

Article

Carbon Dioxide Emissions and Their Driving Forces of Land Use Change Based on Economic Contributive Coefficient (ECC) and Ecological Support Coefficient (ESC) in the Lower Yellow River Region (1995–2018)

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Abstract: Land use change is the second largest source of greenhouse gas emissions after fossil combustion, which can hurt ecological environment severely. Intensive study on land use carbon emissions is of great significance to alleviate environmental pressure, formulate carbon emission reduction policy, and protect ecological development. The lower Yellow River area is an important area of economic development, grain cultivation, and agricultural production in China. Land use change has significant economic, environmental, and ecological impacts in this region. Deep study of land used carbon emissions and its influencing factors in the lower Yellow River area is not only of great significance to the environmental improvement in the Yellow River basin, but also can provide references for the research of other basins. Based on this, this paper studies the land use carbon emissions of 20 cities in the lower Yellow River area from 1995 to 2018. The results showed that from 1995 to 2018, the land use change was characterized by the decrease of the ecological land and the increase of the built-up land significantly. The overall carbon emission of the lower Yellow River area is increasing, and the built-up land is the main factor that leads to the increase of carbon emission, which can be also proven by the analysis of the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model. The economic contributive coefficient (ECC) and ecological support coefficient (ESC) of carbon emission in the lower Yellow River area show a trend of high in Zhengzhou, Jinan, and Zibo and low in Zhoukou, Shangqiu, and Heze, and there was no significant changes during the study period, which indicates that each city did not achieve the coordinated development of the ecological economy. Finally, analysis results of the STIRPAT model indicated that the area of built-up land had the greatest impact on land use carbon emissions, followed by tertiary industry, whereas per capita gross domestic product (GDP) had the smallest impact. For every 1% increase in the area of built-up land, carbon emissions increased by 1.024%. By contrast, for every 1% increase in the contribution of tertiary industry to the GDP and per capita GDP, carbon emissions decreased by 0.051% and 0.034%, respectively. According to the study, there are still many problems in the coordinated development of economy and ecology in

the lower Yellow River area. The lower Yellow River area should control the expansion of built-up land, afforestation, development of technology, reduction of carbon emissions, and promotion of the high-quality development of the Yellow River Basin.

Keywords: carbon emission; land use; economic contributive coefficient (ECC); ecological support coefficient (ESC); STIRPAT model; lower Yellow River area

1. Introduction

Global environmental problems represent the most serious challenges faced by humans [1,2], among which climate change caused by greenhouse gas (GHG) emissions is the major impediment to sustainable development [3]. Land use is an important means of assessing human socioeconomic activities [4]. With societal development, the pattern, breadth, and intensity of land use are continuously changing, exerting profound impacts on all aspects of the environment, thereby aggravating global environmental problems [5]. Human activities are the main driver of the increase in carbon dioxide emissions. The use of fossil fuels and overexploitation of natural resources have led to the rapid growth in GHG concentrations, which has become a problem of great concern in the international community that must be clearly understood and resolved [6–8]. Land use type mirrors socioeconomic activities, such as urban development, food production, and human life [9]. After fossil fuel combustion, land use change is the second largest source of GHG emissions, and unsustainable land use will lead to more GHG emissions into the atmosphere [10,11].

With carbon emissions from land use increasing, researchers have carried out a large body of research to thoroughly analyze the internal mechanisms by which land use releases carbon into the atmosphere via human activities. To mitigate such emissions through low-carbon emission reduction policies, it is important to further analyze the influencing factors of land use carbon emissions. Recent research has focused on the carbon emission mechanisms of urban land expansion and agricultural land internal transformation [12–14], mainly through the impact mechanism of land use carbon emissions [15–17], land use carbon emission effect [18], carbon dynamics of urbanization [19], calculation of land use carbon emission intensity [20,21], and relationship between land use, energy consumption, and carbon emission [22]. Such research provides a scientific basis for formulating scientific carbon dioxide emission reduction policies, among which the Logarithmic Mean Divisia Index (LMDI) method and Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model are the two most common methods. For instance, Zhu [23], Wang [24], and Tan [25] used the LMDI model to study China's carbon dioxide emissions in terms of population, per capita gross domestic product (GDP), energy consumption, and energy consumption structure. More specifically, Guo [26] and Liu [27] analyzed the influencing factors of carbon emissions in Shanghai and Beijing, respectively. However, the LMDI model cannot analyze the influencing factors of carbon emissions in detail, whereas the STIRPAT model can analyze more influencing factors than the LMDI model. Thus, academic applications of the STIRPAT model are increasing. Shi [28] and Fan [29] used the STIRPAT model to analyze the influencing factors of carbon dioxide emissions in the world and countries at different income levels, respectively. Moreover, Wang [30] adopted the improved STIRPAT model, combined with partial least squares regression, to study the effects of urbanization level, economic level, industrial proportion, tertiary industry's proportion of GDP, energy intensity, and research and development output on carbon dioxide emissions in Beijing. These studies have proven that the STIRPAT model is effective for carbon dioxide impact factor analysis.

With the continuous development of China's economy and urbanization, growing areas of agricultural land are being converted into built-up land, and the area of cultivated land is decreasing. As a result, the carbon emissions of land use are increasing, exacerbating related environmental problems [18,31]. Thus, development in China is at a critical point in terms of balancing the

relationship between the economy and the environment through reducing carbon dioxide emissions. Therefore, comprehensive accounting of land use carbon emissions and an in-depth analysis of the driving mechanisms in China are critical to mitigate GHG emissions, formulate rational carbon emission reduction policies, and ensure coordinated economic development and environmental protection [32,33].

Research on the carbon emissions of land use in China have mainly focused on trends in land use carbon emissions [34], land use carbon effect [35,36], and land use low-carbon optimization [37]. The research on land use carbon emissions has mostly focused on the national [38,39] or provincial level, and provincial-scale research has mostly been concentrated in the provinces of Hunan [40], Jiangsu [41], Hubei [42], Liaoning [43], and Henan [44]. By contrast, few studies have investigated land use carbon emissions within cities and river basins. The Yellow River is the sixth longest river in the world and the second largest river in China. It flows through nine provinces and regions, with a basin area of more than 750,000 km². It is an area rich in natural, historical, and cultural resources in China [45]. The lower Yellow River area flows through Henan and Shandong Provinces, and is an important food production area in China. Thus, the economic and environmental developments are important in the lower Yellow River area. However, with the increase in population and advancing urbanization, carbon dioxide emissions are increasing, and environmental problems are becoming increasingly serious. Therefore, it is necessary to study the carbon emissions of land use in the lower Yellow River area to support high-quality sustainable development [46].

