057
X_4	0.400	0.131	0.340	0.111	0.040	0.128
X_5	0.007	0.184	0.024	0.130	0.026	0.137
X_6	0.000	0.592	0.000	0.517	0.000	0.417
X_7	0.000	0.497	0.000	0.427	0.000	0.320
X_8	0.000	0.493	0.000	0.383	0.000	0.484
X_9	0.000	0.481	0.000	0.574	0.000	0.547
X_{10}	0.500	0.115	0.785	0.415	0.932	0.024
X_{11}	0.000	0.651	0.000	0.600	0.000	0.572
X_{12}	0.000	0.427	0.000	0.450	0.000	0.449

Elevation (X_1); terrain slope (X_2); average annual temperature (X_3); average annual precipitation (X_4); GDP (X_5); per capita GDP (X_6); per capita disposable income of rural residents (X_7); agricultural output value (X_8); forestry output value (X_9); resident population (X_{10}); population density (X_{11}); and rural employment (X_{12}).

Table 8. Spatial autocorrelation tests of each ESV in Guizhou Province.

	2000	2010	2018
Moran's I	0.189071	0.187922	0.208962
Z Scores	2.817848	2.800435	3.09133
p Value	0.004835	0.005103	0.001993

We utilized the MGWR model to identify the spatial distribution of the impacts of potential independent variables selected based on their p values ($p < 0.01$) and calculated by the GD model for each ESV. Before the MGWR model was implemented, the independent variables needed to be tested for multicollinearity between them. The high value of the variance inflation factor (VIF) indicated that a significant degree of multicollinearity existed between these variables. If VIF > 7.5, a distinct multicollinearity between each factor and variable redundancy in the model existed. In contrast, if VIF $\leq$ 7.5, no variable redundancy and no multilinear relationship between each factor existed [67].

Group 1 included six potential independent variables: per capita GDP, per capita disposable income of rural residents, agricultural output value, forestry output value, population density, and rural employment (Table 9). In 2000, the VIF values of agricultural output value and rural employment were greater than 7.5 and remained greater than 7.5 in 2018. These results demonstrate that variable redundancy existed in Group 1.

Group 2 included five potential independent variables: per capita GDP, per capita disposable income of rural residents, agricultural output value, forestry output value, and population density (Table 9). The VIF values from 2000 to 2018 were less than 7.5, indicating that the variables in this group had no strong correlation, and therefore these independent variables were used in the MGWR model for subsequent analysis.

The MGWR model provided comparative performance parameters with the OLS and GWR models. Table 10 shows the performance comparison between the OLS, GWR, and MGWR models. A higher adjusted R^2 value indicates a higher explanatory power and model fitness, whereas a lower AICc value signifies model concision and a more reliable regression estimation [66,68]. Table 10 summarizes how the MGWR model defined a nonstationarity relationship for each variable, more accurately reflected the phenomena, and compared the results with OLS and GWR. The AICc values found using MGWR were smaller than those found using OLS and GWR. Moreover, the five driving factors selected in this study explained 79.9%, 77.8%, and 75.2% of the ESV in 2000, 2010, and 2018, respectively.

Table 9. Variance inflation factor (VIF) of potential independent variables in 2000, 2010, and 2018.

Group 1	X_6	X_7	X_8	X_9	X_{11}	X_{12}
2000	4.0538	3.2261	10.6942	2.9255	2.7847	11.0815
2010	3.2997	4.7933	4.9752	2.7548	3.3155	5.4463
2018	3.2598	3.6690	7.1642	4.2891	2.4023	8.5471
Group 2	X_6	X_7	X_8	X_9	X_{11}	
2000	3.4680	3.1247	1.7056	2.9123	2.7550	
2010	3.2987	3.8115	1.1606	2.6833	2.8136	
2018	2.9539	3.6688	1.5667	4.0262	2.2611	

Per capita GDP (X_6); per capita disposable income of rural residents (X_7); agricultural output value (X_8); forestry output value (X_9); population density (X_{11}); and rural employment (X_{12}).

