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Responses of Ecosystem Services to Land Use/Cover Changes in Rapidly Urbanizing Areas: A Case Study of the Shandong Peninsula Urban Agglomeration

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Abstract: The rapid expansion of built-up land, a hallmark of accelerated urbanization, has emerged as a pivotal factor contributing to regional climate change and the degradation of ecosystem functions. The decline in ecosystem service value (ESV) has consequently garnered significant attention in global sustainable development research. The Shandong Peninsula urban agglomeration is crucial for promoting the construction of the Yellow River Economic Belt in China, with its ecological status increasingly gaining prominence. This study investigated the ESV response to land use/cover change (LUCC) through the elasticity coefficient in order to analyze the degree of disturbance caused by land use activities on ecosystem functions in the Shandong Peninsula urban agglomeration. This analysis was based on the examination of LUCC characteristics and ESV from 1990 to 2020. The findings reveal that (1) the Shandong Peninsula urban agglomeration experienced a continuous increase in the proportion of built-up land from 1990 to 2020, alongside a highly complex transfer between different land use types, characterized by diverse transfer trajectories. The most prominent features were noted to be the rapid expansion of built-up land and the simultaneous decline in agricultural land. (2) The analysis of four landscape pattern indices, encompassing Shannon's diversity index, indicates that the continuous development of urbanization has led to increased fragmentation in land use and decreased connectivity. However, obvious spatial distribution differences exist among different districts and counties. (3) The ESV was revised using the normalized difference vegetation index, revealing a slight decrease in the total ESV of the Shandong Peninsula urban agglomeration. However, significant differences were observed among districts and counties. The number of counties and districts exhibiting low and high ESVs continuously increased, whereas those with intermediate levels generally remained unchanged. (4) The analysis of the elasticity coefficient reveals that LUCC exerts a substantial disturbance and influence on ecosystem services, with the strongest disturbance ability occurring from 2000 to 2010. The elasticity coefficient exhibits obvious spatial heterogeneity across both the entire urban agglomeration and within individual cities. Notably, Qingdao and Jinan, the dual cores of the Shandong Peninsula urban agglomeration, exhibit markedly distinct characteristics. These disparities are closely related to their development foundations in 1990 and their evolution over the past 30 years. The ESV response to LUCC displays significant variation across different time periods and spatial locations. Consequently, it is imperative to formulate dynamic management policies on the basis of regional characteristics. Such policies aim to balance social and economic development while ensuring ecological protection, thereby promoting the social and economic advancement and ecological environment preservation of the Shandong Peninsula urban agglomeration.

Keywords: land use/cover; ecosystem service value; Shandong Peninsula urban agglomeration; elasticity

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1. Introduction

Land is an indispensable factor in production and economic development, and its use is of great significance for sustainable human and social development [1]. The landscape pattern represents the most notable manifestation of land use change, and its characteristics can be analyzed from aspects, such as size, quantity, type, shape, and spatial combination, and it plays a key role in land use and ecological processes. Since landscape patterns can be understood from a diversity of perspectives [2], research designing methods to analyze the spatial patterns of landscapes are growing [3–7]. Human activities have modified the environment and climate for many years. Land use and land cover change are one of the major anthropogenic drivers of human-caused climate change [8], and they impact the ecosystem. Land use activities, such as converting natural landscapes to crop fields and cities or changing land management practices across a region, have transformed a large proportion of the Earth's land surface, resulting in profound impacts on hydrology, soil, climate, biodiversity, and ecosystem processes [9]. Landscape pattern analysis is a method for examining the compositional characteristics and spatial configurations of the landscape structure, serving as the foundation for analyzing landscape functions and dynamics. Landscape metrics have been applied widely in the dynamics of landscape patterns; more than 100 landscape metrics have been coined [10–14] and applied in built-up land expansion and urban growth [4,15], soil erosion [7], arid valleys [16,17], ecosystem services [18], and so on. These studies have shown the practicality of using landscape metrics to evaluate landscape ecological issues, such as Shannon's diversity index, Patch Number, and Patch Density, which have been well accepted as the fundamental indicators of landscape configuration [2]. There have been many studies about landscape pattern analysis in land use [1], ecology [19], and climate change [9,20]. Ecological services refer to the life-supporting services and products acquired directly or indirectly via the functions, processes, and structure of ecosystems. The value assessment of ecological services serves as a crucial foundation and basis for ecological compensation decision making, ecological environment protection, environmental economic accounting, and ecological function zoning [21–24]. Ecosystem services establish a connection between the natural environment and human society [25], encompassing four types: cultural services, provisioning services, supporting services, and regulating services [21]. The increase or decrease in the value of ecological services is a vital method for evaluating ecosystem functions and provides an intuitive reflection of the correlation between the ecological environment and regional economic development. Human activities on land not only change the land cover but also reshape the landscape pattern, subsequently influencing the structure and efficiency of ecosystem services. This, in turn, leads to changes in ecosystem components, functions, and spatial patterns, ultimately impacting the value of ecosystem services. Growing populations, along with advancing economic development and climate change, are resulting in the deterioration of the quality of the natural environment [25,26]. Consequently, research on ecosystem services is particularly important. The impacts of anthropogenic and environmental stressors on natural ecosystems can propagate ecosystem functions that may impede ecosystem services [27]. As the economy and society continue to develop and urbanization accelerates, the human disturbance to the natural environment has become increasingly common [28]. As land is the most essential ecosystem element, land use/cover change (LUCC) can have a significant impact on regional ESV [29–31], and this can cause significant environmental impacts, such as soil degradation, deforestation, and biodiversity loss [32], ultimately increasing ecosystem vulnerability and significantly impacting regional sustainable development. The ESV has become an important indicator for assessing the level of sustainable development in the region. Research on how LUCC affects ecosystem services, as assessed through ESV, has gradually increased. Additionally, quantitative evaluation of the influence of LUCC on ESV has become a key area of sustainable development research [25,31,33]. Scholarly interest in the ESV and LUCC has witnessed marked attention among researchers from different countries and launched fruitful research work, such as in China [25], Yemen [34], Bangladesh [35], and India [36]. Rapid urbanization has been an important social and economic phenomenon during the last 50 years [37,38], and urbanization has become a global phenomenon, which has significantly transformed society and the global economy and has become a crucial geospatial process [4,39]. Urban land quadrupled between 1970 and 2000 [40], and its importance is expected to grow in the future. Urbanization, while being an inevitable trend and expanding activity worldwide [41], has changed the interactions among the biosphere, atmosphere, and hydrosphere, resulting in altering ecosystem services decline [42]. Rapid urbanization has profoundly affected natural ecosystems and human livelihoods [43,44], markedly promoting the evolution of landscape patterns and land use [15,38,45,46]. Consequently, amid rapid urbanization, examining the spatial and temporal differences in LUCC and ESV and identifying the impact of landscape pattern evolution on ecological service functions are highly significant. These analyses elucidate the ecological and land challenges faced in urbanization development and facilitate the coordination of economic and ecological development. China is the largest developing country and the most populated country in the world. Since the early 1980s, China has undergone rapid urbanization due to changing demographics and shifting land use [42]. The Shandong Peninsula urban agglomeration is situated on the eastern coast of China and the lower reaches of the Yellow River. It faces Japan and South Korea across the sea to the east, borders the lower reaches of the Yellow River to the west, and is adjacent to the Beijing–Tianjin–Hebei urban agglomeration and the Yangtze River Delta urban agglomeration to the north and south, respectively. It is a vital part of the Bohai Rim region and one of the key coastal urban agglomerations under national development. Additionally, it serves as a crucial blue economic demonstration zone and an efficient ecological economic zone in China. While its ecological role is becoming more prominent, the expansion of the urban agglomeration at the expense of cropland consumption has significantly weakened urban ecological functions and caused man–land contradictions, posing a threat to the overall stability of the ecological environment. Hence, it is imperative to conduct research regarding the influence of LUCC on ecosystems.

This study focuses on the Shandong Peninsula urban agglomeration as the research area. The research on ESV was conducted on the basis of an analysis of the characteristics of land use evolution from 1990 to 2020. Furthermore, the analysis examines the effect of LUCC on ESV to reveal the characteristics of land use quantity and spatial configuration changes within the Shandong Peninsula urban agglomeration, alongside the resulting spatio-temporal differences in ESV. This study aims to offer a reference for the formulation of scientific policies regarding land resource development and protection.

2. Materials and Methods

2.1. Study Area

In 2022, the Shandong Provincial Government issued the Shandong Peninsula Urban Agglomeration Development Plan (2021–2035), which clearly stated that the Shandong Peninsula urban agglomeration covers all 16 cities within Shandong Province. This study focused on those 16 cities as the scope of the Shandong Peninsula urban agglomeration for research purposes. In 2020, the total gross domestic product of the cluster reached RMB 7312.9 billion, with a permanent resident population of 101.527 million. The railway traffic mileage reached 7000 km, including 2110 km of high-speed railways. Additionally, the highway traffic mileage reached 283,000 km, with 7473 km of expressways, thereby forming a relatively complete transportation network system. The Shandong Peninsula urban agglomeration occupies a crucial strategic position in China's overall development landscape. As an important high-efficiency ecological economic zone and a key region for promoting the construction of the Yellow River Economic Belt in China, its ecological status has become increasingly significant (Figure 1).

