

## Article

# Does Urbanization Affect the Carbon-Output Efficiency of Agriculture? Empirical Evidence from the Yellow River Basin

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**Abstract:** Purpose: Improving agricultural carbon-output efficiency is an important path to realize the “double carbon” goal in the Yellow River Basin. In the context of rapid urbanization development, it is significant to explore whether promoting urbanization will affect agricultural carbon-output efficiency. Methods: Based on panel data of 75 cities in the Yellow River Basin from 2000 to 2020, this paper uses the super-DEA model, three-dimensional kernel density model, and Markov chain model to measure and analyze the spatio-temporal evolution of agricultural carbon-output efficiency in the Yellow River Basin. The panel Tobit model is used on this basis to analyze the relationship between urbanization and carbon-output efficiency in agriculture. Results: The results show the following: (1) The level of agricultural carbon-output efficiency in the Yellow River Basin is low and has not reached an effective state, showing a slow downward trend in general where the agricultural carbon-output efficiency in the lower reaches is higher than that in the middle reaches, and the upper reaches has the lowest. (2) Agricultural carbon-output efficiency in the Yellow River Basin has a negative trend of transitioning to a low level overall and maintaining its original level, and it is difficult to realize the leapfrog transfer between states. Agricultural carbon-output efficiency has an obvious spatial spillover effect and “club convergence” phenomenon; the high-efficiency area has a positive driving effect on the neighborhood area, while the low-efficiency area has a negative impact on the neighborhood area. (3) The level of urbanization has a significant positive impact on the carbon-output efficiency of agriculture in the upper, middle, and lower reaches of the Yellow River Basin, which plays an important role in promoting the green development of agriculture.



**Citation:** Song, X.; Wang, C.; Liu, W. Does Urbanization Affect the Carbon-Output Efficiency of Agriculture? Empirical Evidence from the Yellow River Basin. *Agriculture* **2024**, *14*, 245. <https://doi.org/10.3390/agriculture14020245>

Academic Editor: Gbadebo Oladosu

Received: 4 December 2023

Revised: 26 January 2024

Accepted: 30 January 2024

Published: 1 February 2024



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**Keywords:** carbon output; agriculture; spatial-temporal heterogeneity; urbanization

## 1. Introduction

The 17 Sustainable Development Goals (SDGs) are a unified global sustainable development evaluation system proposed at the United Nations Sustainable Development Summit in 2015. The goal of achieving a carbon peak by 2030 and carbon neutrality by 2060, announced by China at the United Nations General Assembly in 2020, is one of the important components of the SDGs [1]. The report of the Party’s 20th National Congress pointed out that promoting green and low-carbon economic and social development is a key link to achieving high-quality development. According to statistics, agricultural carbon emissions account for about 25% of the total greenhouse gas emissions [2], which is one of the important components of China’s carbon emissions, and improving agricultural carbon-output efficiency is an important way to achieve the “double carbon” goal [3]. The Yellow River Basin is an important economic zone and agricultural production base in China, as well as an important ecological barrier in China [4]. Promoting the green modernization of its agriculture is of great practical significance for improving the ecological environment of the Yellow River Basin and achieving high-quality development [5]. In 2020, the total agricultural output value of the nine provinces in the Yellow River Basin was about CNY 2633.46 billion, accounting for 32.94% of the total agricultural output value

of the country. But, at the same time, the agricultural development mode of the Yellow River Basin is extensive, the agricultural carbon emission is large, and the agricultural non-point source pollution has seriously affected the ecological environment of the Yellow River Basin [6]. According to the Bulletin of the Second National Pollution Source Census, in 2017, chemical oxygen demand, ammonia nitrogen, total nitrogen, and total phosphorus pollution in agricultural carbon emissions in the Yellow River Basin accounted for 80.6%, 40.9%, 53.0%, and 74.1% of the total pollutant emissions in the Yellow River Basin, respectively [7]. In addition, ecological problems such as vegetation destruction, soil erosion, and soil degradation are very serious [8]. Since reform and opening, China's urbanization level has continuously increased. In 2020, China's urbanization level reached 63.89%, an increase of nearly 46% compared to 1978. The rapid increase in urbanization rate can promote the transfer of agricultural surplus labor force, the expansion of urban population, and the extension of spatial layout which will help improve the allocation efficiency of agricultural resources, promote the intensive and professional development of agriculture [9], and increase the total demand for high-quality agricultural products [10]. At the same time, it brings advanced agricultural production technology and knowledge to rural areas, thus promoting the improvement of agricultural carbon-output efficiency [11]. However, the non-agricultural transfer of rural labor force will also bring about the problem of rural population aging and part-time employment, which may prompt farmers to invest more agricultural materials such as fertilizers and pesticides in agricultural production and increase the input intensity of agricultural machinery to avoid agricultural production reduction [12–14], bringing negative impacts such as agricultural non-point source pollution, ecological environment degradation, and agricultural land consumption [15–17], thus inhibiting the improvement of agricultural carbon-output efficiency. Therefore, against the background of extensive agricultural production methods in the Yellow River basin, serious ecological environmental pollution, and accelerating urbanization process in China, it is of great practical significance to study the spatio-temporal evolution characteristics of agricultural carbon-output efficiency in the Yellow River Basin and whether the promotion of urbanization will affect the improvement in agricultural carbon-output efficiency. This will improve the development level of agricultural economy, promote ecological environmental protection in the Yellow River Basin, and provide relevant decision references for policymakers.

Agricultural carbon-output efficiency refers to the application of carbon efficiency in the agricultural field, which emphasizes improving resource utilization efficiency while achieving agricultural production goals; optimizing agricultural production technology; and implementing production mode and management measures to reduce carbon emissions and environmental pollution and promote the stable and healthy development of the ecological environment. Improving agricultural carbon-output efficiency is of great significance to realize the coordinated “win–win” and sustainable development of agricultural economic and ecological benefits. Among them, the quantitative aspects of agricultural carbon-output efficiency mainly consider the large-scale crops planted in the Yellow River basin, including wheat, corn, rice, soybean, sweet potato, cotton, oil, and so on. Relevant literature on agricultural carbon-output efficiency mainly focuses on three aspects. First is the accounting of agricultural carbon-output efficiency. Scholars' measurement methods for agricultural carbon-output efficiency mainly include data envelopment analysis (DEA), stochastic frontier analysis (SFA), and their improved models, which take capital, labor, and energy as input indicators and the total output value of agriculture, forestry, animal husbandry and fishery, and carbon emissions as output indicators [18]. For example, Yasmeen, R. et al. calculated the agricultural production efficiency of major (17) agricultural production countries from 1996 to 2018 using data envelopment analysis to explore the relationship between agricultural production and carbon emissions, and the results showed that the United States, Russia, Republic of Korea, Japan, and Italy were countries with efficient agricultural production [19]. Based on the calculation of agricultural carbon emissions, Wu, X.R. et al. used the DEA-Malmquist index to measure the efficiency of agricultural carbon

emissions in 31 provinces (municipalities and districts) in China from 2000 to 2011 and analyzed the provincial differences and variation trends [20]. In addition, a small number of scholars took the agricultural net carbon sink as the expected output. For example, Li, B. et al. used the DEA-BCC-I model to measure the efficiency of the agricultural net carbon sink in 30 provinces (municipalities and districts) in China from 2005 to 2017 and found that the efficiency level of the agricultural net carbon sink in China was generally low and the spatial difference was significant [21]. In addition to producing carbon emissions, agricultural ecosystems also have a powerful carbon sink function. Therefore, it is more scientific and comprehensive to take the agricultural carbon sink as an output index when constructing an agricultural carbon-output efficiency index system. The second aspect focused on by scholars is the spatial-temporal heterogeneity of carbon-output efficiency in agriculture. Most of the existing domestic and foreign studies on the spatial-temporal heterogeneity of agricultural carbon efficiency are at the national and provincial levels. For example, Liu, Q.T. calculated and decomposed the agricultural carbon emission efficiency of 30 provinces in China from 2000 to 2013 and found that the agricultural carbon efficiency of China showed an overall growth trend, while that of eastern, central, and western regions decreased successively [22]. Tian, Y. et al. conducted an effective measurement of agricultural carbon emission efficiency in Hubei Province and analyzed its temporal and spatial differences [23]. They found that agricultural carbon efficiency was in an overall growth trend since 2011, but regional differences were obvious. A total of 15 cities (prefectures) in Hubei Province could be divided into three different groups: high growth, low growth, and decline. The third aspect is the impact of urbanization on the carbon-output efficiency of agriculture. Urbanization is one of the important factors affecting agricultural carbon-output efficiency, but there are big differences in the research conclusions of domestic and foreign scholars on the relationship between urbanization and agricultural carbon-output efficiency, and the results are affected by factors such as the research scale, research samples, and the construction of an input-output index system [24]. The first view holds that urbanization has a positive promoting effect on the carbon-output efficiency of agriculture. For example, Tian, Y. et al. believe that the increase in urbanization level means an increase in construction land, which leads to a reduction in the agricultural land scale, thus affecting the planting industry and promoting an improvement in agricultural carbon emission efficiency [25]. The second view is that urbanization has a negative inhibition effect on agricultural carbon-output efficiency. For example, Cheng, L.L. et al. believe that the rapid expansion of China's urban population will increase the demand for relatively high-carbon agricultural products such as meat, eggs, and milk, and the yield-oriented agricultural policy will lead to ineffective supply of agricultural products, resulting in more carbon emissions [26]. Therefore, promoting urbanization is not conducive to improving agricultural carbon efficiency. The third view holds that there is a non-linear relationship between urbanization and agricultural carbon-output efficiency that is mainly divided into a trend of a "positive U" and an "inverted U". For example, Zheng, H. et al. believe that the urbanization level has a non-linear influence on ecological efficiency in eastern China, which is first negative and then positive [27]. At present, there are few research results on the relationship between urbanization and agricultural carbon-output efficiency, and the academic community has not reached a consensus on its mechanism of impact, so it is still necessary to further explore these issues.