Table 10. Model fit metrics for OLS, GWR, and MGWR.

Model	OLS		GWR		MGWR	
	R^2 (Adjust)	AICc	R^2 (Adjust)	AICc	R^2 (Adjust)	AICc
2000	0.793	130.292	0.776	128.963	0.799	120.204
2010	0.773	138.989	0.776	128.963	0.778	128.428
2018	0.753	146.473	0.750	137.060	0.752	136.653

As shown in Table 11 and Figure 3, from 2000 to 2018, significant negative correlations between ESV and per capita GDP (X_6) existed, whereas the impacts of per capita GDP (X_6) on ESV decreased significantly from 2000 to 2010 and then increased slightly after 2010. The correlation coefficient of per capita GDP (X_6) was higher in the eastern regions of the study area and lower in the western regions in 2000; however, the higher correlation coefficients of per capita GDP (X_6) in 2010 were distributed in the north, and the lower correlation coefficients were distributed in the south. In 2018, the spatial pattern of the correlation coefficient of per capita GDP (X_6) showed a negative trend, with higher values in the west and lower values in the east. The per capita disposable income of rural residents (X_7) had a significant positive correlation with ESV in 2000 but negative correlations with ESV in 2010 and 2018. The higher influence of per capita disposable income of rural residents (X_7) on ESV was higher in 2010 and lower in 2018. The spatial correlation coefficient patterns of per capita disposable income of rural residents (X_7) from 2000 to 2010 were similar, with a higher coefficient in the eastern areas and a lower coefficient in the western areas. In contrast, the spatial pattern in 2018 was reversed.

Table 11. Mean statistics of MGWR coefficients between ESV and driving factors.

	X_6	X_7	X_8	X_9	X_{11}
2000	−0.293	0.070	0.529	−0.011	−0.451
2010	−0.011	−0.124	0.462	0.164	−0.411
2018	−0.051	−0.038	0.454	0.096	−0.471

Per capita GDP (X_6); per capita disposable income of rural residents (X_7); agricultural output value (X_8); forestry output value (X_9); and population density (X_{11}).

