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Quantifying the Spatial Association between Land Use Change and Ecosystem Services Value: A Case Study in Xi'an, China

Yajing Shao ^{1,2,3}, Xuefeng Yuan ^{1,2,*}, Chaoqun Ma ^{1,2}, Ruifang Ma ^{1,2,3} and Zhaoxia Ren ^{1,2}

¹ School of Land Engineering, Chang'an University, Xi'an 710054, China; ynllsyj@163.com (Y.S.); chaoqunm@chd.edu.cn (C.M.); mrf9508@163.com (R.M.); zhaoxiar@chd.edu.cn (Z.R.)

² Key Laboratory of Degraded and Unused Land Consolidation Engineering, Xi'an 710054, China

³ School of Earth Science and Resources, Chang'an University, Xi'an 710054, China

* Correspondence: zyxfyun@chd.edu.cn

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Abstract: The impact of land use and land cover (LULC) change on ecosystem services value (ESV) varies in different spatial locations. Although many studies have focused on quantifying the effect of LULC change on ESV, few have considered the spatial heterogeneity of the relationship between LULC change and ESV. Therefore, this study examines the relationship between ESV and LULC change from a spatial perspective in Xi'an City. We divide the study area into 10,522 grid cells, based on land cover data from 2000 to 2018, and we identify the spatial-temporal dynamics of LULC change. Next, we employ the Benefits Transfer Method (BTM) to evaluate the ESV, and the ESV is corrected by the normalized difference vegetation index (NDVI). A geographically weighted regression (GWR) model and ordinary least squares (OLS) regression model are used to assess the spatial association of LULC change and ESV. The results show that the total ESV loss is 6.57 billion yuan (Chinese yuan), and the loss rate is 12.18%. The distribution of ESV shows an obvious spatial heterogeneity, and the low-value area of ESV expands eastward from the main urban area. More than 50% of total ESV is provided by woodland. From 2000 to 2018, the land use pattern in Xi'an underwent a significant change with the developed land increasing by 64.09%, whereas farmland decreased by 12.49%. Based on the GWR model, the relationship between LULC change and ESV in Xi'an showed a significant negative association and spatial heterogeneity. Our study results provide a new way to effectively identify the relationship between LULC change and ESV, and in turn, to fully understand the ecological trends at the regional scale, laying a foundation for regional sustainable development.

Keywords: land use and land cover change; ecosystem services value; spatial regression; GWR model

1. Introduction

The ecosystem services value (ESV) reflects the ability of ecosystems to provide various products and services for human production and life. Ecosystem services include supporting, regulating, provisioning and cultural services [1]. Land use and land cover (LULC) change are important forces that drive change in the ESV, and in turn, affect landscape patterns and the allocation of ecosystem service functions [2,3]. Some land use activities may lead to increasing negative effects on the ecological environment, such as water pollution, soil salinization, desertification, habitat loss, and biodiversity decline, which will affect the formation and supply of ecosystem services, such as water supply, food production, hydrological cycle, and pollination [4–6]. In the context of economic development, human interference caused approximately 60% of the degradation of ecosystem services from 1965 to 2015 [7]. Changes in LULC mainly affect the structure and function of ecosystems. Quantifying the spatial association between LULC change and ESV is conducive to a comprehensive understanding of

the dynamics of regional natural environments. At the same time, knowledge about LULC change and ESV can be used for the rational allocation of land resources, land management and protection, and ecological protection in the study area.

The term “ecosystem service” first appeared in 1981 [8]. Subsequently, an increasing number of researchers have paid great attention to the ESV assessment. Research methods mainly include physical assessment, energy value analysis, and value assessment [9]. The economic value of the ecosystem services can reflect the importance of various ecosystem services to human survival and help to raise people’s awareness of ecological protection [10]. In order to further reveal the value of various benefits provided by various ecological services for human survival, there have been many useful attempts to monetize the value of ecosystem services. From the perspective of the assessment process, the monetization valuation method of ecosystem service value mainly includes two types. One is the ecological simulation method, which uses economic valuation techniques to assess the value of ecological service functions quantified from a particular ecological model [11–13]. This method requires many parameters, and the calculation process is relatively complicated. Because different types of ecological services use different ecological service models, it is difficult to unify assessment methods and standardize the parameters used to assess the value of each ecosystem service. Therefore, this method is generally applicable to the calculation of the value of small areas or single ecological services [14,15]. The other is the benefit transfer method (BTM), which is a secondary assessment method that transfers existing environmental assessment results to other regions with similar demographic, economic, and ecological characteristics [1,16]. For this method, the ESV is quantified as the product of the equivalent coefficients of various ecological service functions per unit area and their economic value [17,18]. Owing to its simplicity and feasibility, the BTM is widely used in ESV assessment [19–21]. In 1997, Costanza et al. calculated the ESV of 17 ecosystem services provided by 16 major biological communities around the world based on the BTM, and their study first put forward the principles for estimating ESV, laying the foundation for its monetization [22]. Using this foundation and based on China’s ecosystem conditions, Xie et al. put forward an assessment method suitable for China based on expert knowledge from 500 Chinese ecological experts [17,23], which used the economic value of natural food production as a benchmark for calculating the value of various ecological services. This method laid the foundation for quantifying the ESV in China relative to food production in croplands.

Over the past 40 years, owing to the increase in developed land area, conflicts between ecological conservation and land use have increased. More and more studies have begun to emphasize the importance of ecological protection and explore the environmental problems that may arise from LULC change. With the gradual increase in environmental problems, many studies have been conducted to assess the effect of LULC change on ESV [24], with the research scope including global [25], national [26], provincial [27], prefecture-city [28], county [29], township [30], watershed [31], natural reserve region [32], and grid cell [33] scales. These studies are based on the quantitative changes of LULC types and analyze the response of ESV to the LULC change, revealing the ecosystem function changes arising from the conversion between different LULC types. Most of these studies ignore the spatial relationship between LULC changes and ESV. Furthermore, a traditional land use transfer matrix can only describe changes in LULC type and area in the study region, which lacks consideration of the spatial attributes of LULC change. Gradually, some studies have begun to quantify the relationship between LULC change and ESV using methods—such as relevance analysis [34], multiple regression models [35], cross-sensitivity coefficients [36], and gray correlation analysis [37]. However, these methods do not consider the spatial heterogeneity of ESV and are not able to quantify the spatial relationship between LULC change and ESV. It can be seen that the current research is still insufficient to analyze the spatial relationship between LULC change and ecosystem service value [38]. Evidently, LULC change is affected by factors, such as nature, the economy, and policy and has strong spatial heterogeneity [39,40]. Therefore, understanding how to analyze the impact of LULC on ESV from a spatial perspective is the key issue to be addressed in this article.

This study attempted to quantify the spatial heterogeneity of the relationship between LULC change and ESV in Xi'an City. Over the past 18 years, the population of Xi'an has increased by 43.44%. Ever-growing population pressure and developed land area have a significant impact on LULC and ecosystems. Therefore, a quantitative analysis is urgently needed. In order to reflect the spatial heterogeneity of LULC change and ESV, we divided the study area into 10,522 grid cells and used these as the basic unit of research. The ESV shows obvious spatial differences, and the same ecosystem may have different ESV, due to differences in factors, such as biomass and vegetation coverage. The Normalized Difference Vegetation Index (NDVI) is closely related to vegetation coverage, biomass, and productivity and has been widely used as an indicator of ecosystem quality in recent years. [41,42]. Therefore, we used the vegetation coverage coefficient as an indicator to modify the ESV at the grid scale according to the correspondence between vegetation coverage and NDVI. The objectives of the present study were: (1) To evaluate the LULC pattern change in Xi'an city from 2000 to 2018; (2) to analyze the spatial-temporal distribution pattern of ESV in Xi'an City; (3) to quantify dynamic LULC change from 2000 to 2018; and (4) to reveal whether the LULC change in Xi'an City harms ESV from 2000 to 2018.