As seen in a review of existing relevant studies, scholars have conducted many beneficial studies on measuring agricultural carbon-output efficiency, spatio-temporal heterogeneity, and the impact of urbanization on agricultural carbon-output efficiency, which is of reference significance to this paper. However, the following deficiencies still exist: First, in terms of measuring agricultural carbon-output efficiency, most studies only use the total output value of agriculture, forestry, animal husbandry, and fishery as the expected output to build the index system. However, since agriculture has the double effect of carbon emissions and a carbon sink, crops also absorb a large amount of carbon dioxide through photosynthesis during their growth process; this paper adds the agricultural car-

bon sink index as the expected output on this basis. This makes the measurement of the carbon-output efficiency of agriculture more accurate. Second, most of the current studies on agricultural carbon-output efficiency focus on the national and provincial (city) levels, with 31 provinces and regions as the research objects. Few scholars have conducted studies on geographical units such as river basins with more consistent internal characteristics and agricultural production conditions, and there are relatively few studies that have examined agricultural carbon-output efficiency around the Yellow River Basin. Third, existing studies mainly focus on the impact of urbanization on carbon emissions, and few studies have examined the impact of urbanization on agricultural carbon-output efficiency. In addition, there are positive promoting effects, negative inhibiting effects, and non-linear effects in the research conclusions, which are quite different and need to be explored further.

Based on this, this paper uses the panel data of 75 cities in the Yellow River Basin from 2000 to 2020, uses the super-DEA model to measure the agricultural carbon-output efficiency in this special region more accurately, and establishes a three-dimensional kernel density model and Markov chain model to analyze the spatio-temporal evolution characteristics of agricultural carbon-output efficiency in the Yellow River Basin. In addition, the panel Tobit model is used to innovatively explore the relationship between urbanization and agricultural carbon-output efficiency in order to provide references to improve agricultural carbon-output efficiency and promote high-quality agricultural development in the Yellow River Basin.

This paper is organized as follows. The mechanism of influence of urbanization on the carbon-output efficiency of agriculture is introduced in the next section. The introduction of research methods and data usage is given in Section 3. The analysis of the measurement, spatio-temporal evolution, and the impact of urbanization on agricultural carbon-output efficiency in the Yellow River Basin is discussed in Section 4. Finally, some conclusions are given, and some policies are highlighted in Section 5.

## 2. Mechanism of Influence of Urbanization on Carbon-Output Efficiency of Agriculture

Urbanization refers to population transfer from rural areas to urban areas with better living conditions and more employment opportunities. In this paper, the proportion of permanent urban population in the total population of a region is used to represent the level of regional urbanization. The mechanism of influence of urbanization level on agricultural carbon-output efficiency can be mainly divided into positive and negative aspects (Figure 1).

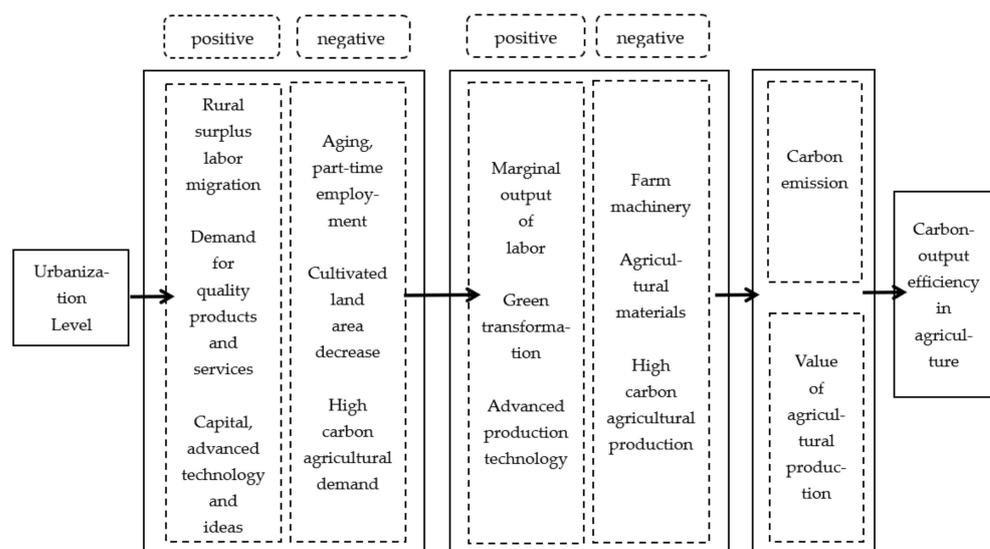


Figure 1. Mechanism of influence of urbanization and agricultural carbon-output efficiency.

First, urbanization has a significant role in promoting the carbon-output efficiency of agriculture. On the one hand, the improvement in the urbanization level drives the increase in the proportion of secondary and tertiary industries, thus promoting the transfer of rural surplus labor force, optimizing the allocation of resources and factors, improving the efficiency of agricultural land use and labor marginal output [28], promoting the specialization of agricultural development and the moderation of production scale [29], promoting the advancement of agricultural technology and improving the efficiency of agricultural technology [30], and thus improving the carbon-output efficiency of agriculture. On the other hand, the increase in urbanization level will lead to a large number of high-quality workers gathering in cities and towns, transforming from agricultural producers to agricultural consumers. With the increase in per capita disposable income of urban residents, it will promote the upgrading of residents' consumption level, which may increase the consumption demand for high life quality and green agricultural products [31]. It makes farmers pay more attention to the protection of the agricultural ecological environment and reduce the use of pesticides and other chemicals in production. This concept of environmental protection is transmitted through the connection between urban farmers and left-behind farmers, thus promoting the transformation of agricultural production mode from traditional extensive production to new green production and promoting the improvement of carbon-output efficiency of agriculture [32]. In addition, the rapid development of urbanization will make a large amount of urban capital gradually return to the countryside in the long run, which is conducive to intensive and large-scale agricultural production and reducing production costs, bringing advanced production technology and management concepts to rural areas, promoting the development of agricultural technology and agricultural machinery, improving production conditions, reducing resource waste, promoting improved rural economic and ecological benefits, and contributing to improved agricultural carbon-output efficiency [33].

Second, urbanization has a significant inhibitory effect on the carbon-output efficiency of agriculture. On the one hand, increasing the urbanization level causes significant rural labor force transfer to cities, and most of the transferred people are young and middle-aged people with a certain level of education and are relatively high-quality employees. Therefore, rural areas face an aging labor force combined with part-time employment [34]. Farmers are encouraged to increase the intensity of the use of agricultural machinery and materials such as pesticides and fertilizers to avoid agricultural production reduction [35], which results in increased carbon emissions. In addition, a large amount of land may be abandoned or divided into urban construction land, thus inhibiting the improvement in the carbon-output efficiency of agriculture. On the other hand, the non-agricultural employment of many rural people has brought an increase in per capita income, and their diet structure, life, and consumption pattern are also changing [36]. The food consumption demand has shown a new trend of health and diversification. The expansion of urban populations has reduced the demand for food and increased the demand for agricultural products such as meat, eggs, and milk. Thus, the production of agricultural products such as meat, eggs, and milk is increased. Since the carbon emissions generated by the consumption of agricultural products such as meat, eggs, and milk with the same weight are higher than that of grain consumption [37], more agricultural carbon emissions will be generated, which will have a negative impact on the carbon-output efficiency of agriculture.

To summarize, urbanization has both promoting and inhibiting effects on the carbon-output efficiency of agriculture, and which specific effect plays a leading role needs to be further explored.

### 3. Methods

#### 3.1. The Super-DEA Model

In this paper, the super-DEA model is used to measure the agricultural carbon-output efficiency in the Yellow River Basin. Efficiency analysis models mainly include two types, parametric and non-parametric, among which data envelopment analysis (DEA) is a

non-parametric linear programming method that is most widely used to evaluate the relative efficiency of production units. The DEA model compares the actual output of each production unit with the best possible output to measure its efficiency under given input conditions. However, the DEA model also has some defects, while the traditional CCR and BCC models usually can only distinguish between “effective” and “invalid” production units and cannot further sort the calculated effective decision units. In order to make up for this defect, the super-DEA model introduces the concept of “super efficiency”, which can be used to further compare and sort the efficient DMU—that is, different efficiency levels can be distinguished among the efficient DMU. The basic mathematical expression of the super-DEA model is as follows:

Let the number of cities in the Yellow River Basin be  $n$ , and every city has  $m$  types of “inputs”, where  $\theta_0^{super}$  is the efficiency index;  $\lambda_j$  is the input and output coefficient;  $x_{ij}$  is the  $i$ th input index of the  $j$ th evaluation object;  $y_{ij}$  is the  $i$ th output index of the  $j$ th evaluation object;  $S_i^-$  is the input relaxation variable; and  $S_i^+$  is the output relaxation variable. The super efficiency model for each region is set as follows:

$$\begin{aligned} & \min \theta_0^{super} \\ & \text{s.t.} \begin{cases} \sum_{j=1, j \neq 0}^n \lambda_j x_{ij} + S_i^- = \theta_0^{super} x_{i0}, i = 1, 2, \dots, m \\ \sum_{j=1, j \neq 0}^n \lambda_j x_{ij} - S_i^+ = \theta_0^{super} y_{i0}, i = 1, 2, \dots, s \\ \sum_{j=1, j \neq 0}^n \lambda_j = 1, \lambda_j \geq 0, j \neq 0 \end{cases} \end{aligned}$$

If  $\theta_0^{super} \geq 1$ , it shows that the city’s input–output reach optimal efficiency; if  $\theta_0^{super} < 1$ , it indicates that the input–output of the city have not reached optimal efficiency, and it is necessary to reduce the input or increase the output to achieve DEA effectiveness [38].