2.2. Data Source and Description

2.2.1. Land Use/Cover

Land use/cover data come from the Landsat-derived annual China Land Cover Dataset (CLCD) [47], abd the CLCD contains 30 m of annual land cover and the dynamics of China from 1990 to 2020. The training samples of the CLCD combine stable samples extracted from China's Land-Use/Cover Datasets (CLUDs) and visually interpreted samples from satellite time-series data, Google Earth, and Google Maps. CLCD data include 9 major land covers: cropland, forest, shrub, grassland, water, snow and ice, barren, impervious, and wetland; the overall accuracy reached 79.31% based on 5463 independent test samples, and CLCD data can be obtained from the following website: http://doi.org/10.5281/zenodo.4417810 (accessed on 4 March 2024) [47]. CLCD data have been applied in many studies, such as cultivated land quality monitoring [48], ecological quality [49], ecosystem services [50], land degradation [51], and land use and land cover patterns [52].

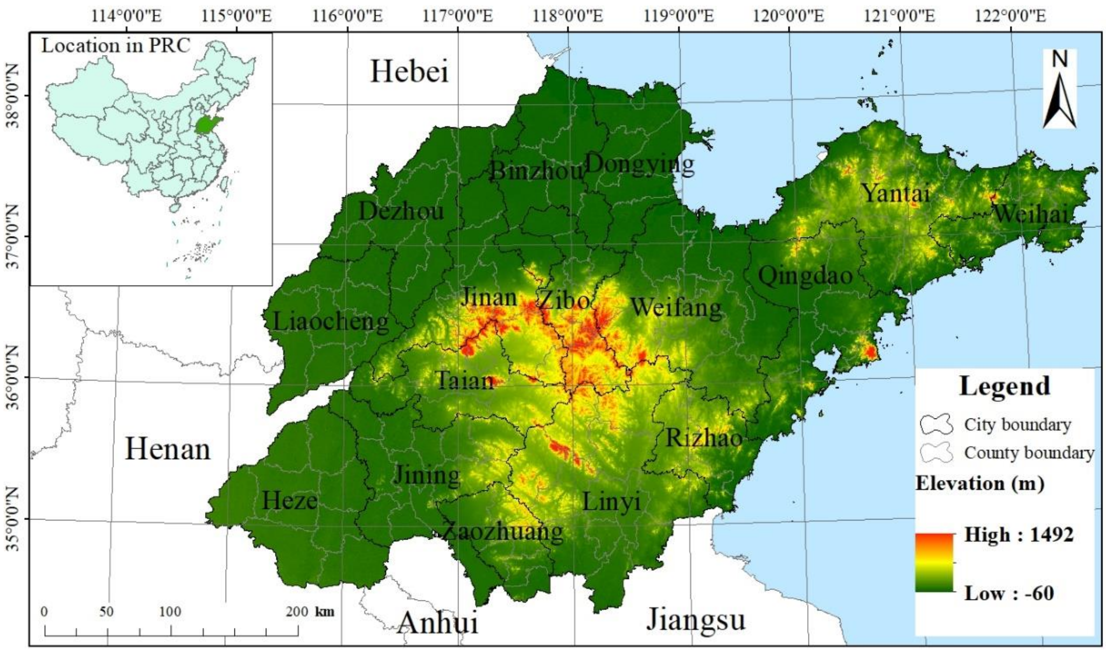

Figure 1. Study area map.

The CLDU includes 6 primary land cover categories and 25 subtypes; the six primary land cover categories include cropland, forest, grassland, water, built-up land, and unused land, and the CLUD has been extensively utilized in land- and landscape-related studies [53–55]. To facilitate the comparative analysis of the findings of this study with existing research, considering the data requirements for ESV research, the seven primary land cover categories in the CLCD (the Shandong Peninsula urban agglomeration has no or little snow/ice and wetland land types in the CLCD) were converted into the six primary land cover categories in the CLUD (as depicted in Table 1).

Table 1. Correspondence table of the land cover classification system.

CLUD	CLCD
Cropland	Cropland
Forest	Forest, shrub
Grassland	Grassland
Water bodies	Water
Built-up land	Impervious
Unused land	Barren

2.2.2. Normalized Difference Vegetation Index

In this research, normalized difference vegetation index (NDVI) data were obtained from the Moderate Resolution Imaging Spectroradiometer data regularly released by NASA (https://modis.gsfc.nasa.gov/, accessed on 4 March 2024). NDVI data have a temporal resolution of 16 days and a spatial resolution of 250 m; after clipping the NDVI data using the vector boundaries of the Shandong Peninsula urban agglomeration, the maximum value compositing method was applied to derive the annual maximum NDVI. Since 250 m resolution NDVI data for 1990 were unavailable, data from 2000 were used to analyze the ESV in 1990 to maintain consistency in the research results.

2.3. Methodology

2.3.1. Land Use Transition Matrix

The land use transition matrix delineates the dynamic exchange of land types within a specific region over defined periods of time. It provides insights into how areas of different land types evolve between the beginning and end of each period. The land use transition matrices were constructed for the periods of 1990–2000, 2000–2010, 2010–2020, and 1990–2020 by utilizing the land use/cover data of five years (1990, 2000, 2010, and 2020). These matrices were developed to examine the characteristics of LUCC in the Shandong Peninsula urban agglomeration.

2.3.2. Landscape Pattern Metrics

Landscape pattern analysis has become a key research topic in landscape ecology [56–58]; in the studies on landscape patterns, the primary data mainly come from categorization maps such as vegetation, soil, and land use/cover maps. Therefore, the landscape metrics approach is more applicable than the others [59]. A variety of landscape metrics have been proposed and applied to quantify different spatial characteristics of land use/cover, such as heterogeneity [60], shape complexity [61], fragmentation [62], and land patterns [4,63]. In this study, we chose four landscape metrics to characterize the land use pattern, including Patch Density, Perimeter Area Ratio_Mean, the aggregation index, and Shannon's diversity index. Descriptions of the landscape metrics are presented in Table 2.

Table 2. Landscape metrics used in this study.

Metrics	Formula	Description
Patch Density (PD)	$PD = \frac{n_i}{A}$	n_i represents the number of patches of type i, and A represents the total landscape area. PD > 0, with no upper limit. PD reflects the degree of landscape fragmentation and spatial heterogeneity.
Shannon's Diversity Index (SHDI)	$SHDI = \sum_{i=1}^{m} P_i \times \ln(P_i)$	It primarily reflects the heterogeneity of the landscape. The value range is SHDI $\geq$ 0.
Aggregation Index (AI)	$AI = 2\ln(\mathrm{n}) + \sum_{i=1}^{n}\sum_{j=1}^{n} P_{ij}\ln(P_{ij})$	The patch aggregation index (AI) describes the degree of patch aggregation in a landscape, reflecting the dispersion of landscape elements within the landscape. The patch AI ranges from 0 to 100.
Perimeter Area Ratio_Mean (PARA_MN)	$PARA\_MN = \frac{p_{ij}}{a_{ij}}$	The ratio of the perimeter to the area.

2.3.3. ESV Estimation

Building on the research findings of Costanza et al. on the global ESV [64], Xie Gaodi et al. constructed the China Ecosystem Service Value Equivalence Table [65,66] by conducting a questionnaire survey among multiple experts in the field of ecology in China. The research results from 2007 had a higher number of questionnaires and a higher questionnaire response rate, making them more credible and scientifically robust. Consequently, this study utilizes these results as the National Basic Equivalent Factor Table. Through an investigation of the China Agricultural Product Price Survey Yearbook (2021), the average unit price of main grain crops was calculated. Based on the principle that the ESV per unit area of farmland equals 1/7 of the market economic value of the average grain yield [66], the basic equivalent factor table for the Shandong Peninsula urban agglomeration was obtained (as depicted in Table 3).

Table 3. Equivalent table of ecosystem services value per unit area in the Shandong Peninsula urban agglomeration (RMB/hm^{-2} a^{-1}).

Ecosystem Services	Forest	Grassland	Cropland	Water Bodies	Unused Land
provisioning services	7068.79	1687.11	2968.46	1879.32	128.14
regulating services	30,325.32	12,599.96	8222.01	77,286.86	1110.50
supporting services	18,216.55	8777.26	5317.61	8200.65	1217.28
cultural services	4442.02	1857.96	363.05	9482.00	512.54

There is a significant impact of vegetation coverage on the level of ecosystem services in land use types with vegetation cover, for instance, cropland, forest, and grassland [67]. This study utilized the NDVI to assess the vegetation status within the region and further revised the ESV of the research units. The formulas are as follows:

$$C_{ik} = \frac{NDVI_{ik}}{\overline{NDVI_i}} \tag{1}$$

$$ESV = \sum_{i=1}^{a} \sum_{j=1}^{b} \sum_{k=1}^{c} A_{ij} B_{ik} C_{ik} \tag{2}$$

C_{ik} represents the NDVI revision coefficient of the ith land use type in the kth research unit. $NDVI_{ik}$ represents the NDVI value of the ith land use type in the kth unit, and $\overline{NDVI_i}$ represents the mean NDVI value of the ith land use type. ESV denotes the total ESV. A_{ij} represents the jth ESV coefficient of the ith land use type. B_{ik} represents the area of the ith land use type in the kth research unit. C_{ik} represents the NDVI revision coefficient of the ith land use type in the kth research unit. Furthermore, i, j, and k represent the land use type, ecosystem service type, and research unit number, respectively.