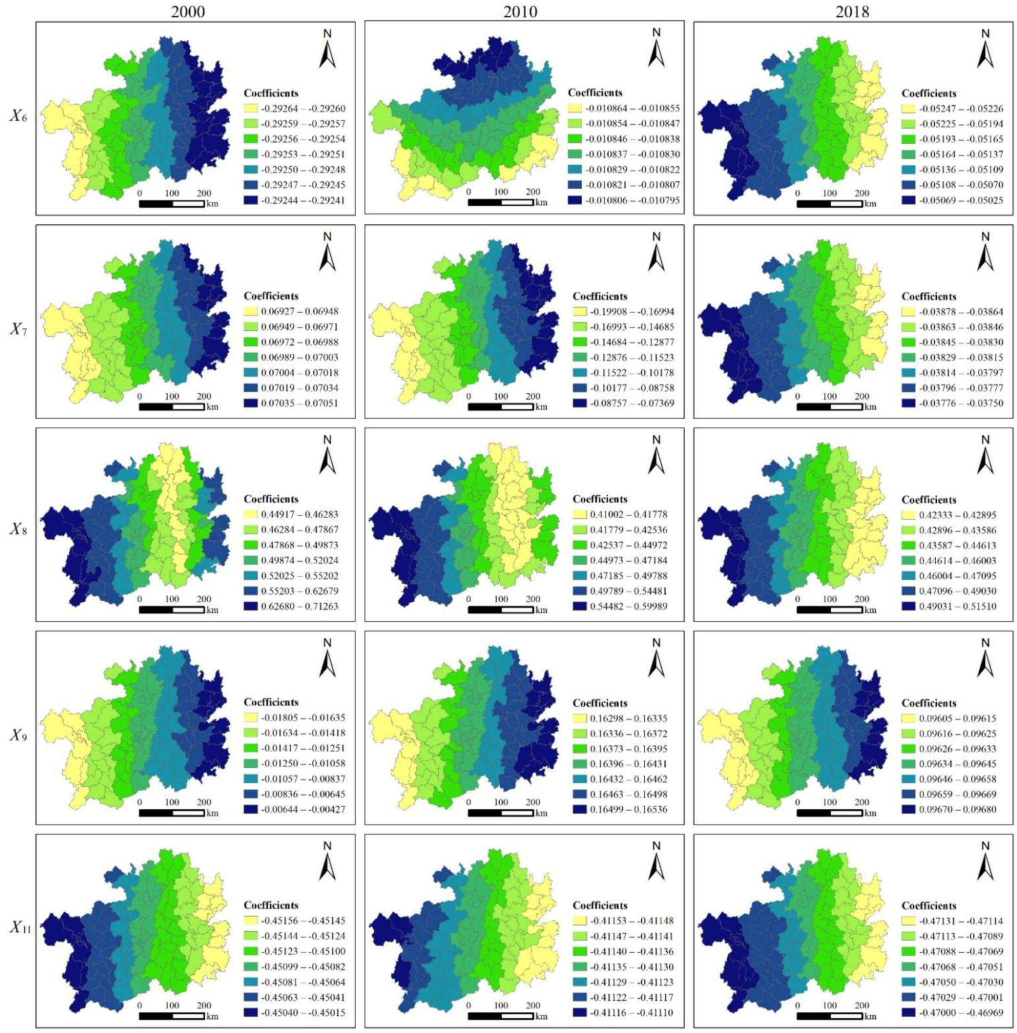

Figure 3. MGWR coefficients between ESV and driving factors in 2000, 2010, and 2018 in Guizhou Province. Per capita GDP (X_6); per capita disposable income of rural residents (X_7); agricultural output value (X_8); forestry output value (X_9); and population density (X_{11}).

Among the five driving factors, agricultural output value (X_8) primarily influenced ESV throughout the whole study period, with a significantly positive correlation, whereas the effects of agricultural output value (X_8) on ESV consistently declined. The lower correlation coefficient of the agricultural output value (X_8) was scattered in the middle of the study area in 2000 and then gradually extended in the eastern regions in 2010. Meanwhile, the higher correlation coefficient was distributed in both the east and the west of the study region in 2000, whereas it was distributed only in the west in 2010. Additionally, the spatial pattern of the correlation coefficient exhibited an increase from east to the west in 2018. ESV had a significant negative correlation with the forestry output value (X_9) in 2000 and a positive correlation in both 2010 and 2018. The influence of the forestry output value (X_9) on the ESV increased dramatically in the first decade and thereafter dropped. Furthermore, the spatial patterns of correlation coefficients from 2000 to 2018 were consistent: higher coefficients existed in the eastern areas and were lower in the western areas. Population density (X_{11}) was negatively correlated with ESV in the study period; its effects on ESV declined from 2000 to 2010 and rose from 2010 to 2018. A higher correlation coefficient appeared in the west, and a lower correlation coefficient appeared in the east of the study area from 2000 to 2018. The five selected driving factors were distinctly correlated with ESV, and there were apparent distinctions in the spatial variations in the correlation property and intensity. The results indicate that different factors dominate ESV in different regions—that is, zoning management was critical to promoting sustainable growth in them. In general, economic and social factors were the predominant drivers for regional ESV, which meant that optimizing both economic policies and human activities would most significantly improve regional ESV.

4. Discussion

4.1. Limitations of Value Estimate

In this study, ESV was calculated by the equivalent value table proposed by Costanza et al. [6] which has been applied by a number of researchers for similar studies [21,69,70] and improved by Xie et.al. [28,29]. This value technique to assess the economic value of ecosystem services was just one of many methods used for the environmental valuation [1,71], but important in studying the ESV in response to land ecosystem changes; however, based on assuming spatial homogeneity of services within ecosystems, the environmental suitability of a particular land use was not considered, and the equivalent values of ES were rough and, usually, underestimated the contributions of some land use types [21,72,73]. For instance, due to varied topography in Guizhou Province, cultivated lands located either on a steep slope or in a flat area received a similar estimation, although their ESV could greatly differ, for example, concerning the provisions of food or protection against rocky desertification and erosion, while the same is true for forests found either in a suitable or non-suitable area. Such environmental and ecological heterogeneity should be taken into account in the future development of ecosystem service value coefficients to improve the understandings of the regional characteristics of ecosystem service values.

