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The spatial coupling of land use carbon emissions and ecosystem service value and its influence mechanism at county level in China

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Abstract: *Based on the county spatial scale and the 2000-2020 time scale (every 10 years), based on the analysis of land use change, this study conducted a study on the spatial-temporal evolution of carbon emissions and ecosystem service value, and analyzed the spatial correlation between land use carbon emissions and ecosystem service value. The effects of natural environment and social economic factors on the value of ecosystem services were discussed in order to provide reference for the scientific use and management of national land, the improvement of ecological environment quality and the development of low-carbon economy.*

Keywords: *Land use carbon emissions; Ecosystem service value; Spatial correlation; Influencing mechanism; County territory*

1. Introduction

Ecosystem services are the set of natural conditions and functions that ecosystems and their ecological processes create to sustain human existence[1]. One category is ecosystem functions that are practically guaranteed for human survival and life, which provide supporting services, regulating services and cultural services. As the world's largest developing country, China's carbon emissions per unit of product are much higher than those of developed countries and most developing countries due to the constraints of its extensive mode of economic growth, energy structure, energy technology and equipment, and management level. Land use is an important factor contributing to the rapid growth of carbon emissions, and also affects the health of land ecosystems by changing the structure and function of land ecosystems, and thus plays a decisive role in maintaining the service function of ecosystems. China has also made positive and effective efforts to address the current environmental problems of global warming and the increase in extreme weather disasters. And in 2012, the 18th CPC National Congress incorporated construction of ecological civilization into the Five-sphere Integrated Plan, and wrote ecological civilization into the Party constitution. In 2015, the China’s 13th Five-Year Plan(2016-2020) highlighted green development. And in 2020, Chinese leader proposed the goal of peaking carbon dioxide emissions and going carbon neutral in general debate at the 75th United Nations General Assembly. The Report to the 20th National Congress of the Communist Party of China also highlighted the promotion of green development, the promotion of harmonious coexistence between humanity and nature, and the enhancement of the carbon sink capacity of ecosystem. Therefore, this study has a certain significance in guiding the coordinated development of the region and the country, understanding the land use under the perspective of ecosystem services, and providing a theoretical basis for the realization of the goal of carbon neutrality.

In the past decade, scholars at home and abroad have carried out a large number of studies on the results of carbon emissions from land use, and the research content of the topics involving the ecosystem services value has gradually become complete. Most of the relevant domestic research uses methods such as land use carbon emission accounting method[2], carbon balance accounting methods[3], and spatial measurement models[4] to investigate land use carbon emission accounting, factors influencing carbon emissions[5], as well as the relationship between carbon emissions and economic development[6] from national[7], provincial[8], urban[9], and watershed scales[10]. In analyzing the relationship between land use carbon emissions and ecosystem service value, foreign scholars have not focused on the spatio-temporal correlation between the two, but have concentrated on the research of the two from different angles and scales[11-12] . In summary, further summarizing the existing literature, it is found that there are fewer

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studies on the spatio-temporal coupling between land use carbon emissions and ecosystem service value, and that the research on counties, as the largest ecological background system and the main administrative unit in China, has not yet been carried out completely.

2. Materials and methods

2.1 Study area

According to the Constitution of the People's Republic of China, there are making a total of 2,846 county-level administrative region. However, due to the lack of energy consumption data in some areas, the study area for this project is total of 30 provincial-level administrative districts, 326 prefectural-level administrative regions, and 2,732 county-level administrative regions. excluding the Xizang Autonomous Region, the Hong Kong Special Administrative Region, the Macao Special Administrative Region, and Taiwan Province, ***(fig1)***.

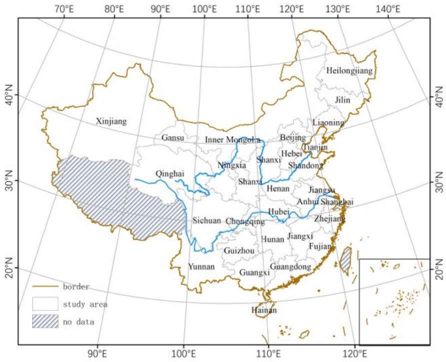

Fig. 1 Study area

2.2 Data sources

For the purpose of data analysis, comparison and visualization expression, this paper obtains the household registered population, GDP, and urbanization rate of counties (districts) from statistical yearbooks as well as the reports on the work of the governments of provinces, counties and municipalities. To derive the spatio-temporal relationship between carbon emissions from land use and ecosystem service value in Chinese counties, this paper uses land use data from Xin Huang's team at Wuhan University; the data is based on Landsat data, constructed with spatio-temporal features, and combined with the Random Forest classifier to obtain the classification results; based on the 5,463 visually deciphered samples, the overall accuracy of the CLCD reaches 80%. The energy consumption data, standard coal conversion coefficients, standard coal conversion coefficients of various fossil energy sources, and energy consumption data of each province for the years 2000, 2010, and 2020 used in this paper are from the China Energy Statistical Yearbook; the carbon emission coefficients of fossil energy sources are from the 2006 IPCC Guidelines for National Greenhouse Gas Inventories.

2.3 Methods

2.3.1 Carbon emissions estimation

Carbon emissions in the study area: Based on the area of each type of land use in each county in China from 2000 to 2021, this study estimates the carbon emissions of each type of land use in each county in China. The specific calculation method is to multiply the area of each type of land in each county and the corresponding carbon emission coefficients of each type of land and then sum them up. The formula is as follows:

$$E_K = \sum e_i = \sum S_i \times \delta_i \tag{1}$$

In ***(Eq.(1))***, E_K denotes direct carbon emissions; e_i denotes the carbon emissions of each site type; S_i and δ_i denote the area and carbon emission coefficients of the site types, respectively. i area and carbon emission coefficients, see ***(Table 1)***.