2.3.4. Elasticity of ESV Change in Relation to LUCC

Elasticity is an indicator that measures the degree of response of one variable to changes in another variable, and it is generally quantified using elasticity coefficients. In this study, elasticity coefficients are utilized to examine the percentage change in ESV resulting from LUCC [67,68]. The formulas are as follows:

$$E = \left| \frac{(ESV_{t_2} - ESV_{t_1})/ESV_{t_1}}{LUP} \right| \tag{3}$$

$$LUP = \frac{\sum_{i=1}^{n} \Delta L_i}{\sum_{i=1}^{n} L_i} \tag{4}$$

In the formula, E represents the elasticity of ESV in response to LUCC. Moreover, t_1 represents the initial period of the research, while t_2 represents the end period. LUP represents the percentage of LUCC. ΔL_i represents the area of LUCC for land use type i and L_i represents the total area of land use type i. Herein, the value of i is six, representing the six land use types considered in this study.

3. Results and Discussion

3.1. Characteristics of LUCC in the Shandong Peninsula Urban Agglomeration

3.1.1. Characteristics of Land Use/Cover Scale and Transfer

Figure 2 illustrates the land use/cover patterns of the Shandong Peninsula urban agglomeration in 1990, 2000, 2010, and 2020. Cropland is the predominant land use type in the Shandong Peninsula urban agglomeration, representing over 68.5% of the total area throughout the years and being widely distributed across various cities. Built-up land ranks second to cropland, consistently comprising more than 11.08% of the total area throughout the years. It exhibits a wide overall distribution range but demonstrates a clear agglomeration trend. The area of forests is relatively large, consistently representing over 4.15% of the total area over the years. Moreover, its distribution is highly concentrated, primarily in the northeastern and central regions. Grassland occupies less than 3% of the total area and is primarily distributed in the northeastern and central regions, exhibiting a spatial distribution range essentially consistent with that of forests. The proportions of water bodies and unused land are relatively small. Water bodies are mainly present in the southern and northern regions, while unused land is mainly located in the northern coastal areas.

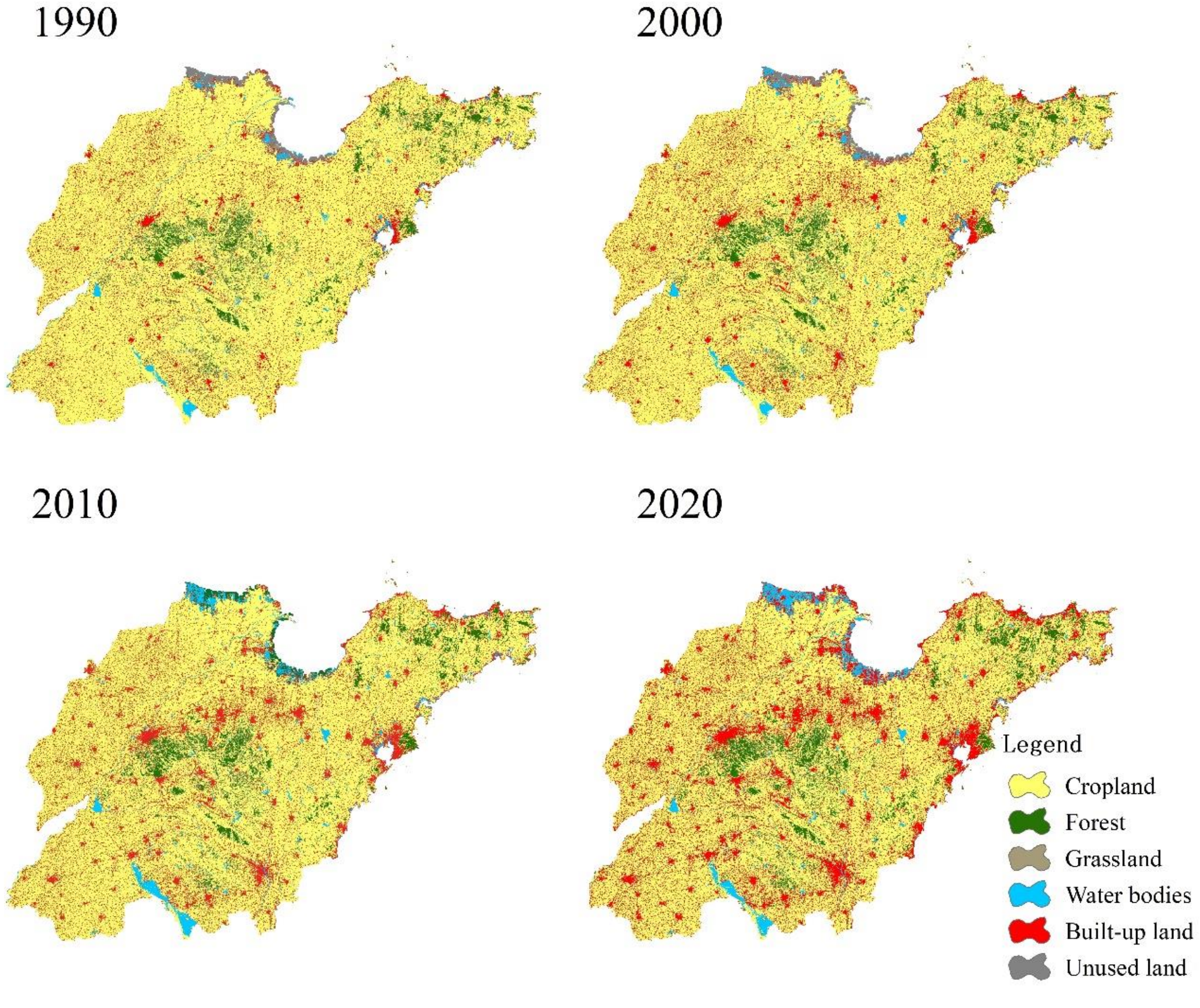

Figure 2. Spatial distribution of land use/cover in the Shandong Peninsula urban agglomeration from 1990 to 2020.

Precise data concerning the proportions and areas of various land use types were acquired (Table 4) for further assessment of the characteristics of LUCC in the Shandong Peninsula urban agglomeration. In general, cropland, grassland, and unused land have been decreasing, while built-up land, water bodies, and forests have been increasing. Specifically, the most notable decrease was observed in cropland, with a reduction of 10.45% (16,275.22 km^2) over 30 years from 1990 to 2020. The decrease was the largest from 2000 to 2010 and the smallest from 1990 to 2000. The increase in built-up land was particularly notable, with a growth of 10.73% (16,709.09 km^2) over 30 years, and the growth rate gradually accelerated from 3.36% in 1990–2000 to 3.95% in 2010–2020. The increase in forest area was relatively small, with a growth of 0.88% (1374.54 km^2) over 30 years, and there was a slight increase in all periods, except for a minor decrease from 2000 to 2010. The water body area experienced a 1.54% increase (2399.10 km^2) over 30 years, with the largest increase occurring between 2000 and 2010. Grassland and unused land slightly decreased, with minor variations in the rate of decrease across different time periods.

Table 4. Statistics of land use area from 1990 to 2020.

