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Land-Use/Land-Cover Changes and Their Influence on the Ecosystem in Chengdu City, China during the Period of 1992–2018

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Abstract: Due to urban expansion, economic development, and rapid population growth, land use/land cover (LULC) is changing in major cities around the globe. Quantitative analysis of LULC change is important for studying the corresponding impact on the ecosystem service value (ESV) that helps in decision-making and ecosystem conservation. Based on LULC data retrieved from remote-sensing interpretation, we computed the changes of ESV associated with the LULC dynamics using the benefits transfer method and geographic information system (GIS) technologies during the period of 1992–2018 following self-modified coefficients which were corrected by net primary productivity (NPP). This improved approach aimed to establish a regional value coefficients table for facilitating the reliable evaluation of ESV. The main objective of this research was to clarify the trend and spatial patterns of LULC changes and their influence on ecosystem service values and functions. Our results show a continuous reduction in total ESV from United States (US) $1476.25 million in 1992, to US $1410.17, $1335.10, and $1190.56 million in 2001, 2009, and 2018, respectively; such changes are attributed to a notable loss of farmland and forest land from 1992–2018. The elasticity of ESV in response to changes in LULC shows that 1% of land transition may have caused average changes of 0.28%, 0.34%, and 0.50% during the periods of 1992–2001, 2001–2009, and 2009–2018, respectively. This study provides important information useful for land resource management and for developing strategies to address the reduction of ESV.

Keywords: ecosystem service value; ecosystem service functions; remote sensing; maximum likelihood classification; spatial patterns; urban expansion; value coefficients; GIS

1. Introduction

Ecosystems are important for living on Earth and also for survival of the human population [1–3] and livelihood [4–8]. A good ecosystem covers food, water, and other raw materials, as well as environmental (e.g., hydrological system and climate) and cultural services (e.g., recreation and culture values), which have a direct impact on population, while also supporting services (e.g., pollination and soil formation) that have a relatively indirect impact [4,6,9,10]. Economic assessment of these services can quantify the benefits derived from the ecosystem [11–13], an important tool for raising citizen awareness, helping develop management knowledge of natural capital, improving decision-making for limited resources in competitive demand, and providing incentives to protect the ecosystems [14–19].

The evaluation method of ecosystem service value (ESV) can be divided into four categories: (1) cost-based approaches, such as avoided cost and replacement cost; (2) revealed preference approaches, such as market prices and travel cost; (3) stated preference approaches, such as contingent valuation and choice experiments; and (4) the benefits transfer method (BTM) [10]. Most notably, in 1997, Costanza et al. used BTM to estimate global ESV with an average of United States (US) $33 trillion (in 1995) per year [4]. Since then, many academics utilized BTM for ESV evaluation to examine various natural resources including farmland [20,21], forest [22], grassland [23], and wetland [24,25], and although criticized in some cases for uncertainty, this ESV assessment method proposed by Xie et al. [4] is still widely used because of its feasibility, especially in areas where data are scarce [26,27].

The ecosystem is directly affected by changes in land use/land cover (LULC). However, due to the development of society and the rapid increase in population, the speed, degree, and intensity of LULC changes are now faster compared to the past, and a large number of landscapes on Earth are getting disturbed [28]. For instance, in the tropics, more than 55% of new agricultural land was at the expense of intact forests, while 28% was associated with disturbed forests from 1980–2000 [29]. Changes in LULC influence ecosystem services by increasing the availability of certain services while reducing other services that influence the ability of the biosystem to support human needs, further impacting ecological degradation [21]. Studies showed that 1% of land conversion led to an average change in ESV of 0.10% during the period of 2000–2008 in China [30].

Efforts are being made to understand, model, evaluate, and manage ecosystem services and natural capital [31]. For example, based on the proxy-based method and geographically weighted regression (GWR), Su et al. described the ESV changes in Shanghai's surrounding areas (China) and their relationship with urbanization, and the results showed that the total ESV dropped from 4718.1 to 3263.6 million yuan from 1994–2006 [32]. Taking the Munessa Shashemene landscape on the Ethiopian plateau as an example, Kindu et al. used revised conservative value coefficients to estimate the response of ESV changes to LULC dynamics during the period of 1973–2012 [33]. The decline in ESV reflected the impact of ecological degradation in the study area, and further research was recommended to explore future options and develop intervention strategies. Xie et al. used the equivalent value factor table of the Chinese terrestrial ecosystem to study the response of the ecosystem to LULC changes at the national, basin, and regional levels [34].

As an important commodity as a grain production base, the contradiction between food security and ecological civilization in Chengdu Plain is becoming more prominent due to the rapid growth of cities and the associated environment [35]. A study of LULC changes and their influence on the value of ecosystem services in Chengdu has important practical implications for ensuring food security while protecting ecological civilization for the evaluation of ecosystem services in southwest China [36]. However, to date, efforts in the quantitative analysis of the impact of LULC changes on ESV and the spatiotemporal variability and regional differences of ESV changes in Chengdu are very limited. This is the first study of its kind in Chengdu (the core city in southwest China) that contributes to the qualitative and quantitative analysis of LULC changes and their influence on the ecosystem based on regional value coefficients. The main aims of the present study were (1) to unfold LULC changes and spatial patterns in Chengdu for the period of 1992–2018; (2) to assess total ESV response to LULC changes and the spatial contribution of individual ecosystem service functions changes during this period based on modified coefficients; (3) to analyze ESV changes in different ecosystems through locally modified coefficients, compared with two kinds of global coefficients proposed by Costanza et al. in 1997 and 2014 [4,31]; and (4) to determine the elasticity of ecosystem service changes with respect to LULC changes.

2. Materials and Methods

2.1. Description of the Study Area

Chengdu, located in the central part of Sichuan Province, is the capital of the Sichuan Province and one of the sub-provincial cities in China. The province is the science and technology center, trade center, financial center, and transportation and communication hub of southwest China [37]. Geographically, Chengdu is located between 30°05′ and 31°26′ north and 102°54′ and 104°53′ east (Figure 1). The land area covers 14,335 km^2, accounting for 2.95% of the province's total area, of which the built-up area is 837.27 km^2. The resident population of Chengdu reached 15.92 million with an urbanization rate of 70.62%, and the gross domestic product (GDP) of Chengdu ranked first among China's sub-provincial cities in 2016, at US $183.22 billion [38]. Chengdu has 11 districts, four counties, and four county-level cities.

The climate of the study area is subtropical monsoon, with an average annual temperature of about 18 °C and an average annual precipitation of more than 1000 mm [39]. Natural resource conditions make Chengdu an important agriculturally producing area [40]. As a significant ecological buffer zone, the ecological environment of Chengdu has an important impact on the ecological security of the Yangtze River Basin and the Three Gorges reservoir area [36]. However, the rapid increase in related resource consumption resulted in resource inefficiency, which led to an increasingly prominent contradiction between Chengdu's economic development and environmental protection. Assessing land-use changes and their influence on ESV is important for improving resource utilization and promoting sustainable development.