ISSN 2616-5872 Vol.5, Issue 10: 37-48, DOI: 10.25236/AJEE.2023.051006

Table 1 Carbon emission coefficients for land use types

Land use type	Carbon emission coefficient (t/hm^2)
Cultivated land	0.422
Woodland	-0.644
Grass land	-0.022
Water areas	-0.253
Unutilized land	-0.005

Since carbon emission from construction land is the main carbon source, in order to improve the accuracy of land use carbon emission, the carbon emission from construction land will be indirectly estimated based on the panel data of China's fossil energy consumption from 2000 to 2021 using the carbon emission coefficient method. Nine kinds of energy consumption were selected, including raw coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, natural gas and electrical power. The energy consumption data of China Energy Statistical Yearbook, standard coal conversion coefficient and carbon emission coefficient of 2006 IPCC Guidelines for National Greenhouse Gas Inventories were used for estimation, see***(Table 2)***. Finally, by summing up the carbon emissions from other land use types and the carbon emissions from construction land use, then assigning the values to the map of the study area, the spatial-temporal evolution of carbon emissions from land use in the study area can be derived, and the carbon sources and sinks of the country can be compared, so as to explore the main direction of China's future green and low-carbon routes.

Table2 Standard coal coefficients and carbon emission coefficients for different energy sources

Types of energy	Standard coal conversion coefficient (tec/t)	Carbon emission coefficient
Raw coal	0.7143	0.7559
Coke	0.9714	0.8550
Crude oil	1.4248	0.5857
Gasoline	1.4714	0.5538
Kerosene	1.4714	0.5714
Diesel fuel	1.4571	0.5921
Fuel oil	1.4286	0.6185
Natural gas	1.2143	0.4483
Electrical power	0.4040	0.7935

The formula for calculating carbon emissions from construction land is as follows:

$$E_P = \sum E_j = \sum\left(e_j \times \theta_j \times \beta_j\right) \tag{2}$$

In ***(Eq.(2))***, E_P is the carbon emission from construction land, andE_j is the carbon emissions from various fossil energy sources, e_j is the carbon emission from$j$ is the consumption of all kinds of fossil energy, andθ_j is the conversion coefficients of various fossil energy sources standard coal in the appendix of China Energy Statistical Yearbook.β_j is the jth fossil energy carbon emission factor in the 2006 IPCC Guidelines for National Greenhouse Gas Inventories.

2.3.2 Ecosystem services value

Table 3 ESI coefficients of various land use types and various ecosystem functions

Type	Subtype	Cultivated land	woodland	Grass lands	wetland	Water areas	Construction land	unutilized land
Supplying Services	Food	100.00	33.00	43.00	36.00	53.00	2.00	0.00
	Raw materials	13.00	100.00	12.00	8.00	12.00	1.34	0.00
Regulating services	Gas regulation	17.00	100.00	35.00	56.00	12.00	1.39	0.00
	Climate regulation	7.00	30.00	12.00	100.00	15.00	0.96	0.00
	Water supply	4.00	22.00	8.00	72.00	100.00	0.37	0.00
	Waste treatment	9.00	12.00	9.00	97.00	100.00	1.75	0.00
Supporting Services	Soil formation retention	37.00	100.00	56.00	50.00	10.00	4.23	0.00
	Biodiversity protection	23.00	100.00	41.00	82.00	76.00	8.87	0.00
Cultural service	Recreation and culture	4.00	44.00	19.00	100.00	95.00	5.12	0.00

This study is based on the purpose of ecological environmental protection, based on the area data of land use types in each county in China. And reference to Chen Wanxu and other scholars using the

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transfer of benefits method to derive the ESI coefficients of each land use type in the county study, see (***Table 3)***, based on the area of the land use category were multiplied by the ESI coefficients of the nine types of ecosystem functions weighted by the ESI coefficients to calculate the ESV of the counties in China. The calculation formulas are as follows:

$$V_{ES} = \sum_{j=1}^{n} V_{ESj} = \sum_{j=1}^{m} \sum_{i=1}^{n} W_{ij} \times LA_{(i,t)} \tag{3}$$

In ***(Eq.(3)),*** W_{ij} is the ESI coefficient of class j ecosystem function of class i land use type, $LA_{(i,t)}$ is the area of the ith land use type at time t. m is 9, indicating the number of ecosystem functions, n is 7, indicating the number of land use types (wetlands and watersheds are calculated here). The ecosystem services value of each county in China from 2000 to 2021 can be calculated, which leads to the spatio-temporal relationship of ESV during the 21-year period.

2.3.3 Spatial autocorrelation analysis

In this stage, based on the results of the previous land use carbon emission and ESV calculations, GeoDa 4.0 will be used to apply global bivariate Moran's I and local bivariate Moran's I research methods to these two variables. The global bivariate Moran's I method mainly investigates Whether there is a spatial correlation between the two variables and the degree of correlation on the spatial scale of the county. while the local bivariate Moran's I method mainly shows the spatial correlation between the two variables at the county spatial scale. The formula is as follows:

$$I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \tag{4}$$

$$I_i = \frac{(x_i - \bar{x}) \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})}{S^2} \tag{5}$$

In ***(Eq.(4)(5)),*** The equations I and I_i are the global bivariate Moran's I and local bivariate Moran's I for land use carbon emissions and ESV, respectively.n is the number of counties and districts in the study area.w_{ij} is an $n \times n$ spatial weight matrix. x_i and x_j are the attribute values of the counties and districts, and $\bar{x}$ is the mean of the attribute values, and S^2 is the variance. Based on the calculation of local bivariate Moran's I values, this project analyzed the bivariate LISA clustering map with visual local spatial correlation using ArcMap10.2, and Finally, the spatial clustering and discrete results between land use carbon emissions and ESV are explored, and the spatial autocorrelation relationship between the two variables is obtained.