Period	Item	Cropland	Forest	Grassland	Water Bodies	Built-up Land	Unused Land
1990	Area (km^2)	122,964.72	6456.93	4656.78	2419.38	17,258.58	1983.97
	Proportion (%)	78.95	4.15	2.99	1.55	11.08	1.27
2000	Area (km^2)	118,234.70	6762.41	3590.28	2961.29	22,487.88	1703.78
	Proportion (%)	75.92	4.34	2.31	1.90	14.44	1.09
2010	Area (km^2)	112,393.32	6650.25	2973.56	4646.44	27,813.68	1263.06
	Proportion (%)	72.17	4.27	1.91	2.98	17.86	0.81
2020	Area (km^2)	106,689.51	7831.47	2081.00	4818.48	33,967.67	352.21
	Proportion (%)	68.50	5.03	1.34	3.09	21.81	0.23
1990–2000	Change (km^2)	−4730.02	305.48	−1066.50	541.90	5229.30	−280.18
	Change (%)	−3.04	0.20	−0.68	0.35	3.36	−0.18
2000–2010	Change (km^2)	−5841.38	−112.16	−616.72	1685.15	5325.80	−440.72
	Change (%)	−3.75	−0.07	−0.40	1.08	3.42	−0.28
2010–2020	Change (km^2)	−5703.82	1181.22	−892.56	172.05	6153.99	−910.85
	Change (%)	−3.66	0.76	−0.57	0.11	3.95	−0.58
1990–2020	Change (km^2)	−16,275.22	1374.54	−2575.78	2399.10	16,709.09	−1631.76
	Change (%)	−10.45	0.88	−1.65	1.54	10.73	−1.05

The land use transition matrix for different years was analyzed thoroughly, and the results are displayed in a chord chart format (Figure 3). In the chordal chart, different colors indicate different land use/cover types, arrows indicate the direction of land use transition, and thicker arrows indicate larger transitions. The transition characteristics observed across the three stages, 1990–2000, 2000–2010, and 2010–2020, remain largely consistent. Notably, cropland consistently exhibits the largest transfer-out area, while built-up land consistently exhibits the largest transfer-in area. However, variations were noted between the stages. The total area of transition shows a gradual upward trend, rising from 11,210.09 km^2 in 1990–2000 to 11,503.42 km^2 in 2000–2010, and reaching 12,679.41 km^2 in 2010–2020. Simultaneously, significant differences exist in the direction of the transition. In 1990–2000, the main types of transitions with larger areas included cropland to built-up land (5303.98 km^2), grassland to cropland (996.35 km^2), forest to cropland (750.71 km^2), and cropland to water bodies (663.6 km^2). In 2000–2010, the primary types of transitions with larger areas included cropland to built-up land (5622.86 km^2), cropland to water bodies (1158 km^2), grassland to cropland (848.82 km^2), forest to cropland (674.15 km^2), and cropland to grassland (521.45 km^2). From 2010 to 2020, the main types of transitions with larger areas consisted of cropland to built-up land (5704.9 km^2), cropland to forest (1259.66 km^2), grassland to cropland (892.13 km^2), water bodies to cropland (667.98 km^2), cropland to water bodies (576.82 km^2), and cropland to grassland (513.22 km^2). Assessing the overall changes over the period of 30 years (1990–2020), the transitions between types of land use/cover in the Shandong Peninsula urban agglomeration were noted to exhibit high complexity, with diverse transition trajectories. The total transition area reached 26,900.07 km^2. The transfer out of cropland is the most significant, with 16,006.03 km^2 transferred to built-up land, 1682.51 km^2 transferred to water bodies, and 1172.84 km^2 transferred to forests. The most significant transfer in is of built-up land. Apart from the substantial transfer in from cropland, the areas of unused land, water bodies, and grassland transferred to built-up land are also relatively large, reaching 657.21 km^2, 399.28 km^2, and 348.92 km^2, respectively. The transition of other types is also relatively complex. Forests primarily transfer to built-up land and cropland, grassland primarily transfers to built-up land, cropland, and forests, the unused land primarily transfers to built-up land and cropland, and water bodies primarily transfer to built-up land and cropland.

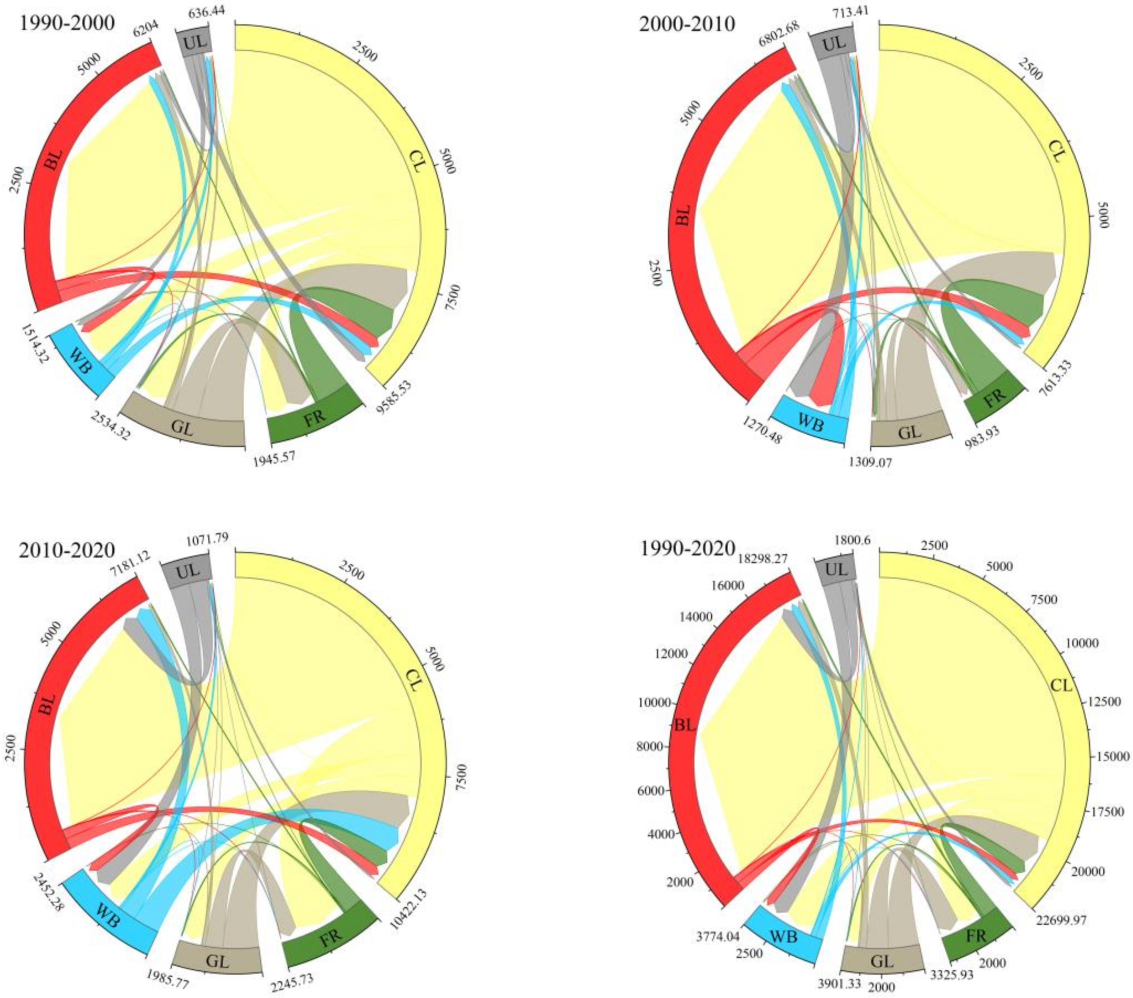

Figure 3. Chord chart of land use transitions for various land use types from 1990 to 2020 (unit: km^2).

The transition between various land use types has become very active; from the perspective of the total amount of land use transfer, cropland consistently exhibits the largest transfer-out area, while built-up land consistently exhibits the largest transfer-in area. The intuitive manifestation of this in terms of land use scale is the continuous rise observed in the proportion of built-up land and the simultaneous decrease in the proportion of cropland, forests, and other land use types. In addition to the frequent transition between cropland and built-up land, the transfer in and transfer out of grassland and forests are also significant indicators of the diversity of land use transformation trajectories in the Shandong Peninsula urban agglomeration. The main reason is that with the continuous advancement of reform and opening up, the development of each city in this urban agglomeration has entered a new stage. The level of urbanization in each city has been continuously improving, accompanied by continuous expansion of the built-up areas, resulting in an unprecedented demand for land use. Simultaneously, the changes in land use scale exhibit spatial heterogeneity due to the differences in the development foundation and natural environment of each city.

3.1.2. Characteristics of Land Use/Cover Patterns

To further explore fragmentation, diversity, and other characteristics of land use in the Shandong Peninsula urban agglomeration and refine the research scale, four landscape pattern indices, including the SHDI, were calculated for each district and county using Fragstats 4.2 software. The resulting data are depicted in Figures 4–7.