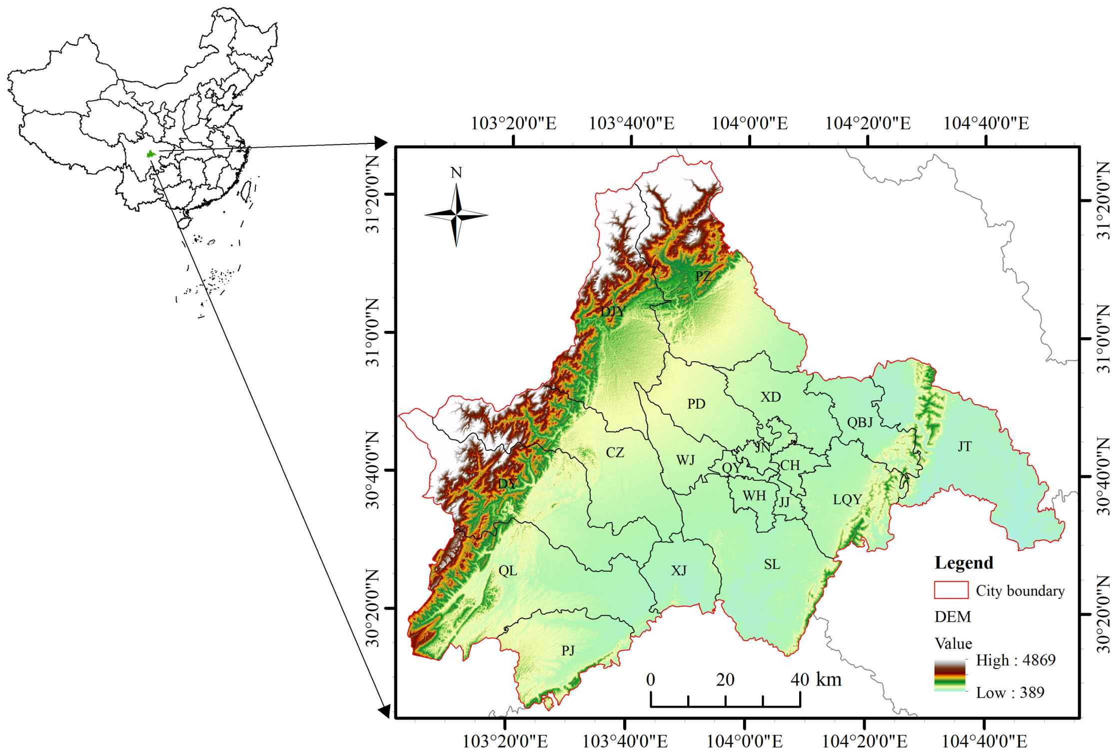

Figure 1. Location map of Chengdu City. The letters in the figure represent the abbreviations of the district names.

2.2. Data Collection and LULC Dataset

Landsat-5 Thematic Mapper (1992, 2001, and 2009) and Landsat-8 Operation Land Imager/Thermal Infrared Sensor (2018) satellite images were used for the LULC change analysis with 30-m spatial resolution, which were taken from the United States Geological Survey (USGS;

https://glovis.usgs.gov/). The administrative division vector border data of Chengdu were obtained from the National Science and Technology Infrastructure of China (http://nnu.geodata.cn:8008/). Additionally, some characteristic information about LULC type for remote-sensing interpretation was obtained through field survey.

Satellite images were preprocessed for geometric correction, radiometric calibration, atmospheric correction, mosaicking, and cropping before classification [41–43]. The Fast Line-of-Sight Atmospheric Analysis of Hypercubes (FLAASH) module was applied to eliminate atmospheric effects using the ENVI 5.3 Software [44]. For extracting useful LULC information, the maximum-likelihood classification (MLC) algorithm, a supervised classification method, was applied to land-use classification, which is considered to be a simple and powerful method when using sufficiently accurate samples in training [45,46]. Chengdu was divided into six classes: farmland (paddy fields and dry land), forest land (dense trees, shrubs, sparse woodlands, and other wooded land), grassland (various types of grasses with coverage above 5%), water area (river canal, lake, pond, and reservoir), construction land (urban and rural residential areas, transportation land, industrial and mining land, and water conservancy facilities), and unused land. Training samples were collected via the method of on-screen selection of accurate polygons based on high-resolution Google Earth images and existing LULC maps from the Chinese Academy of Sciences Resource and Environmental Data Cloud Platform (http://www.resdc.cn/), which was previously field checked [47]. The uniformity of training samples and their representation throughout the entire image were evaluated by Jeffries-Matusita (JM) distance. The training samples were evenly distributed in the study area. A total of 450 training samples (75 polygons in each LULC) were collected throughout the whole image in each period. In this study, the JM distance for each period was greater than 1.9, indicating good separability of training samples [48]. Furthermore, there was no probability threshold so that each pixel was classified to the category with highest likelihood [48]. After classifying, the LULC datasets for the four periods were obtained.

The accuracy of LULC classification was evaluated based on ground-truth samples which were collected from reference data including Google Earth satellite images, field survey data, and existing LULC maps. Four groups of random sampling points were created using the ArcGIS v.10.1 software for four periods, and each group consisted of 450 points. A similar approach was taken by Gashaw et al. [43] and Tilahun et al. [49]. We got total accuracies of 86.33, 87.33, 87.00, and 87.66% for the 1992, 2001, 2009, and 2018 classification results, respectively, while corresponding kappa coefficients were 0.76, 0.76, 0.79, and 0.83. Therefore, the LULC dataset used for the present changes in LULC in Chengdu was reliable [50].

2.3. LULC Changes

LULC changes have an impact on the ecosystem and its function [51]. Here, we carried out quantitative analysis of LULC changes of Chengdu City using two indices to reveal regional differences and changing trends [51,52]. The two indices are defined as follows:

$$K = \frac{A_{final} - A_{initial}}{A_{initial}} \times \frac{1}{T} \times 100\%, \quad (1)$$

where K refers to the land-use dynamic index for a single land-use category, A_{final} and $A_{initial}$ are the areas of a certain land use at the final and initial years of a period, respectively, and T is the study period. If T is one year, K refers to the annual change rate. The land-use dynamic degree of the study period (T) is defined as

$$S = \left(\sum_{i,j}^{n} \left(\frac{\Delta A_{i \to j}}{A_i} \right) \right) \times \frac{1}{T} \times 100\%, \quad (2)$$

where A_i is the area of land-use category i at the initial year of the period, $\Delta A_{i \to j}$ is the total area of land-use category i converted into land-use category j, and n represents the types of land use (farmland, forest land, grassland, water area, construction land, and unused land).

2.4. Assignment of Ecosystem Services Values

Costanza et al. [4] estimated the global economic value of 17 ecosystem services for 16 biomes using BTM, based on existing studies and original calculations. Since then, studies on global and regional ecosystem service value assessments developed rapidly [20,33,53]. However, owing to the low estimate of the unit value of farmland and uncertainties, this work received some critiques [34]. Costanza et al. provided an updated unit ecosystem service value to estimate the global value of ecosystem services in 2011, which was US $125 trillion/year in 2007 (Table 1), which caused large deviations in China [31]. As a result, on the basis of a questionnaire survey of 700 ecological experts, Xie et al. developed a table of ecosystem service value equivalent factors for China, which divided ecosystem services into four types and nine sub-types (Table 1) [54]. This method assumed that the equivalent value per unit area of food production of farmland is 1; thus, the equivalent value of other ecosystems can be quantified by comparing their utility to food production on farm land [30]. The table of ecosystem service value equivalent factors was considered as a modification of the method proposed by Costanza et al. (2014) [10].

In order to revise unit ecosystem service values from a national scale to a regional scale, this study employed ecosystem service value developed for China by Xie et al. in 2008 [54], but proposed a correction coefficient based on the net primary productivity (NPP) for Chengdu. The correction coefficient formula is as follows:

$$CC_i = \frac{NPP_{li}}{NPP_i}, \quad (3)$$

where CC_i denotes the correction coefficient of a certain i-th land ecosystem, NPP_i is the NPP of a certain i-th land ecosystem in China, and NPP_{li} is the NPP of a certain i-th land ecosystem in Chengdu [55–59]. The ecosystem service value coefficients of each land ecosystem in Chengdu were obtained (Table 1).