4.2. Patterns of ESV Changes

The quantitative results of our study in three years (2000, 2010 and 2018) revealed the extent of ESV changes from 2000 to 2010 but also the decrease from 2010 to 2018 that occurred as a result of land use dynamics throughout the whole studying period. In particular, we found that various land use types affected the ESV differently; forestland had the most significant effect, followed by cultivated land and grassland; these findings are consistent with the research of Pan et al. [58]. From 2000 to 2010, the raise in the area's forest coverage led to a significant increase in ESV; however, this was accompanied by a decrease in the value of food production, owing to the decrease in cultivated land area. Previous studies have found that the process of urbanization in China significantly negatively affected the ecological environment and weakened regional ESV [74–76]. From 2010 to 2018, rapid urbanization and construction land growth in Guizhou Province exceeded the vegetation coverage growth, resulting in the decline in ESV. Severe pressure exists to implement stricter ecological protection as a result of these overall changes in land use and ESV. In general, while our study showed that conversion among cultivated lands, forestlands, grasslands and construction lands was quite intense and common in the study area, it also showed that the decline of ESV were mainly linked with the huge conversion of forests, which is identified to be the main provider of ecosystem services [77]. Findings from the literature also expressed that such changes were common in affecting the corresponding ecosystem service values in other study areas. For instance, Mekuria et al. (2021) evaluated the changes in land use over a period of 47 years (1973–2020) resulting in a total loss of USD 62,110.4 $\times$ 10^6 in ESV [14]. Kusi et al. (2022) revealed that an increase in all the land use categories caused an increase in the total ecosystem service value at USD 5.1 billion between 1992 and 2015 in Morocco [21]. On the other hand, in San Antonio, Texas, Kreuter et al. (2001) estimated that there appeared to be only a 4% net decline in the estimated annual value of ecosystem services ($5.58/ha per year) which could be attributed to the neutralizing effect of a 403% increase in the area of the woodlands between 1976 and 1991 [70]. Crespin et al. (2016) reported that ESV in El Salvador decreased by 2.6% from USD 9764.4 million per year to USD 9505.9 million per year during the 1998–2011 period and this loss was provided by tropical forests that account for 90% [78]. All these studies mirror our findings that land use dynamics have resulted in a significant change of ecosystem service values.

4.3. Evolution Mechanism of ESV

According to the spatial distribution of ESV in county-level regions, significant imbalances in the ESV per hectare existed between counties, with higher ESV located in the eastern region and lower ESV in the western region. In the west, this low ESV may be partially due to lower vegetation coverage and a more fragile ecological environment, making land use changes difficult. Residents living in this area have been forced to cultivate scattered sloping farmlands for the sake of basic food demand, giving rise to an increase in landscape fragmentation but a decrease in vegetation coverage [59]. In addition, changes in ESV per hectare indicate that ESV increases per hectare largely existed in the former period (2000–2010), mainly because urbanization efforts lagged behind ecological protection in these regions. Decreases in ESV per hectare became dominant in the latter period (2010–2018), although growth continued in a select few counties due to strict water resource protection for the Chishui River, Wujiang River, Beipanjiang River, Nanpanjiang River, and Qingshuijiang River. This transition principally arose from an expressway network integrating Guizhou with nearby economic zones, which has become an accelerator for the economy and urbanization but has reduced the regional ESV.

Efficient spatial planning of ecological protection and ecosystem management must include the identification of the dominant factors affecting ESV [49,79]. In our research, we detected significant correlations between ESV and selected driving factors using the GD model. Our results showed that socioeconomic factors (i.e., anthropogenic factors) dominated the spatial distribution of regional ESV changes; however, natural factors (including geomorphological factors and climate) had an insignificant explanatory power on the spatial differentiation of ESV changes. Regarding socioeconomic factors, population density, with a higher value in higher ESV areas, was not only the beneficiary of the ecological system but also the most significant factor in the ecological processes that altered the environment [80]. In particular, the impact of forestry output value on ESV became stronger, which may explain the benefits of implementing ecological engineering, which improves ESs and increases economic income from forests to prompt civilian involvement in the Grain for Green Program (GFGP).