2. Materials and Methods

2.1. Study Area

Xi'an (Figure 1; 107°41'–109°49' E and 33°39'–34°44' N) is located in the mid-western region of China and is the most populous city of Shaanxi province. Xi'an is an important hub connecting the five northwestern provinces. Xi'an has a north-south width of 116 km and an east-west length of 204 km with a total land area of 10,108 km². The altitude ranges from 207 to 3754 m. The highest terrain is in the south, and the lowest terrain is in the north. There are 13 districts in the study area (Figure 1b). Among them, Xincheng, Beiling, Yanta, Baqiao, Weiyang, and Lianhu are the central urban areas (Figure 1c). As an important central city in mid-western China, from 2000 to 2018, GDP in Xi'an increased from 73.39 to 834.99 billion yuan (Chinese yuan) [43]. The permanent resident population in Xi'an increased from 7.41 to 9.62 million from 2000 to 2018, the urban proportion of which increased from 4.50 to 7.06 million. In the past 18 years, the urbanization rate increased from 60.77% to 73.42%. With the construction of the Guanzhong Plain Urban Agglomeration, the conflict between LULC change and ESV has intensified. Therefore, studying the relationship between LULC change and the ESV in this region is urgent.

2.2. Data Collection and Processing

2.2.1. Data Collection

In the present study, land use data and the NDVI for the study area were retrieved from the Data Center of Resources and Environment Science of the Chinese Academy of Sciences (<http://www.resdc.cn>) for five periods: 2000, 2005, 2010, 2015, and 2018. The data resolutions of land use data and NDVI were 30 × 30 m and 1000 × 1000 m, respectively. The land use vector data in 2000, 2005, 2010, 2015, and 2018 were obtained using ENVI 5.1 software. According to the Standard of Classification of Land Use Status (GB/T 21010-2007), land use in Xi'an City was classified into six LULC types: woodland, grassland, farmland, water bodies, unused land, and developed land. Based on the Kappa coefficient test, the interpretation accuracy was 85.63%, 86.95%, 88.21%, 90.55%, and 88.31% in the five periods. Digital elevation model (DEM) data for Xi'an City were derived from the ASTER-GDEM 30-m resolution digital elevation data retrieved from the Geospatial Data Cloud (<http://www.gscloud.cn/>). The data for the city's administrative divisions were derived from the national 1:1,000,000 basic geographic database (<http://www.webmap.cn>). In addition, statistical data for the sowing area and unit price of rice, wheat, and corn from 2000 to 2018 in Xi'an were obtained from the Xi'an statistical yearbook (2001–2019) and were used to quantify the economic value of the ecological equivalent coefficient.

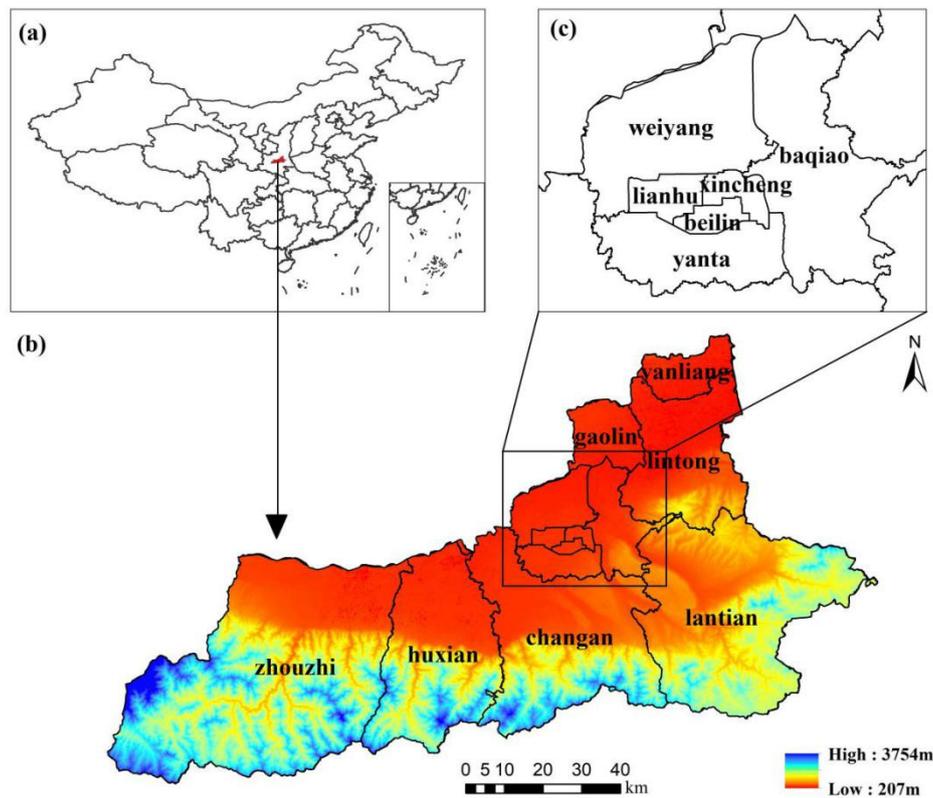


Figure 1. The location of Xi'an in China (a), the village boundary and digital elevation model (DEM) map of Xi'an (b), and the central urban areas of Xi'an City (c).

2.2.2. Data Processing

In order to better represent the spatial differences in the ESV, we used grid cells as the basic evaluation unit. At the same time, considering the consistency of the spatial resolution of the research data, a grid of 1×1 km was prepared as the basic research unit. During grid processing, the research area was divided into 10,522 grid cells using the Create Fishnet tool included in the GIS (ArcGIS 10.5) software. We extracted the land use data from 2000, 2005, 2010, 2015, and 2018 with a 1 km grid and obtained the area of various LULC types of each grid for the five periods. The proportion of unused land was less than 0.05%, and will thus not be discussed in the present study.

2.3. Methods

2.3.1. Transition Matrix of LULC Types

The land use transition matrix was employed to describe the quantity and direction of the conversion between various LULC categories during the study period according to the following formula:

$$S_{ij} = \begin{bmatrix} S_{11} & S_{12} & S_{13} & \cdots & S_{1n} \\ S_{21} & S_{22} & S_{23} & \cdots & S_{2n} \\ S_{31} & S_{32} & S_{33} & \cdots & S_{3n} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ S_{n1} & S_{n2} & S_{n3} & \cdots & S_{nn} \end{bmatrix} \quad (1)$$

where i and j refer to different LULC categories. S_{ii} or S_{jj} refer to an unchanged land use condition. S_{ij} refers to the transition i to j in the LULC categories, while S_{ji} refers to the opposite transition (from j to i). n is LULC categories. S refers to the land area (hm^2).

2.3.2. Land Use Change Dynamic Degree

The land use dynamic degree (LUDD) is an important factor to quantitatively evaluate the change rate of LULC types in a certain region. In this study, the LUDD was used to reveal the variation of LULC types. The LUDD includes the single land use dynamic degree (SLUDD) and the comprehensive land use dynamic degree (CLUDD) [44]. The SLUDD indicates the change rate for a specific LULC type within a certain period in the study area, and the CLUDD indicates the change rate for all LULC types within a certain period [45]. The equations for the SLUDD and CLUDD are as follows:

$$SLUDD_{mi} = \frac{LU_{mib} - LU_{mia}}{LU_{mia}} \times \frac{1}{t_b - t_a} \times 100\% \quad (2)$$

where $SLUDD_{mi}$ is the single land use dynamic degree of LULC type i in grid m , m is the number of the grid (in this study, $m = 1, 2, 3 \dots 10, 522$); LU_{mia} and LU_{mib} are the area of LULC type i in grid m at t_a and t_b time, respectively.

$$CLUDD_m = \left[\frac{\sum_{i=1}^n \Delta LU_{m,i-j}}{\sum_{i=1}^n LU_{m,i}} \right] \times \frac{1}{T} \times 100\% \quad (3)$$

where $CLUDD_m$ is CLUDD of grid m , $\Delta LU_{m,i-j}$ is the absolute value of the area of LULC type i converted to LULC type j in grid m during the study period T , and $LU_{m,i}$ is the area of LULC type i in grid m at the beginning of the study period.