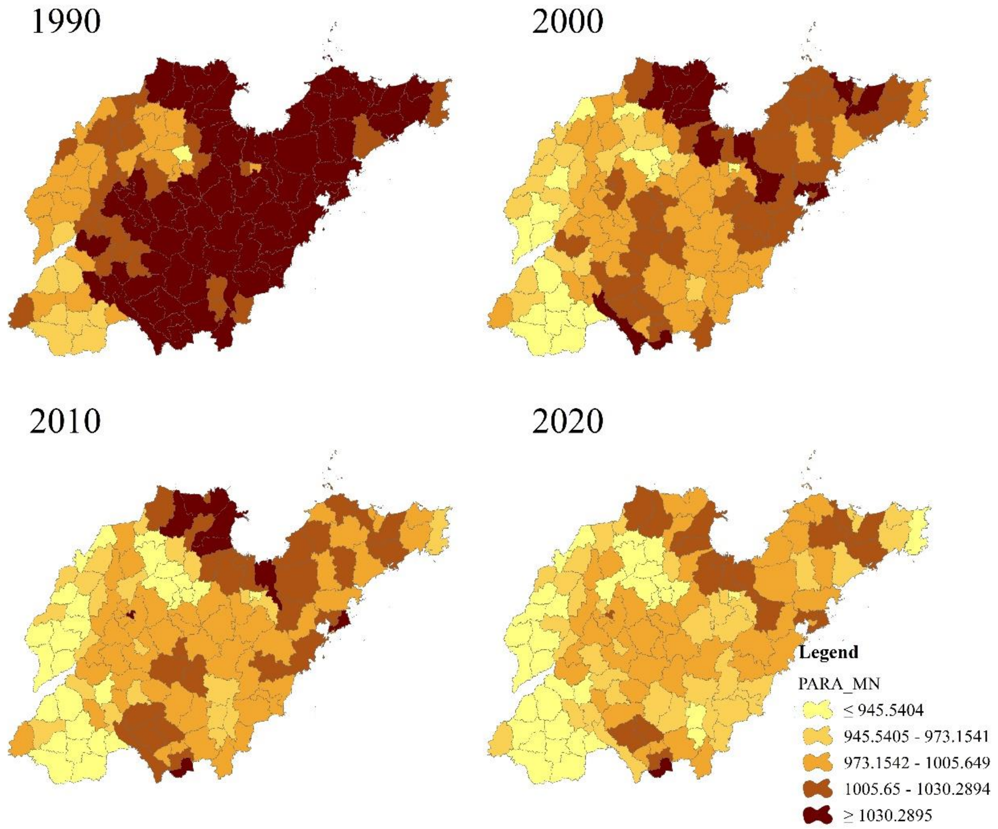

Figure 4. Spatial distribution of the PARA_MN index.

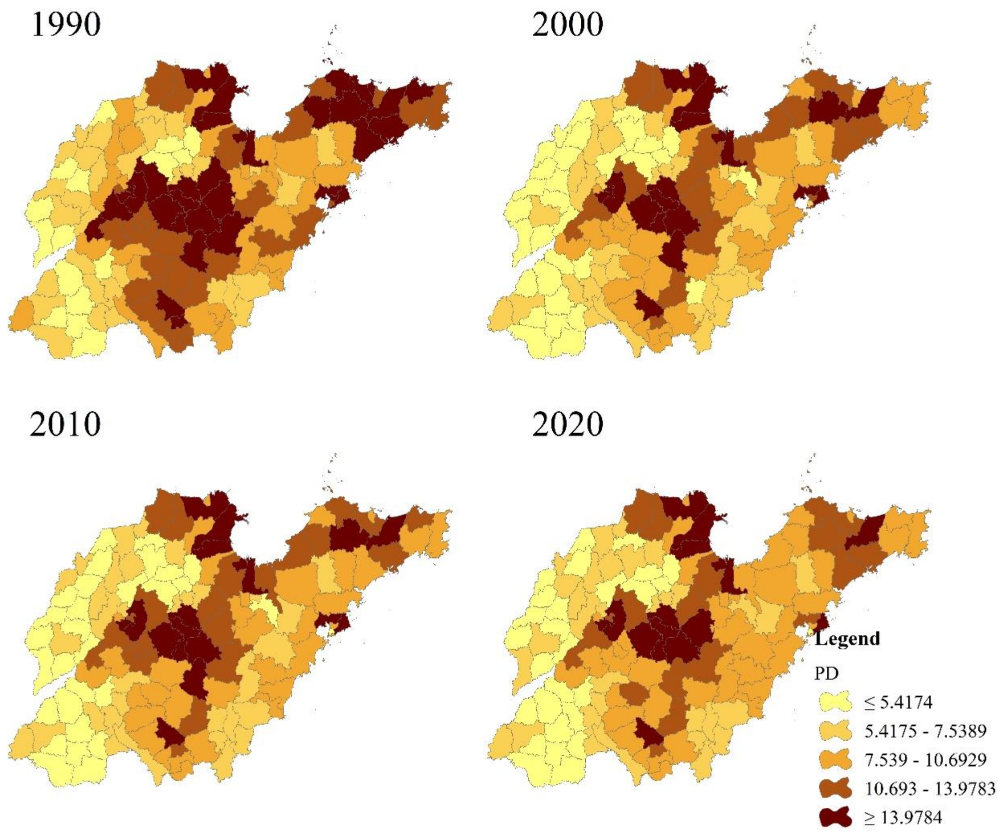

Figure 5. Spatial distribution of the PD index.

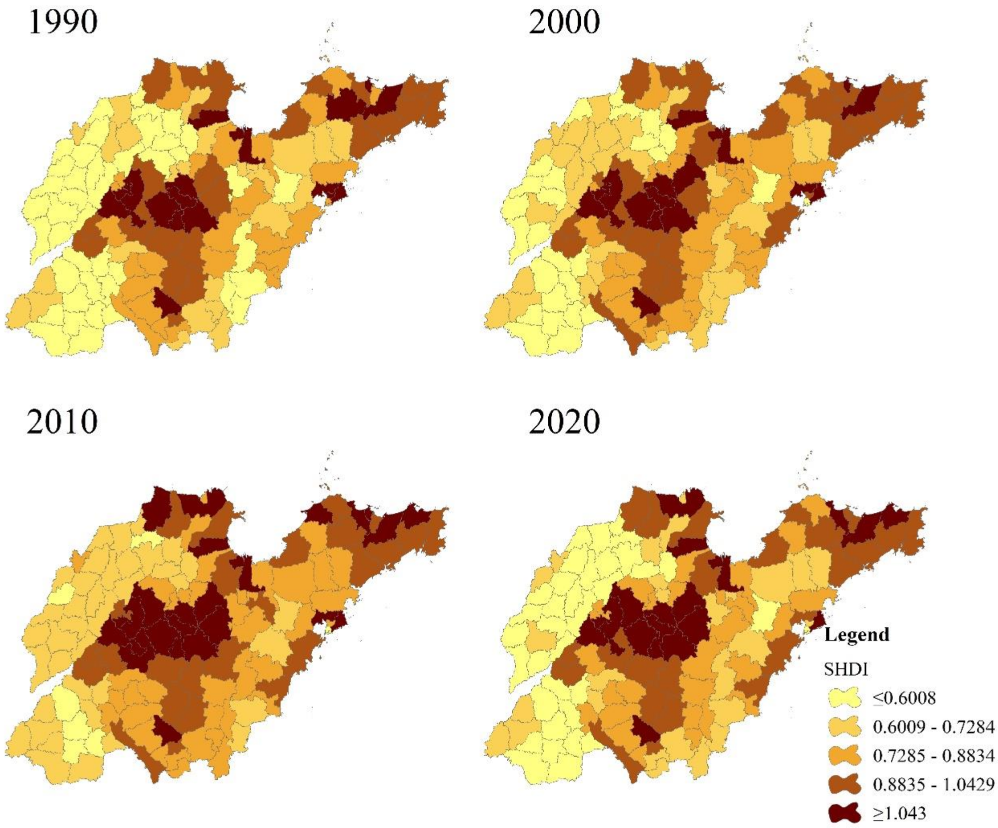

Figure 6. Spatial distribution of the SHDI.

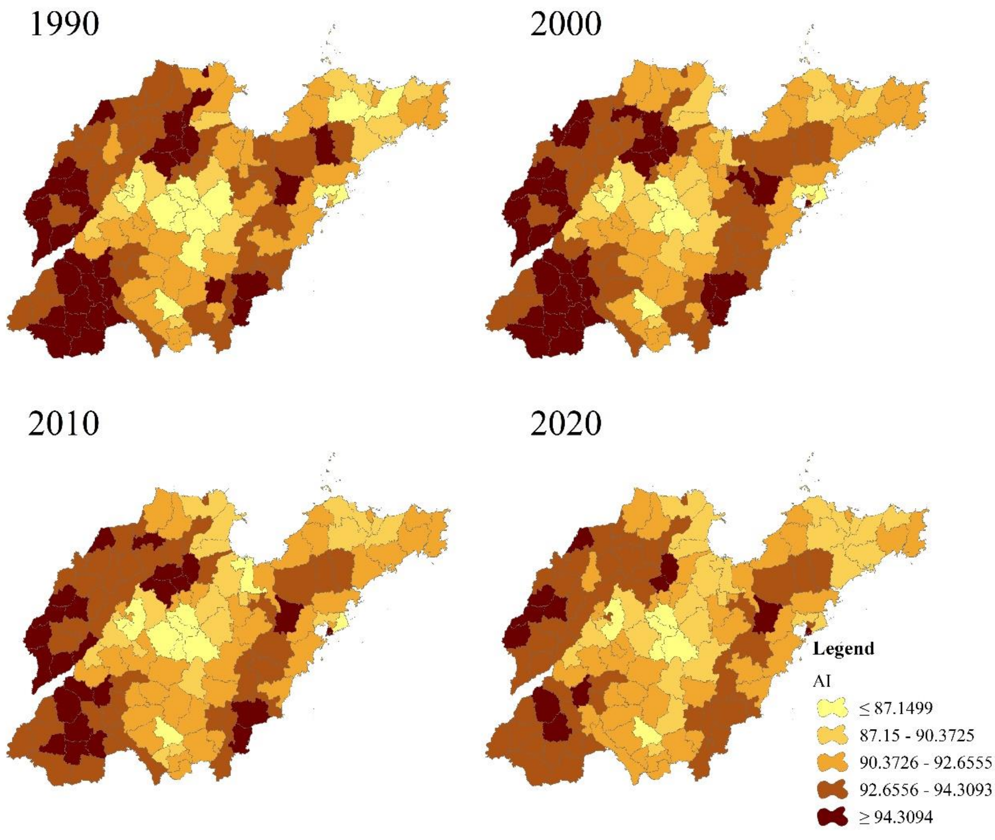

Figure 7. Spatial distribution of the AI index.

