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Will Urbanization Affect the Low-Carbon Efficiency of Agriculture?—Based on Empirical Evidence from the Yellow River Basin

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Abstract: The improvement of agricultural low-carbon efficiency is an important path to promote the realization of the "double carbon" goal in the Yellow River Basin. In the context of rapid urbanization development, it is of great significance to explore whether the promotion of urbanization will affect the agricultural low-carbon efficiency. Based on the panel data of 75 cities in the Yellow River Basin from 2000 to 2020, this paper uses super-DEA model, three-dimensional kernel density model and Markov chain model to measure and analyze the spatio-temporal evolution of agricultural low-carbon efficiency in the Yellow River Basin, on this basis, the panel Tobit model is used to analyze the relationship between urbanization and low-carbon efficiency in agriculture. The results show that: (1) The level of agricultural low-carbon efficiency in the Yellow River Basin is low and has not reached the effective state, showing a slow downward trend in general, among which, the agricultural low-carbon efficiency in the lower reaches is higher than that in the middle reaches, and the upper reaches is the lowest. (2) The agricultural low-carbon efficiency in the Yellow River Basin has a negative trend of transferring to the low level on the whole, and tends to maintain the original state level, and it is difficult to realize the leapfrog transfer between states. Agricultural low-carbon efficiency has obvious spatial spillover effect and "club convergence" phenomenon, high efficiency area has a positive driving effect on the neighborhood area, while low efficiency area has a negative impact on the neighborhood area. (3) The level of urbanization has a significant positive impact on the low-carbon 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. Finally, based on the above research conclusions, relevant policy recommendations were put forward, in order to provide references for promoting the improvement of low-carbon agricultural efficiency and promoting high-quality agricultural development in the Yellow River Basin.

Keywords: Yellow River Basin; low-carbon efficiency in agriculture; spatial-temporal heterogeneity; urbanization; Markov chain

1. Introduction

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 achieve high-quality development. According to statistics, agricultural carbon emissions account for about 25% of the total greenhouse gas emissions [1], which is one of the important components of China's carbon emissions, and the improvement of agricultural low-carbon efficiency is an important way to achieve the "double carbon" goal [2].The Yellow River Basin is an important economic zone and agricultural production base in China, as well as an important ecological barrier in China [3]. 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 [4].According to statistics, the total agricultural output value of the nine provinces in the Yellow River Basin is about 2,633.46 billion yuan in 2020, 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[5]. 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 [6].In addition, ecological problems such as vegetation destruction, soil erosion and soil degradation are also very serious in the Yellow River Basin [7]. Since the reform and opening up, China's urbanization level has been continuously improving. According to the data of the National Bureau of Statistics, China's urbanization level has reached 63.89% in 2020, an increase of nearly 46% over 1978.The rapid increase of urbanization level can promote the transfer of agricultural surplus labor, improve the efficiency of agricultural resource allocation, and increase the total demand for agricultural products, but it may also bring negative impacts such as agricultural non-point source pollution, ecological environment degradation and agricultural land consumption [8].Therefore, in the context of the accelerating process of high-quality development and urbanization in the Yellow River Basin, it is of great significance to study the spatio-temporal evolution characteristics of agricultural low-carbon efficiency in the Yellow River Basin and whether the promotion of urbanization will affect the improvement of agricultural low-carbon efficiency, which will improve the development level of agricultural economy and promote ecological environmental protection in the Yellow River Basin.

Agricultural low-carbon 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, production mode and management measures to reduce carbon emissions, reduce environmental pollution, and promote the stable and healthy development of ecological environment. The improvement of agricultural low-carbon efficiency is of great significance to realize the coordinated "win-win" and sustainable development of agricultural economic and ecological benefits.By combing relevant literature, it is found that the existing studies on agricultural low-carbon efficiency mainly focus on the following three aspects: First, the accounting of agricultural low-carbon efficiency. Scholars' measurement methods for agricultural low-carbon 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 total output value of agriculture, forestry, animal husbandry and fishery and carbon emissions as output indicators [9].For example, Yasmeen, R. et al. calculated the agricultural production efficiency of major (17) agricultural producing countries from 1996 to 2018 by using data envelopment analysis to explore the relationship between agricultural production and carbon emissions, and the results showed that the United States, Russia, South Korea, Japan and Italy were countries with efficient agricultural production [10].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 [11].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 agricultural net carbon sink in 30 provinces (municipalities and districts) in China from 2005 to 2017, and found that the efficiency level of agricultural net carbon sink in China was generally low and the spatial difference was obvious [12].In addition to producing carbon emissions, agricultural ecosystems also have a powerful carbon sink function. Therefore, it will be more scientific and comprehensive to take agricultural carbon sink as an output index in the construction of agricultural low-carbon efficiency index system.Second, the spatial-temporal heterogeneity of low-carbon 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