With this background, this study analyzed the spatiotemporal changes in land use carbon emissions in the lower Yellow River area from economic and ecological aspects, and analyzed the influencing factors of land use carbon emissions. To this end, this study used economic and land use data from 20 prefecture-level cities in Henan and Shandong Provinces from 1995 to 2018 and applied the STIRPAT model to them. This study provides a theoretical reference for the low-carbon development of the lower Yellow River area and similar regions, and provides a reference for the optimization of regional land use structure and reducing the environmental problems caused by increasing carbon emissions.

2. Material and Methods

2.1. Study Area

The total length of the lower Yellow River area from Taohuayu to Lijin is 786 km, with a drainage area of 23,000 km² that accounts for 3% of the area of the Yellow River Basin. This area experiences a temperate monsoon climate. The lower reaches of the Yellow River flow through two provinces, Henan and Shandong. It is an important grain producing area in China, with well-developed agriculture and fertile land. Henan and Shandong are the most populous and agricultural provinces in China, and they are in the stage of urbanization. Based on the close relationship between regional economic development and the lower reaches of the Yellow River and the integrity of prefecture level administrative divisions, we referred to relevant literature [47,48]. This study selected 20 prefecture-level cities in Shandong and Henan provinces, which are the affected areas of the lower reaches of the Yellow River, as the study areas (Figure 1). Considering the development of the lower Yellow River area in recent decades and the availability of data, this study selected 1995–2018 data to analyze.

2.2. Data Sources

The data sources of land use carbon emissions research in the lower Yellow River area mainly included statistical yearbook data, remote sensing imagery data, and data from previous research.

1. Statistical yearbook data: This study obtained GDP, population, per capita GDP, and tertiary industry contribution to GDP for the 20 prefecture-level cities in the lower Yellow River area for 1995, 2005, 2010, and 2018. The data for 1995, 2005, and 2010 were from the 1996, 2006, and 2011 Henan Statistical Yearbook and the Shandong Statistical Yearbook. Social data for 2018

were obtained from the statistical websites of the investigated cities (Table S1) (Note: This study standardized the data before analysis).

2. Remote sensing imagery data: Remote sensing imagery data were obtained from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (<http://www.resdc.cn>).
3. Research data: This study obtained carbon emission coefficients of land use (cultivated land, woodland, unused land, built-up land, and water area) [49,50].

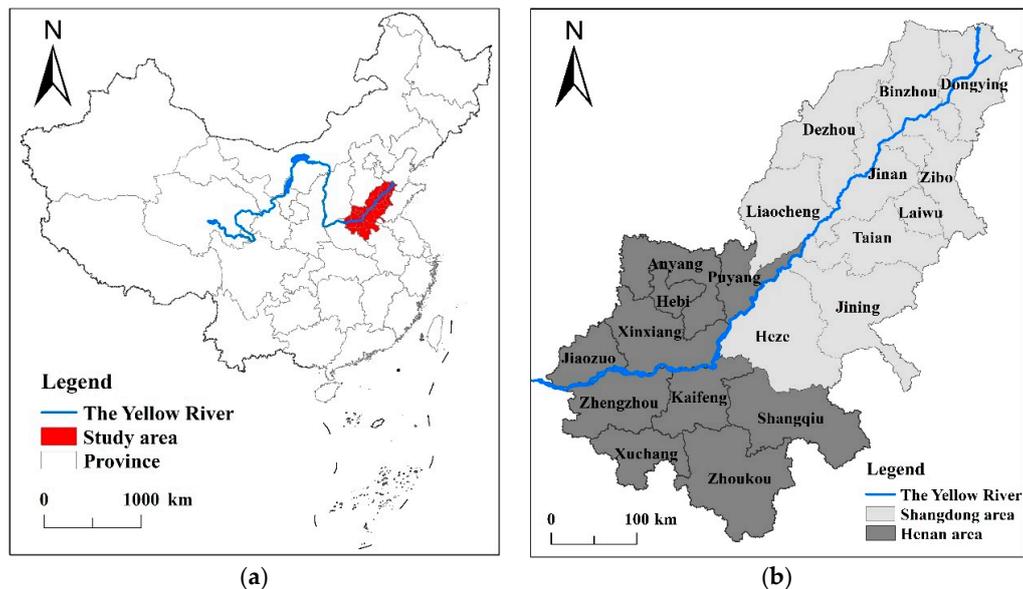


Figure 1. Map showing the study area, Henan and Shandong Provinces, and the Yellow River. (a) Location of the study area with China, (b) map of Henan and Shandong Provinces.

2.3. Methods

2.3.1. Dynamic Degree of Land Use

The dynamic degree of a single land use type expresses the quantity change of a given land use type within a given time range in a defined research area [51,52] and is calculated as follows:

$$K = \frac{U_b - U_a}{U_a} \times 100\% \quad (1)$$

where K is the single dynamic degree of a given land use type and $U_a - U_b$ is the beginning and the end of the considered period of the areas of the land use type.

2.3.2. Carbon Emission/Absorption Model of Land Use

Based on land use data from 1995, 2005, 2010, and 2018 in the lower Yellow River area and combined with previous research [53], the carbon emissions of cultivated land, woodland, water area, built-up land, and unused land in 20 prefecture-level cities were calculated in the lower Yellow River area.

1. The land use carbon emissions of cultivated land, woodland, water area, and unused land, other than built-up land, were calculated as [49]:

$$EU_{ce} = \sum S_i \times \varepsilon_i \quad (2)$$

where EU_{ce} is the land use carbon emissions, S_i is the area of the i -th land type, and ε_i is the carbon emission coefficient per unit area corresponding to the i -th land use type. Positive values

represent emissions and negative values represent absorption. Table 1 presents the carbon emission coefficients of each land use type, except built-up area, as previously calculated [53].