4.4. Sustainable Development Implications

Despite the acknowledged limitations of rough estimations, this comprehensive framework for understanding the complex interactions between ESV and socioeconomic systems in Guizhou Province can positively contribute to policy-making, ecosystem service maintenance, territorial spatial planning, and ecological environmental managements for sustainable use of land resources. As a representative of karst landforms and China's national ecological civilization pilot zone, Guizhou is an important ecological security screen in the upper reaches of the Yangtze and Pearl Rivers, and thus, the ecological environment should be prioritized.

According to our results, targeted measures to alleviate the contradiction between ES and urbanization demands should be implemented. For instance, urban renewal planning and ecological red lining can be employed to minimize construction land and reduce pressure on cultivated land. Additionally, our findings show that anthropogenic factors had a significant effect on ESV, with spatial heterogeneity at the county-level scale. Therefore, we suggest that natural capital protection measures should be implemented according to regional variations of the primary driving factors [69]. The western region should focus on improving the agricultural output value, and the eastern regions should focus on the promotion of ecological and economic benefits from mixed forests [81–83]; however, as the only province without flatland in China, Guizhou has been confronted with a series of factors restricting the improvement of agriculture, such as a reduction in cultivated land, a weak foundation in agriculture, and a severe shortage of water. Therefore, these findings suggest that the development of agricultural technology for characteristic agriculture with comprehensive land consolidation could significantly increase the area's agricultural output value, leading to an increase in ESV in the Guizhou Province.

5. Conclusions

In this study, we analyzed the response of Guizhou Province's ESV changes from 2000 to 2018 and constructed an improved framework to identify the natural and socioeconomic factors from a geospatial perspective. In contrast to previous studies, our research provides a straightforward and flexible approach that incorporates the MGWR model with the GD model to better characterize the spatial distribution of ESV, understand the dominant factors affecting ESV, and identify the contribution of each factor to the ESV for this karst region of China.

Our results demonstrated a significant increase in ESV at first and then a subsequent decline during the later stage of the study period. In general, forestland was the dominant ecological land in Guizhou Province, followed by cultivated land and grassland, which have greatly improved due to regulation services and biodiversity protection, constituting the main ecosystem body in Guizhou Province. Meanwhile, the GD and MGWR models explicitly revealed the interaction effects and complex nexus between ESV and its driving forces. The results of the spatial recognition models show that the socioeconomic factors were robustly correlated with ESV from 2000 to 2018, with obvious diversity in the spatial variation of correlation properties and intensity, among which population density had a significantly negative effect on ESV, whereas the agricultural output and forestry output values had significantly positive effects. We expect the findings of our research and our proposed policy suggestions to provide notable references to land administrators and policy-makers for adopting suitable land resource conservation and management plans, thereby improving the overall ecological status in karst areas.

Author Contributions: L.Y. analyzed the data and wrote the manuscript. H.J. designed the experiments and provided editorial advice. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: (1) land-use maps from 2000, 2010, and 2018 provided by the Resource and Environment Science and Data Central (http://www.resdc.cn, accessed on 19 September 2020); (2) a digital elevation model (DEM), the average annual temperature, and the average annual precipitation obtained from the Resource and Environment Science and Data Central (http://www.resdc.cn, accessed on 19 September 2020); and (3) statistical data, including grain yield, grain price, GDP data primarily collected from the Statistical Yearbooks of Guizhou Province (http://data.cnki.net, accessed on 29 September 2020), and the statistical bulletin of national economic and social development of Guizhou Province (http://stjj.guizhou.gov.cn, accessed on 29 September 2020).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