The PARA_MN index reflects the shape characteristics of different land use types and refers to the ratio of the perimeter to area. A higher value indicates a more complex and irregular shape of land use within the study area, and it has an impact on the functions of the ecosystems. It was found that from 1990 to 2020, the overall trend showed a continuous decrease, and the overall shape of land use became more regular. Different years exhibited a certain clustering trend. In 1990, the overall pattern was dominated by contiguous high values, with contiguous low-value areas only existing in the western cities of Binzhou, Dezhou, Liaocheng, and Heze. In 2000, the high-value areas were greatly reduced, with high-value clustering areas only existing in Zaozhuang in the south and Dongying in the north. In 2010, the high-value areas further decreased, mainly located in Dongying and its surrounding areas. In 2020, the high-value areas further declined, and the low-value areas gradually expanded, eventually forming a distribution pattern with the highest values in the south and north and the lowest values in the southwest and northwest.

The PD index, expressed as the number of patches per hectare and representing the complexity of the landscape on a map for each study area, reflects the degree of ecological land fragmentation and spatial heterogeneity. The PD index reflects the degree of landscape fragmentation, with higher values indicating greater land fragmentation and heterogeneity in each district and county and a greater impact on the protection of ecological land. It was observed that spatially, the distribution patterns were generally consistent across the four years. Districts and counties with high values were primarily located in Jinan and Dongying cities, while districts and counties with low values were primarily distributed in Dezhou, Liaocheng, Heze, and Jining cities. Temporally, apart from the year 1990 with a larger number of high-value districts and counties, the number remained relatively stable in other years. It was observed that as time evolves, a distribution pattern eventually forms, with the central and northern regions exhibiting the highest values, followed by the eastern, southwestern, and southeastern regions exhibiting the lowest values.

The SHDI index reflects changes in the number and proportion of various patch types, serving as a crucial indicator of landscape heterogeneity, with higher values indicating greater heterogeneity in land use types. An increase in its value indicates a rise in the number of patch types within the landscape and a tendency towards a more balanced distribution of their areas [69]. When there is a greater variety of patch types evenly distributed across the study area, it maximizes the landscape diversity and stability of the ecosystem. Analysis reveals that the distribution trends in 1990 and 2000 were essentially consistent, with high-value areas mainly located in Jinan and its surrounding areas, Qingdao, and Yantai, while low-value areas were primarily distributed in cities like Binzhou, Dezhou, Heze, Liaocheng, and Jining. The distribution trends in 2010 and 2020 were also consistent, with expanding high-value areas primarily situated in the contiguous regions of Jinan–Taian–Zibo, as well as in cities like Dongying, Yantai, and Qingdao. Overall, the distribution exhibits high-value areas around Jinan, Yantai, and Qingdao, while cities in the southwest and northwest, such as Binzhou, Dezhou, Liaocheng, and Jining, consistently remain in low-value areas.

The AI index reflects the degree of patch aggregation and represents the dispersion of landscape elements within the landscape. A smaller value indicates greater landscape fragmentation, suggesting increased patch isolation. When approaching 0, it indicates a maximum fragmentation of patches within the landscape. Conversely, larger values suggest higher levels of patch aggregation, indicating increased clustering among patches in the landscape [69], it is an important indicator of ecosystem diversity. Analysis reveals that the distribution trends in 1990 and 2000 were essentially consistent, with high-value areas mainly present in cities like Binzhou, Liaocheng, Heze, Jining, and Linyi, while low-value areas were primarily located in cities like Jinan, Zibo, Qingdao, and Yantai. The distribution trends in 2010 and 2020 were also generally consistent, with the range of low-value areas further expanding and the range of high-value areas shrinking. The high-value areas were mainly located in cities such as Dezhou, Liaocheng, and Heze in the northwest and southwest, while the low-value areas were mainly situated in the contiguous region of Jinan–Taian–Zibo, as well as in cities like Dongying, Yantai, Qingdao, and Weihai. Overall, there exists a low-value clustering area around Jinan, Yantai, and Qingdao, while cities such as Dezhou, Liaocheng, and Jining in the northwest and southwest consistently remain in the high-value region. Amidst the continuous evolution in land use transfer and proportion, there was a significant change in the values of the PARA-MN, PD, SHDI, and AI indices, and the land pattern characteristics of the Shandong Peninsula urban agglomeration have become more complex, with significant shifts in the degree of land use fragmentation, connectivity, and diversity. Significant spatial distribution differences exist in the Shandong Peninsula urban agglomeration as a whole, and within each city, land use fragmentation, connectivity, and diversity exhibit an obvious spatio-temporal heterogeneity. This is markedly correlated with the location conditions and development levels of each district and county.

3.2. Evolution of ESV

The ESV of the Shandong Peninsula urban agglomeration as a whole and each district and county was calculated, and the ESV of each district and county was mapped on the basis of land use/cover data, the NDVI, and the ESV equivalent per unit area (Figure 8). Through the analysis of the Shandong Peninsula urban agglomeration as a whole, it can be found that the total ESV shows a downward trend, decreasing from RMB 281.84 billion in 1990 to RMB 278.973 billion in 2020.

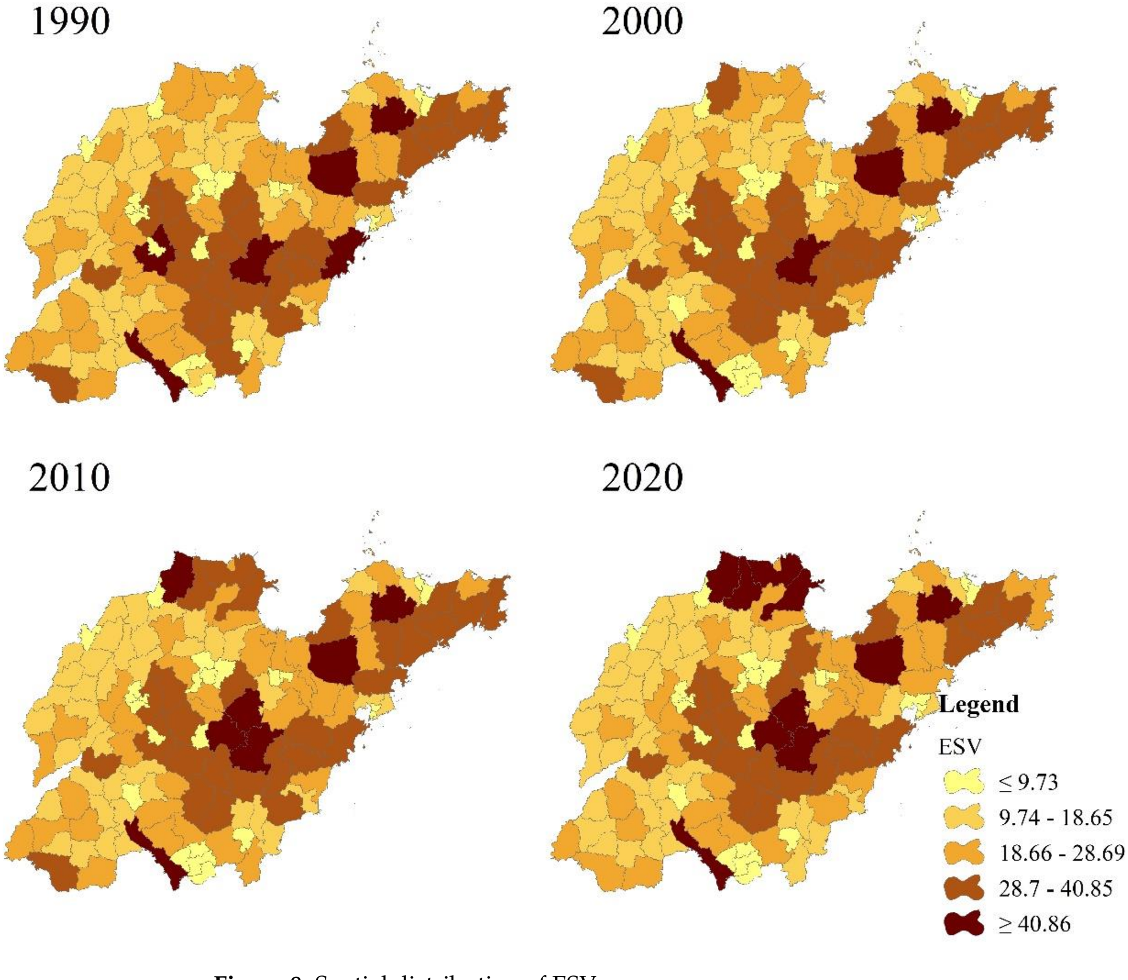

Figure 8. Spatial distribution of ESV.