- The carbon emissions of built-up land were calculated by multiplying the area of built-up land with carbon sources and sinks, as follows [50]:

$$EU_{cb} = \sum S_i \times \xi_i \times \delta_i \quad (3)$$

where EU_{cb} is the carbon emission of built-up land, ξ_i is the carbon source coefficient of built-up land, 56.46 t/hm²·a (ton/square hectometer·annually), and δ_i is the carbon sink coefficient of built-up land, 2.38 t/hm²·a.

- Based on Equations (2) and (3), the total land use carbon emission was obtained, as follows:

$$EU = EU_{ce} + EU_{cb} \quad (4)$$

where EU is the total carbon emission, EU_{ce} is the carbon emission of land use other than built-up land, and EU_{cb} is the carbon emission of built-up land.

Table 1. Carbon emission or absorption coefficients for different land use types.

Land Use Type	Carbon Emission Coefficient (kg/m ² ·a)
Cultivated land	0.4595
Woodland	−0.6125
Water area	−0.0253
Unused land	−0.0005

2.3.3. Carbon Emission Equity Evaluation Model

According to the Lorenz curve, the Gini coefficient is put forward by the Italian economist Gini, which is widely used as a comprehensive index to investigate the difference of income distribution among residents [54,55]. In this paper, the Gini coefficient and carbon emission characteristics are combined, and the carbon emission equity evaluation model is cited [56] (Figure 2).

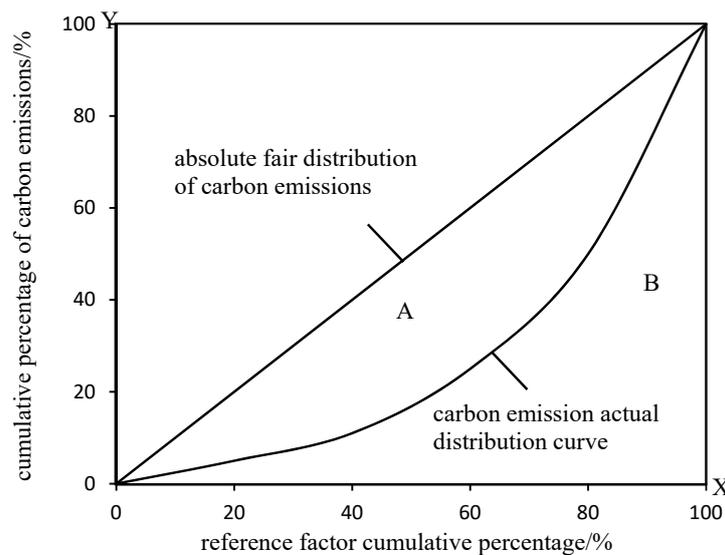


Figure 2. Carbon emission Lorenz curve.

Economic Efficiency Model of Carbon Emission

In the carbon emission economic efficiency model, the vertical axis OY represents the percentage of carbon emissions in the whole region, and the horizontal axis OX represents the percentage of GDP

in each region. Its significance is to take the GDP of each region as a reference. To emit a certain proportion of carbon, it is necessary to contribute the corresponding proportion of GDP. From the economic point of view, on the basis of assuming the absolute average of carbon emissions, if the proportion of carbon emissions in a certain region is greater than the contribution rate of GDP, it is considered that the economic efficiency is relatively low, and it encroaches on the interests of other regions; otherwise, the economic efficiency is relatively high, and it contributes to other regions. Here, the economic contributive coefficient (ECC) is used to measure the fairness of economic contribution of carbon emission in each region [57]. The formula of ECC is as follows:

$$ECC = \frac{G_j}{G} / \frac{C_j}{C} \quad (5)$$

where G_j is the GDP of city j , G is the total GDP of the 20 investigated prefecture-level cities in the lower Yellow River area, C_j is the carbon emissions of city j , and C is the sum of the carbon emissions of the 20 prefecture-level cities in the lower Yellow River area. If $ECC > 1$, the economic contribution rate of city j exceeds the contribution rate of carbon emissions from land use, indicating a relatively high economic efficiency of carbon emissions; if $ECC < 1$, the economic efficiency of carbon emissions in city j is relatively low.

Ecological Pressure Model of Carbon Emission

In the carbon emission ecological pressure model, the vertical axis OY represents the percentage of carbon emissions in each region in the entire region, and the horizontal axis OX represents the percentage of carbon absorption by carbon sinks in each region. The significance lies in taking carbon absorption of carbon sinks of various regions as a reference. Emitting a certain proportion of carbon, it is necessary to contribute a corresponding proportion of carbon absorption. From the ecological point of view, assuming the absolute average of carbon emissions, if the proportion of carbon emissions in a certain region is greater than the contribution rate of carbon sink to carbon absorption, it infringes the interests of other regions; otherwise, it has relatively high ecological capacity, which has an important contribution to reducing the pressure of carbon emissions on the ecological environment. Here, the ecological support coefficient (ESC) is used to measure the fairness of carbon ecological capacity contribution of each region [57]. The formula of ESC is as follows:

$$ESC = \frac{CA_j}{CA} / \frac{C_j}{C} \quad (6)$$

where CA_j is the amount of carbon absorbed by the carbon sink in city j , and CA is the total amount of carbon absorbed by the carbon sinks of the 20 prefecture-level cities in the lower Yellow River area. If $ESC > 1$, the contribution rate of carbon sinks in city j to carbon absorption is greater than the contribution rate of carbon emissions, which has a positive effect on the absorption of carbon emissions in the lower Yellow River area and contributes to other regions. If $ESC < 1$, the contribution rate of the carbon sinks in city j to carbon absorption is less than the contribution rate of carbon emissions and will have a negative impact on the carbon emissions in the lower Yellow River area.

2.3.4. STIRPAT Model

The predecessor of the STIRPAT model is the classic IPAT (Impact, Population, Affluence, Technology) model. The IPAT model was proposed by Ehrlich [58] in 1971, and reflects the relationship between population, economy, technology, and the environment. The formula as follows:

$$I = P \times A \times T \quad (7)$$

where I , P , A , and T represent Impact, Population, Affluence, and Technology, respectively.