Table 1. Details of corrected ecosystem service value per unit area for ecosystem service functions of each land ecosystem type. LULC—land use/land cover; US—United States.

Ecosystem Services	Sub-types	Each LULC Type Ecosystem Service Value Coefficients (US$/hm^2/year)					
		Farmland	Forest Land	Grassland	Water Area	Construction Land	Unused Land
Provisioning services	Food production	78.94	27.40	30.42	30.99	0	1.17
	Raw material	30.79	247.45	25.47	20.47	0	2.34
Regulation services	Gas regulation	56.84	358.72	106.13	29.82	0	3.51
	Climate regulation	76.58	337.96	110.38	120.46	0	7.60
	Hydrological regulation	60.79	339.62	107.55	1097.61	0	4.09
	Waste treatment	109.73	142.82	93.40	868.38	0	15.20
Supporting services	Soil conservation	116.05	333.81	158.49	23.98	0	9.94
	Biodiversity protection	80.52	374.50	132.32	200.57	0	23.39
Cultural services	Recreation and culture	13.42	172.72	61.56	259.64	0	14.03
	Total	623.65	2334.99	825.73	2651.91	0	81.28
Costanza et al. in 1997 [4]		126	1338	321	11727	0	0
Costanza et al. in 2014 [31]		5567	3800	4166	12512	6661	0

2.5. Calculation of ESV

Based on ecosystem service value coefficients in Table 1, this study calculated the total ESV in Chengdu and each district, as employed in other researches [24,60–62], as follows:

$$ESV_t = \sum_{i=1}^{n} (A_{it} \times VC_i), \quad (4)$$

where ESV_t is the assessed total ESV at time t, A_{it} is the area (hm^2) of land-use type i at time t, and VC_i is the ecosystem service value coefficient of land-use type i in Table 1.

The change rate of ESV through the study period was estimated using the following formula:

$$ESV_{cr} = \left(\frac{ESV_{final\ year} - ESV_{initial\ year}}{ESV_{initial\ year}} \right) \times 100\%, \tag{5}$$

where ESV_{cr} is the change rate of the initial year to the final year, and $ESV_{initial\ year}$ and $ESV_{final\ year}$ refer to the total ESV at the beginning and end of the year, respectively.

The value of individual ecosystem service functions was calculated using the following expression:

$$ESV_{ft} = \sum_{i=1}^{n} \left(A_{it} \times VC_{fi} \right), \tag{6}$$

where ESV_{ft} is the assessed ESV of individual function f at time t, A_{it} is the area (hm^2) of land-use type i at time t, and VC_{fi} is the ecosystem service value coefficient of individual function f for land-use type i.

2.6. Elasticity for the Response of ESV to LULC Changes

In economics, elasticity is an indicator of how well an economic variable responds to another economic variable [30]. In order to discuss the response of ESV to LULC changes, this paper used an elasticity indicator, which can be applied to measure the percentage change of ESV due to the percentage change of LULC.

$$EEL = \left| \frac{\left(\frac{ESV_{final\ year} - ESV_{initial\ year}}{ESV_{initial\ year}} \right) \times \frac{1}{T} \times 100\%}{LTP} \right|; \tag{7}$$

$$LTP = \frac{\sum_{i=1}^{n} \Delta LCA_i}{\sum_{i=1}^{n} LCA_i} \times \frac{1}{T} \times 100\%. \tag{8}$$

In the above expressions, EEL is the elasticity for the response of ESV to LULC changes, $ESV_{final\ year}$ and $ESV_{initial\ year}$ have the same meanings as in Equation (5), LTP is the land transition percentage, which can display the transition speed and degree of LULC changes, ΔLCA_i is the converted area of LULC category i, LCA_i is the area of LULC category i, and T represents the research period.

3. Results

3.1. LULC Patterns in Chengdu

3.1.1. LULC of Chengdu from 1992–2018

Based on remote-sensing images, four maps of LULC patterns of Chengdu during the period of 1992–2018 were obtained (Figure 2). In terms of spatial distribution of LULC in Chengdu, Figure 2 shows that the farmland was mainly distributed in flat areas in the east and central regions of Chengdu, while the construction land was mainly distributed in the downtown area of Chengdu and the centers of various districts and counties. Moreover, the forest land and grassland were mainly distributed in the southwest and northwest regions of the study area. Farmland continuously represented the most dominant LULC type, with proportions of 59.56% in 1992, 62.00% in 2001, 58.71% in 2009, and 51.86% in 2018 relative to the total area, while unused land comprised the smallest LULC proportion (Table 2).

LULC in Chengdu changed dramatically during the period 1992 to 2018, which was characterized by a decline in farmland, forest land, and water area, and an increase in grassland, construction land, and unused land (Figure 2; Table 2). The farmland decreased from 59.56% (717,033.15 hm^2) in 1992 to

51.86% (624,366.81 hm^2) in 2018, forest land from 34.40% (414,105.48 hm^2) to 26.47% (318,693.69 hm^2), and water area from 1.37% (16,509.15 hm^2) to 1.01% (12,126.96 hm^2). On the contrary, grassland increased from 1.85% (22,228.11 hm^2) in 1992 to 2.5% (30,102.30 hm^2) in 2018, and construction land from 2.83% (34,057.17 hm^2) to 18.16% (218,631.96 hm^2), while the area of unused land was extremely limited with an increase of 31.95 ha. Moreover, in order quantify LULC changes, a change matrix of LULC conversion in Chengdu for the period of 1992–2018 was obtained (Table 3). The percentage of reservation of unchanged forest land was 68.26%, of which about 23.62% and 4.70% of the forest land was converted to farmland and grassland, respectively, while the spread of construction land was mainly due to the reduction in farmland and water area, accounting for 24.10% and 23.94%, respectively (Table 3).

The land-use dynamic index K of a single land-use category (Table 2) and the land-use dynamic degree S of study period T was calculated using Equations (1) and (2). The K of the forest land was negative, which means its area decreased continuously during the period of 1992 to 2018, while the area of construction land increased continuously in that $K > 0$. Although the K of the unused land varied greatly, its area change performance was not obvious in LULC maps because of its small absolute area. Furthermore, the K of unused land reached its maximum value in 2001–2009, which indicated the remarkable area change during this period. It is suggested that the reason for the significant change in the area of unused land was caused by the 2008 Wenchuan earthquake [38]. The intense earthquakes caused geological changes, causing the landscape to become fragmented, and secondary disasters such as landslides, collapses, and mudslides led to an increase in unused land. Table 2 shows the largest land-use dynamic degree S showing largest changes in LULC during the period of 1992–2001.