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decreased successively [13].Tian,Y. et al. conducted an effective measurement of agricultural carbon emission efficiency in Hubei province and analyzed its temporal and spatial differences [14]. They found that agricultural carbon efficiency was in an overall growth trend since 2011, but regional differences were obvious. 15 cities (prefectures) in Hubei Province could be divided into three different groups: high growth, low growth and decline.Third, the impact of urbanization on the low-carbon efficiency of agriculture. Urbanization is one of the important factors affecting agricultural low-carbon efficiency, but there are big differences in the research conclusions of domestic and foreign scholars on the relationship between urbanization and agricultural low-carbon efficiency, and the results are affected by factors such as research scale, research samples and the construction of input-output index system [15].The first view holds that urbanization has a positive promoting effect on the low-carbon efficiency of agriculture. For example, Tian,Y.et al. believe that the increase of urbanization level means the increase of construction land, which leads to the reduction of agricultural land scale, thus affecting the planting industry and promoting the improvement of agricultural carbon emission efficiency [16].The second view is that urbanization has a negative inhibition effect on low-carbon agricultural 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 a large number of ineffective supply of agricultural products, resulting in more carbon emissions [17]. Therefore, the promotion of urbanization is not conducive to the improvement of agricultural carbon efficiency.The third view holds that there is a nonlinear relationship between urbanization and agricultural low-carbon efficiency, which is mainly divided into "positive U" and "inverted U". For example, Zheng,H.et al. believe that urbanization level has a nonlinear influence on ecological efficiency in eastern China, which is first negative and backward positive [18]. At present, there are few research results on the relationship between urbanization and agricultural low-carbon efficiency, and the academic community has not reached a consensus on its impact mechanism, so it is still necessary to further explore.

Through the review of existing relevant studies, it can be seen that scholars have conducted many beneficial studies on the measurement of agricultural low-carbon efficiency, spatio-temporal heterogeneity, and the impact of urbanization on agricultural low-carbon efficiency, which is of reference significance to this paper. However, there are still the following deficiencies: First, in terms of the measurement of agricultural low-carbon 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 emission and carbon sink, crops will also absorb a large amount of carbon dioxide through photosynthesis during their growth process, this paper adds the agricultural carbon sink index as the expected output on this basis. Make the measurement of low-carbon efficiency of agriculture more accurate; Second, most of the current studies on agricultural low-carbon efficiency focus on the national and provincial (city) level, 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 on agricultural low-carbon efficiency around the Yellow River Basin. Third, existing studies mainly focus on the impact of urbanization on carbon emissions, and few studies on the impact of urbanization on low-carbon agricultural efficiency. In addition, there are positive promoting effects, negative inhibiting effects and nonlinear effects in the research conclusions, which are quite different and need to be further explored.

Based on this, this paper uses the panel data of 75 cities in the Yellow River Basin from 2000 to 2020, uses super-DEA model to measure agricultural low-carbon efficiency, and establishes three-dimensional kernel density model and Markov chain model to analyze the spatio-temporal evolution characteristics of agricultural low-carbon efficiency in the Yellow River Basin. The panel Tobit model was used to explore the relationship between urbanization and agricultural low-carbon efficiency, in order to provide references for promoting the improvement of agricultural low-carbon efficiency and promoting high-quality agricultural development in the Yellow River Basin.

2. Influence mechanism of urbanization on low-carbon efficiency of agriculture

Urbanization refers to the process of 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 influence mechanism of urbanization level on agricultural low-carbon efficiency can be mainly divided into positive and negative aspects:

First, urbanization has a significant role in promoting the low-carbon efficiency of agriculture. On the one hand, the improvement of urbanization level drives the increase of the proportion of secondary and tertiary industries, thus promoting the transfer of rural surplus labor force, improving the efficiency of agricultural land use and labor marginal output [19], promoting the specialization of agricultural development and the moderation of production scale [20], and thus improving the low-carbon efficiency of agriculture.On the other hand, the improvement of urbanization level will lead to the gathering of a large number of high-quality labor population in cities and towns, which will transform the original agricultural producers into agricultural consumers, greatly increase the demand for high-quality life quality and agricultural products, and further promote the transformation of agricultural production mode from traditional extensive production to new green production [21].Promote low-carbon efficiency in agriculture.In addition, the rapid development of urbanization will also lead to the continuous reduction of agricultural arable land, but in the long run, the gradual return of urban capital to the countryside will also be conducive to agricultural intensive and large-scale production and reduce production costs. At the same time, a large number of urban capital flows into rural areas, bringing advanced production technology and management concepts to rural areas, promoting the development of agricultural technology and agricultural machinery, improving production conditions, thereby reducing resource waste, promoting the improvement of rural economic and ecological benefits, and contributing to the improvement of low-carbon agricultural efficiency [22].

Second, urbanization has a significant inhibitory effect on the low-carbon efficiency of agriculture. On the one hand, the improvement of urbanization level makes a large number of 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 relatively high quality. Therefore, rural areas are faced with the situation of labor force aging, feminization and part-time employment [23]. Farmers are encouraged to increase the intensity of use of agricultural machinery and the use of agricultural materials such as pesticides and fertilizers to avoid agricultural production reduction [24], resulting in increased carbon emissions. In addition, a large amount of land may be abandoned or divided into urban construction land, thus inhibiting the improvement of low-carbon efficiency of agriculture.On the other hand, the non-agricultural employment of a large number of rural people has increased the per capita income, and their living and consumption patterns are also changing. The expansion of urban population increases the demand for high-carbon agricultural products such as meat, eggs and milk, resulting in a large amount of agricultural carbon emissions, which has a negative impact on the low-carbon efficiency of agriculture.