2.3.4 Polynomial logit regression analysis

Based on the previous step of LISA agglomeration map to classify the spatial correlation into four categories of high - high, high - low, low - high, low - low, in order to explore the influence factors of the spatial correlation between land use carbon emissions and ESV, polynomial Logit model to meet the research requirements, so this paper constructed a Logit model, the equation is as follows:

$$Logit(P_1/P_2) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \tag{6}$$

In ***(Eq.(6)),*** $Logit(P_1/P_2)$ is the natural logarithm of the probability ratio of any two types; X_1 is the natural environment factor, including slope, precipitation, and temperature; X_2 is the socio-economic factor, including GDP, urbanization rate, and population;β_t is the parameter vector, where$t$ = 0,1,2.

Regression equations were constructed to analyze the low ESV-low land use carbon emissions analogy as a reference for the high-high, high-low, and low-high types:

$$Logit(P_{\text{high-high}}/P_{\text{low-low}}) = \beta_{\text{high-high0}} + \beta_{\text{high-high1}} X_1 + \beta_{\text{high-high2}} X_2 \tag{7}$$

$$Logit(P_{\text{low-high}}/P_{\text{low-low}}) = \beta_{\text{low-high0}} + \beta_{\text{low-high1}} X_1 + \beta_{\text{low-high2}} X_2 \tag{8}$$

$$Logit(P_{\text{high-low}}/P_{\text{low-low}}) = \beta_{\text{high-low0}} + \beta_{\text{high-low1}} X_1 + \beta_{\text{high-low2}} X_2 \tag{9}$$

3. Analysis of results

3.1 Spatial-temporal evolution of land use carbon emissions

This paper utilizes the estimation formula of carbon emission and calculates it by collecting relevant data. Finally, the corresponding land use carbon emissions of Chinese counties in the period of 2000-2020 are derived, and divided into seven intervals, and the temporal and spatial evolution of carbon

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emissions in Chinese counties during the 20-year period is more intuitively derived by using a graphical method ***(fig 2)***. The results are as follows: under the effect of land use change, the temporal evolution of land use carbon emissions is obvious during 2000-2020. The total land use carbon emissions are 4.81×10^8 t, 11.37×10^8 t and 12.39×10^8 t in 2000, 2010 and 2020, respectively. And the overall trend is mainly showing an increasing trend, but the rate of growth of the total land use carbon emissions shows the following pattern The growth rate of total land use carbon emission is characterized by "fast first and then slow". The maximum value of carbon emissions from land use in counties increased from 7.34×10^6 t in 2000 to 2.99×10^7 t in 2020, a 4.1-fold increase in 20 years. In spatial comparison, the low values of carbon emissions are mostly distributed in the south and northwest of China, and the high values are mainly distributed in the northeast of China, where heavy industry is the pillar industry. Again from the perspective of space and time, during the 20 years with the economic development, increasing urbanization level, and increasing construction land, the county carbon emission reaches in the 1-3 intervals decreases year by year, and shifts to higher ranges; the number of areas reaches in the 4-5 intervals increases year by year, and the 2020 is located in the 4-5 intervals the largest number of areas; There was a slight increase in reaching the 6-7 range. Furthermore, the area in the 4-7 range presented a clumpy distribution, mainly concentrated in densely populated areas.

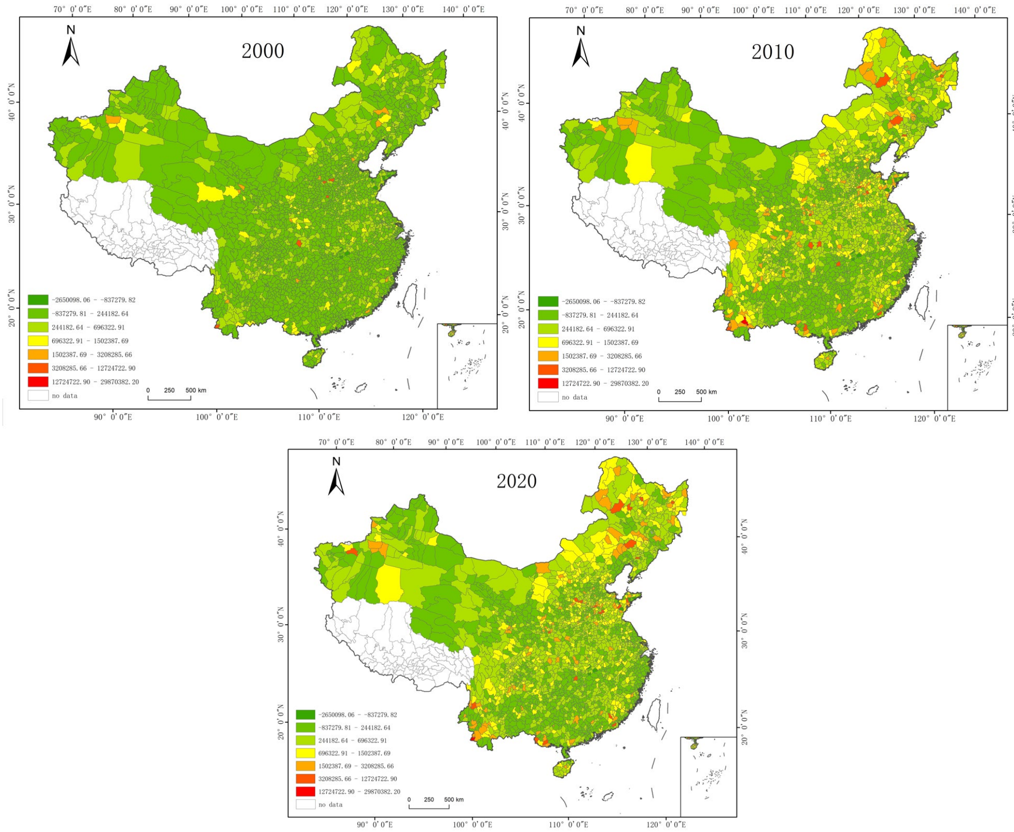

Fig. 2 Spatial-temporal evolution of carbon emissions from county land use in China, 2000-2020