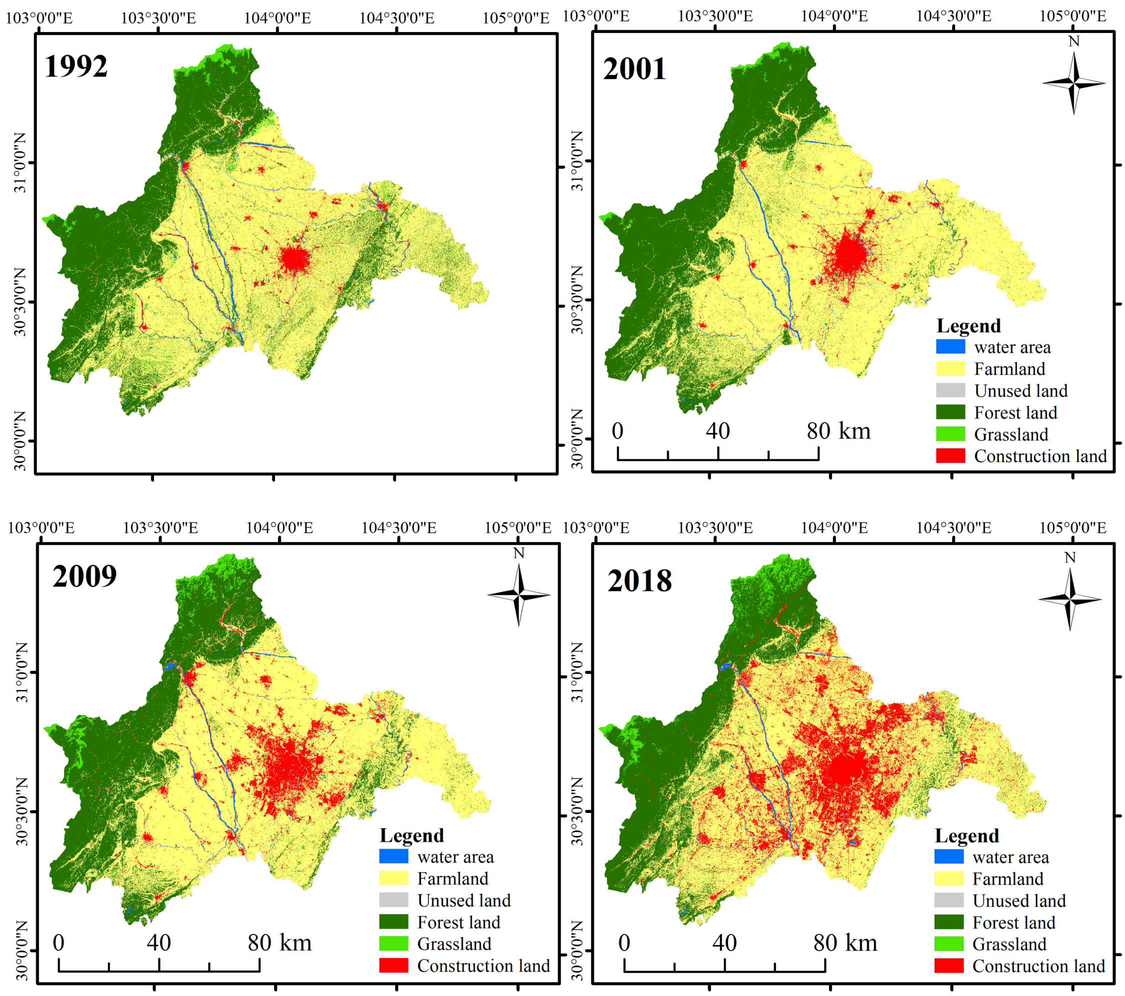

Figure 2. Land-use/land-cover (LULC) patterns of Chengdu in the years 1992, 2001, 2009, and 2018.

Table 2. Changes in LULC in Chengdu during the period of 1992–2018.

Land-Use Type	Percentage of Land-Use Type (%)				Land-Use Dynamic Index K (%)			
	1992	2001	2009	2018	1992–2001	2001–2009	2009–2018	1992–2018
Farmland	59.56	62.00	58.71	51.86	0.46	−0.66	−1.30	−0.50
Forest land	34.40	31.74	29.74	26.47	−0.86	−0.79	−1.22	−0.89
Grassland	1.85	0.83	2.05	2.50	−6.11	18.37	2.44	1.36
Water area	1.37	1.38	1.18	1.01	0.09	−1.84	−1.62	−1.02
Construction land	2.83	4.05	8.26	18.16	4.80	13.00	13.30	20.84
Unused land	0.0010	0.0026	0.0559	0.0037	16.43	260.71	−10.38	9.89
Land use dynamic degree S (%)					29.20	29.12	25.70	11.37

Table 3. Percentage of LULC conversion in Chengdu from 1992 to 2018.

2018 (%)	1992 (%)					
	Farmland	Forest Land	Grassland	Water Area	Construction Land	Unused Land
Farmland	71.06	23.62	28.10	28.94	17.52	0
Forest land	4.22	68.26	23.79	1.38	0.75	63.04
Grassland	0.23	4.70	40.06	0.14	0.12	36.96
Water area	0.38	0.24	0.60	45.59	2.14	0
Construction land	24.10	3.17	7.42	23.94	79.47	0
Unused land	0.001	0.008	0.004	0.002	0	0
Direction of change	↓	↓	↑	↓	↑	↑

3.1.2. Spatial Patterns of LULC Changes during the Period of 1992–2018

To demonstrate the spatial patterns of LULC change hotspots for each LULC type during the period of 1992–2018, the grid-based variation intensity was calculated based on the ArcGIS 10.3 software neighborhood analysis tool. Here, the transfer map of each LULC type was re-divided into non-overlapping grids 1.8 km × 1.8 km, and the LULC change information in each grid was counted [10]. Figure 3 shows the spatial patterns of the change hotspots.

During this period, the most notable features show a massive expansion of urban areas and the shrinkage of farmland around the original urban area, as well as the significant reduction in forest area in the eastern hilly areas (Figure 3). Among them, the annual growth rate of construction land area was 20.84%, causing a total growth of 184,574.79 hm^2 in the period of 1992–2018, which was 4.8 times the total area of grassland, water, and unused land in 1992. Similarly, the grassland area enhanced by 7874.19 hm^2 with an annual growth rate of 1.36%. Conversely, compared to the initial area in 1992, the loss of forest land in 2018 was the highest 7.92%, followed by the loss of farmland by 7.70%, while water area showed a minimal decline of 0.36%.

The reduced farmland area was mainly in Shuangliu (16,815.15 hm^2), Xindu (12,430.71 hm^2), Pidu (11,053.62 hm^2), Qionglai (9622.80 hm^2), and Pengzhou (8035.56 hm^2), which are all distributed around initial urban areas, accounting for 62.54% of the total converted farmland. The hotspots map shows the primary procedure of LULC changes was the transition between farmland, forest land, and construction land. The hotspots of farmland were dominated by the expansion of construction land (Figure 3). During the study period, the ecologically important types of LULC in Chengdu decreased due to the reduction in natural vegetation and water areas, which means that the impact of human activities on natural ecosystems was more serious.