2.3.3. Estimation of ESV

Based on BTM, we calculated the ESV in Xi'an at grid scale [23,24]. The key to this method is to determine the equivalent coefficient and quantify its economic value [46]. The equivalent coefficient reflects the relative contribution of various ecological services to the ecosystem (relative weight). As the value of ecological services has certain non-market characteristics, it is difficult to objectively quantify the equivalent coefficient of ecological service [22]. In this method, the calculation of all ecological service values is based on the same benchmark (standard equivalent), so it is more conducive to calculate the comprehensive value of ecological services [47,48]. In 2008, Xie proposed an ecosystem service equivalent coefficients table, and defined the economic value of natural crops of 1 hectare of farmland can be used as the standard equivalent [17]. This took into account the importance of various ecological services in maintaining human production and life, and was based on a comprehensive analysis of statistical data.

The ecosystem services in Xi'an City were divided into 4 level one and 11 level two categories. We compared the LULC types in Xi'an with the LULC types in the equivalent coefficients table of ecological services value proposed by Xie, and directly quoted the equivalent coefficients of the water bodies. For the LULC types not included in the table, we applied the BTM and used similar LULC types as a proxy for calculating the value of ecological services, such as farmland, woodland, and grassland. Based on the nearest equivalent ecosystems, the equivalent coefficient of the farmland was the mean value of dry land and paddy fields. Similarly, the equivalent coefficient of woodland was the mean of broad-leaved forest and shrub, and the equivalent coefficient of grassland was represented by grassland and meadow. In many previous studies, the ESV of developed land was nil [17,36,49,50]. As the developed land is mostly impermeable surface, it does not belong to the ecosystems and can provide a few natural ecosystem services. The function of developed land still depends on the ecosystem and has an impact on service supply of the ecosystem. For example, developed land may harm the water supply, gas regulation, and environmental purification and a positive impact on food supply and cultural services [46]. Referring to the research of Kang et al., we defined the ecological equivalent coefficient of developed land in the present study [51]. The equivalent coefficient of per unit area for all ecosystem services is shown in Table 1.

Table 1. The coefficient of unit area ecosystem service values for different. Land use and land cover (LULC) categories in Xi'an (based on data from Xie et al., 2008 and Kang et al. 2019) [17,51].

Service Type	Secondary Classification	Farmland	Woodland	Grassland	Water Area	Developed Land
Provisioning	Food production	1.11	0.24	0.23	0.80	0.01
	Raw materials	0.25	0.55	0.34	0.23	0.00
	Water supply	−1.31	0.28	0.19	8.29	−7.51
Regulating	Gas regulation	0.89	1.79	1.21	0.77	−2.42
	Climate regulation	0.47	5.37	3.19	2.29	0.00
	Waste recycling	0.14	1.61	1.05	5.55	−2.46
	Hydrological regulation	1.50	4.05	2.34	102.24	0.00
Supporting	Soil conservation	0.52	2.19	1.47	0.93	0.02
	Nutrient cycling	0.16	0.17	0.11	0.07	0.00
	Biodiversity	0.17	1.99	1.34	2.55	0.34
Cultural	Aesthetic landscape	0.08	0.88	0.59	1.89	0.01

In the study of Xie et al. (2008), the economic value of a standard equivalent coefficient can be calculated by the net profit (excluding labor input costs) per hectare of a farmland's average, annual, natural food production, which is easily traceable through well-functioning markets. The output of natural products is assumed to be 1/7 of the actual food output [17,23,52]. According to the grain yield, sown area, and average price of wheat, corn, and soybeans in Xi'an City, the economic value of the unit equivalent coefficient was calculated using the following equation:

$$E = \frac{1}{7} \sum_{i=1}^n \frac{m_i p_i q_i}{S} \times CPI \quad (4)$$

where E is the economic value of the ecological service equivalent in unit area (Chinese yuan·year^{−1}·hm^{−2}); i is the crop type ($i = 1, 2, 3 \dots n$); p_i , q_i , and m_i are the average price (yuan/t), unit area yield (t/hm²), and sown area (hm²) of grain crops, respectively, in 2000–2018; and S is the total sown area (hm²). The price of grain crops was revised by the Consumer Price Index (CPI) to reduce the effects of rising prices on value. CPI is the average change in consumer price in percent. The economic value of unit ecological services in Xi'an was calculated to be 3253.92 yuan·year^{−1}·hm^{−2}. The ESV per unit area of each ecosystem service can be quantified using Equation (5). The ESV per unit area for all ecosystem services is shown in Table 2.

$$VC_{if} = w_{if} E \quad (5)$$

where VC_{if} is the value coefficient of ecosystem service function f for LULC type i ($i = 1, 2, 3, \dots, n$) and w_{if} is the equivalent coefficient of the ecosystem services function f for LULC type i .

At present, the rate of forest cover in Xi'an is nearly 30%. Based on the calculation, the amount of biomass is closely related to the value ESV. The NDVI can reflect the conditions of ecological services per unit area regional climate and natural resources, especially in areas with high vegetation coverage [53]. Therefore, the NDVI was used to revise the ESV in each grid. The ESV of different LULC types and each grid can be calculated with Equations (6) and (7), and the vegetation condition index of the grid can be calculated with Equation (8)

$$ESV_{mi} = \sum_{f=1}^n (A_{mi} \times VC_{if} \times \frac{V_m}{V}) \quad (6)$$

$$ESV_m = \sum_{i=1}^n ESV_{mi} \quad (7)$$

$$V_m = \frac{NDVI_m - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}} \quad (8)$$

where ESV_{mi} is the ESV of LULC type i in grid m , A_{mi} is the area of LULC type i in grid m , and ESV_m is the total ESV of grid m ($m = 1, 2, 3, \dots, 10522$). V is the average vegetation condition index of China. V_m is the vegetation condition index of grid m , $NDVI_m$ is the annual average NDVI value for grid m , and $NDVI_{max}$ and $NDVI_{min}$ represent the maximum and minimum annual average NDVI in China, respectively.

Table 2. Ecosystem services value (ESV) per unit area of each LULC category in Xi'an (yuan·ha⁻¹year⁻¹).

Service Type	Secondary Classification	Farmland	Woodland	Grassland	Water Area	Developed Land
Provisioning	Food production	3595.58	780.94	759.25	2603.14	32.54
	Raw materials production	797.21	1773.39	1117.18	748.40	0.00
	Water supply	-4246.37	911.10	618.24	269,75.00	-24,436.94
	Gas regulation	2895.99	5824.52	3926.40	2505.52	-7874.49
Regulating	Climate regulation	1513.07	17,457.28	10,380.00	7451.48	0.00
	Waste recycling	439.28	5222.54	3427.46	18,059.26	-8004.64
	Hydrological regulation	4864.61	13,162.11	7603.33	332,680.78	0.00
Supporting	Soil conservation	1692.04	7109.82	4783.26	3026.15	65.08
	Nutrient cycling	504.36	536.90	368.78	227.77	0.00
	Biodiversity	553.17	6475.30	4349.41	8297.50	1106.33
Cultural	Aesthetic landscape	244.04	2847.18	1919.81	6149.91	32.54
	Total	12,852.98	62,101.08	39,253.12	408,724.91	-39,079.58

2.3.4. Spatial Relationship between LULC Change and ESV

In the present study, the geographically weighted regression (GWR) model was employed to explore the impact of LULC change on ESV. The GWR model is a typical spatial linear regression model that incorporates the spatial information of variables into the regression analysis and considers the spatial heterogeneity and spatial non-stationarity between variables [54,55]. The Geostatistical Analyst function of ArcGIS 10.5 was used for this purpose. The GWR model is a spatial extension of the traditional method, but it is somewhat inadequate in the diagnosis of the goodness of fit [56,57]. Therefore, it is generally necessary to carry out ordinary least squares (OLS) regression analysis during the GWR analysis to verify the feasibility and accuracy of the GWR model. In the process of constructing the GWR and OLS model, we used the grid as the basic computing unit, and the sample size was 10,522, the changes in CLUDD comprised the independent variable, and changes in ESV the dependent variable. The calculations for the GWR and OLS models are shown in Equations (9) and (10):

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^p \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \quad (9)$$

$$y_i = \beta_0 + \sum_{k=1}^p \beta_k x_{ik} + \varepsilon_i \quad (10)$$

where y_i is the value of the dependent variable in grid i , (u_i, v_i) are the coordinates of grid i , $\beta_0(u_i, v_i)$ is the regression constant of grid i , β_0 is a constant term, $\beta_k(u_i, v_i)$ is the k th regression parameter of grid i , P is the number of independent variables, x_{ik} is the value of independent variable x_k in grid i , and ε_i is a random variable.