### 3.2. Kernel Density Estimation

In order to clarify the distribution dynamics and evolution law of agricultural carbon-output efficiency in the Yellow River Basin as a whole and in various regions, the kernel density estimation method was used to analyze the distribution position, distribution trend, polarization trend, and distribution ductility of agricultural carbon-output efficiency in the Yellow River Basin. Among them, the distribution location reflects the level of agricultural carbon emission. The distribution trend reflects the spatial difference size and polarization trend of agricultural carbon emissions, in which the width and height of wave peaks reflect the difference size, and the number of wave peaks describes the polarization trend [39]. The distribution ductility reflects the spatial difference between the regions with the highest agricultural carbon emissions and other regions in the study area, and the longer the tail, the greater the difference [40].

For independent and evenly distributed sample data  $x_1, x_2, \dots, x_n$ , the kernel density is estimated in the form of

$$\hat{f}_h(x) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x_i - \bar{x}}{h}\right)$$

$\hat{f}_h(x)$  is the density function,  $K\left(\frac{x-x_i}{h}\right)$  is the kernel function,  $h$  is bandwidth,  $n$  is the number of observations (i.e., the total number of regions),  $i$  denotes the region,  $x_i$  represents independent and identically distributed observations, and  $\bar{x}$  is the mean.

### 3.3. Spatial Markov Chains

In this paper, the spatial correlation and evolution characteristics of agricultural low carbon efficiency were analyzed using the spatial Markov chain model, and the long-term

evolution trend was predicted. The Markov chain is a random process with discrete time and state with Markov properties. In this random process, given the current knowledge or information, the future state is only related to the current state and not to the past state; that is, the event has “no after-effect”, also known as “Markov” [41]. Agricultural carbon-output efficiency has a Markov property, so this paper adopts the Markov chain method to analyze the changing trend and temporal and spatial characteristics of agricultural carbon-output efficiency in the Yellow River Basin. The Markov chain discretized the agricultural carbon-output efficiency data into  $k$  state types, calculated the probability distribution of the  $k$  types, and approximated the evolution of agricultural carbon-output efficiency as a Markov process. In this paper, the agricultural carbon-output efficiency values ( $E$ ) in the Yellow River Basin were divided into four types according to the following quartile:  $k = 1$  means low agricultural carbon-output efficiency ( $E \leq 0.25$ ),  $k = 2$  means medium–low agricultural carbon-output efficiency ( $0.25 < E \leq 0.5$ ),  $k = 3$  means medium–high agricultural carbon-output efficiency ( $0.5 < E \leq 0.75$ ), and  $k = 4$  means high agricultural carbon-output efficiency ( $E > 0.75$ ). A Markov probability transfer matrix with  $k = 4$  was constructed (Table 1):

**Table 1.** Markov transition probability matrix  $M$  ( $k = 4$ ).

$t \setminus t + 1$	1	2	3	4
1	$P_{11}$	$P_{12}$	$P_{13}$	$P_{14}$
2	$P_{21}$	$P_{22}$	$P_{23}$	$P_{24}$
3	$P_{31}$	$P_{32}$	$P_{33}$	$P_{34}$
4	$P_{41}$	$P_{42}$	$P_{43}$	$P_{44}$

Where  $p_{ij}$  represents the probability value of the transformation of the space unit of agricultural carbon-output efficiency type  $i$  to type  $j$  in year  $t + 1$ . The calculation formula is

$$p_{ij} = \frac{n_{ij}}{n_i}$$

$n_{ij}$  represents the sum of the number of cities transferred from provinces of type  $i$  in year  $t$  to type  $j$  in year  $t + 1$  during the study period, and  $n_i$  represents the sum of the number of cities of type  $i$  in all years.

Traditional Markov chains are mostly applied to time series analysis, ignoring the important influence of the spatial spillover effect caused by geographical proximity on the state transition of agricultural carbon-output efficiency. Therefore, spatial Markov chains introduce the concept of “spatial lag” into the transfer probability matrix and decompose the traditional Markov transfer probability matrix into a  $k \times k$  conditional transfer probability matrix (Table 2):

**Table 2.** Spatial Markov probability transition matrix  $N$  ( $k = 4$ ).

Lag	$t \setminus t + 1$	1	2	3	4
1	1	$P_{11 1}$	$P_{12 1}$	$P_{13 1}$	$P_{14 1}$
	2	$P_{21 1}$	$P_{22 1}$	$P_{23 1}$	$P_{24 1}$
	3	$P_{31 1}$	$P_{32 1}$	$P_{33 1}$	$P_{34 1}$
	4	$P_{41 1}$	$P_{42 1}$	$P_{43 1}$	$P_{44 1}$
2	1	$P_{11 2}$	$P_{12 2}$	$P_{13 2}$	$P_{14 2}$
	2	$P_{21 2}$	$P_{22 2}$	$P_{23 2}$	$P_{24 2}$
	3	$P_{31 2}$	$P_{32 2}$	$P_{33 2}$	$P_{34 2}$
	4	$P_{41 2}$	$P_{42 2}$	$P_{43 2}$	$P_{44 2}$

Table 2. Cont.

Lag	t\ t + 1	1	2	3	4
3	1	P <sub>11 3</sub>	P <sub>12 3</sub>	P <sub>13 3</sub>	P <sub>14 3</sub>
	2	P <sub>21 3</sub>	P <sub>22 3</sub>	P <sub>23 3</sub>	P <sub>24 3</sub>
	3	P <sub>31 3</sub>	P <sub>32 3</sub>	P <sub>33 3</sub>	P <sub>34 3</sub>
	4	P <sub>41 3</sub>	P <sub>42 3</sub>	P <sub>43 3</sub>	P <sub>44 3</sub>
4	1	P <sub>11 4</sub>	P <sub>12 4</sub>	P <sub>13 4</sub>	P <sub>14 4</sub>
	2	P <sub>21 4</sub>	P <sub>22 4</sub>	P <sub>23 4</sub>	P <sub>24 4</sub>
	3	P <sub>31 4</sub>	P <sub>32 4</sub>	P <sub>33 4</sub>	P <sub>34 4</sub>
	4	P <sub>41 4</sub>	P <sub>42 4</sub>	P <sub>43 4</sub>	P <sub>44 4</sub>

$P_{kij}$  represents the probability that the region will shift from the initial state type  $i$  to type  $j$  at the next time under the condition that the spatial lag type is  $k$ . The specific calculation formula of the spatial lag value is as follows:

$$Lag_a = \sum_{b=1}^n Y_b W_{ab}$$

$Lag_a$  is the spatial lag value of region  $a$ ;  $Y_b$  is the observed value of region  $b$ ;  $W_{ab}$  is the spatial weight matrix, representing the spatial relationship between region  $a$  and region  $b$ ; and  $n$  is the total number of cities in the Yellow River Basin. The spatial weight can be determined by the proximity criterion—that is, the  $W_{ab}$  value is 1 if two regions are adjacent; otherwise, it is 0.

### 3.4. Panel Tobit Model

This paper uses the Tobit model to analyze the impact of urbanization on the low carbon efficiency of agriculture in the Yellow River Basin. When the super-DEA model is used to measure agricultural carbon-output efficiency, the value range of efficiency is limited; that is, its value should be greater than 0. For restricted dependent variables, the Tobit model is generally used for regression analysis so as to analyze its main influencing factors more scientifically. The specific form of the Tobit model is as follows:

$$y_{it} = \beta_0 + \sum_{t=1}^n \beta_t x_{it} + \mu_i + \varepsilon_{it}$$

$y_{it}$  represents agricultural carbon-output efficiency,  $x_{it}$  represents the explanatory variable,  $\beta_0$  represents the intercept term,  $\beta_t$  represents the estimated coefficient of the explanatory variable,  $i = 1, 2, \dots, 75$ ,  $t = 1, 2, \dots, n$ ,  $n$  is the number of independent variables,  $\mu_i$  is the individual effect, and  $\varepsilon_{it}$  is the random error term [42].

### 3.5. Data Declaration

Panel data from 75 cities in the Yellow River Basin from 2000 to 2020 were selected as sample data in this paper. Considering the availability of data, Hulunbuir and Laiwu were excluded from the sample data. The data used in this paper were from the China Statistical Yearbook and the provincial and municipal Statistical Yearbook (2000–2020), and missing data in some years were supplemented by the interpolation method.