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

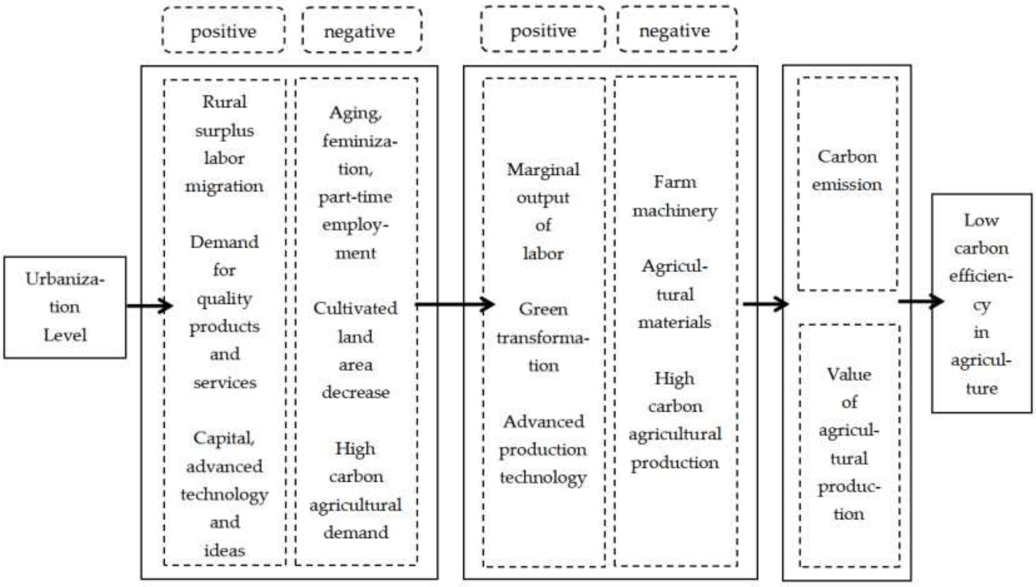

Figure 1. Influence mechanism of urbanization and low-carbon efficiency of agriculture.

3. Research method

3.1. The super-DEA model

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 performance under given input conditions.But DEA model also has some defects, the traditional CCR and BCC models usually can only distinguish between "effective" and "invalid" production units, and can not further sort the calculated effective decision units.In order to make up for this defect, super-DEA model introduces the concept of "Super efficiency", which can further compare and sort the efficient DMU, that is, different efficiency levels can be distinguished among the efficient DMU. The basic mathematical expression of Super-DEA model is as follows:

Let the number of cities in the Yellow River Basin be n, every city has m types of "inputs", where θ_0^{super} is the efficiency index; λ_j is the input and output coefficient; x_{ij} is the ith input index of the jth evaluation object; y_{ij} is the ith output index of the jth evaluation object; S_i^- is the input relaxation variable; S_i^+ is the output relaxation variable. The super efficiency model for each region is set as follows:

$$min\,\theta_0^{super}$$

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

If $\theta_0^{super} \geq 1$, it shows that the city's input-output reaches the optimal efficiency; If $\theta_0^{super} < 1$, it indicates that the input-output of the city has not reached the optimal efficiency, and it is necessary to reduce the input or increase the output to achieve DEA effectiveness [25].

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3.2. Kernel density estimation

In order to clarify the distribution dynamics and evolution law of agricultural low-carbon 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 low-carbon 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 [26]. 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 [27].

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

$$\widehat{f_h}(x) = \frac{1}{nh}\sum_{i=1}^{n} K(\frac{x_i - \bar{x}}{h})$$

$\widehat{f_h}(x)$ is the density function; $K(\frac{x-x_i}{h})$ is the kernel function,h is bandwidth, n is the number of observations (i.e. the total number of regions), i stands for regions, x_i represents independent, identically distributed observations, $\bar{x}$ is the mean.

3.3. Spatial Markov chains

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, but not to the past state, that is, the event has "no after-effect", also known as "Markov" [28]. Agricultural low-carbon efficiency has a Markov property, so this paper adopts Markov chain method to analyze the changing trend and temporal and spatial characteristics of agricultural low-carbon efficiency in the Yellow River Basin.The Markov chain discretized the agricultural low-carbon efficiency data into k state types, calculated the probability distribution of k types, and approximated the evolution of agricultural low-carbon efficiency as a Markov process. In this paper, the agricultural low-carbon efficiency values in the Yellow River Basin were divided into four types according to the quartile: k=1 means low agricultural low-carbon efficiency (less than 0.25), k=2 means medium low agricultural low-carbon efficiency (between 0.25 and 0.5), k=3 means medium high agricultural low-carbon efficiency (between 0.5 and 0.75), k=4 means high agricultural low-carbon efficiency (greater than 0.75). A Markov probability transfer matrix with k=4 is constructed:

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

t\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 low-carbon 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 spatial spillover effect caused by geographical proximity on the state transition of low-carbon efficiency in agriculture. Therefore, spatial Markov chains introduce the concept of "spatial lag" into the transfer probability matrix, and decompose the traditional Markov transfer probability matrix into k×k conditional transfer probability matrix:

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

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

$P_{ki|j}$ represents the probability that the region will shift from 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, 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

In this paper, Tobit model was used to analyze the main influencing factors of agricultural low-carbon efficiency in the Yellow River Basin. When super-DEA model is used to measure agricultural low-carbon efficiency, the value range of efficiency is limited, that is, its value should be greater than 0. For restricted dependent variables, Tobit model is generally used for regression analysis, so as to analyze its main influencing factors more scientifically. The specific form of 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 low-carbon efficiency, x_{it} represents explanatory variable, β_0 represents intercept term, β_t represents estimated coefficient of explanatory variable, $i = 1,2,\ldots,75$, $t = 1,2,\ldots,n$,n is the number of independent variables, μ_i is the individual effect, and ε_{it} is the random error term [29].

3.5. data declaration

Panel data of 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 are all from China Statistical Yearbook and provincial and municipal statistical Yearbook (2000-2020), and the missing data in some years are supplemented by 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 all derived from IPCC [30], Oak Ridge National Laboratory of the United States, IREEA (Institute of Agricultural Resources and Ecological Environment, Nanjing Agricultural University) and other existing literatures [31,32]. The carbon absorption rate and economic coefficient of various crops refer to relevant literatures such as Wang,X.L. [33] and Han,Z.Y.[34]. Among them, the annual breeding amount of cattle, horses, sheep and other livestock in the carbon emission of animal husbandry is respectively 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, and 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 and Analysis

4.1. Measuring low-carbon efficiency in agriculture

In this paper, the super-DEA model is used to measure the agricultural low-carbon efficiency in the Yellow River Basin. The required indexes include 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 [35]. With reference to the existing literature, this paper takes the input of various production factors, land and labor as input indicators. Respectively, 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 (ten thousand yuan) and agricultural carbon sink (tons) were used as expected output indicators.

As can be seen from Table 3, the overall agricultural low-carbon 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 slow decline trend. 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. While increasing the use of various production factors to increase the expected output, it also brings about the increase of non-expected output, causing damage to the ecological environment.The possible reason 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, and 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 concept, which gradually enhanced farmers' awareness of ecological protection, and the promotion of agricultural science and technology, so that the extensive agricultural production mode 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 the undesirable output has declined.In addition, under the influence of a series of policies such as the reform of traditional agricultural tax, the rapid development of planting industry was promoted. As an

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important agricultural production base in China, the scale production of wheat, cotton and other crops in the Yellow River Basin increased significantly during this period, resulting in a rapid increase in agricultural carbon sink of expected output and a significantly higher growth rate than agricultural carbon emission.

From the agricultural low-carbon 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. Before 2010, the agricultural low-carbon efficiency has reached an effective state in most years, but after that, the efficiency has a slow decline trend and is less than 1, from 1.023 in 2000 to 0.951 in 2020, a decrease of about 7.09%. Secondly, the agricultural low-carbon 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. During 2000-2015, the efficiency declined slowly in a fluctuation, and after 2016, the agricultural low-carbon efficiency began to rise steadily, but it was still less than 1.The upstream region has the lowest efficiency, all of which are less than 1 during the sample period. Similar to the middle region, its agricultural low-carbon efficiency continued to decline during 2000-2015, and improved after 2016, with a decrease of about 8.78% during the sample period. The possible reason is that the economic and social conditions of the downstream areas are relatively superior, with advanced agricultural science and technology, higher crop output, less energy consumption, so the low-carbon efficiency of agriculture is relatively higher than that of 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 emission is at a high level, which hinders the improvement of low-carbon agricultural efficiency. Moreover, due to climate change, overgrazing and other reasons, the grassland in Inner Mongolia is gradually degraded and the ecological environment is seriously damaged. The low-carbon efficiency of agriculture is the lowest in the Yellow River Basin.

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

time/region	upstream	midstream	downstream	totality
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