3.2 Spatial-temporal evolution of ESV

In order to explore the spatial-temporal evolution of ESV in Chinese counties during the past 20 years, this paper applies ESV calculation coefficients and collects land use data into the relevant formula to calculate the ESV values of counties, reclassify them into five levels and make graphs to express them visually. Analyzing the spatial distribution of ESV, it can be seen that the spatial difference of ESV in Chinese counties is obvious ***(fig 3)***. In general, ESV in the western region is overall higher than that in the eastern region.The regions belonging to the middle, higher, and higher levels of ESV were mainly distributed in western Xinjiang, Gansu, and northeast Heilongjiang. The high ESV levels in this type of region are mainly due to the spread of woodland and grassland, and relatively little construction land. The regions with low ESV and low levels of ESV were mainly distributed in areas with developed economies and intensive construction land in the east. Through the calculation of 2000, 2010, 2020, three-year The total amount of ESV in 2000, 2010 and 2020 is 2.22×10^7 yuan/hm^2, 2.23×10^7 yuan/ hm^2 and 2.22×10^7 yuan/ hm^2, respectively. Which indicates that the total amount of ESV in counties in China

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during the period of 2000-2020 shows a fluctuating change of increasing and then decreasing. The total amount of ESV in 2000 is lower than that in 2010, which is associated with the pending development of the economy and incomplete function of ecosystem services. The total amount of ESV in 2000 is lower than the total amount of ESV in 2010. The total amount of ESV in 2020 is also lower than the total amount of ESV in 2010, and it is assumed that it is related to the unreasonable development of the society that affects the value of ecological environment. Comparing the distribution of ESV in counties of China in 2000, 2010 and 2020, it is found that during the period of 20 years, the number of ESV belonging to the low and lower-grade areas has increased year by year, and that the number of medium- and high-grade areas has decreased year by year, while the change of high-grade areas is not obvious. The change of high grade areas is not obvious.

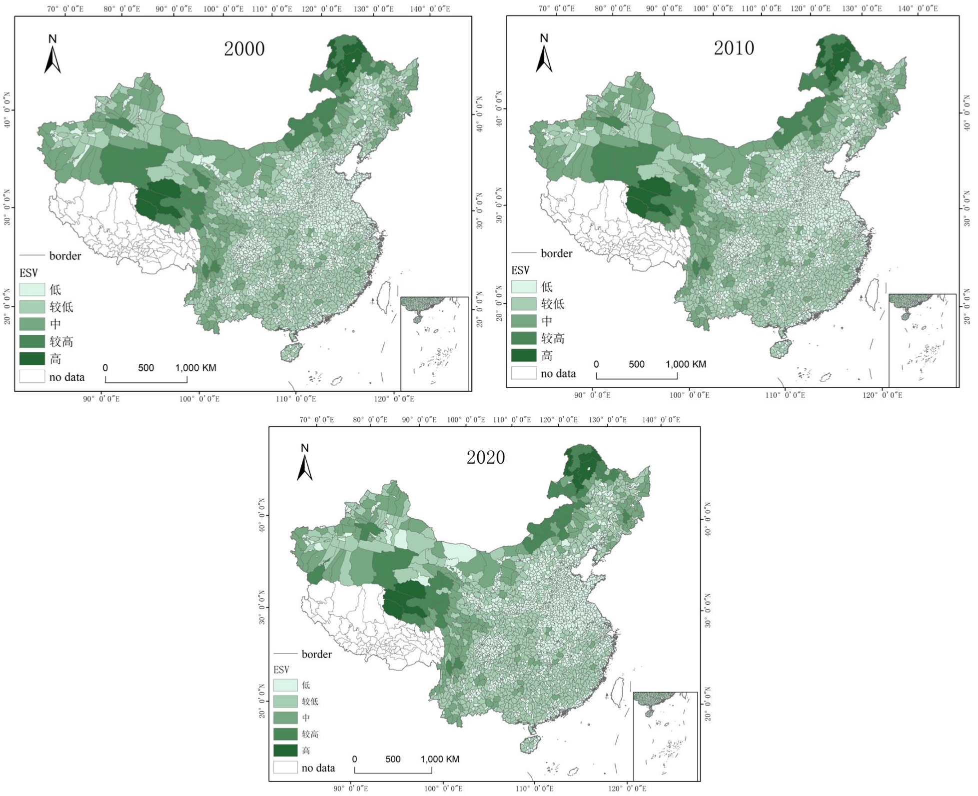

Fig. 3 Spatial-temporal evolution of ESV in Chinese counties, 2000-2020

3.3 Spatial correlation of land use carbon emissions and ESV

Based on the bivariate spatial autocorrelation model, the spatial correlation law between the pre-calculated county land use carbon emissions and ESV was analyzed by using GeoDa4.0 ***(Table 4)***. It is concluded that there is a negative spatial correlation between land use carbon emission domain ESV, and Moran's I is negative in all years, and the P value is less than 0.001, which indicates that ESV gradually decreases with the increase of land use carbon emission, and the Moran's I index decreases year by year, which indicates that the spatial correlation between the two is weakened.