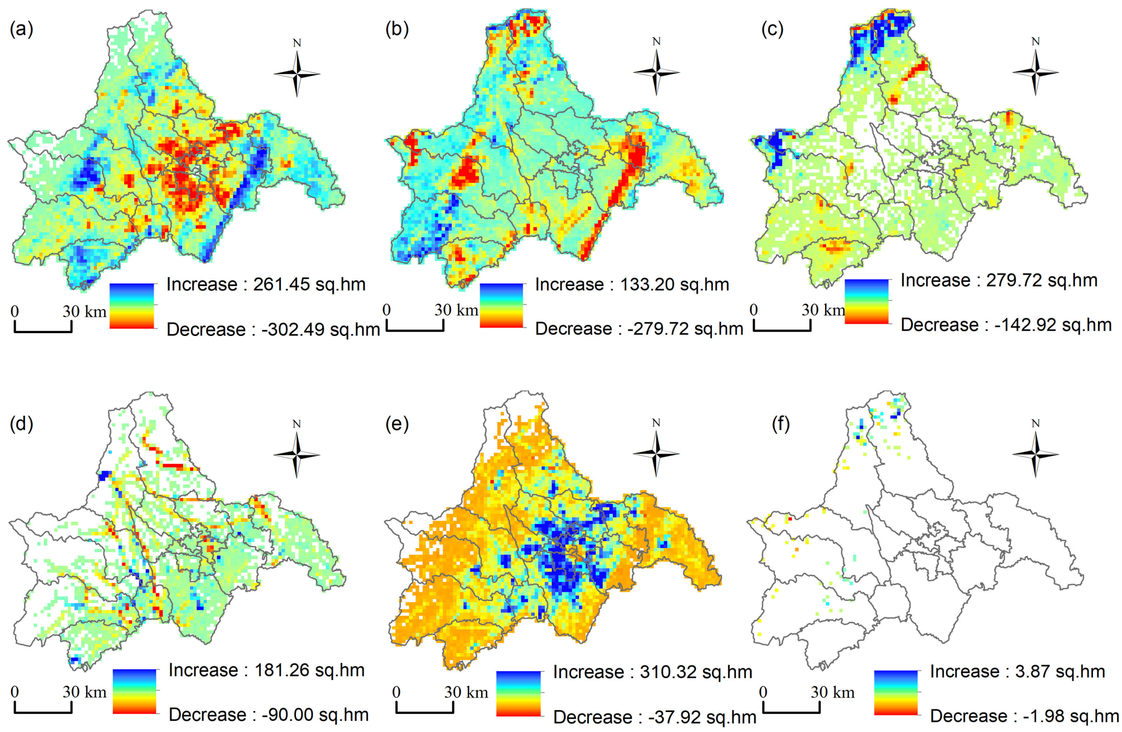

Figure 3. Hotspots of LULC changes for each type from 1992 to 2018 for (**a**) farmland, (**b**) forest land, (**c**) grassland, (**d**) water area, (**e**) construction land, and (**f**) unused land.

3.2. Assessing Changes in Ecosystem Services in Chengdu

3.2.1. Changes in Total ESV

The ecosystem service values (ESV) and changes in total ESV (Table 4) were evaluated in Chengdu for the years 1992, 2001, 2009, and 2018 using modified coefficients. On a whole, the total ESVs of the entire study landscape were about US $1476.3, $1410.2, $1335.1, and $1190.6 million in 1992, 2001, 2009, and 2018, respectively (Table 4). As a result, the value of ecosystem services in Chengdu lost US $285.70 million, accounting for 19.35% of the total value of ecosystem services in 1992. Although the ecosystem service value of each LULC type varied across the entire study landscape for different reference years, the values showed a similar sequence (Figure 4). The forest land showed the highest proportion, while the percentage of unused land was lowest. For example, at the end of the study period (2018), forest land accounted for the largest section, i.e., US $744.15 million (62.50%), while farmland, water area, and grassland accounted for about US $389.39 million (32.71%), $32.16 million (2.70%), and $24.86 million (2.09%), respectively, of the total ESV across the entire landscape.

The changes in ESV demonstrated an obvious reduction during the first (1992–2001), second (2001–2009), third (2009–2018), and entire (1992–2018) periods. The loss in total ESV over the first study period was about US $66.08 million, corresponding to a change rate of 4.48%. The total ESV dropped further, amounting to approximately US $75.07 million and $144.50 million of the total ESV in 2001 and 2009 over the second and third periods, respectively. During the period of 1992–2018, the total ESV lost approximately US $285.70 million, with a change rate of 19.35%. Moreover, the ESV of each LULC type changed, with notable reductions in the ESVs of forest and farmland, which were reduced by US $222.80 and $57.79 million, with change rates of 23.04% and 12.92%, respectively, during the period of 1992–2018. Although the loss in ESV in the water area was less than that of the farmland and forest land, amounting to US $11.62 million, its change rate reached 26.48%. In contrast, the ESV of grassland increased by US $6.51 million, equivalent to 35.33% of the grassland ESV in 1992.

Table 4. Assessed ecosystem service values (ESVs; US$ in millions) for each LULC type of Chengdu using modified coefficients. C—change; CR—change rate (calculated using Equation (5)).

Land Use Type	1992	2001	2009	2018	1992–2001		2001–2009		2009–2018		1992–2018	
	ESV	ESV	ESV	ESV	*C*	*CR* (%)	*C*	*CR* (%)	*C*	*CR* (%)	*C*	*CR* (%)
Farmland	447.18	465.52	440.8	389.39	18.34	4.09	−24.72	−5.31	−51.41	−11.66	−57.79	−12.92
Forest land	966.93	892.24	836.2	744.15	−74.69	−7.73	−56.04	−6.28	−92.05	−11.01	−222.80	−23.04
Grassland	18.35	8.25	20.39	24.86	−10.1	−54.89	12.14	145.78	4.47	22.06	6.51	35.33
Water area	43.78	44.15	37.66	32.16	0.37	0.91	−6.49	−14.71	−5.5	−14.59	−11.62	−26.48
Construction land	0	0	0	0	0	-	0	-	0	-	0	-
Unused land	0.001	0.0025	0.0547	0.0036	0.0015	200	0.0522	1733.3	−0.051	−92.73	0.0026	300
Total	1476.3	1410.2	1335.1	1190.6	−66.08	−4.48	−75.07	−5.33	−144.50	−10.82	−285.70	−19.35

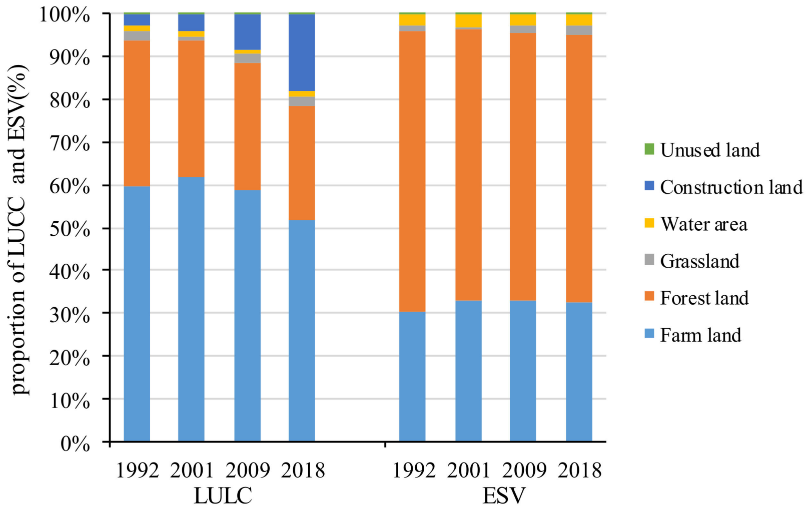

Figure 4. Proportions of LULC changes (%) and ecosystem service values (ESVs; %) during the period of 1992 to 2018 in Chengdu.

3.2.2. Spatial Patterns of Individual Ecosystem Service Function Changes

In order to reveal the regional differences in the ecosystem service functions, the spatial patterns of the change rates of ecosystem service function values in different districts of Chengdu are shown in Figure 5, using the method of natural breaks. The value of all ecosystem service functions, which included food production, raw material, gas regulation, climate regulation, hydrological regulation, waste treatment, soil conservation, biodiversity protection, and recreation and culture (Table 1), were reduced significantly throughout the entire study area (Figure 2). The change rate was highest (−82.35%) in Wuhou for total ESV in different districts, while Qionglai shows the lowest ESV reduction rate (−1.94%). Across the ecosystem service function values of the entire study area, the change rate varied from −14.22% to −21.17% for the ESVs of food production and recreation and culture, respectively. The decline in the value of ecosystem services was mainly attributed to the reduction in the area of farmland and forest land. However, the increase in construction land did not increase the value of ecosystem services, because its value coefficient was zero, which ultimately led to a dramatic decrease in the value of individual ecosystem service functions in each district.