To make the IPAT model more practical, Diezt [59] proposed the regression model of the IPAT equation, namely the STIRPAT model:

$$I = \alpha P^\beta A^\gamma T^\delta e \quad (8)$$

where I represents environmental impact; P represents the population; A represents affluence; T represents technology; α is a model coefficient; β , γ , and δ are human-driven indices of P , A , and T ; and e is the residual term. To better analyze and describe the relationship between various human factors and the impact of environmental pressure in practical applications, Equation (8) is usually transformed into its logarithmic form as follows:

$$\ln I = \alpha + \beta \ln P + \gamma \ln A + \delta \ln T + \ln e \quad (9)$$

where α is a constant term; β , γ , and δ are the elastic coefficients of the human driving factors P , A , and T , respectively, which means that P , A , and T are the percentage of the change in environmental pressure impact caused by 1% of each change; and e is the residual term.

Based on previous studies [60–62], this study extended the STIRPAT model to characterize the impact of environmental pressure by land use carbon emissions, and constructed the following model:

$$\ln C = \alpha + \beta \ln P + \gamma \ln A + \delta \ln S + \rho \ln I + \ln e \quad (10)$$

where C is the carbon emission of land use ($\times 10,000$ t); α is the constant term of the model; P is the population ($\times 10,000$ people); A is wealth, characterized by per capita GDP (yuan/person); S is the area of built-up land (km^2); I is the contribution of tertiary industry to GDP (%); β , γ , δ , and ρ are the elastic coefficients of P , A , S , and I , respectively; and e is the residual term of the model.

2.3.5. Ordinary Least Squares

Ordinary least squares is a common multivariate linear regression model for parameter estimation. Suppose there are a series of explanatory variables observations X_{ij} and explained variables Y_j of $i = 1, 2, \dots, m, j = 1, 2, \dots, n$ [63,64]. The general formula is:

$$Y_j = \beta_0 + \sum_{i=1}^n \beta_i x_{ij} + \varepsilon_i (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \quad (11)$$

where ε is the error term and β_0 is the regression constant. Here, when using the STIRPAT model based on the EViews software (IHS Markit, London, UK), the common least squares method was used to perform regression analysis of the influencing factors of land use carbon emissions.

3. Results

3.1. Land Use Changes

To analyze the changes in land use area in the lower Yellow River area from 1995 to 2018, the land use change area and dynamic degree of single land use types in the lower Yellow River area were calculated using Equation (1) (Table 2). The areas of cultivated land and unused land decreased continuously, while the areas of built-up land and water increased substantially (Table 2). Meanwhile, the area of woodland first decreased, then increased, and finally decreased over time. The area of built-up land increased the most from 2010 to 2018, by 4637 km^2 , representing a dynamic degree of 19.48. Similarly, the areas of cultivated land and unused land decreased the most from 2010 to 2018, by 3376 km^2 and 682 km^2 , respectively, representing dynamic degrees of 3.17 and -43.41 , respectively. The area of woodland increased slightly in 2005 and 2010 but decreased in 2020 and 2018. Thus, from 2010 to 2018, with continuous economic development, more cultivated land and forest land was occupied and the area of built-up land increased significantly.

Table 2. Changes in land use area and single dynamic degree in the lower Yellow River area from 1995 to 2018.

Land Use Type	1995–2005		2005–2010		2010–2018	
	Area (km ²)	Dynamic Degree (%)	Area (km ²)	Dynamic Degree (%)	Area (km ²)	Dynamic Degree (%)
Cultivated land	−788	−0.73	−819	−0.76	−3376	3.17
Woodland	−40	−0.65	16	0.26	−692	−11.23
Water area	248	5.26	135	2.72	1970	38.67
Unused land	−539	−23.62	−172	−9.87	−682	−43.41
Built-up land	1712	8.08	900	3.93	4637	19.48

3.2. Spatiotemporal Trends in Land Use Carbon Emissions

Intense changes in land use were observed in the lower Yellow River area during 1995–2018. This study calculated the carbon emissions of all cities in the lower Yellow River area using Equations (2) and (3). Overall, carbon emissions in the lower Yellow River area increased from 1995 (1.6×10^8 t) to 2018 (1.97×10^8 t). This rise was attributed to increases in carbon sources, where the main land use type acting as a carbon source was built-up land followed by cultivated land. In 2010, the carbon emissions of built-up land accounted for more than 73% of the total carbon sources and this proportion increased over time.

To further analyze the contribution of built-up land to carbon sources, the proportions of carbon sources of built-up land was calculated for the 20 prefecture-level cities in 2010 and 2018 (Table 3). In 2010, the proportions of built-up land of all carbon sources of 15 cities exceeded 70%. By 2018, the proportion increased and exceeded 80% in Zhengzhou, Jinan, Zibo, and Laiwu. By contrast, woodland accounted for the largest proportion of total carbon sinks, while water areas and unused land accounted for a small proportion; the magnitudes of change in these proportions during the study period were not significant.

Table 3. Proportion of built-up land carbon emissions in prefecture-level cities of the lower Yellow River area in 2010 and 2018.

Region	2010	2018
Zhengzhou	74%	86%
Kaifeng	70%	74%
Anyang	70%	74%
Hebi	70%	76%
Xinxiang	71%	75%
Jiaozuo	70%	78%
Puyang	74%	78%
Shangqiu	75%	76%
Xuchang	73%	76%
Zhoukou	74%	75%
Jinan	74%	82%
Zibo	78%	83%
Dongying	78%	78%
Jining	71%	77%
Taian	71%	76%
Laiwu	72%	81%
Dezhou	70%	71%
Liaocheng	73%	78%
Binzhou	78%	75%
Heze	74%	77%

To facilitate the comparison of regional carbon emission differences, this study divided carbon emissions into five levels according to the land use carbon emissions in 1995–2018 using the natural

interruption method: $1-3.5 \times 10^6$ t, very low carbon emissions; $3.5-6.5 \times 10^6$ t, low carbon emissions; $6.5-8 \times 10^6$ t, moderate carbon emissions; $8-11.5 \times 10^6$ t, high carbon emissions; and $11.5-18 \times 10^6$ t, very high carbon emissions indicative of serious pollution. Using Equation (4), the distribution of carbon emissions of prefecture-level cities was calculated in the lower Yellow River area from 1995 to 2018 (Figure 3).