3. Results

3.1. LULC Change in Xi'an from 2000 to 2018

According to the land use pattern in Xi'an over the past 18 years (Table 3), more than one-third of the total area was occupied by farmland during the entire study period, followed by woodland and grassland, accounting for approximately 30% and 20%, respectively. In a comparison of the area changes in the five LULC categories, the developed land showed the greatest increase both in area and

percentage. The overall area of developed land has increased by 64.09% since 2000. From 2000 to 2018, the farmland decreased the most, followed by grassland and woodland, with decrease rates of 12.49%, 2.22%, and 0.05%, respectively.

Table 3. The area of LULC types in Xi'an from 2000 to 2018.

LULC Types	2000		2018		2000–2018	
	hm ²	%	hm ²	%	Change Area (hm ²)	Change Rate (%)
Farmland	398,331.60	39.46	348,575.06	34.54	−49,756.54	−12.49
Woodland	301,149.11	29.83	301,006.06	29.82	−143.05	−0.05
Grassland	214,614.75	21.26	209,859.88	20.79	−4754.87	−2.22
Water bodies	12,282.98	1.22	13,586.51	1.35	1303.53	10.61
Developed land	83,061.27	8.23	136,297.01	13.50	53,235.74	64.09
Total	1,009,439.71	1	1,009,324.52	1	-	-

To show the conversion relationships among various LULC types over the past 18 years, we calculated the LULC transfer matrix in Xi'an from 2000 to 2018 (Table 4). The area of farmland converted to non-farmland was 59,285.06 hm², which was mainly converted to developed land, grassland, and water bodies (accounting for 82.77%, 8.35%, and 5.56%, respectively). Because of the large reduction of farmland area, grassland became the main source of supplementary farmland in this period. Grassland was converted into farmland, woodland, and developed land, accounting for 58.23%, 18.62%, and 16.29%, respectively. Meanwhile, a substantial amount of woodland was occupied by urban development, water conservancy facilities construction, and agricultural production, accounting for 84.13%, 8.39%, and 4.88% of the reduction in woodland, respectively.

Table 4. Land use transfer matrix in Xi'an from 2000 to 2018 (hm²).

2000 \ 2018	Farmland	Woodland	Grassland	Water Bodies	Developed Land
	Farmland	338,990.97	1964.33	4952.16	3297.56
Woodland	216.09	296,672.09	115.28	371.93	3728.03
Grassland	6003.96	1919.65	204,282.36	707.69	1679.88
Water bodies	1013.60	336.26	353.31	9130.38	1449.43
Developed land	2350.43	113.67	156.77	78.95	80,361.44

3.2. Changes in Land Use Dynamic Degree

3.2.1. Temporal Analysis of LULC Dynamics

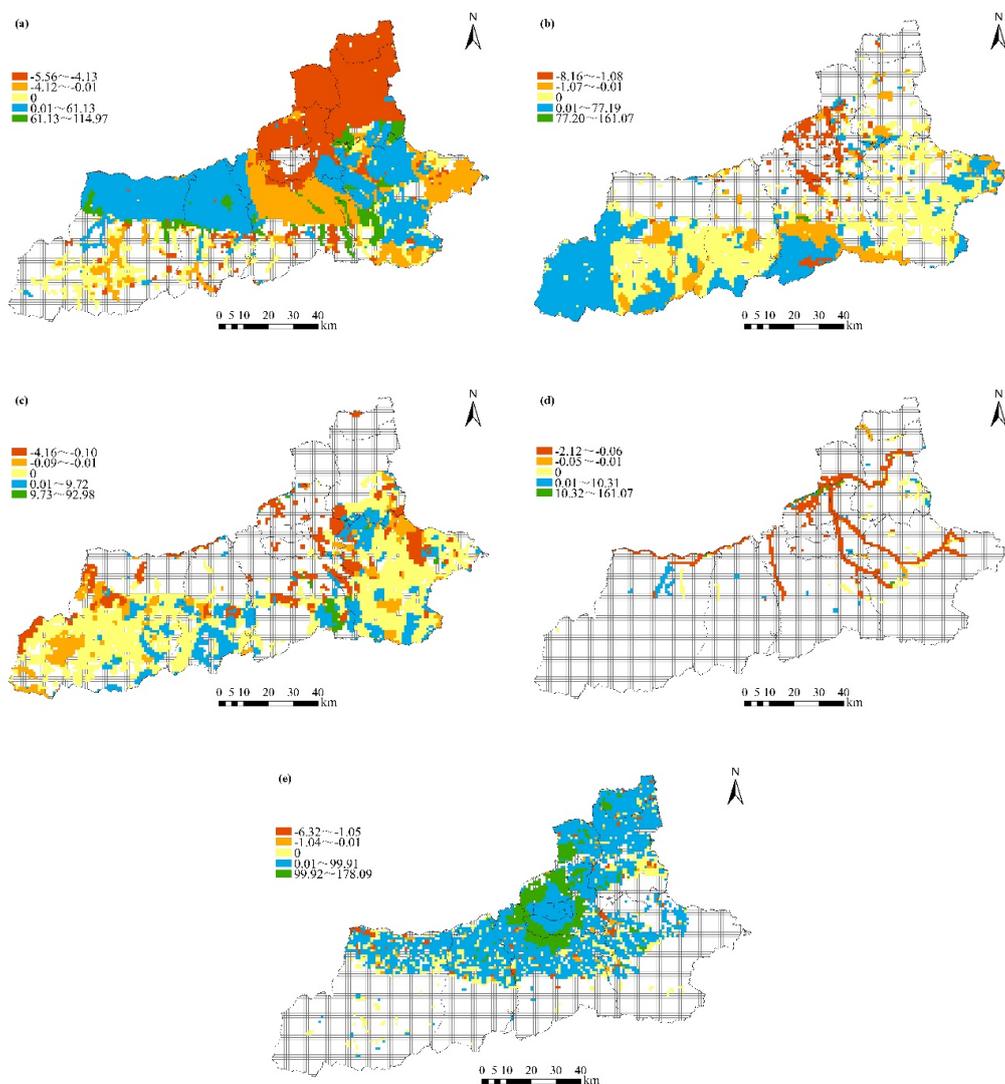
From 2000 to 2018, the CLUDD in Xi'an was 0.3% (Table 5). The CLUDD gradually increased from 2000 to 2015 and was highest in 2010–2015. This indicated that Xi'an experienced rapid land use change during this period, with the CLUDD at 0.45%. After 2015, the CLUDD gradually decreased, and it was the lowest from 2015 to 2018 at 0.16%. Comparing the changes in different LULC types, the change rate of developed land, water bodies and farmland was relatively high. From 2000 to 2018, the water bodies and developed land showed an increased trend, whereas the farmland, woodland and grassland showed a decreased trend. Evidently, the SLUDD of developed land has shown a continuously increasing trend from 2000 to 2018 (2.43%, 2.69%, 4.27%, and 2.10% in 2000–2005, 2005–2010, 2010–2015, and 2015–2018, respectively), whereas a continuous decrease was documented in the change in farmland (−0.72%, −0.48%, −1.08%, and −0.55% in 2000–2005, 2005–2010, 2010–2015, and 2015–2018, respectively).

Table 5. Land use dynamic degree in Xi'an from 2000 to 2018 (%). CLUDD, comprehensive land use dynamic degree.