Table 4 Results of spatial autocorrelation between land use carbon emissions and ESV

Year	**Moran's I exponents**	**P-value**	**Z-score**
2000	-0.266	<0.001	-27.9669
2010	-0.234	<0.001	-32.625
2020	-0.200	<0.001	-21.2387

The LISA cluster diagram of land use carbon emissions and ESV is then compared and analyzed ***(fig. 4)***, in which the yellow area indicates that the local ecosystem service value and land use carbon emissions are both low; the large blue area indicates that the county's ecosystem service value is high, but the land use carbon emissions are low; the green area indicates that the county's ecosystem service value is low, but the land use carbon emissions are high; and the red area indicates that the county has high land use carbon emission and high ecosystem service value. After analysis, the spatial correlation

ISSN 2616-5872 Vol.5, Issue 10: 37-48, DOI: 10.25236/AJEE.2023.051006

pattern between county land use carbon emissions and ESV is as follows: First, the high ESV low carbon emission aggregation areas are stably distributed in the southeast of China, Qinghai, Sichuan, Yunnan, northeast Heilongjiang and other regions during the period of 2000-2020, and the high - low aggregation areas are mainly concentrated in the mountainous, plateau, hilly and other terrain uneven areas. Second, the low - low aggregation areas are sporadically distributed in the high and low concentration areas, probably due to the impact of human activities, which led to the destruction of the ecological environment and thus the reduction of ESV. Third, the high and high concentration areas were fragmentedly distributed in Inner Mongolia and the eastern coastal areas during the past 20 years, of which the high and high concentration areas in Inner Mongolia showed a small-scale diffusion phenomenon during the past 20 years, which was mainly due to the influence of the Yellow River Basin in the region and the sparse land area, with relatively few human activities. Fourthly, low-high agglomeration areas were mainly distributed in clusters in regions with high levels of urbanization and developed economies, such as the Guangdong-Hong Kong-Macao Greater Bay Area, the Yangtze River Delta urban agglomeration, and the Beijing-Tianjin-Hebei urban agglomeration.

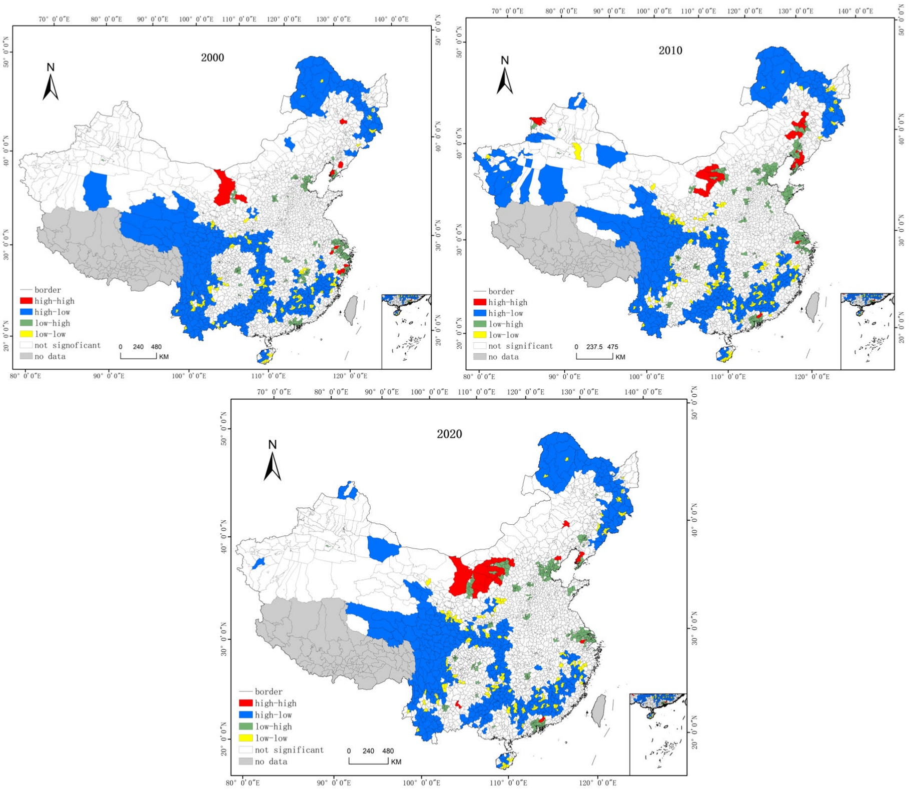

Fig. 4 LISA clustering of land use carbon emissions and ESV in Chinese counties, 2000-2020

3.4 Factors influencing spatial correlation

3.4.1 Statistical analysis based on spatial clustering results

There are many factors affecting the spatial correlation between land use carbon emissions and ESV. In the study of factors influencing the spatial differentiation of ESV, Geng Tianwei[13] mainly selected 12 variables, namely, topographic relief, closed forest area, average annual precipitation, average annual temperature, GDP, per capita GDP, per capita income of urban and rural residents, total retail sales of social consumer goods, per capita cultivated land area, land reclamation rate, total population, population density. Li Zijian [14] mainly selected from the elevation, slope, precipitation, air temperature, NDVI, HAI, land average GDP, population density, road density and other 9 driving factors. In the study of the influencing factors of land use carbon emissions, Wang Tao[15] mainly carried out regression analysis from two variables, namely, total population and GDP. Feng Jie[16] mainly carried out regression analysis from five variables, namely, output value of the first, second and tertiary industries, fixed assets investment volume, and the number of population. In the selection of influencing factors, this paper fully drew on the above literature, and selected variables that may influence the spatial correlation between land use carbon emissions and ESV. Four natural variables containing elevation, temperature, precipitation, and slope, and five socio-economic variables containing output value of the secondary

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industry, output value of the tertiary industry, population, urbanization rate, and GDP were finally selected. Considering the availability of the data, the above data were obtained from the 2020 Statistical Yearbook of China's Counties, as well as the 2020 governmental work reports, statistical bulletins of the counties. Therefore, these six factors are only relevant to the value of land use carbon emissions and ecosystem services in 2020,see ***(Table5)***.