The spatial distribution map of ESV reflects the spatial distribution and changes of ESV in each district and county within the urban agglomeration. It was found that the distribution patterns of ESVs in each county and district over the years are basically consistent, with only minor differences. Subsequently, the ESVs of different counties and districts over the years were computed (Table 5). The analysis revealed that the number of counties and districts with ESVs between RMB 974 million and RMB 1.865 billion was the highest, and all were above 40. The number of counties and districts with ESVs between RMB 1.866 billion and RMB 2.869 billion was the second highest, and all were above 30. The number of districts and counties with ESVs $\leq$ RMB 973 million and between RMB 2.87 billion and RMB 4.085 billion was all above 20, while those with ESVs $\geq$ RMB 4.086 billion were the least. It was observed that as time progressed, the number of counties and districts with ESVs $\leq$ RMB 973 million exhibited an increasing trend, rising from 23 in 1990 to 26 in 2020. The number of counties and districts with ESVs between RMB 974 million and RMB 1.865 billion remained basically stable. Meanwhile, the number of counties and districts with ESVs between RMB 1.866 billion and RMB 2.869 billion showed a decreasing trend. Moreover, the number of counties and districts with ESVs between RMB 2.87 billion and RMB 4.085 billion depicted a trend of an initial increase and then decrease, but the overall number decreased markedly. The number of districts and counties with ESVs $\geq$ RMB 4.086 billion generally increased, with only a decrease in 2000. Regarding spatial distribution, the number of districts and counties with lower ESVs ($\leq$RMB 973 million) gradually increased. They were noted to be primarily distributed in the core areas of each city, such as Licang, Shibei, and Shinan Districts in Qingdao City; Lixia, Huaiyin, and Tianqiao Districts in Jinan City; Kuiwen and Weicheng Districts in Weifang City; Zhifu and Laishan Districts in Yantai City; Zhangdian and Zhoucun Districts and Huantai County in Zibo City; Shizhong and Xuecheng Districts in Zaozhuang City; and Decheng District in Dezhou City. These areas experienced rapid economic development from 1900 to 2020, with the main characteristic being the increase in built-up land. The number of districts and counties with higher ESVs ($\geq$RMB 4.086 billion) gradually increased, primarily distributed in Yiyuan County in Zibo City, Linqu County in Weifang City, Weishan County in Jining City, Wudi County in Binzhou City, Yishui County in Linyi City, Qixia in Yantai City, and Pingdu in Qingdao City. These areas possess abundant forest or water resources. There are important natural reserves in the Shandong Peninsula urban agglomeration, such as the Weishan Lake Nature Reserve, Dazeshan Provincial Nature Reserve, Yashan Nature Reserve, and Yishan Forest Park. These reserves form the foundation of the ecological environment of the Shandong Peninsula urban agglomeration and play a critical role in its economic and social development and ecological construction.

Table 5. Statistics of ESV (unit: RMB 100 million).

	≤9.73	**9.74–18.65**	**18.66–28.69**	**28.7–40.85**	**≥40.86**
1990	23	45	37	25	6
2000	25	44	36	27	4
2010	25	42	34	28	7
2020	26	45	34	21	10

Revising the ESV through the NDVI can effectively compensate for the differences in ESV caused by varying vegetation coverage levels. With the occupation of cropland and forests, the total ESV of the urban agglomeration has slightly decreased. Simultaneously, significant differences exist among districts and counties, with the number of those with low and high ESVs continuously increasing, while those with medium-level ESVs generally remain unchanged. As urban expansion progresses, the occupation of cropland and other land types will inevitably result in more districts and counties exhibiting low ESVs. Moreover, urbanization has intensified the focus on ecological and environmental issues. Governments at all levels are constantly proposing various ecological and environmental conservation policies while developing the economy, resulting in a growing trend in the number of counties and districts having elevated ESV.

3.3. Response of ESV to Land Use/Cover Changes

Previous studies from multiple perspectives have demonstrated that changes in land use notably influence ecosystem services, such as changes in ESV due to urbanization [68] and alterations in ESV driven by landscape changes [70]. Elasticity has been widely applied in research related to ecosystems, such as ESV and LULC changes [34,70], influencing mechanisms of ESV evolution [71], ecosystem health assessment [72], and so on. This study investigates the effect of LUCC on ecosystem services in the Shandong Peninsula urban agglomeration by calculating elasticity. The average elasticity of ESV changes in the urban agglomeration relative to LUCC during 1990–2000, 2000–2010, and 2010–2020 was 0.5060, 0.8785, and 0.6761, respectively. This implies that the disturbance and impact of LUCC on ecosystem services were relatively strong. However, variations were observed in different time periods. The disturbance capacity was the strongest during 2000–2010 and the weakest during 1990–2000. This is primarily attributed to the slight increase in ESV of the urban agglomeration during 2000–2010, coupled with the overall complexity of LUCC. Specifically, there were both transfers from land use types with high ESV to those with low ESV and transfers from land use types with low ESV to those with high ESV, resulting in a relatively large overall elasticity coefficient.

From 1990 to 2020, the overall level of the elasticity coefficient was observed at 0.5324, which is relatively high. To further assess the response of LUCC to ecosystem services in various districts and counties of the Shandong Peninsula urban agglomeration, the elasticity coefficients of each district and county from 1990 to 2020 were calculated and mapped (Figure 9). The analysis reveals that the elasticity coefficients exhibit significant spatial heterogeneity. Firstly, the Shandong Peninsula urban agglomeration as a whole presents a concentric structure, with relatively lower values in the central region and higher values in the surrounding areas. The districts and counties with higher elasticity coefficients are primarily located in cities such as Dongying and Weihai. Secondly, similar concentric structures exist within each city. For instance, Jinan City exhibits a concentric distribution structure with Huaiyin District and Lixia District at its core, while Qingdao City displays a concentric structure with Shinan District and Shibei District at the center. Further analysis, as detailed in Table 6, reveals significant variations in the average elasticity coefficients among cities, with Dongying City exhibiting an average value of 1.1055 and Jinan City exhibiting a value of 0.2297. Simultaneously, significant differences were noted among the districts and counties within each city. In Weifang City, the difference in elasticity coefficients among its districts and counties was observed to be the largest, with the highest district being 30.88-fold that of the lowest. In Heze City, the difference in elasticity coefficients among its districts and counties was observed to be the smallest, with the highest district being only 1.97-fold that of the lowest.

Further analysis revealed that regions with higher development levels, such as Jinan and Yantai, exhibited a smaller average elasticity coefficient. This suggests that LUCC has a weaker ability to disturb ecosystem services in these areas. One contributing factor is the diversity of LUCC observed in these regions, including the transition from cropland and forest land to built-up land, as well as the transition from water bodies and forest land to cropland. The decline in ESV per unit area due to LUCC is relatively small. Another factor is the rapid expansion of built-up land in certain areas, especially the most active transition from cropland with relatively low ESV to built-up land. This results in a smaller percentage change in ESV compared to a relatively larger percentage change in LUCC, contributing to an overall lower elasticity coefficient. Taking the Licheng District of Jinan City as an example, the proportion of built-up land increased from 19.59% in 1990 to 40.15% in 2020, marking a rise of 20.56%, while the proportion of cropland decreased from 50.79% in 1990 to 33.05%. Cities such as Dongying, Binzhou, and Heze have larger overall elasticity coefficients, indicating that LUCC has a stronger ability to disturb ecosystem services in these areas. This is primarily because although the economic development level in these regions is relatively lower compared to cities like Jinan, the intensity of development, construction, and human activities is higher, resulting in a decline in ecosystem service functions. However, the elasticity coefficient is higher due to the overall weaker LUCC compared to Jinan and other regions. Moreover, as another core city in addition to Jinan, Qingdao exhibits a very high overall elasticity coefficient, indicating that LUCC has a very strong ability to disturb ecosystem services, exhibiting characteristics opposite to Jinan. The main reason is that in 1990, urban development in Qingdao had already reached a very high level, with the proportion of built-up land in Shibei District and Shinan District reaching 83.70% and 78.43%, respectively. In 2020, the proportion of built-up land increased to 95.54% and 89.86%, while the proportions of cropland, forest land, and water bodies were extremely small, resulting in a relatively small total ESV and a stronger ability of LUCC to disrupt ecosystem services.