The spatial distribution of ecosystem service function values presented an obvious circular structure, demonstrating a drastic reduction zone of the central city (in Jinniu, Wuhou, Jinjiang, Chenghua, and Qingyang) as the first circle, a reduction zone around the urban zone as the second circle, and the outermost zone as the third circle. For example, in terms of the change rate of waste treatment (Figure 5f), located in the third circles of Pengzhou, Dujiangyan, Chongzhou, Dayi, Qionglai, and Pujiang in western Chengdu, and Jintang in the east, the rates of change were smaller than those of the first and second circles. Except for the increase in food production in Pujiang (8.45%), raw material in Qionglai (0.91%), and recreation and culture in Qionglai (0.09%), the value of ecosystem service functions in other districts decreased, among which the highest reduction rate was in Wuhou for raw material (−86.68%). Furthermore, the ESV gap in different districts was obvious (Figure 6). In 1992, the ESV ranged from US $3.15 million (in Jinjiang) to US $210.08 million (in Dayi), compared to the range of US $1.01 million (in Qingyang) to US $188.25 million (in Dujiangyan) in 2018.

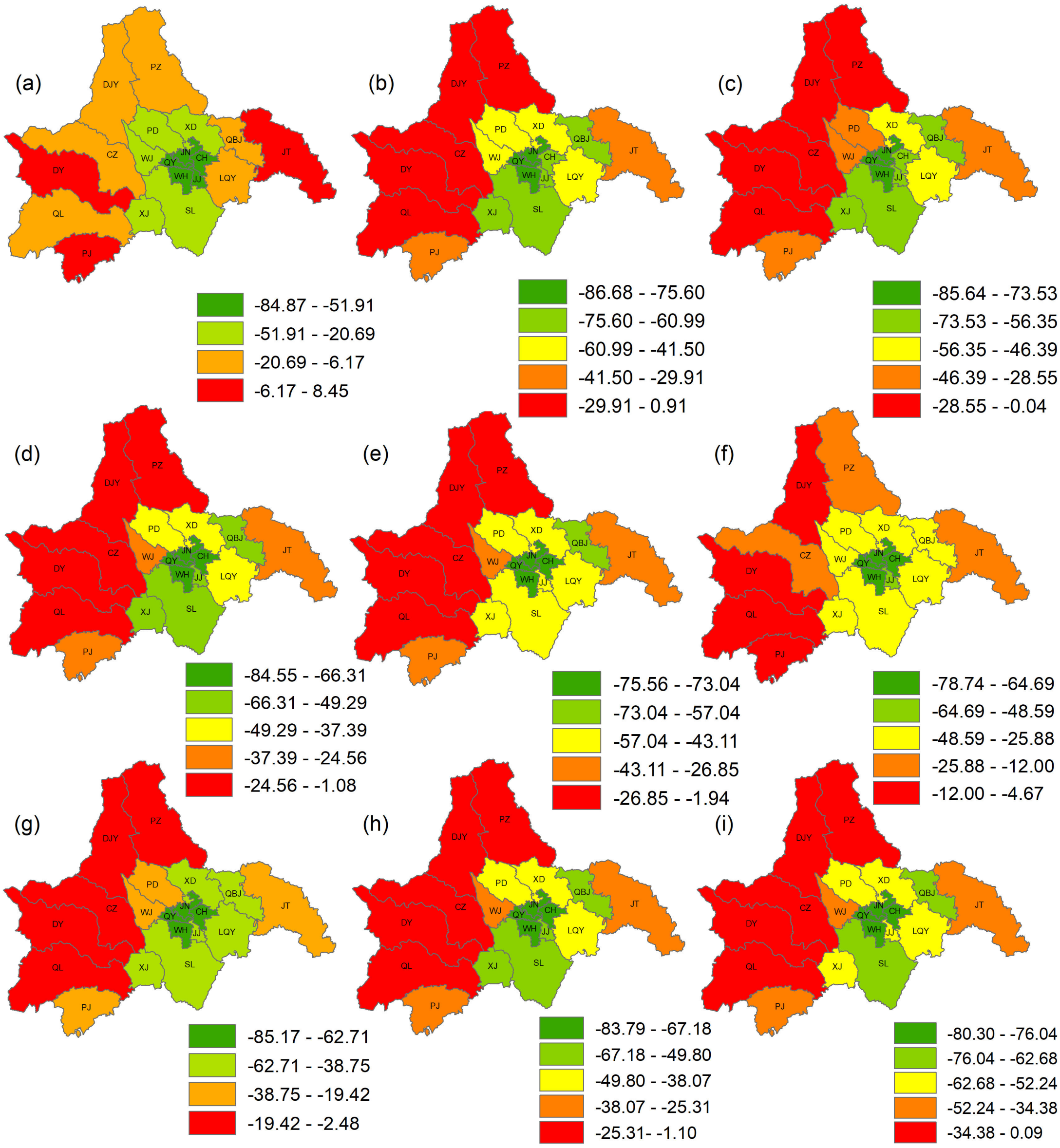

Figure 5. ESV change rates (%) for individual ecosystem functions of (**a**) food production, (**b**) raw material, (**c**) gas regulation, (**d**) climate regulation, (**e**) hydrological regulation, (**f**) waste treatment, (**g**) soil conservation, (**h**) biodiversity protection, and (**i**) recreation and culture. The letters in the figure represent the abbreviations of the district names.

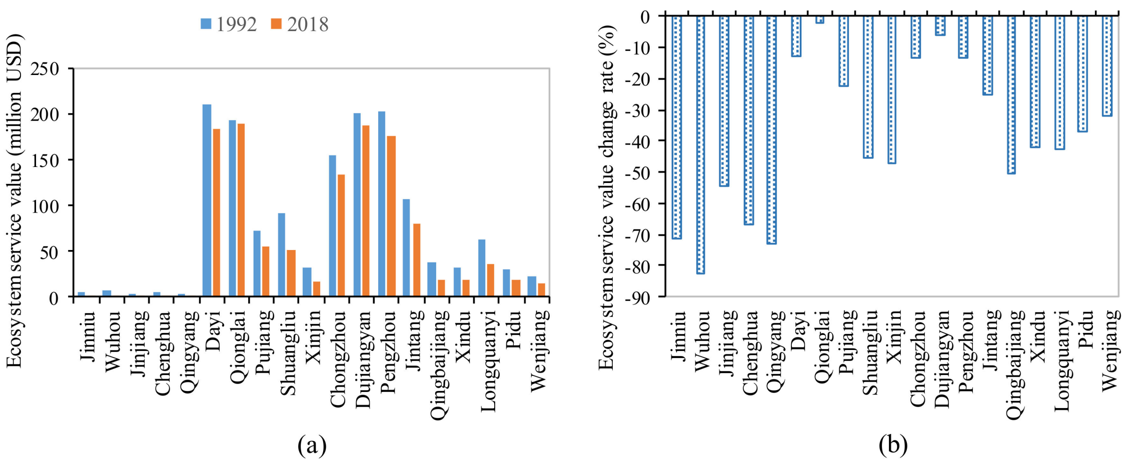

Figure 6. (**a**) Ecosystem service values (US$ in millions) for each district, and (**b**) ESV change rates (%) from 1992 to 2018.