Table 5 Description of Explanatory Variables for Impact Factors

	Explanatory variable	Unit	Average value	Standard deviation
Natural dimension	Elevation	m	937.38	1064.49
	Temperature	℃	11.47	6.12
	Measured quantity of rain	mm	1063.57	486.52
	Slope	°	13.97	7.84
Socio-economic dimension	Output value of the secondary industry	ten thousand yuan	1988140	7269325.68
	Output value of the Tertiary industry	ten thousand yuan	3383120	14903641.4
	Population	ten thousand	48.90	60.16
	Urbanization	%	59.50	23.36
	GDP	billions	466.23	1550.41

Only significant variables are statistically analyzed below. Classify the urbanization rate of counties and districts into five intervals: <20%, 20%-40%, 40%-60%, 60%-80%, and 80%-100% ***(Table 6)***. The number of counties and districts in each interval is 13, 156, 328, 152, and 195, respectively. Each accounting for 1.54%, 18.48%, 38.86%, 18.01%, and 23.10% of the total. The urbanization rates of counties and districts of the high-high type, low-low type, and low-high type are mostly >40%, accounting for 86.36%, 82.81%, and 98.51% of the counties and districts of this type, respectively. While the urbanization rates of the high-low type are mostly in the range of 20%-60%, accounting for 82.78% of the counties in this type. The population size of counties was divided into five intervals: <200,000, 200,000-600,000, 600,000-1,000,000, 1,000,000-1,400,000, and >1,400,000 ***(Table 6)***, with the number of counties in each of these five intervals accounting for 26.66%, 47.51%, 17.18%, 4.85%, and 3.79% of the total. The high - high type, low - low type, and high - low type counties and districts have a majority of populations of less than 600,000 people; while the low - high type counties and districts have a majority of populations between 200,000 and 1,000,000 people.

Table 6 The counties in different levels of population and urbanization rate

Population /10,000 people	High-high	Low-low	Low-high	High - low	Urbanization rate/%	High-high	Low-low	Low-high	High - low
<20	10	52	15	148	<20	0	3	2	8
20-60	7	66	97	231	20-40	3	19	2	132
60-100	5	9	93	38	40-60	10	57	42	219
100-140	0	0	35	6	60-80	8	29	64	51
>140	0	1	30	1	80-100	1	20	160	14

The average annual temperatures of counties were divided into five intervals of <0℃, 0-6℃, 6-12℃, 12-18℃ and >18℃ ***(Table 7)***, and the numbers of counties and districts within these five intervals of area were 41, 126, 173, 370 and 134, respectively. Which accounted for 4.86%, 14.93%, 20.50%, 43.84% and 15.88% of the total number of counties and districts, respectively. Most of the low-low type and high-low type counties had temperatures >6℃; all of the low-high type counties had mean temperatures >0℃; and most of the high-high type counties had mean temperatures distributed in the 6-12℃range. The average annual precipitation of counties was divided into five intervals of <450 mm, 450-900 mm, 900-1350 mm, 1350-1800 mm, and >1800 mm ***(Table 7)***, and the numbers of counties and districts within these five intervals of area were 63, 291, 226, 199, and 65, respectively. Which each accounted for 7.46, 34.48, 34.48, and 23.58 percent of the total number of counties and districts, respectively. 26.78%, 23.58%, and 7.70%. The distribution of areas with low precipitation is mainly in the high-high type of counties; while the average precipitation in the low-high type and high-low type of counties is mostly distributed in the range of 450-1800 mm; and the distribution of the low-low type of counties in the various temperature zones is relatively more balanced.

ISSN 2616-5872 Vol.5, Issue 10: 37-48, DOI: 10.25236/AJEE.2023.051006

Table 7 Distribution of county types within different temperature and precipitation ranges

Temperature/°C	High-High	Low-Low	Low-high	High - low	Precipitation/mm	High-High	Low-Low	Low-high	High - low
<0	0	2	0	39	<450	16	2	33	12
0-6	4	25	10	87	450-900	3	42	116	130
6-12	15	20	75	63	900-1350	2	28	80	116
12-18	2	57	150	161	1350-1800	0	42	24	133
>18	1	24	35	74	>1800	1	14	17	33

The GDP of counties and districts was divided into five intervals: <10 billion yuan, 10-20 billion yuan, 20-30 billion yuan, 30-40 billion yuan, and >40 billion yuan ***(Table 8)***, with the number of counties in each interval accounting for 36.49%, 24.29%, 9.60%, 5.81%, and 23.82% of the total. The high - high type, low - low type, and high - low type of counties and districts have a predominantly <$20 billion GDP, accounting for 50%, 79.69%, and 84.43% of the counties and districts of this type, respectively. The majority of the low - high type of counties and districts have a GDP of > 30 billion dollars, accounting for 74.81% of the counties of this type.

Table 8 Distribution of county types within different GDP levels and slopes

GDP /billion dollars	High-High	Low-Low	Low-high	High - low	elevation /°	High-High	Low-Low	Low-high	High - low
<100	4	71	12	221	<5	8	1	139	0
100-200	7	31	30	137	5-10	9	12	93	46
200-300	2	14	26	39	10-15	3	27	33	65
300-400	3	6	24	16	15-25	2	83	5	251
>400	6	6	178	11	>25	0	5	0	62

Topography is an important factor in natural geography that affects ecological values, and slope is an important factor that affects spatial pattern. The slope is categorized into five ranges, including <5°, 5°-10°, 10°-15°, 15°-25°, and >25° ***(Table 8)***. The number of counties and districts whose slopes are in the range of 0-15° is 436, accounting for 51.66% of the total. The number of counties and districts whose slopes are in the range of 15° or more accounts for 48.34% of the total.