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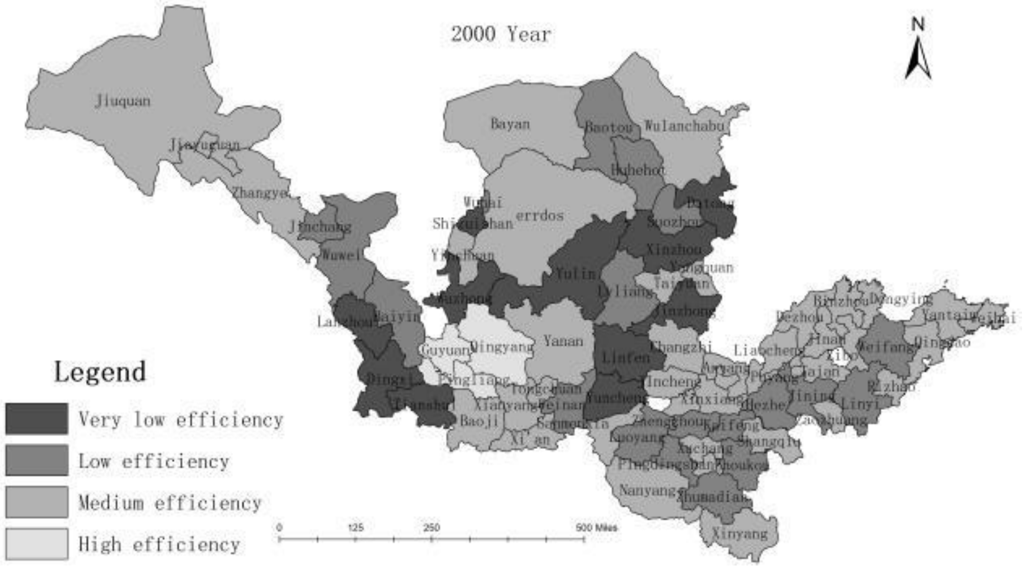
The agricultural low-carbon efficiency values of the Yellow River Basin in 2000, 2010 and 2020 were selected respectively, and the ArcGIS10.8 software was used to delineate the spatial distribution map of agricultural low-carbon efficiency in the Yellow River Basin, and the efficiency values were divided into four levels: low efficiency, low efficiency, medium efficiency and high efficiency, as shown in Figure 2.

From the changes from 2000 to 2020 in Figure 2, it can be seen that the agricultural low-carbon efficiency in the Yellow River Basin has always been relatively low, and the improvement rate is not large, and only a few cities have reached the high efficiency level. In 2000, Guyuan City, Qingyang City and Pingliang City belong to 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 the medium efficiency to the high efficiency area, and the agricultural low-carbon efficiency has been improved.

From the perspective of spatial distribution, the agricultural low-carbon 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, and the agricultural low-carbon efficiency in the upper reaches is low, and the improvement potential is huge. Specifically, in 2000, Datong City, Jinzhong City, Yulin City, Lanzhou City and other regions at a low level of efficiency, Luoyang city, Zhumadian City, Wuwei City, Baotou City and other regions at a low level of efficiency, are mainly located in Shanxi, Shaanxi and Henan three large agricultural provinces. In 2010, except for Jiayuguan City, Gansu Province was in a state of low efficiency and 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, and the former low efficiency and low efficiency areas were connected, and the spatial correlation was further enhanced.



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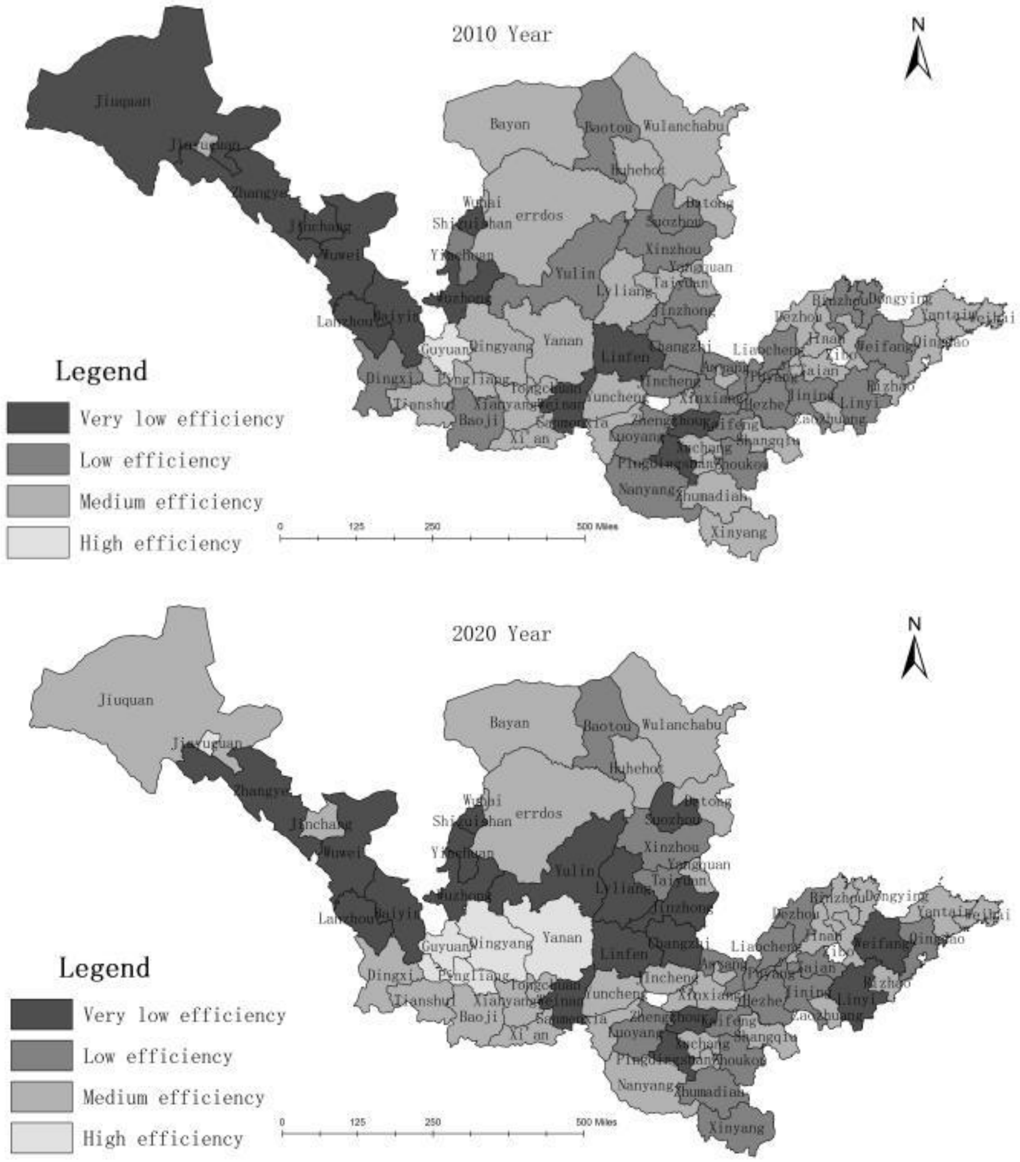