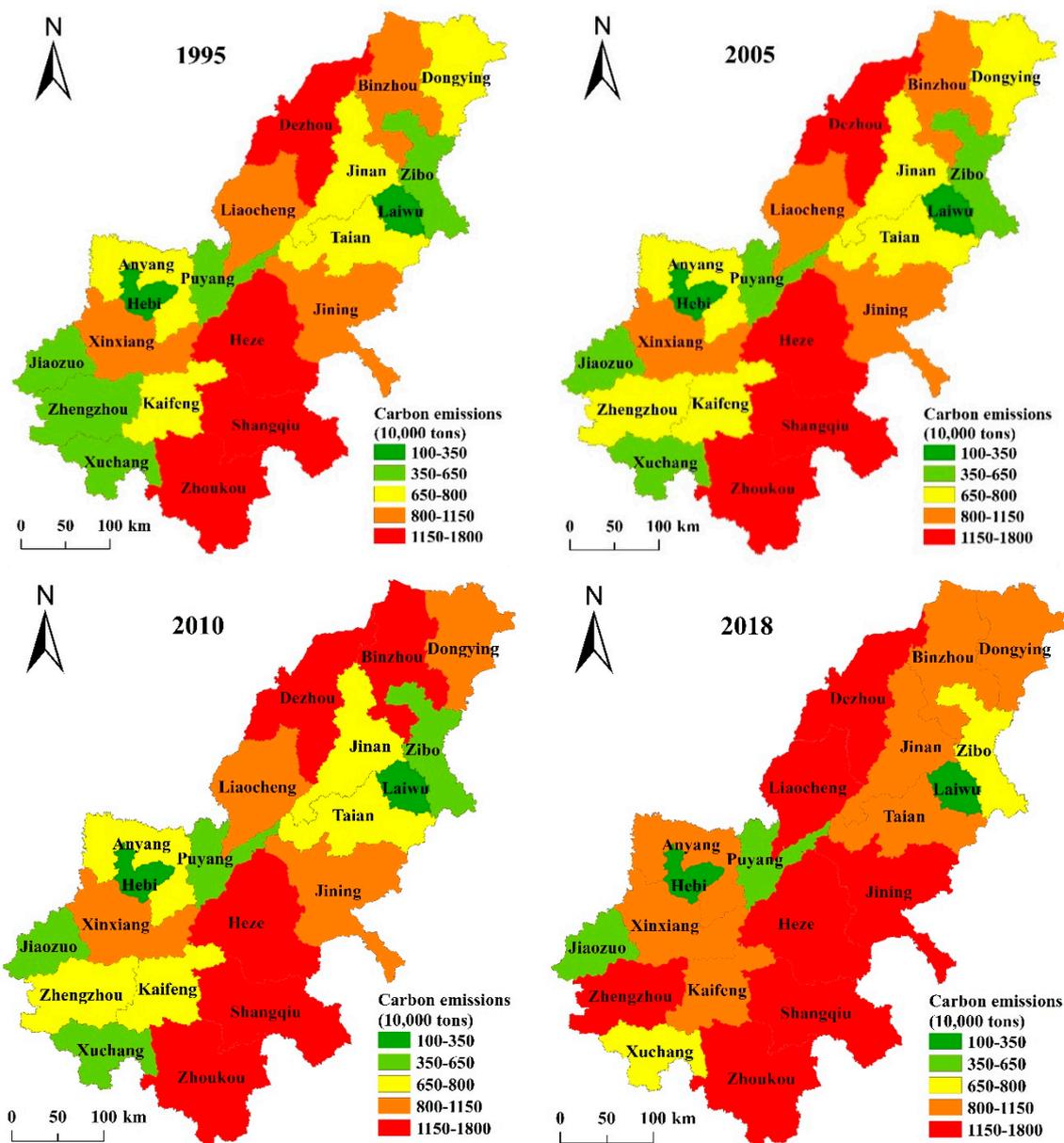


Figure 3. Distribution of land use carbon emissions in prefecture-level cities of the lower Yellow River area from 1995 to 2018.

With continuous economic development, carbon emissions increased. For instance, in 1995, four cities (Dezhou, Heze, Shangqiu, and Zhoukou) had very high carbon emissions (11.5 million tons), however, seven cities (Dezhou, Liaocheng, Jining, Heze, Shangqiu, Zhoukou, and Zhengzhou) had very high emissions in 2018. Moreover, the only cities with carbon emissions below 3.5 million tons were Laiwu and Hebi. With the continuous development of the economy, carbon emissions in all regions are increasing. The number of cities with carbon emissions between 800 and 11.5 million tons has increased from four in 1995 to seven in 2018. Among the cities, Zhengzhou’s carbon emissions

increased the most from 1995 to 2018, along with an increase in GDP of 975.34 billion yuan, from 38.99 billion yuan to 1014.33 billion yuan. This showed that carbon emissions increased along with economic development, and that Zhengzhou had not achieved sustainable economic development and environmental protection. By contrast, in all study years, only Laiwu and Hebi had very low carbon emissions.

To analyze the relationship between the growth of carbon emissions and GDP of the 20 cities in the lower Yellow River area, the GDP growth and carbon emissions were calculated for the 20 cities at the prefecture level from 1995 to 2018 (Table 4). Zhengzhou, Jinan, Zibo, and Jining had higher GDP growth, as well as relatively high increments of carbon emissions (Table 4), indicating that carbon emissions increased along with continuous economic development. Moreover, Zhengzhou, Jinan, Zibo, and Jining did not adequately address environmental issues while developing their economies. By contrast, Dongying also had relatively high GDP growth, but its carbon emission increment was not high, indicating that Dongying better balanced environmental protection efforts and economic development.

Table 4. Gross Domestic Product (GDP) growth and growth rates of prefecture-level cities from 1995 to 2018.