Land Use Types	2000–2005	2005–2010	2010–2015	2015–2018	2000–2018
Farmland	−0.72	−0.48	−1.08	−0.55	−0.69
Woodland	−0.01	0.13	−0.06	−0.12	−0.01
Grassland	0.10	−0.50	−0.05	0.01	−0.12
Water bodies	5.25	0.18	−1.14	−2.64	0.59
Developed land	2.43	2.69	4.27	2.10	3.56
CLUDD	0.28	0.29	0.45	0.16	0.30

3.2.2. Spatial Analysis of LULC Dynamics

Considering the spatial heterogeneity of LULC change, we calculated the CLUDD of each grid and the SLUDD of various LULC types in the grid using ArcGIS 10.5 to further reveal the spatial changes in LULC in Xi'an City from 2000 to 2018. The SLUDD of each LULC type is shown in Figure 2, and the CLUDD of Xi'an City is shown in Figure 3.

**Figure 2.** The single land use dynamic degree (SLUDD) of farmland (a), woodland (b), grassland (c), water bodies (d), and developed land (e) in Xi'an from 2000 to 2018.

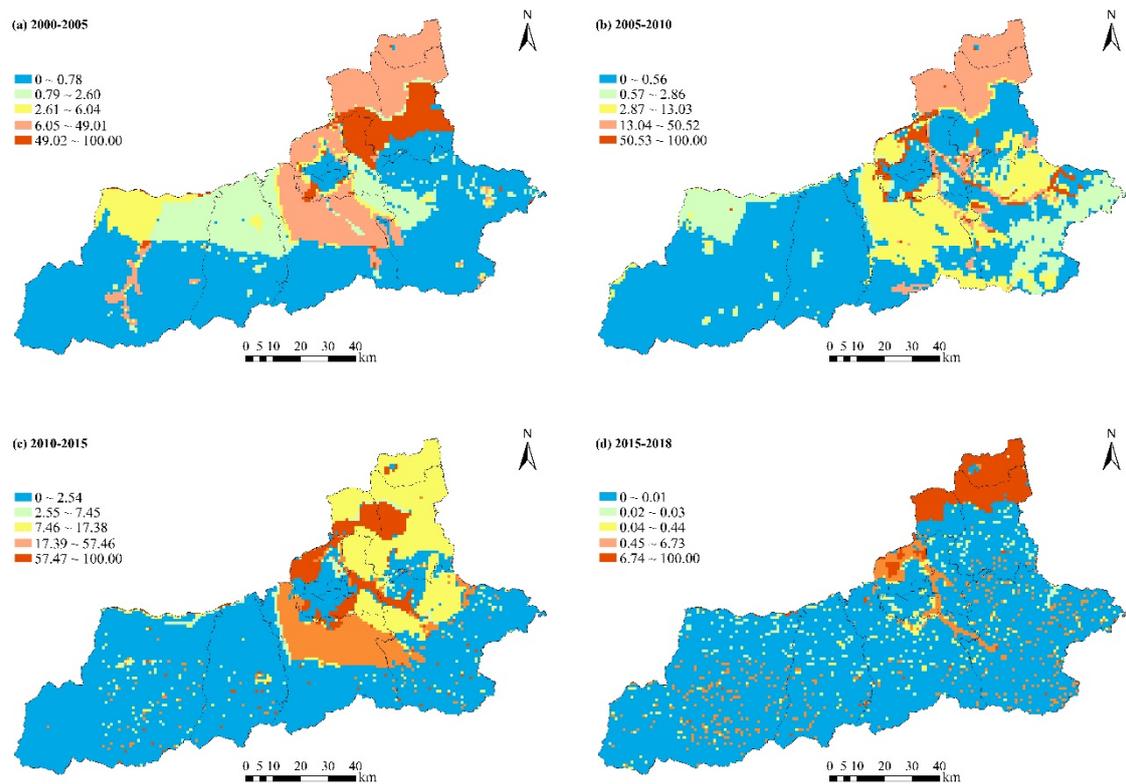


Figure 3. The CLUDD in Xi'an from 2000 to 2005 (a), 2005 to 2010 (b), 2010 to 2015 (c), and 2015 to 2018 (d) (%).

Based on the spatial characteristics of the SLUDD (Figure 2), there were obvious regional characteristics in the distribution of the SLUDD. From 2000 to 2018, the farmland in main urban areas (Baqiao, Weiyang, Yanta) and northern areas (Yanliang, Lintong, Gaoling) of Xi'an experienced the fastest reduction, with the SLUDD ranging from -5.56% to -4.13% . At the same time, the farmland in the northern Chang'an and the eastern Lantian County also decreased, and the SLUDD ranged from -4.12% to -0.01% . The area of woodland distributed around the central urban area decreased, with a dynamic degree of -8.16% to -1.08% , whereas the woodland in eastern Zhouzhi and southern Changan County increased. From 2000 to 2018, the grassland area in Xi'an both increased and decreased. The change in grassland area mainly occurred in the southern area of Xi'an City. The developed land around the central urban area increased significantly, and the dynamic rate of land change was between 99.92% and 178.09% .

The change in land use dynamics was closely related to urban development. Between 2000 and 2018, the CLUDD in the northern area was significantly higher than in other areas (Figure 3). The high-value areas of CLUDD were primarily around the main urban area and the northeast of Xi'an. Southern Xi'an is bordered by the northern foothills of the Qingling Mountains. Owing to its topography and landform limitations, the southern area was dominated by woodland and grassland, and the economic development of the southern area was slower than that of other regions. Therefore, the southern area was characterized by the mutual transformation between woodland and grassland.

3.3. Temporal and Spatial Distribution Characteristics of ESV

3.3.1. Temporal Change Characteristics of ESV

In 2000–2018, the total ESV loss was 6.75 billion Chinese yuan, representing a decrease of 12.18% (Table 6). According to the change rate of ESV for four phases (2000–2005, 2005–2010, 2010–2015, 2015–2018), the study period can be divided into thirds: A “decrease period” from 2000 to 2010,

an “increase period” from 2010 to 2015, and a second “decrease period” from 2015 to 2018. In 2000–2010, the total ESV experienced a continuous decline, decreasing by 8.51% from 53.96 billion yuan to 49.37 billion yuan. In 2010–2015, the total ESV increased by 0.88% from 2010 to 2015, from 49.37 to 49.80 billion yuan. After 2015, the total ESV decreased by 4.85%. From 2000 to 2018, the ESV of farmland, woodland, grassland and developed land continuously reduced, except for water bodies. The ESV of different land types was varied. Our results showed that the ESV in Xi’an was mainly derived from the ecosystem services provided by woodland. From 2000 to 2018, the woodland provided more than half of the value of ecological services in the study area, followed by the grassland and farmland, which accounted for approximately 23% and 13%, respectively. The woodland ecosystem had the greatest impact on the ESV in Xi’an. This was mainly because the woodland in the study area covered a large area and had a high ESV coefficient.

Table 6. Changes of ESV in Xi’an from 2000 to 2018 (million yuan, %).

		Farmland	Woodland	Grassland	Water Bodies	Developed Land	Total
2000	ESV	7662.73	27,990.80	12,608.65	7513.97	−1820.34	53,955.81
	Proportion	14.20	51.88	23.37	13.93	−3.37	100
2018	ESV	6071.16	25,330.61	11,162.85	7525.07	−2704.44	47,385.24
	Proportion	12.81	53.46	23.56	15.88	−5.71	100
2000–2005	ESV change	−910.21	−2415.71	−1029.37	1157.05	−45.30	−3243.54
	Change rate	−11.88	−8.63	−8.16	15.40	−2.49	−6.01
2005–2010	ESV change	−279.64	−289.90	−486.86	−76.38	−213.59	−1346.38
	Change rate	−4.14	−1.13	−4.20	−0.88	−11.45	−2.65
2010–2015	ESV change	−118.72	880.76	394.15	−183.33	−539.37	433.49
	Change rate	−1.83	3.48	3.55	−2.13	−25.94	0.88
2015–2018	ESV change	−283.00	−835.35	−323.72	−886.25	−85.83	−2414.14
	Change rate	−4.45	−3.19	−2.82	−10.54	−3.28	−4.85
2000–2018	ESV change	−1591.57	−2660.20	−1445.80	11.09	−884.10	−6570.57
	Change rate	−20.77	−9.50	−11.47	0.15	−48.57	−12.18

3.3.2. Spatial Change Characteristics of ESV

The ESV in Xi’an City showed significant heterogeneity. In 2000, the ESV in the north of Xi’an (Yanliang, Lintong, and Gaoling County) was higher than in other counties (Figure 4). The proportion of high-value areas ($0.41 \leq \text{ESV} \leq 0.60$ million Chinese yuan) reached 20.48%, and low-value areas ($0 \leq \text{ESV} \leq 0.1$ million Chinese yuan) reached 46.11%. After 2000, ESV began to decrease gradually in the northeast region of Xi’an, and the low-ESV area increased. In 2018, the proportion of high-value areas reached 9.22%, and that of low-value areas reached 68.41%. The ESV in the west of Zhouzhi County and the southern part of Chang’an County was significantly higher than that in other regions, and these areas are concentrated distribution areas of high value. Yanliang, Gaolin, and Lantian County, as well as the east of Zhouzhi County and the main urban area of Xi’an City, are the gathering areas of low ecological service. From 2000 to 2018, the ESV in the south of Xi’an changed slowly, while the ESV around the main urban area and in the north changed significantly.