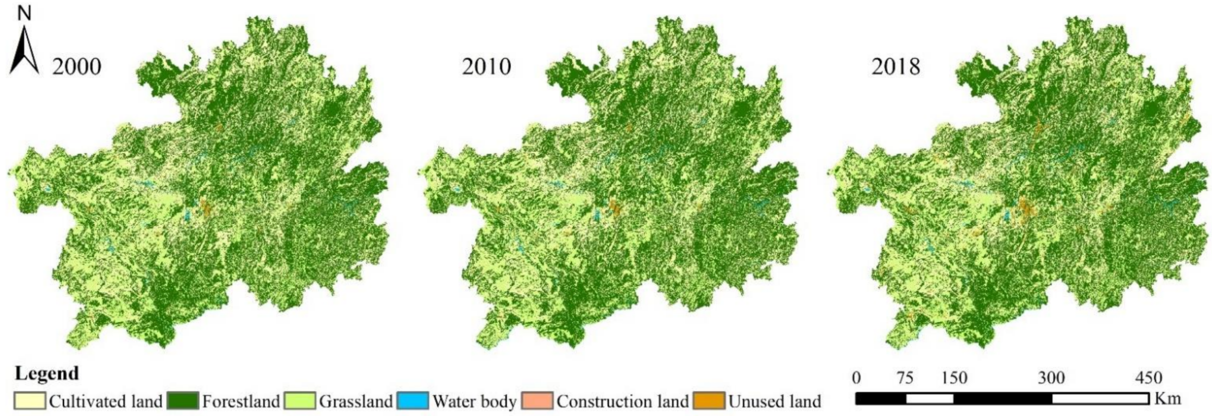

Figure A1. Spatial distribution of land use in 2000, 2010 and 2018.

Table A1. The annual ESV for each land use type per hectare in Guizhou Province (CNY/ha yr).

Ecosystem Service and Functions	Cultivated Land	Forestland	Grassland	Water Body	Construction Land	Unused Land
Food production	1590.60	530.20	681.69	833.17	0.00	25.25
Raw material	631.19	4746.55	580.69	555.45	0.00	75.74
Gas regulation	1136.14	6867.35	2398.52	807.92	0.00	100.99
Climate regulation	1540.10	6463.39	2474.26	3282.19	0.00	201.98
Water supply	1237.13	6513.88	2423.77	29,867.91	0.00	100.99
Waste treatment	2221.79	2726.74	2095.55	23,631.75	0.00	403.96
Soil formation and retention	2348.03	6387.64	3559.91	656.44	0.00	277.72
Biodiversity protection	1615.85	7170.32	2979.22	5453.48	0.00	631.19
Recreation and culture	277.72	3307.44	1388.62	7069.33	0.00	378.71
Total	12,598.55	44,713.50	18,582.23	72,157.64	0.00	2196.54