3.4.2 Analysis of factors influencing spatial clustering of land use carbon emissions and ESV

The polynomial Logit regression model was used to analyze the factors influencing the spatial correlation between land use carbon emissions and ESV ***(Table 9)***. In terms of the goodness of fit of the polynomial Logit regression model, the model chi-square statistic was 1027.47, which was significant at the 1% level, indicating that the model fit was good.

Table 9 Logit regression results for polynomials referenced to low ESV versus low land use carbon emissions

variant	Low-high type	High-low type	High-High Type
Secondary value added	5.02e-08	2.01e-07	2.43e-07
Tertiary value added	1.16e-07	-6.77e-07*	-6.32e-07
GDP	8.39e-07***	4.00e-07**	1.06e-07***
Urbanization rate	0.002	-0.040***	-0.064***
Demographic	-0.015	0.020**	-0.024
Altitude	-0.0004	-0.0001	0.0005
Elevation	-0.255***	0.053*	-0.328***
Precipitation	-0.006***	0.002***	-0.004***
Temperatures	0.310***	-0.198***	0.142*
N		844	
Pseudo R^2		0.575	
Chi^2		1057.99	

Note: *, **, and *** indicate significant at the 10%, 5%, and 1% statistical levels, respectively.

According to the results of the above table, using the low-low category model as a control, in the low-high category model, there are four variables of GDP, slope, precipitation, and temperature that are significant, and the regression coefficients are 8.39×10^{-7}, -0.255, -0.006, and 0.310, respectively. Among them, GDP and temperature are significantly and positively correlated with the model of the low- high agglomeration area, slope and precipitation are significantly and negatively correlated with the model of the low- high agglomeration area, and the urbanization rate, population are not correlated with the low-high aggregation area. This proves that when located in the low ESV area at the same time, if the local GDP grows and the temperature changes to high temperature, the land use carbon emissions in this type of area increase, because the GDP growth means the local economic development and the intensification of human activities. The increase in temperature symbolizes the ecological destruction and land use carbon emission increase climate warming. Conversely, an increase in slope, which is detrimental to local economic development and urban sprawl, decreases land use carbon emissions in this category. An increase in average precipitation favors local water conservation as well as the growth of green vegetation, creating a good ecological environment.

In the high - low type model there are six variables of tertiary value-added, GDP, urbanization rate, population, slope, precipitation, and temperature are significant, and the regression coefficients are -6.77×10^{-7}, -4.00×10^{-7}, -0.04, 0.02, 0.053, 0.002, and -0.198, respectively. Among them, population, slope, and precipitation are significantly positively correlated with the model of high-low agglomerated area, and urbanization rate, temperature are significantly negatively correlated with the high-low agglomeration area model, and GDP is not correlated with the distribution of high-low agglomeration area. When also located in low land use carbon emission areas, areas with higher ESV values have higher slopes and greater average precipitation. For each unit increase in county urbanization rate, the ratio of the occurrence of high - low category areas relative to low - low category areas is exp(-0.04) = 0.96 times. It indicates that areas with higher ecosystem service value and lower land use carbon emissions are among the areas with slower urbanization. When also located in high ecosystem service value areas, areas with higher land use carbon emissions have faster urbanization and higher temperatures, creating a climate conducive to local economic development, resulting in greater land use change and higher carbon emissions.

In the high-high type model, there are five significant variables, GDP, urbanization rate, slope, precipitation, and temperature, with regression coefficients of 1.06×10^{-7}, -0.064, -0.328, -0.004, and 0.142, respectively. Among them, GDP and temperature are significantly positively correlated with the model of high-high agglomerated areas. And urbanization rate, population, slope, and precipitation are significantly negatively correlated with the model of high-high agglomerated areas. By calculating the county urbanization rate, population, slope, and precipitation increase by one unit, respectively. The ratio of the occurrence of high - high category areas relative to low - low category areas is 0.94, 0.72, and 0.99 times, respectively. It indicates that the correlation between ecosystem service value and land use carbon emission is lower in areas with higher urbanization rate, higher slope, and higher precipitation, which is due to the rational use of natural factors for development in the area. When simultaneously located in areas with higher ESV values, the higher the GDP, the greater the land use change and the increase in its carbon emissions.

4. Results and analysis

The results show that: (1) the total amount of carbon emissions in the past 20 years showed a trend of "fast and then slow" growth, with a spatial pattern of high in the northeast and low in the south and northwest, and from a spatial-temporal point of view, the areas in the 1-3 intervals were shifted to higher ranges year by year, and the areas with high carbon emissions showed a cluster-like distribution and were mainly concentrated in the densely populated areas. (2) During the period of 2000-2020, the spatial difference of ESV in Chinese counties is obvious, in general, ESV in western region is higher than that in eastern region, and the total amount of ESV shows the fluctuation change of increasing and then decreasing. And during the period of 20 years, the number of ESV belonging to the low and lower ranked areas is increasing year by year, the number of middle and higher ranked areas is decreasing year by year, and the change of the high ranked areas is not obvious. (3) There is a negative correlation between carbon emissions and ESV, and the spatial correlation between the two is weakening. In terms of spatial distribution, during the past 20 years, the high-low aggregation area is stably distributed in the southeast, west and northeast Heilongjiang and other regions of China, the low-low aggregation area is sporadically distributed in the vicinity of the high-low aggregation area. the high-high aggregation area is fragmentedly distributed in Inner Mongolia and the eastern coastal areas, and the high-high aggregation area in Inner Mongolia has seen a small-scale diffusion phenomenon during the past 20 years. The low-high aggregation areas are mainly located in highly urbanized and economically developed areas, and are distributed in clusters. (4) When located in low ESV areas, land use carbon emissions increased in areas with higher GDP growth and higher average temperature. when located in low land use carbon emission areas, areas with higher ESV values had higher slopes and higher average precipitation. The correlation between the value of ecosystem services and land use carbon emissions was lower in areas with higher urbanization rates, larger populations, higher slopes, and higher precipitation.