Region	1995 GDP (100 Million Yuan)	2005 GDP (100 Million Yuan)	2010 GDP (100 Million Yuan)	2018 GDP (100 Million Yuan)	GDP Growth from 1995 to 2018 (100 Million Yuan)	Carbon Emission growth from 1995 to 2018 (10,000 Tons)
Zhengzhou	389.9	1660.6	4040.9	10143.3	9753.4	650.4
Kaifeng	123.4	408.0	927.2	2002.2	1878.9	110.4
Anyang	189.1	557.5	1315.6	2393.2	2204.1	125.5
Hebi	54.8	186.2	429.1	862.0	807.1	48.0
Xinxiang	210.3	544.2	1189.9	2526.6	2316.3	174.9
Jiaozuo	228.1	584.0	1245.9	2371.5	2143.4	128.4
Puyang	122.5	384.0	775.4	1654.5	1532.0	101.0
Shangqiu	163.1	560.8	1143.8	2389.0	2225.9	110.3
Xuchang	126.1	605.5	1316.5	2830.6	2704.6	73.0
Zhoukou	195.1	595.5	1228.3	2687.2	2492.1	122.1
Jinan	481.5	1876.6	3910.5	7856.6	7375.0	406.4
Zibo	404.5	1431.0	2866.8	5068.4	4663.9	215.6
Dongying	229.3	1166.1	2359.9	4152.5	3923.2	143.5
Jining	368.2	1266.3	2542.8	4930.6	4562.4	319.2
Taian	205.2	855.7	2051.7	3651.5	3446.4	185.0
Laiwu	69.2	256.3	546.3	1005.7	936.5	71.3
Dezhou	184.4	831.8	1657.8	3380.3	3195.9	124.9
Liaocheng	164.5	693.1	1622.4	3152.2	2987.7	307.8
Binzhou	151.8	667.3	1551.5	2640.5	2488.7	86.2
Heze	168.5	450.9	1227.1	3078.8	2910.3	226.1

3.3. ECC and ESC of Carbon Emissions

3.3.1. ECC of Carbon Emissions

In order to analyze the economic benefits of carbon emission of 20 cities in the lower Yellow River area, the ECC value of carbon emissions of each city was obtained by Equation (5) and divided into five grades (Figure 4): 0–0.5, very low; 0.5–1, low; 1–1.5, moderate; 1.5–2, high; and 2–4, very high. In 1995, 10 cities had carbon emission ECCs > 1: Dongying, Zibo, Jinan, Laiwu, Tai'an, Jining, Anyang, Hebi, Jiaozuo, and Zhengzhou. Anyang and Hebi had carbon emission ECCs of 1–1.5 in 1995, but <1 by 2005. During this time, the GDPs of Anyang (1995, 18.913 billion yuan; 2005, 55.746 billion yuan) and Hebi (1995, 5.479 billion yuan; 2005, 18.624 billion yuan) grew rapidly. Thus, these two cities did not effectively balance economic development and emission reductions during these 10 years of development.

According to Table 3 and Figure 4, the GDP of Zhengzhou, Jinan, and Zibo was relatively high, but their ECC was always at a high level. It shows that although these three cities produced large amounts of carbon dioxide emissions during the course of economic development, the economic efficiency of their carbon emissions were higher than those of other cities in the lower Yellow River area.

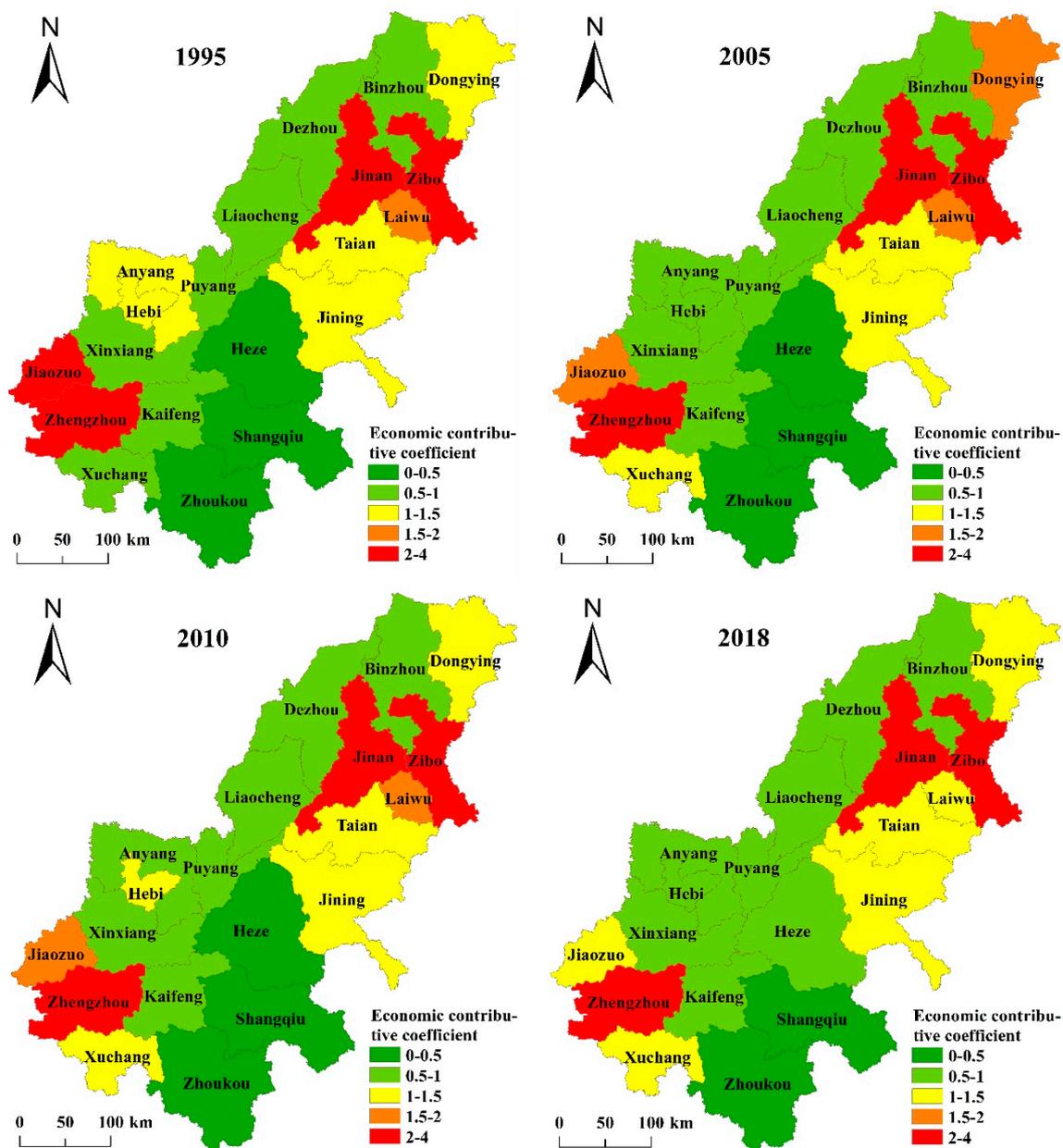


Figure 4. Spatial distribution of the carbon emissions economic contributive coefficient in prefecture-level cities of the lower Yellow River area from 1995 to 2018.