Figure 2. Distribution map of agricultural low-carbon efficiency in Yellow River Basin in 2000, 2010 and 2020.

4.2. Time evolution trend of agricultural low-carbon efficiency

In order to clarify the dynamic evolution of agricultural low-carbon efficiency in the Yellow River Basin from the time dimension, this paper uses Matlab software to draw the kernel density estimation maps of agricultural low-carbon efficiency in the Yellow River Basin as a whole and the upper, middle and lower reaches from 2000 to 2020, and analyzes the distribution position, distribution form, distribution ductility and number of wave peaks respectively. As shown in Figure 3.

From the perspective of 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 low-carbon 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 the agricultural low-carbon efficiency in the upstream region has improved in recent years, the efficiency in the middle and downstream regions has decreased more significantly than that in the upstream region. The possible reason 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 ecological environment. With the support of the national policy to encourage agricultural development in the Yellow River Basin, agricultural production factors continue to increase, agricultural carbon emissions gradually increase, and agricultural low-carbon efficiency gradually decreases.

From the perspective of distribution pattern, the height of the main peak of overall agricultural low-carbon 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 low-carbon efficiency in the Yellow River Basin fluctuated frequently during the sample period, and the relative gap of agricultural low-carbon efficiency among different regions showed a gradually decreasing trend. The peak of the wave in the upstream and middle regions showed a trend of "up-down-up", indicating that the differences in agricultural low-carbon efficiency in the region showed a trend of "narrowing - expanding - narrowing", and the differences among cities were narrowing 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 of the overall agricultural low-carbon efficiency in the Yellow River Basin decreased continuously during the sample period.

In terms of distribution and ductility, there are obvious right-trailing phenomena in the whole, upper and middle reaches of the Yellow River Basin, indicating that the development of low-carbon efficiency in agriculture in this region is unbalanced and there are certain spatial differences. The possible reason is that the agricultural low-carbon 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 low-carbon 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 of agricultural low-carbon efficiency in all regions are not large and at a high level.

In terms of the number of wave peaks, the distribution of agricultural low-carbon efficiency in the whole, 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 gradual rise in fluctuations, and the polarization phenomenon increases with the passage of time. However, the peak of agricultural low-carbon efficiency in the Yellow River Basin is basically unchanged and relatively stable. The peak value in the downstream area showed a trend of slow decline in the fluctuation, indicating that the polarization phenomenon in this area was gradually weakening.

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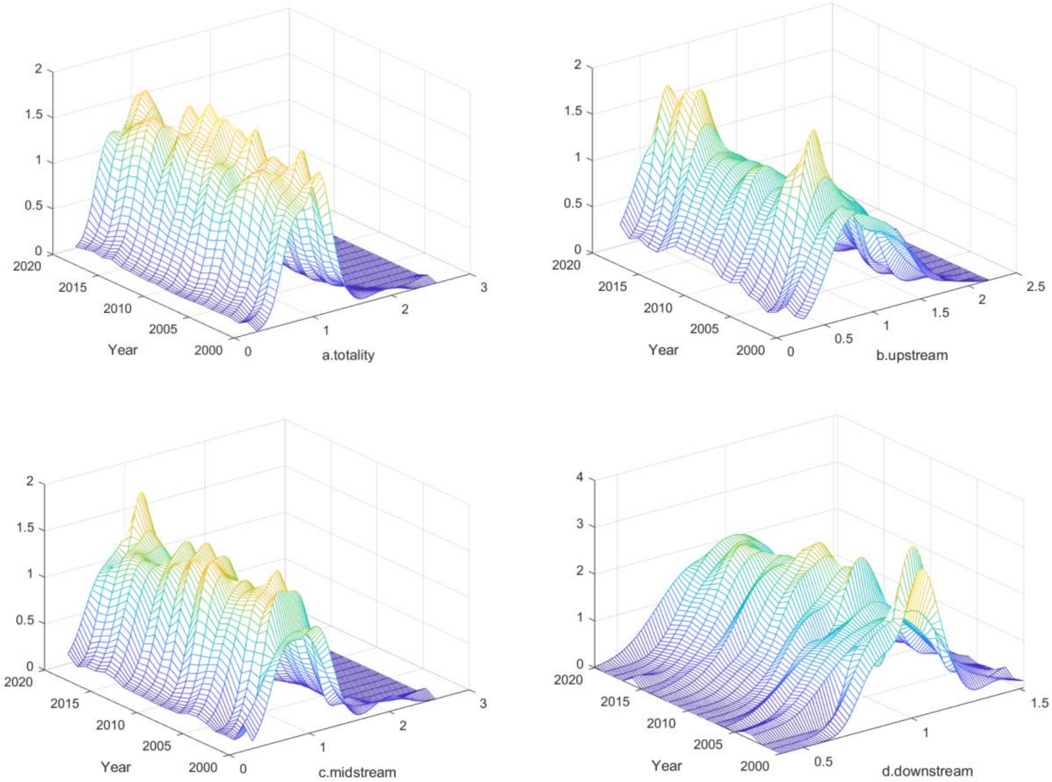