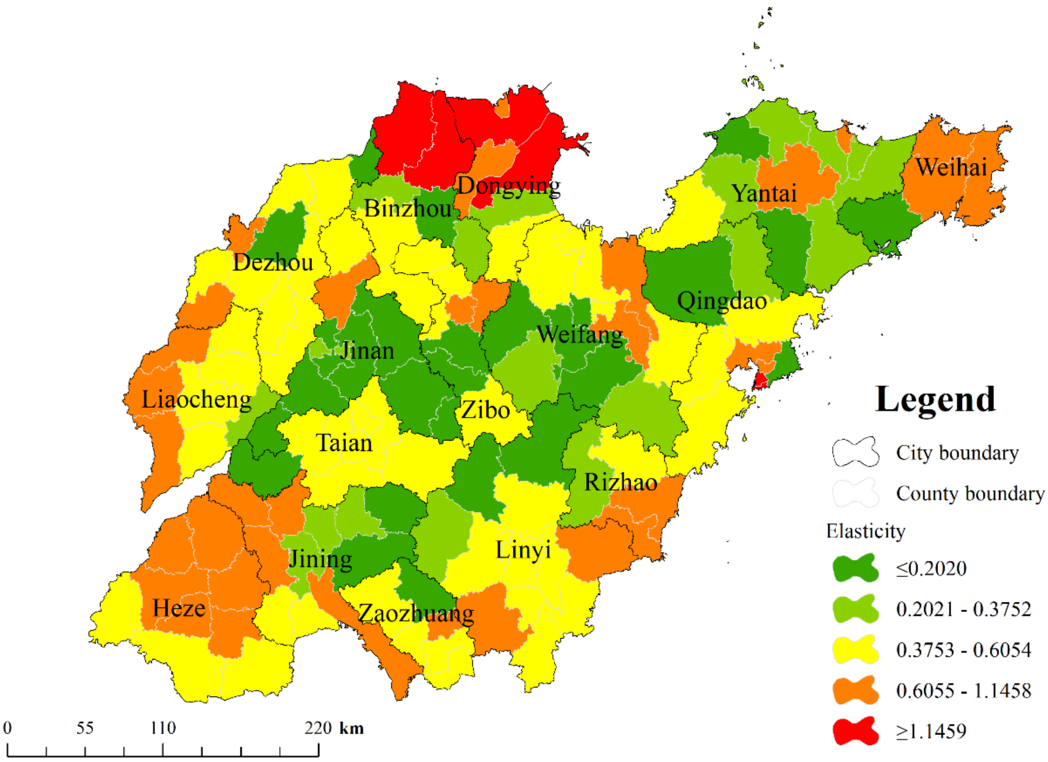

Figure 9. Spatial distribution of elasticity coefficients from 1990 to 2020.

Table 6. Elasticity coefficients of each city from 1990 to 2020.

City	Average	Maximum	Minimum
Dongying City	1.1055	2.4231	0.2742
Qingdao City	1.0195	3.6696	0.1624
Binzhou City	0.9436	2.8801	0.1564
Heze City	0.6389	0.7803	0.3963
Liaocheng City	0.5932	0.9768	0.3512
Rizhao City	0.5674	0.8550	0.3618
Weihai City	0.5202	0.6672	0.1063
Zaozhuang City	0.4672	0.6783	0.0735
Jining City	0.4595	0.8038	0.0811
Dezhou City	0.4441	0.6484	0.1468
Weifang City	0.4420	1.1458	0.0371
Zibo City	0.4313	0.6348	0.0235
Linyi City	0.4013	0.7118	0.0285
Taian City	0.3947	0.5235	0.0277
Yantai City	0.3453	0.8753	0.0497
Jinan City	0.2297	0.6625	0.0331

Although the elasticity coefficients vary across different time periods and regions, the overall impact of LUCC on ecosystem services remains significant. The concentric distribution structure of the elasticity coefficients within the Shandong Peninsula urban agglomeration as a whole and within individual cities is primarily attributed to differences in natural endowments, urban development foundations, and development rates. Cities with higher development levels, such as Jinan, have lower average elasticity coefficients, while cities with lower development levels, such as Binzhou, demonstrate higher overall elasticity coefficients. However, Jinan and Qingdao, the dual cores of economic development in the Shandong Peninsula urban agglomeration, exhibit stark differences, highlighting the complexity and varied effects of LUCC on ecosystem services. Therefore, it is necessary to fully take into account the impact of LUCC on ecosystem services when formulating policies related to land use and ecological protection. LUCC in the Shandong Peninsula urban agglomeration has undergone a typical trajectory from cropland land conversion to built-up land area. The increasing scale of the occupation of ecological lands [73], such as forests, grassland, wetlands, and water bodies, by urban construction land required for extending living space, agricultural land required for extending living space, and cropland land required for crop production is resulting in a considerable loss of biodiversity [74,75]. The man–land contradiction has become an urgent problem to be solved. Land use/cover changes have extensive impacts on ecosystem services [25], and the results based on the elasticity coefficient indicate that the level response of ESV to LUCC has significant differences between different time periods and regions. Hence, we need to consider the relationship between ESV and LUCC within a synthesis system, especially in regional climate analysis, sustainable land management practices, conservation policies, and ecological restoration efforts.

4. Conclusions

In the context of rapid urbanization, this research examined the characteristics of LUCC and the evolution of ESV in the Shandong Peninsula urban agglomeration on the basis of the land use/cover data from 1990, 2000, 2010, and 2020. Furthermore, the response of ESV to LUCC was analyzed using the elasticity coefficient, drawing the aforementioned conclusions. (1) The economic and social development and urbanization level of the Shandong Peninsula urban agglomeration have been continuously improving alongside the ongoing advancement of reforms and opening up of China. The most intuitive manifestation of this in terms of land use scale is the increasing proportion of built-up land. From the perspective of different LUCC transitions, the transfers between different land use types are highly complex. The rapid expansion of built-up land and the rapid decline in the proportion of cropland have become the most intuitive characteristics of LUCC in the Shandong Peninsula urban agglomeration. (2) By calculating the PARA_MN, PD, SHDI, and AI indices for each district and county to analyze the pattern characteristics of LUCC, it is evident that with the ongoing urbanization, the land use in the Shandong Peninsula urban agglomeration is moving towards increased fragmentation and reduced connectivity. However, there are obvious spatial distribution differences in LUCC pattern changes due to the differences in location conditions and development levels of each district and county. (3) Since the degree of vegetation coverage significantly impacts the ecological service level of the same land use type, the ESV was further revised using the NDVI. The results indicate a slight decrease in the total ESV of the urban agglomeration, but the changes in each district and county vary greatly. Overall, the number of districts and counties with high and low ESVs continues to increase, while those at the middle level remain unchanged. This is not only related to the fact that the expansion of built-up land encroaches on forests and cropland, resulting in reduced ESVs in some districts and counties, but is also directly linked to the preservation of crucial ecological function areas, such as important water sources and nature reserves in the urban agglomeration. (4) The analysis of the elasticity coefficient indicates that LUCC significantly impacts ecosystem services. The average elasticity coefficient is smaller in more developed cities, such as Jinan and Yantai, while it is larger in cities like Binzhou and Heze. Simultaneously, the dual core of economic development in the Shandong urban agglomeration, Jinan, and Qingdao exhibit significant differences, which are closely related to the development foundation of the two cities in 1990 and their development over the past 30 years.

Ecosystem services, serving as a bridge and link between human well-being and the natural environment, have emerged as a crucial topic in the area of physical and human geography. Research in this area focuses on the evaluation of their value and relationship with other factors. This study takes the strategically important Shandong Peninsula urban agglomeration as its research subject. It examines the scale and pattern characteristics of land use, the evolution of ESV, and the response of ESV to LUCC from multiple dimensions, such as temporal evolution and spatial distribution. This study holds significant value for the in-depth exploration of the strength of the response of ESV to LUCC. Moreover, it offers insights into the development priorities of different regions within the Shandong Peninsula urban agglomeration and provides data support for formulating economic and social development policies and ecological conservation policies in different regions. All municipalities must pay attention to the existing land use problems, such as the rapid reduction in cropland and grassland, and strengthen the protection and supervision of ecological land, increase the level of the redevelopment of inefficient built-up land, and guide the concentration of urban construction activities within urban growth boundaries to prevent the uncontrolled spread of cities, and the scale and ecosystem service value of land use should be protected. At the same time, the impact of land use on regional climate change also needs attention.

However, this study is limited in certain respects. Firstly, elasticity is a measure of how responsive a variable is to changes in another variable. This study only examines the response of ESV to LUCC through elasticity coefficients, but there is no further analysis of why this result occurred. Secondly, this study only analyzed the elasticity coefficient from 1990 to 2020, without analyzing the significant differences between different time periods and regions or exploring the response mechanism of ecosystem services; in future research, an analysis can be conducted from two dimensions: temporal and spatial. Thirdly, potential biases exist in data collection about land use/cover and ecosystem services value; meanwhile, there are also environmental factors that influence the accuracy of the measurements, such as the resolution of NDVI data. Fourthly, land use activities have transformed a large proportion of the Earth's land surface, resulting in profound impacts on climate, biodiversity, and ecosystem processes, and the future requires a comprehensive consideration of the combined effects of land use, climate, and ecosystems. Consequently, future research should incorporate the study of response mechanisms to provide more explicit policy guidance and strategies for balancing economic development and ecological development in different cities and improve the accuracy of the data in research.

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