3.4. Spatial Relationship between LULC Change and ESV

3.4.1. OLS Model and GWR Model

To further reveal the spatial relationship between LULC change and ESV, this study took the CLUDD in 2000–2005, 2005–2010, 2010–2015, and 2015–2018 as independent variables and the change of ESV in each period as the dependent variables based on an OLS model and a GWR model. The results of the OLS model are shown in Table 7.

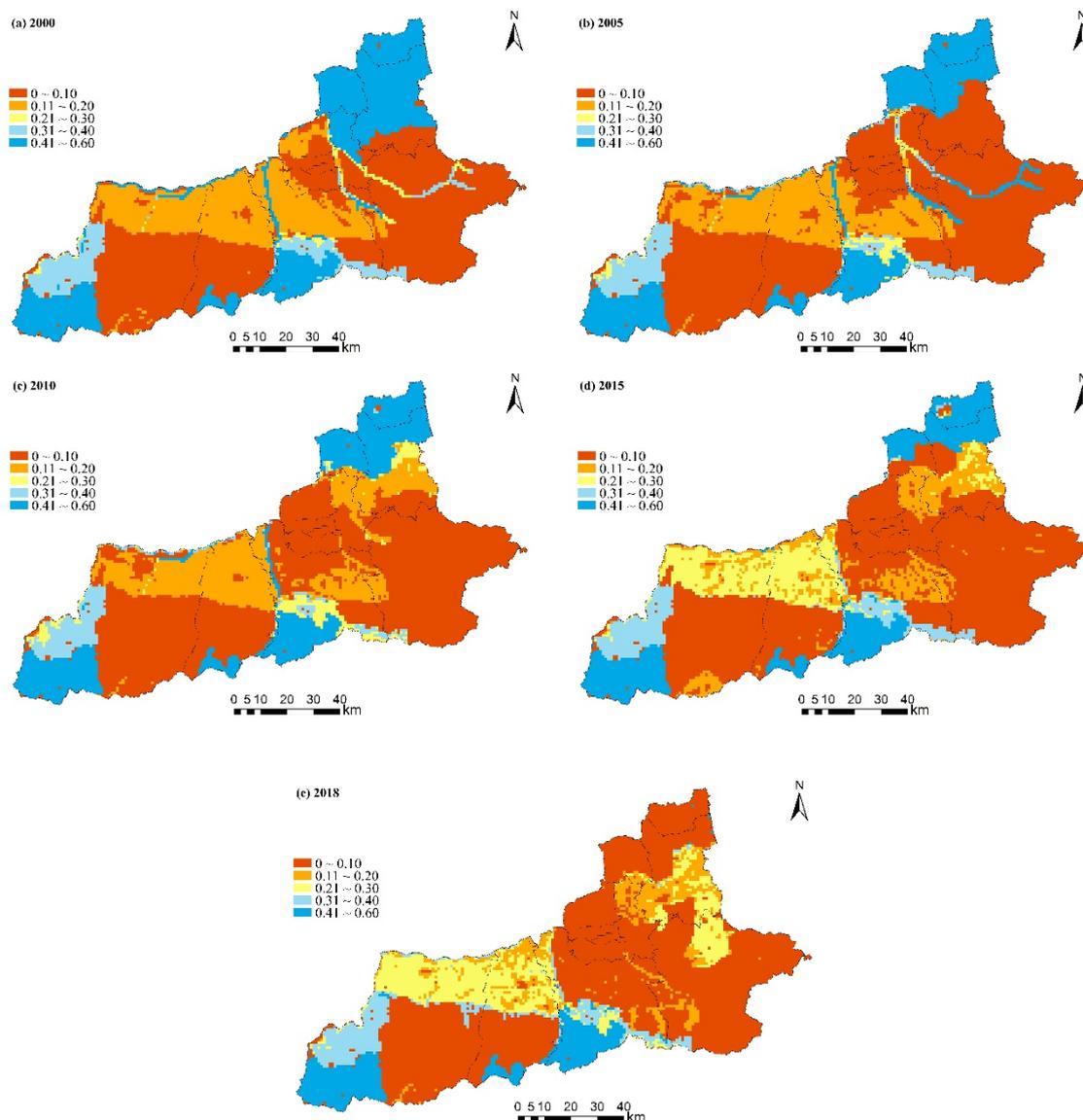


Figure 4. Spatial distribution characteristics of ESV of Xi’an City from 2000 to 2018 (million yuan). (a) Spatial distribution characteristics of ESV in 2000. (b) Spatial distribution characteristics of ESV in 2005. (c) Spatial distribution characteristics of ESV in 2010. (d) Spatial distribution characteristics of ESV in 2015. (e) Spatial distribution characteristics of ESV in 2018.

Table 7. Parameter estimation and test results in the ordinary least squares (OLS) model.

Time	Variables	Parameter Estimate	Standard Error	t Value	p Value
2000–2005	CLUDD _{2000–2005}	−991,985.16	4967.12	−199.71	0.000
2005–2010	CLUDD _{2005–2010}	−382,928.39	963.08	−9.12	0.000
2010–2015	CLUDD _{2010–2015}	−368,909.53	4362.80	−84.56	0.000
2015–2018	CLUDD _{2015–2018}	−706,832.99	3332.93	−212.07	0.000

Comparing the parameters of the independent variables from 2000–2005, 2005–2010, 2010–2015, and 2015–2018 (Table 6), the increase in land use dynamics in Xi’an City result in a decrease in the ESV. During the past 18 years, the impact of CLUDD on the ESV has first decreased and then increased. From 2000 to 2005, the CLUDD had the most significant impact on the ESV. According to the regression results, for every unit increase of CLUDD, the ESV was reduced by 991,985.16 units. From 2010 to 2015,

the CLUDD has the least impact on the ESV. For every unit increase of CLUDD, the ESV decreased by 368,909.53 units.

Considering the spatial heterogeneity of LULC and ESV, we applied a GWR model to express the degree of the local impact of CLUDD on the ESV. The prerequisite for GWR model analysis is that there must be a spatial association between variables. Therefore, we pretested the spatial correlation of the ESV before modeling and analysis. The spatial statistical tools of ArcGIS software were used to perform Global auto correlation analysis. The results showed that the Moran's I values of the ESV in 2000, 2005, 2010, 2015, and 2018 were 0.82, 0.85, 0.78, 0.72, and 0.81, respectively, revealing that the ESV in this area had strong agglomeration characteristics. The comparison of the fitting effect between the GWR model and OLS model is shown in Table 8.

Table 8. Comparison of fitting effect between the OLS model and geographically weighted regression (GWR) model. AIC, Akaike information content criterion.