3.2.3. ESV Change in Different Ecosystem Types from 1992 to 2018

To show the ESV change in different ecosystem types and the impact of ecosystem service value coefficients on ESV, we compared the differences in ESV for different LULC types using three coefficients for the period of 1992–2018 (Table 5, Figure 7), based on coefficients modified by NPP (marked as ESV_a), and proposed by Costanza et al. in 1997 [4] (marked as ESV_b) and Costanza et al. in 2014 [31] (marked as ESV_c). Due to the same study area, the total ESV calculated by the three coefficients showed the same trend. From the ESV_b, the ecosystem service value of forest land continued decreasing during the period of 1992–2018, reducing from US $966.93 million to $744.15 million, while the ESVs of farmland and water area generally decreased in the corresponding period, reducing from US $447.18 million to $389.39 million, and $43.78 million to $32.16 million, respectively, although there was a slight increase from 1992–2001. Meanwhile, the ESV of unused land increased sharply over the period of 2001–2009, although there was almost no change during the period of 1992–2001, while the ESV of grassland decreased over the period of 1992–2001 and increased during the period of 2001–2018 with an overall increase of US $6.5 million. The ESV_c was always found to be greater than ESV_a and ESV_b, except for the value of the ecosystem services of the unused land (Figure 7). The ESV_b values of farmland, forest land, and grassland were less than ESV_a and ESV_c values, while the ESV_b of water area was between that of ESV_a and ESV_c (Figure 7).

The ESV showed variations during the period of 1992 to 2018. The total ESVs were about US $845.16 million, $803.78 million, $742.68 million, and $656.96 million in 1992, 2001, 2009, and 2018, respectively, using the global coefficients of Costanza et al. in 1997 [4], whereas the total ESV changed to US $6091.34 million, $6182.27 million, $6238.89 million, and $6420.33 million in corresponding years when using global coefficients developed by Costanza et al. in 2014 [31]. These estimates were 0.5 and four times that of the estimates obtained using the modified coefficients.

Table 5. Ecosystem service value coefficients of different ecosystem types (US$ in millions).

LULC Types	Farmland	Forest Land	Grassland	Water Area	Construction Land	Unused Land
Modified coefficients	623.65	2334.99	825.73	2651.91	0	81.28
Costanza et al. in 1997 [4]	126	1338	321	11727	0	0
Costanza et al. in 2014 [31]	5567	3800	4166	12512	6s661	0

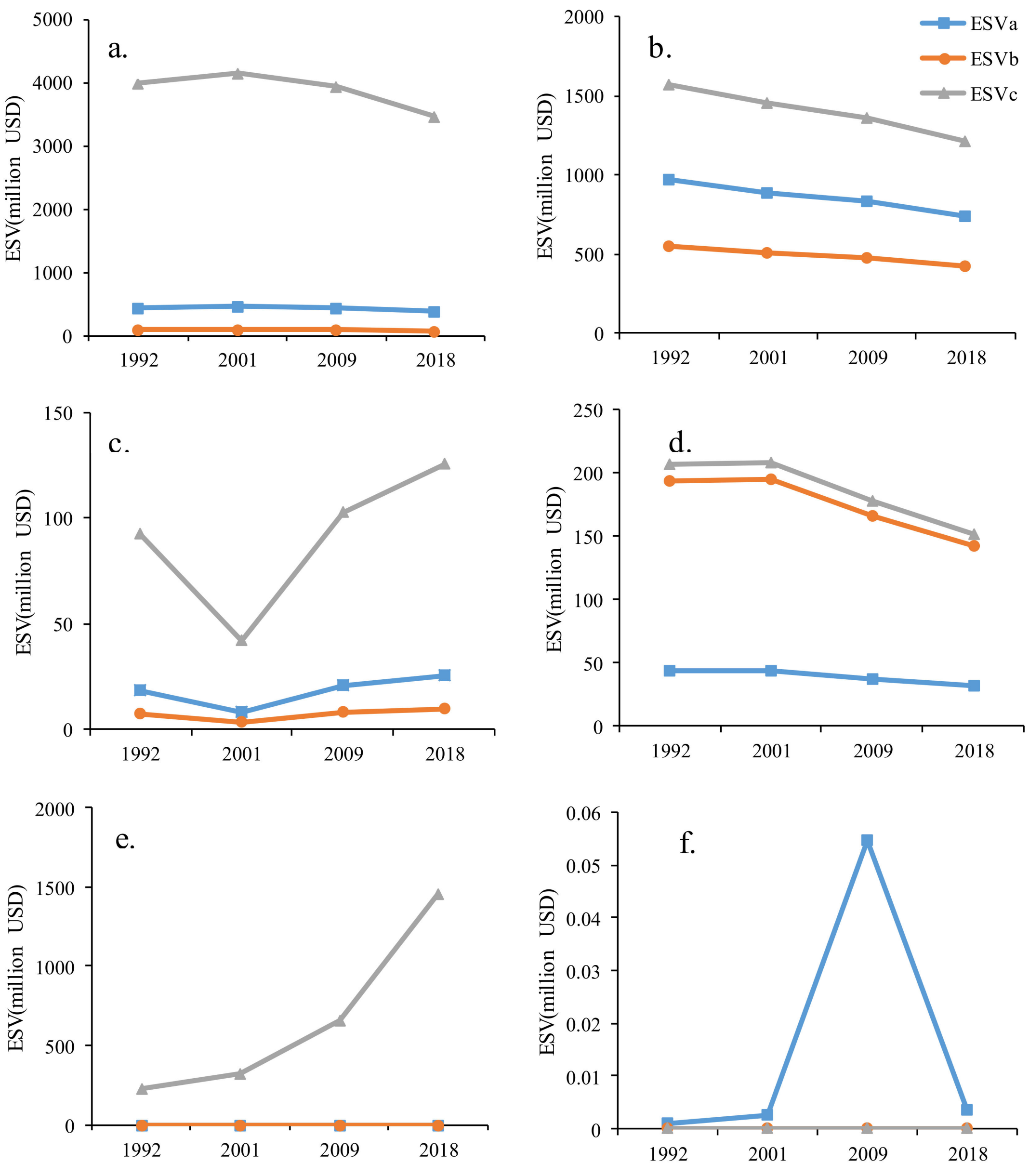

Figure 7. ESVs of different ecosystems of (**a**) farmland, (**b**) forest land, (**c**) grassland, (**d**) water area, (**e**) construction land, and (**f**) unused land (ESV_a calculated using own modified coefficients; ESV_b calculated using the coefficient proposed by Costanza et al. in 1997 [4]; ESV_c calculated using the coefficient proposed by Costanza et al. in 2014 [31]).

3.2.4. Elasticity of Ecosystem Service Value Change in Response to LULC Changes

The elasticity of the ecosystem service value change responding to LULC changes during the periods of 1992–2001, 2001–2009, and 2009–2018 were 0.28, 0.34, and 0.50, respectively, indicating that a transition of 1% of land area would cause average changes of 0.28%, 0.34%, and 0.50% in ESV, respectively (Figure 8). Using coefficients proposed by Costanza et al. in 1997 [4] and in 2014 [31], the elasticity changed to 0.31 and 0.09 during the period of 1992–2001, 0.49 and 0.06 for the period of 2001–2009, and 0.54 and 0.14 for the period of 2009–2018, respectively. Some studies indicated that the elasticity of ESV with respect to LULC in China for the periods of 1988–2000 and 2000–2008 were 0.12 and 0.33, respectively, using the unit value from Costanza et al. in 2014 [30]. Although the elasticity increased notably, the response of ESV to LULC changes was still not obvious in China [30]. High elasticity, where ESV changes were sensitive to LULC, mainly situated in areas with low ESV values, were concentrated in the central part of the North China Plain, northeastern China, and central northwestern China [30].

In general, elasticity continued increasing, indicating that ecosystem services were increasingly responsive to LULC changes in Chengdu. The higher the elasticity, the greater the likelihood that a slight change in LULC can result in a considerable change in the ESV.