The carbon emission coefficient of different kinds of agricultural materials, the formula for calculating the average annual feeding amount of livestock, and the greenhouse gas emission coefficient in the process of gastrointestinal fermentation and manure management used in this paper are derived from the IPCC [43], Oak Ridge National Laboratory of the United States, Institute of Agricultural Resources and Ecological Environment (IREEA), Nanjing Agricultural University, and other existing literature [44,45]. The carbon absorption rate and economic coefficient of various crops refer to relevant literature such as Wang, X.L. [46] and Han, Z.Y. [47]. Among them, the total annual carbon emission of cattle, horses, sheep, and other livestock due to animal husbandry can be calculated using the number of livestock at the end of the year, while the annual breeding amount of pigs,

rabbits, poultry, and other animals is adjusted according to the formula. The impact of different annual temperatures on the carbon emission coefficient is taken into account so that the total greenhouse gas emission is more accurate.

## 4. Results

### 4.1. Measuring Carbon-Output Efficiency in Agriculture

In this paper, the super-DEA model is used to measure agricultural carbon-output efficiency in the Yellow River Basin. The required indexes include the input index and output index. When constructing the index system, the overall and coordinated development among resource conservation, environmental friendliness, and agricultural economic growth should be comprehensively considered [48]. With reference to the existing literature, this paper takes the input of various production factors, land, and labor as input indicators. This includes the amount of fertilizer applied (tons); the amount of pesticide applied (tons); the amount of agricultural film used (tons); the amount of agricultural diesel used (tons); the effective irrigation area (thousands of hectares); the total power of agricultural machinery (kilowatts); the total sown area of crops (thousands of hectares); and the employees of agriculture, forestry, animal husbandry, and fishery (10,000 people). At the same time, the agricultural carbon emission (tons) is taken as the non-expected output index. The total output value of agriculture, forestry, animal husbandry, and fishery (CNY 10,000) and the agricultural carbon sink (tons) were used as expected output indicators. Agricultural carbon emissions include agricultural material carbon emissions and animal husbandry carbon emissions. In calculating carbon emissions from livestock farming, pigs, sheep, cattle, poultry, and rabbits were selected. The calculation of agricultural carbon sink mainly includes 18 crops such as wheat, corn, rice, soybean, sweet potato, cotton, and oil.

As can be seen in Table 3, the overall agricultural carbon-output efficiency of the Yellow River Basin in most years is less than 1; that is, it has not reached the effective state, and the overall efficiency is relatively stable and has a trend of slow decline. After 2016, it has improved, from 1.006 in 2000 to 0.944 in 2020, a decline of about 6.17%. It can be seen that the overall quality of agricultural development in the Yellow River Basin is low and the efficiency is not high. Increasing the use of various production factors to increase the expected output also causes an increase in non-expected output, causing damage to the ecological environment. A possible reason for this is that before 2015, with the support of the No. 1 document of the Central Committee, the state adopted a series of measures, such as adjusting the agricultural structure and reforming rural taxes and fees, so that farmers' production enthusiasm was greatly increased, agriculture developed rapidly, the use of production factors such as diesel and fertilizer in the agricultural production process increased, and carbon emissions rose rapidly. After 2016, the No. 1 central document pointed out that to promote the development of eco-friendly agriculture, the 19th National Congress of the Communist Party of China proposed a series of policies and measures and the promulgation of documents such as green development and sustainable development concepts, which gradually enhanced farmers' awareness of ecological protection and the promotion of agricultural science and technology so that extensive agricultural production in the Yellow River Basin has been effectively improved. In addition, affected by the COVID-19 epidemic in 2019, the efficiency of livestock breeding has been reduced, which in turn has reduced the carbon emissions of animal husbandry, and undesirable output has declined. In addition, under the influence of a series of policies, such as the reform of the traditional agricultural tax, rapid development of the planting industry was promoted. As an important agricultural production base in China, the scale of production of wheat, cotton, and other crops in the Yellow River Basin increased significantly during this period, resulting in a rapid increase in the agricultural carbon sink of the expected output and a significantly higher growth rate than agricultural carbon emissions.

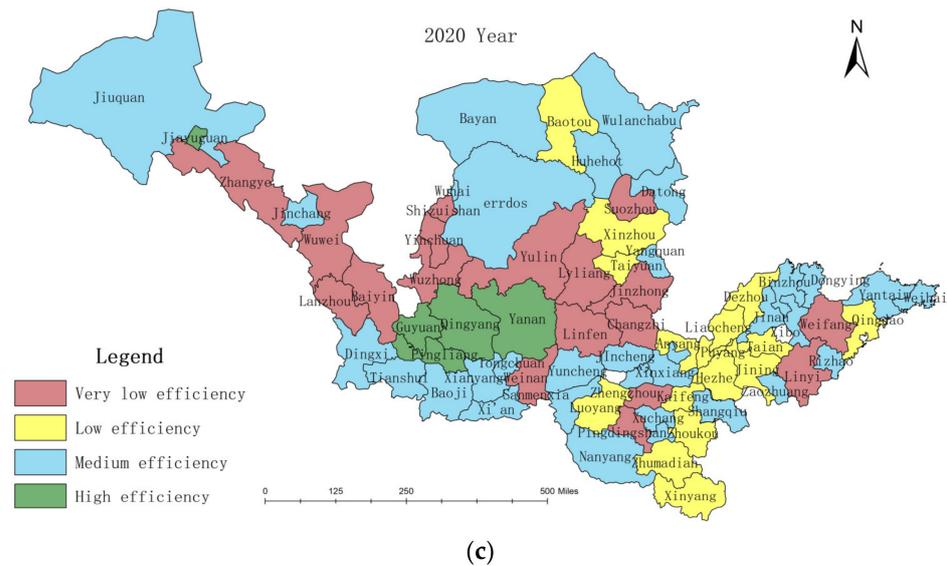
**Table 3.** Agricultural carbon-output efficiency in the Yellow River Basin from 2000 to 2020.

Time/Region	Upstream	Midstream	Downstream	Total
2000	0.9751	1.0118	1.0235	1.0061
2001	0.9790	0.9974	1.0135	0.9985
2002	0.9537	0.9924	1.0592	1.0074
2003	0.9097	1.0009	0.9889	0.9707
2004	0.8997	1.0013	0.9840	0.9662
2005	0.8874	0.9660	1.0084	0.9604
2006	0.8949	0.9582	1.0096	0.9603
2007	0.9145	0.9654	1.0247	0.9741
2008	0.9386	0.9645	1.0149	0.9768
2009	0.8823	0.9502	1.0368	0.9647
2010	0.8862	0.9961	1.0029	0.9679
2011	0.9117	0.9702	0.9987	0.9648
2012	0.8807	0.9881	0.9896	0.9586
2013	0.8530	1.0128	0.9561	0.9461
2014	0.8492	0.9871	0.9833	0.9470
2015	0.8229	0.9481	0.9678	0.9207
2016	0.8898	0.9288	0.9393	0.9219
2017	0.8774	0.9437	0.9725	0.9363
2018	0.8892	0.9522	0.9886	0.9486
2019	0.8887	0.9748	0.9864	0.9552
2020	0.8895	0.9816	0.9510	0.9440

Given the agricultural carbon-output efficiency of the three regions, it can be seen that the overall efficiency of the downstream region is higher than that of the middle and upstream regions (Figure 2). Before 2010, agricultural carbon-output efficiency reached an effective state in most years, but after that, efficiency experienced a trend of slow decline and was less than 1, from 1.023 in 2000 to 0.951 in 2020, a decrease of about 7.09%. Secondly, the agricultural carbon-output efficiency in the middle reaches of the sample period showed an overall trend of “upgrade–downgrade–increase” and only reached an effective state in a few years. From 2000–2015, efficiency declined slowly with fluctuation, and after 2016, agricultural carbon-output efficiency began to rise steadily, but it was still less than 1. The upstream region has the lowest efficiency, which is less than 1 during the sample period. Like the middle region, its agricultural carbon-output efficiency continued to decline from 2000–2015 and improved after 2016, with a decrease of about 8.78% during the sample period. A possible reason for this is that the economic and social conditions of the downstream areas are relatively superior, with advanced agricultural science and technology, higher crop output, and less energy consumption, so the carbon-output efficiency of agriculture is relatively higher than in other areas. However, Shandong Province and Henan Province, as important grain provinces in China, have a large proportion of input in agricultural production factors, a high level of development of animal husbandry and planting, and a large carbon sink and carbon emissions, so the overall efficiency is still relatively low. The terrain in the upstream region is very steep and diverse, and the natural resources are relatively poor. Inner Mongolia and Qinghai Provinces are rich in grassland resources, and the agricultural production mode is mainly animal husbandry, so the agricultural carbon emissions are high, hindering the improvement in agricultural carbon-output efficiency. Moreover, due to climate change, overgrazing, and other reasons, the grassland in Inner Mongolia has gradually degraded, and the ecological environment has been seriously damaged. The carbon-output efficiency of agriculture is the lowest in the Yellow River Basin.

Agricultural carbon-output efficiency values of the Yellow River Basin in 2000, 2010, and 2020 were selected; ArcGIS10.8 software was used to delineate the spatial distribution map of agricultural carbon-output efficiency in the Yellow River Basin, and the efficiency values were divided into four levels: Very low efficiency, low efficiency, medium efficiency, and high efficiency, as shown in Figure 3.