3.3.2. ESC of Carbon Emissions

To further analyze the ecological development of the 20 prefecture-level cities in the lower Yellow River area, this study calculated the ESCs of each city using Equation (6), and divided the values into five levels (Figure 5): 0–1, very low; 1–1.5, low; 1.5–2, moderate; 2–3, high; and 3–4, very high. During 1995–2018, the ESCs of Jinan, Zibo, Laiwu, and Jiaozuo all exceeded 1.5, indicating that these cities achieved a better balance of environmental production and economic development. Among them, the ESCs of Laiwu always exceeded 2 and even surpassed 3 in 1995 and 2010, indicating that the contribution rate of carbon sequestration to carbon absorption in Laiwu was greater than that of carbon sources to carbon emissions; overall, this had a beneficial effect on the elimination of carbon emissions in the lower Yellow River area.

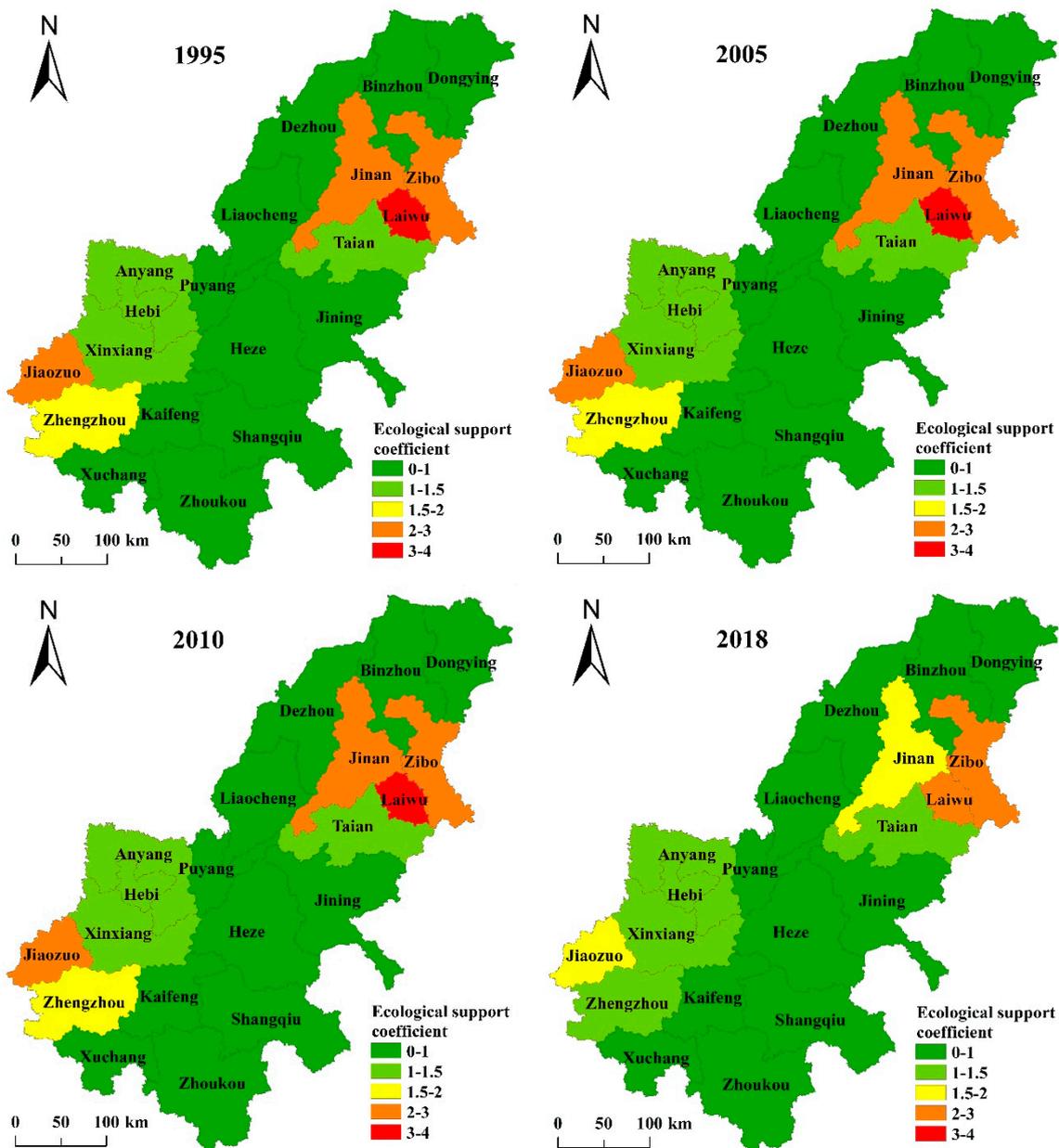


Figure 5. Spatial distribution of ecological support coefficients in prefecture-level cities of the lower Yellow River area from 1995 to 2018.

During the study period, 11 cities (Dongying, Binzhou, Dezhou, Liaocheng, Puyang, Jining, Heze, Shangqiu, Kaifeng, Zhoukou, and Xuchang) always had very low ESCs, indicating that the contribution rate of carbon sinks to carbon emission absorption in these 11 cities was less than that of carbon sources. Thus, these 11 cities did not effectively promote regional environmental protection efforts during 1995–2018. Notably, Zhengzhou had moderate ESCs in 1995 and 2010, but a low ESC in 2018. As the provincial capital, the economic development of Zhengzhou is very important. From 2010 to 2018, its built-up land increased by 987 km², which led to the continuous increase of carbon emissions of built-up land and decrease in the ecological carrying capacity coefficient.

3.4. STIRPAT Model Results

According to Equation (10), the data of land use carbon emissions, population, per capita GDP, built-up land area, and tertiary industry's proportion of GDP of the 20 prefecture-level cities in the lower Yellow River area were standardized.