Model	Index	2000–2005	2005–2010	2010–2015	2015–2018
GWR	AIC	262,807.53	262,110.71	256,629.11	257,128.35
	R ²	0.93	0.66	0.87	0.94
	Adjusted R ²	0.93	0.66	0.87	0.94
OLS	AIC	274,740.70	270,561.92	272,168.25	269,186.61
	R ²	0.79	0.23	0.40	0.81
	Adjusted R ²	0.79	0.23	0.40	0.81

According to the Akaike information content criterion (AIC), if the difference between the AIC values of the two models is greater than 3, it indicates that there is a significant difference between the two models, and the model with a lower AIC value has a better fit [58]. Based on the regression results of the two models (Table 8), the GWR model had the largest R² and the smallest AIC in the four study periods. In the four periods, the goodness of fit of the GWR model reached 0.93, 0.66, 0.87, and 0.94, while the goodness of fit of the OLS model only reached 0.79, 0.23, 0.40, and 0.81. This means that during 2000–2018, the GWR model explained 85% of ESV changes on average. However, the OLS model only explained 55.75% of ESV changes on average. This clearly indicated that the GWR model could better explain ESV change at the local level, as the fitting effect for the GWR model was 29.25% higher than that for the OLS model. Therefore, compared with the OLS model, it was reasonable and feasible to use the GWR model for regression analysis of land use dynamics and ESV.

3.4.2. Spatial Relationship between LULC Change and ESV

To further reveal the relationship between LULC change and ESV change, we also calculated the regression coefficients of each grid using the GWR model. The regression coefficients in 2000–2005, 2005–2010, 2010–2015, and 2015–2018 were quite different (Table 9). Changes in LULC on the ESV had both positive and negative effects. The relationship between ESV and LULC change was affected by the type of LULC change, the quantities of dominant LULC types, and the change models. From 2000 to 2005, the positive coefficients accounted for 44.31%, and the negative coefficients accounted for 55.69%. After 2005, the negative coefficients accounted for more than 80%. In summary, the impact of LULC change on the ESV was mainly negative from 2000 to 2018, which indicated that an increase in the rate of LULC change may simultaneously cause a decrease in ESV.

Taking the LULC change and ESV change of each grid as independent variables and dependent variables, respectively, we obtained the regression results in each grid based on the GWR model. The regression coefficient of each grid could reflect the difference in the influence of LULC change on the ESV in different research areas. According to the spatial distribution characteristics of regression coefficients, the relationship between LULC change and ESV included both negative and positive effects from 2000 to 2018 (Figure 5). After 2005, the proportion of negative coefficients was more

than 80%. While the rate of LULC change increased, the growth rate of ESV decreased. From 2000 to 2005, the coefficients were mainly between $-415,322.15$ and 0 . There were 4662 positive and 5860 negative relationship grids, accounting for 44.31% and 55.69% of the study area, respectively. The positively correlated regions were mainly distributed in the southern area of Xi'an. From 2005 to 2010, there were 2005 positively and 8517 negatively correlated grids (19.06% and 80.94%, respectively). The area of positively correlated regions decreased. From 2010 to 2015, there were 106 positively and 10,416 negatively correlated grids (1.01% and 98.99%, respectively). After 2015, the coefficients were mainly between $-54,627.23$ and 0 . There were 862 positive and 9660 negative relationship grids, accounting for 8.19% and 91.81%, respectively. Overall, the negative relationship between LULC change and ESV change was dominant in Xi'an from 2000 to 2018. Moreover, the negative relationship area gradually increased.

Table 9. Statistics of regression coefficients in the GWR model.

Variables	2000–2005	2005–2010	2010–2015	2015–2018
Maximum	6,636,170.72	1,061,681.11	131,742.95	298,070.76
Minimum value	$-37,014,722.51$	$-842,885.74$	$-1,383,819.72$	$-9,361,097.92$
Mean	3,973,946.31	85,747.60	$-266,186.91$	$-254,871.44$
Median	$-44,544.24$	$-157,490.59$	$-109,482.45$	$-94,995.56$
Positive coefficients Proportion (%)	44.31	19.06	1.01	8.19
Negative coefficients Proportion (%)	55.69	80.94	98.99	91.81

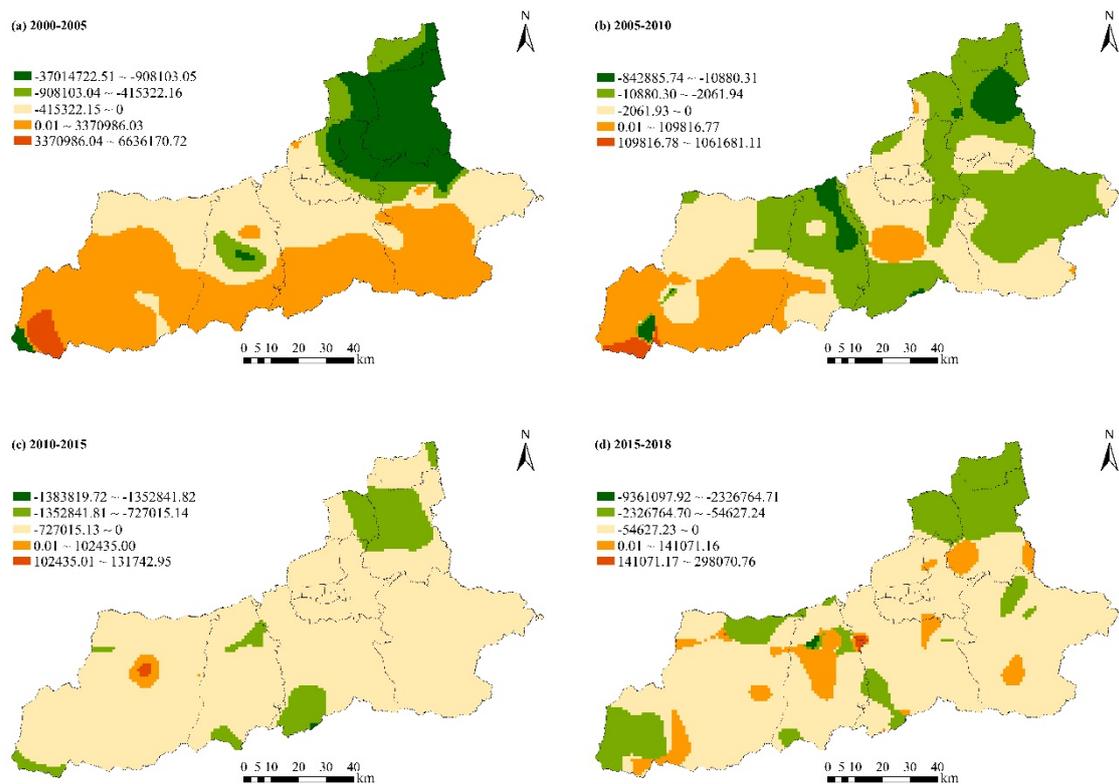


Figure 5. Spatial distribution of regression coefficients for ESV in the GWR model from 2000 to 2005 (a), 2005 to 2010 (b), 2010 to 2015 (c), 2015 to 2018(d).