Figure 3. The dynamic evolution of agricultural low-carbon efficiency in the whole, upper, middle and lower reaches of the Yellow River Basin.

4.3. Dynamic evolution of low-carbon efficiency in agriculture

In order to further explore the spatial dynamic evolution of agricultural low-carbon efficiency among cities in the Yellow River Basin, this paper first calculated the global Moran's I index of agricultural low-carbon efficiency in the Yellow River Basin during 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 showed 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 low-carbon efficiency. In other words, local efficiency will be positively affected by the efficiency of neighboring regions, and it will also affect neighboring regions. In terms of geography, low-carbon efficiency mostly presents "high-high" and "low-low" clusters.

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

According to the calculation result of T=1, (1) the transfer probability values on the diagonal of the matrix are significantly greater than the non-diagonal probability values, indicating that the agricultural low-carbon 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 low state and high state are 0.8306 and 0.8307 respectively, while those in low state and high state are 0.7037 and 0.6801 respectively, indicating that the agricultural low-carbon efficiency in the Yellow River Basin has a typical "club convergence" phenomenon [36], that is, the low state and high state are most likely to maintain their

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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 adjacent diagonal is 16.40% and the minimum value is 12.10%, while the maximum probability of not adjacent diagonal is 3.76% and the minimum value is 0.53%. It shows that the improvement of low-carbon efficiency is a continuous slow process in a short time, and can not 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 low-carbon efficiency in the Yellow River Basin.

In addition, the traditional Markov probability transfer matrix is compared with the spatial Markov probability transfer matrix in the T=2-5 state, and the change of the transition probability under different neighborhood background is 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, P23|4=0.1092>P21|4=0.0756, P23|5=0.2105>P21|5=0.1579. Only in the middle and high state, the probability of upward transfer is smaller than the probability of downward transfer. 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, P32|3=0.1515>P34|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 low to high neighborhood state shows a downward trend. Based on the traditional Markov chain, the paper further explains the phenomenon of "club convergence" in the low-carbon efficiency development in the Yellow River Basin.

Table 4. Moran's I of Low-carbon 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, the same below.

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

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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

4.4. Analysis on the impact of urbanization on low-carbon efficiency of agriculture

4.4.1. Index selection

There are many influencing factors for agricultural low-carbon efficiency. For further specific exploration, according to the existing research conclusions, urbanization level is one of the important influencing factors for agricultural low-carbon efficiency. Therefore, this paper takes agricultural low-carbon efficiency as the explained variable and 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 urbanization level, based on the existing literature and considering the availability of variable data, this paper selects six influencing factors such as the level of energy-saving technology in agricultural production, multiple cropping index, agricultural industrial structure, agricultural economic development level, agricultural scale level and government intervention as control variables for specific analysis, as shown in Table 6.

Table 6. Influencing factors of agricultural low-carbon 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/ 100 million yuan)
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 (10,000 yuan/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:

$$y_{it} = \beta_0 + \beta_1 lnurb_{it} + \beta_2 lnetl_{it} + \beta_3 lnmci_{it} + \beta_4 lnis_{it} + +\beta_5 lneco_{it} + \beta_6 lnsc_{it} + \beta_7 lngov_{it} + \varepsilon_{it}$$

$\boldsymbol{y_{it}}$ is low-carbon efficiency in agriculture; *i* stands for region; *t* stands for time; $\boldsymbol{\beta_0}$ is a constant term; urb is the level of urbanization; *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; $\boldsymbol{\varepsilon_{it}}$ is the random disturbance term. The specific regression results of Tobit model are shown in Table 7.

Table 7. Regression results of influencing factors of agricultural low-carbon 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: Outside parentheses are coefficients, inside parentheses are standard errors.