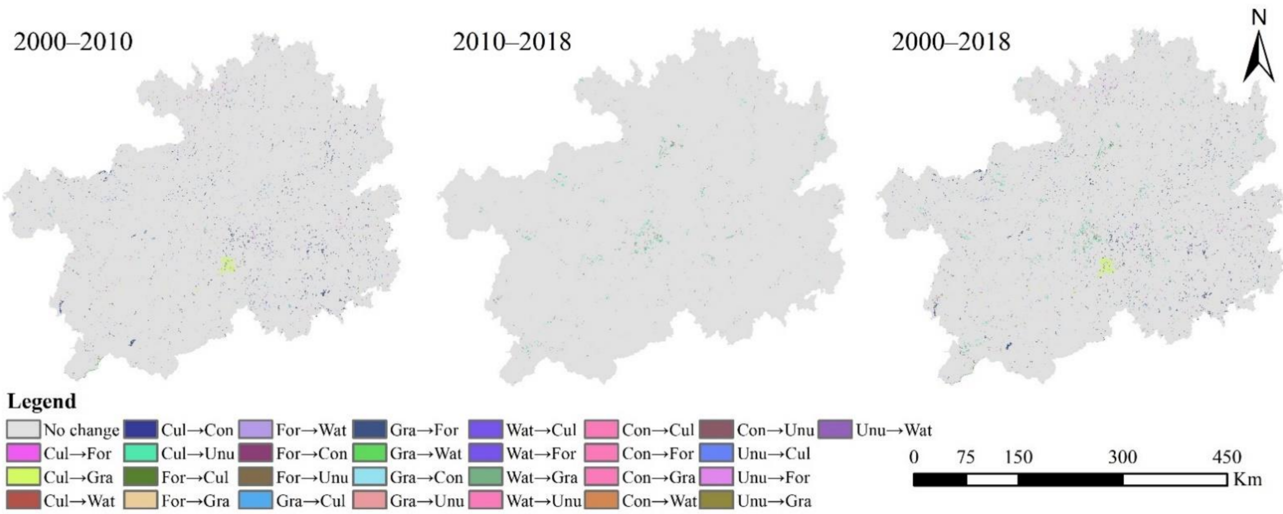

Figure A2. Spatial distribution of land use change from 2000 to 2018. Cultivated land (Cul); Forestland (For); Grassland (Gra); Water body (Wat); Construction land (Con); Unused land (Unu); → (transfer to).

Table A2. Land use and ESV changes in Guizhou Province in 2000, 2010, 2018, 2000–2010, and 2010–2018.

Land Use Types		Cultivated Land	Forestland	Grassland	Water Body	Construction Land	Unused Land	Total
2000	Land area (10^4 ha)	493.73	918.99	329.99	9.18	8.80	0.40	1761.09
	ESV (Million CNY)	62,203.13	410,912.34	61,320.15	6622.81	0.00	8.77	541,067.21
2010	Land area (10^4 ha)	491.82	933.88	315.55	9.94	9.60	0.30	1761.09
	ESV (Million CNY)	61,962.49	417,571.63	58,636.76	7169.54	0.00	6.54	545,346.97
2018	Land area (10^4 ha)	484.46	931.01	313.29	10.41	21.61	0.31	1761.09
	ESV (Million CNY)	61,034.60	416,288.40	58,216.24	7513.01	0.00	6.71	543,058.97
2000–2010	Land area (10^4 ha)	−1.91	14.89	−14.44	0.76	0.80	−0.10	0.00
	ESV (Million CNY)	−240.65	6659.29	−2683.38	546.73	0.00	−2.23	4279.76
2010–2018	Land area (10^4 ha)	−7.36	−2.87	−2.26	0.48	12.01	0.01	0.00
	ESV (Million CNY)	−927.88	−1283.24	−420.52	343.47	0.00	0.17	−2288.00
2000–2018	Land area 10^4 ha)	−9.28	12.02	−16.70	1.23	12.82	−0.09	0.00
	ESV (Million CNY)	−1168.53	5376.05	−3103.90	890.20	0.00	−2.06	1991.76

Table A3. Value changes of different ecosystem service functions in Guizhou Province in 2000, 2010, and 2018.

Ecosystem Service Functions	ESV (Million CNY)			Changes of ESV (Million CNY)		
	2000	2010	2018	2000–2010	2010–2018	2000–2018
Food production	15,051.87	15,008.30	14,864.48	−43.57	−143.82	−187.39
Raw material	48,704.21	49,319.34	49,126.14	615.13	−193.20	421.93
Gas regulation	76,709.22	77,369.95	77,038.76	660.73	−331.19	329.54
Climate regulation	75,468.79	76,069.34	75,730.07	600.56	−339.28	261.28
Water supply	76,710.04	77,532.73	77,342.00	822.70	−190.73	631.96
Waste treatment	45,113.93	45,353.63	45,176.83	239.70	−176.80	62.90
Soil formation and retention	82,103.57	82,500.67	82,067.00	397.10	−433.67	−36.57
Biodiversity protection	84,206.70	84,854.20	84,487.99	647.49	−366.20	281.29
Recreation and culture	36,998.90	37,338.83	37,225.71	339.93	−113.12	226.81
Total ESV	541,067.23	545,346.99	543,058.99	4279.76	−2288.00	1991.76

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