The dual-carbon target and ecological issues have been hotly debated by all walks of life. In this paper, based on the value of land use carbon emissions and ecosystem services at the county level, reached the spatial-temporal evolution characteristics, spatial correlation. And divided into four types of areas, the launch of energy-saving emission reduction policies can be based on this partition, to develop a more refined, more appropriate strategy. It can promote the development of green economy and at the same time provide scientific support for the proposal of ecological and environmental protection policies. For high-high type regions, local carbon emissions were reduced through the transformation and upgrading of energy consumption structures or the introduction of low carbon industrial technology. For high-low type regions, local resources should be used to develop a green economy and effectively protect the ecological environment. For low-high type regions, more attention should be paid to exploring the causes of environmental damage and restoration of the local ecological environment. However, there are still some shortcomings in this paper, such as in the analysis of the spatial-temporal evolution of carbon emissions and ESV, not more detailed from the point of view of the temporal evolution of land use, and the impact of changes in the type of land use on the two and the law to be grasped. Secondly, due to the missing values in the statistical data and the estimation method, the accuracy of the calculation of carbon emissions and ESV needs to be improved, and the study area needs to be expanded. The factors affecting carbon emissions and ESV need to be further explored. In the future, we will continue to optimize these aspects.

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References

[1] LU Zhou Yangfan, XU Duanyang, ZHANG Xujiao, et al. Impacts of land use change on ecosystem services in the arid desert area of Alxa[J]. Research on Soil and Water Conservation, 2019,26(06):296-302.

[2] PENG Wenfu, ZHOU Jieming, XU Xinliang, et al. Spatial and temporal patterns of carbon emissions and carbon footprint effects in Sichuan Province based on land use change[J]. Journal of Ecology, 2016,36(22):7244-7259.

[3] Feng Wei, Zhao Rongqin, Xie Zhixiang et al. Land use carbon emission efficiency and its spatial and temporal pattern under the carbon neutral target--a case study of 72 prefecture-level cities in the Yellow River Basin[J]. China Land Science, 2023,37(01):102-113.

[4] Jia Qi. Land use evolution and its ecosystem service value response in Gongyi City, Henan Province[J]. Soil and Water Conservation Bulletin, 2020,40(06):249-258.

[5] Zhou Jingru, Zhao Huafu, Wu Jinhua. Research on the evolutionary characteristics of the relationship between intensive land use and carbon emission in Guanzhong urban agglomeration[J]. China Land Science, 2017,31(11):55-61.

[6] Yu Zhuohui, Mao Shiping. Decoupling analysis of net carbon emissions from agriculture and economic growth in China[J]. China Population-Resources and Environment, 2022,32(11):30-42.

[7] Yuan Kaihua, Mei Yun, Chen Yinrong, et al. Spatio-temporal evolution and influence mechanism of intensive utilization of construction land and carbon emission efficiency in China[J]. Resource Science, 2017,39(10):1882-1895.

[8] ZHOU Jia, WANG Yuxuan, LIU Xuerong et al. Research on spatial and temporal differences in carbon emissions and carbon compensation in Chinese provinces based on land use change[J]. Geoscience, 2019,39(12):1955-1961.DOI:10.13249/j.cnki.sgs.2019.12.014.

[9] Wen Feng, Lu Chunyang. Spatial and temporal pattern differentiation of land use carbon emission effects in Chongqing[J]. Research on Soil and Water Conservation, 2016,23(4):257-262.

[10] Wang Dan, Jing Yande, Han Shanmei, Gao Mingxiu. Spatial and temporal relationship analysis between land use carbon emissions and its ecosystem service value in Nanshihu Lake Basin based on grid[J]. Journal of Ecology, 2022,42(23):9604-9614.

[11] Shaofeng Yuan, Congmou Zhu, Lixia Yang, Fenghua Xie. Responses of Ecosystem Services to Urbanization-Induced Land Use Changes in Ecologically Sensitive Suburban Areas in Hangzhou,China[J].International Journal of Environmental Research and Public Health,2019,16(7).

[12] Raju Rai, Yili Zhang, Basanta Paudel, Bipin Kumar Acharya, Laxmi Basnet. Land Use and Land Cover Dynamics and Assessing the Ecosystem Service Values in the Trans-Boundary Gandaki River Basin,Central Himalayas[J]. Sustainability,2018,10(9)

[13] Geng Tianwei, Chen Hai, Zhang Xing et al. Characterization of spatio-temporal evolution of ecosystem service value and analysis of influencing factors in Shaanxi Province based on GWR[J].

ISSN 2616-5872 Vol.5, Issue 10: 37-48, DOI: 10.25236/AJEE.2023.051006

Journal of Natural Resources, 2020, 35(07):1714-1727.
[14] Zijian Li, Jiangping Chen, Weikang Zhang et al. Analysis of the evolution of ecosystem service value and influencing factors in Hubei Province[J]. Surveying and Mapping Science, 2023,48(01):245-257.DOI:10.16251/j.cnki.1009-2307.2023.01.026.
[15] Wang Tao, Feng Jie. Research on the evolution of carbon emissions from land use and analysis of influencing factors in Shaanxi Province[J]. Environmental Science and Management, 2016,41(12):25-29.
[16] Feng Jie, Zhang Sheng, Wang Tao. Analysis of carbon emissions from interprovincial land use and its influencing factors in China[J]. Statistics and Decision Making, 2019,35(05):141-145.DOI:10.13546/j.cnki.tjyjc.2019.05.031.