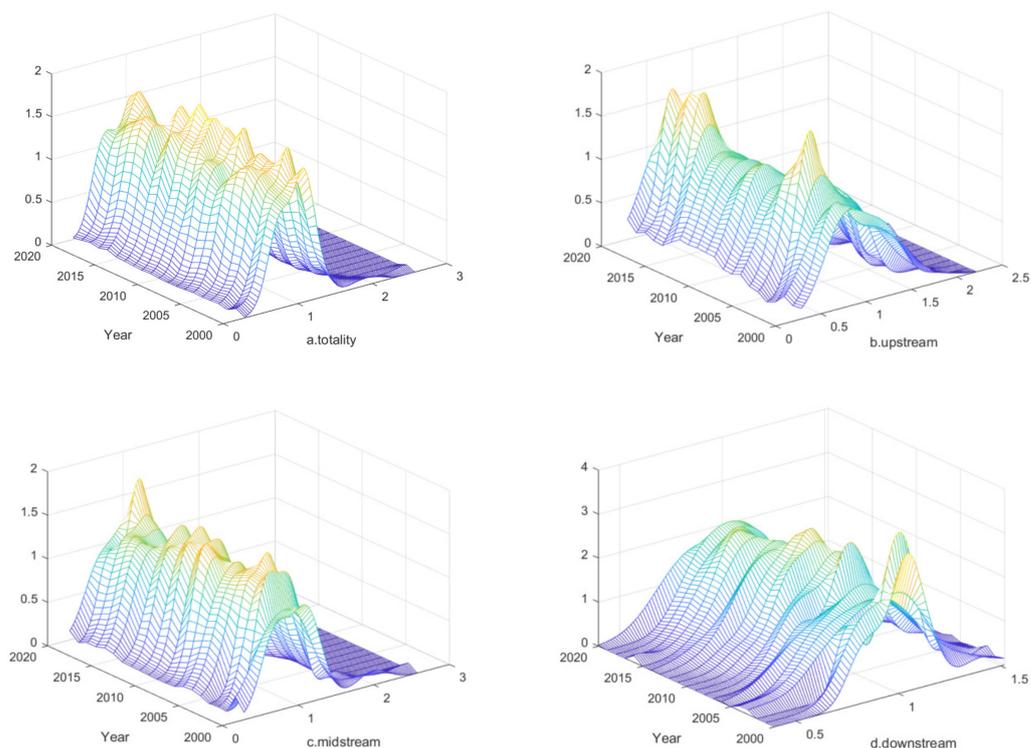
**Figure 3.** Distribution map of agricultural carbon-output efficiency in Yellow River Basin in (a) 2000, (b) 2010, and (c) 2020.

Given the changes from 2000 to 2020 in Figure 3, agricultural carbon-output efficiency in the Yellow River Basin has always been relatively low, the rate of improvement is not great, and only a few cities have reached the high-efficiency level. In 2000, Guyuan City, Qingyang City, and Pingliang City were part of the high-efficiency area. In 2010, Qingyang City and Pingliang City withdrew from the high-efficiency area and fell to the medium-efficiency level. In 2020, the two cities returned to the high-efficiency level, while Yan'an City also improved from a medium-efficiency to high-efficiency area, and the agricultural carbon-output efficiency improved.

From the perspective of spatial distribution, agricultural carbon-output efficiency in the Yellow River Basin shows obvious agglomeration characteristics and is distributed in centralized contiguous areas, among which the medium- and high-efficiency areas are mainly concentrated in the middle and lower reaches of the Yellow River Basin; the agricultural carbon-output efficiency in the upper reaches is low; and the improvement potential is huge. Specifically, in 2000, Datong City, Jinzhong City, Yulin City, Lanzhou City, Luoyang City, Zhumadian City, Wuwei City, Baotou City, and other regions at a low level of efficiency are mainly located in three large agricultural provinces of Shanxi, Shaanxi, and Henan. In 2010, except for Jiayuguan City, Gansu Province was in a state of low efficiency, with serious environmental pollution and obvious spatial agglomeration distribution characteristics. In 2020, the efficiency level of Taiyuan City, Luliang City, Dezhou City, Jincheng City, and other regions decreased; the former low-efficiency areas were connected; and the spatial correlation was further enhanced.

#### 4.2. Time Evolution Trend of Agricultural Carbon-Output Efficiency

In order to clarify the dynamic evolution of agricultural carbon-output efficiency in the Yellow River Basin from the time dimension, this study uses Matlab (R2023a) software to draw kernel density estimation maps of agricultural carbon-output efficiency in the Yellow River Basin as a whole and the upper, middle, and lower reaches from 2000 to 2020. It also analyzes the distribution position, distribution form, distribution ductility, and number of wave peaks, as shown in Figure 4.



**Figure 4.** The dynamic evolution of agricultural carbon-output efficiency in the whole and upper, middle, and lower reaches of the Yellow River Basin.

From the perspective of the distribution position, the center of the density distribution curve in the Yellow River Basin as a whole and in the upper, middle, and lower reaches of the region remained basically unchanged and slightly shifted to the left, indicating that in recent years, the agricultural carbon-output efficiency in the Yellow River Basin has shown a slight downward trend, which is consistent with the overall analysis mentioned above. Among them, the center of density function in the upstream region continuously shifted to the left from 2000 to 2015 and gradually shifted to the right after 2016, while the middle and downstream regions continued to shift slowly to the left amid fluctuations. Although agricultural carbon-output efficiency in the upstream region has improved in recent years, the efficiency in the middle and downstream regions has decreased more significantly than in the upstream region. A possible reason for this is that the overall agricultural development mode in the Yellow River Basin is relatively extensive, and the growth of agricultural output is achieved at the expense of the ecological environment. With the support of national policy to encourage agricultural development in the Yellow River Basin, agricultural production factors continue to increase, agricultural carbon emissions gradually increase, and agricultural carbon-output efficiency gradually decreases.

From the perspective of the distribution pattern, the height of the main peak of overall agricultural carbon-output efficiency in the Yellow River Basin experienced a change process of “down–up–down–down–up”, and the width of the main peak gradually narrowed, indicating that the overall agricultural carbon-output efficiency in the Yellow River Basin frequently fluctuated during the sample period, and the relative gap of agricultural carbon-output efficiency among different regions showed a gradually decreasing trend. The wave’s peak in the upstream and middle regions showed a trend of “up–down–up”, indicating that the differences in agricultural carbon-output efficiency in the region showed a trend of “narrowing–expanding–narrowing” and that the differences among cities narrowed continuously during the sample period. On the other hand, the difference between cities in the downstream area is gradually expanding, but the degree of the expansion of the difference is smaller than that of the difference between upstream and midstream cities. Therefore, under the joint action of the three regions in the upper, middle, and lower

reaches, the internal differences in the overall agricultural carbon-output efficiency in the Yellow River Basin decreased continuously during the sample period.

Regarding distribution and ductility, there are obvious right-trailing phenomena in the whole and upper and middle reaches of the Yellow River Basin, indicating that the development of carbon-output efficiency in agriculture in this region is unbalanced and there are certain spatial differences. A possible reason for this is that the agricultural carbon-output efficiency of Hohhot in the upper reaches of the Yellow River Basin and Taiyuan, Xi'an, Tianshui, and other central cities in the middle reaches of the Yellow River Basin is relatively high, resulting in a right-trailing density distribution curve and further widening the gap in agricultural carbon-output efficiency in the Yellow River Basin. However, there is no obvious trailing phenomenon in the downstream area, indicating that its spatial distribution is more balanced, and the differences in agricultural carbon-output efficiency in all regions are not large and at a high level.

In terms of the number of wave peaks, the distribution of agricultural carbon-output efficiency in the whole and upper and middle reaches of the Yellow River Basin has obvious polarization characteristics. The peaks of density distribution curves in both upstream and downstream regions show a trend of a gradual rise in fluctuations, and the polarization phenomenon increases with the passage of time. However, the peak of agricultural carbon-output efficiency in the Yellow River Basin is basically unchanged and relatively stable. The peak value in the downstream area showed a trend of a slow decline in the fluctuation, indicating that the polarization phenomenon in this area was gradually weakening.

#### 4.3. Dynamic Evolution of Carbon-Output Efficiency in Agriculture

In order to further explore the spatial dynamic evolution of agricultural carbon-output efficiency among cities in the Yellow River Basin, this study first calculated the global Moran's I index of agricultural carbon-output efficiency in the Yellow River Basin from 2000–2020, as shown in Table 4. From 2000 to 2007, Moran's I was significant and positive at the level of 10% or above, but after 2007, only a few years had a significant level, and in some years, Moran's I was less than 0 and not significant. Therefore, in general, there was a relatively obvious spatial positive correlation between agricultural carbon-output efficiency. In other words, local efficiency will be positively affected by the efficiency of neighboring regions, and it will also affect neighboring regions. Regarding geography, carbon-output efficiency mostly presents "high-high" and "low-low" clusters.

**Table 4.** Moran's I of carbon-output efficiency in agriculture in Yellow River Basin.

Year	2000	2001	2002	2003	2004
Moran's I	0.017 **	0.018 **	0.034 ***	0.021 **	0.028 ***
Year	2005	2006	2007	2008	2009
Moran's I	0.029 ***	0.021 **	0.013 *	−0.003	0.031 ***
Year	2010	2011	2012	2013	2014
Moran's I	0.004	−0.008	0.002	−0.005	0.013 *
Year	2015	2016	2017	2018	2019
Moran's I	0.022 **	0.004	−0.022	−0.021	−0.027
Year	2020				
Moran's I	0.013 *				

Note: \*\*\*, \*\*, and \* are significant at 1%, 5%, and 10% levels, respectively.