Ordinary least square regression analysis was carried out using the EViews software (IHS Markit, <http://www.eviews.com/home.html>), and the model regression results were obtained (Table 5).

Table 5. STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model regression results.

Variable	Regression Coefficient	Standard Error	t	P
α	−0.2133	0.0686	−3.109	0.0026
$\ln P$	0.0098	0.008	1.232	0.2218
$\ln A$	−0.0338	0.005	−6.369	0.0000
$\ln S$	1.024	0.0105	97.165	0.0000
$\ln I$	−0.0511	0.0189	−2.708	0.0084

Note: $R^2 = 0.9943$, F-statistic = 3270.501, Prob (F-statistic) = 0.0000.

The degree of fit of the model reached 99.43%, and the F-statistic passed the significance level of 1% [6], indicating that the model fit very well (Table 5). At the 1% level, land use carbon emissions were significantly negatively correlated with per capita GDP and tertiary industry's proportion of GDP, but significantly positively correlated with built-up land area; there was no significant correlation between land use carbon emissions and population. The coefficients of per capita GDP, tertiary industry's proportion of GDP, and built-up land area were −0.0338, −0.0511, and 1.024, indicating that for every 1% increase in per capita GDP or tertiary industry's proportion of GDP, the carbon emissions from land use decreased by 0.0338% or 0.0511%, respectively, and for every 1% increase in built-up land area, the carbon emissions from land use increased by 1.024%.

The reason for the negative correlation between land use carbon emissions and per capita GDP may be that as people's economic situation improves so does their understanding of environmental problems, fostering an interest in the development of a low-carbon cycle. Similarly, the negative correlation between the tertiary industry's proportion of GDP and land use carbon emissions may be explained by technological advancements that occur with continuous socioeconomic development, resulting in strengthened control of carbon emissions due to technological improvements and cleaner production processes. Finally, the positive correlation between built-up land area and land use carbon emissions showed that built-up land was the main source of carbon emissions, and that the expansion of built-up land has a clear incremental effect on carbon emissions.

4. Discussion

This study combined multiple models to analyze the spatiotemporal characteristics and driving factors of land use carbon emissions from the lower Yellow River area from different perspectives. It provides a basis for improving land use in the later stage of economic development and achieving a balance between environmental protection efforts and high-quality socioeconomic development in the Yellow River Basin. Moreover, it enriches the relevant literature on land use carbon emissions and provides a reference for regional environmental and ecological protection.

This study combined analyses of ESC, ECC, and driving factors of carbon emissions. The results showed that land use carbon emissions in the lower Yellow River area are generally high in the north and south, and low in the east and west. Moreover, with rapid economic development in China, the carbon emissions of the prefecture-level cities increased to varying degrees. In areas with rapid economic development, the corresponding land use carbon emissions also grew rapidly, consistent with previous work [29]. The economy of Dongying grew rapidly in 1995 and 2018, but its carbon emissions did not increase much. Other cities should learn from the governance of Dongying City to ensure the coordinated development of economy and ecology. In the lower Yellow River area, ECC and ESC values of carbon emissions were higher in the east and west, and lower in the north and south. During the study period, despite economic development, the overall ECC of carbon emissions in the lower Yellow River area did not increase. This showed that some cities did not adequately support

environmental protection efforts, resulting in an overall low ECC of carbon emissions. Furthermore, there were no obvious changes in the ESC over time. This showed that the environmental problems in the lower Yellow River area have not improved, and greater effort should be made to balance economic development and environmental protection.

From the influencing factors of land use carbon emissions in the lower Yellow River area, built-up land area had the greatest impact on carbon emissions, followed by tertiary industry, whereas per capita GDP had the lower impact. Moreover, land use carbon emission was negatively correlated with tertiary industry and positively correlated with built-up land area, consistent with a previous study [6]. Unexpectedly, land use carbon emission was also negatively correlated with per capita GDP. This might be because, as people's economic situation improves, they may become more aware of environmental problems and strive to reduce carbon emissions from land use.

5. Conclusions

Land use change is the main driver of carbon emissions, which can damage the ecological environment. Intensive study on land use carbon emissions is of great significance to alleviate environmental pressure, formulate carbon emission reduction policies, and protect ecological development. The lower Yellow River has experienced rapid industrialization and urbanization with drastic land use changes during 1995–2018. This paper takes the lower Yellow River as the research area, through calculating the carbon emissions of land use in 20 cities in the lower Yellow River, combined with the economy and ecology of each city, and analyzes the driving factors of land use carbon emissions. Research found, from 1995 to 2018, land use change was characterized by the decrease of the ecological land and the increase of the built-up land. Overall, carbon emissions increased; built-up land was the main carbon source, while woodland was the main carbon sink. The economic contribution coefficient of carbon emission in the lower Yellow River has not changed much as a whole. The ECC value of Zhengzhou, Jinan, and Zibo has always been at a high level, which shows that these three cities pay attention to energy conservation and emission reduction while developing GDP. The ESC value of 20 cities in the lower Yellow River was generally on the low side. Considering the driving factors of carbon emission, the continuous increase of built-up land in the lower reaches of the Yellow River leads to the same increase of carbon sink and continuous decrease of carbon source. Land use carbon emission was significantly negatively correlated with per capita GDP and tertiary industry's proportion of GDP, and significantly positively correlated with built-up land area.

In this paper, the ECC, ESC, and driving factors of land use carbon emission in the lower Yellow River were analyzed to enrich the research of carbon emission in the basin. Most scholars analyzed the driving factors of carbon emission from the economic aspect. This paper adds ecological factors, which provide more reference for other scholars. At the same time, it laid the theoretical foundation for the coordinated development of economy and ecology in the lower Yellow River. While developing the economy, each region should pay more attention to ecological development and control the rapid expansion of built-up land, while promoting the economical and intensive use of existing built-up land.

In addition to the above conclusions, this study had some limitations. The land use carbon emission was related to many factors, such as the first industry, the second industry, the environmental awareness of people, and so on. This study combined economic and ecological data. To analyze, in the future, more factors should be considered to study the land use carbon emission.

Supplementary Materials: The following are available online at <http://www.mdpi.com/1996-1073/13/10/2600/s1>, Table S1. Website of data source.

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