4. Discussion

4.1. Spatiotemporal Changes of ESV Response to LULC Change

The total ESV decreased by 12.18% from 2000 to 2018. From 2000 to 2010, the ESV in Xi'an City continued to decline, and the total ESV loss was 4.59 billion yuan, with a decrease rate of 8.51%. After 2000, the decreasing trend has gradually slowed down. It is worth noting that the ESV increased by 0.88% from 2010 to 2015, which may benefit from the implementation of the Grain for Green Project. Since 1999, China has implemented the Grain for Green Project, which is a major ecological restoration project [59]. In the implementation stage of the first round of the Grain for Green Project (2000–2010), a large amount of farmland was converted into woodland [60,61]. The area of woodland has increased significantly. From 2000 to 2010, the woodland area of Xi'an increased by 1866.47 hm². After 2010, the project has entered a stage of consolidation and maintenance. Owing to the implementation of the Grain for Green Project, the vegetation coverage of Xi'an increased significantly, the biological abundance index also increased accordingly, and the ecological environment was significantly improved. From 2015 to 2018, the ESV decreased by 4.85%. The expansion of developed land caused a significant decline in the ESV. We found that the ESV decrease was caused by the developed land occupation of farmland, woodland, and grassland amounted to 0.15 billion yuan, 0.18 billion yuan, 0.33 billion yuan, and 0.12 billion yuan ESV losses during 2000–2005, 2005–2010, 2010–2015, and 2015–2018, respectively. The spatial characteristics of the land use change dynamic degree reflected that human interference and economic development showed clear regional differences in Xi'an City. The comprehensive land use dynamic degree in the northern region was higher than that in the southern region, while the ESV of the central area of Xi'an City was generally lower than that of the northern and southern areas. The urban core areas such as Yanta, Weiyang and Beilin Districts are the gathering areas for low ecological service value. The ESV in the core urban areas was significantly lower than that in the surrounding areas. This result is consistent with that reported by Li et al. [62]. On the whole, the low ESV area in Xi'an was continuously increased from 2000 to 2018. Compared with the southern region of Xi'an, the changes in the value of ecological services in the northern area were more obvious. This was because the southern region of Xi'an City is close to the northern foot of the Qinling Mountains and has high vegetation coverage. Woodland areas are closely related to regional climate regulation, hydrological regulation, and soil conservation [63]. Our results indicated that woodland had the greatest impact on the ESV of Xi'an City, and the contribution rate of woodland to the total ESV in Xi'an was more than 50% from 2000 to 2018. Therefore, woodland is the most critical factor to maintain the stability of the regional ecosystem. This was consistent with the results of Ayanlade and Proske [64] and Arowolo et al. [24]. In general, the land use pattern in Xi'an was greatly affected by the natural environment and human interference between 2000 and 2018, causing the ESV to change accordingly. Effectively controlling the conversion of farmland and woodland to developed land is of great significance for maintaining sustainable development of regional ecosystems. Therefore, to maintain the stability of the regional ecosystem, not only do we need to maintain the stable quantity of farmland and woodland, but we also have to take reasonable measures to improve the quality of farmland and woodland.

4.2. The Implication of the Relationship between LULC Change and ESV

Evidently, clearly understanding the spatial heterogeneity of the relationship between LULC change and the ESV can accurately guide the project implementation of land use planning and regional ecological protection [65]. From 2000 to 2018, the association between LULC change and ESV showed a significant negative relationship. This provided effective evidence that rapid land use changes may lead to ESV reduction [66]. The relationship between LULC change and ESV varies over time and location. It is worth noting that there were 4662 positive relationship grids scattered in the southern area of Zhouzhi, Huxian, Chang'an, and Lantian in 2000–2005. This is mainly because these areas are dominated by woodland, grassland and farmland and belong to the ecological protection area of Xi'an. The implementation of the Grain for Green Project had the most significant effect on land use

changes in these areas. A large amount of farmland was converted to woodland, which leads to a significant increase in ESV. This also means that the types and patterns of LULC changes have an effect on the relationship between LULC change and ESV. After 2005, the proportion of negative relationship grids was more than 80%. In the context of urbanization, the increase in the land use dynamic degree in Xi'an resulted in a decline in the ESV. Owing to the implementation of the construction programs "one belt and one road" and "big Xi'an," an increase in developed land area is inevitable, and the conflict between land use and ecological conservation is growing. The low-value areas of ESV in Xi'an were mainly distributed in the central and eastern areas, with the main urban area as the core and continuously expanding to the surroundings, which will lead to certain ecological security risks. The relationship between LULC change and ESV should be taken as an important reference factor in urban planning projects and ecological protection zone construction. From the perspective of the relationship between LULC change and ESV in Xi'an, ecological management of the northern region should be strengthened in the future. The southern region should delineate a red line of ecological protection to control the influence of urban development on the ecosystem. Future land planning and natural protection work should be coordinated and rationally arranged, with emphasis on protecting ecological land, such as woodlands and grasslands, reducing the destruction of ecological land through the expansion of developed land, and thus, improving overall ecosystem services.

4.3. Limitations and Future Directions

In the present study, we attempted to quantify the spatial association between ESV change and LULC change, using the benefit transfer method. Based on this method, the ESV of diverse ecosystem functions can be easily assessed, but it may not accurately capture the willingness-to-pay for ecosystem services or consumer products. The application of this method needs to be based on a certain assumption that the natural food production of farmland is one of the most basic ecological services in the study area and can be used as a benchmark for calculating the value of other ecological services, which may increase the subjectivity in the ecological service value assessment. As the value of non-market services provided by the value of ecological services is difficult to estimate, there are currently no scientifically unified evaluation methods. Although BTM has certain limitations, it is still an effective method to quantify the value of ecosystem services before proposing a standardized method of ecosystem service value assessment. In the present study, we modified the price of the food crops using the CPI to improve the evaluation accuracy. Moreover, calculating ESV at the grid scale facilitated better reflection of spatial distribution patterns and reduction of the limitations of administrative boundaries. However, there are still some limitations. When quantifying the ESV, we used the statistical data of grain yield, sown area, and average price of wheat, corn and soybeans in Xi'an City from 2000 to 2018 to calculate the ESV per unit area. These statistical data can only reflect average regional states, and cannot reflect the differences within the region. Future studies should further analyze the spatial heterogeneity of the economic value of equivalence factors. Additionally, the ESV in each area will vary with the scale of the study. Therefore, the differences between equivalence factors should be explored at different research scales, and the sensitivity of ESV to changes in the scale of the study should be explored in the future. GWR model could better reveal the spatial association between LULC change and ESV change, and further explain the spatial distribution of their relationship, linking the relationship between the two to the spatial location. This method provided new research ideas for quantifying the relationship between LULC change and ESV. In the OLS and GWR models, the whole population of grids, instead of randomly selected samples, was used for the regression models. The 10,522 grid samples of Xi'an City used for regression analysis can be regarded as samples randomly selected from the "super sample" of China, but still, fail to fully consider the uncertainty generated by random sampling. Therefore, it is still necessary to explore a better coupling model to further reveal the response mechanism of ESV to LULC change.

5. Conclusions

We analyzed the spatial association between ESV change and LULC change in Xi'an from 2000 to 2018 using the benefit transfer method. NDVI has a positive correlation with the ESV [67]. NDVI is the indicator of regional climate conditions, and can reflect the food productivity of the study area. Therefore, using the vegetation coverage index as a correction factor in the revision of the ecosystem service value can better reflect the spatial differences in the ESV. Our results indicated that a large amount of farmland, woodland, and grassland was used for urban development and construction, which is a common land use change model during the urban development process, especially in areas with rapid urbanization. The area of developed land increased by 64.09%, from 83,061.27 km² in 2000 to 136,297.01 km² in 2018. The trend is predicted to continue in the context of urbanization. Over the past 18 years, the change rate in farmland and grassland was −0.69 and −0.12, respectively. We found that the rate of land use change of woodland only changed slightly during 2000–2018. Owing to the execution of the Grain for Green Project, the forest area of Xi'an City increased by 955.08 hm² from 2000 to 2015. Woodland provided more than 50% of the ecosystem service value in the study area, so maintaining the stability of the woodland is beneficial to the policy implementation of ecological protection in Xi'an City. To ensure the dynamic balance of regional farmland area, grassland has become the main source of supplementary arable land. Therefore, it is wise to implement strict woodland protection policies to improve the ESV when the occupation of farmland by urban expansion becomes an inevitable trend.

The total ESV of Xi'an City decreased by 6.57 billion yuan from 2000 to 2018—representing a decrease of 12.18%, mainly because of the decrease of farmland area and increase of developed land. The OLS model showed the global characteristics of the spatial relationship between LULC change and ESV, while the GWR model revealed the regional characteristics of the impact mechanism of LULC change on the ESV. LULC changes have significant negative effects on ESV. Simultaneously, the relationship between LULC changes and ESV changes with time and space. Therefore, it is wise to formulate the ecological protection programs based on the heterogeneity of the spatial relationship between LULC change and ESV and effectively control the disorderly increase of developed land. This will ensure the dynamic balance of farmland area and protect the healthy development of woodland so, therefore improving the natural resource conditions and increasing the value of ecological services.

Author Contributions: Y.S. put forward research ideas and carried out the analysis; R.M. and C.M. created the figures; X.Y. and Z.R. revised the paper. All authors have read and agreed to the published version of the manuscript.

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