On this basis, in order to further analyze the influence of different state neighborhoods on urban carbon-output efficiency transfer, this paper constructs the traditional Markov probability transfer matrix and the spatial Markov probability transfer matrix with the introduction of a "space lag" condition and divides agricultural carbon-output efficiency into four states: low, medium and low, medium and high, and the upward transfer from a lower state to higher state. The transition from a higher state to a lower state is a downward transition, and the probability value of each state to another state in different neighborhoods

was calculated, as shown in Table 5, where T = 1 is the traditional Markov probability transition matrix, and T = 2–5 is the spatial Markov probability transition matrix.

**Table 5.** Markov chain transition probability matrix.

Time Span	Type	Low	Medium to Low	Medium to High	High	Sample Size
T = 1	Low	0.8306	0.1210	0.0376	0.0108	372
	Medium to low	0.1429	0.7037	0.1243	0.0291	378
	Medium to high	0.0349	0.1640	0.6801	0.1210	372
	High	0.0053	0.0185	0.1455	0.8307	378
T = 2	Low	0.9574	0.0000	0.0426	0.0000	47
	Medium to low	0.2857	0.3571	0.2857	0.0714	14
	Medium to high	0.0952	0.1905	0.5238	0.1905	21
	High	0.0000	0.0000	0.1304	0.8696	23
T = 3	Low	0.8286	0.1265	0.0367	0.0082	245
	Medium to low	0.1681	0.6858	0.1150	0.0310	226
	Medium to high	0.0216	0.1515	0.7100	0.1169	231
	High	0.0095	0.0142	0.1706	0.8057	211
T = 4	Low	0.7111	0.2444	0.0222	0.0222	45
	Medium to low	0.0756	0.7983	0.1092	0.0168	119
	Medium to high	0.0408	0.1837	0.6633	0.1122	98
	High	0.0000	0.0313	0.1042	0.8646	96
T = 5	Low	0.8286	0.0857	0.0571	0.0286	35
	Medium to low	0.1579	0.5789	0.2105	0.0526	19
	Medium to high	0.0909	0.1818	0.5909	0.1364	22
	High	0.0000	0.0208	0.1250	0.8542	48

According to the calculation result of T = 1, (1) the transfer probability values for the diagonal of the matrix are significantly greater than the non-diagonal probability values, indicating that the agricultural carbon-output efficiency of each city maintains the original state and has high stability at a higher probability. (2) On the diagonal, the values of elements in a low state and high state are 0.8306 and 0.8307, respectively, while those in a low state and high state are 0.7037 and 0.6801, respectively, indicating that the agricultural carbon-output efficiency in the Yellow River Basin has a typical “club convergence” phenomenon [49]; that is, the low state and high state are most likely to maintain their original state in the next stage. (3) The probability of transfer between different states is small, and the possibility of transfer between adjacent states is significantly greater than the possibility of “leap-over” transfer. Specifically, the maximum probability of an adjacent diagonal is 16.40%, and the minimum value is 12.10%, while the maximum probability of an adjacent diagonal is 3.76%, and the minimum value is 0.53%. This shows that the improvement in carbon-output efficiency is a continuous, slow process over a short time and cannot realize the rapid development of a jump. (4) The probability of downward transfer of each state is generally greater than that of upward transfer, indicating that there is a negative trend of downward transfer of agricultural carbon-output efficiency in the Yellow River Basin.

In addition, the traditional Markov probability transfer matrix was compared with the spatial Markov probability transfer matrix in the T = 2–5 state, and the change of the transition probability against different neighborhood backgrounds was explored. The results show that (1) when the efficiency of neighboring cities is higher than its own efficiency, the probability of upward transfer in this region is greater than that of downward transfer. Specifically,  $P_{23|4} = 0.1092 > P_{21|4} = 0.0756$ ,  $P_{23|5} = 0.2105 > P_{21|5} = 0.1579$ . The probability of upward transfer is only smaller than that of downward transfer in middle and high states. However, in general, the high-efficiency region still has a positive promoting effect on the neighboring region, driving the efficiency of the surrounding cities to improve. (2) When the efficiency of neighboring cities is lower than its own efficiency,

the probability of downward transfer in this region is greater than that of upward transfer. Specifically,  $P_{32|3} = 0.1515 > P_{34|3} = 0.1169$ . The probability of upward and downward transfer is the same for cities in the medium–low and medium–high states, but in general, the low-efficiency region still has a negative impact on its neighbors. (3) The higher the efficiency of adjacent regions, the more obvious the positive spillover effect on the region, while the lower the efficiency of adjacent regions, the more significant the negative effect. For example, when the efficiency is at a low level, when the neighborhood efficiency is low, medium–low, medium–high, and high, the upward transfer probability of the region is 0.0000, 0.1265, 0.2444, and 0.0857, respectively, showing an overall upward trend. However, when the efficiency of this region is at a high level, the probability of its downward transfer from a low to a high neighborhood state shows a downward trend. Based on the traditional Markov chain, this paper further explains the phenomenon of “club convergence” in terms of carbon-output efficiency development in the Yellow River Basin.

#### 4.4. Analysis of the Impact of Urbanization on Carbon-Output Efficiency of Agriculture

##### 4.4.1. Index Selection

There are many factors influencing agricultural carbon-output efficiency. According to the existing research conclusions, the urbanization level is one of the most important factors influencing agricultural carbon-output efficiency. Therefore, this paper takes agricultural carbon-output efficiency as the explained variable and the urbanization level as the core explanatory variable and uses panel data of prefecture-level cities in the Yellow River Basin from 2000 to 2020 to establish a Tobit model for analysis. In addition to the core explanatory variable of the urbanization level, based on the existing literature and considering the availability of variable data, this paper selects six influencing factors, including the level of energy-saving technology in agricultural production, the multiple cropping index, the agricultural industrial structure, the agricultural economic development level, the agricultural scale level, and government intervention as control variables for specific analysis, as shown in Table 6.

**Table 6.** Factors influencing agricultural carbon-output efficiency in the Yellow River Basin.

Variable	Description
Urbanization level	District resident population/District total population (%)
Technical level of energy saving in agricultural production	Total power of agricultural machinery/Total output value of agriculture, forestry, animal husbandry, and fishery (kW/CNY 100 million)
Cropping index	Grain sown area/Crop sown area (%)
Agricultural production structure	Output value of agriculture and animal husbandry/Total output value of agriculture, forestry, animal husbandry, and fishery (%)
The level of agricultural economic development	Total output value of agriculture, forestry, animal husbandry, and fishery/Employees of agriculture, forestry, animal husbandry, and fishery (CNY 10,000/person)
Scale level of agriculture	Area of farmland operated by rural households (mu/person)
Government intervention	Fiscal expenditure on agriculture/Total fiscal expenditure (%)

In addition, in order to eliminate the impact of heteroscedasticity, this paper performs logarithmic processing on the index data of all influencing factors, and the final model is set as follows:

$$y_{it} = \beta_0 + \beta_1 \ln urb_{it} + \beta_2 \ln etl_{it} + \beta_3 \ln mci_{it} + \beta_4 \ln nis_{it} + \beta_5 \ln eco_{it} + \beta_6 \ln sc_{it} + \beta_7 \ln gov_{it} + \varepsilon_{it}$$

$y_{it}$  is carbon-output efficiency in agriculture,  $i$  denotes the region,  $t$  stands for time,  $\beta_0$  is a constant term,  $urb$  is the level of urbanization, and  $etl$  is the technical level of

energy saving in agricultural production. *mci* is multiple species index, *is* is the agricultural industrial structure, *eco* is the level of agricultural economic development, *sc* is the scale level of agriculture, *gov* is for government intervention, and  $\varepsilon_{it}$  is the random disturbance term. The specific regression results of the Tobit model are shown in Table 7.

**Table 7.** Regression results of influencing factors of agricultural carbon-output efficiency in Yellow River Basin.

Variable/Region	Totality	Upstream	Midstream	Downstream
Urbanization level	0.08 *** (0.014)	0.13 *** (0.033)	0.105 *** (0.03)	0.035 ** (0.015)
Technical level of energy saving in agricultural production	−0.093 *** (0.014)	−0.207 *** (0.034)	−0.06 *** (0.023)	−0.076 *** (0.018)
Cropping index	0.07 *** (0.02)	0.225 *** (0.049)	0.108 (0.129)	0.011 (0.013)
Agricultural production structure	−0.067 *** (0.016)	−0.118 *** (0.033)	−0.063 (0.04)	−0.007 (0.016)
The level of agricultural economic development	0.058 *** (0.015)	0.07 ** (0.027)	0.113 *** (0.034)	−0.029 (0.019)
Scale level of agriculture	−0.021 * (0.012)	−0.064 ** (0.028)	0.014 (0.061)	−0.009 (0.009)
Government intervention	−0.024 *** (0.008)	−0.018 (0.014)	−0.045 *** (0.014)	0.006 (0.015)

Note: Values outside parentheses are coefficients, and values inside parentheses are standard errors. \*\*\*, \*\*, and \* are significant at 1%, 5%, and 10% levels, respectively.