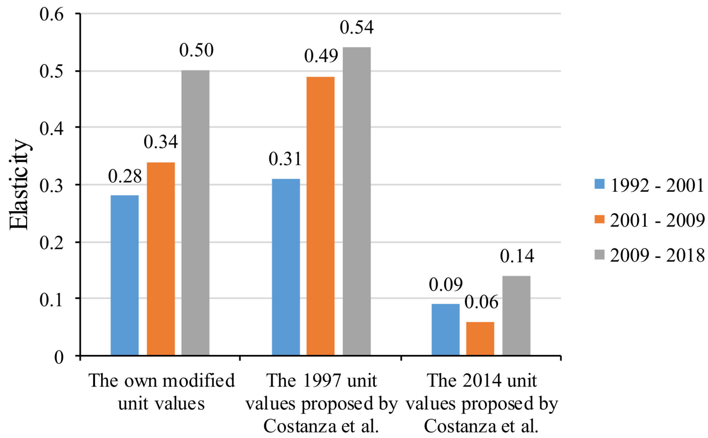

Figure 8. Elasticity of ecosystem service value changes in response to LULC changes based on different unit values.

4. Discussion

The present study quantified and mapped the LULC changes and their influence on the ecosystem in Chengdu from 1992 to 2018. Results demonstrated that urban expansion is the main reason for the high level of total ESV loss at the expense of farmland and forest land coverage. The trend of LULC changes is in conformity with other findings in Chengdu, but the trend and absolute value of total ESV were significantly different, even resulting in opposite conclusions [36,38]. According to Li et al. [38], the ESV of Chengdu increased by 75.46% from 2000–2015, which was calculated using a corrected equivalent factor of ESV with a marginal value correction factor and CPI (Consumer Price Index) accumulation coefficient. This method obtained a table of ESV coefficients that increased over time; thus, despite the notable reduction in the area of farmland and forest land, the increased coefficient compensated for the decrease in ESV due to the reduction in area, and finally concluded that the ESV increased significantly. Peng et al. showed that the ESV of Chengdu was mainly composed of farmland and forest land, and it continuously declined substantially from 1978 to 2010, which was consistent with the findings of this paper [36]. However, the above studies did not consider the spatial heterogeneity of the LULC changes and the spatial pattern of individual ecosystem service functions in Chengdu, which were the focus of this paper.

The loss in ESV caused by an excessive pursuit of economic benefits is a very common phenomenon in China, especially in the process of regional development and urban expansion. A number of studies on the impact of land-use change on ESV were conducted elsewhere in China and yielded meaningful results [24,55,60,63]. Hu et al. reported that the huge loss of ecosystem services in Xishuangbanna was attributed to the sudden shift in land use from tropical forests and swidden fields to large rubber plantations from 1988–2006, and they pointed out that the cost of a GDP increase of US $1 corresponds to at least a US $1.39 reduction in ESV in the agricultural economy [22]. Wang et al. indicated that, due to population growth and accompanying food requirements, the expansion of cultivated areas through the zealous exploitation of grassland and marginal forest land caused tremendous damage to the ecological environment, such as the decline of ecosystem services and land degradation [61]. Zhang et al. explored the commonalities and differences in the influence of LULC on ESV between three coastal urban agglomerations and demonstrated that, if a nature reserve is established and protection laws and policies are applied, it is not inevitable that urban expansion will result in a net reduction in ESV [63].

Globally, due to historical and policy reasons, there are completely different land-use structures and trends [64–69]. Many studies in European countries indicated that the growth of forest land and abandonment of agricultural areas are common issues across Europe, which had a great impact on biodiversity and landscape [70,71]. For example, in Poland and Hungary from 2002–2016, the trend of LULC changes could be depicted with a quadratic function using a statistical method, and the trend of agricultural land was negative while the trend of forest land was positive [66,68]. This is contrary to the changes of forest land area for some cities mentioned above in China. However, based on a case of a great agricultural region in the Czech Republic from 1845–2010, a study revealed that the spread of arable land and agricultural intensification led to an increase in provisioning services, while cultural and regulation services were remarkably reduced by analyzing long-term LULC data. However, in most developing countries such as Ethiopia, the loss rate of ecosystem services is high, which was interpreted as an increase in farmland and settlements, but a decrease in forest land [64].

There are several uncertainties and limitations in the ESV assessment. For instance, the benefits transfer method which was adopted in this study assumes the homogeneity of ESV and no change within each LULC class [30,33]. However, the heterogeneity and complexity of human–environmental systems can cause inevitable errors by value generalization and transfer [30]. Also, this approach is not reliable and valid until building the empirical relationships required between ecosystem characteristics and services [72,73]. Despite many researches commenting on the impact of accurate value coefficients for ESV evaluation, it is often rarely questioned for dynamic analyses as opposed to cross-sectional analyses, because the accuracy of value coefficients affects the ESV at certain points in time more than the estimates of directional change of ESV for a time series [33,63]. In addition, a number of studies calculated the coefficient of sensitivity (CS) to validate the reliability of research results and the value coefficients (VCs) of ESV were adjusted by ±50% in most cases [22,33,47,64]. However, using the CS method to test the trustworthiness of evaluation results was criticized, because the value of CS is often less than 1 even when VCs were adjusted by ±25%, which indicates erroneously robust coefficients [74]. Hence, this study did not carry out CS analysis.

5. Conclusions

This study emphasizes the important link between LULC changes and influences on the function and structure of ecosystem services. It is vital for Chengdu to explore how ecosystem services respond to LULC transformation and to ensure sustainable urban development. We believe that this study can serve as a reference and basis for improving decision-making involving the management of land resources, and contribute to a trade-off between urban expansion and the reduction in ecosystem services.

In this study, we used net primary productivity to calibrate the ecosystem service value equivalents per unit area of China's terrestrial ecosystems, and thus, established an ESV assessment model for Chengdu, and analyzed the impact of LULC changes on ESV during the period of 1992 to 2018. Remote sensing, map visualization, and geographic information system (GIS) technologies were applied to obtain LULC datasets and spatial patterns for the changes in LULC and ESV. Our results indicate that a decline in farmland, woodland, and water area, and a rapid expansion of construction land over for the period of 1992–2018 resulted in a continuous loss of total ESV to the tune of US $285.7 million using modified coefficients, and US $188.20 million and $328.99 million using global value coefficients in 1997 and 2014, respectively. The reduction in farmland which was mainly distributed around urban areas and forest land of the entire study area was the main contributor to the noteworthy loss of ESV. Furthermore, during the entire study period, the value of individual ecosystem functions also declined, with the maximum and minimum change rates being for food production (−14.22%) and entertainment culture (−21.17%). We also calculated the elasticity, and results showed that elasticity continued increasing significantly from 0.28 to 0.50, indicating that ecosystem services were increasingly responsive to LULC changes in Chengdu.

The decline in the value of ecosystem services reflects, to some extent, the impact of ecological degradation in Chengdu. Under the current rapid urban development model, urban land use should focus on improving land-intensive use efficiency, rather than sacrificing farmland and forest land to expand urban areas. Moreover, it is necessary to adopt appropriate ecological protection measures to achieve the balance between economic development and ecological environment health. The experience of Liaodong Peninsula which maintained ecosystem services by building a nature reserve can be used as a model [63]. In China, it is becoming increasingly urgent to realize the utmost importance of ecosystem conservation in the current process of rapid urbanization. The ecosystem service value assessment at the regional level should be regarded as a conservation strategy to promote decision-making for resource conservation and sustainable utilization. Beyond the completion of these findings, we recommend that a further challenge will be to continuously put forward specific alternative strategies and future planning for improving the ecological environment and ecological services, and for reducing the impact of human activities in the study area and elsewhere in China.

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