#### 4.4.2. Aggregate Result Analysis

According to the analysis results in Table 7, the estimated coefficient of urbanization level on agricultural carbon-output efficiency is positive and significant at the 1% level, indicating that the improvement in the urbanization level has a significant promoting effect on agricultural carbon-output efficiency. China's Yellow River Basin has a large population and little land, and the urbanization process has driven a large number of rural people to shift to urban non-agricultural industries, realizing the effective allocation of agricultural production factors [50,51] and promoting the intensive and large-scale development of agricultural production modes. In addition, with the increase in the urbanization level, people's demand for greener and higher-quality agricultural products is increasing, which promotes the green transformation of agricultural production mode in various regions and positively promotes the carbon-output efficiency of agriculture, which is consistent with the above-mentioned theoretical analysis results.

In terms of control variables, (1) the estimated coefficient of the energy-saving technology level in agricultural production is significantly negative at the 1% level, indicating that it has a significant inhibitory effect on agricultural carbon-output efficiency. The possible reason for this is that the lower the level of energy-saving technology in agricultural production, the more energy needs to be consumed per unit of agricultural output value and the greater the input of agricultural materials such as fertilizers and pesticides, and thus the more carbon emissions will be generated [52]. This indicates that the overall level of agricultural production technology and management in the Yellow River Basin needs to be improved, and the traditional extensive agricultural production mode should be changed. This should be combined with the use of modern information technology to improve the efficiency of resource utilization [53] and promote agricultural carbon-output efficiency. (2) The regression coefficient of the multiple cropping index was positive and passed the significance test at the 1% level, indicating that the increase in the multiple cropping index significantly promoted the improvement in agricultural carbon-output efficiency. Due to the short production cycle of cash crops; the required consumption of fertilizer, pesticides, and other resources; and the high degree of intensification [54], compared with food crops, the resource utilization rate is generally lower [55], resulting in more carbon emissions. Therefore, with the increase in the multiple cropping index, the sowing area of cash crops is relatively reduced, the degree of environmental pollution is

reduced, and the carbon-output efficiency of agriculture is promoted. (3) The regression coefficient of agricultural industrial structure is negative and passes the significance test at the 1% level, which indicates that the increase in the proportion of agricultural output value significantly restrains the improvement in agricultural carbon-output efficiency. The main reason for this result is that the carbon emissions created by agriculture and animal husbandry production account for a large proportion, which will have a greater negative impact on the environment and, although the economic benefits are high, they still cannot make up for the unexpected output. Therefore, the Yellow River Basin should actively optimize its own agricultural industrial structure, promote the high-grade development of the agricultural industrial structure, and continuously improve the output and quality of agricultural products while reducing the environmental pollution in the production process so as to comprehensively promote the improvement in agricultural carbon-output efficiency. (4) The regression coefficient of the agricultural economic development level on agricultural carbon-output efficiency is positive and passes the significance test at the 1% level, which indicates that the improvement in the agricultural economic development level has a strong promoting effect on agricultural carbon-output efficiency. The possible reason for this is that the per capita gross agricultural output value is higher. On the one hand, this means that farmers have a higher living standard and have the economic ability to improve agricultural production methods, use more advanced and green agricultural machinery and equipment, and improve agricultural production efficiency. On the other hand, the increase in farmers' income can also promote their awareness of green environmental protection, increase the production and consumption of high-quality and pollution-free agricultural products, and play an indirect role in promoting the improvement in carbon-output efficiency in agriculture. (5) The regression coefficient of the agricultural scale level is significantly negative at the level of 10%, and its significance is lower than all other variables, indicating that the improvement in agricultural scale level inhibits the improvement in agricultural carbon-output efficiency to a certain extent. The higher the scale of agriculture, the more farmland per capita management area of rural residents; on the one hand, this is conducive to large-scale agricultural production and improved labor productivity. On the other hand, large-scale operation is not conducive to the fine management of agricultural production [56]. According to the regression results, the per capita cultivated land area in the Yellow River Basin is large overall, and the continuous improvement in the agricultural scale level is not conducive to the improvement in agricultural carbon-output efficiency. (6) The regression coefficient of government intervention is negative and passes the significance test at the 1% level, which has an inhibitory effect on agricultural carbon-output efficiency. The possible reasons for this are that, on the one hand, the increase in fiscal expenditure on agricultural support can stimulate the production enthusiasm of farmers and encourage them to expand the scale of operation and invest more in agricultural production factors to increase output, resulting in more resource waste and agricultural non-point source pollution [57]. On the other hand, the structural allocation of financial support for agriculture is not reasonable, the policy of benefiting farmers tends to alleviate poverty, and the protection of the ecological environment is not paid enough attention to [58], which is not conducive to carbon-output efficiency of agriculture.

#### 4.4.3. Analysis of Results by Region

In order to further analyze the impact of different regional urbanization levels on agricultural carbon-output efficiency, this paper divides the Yellow River Basin into three regions, namely the upper, middle, and lower reaches, and conducts regression analysis. The results are shown in Table 7. In terms of core variables, the regression coefficients of urbanization level for the upper, middle, and lower reaches are all positive, and all pass the significance test at 5% or above, indicating that urbanization level has a significant positive effect on agricultural carbon-output efficiency in all regions of the Yellow River Basin. The main reason for this is that with the continuous improvement in the urbanization level of the Yellow River Basin, on the one hand, farmers' awareness of energy conservation and

environmental protection has been enhanced, and they have reduced the use of pesticides in the agricultural production process and started to use new green energy-saving machinery and equipment, effectively reducing carbon emissions. On the other hand, the government will provide more funds to improve the rural ecological environment, which will effectively improve the carbon-output efficiency of agriculture.

In terms of control variables, (1) the regression coefficients of the energy-saving technology level in agricultural production are all negative and pass the significance test at the 1% level, indicating that the energy-saving technology level in agricultural production in the upper, middle, and lower reaches has a significant inhibition effect on agricultural carbon-output efficiency. All regions in the Yellow River Basin should pay attention to improving the level of energy-saving technology in agricultural production and reducing the energy consumption required in the production process. (2) The regression coefficient of the multiple cropping index in the upstream region was positive and passed the significance test at the 1% level, which had a significant promoting effect. However, the middle and downstream areas did not pass the significance test, indicating that the positive promoting effect of the multiple cropping index on agricultural carbon-output efficiency was not significant. The possible reason for this is that Henan Province, located in the middle and lower reaches of the Yellow River Basin, is China's main grain-producing area with a large population, a high degree of agricultural intensification and multiple cropping index, and limited space for improving agricultural carbon-output efficiency. (3) The regression coefficients of the agricultural industrial structure in all regions were negative, but only the upstream region passed the significance test at the 1% level. The possible reason for this is that Inner Mongolia is a large province of animal husbandry in China, and the output value of agriculture and animal husbandry accounts for a relatively large proportion, and animal husbandry produces significant carbon emissions, which significantly inhibits the improvement in agricultural carbon-output efficiency. (4) The regression coefficients of the agricultural economic development level in the upper and middle reaches are both positive and pass the significance test at 5% and 1%, respectively. In the downstream area, the regression coefficient of agricultural economic development level is negative, but the result is not significant. The development level of agricultural economy in the upper and middle reaches is relatively low, and the level of agricultural infrastructure construction and production technology has large room for improvement. Therefore, the development of the agricultural economy helps to promote the progress of advanced green agricultural technology and lays a good economic and technical foundation for improving carbon-output efficiency in agriculture. However, Shandong and Henan Provinces, located in the lower reaches of the Yellow River Basin, have a higher level of agricultural development, and the improvement in the agricultural economic level may prompt farmers to invest more in production factors that cause redundancy and generate more carbon emissions, which will not help improve the carbon-output efficiency of agriculture. (5) The regression coefficients of the agricultural scale level in both upstream and downstream regions are negative, but only the upstream region passes the significance test at a 1% level, and the agricultural scale level in the middle reaches has a positive promoting effect on agricultural carbon-output efficiency, but the effect is not significant. This indicates that the per capita cultivated land area in the middle reaches is small and has not fully realized economies of scale, while the per capita cultivated land area in the upper reaches is large. If the agricultural scale level continues to be increased, the environmental pressure will be increased, which is not conducive to improving the carbon-output efficiency of agriculture. Therefore, all regions should combine their own conditions to maintain the scale level of agriculture in a moderate state, improve production efficiency, and reduce carbon emissions. (6) The regression coefficient of government intervention in the middle reaches is negative and passes the significance test at the 1% level, while the regression results upstream and downstream are not significant, among which the regression coefficient downstream is positive. The possible reason for this is that the financial support funds for agriculture in the middle reaches of the region have not reached a reasonable allocation; the subsidies

are mainly concentrated on fertilizer, pesticides, and other aspects; and the improvement of the ecological environment does not receive enough attention, which has a significant negative impact on the carbon-output efficiency of agriculture.

#### 4.4.4. Robustness Test

In order to test the accuracy of the empirical results of the Tobit model, this study divided the research samples into two parts from 2000 to 2010 and 2011 to 2020 and tested the empirical results of the Yellow River Basin as a whole and the upper, middle, and lower reaches, respectively, as shown in Tables 8 and 9. Regarding the overall test results of the Yellow River Basin, the sub-sample regression results of the agricultural energy-saving technology level and agricultural economic development level are consistent with the full sample regression results. The sample regression results of agricultural industrial structure from 2000–2010 are insignificant, but the regression coefficient is still negative. The sample regression results of urbanization level, multiple cropping index, agricultural scale level, and government intervention from 2011–2020 are insignificant, but the regression coefficients are consistent with the full sample regression results. Regarding the test results of the upper, middle, and lower reaches of the Yellow River Basin, the significance and regression coefficient of some variables have changed due to the large number of variables involved, but the conclusions reached are basically consistent with the above, and the regression results can be considered robust in general.

**Table 8.** Test results of 2000–2010.

Variable/Region	Total	Upstream	Midstream	Downstream
Urbanization level	0.047 ** (0.019)	0.103 *** (0.038)	0.017 (0.043)	0.043 ** (0.021)
Technical level of energy saving in agricultural production	−0.106 *** (0.026)	−0.035 (0.061)	−0.324 *** (0.055)	−0.04 (0.029)
Cropping index	0.132 *** (0.045)	0.102 (0.08)	0.3 * (0.18)	0.041 (0.039)
Agricultural production structure	−0.033 (0.024)	−0.117 ** (0.046)	−0.021 (0.053)	0.048 * (0.025)
The level of agricultural economic development	0.082 *** (0.023)	0.163 *** (0.041)	0.069 (0.057)	0.007 (0.028)
Scale level of agriculture	−0.033 *** (0.012)	−0.063 ** (0.027)	−0.114 (0.085)	−0.021 ** (0.008)
Government intervention	−0.031 *** (0.009)	−0.019 (0.016)	−0.045 *** (0.016)	0.008 (0.023)

Note: \*\*\*, \*\*, and \* are significant at 1%, 5%, and 10% levels, respectively.

**Table 9.** Test results of 2010–2020.

Variable/Region	Total	Upstream	Midstream	Downstream
Urbanization level	0.011 (0.026)	−0.026 (0.052)	−0.041 (0.048)	−0.008 (0.027)
Technical level of energy saving in agricultural production	−0.056 *** (0.018)	−0.295 *** (0.044)	0.037 (0.024)	0.019 (0.031)
Cropping index	0.029 (0.02)	0.156 *** (0.057)	−0.33 (0.214)	−0.002 (0.012)
Agricultural production structure	−0.053 * (0.028)	−0.154 * (0.08)	0.024 (0.064)	−0.055 *** (0.019)
The level of agricultural economic development	0.049 ** (0.024)	0.096 ** (0.047)	0.1 ** (0.049)	0.055 * (0.033)
Scale level of agriculture	0.048 (0.035)	−0.019 (0.055)	0.13 * (0.077)	0.022 (0.044)
Government intervention	−0.008 (0.019)	0.032 (0.038)	0.007 (0.032)	−0.014 (0.022)

Note: \*\*\*, \*\*, and \* are significant at 1%, 5%, and 10% levels, respectively.

## 5. Discussion

Based on the panel data of 75 cities in the Yellow River Basin from 2000 to 2020, this paper used the super-DEA model for the first time to measure the carbon-output efficiency of agriculture. Then, the theoretical logic of urbanization's impact on the carbon-output efficiency of agriculture is established. The three-dimensional kernel density model and Markov chain model were used to measure the dynamic evolution and regional differences of agricultural carbon-output efficiency under spatio-temporal heterogeneity. The panel Tobit model analyzed the relationship between urbanization and low carbon efficiency in agriculture. In terms of agricultural carbon-output efficiency, this paper comprehensively considers the coordinated and overall development of resource conservation, environmental friendliness, and agricultural economic growth, as well as agricultural carbon emissions and carbon sinks, among which agricultural carbon emissions include carbon emissions from agricultural materials and carbon emissions from animal husbandry. In calculating carbon emissions from animal husbandry, pigs, sheep, cattle, poultry, and rabbits were selected. A total of 18 crops, such as wheat, corn, rice, soybean, sweet potato, cotton, and oil, were selected for carbon sink calculation. Yuan, P. et al. measured the agro-ecological efficiency of 59 prefecture-level cities in the Yellow River Basin from 2000 to 2018 and concluded that the average efficiency showed a fluctuating upward trend, which was slightly different from the study in this paper [59]. The efficiency value obtained in this paper showed a slow downward trend in general, and the efficiency value in the downstream region was higher than that in the middle reaches, and the upstream region had the lowest. There are few existing studies on the impact of urbanization on agricultural carbon-output efficiency, and the research conclusions are quite different. In this paper, it is concluded that urbanization level has a significant positive impact on agricultural carbon-output efficiency in the upper, middle, and lower reaches of the Yellow River Basin. This may be due to the different measurement and analysis results obtained by scholars using different indicator systems, as well as the differences between the study area and the measurement, making the results incomparable. Therefore, it is urgent to study this area. The research area of this paper is still relatively macro, so in the future, more detailed and specific county-level data will be used for research, so as to more pertinently reflect the spatio-temporal change characteristics of local agricultural carbon-output efficiency and propose corresponding countermeasures and suggestions. In this paper, only a single urbanized population is used to represent the level of urbanization. In the context of accelerating new-type urbanization and promoting high-quality agricultural development in China, especially in the Yellow River basin, a more diversified and comprehensive indicator system needs to be established in the future to make a more accurate evaluation of the level of urbanization. In addition, due to the availability and operability of data, this paper only includes some indicators to evaluate agricultural carbon-output efficiency, and with the continuous enrichment and change of the connotation of agricultural carbon-output efficiency, its index system needs to be further improved and amended in the future.

## 6. Conclusions

In this paper, the super-DEA model is used to measure the agricultural carbon-output efficiency of 75 cities in the Yellow River Basin from 2000 to 2020, and the nuclear density estimation method and Markov chain model are used to conduct an in-depth analysis of the spatio-temporal evolution of agricultural carbon-output efficiency. On this basis, the panel Tobit model explores the relationship between urbanization and agricultural carbon-output efficiency. Finally, the following conclusions and relevant policy recommendations are put forward as follows.

First, the overall level of agricultural carbon-output efficiency in the Yellow River Basin is low and has not reached the effective state, showing a slow downward trend. From a regional perspective, the level of agricultural carbon-output efficiency in the lower reaches > middle reaches > upper reaches showed a downward trend from 2000 to 2015, and gradually rebounded after 2016. The overall agricultural carbon-output efficiency in the Yellow River

Basin is relatively low and has great potential for improvement. Therefore, we should attach importance to the application of science and technology in agriculture, promote the development of green agricultural modernization, change the previous extensive agricultural production mode, use organic fertilizers and low-carbon agricultural machinery and equipment, and use green high-tech innovations to improve resource utilization efficiency and reduce environmental pollution.

Second, the internal differences of the overall agricultural carbon-output efficiency in the Yellow River Basin decreased continuously during the sample period, and there was a significant spatial positive correlation. According to the traditional Markov chain, agricultural carbon-output efficiency has a negative trend of transferring to a low level on the whole and tends to maintain the original state, and it is difficult to realize the leap-forward transfer between states. According to the spatial Markov chain, there is an obvious spatial spillover effect and “club convergence” phenomenon of agricultural carbon-output efficiency, and the high-efficiency area has a positive driving effect on the neighborhood area, while the low-efficiency area has a negative impact on the neighborhood area. Therefore, regional cooperation and exchanges should be strengthened. Cities with high agricultural carbon-output efficiency should play a positive driving role, share successful experiences with neighboring cities with low efficiency, share advanced low-carbon agricultural technologies and scientific research results, and improve agricultural production efficiency. Cities with low agricultural carbon efficiency should take the initiative to learn from neighboring cities with high efficiency, combine their own environment and specific development conditions, improve agricultural production and management methods, enhance agricultural carbon-output efficiency, and narrow the gap between them and neighboring cities. Specifically, long-term comprehensive real-time monitoring can be carried out through the establishment of a carbon emission pollution linkage early warning mechanism in neighboring regions so as to strengthen exchanges and cooperation between regions to improve agricultural carbon-output efficiency [60].

Third, in the Yellow River Basin as a whole, the urbanization level, multiple cropping index, and agricultural economic development level all have significant positive impacts on agricultural carbon-output efficiency, while the level of energy-saving technology in agricultural production, the agricultural industrial structure, the agricultural scale level, and government intervention have significant inhibitory effects on agricultural carbon-output efficiency. The influencing factors and directions of agricultural carbon-output efficiency in the upper, middle, and lower reaches differ from those in the Yellow River Basin. More attention should be paid to the significant factors influencing agricultural carbon-output efficiency. This can promote the urbanization rate and the level of agricultural economic development, improve the crop planting structure, give play to the important role of the government in improving the agricultural ecological environment, rationally allocate financial funds to support agriculture, increase investment in agricultural ecological protection, encourage farmers to cultivate low-carbon awareness, and improve the level of energy saving technology in agricultural production. Moreover, improving the relevant legal system construction and institutional guarantee will promote agricultural carbon-output efficiency.

**Author Contributions:** Software, C.W.; Formal analysis, C.W.; Writing—original draft, X.S.; Supervision, W.L. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by the Social Science Major Project of Shaanxi Province (2021ND0378), China Postdoctoral Science Foundation (2021M692655), and Research Funds of Northwest A&F University (Z1090220194). Social Science Foundation of Ministry of Education (21YJC630086).

**Institutional Review Board Statement:** Not applicable.

**Data Availability Statement:** The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

**Acknowledgments:** We also appreciate the constructive suggestions and comments on the manuscript from the reviewer(s) and editor(s).

**Conflicts of Interest:** The authors declare no conflicts of interest.

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