4.4.2. Aggregate result analysis

According to the analysis results in Table 7, it can be seen that the estimated coefficient of urbanization level on agricultural low-carbon efficiency is positive and significant at 1% level, indicating that the improvement of urbanization level has a significant promoting effect on agricultural low-carbon 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 [37,38], and promoting the intensive and large-scale development of agricultural production modes. In addition, with the improvement of 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 then positively promotes the low-carbon efficiency of agriculture, which is consistent with the above-mentioned theoretical analysis results.

In terms of control variables, (1) the estimated coefficient of energy-saving technology level in agricultural production is significantly negative at 1% level, indicating that it has a significant inhibitory effect on agricultural low-carbon efficiency. The possible reason is that the lower the level

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of energy-saving technology in agricultural production, the more energy needed to be consumed per unit of agricultural output value, and the greater the input of agricultural materials such as fertilizers and pesticides, the more carbon emissions will be generated [39], indicating 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. Combined with the use of modern information technology to improve the efficiency of resource utilization [40], and then promote the promotion of low-carbon agricultural efficiency. (2) The regression coefficient of the multiple cropping index was positive and passed the significance test at 1% level, indicating that the increase of the multiple cropping index significantly promoted the improvement of agricultural low-carbon efficiency. Due to the short production cycle of cash crops, the required consumption of fertilizer, pesticides and other resources, high degree of intensification [41], and compared with food crops, the resource utilization rate is generally lower [42], resulting in more carbon emissions. Therefore, with the increase of multiple cropping index, the sowing area of cash crops is relatively reduced, the degree of environmental pollution is reduced, and the low-carbon 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 of agricultural low-carbon efficiency. The main reason is that the carbon emissions brought by agriculture and animal husbandry production account for a large proportion, which will have a greater negative impact on the environment, although the economic benefits are also high, but still can not 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 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 of agricultural low-carbon efficiency. (4) The regression coefficient of agricultural economic development level on agricultural low-carbon efficiency is positive and passes the significance test of 1% level, which indicates that the improvement of agricultural economic development level has a strong promoting effect on agricultural low-carbon efficiency. The possible reason is that the per capita gross agricultural output value is higher. On the one hand, it 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 of low-carbon efficiency in agriculture.(5) The regression coefficient of agricultural scale level is significantly negative at the level of 10%, and its significance level is lower than all other variables, indicating that the improvement of agricultural scale level inhibits the improvement of agricultural low-carbon efficiency to a certain extent. The higher the scale level of agriculture, the more farmland per capita management area of rural residents, on the one hand is conducive to the formation of large-scale agricultural production, improve labor productivity; On the other hand, large-scale operation is not conducive to the fine management of agricultural production [43]. According to the regression results, the per capita cultivated land area in the Yellow River Basin is large on the whole, and the continuous improvement of agricultural scale level is not conducive to the improvement of agricultural low-carbon efficiency.(6) The regression coefficient of government intervention is negative and passes the significance test at 1% level, which has an inhibitory effect on agricultural low-carbon efficiency. The possible reasons lie in that, on the one hand, the increase of fiscal expenditure on agricultural support can stimulate the production enthusiasm of farmers, encourage them to expand the scale of operation and invest more agricultural production factors to increase output, resulting in more resource waste and agricultural non-point source pollution [44]. On the other hand, the structural allocation of financial support for agriculture is not reasonable, the policy of benefiting farmers tends to poverty alleviation, and the protection of ecological environment

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is not paid enough attention to [45], which is not conducive to the improvement of low-carbon efficiency of agriculture.

4.4.3. Analysis of results by region

In order to further analyze the impact of different regional urbanization on agricultural low-carbon efficiency, this paper divides the Yellow River Basin into three regions, namely the upper, middle and lower reaches, and conducts regression analysis respectively. 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 promoting effect on agricultural low-carbon efficiency in all regions of the Yellow River Basin. The main reason is that with the continuous improvement of 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 low-carbon efficiency of agriculture.

In terms of control variables, (1) the regression coefficients of energy-saving technology level in agricultural production are all negative and pass the significance test at 1% level, indicating that energy-saving technology level in agricultural production in the upper, middle and lower reaches has a significant inhibition effect on agricultural low-carbon 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 multiple cropping index in the upstream region was positive and passed the significance test at 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 multiple cropping index on agricultural low-carbon efficiency was not significant. The possible reason 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 a limited space for improving agricultural low-carbon efficiency. (3) The regression coefficients of agricultural industrial structure in all regions were negative, but only the upstream region passed the significance test at 1% level. The possible reason 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, while animal husbandry will produce huge carbon emissions, which significantly inhibits the improvement of low-carbon efficiency of agriculture.(4) The regression coefficients of 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 a large room for improvement. Therefore, the development of agricultural economy helps to promote the progress of advanced green agricultural technology, and lays a good economic and technical foundation for the improvement of low-carbon 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 of agricultural economic level may prompt farmers to invest more production factors to cause redundancy and generate more carbon emissions, which will not help improve the low-carbon efficiency of agriculture.(5) The regression coefficients of agricultural scale level in both upstream and downstream are negative, but only the upstream region passes the significance test at 1% level, and the agricultural scale level in the middle reaches has a positive promoting effect on agricultural low-carbon 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 low-carbon 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

 doi:10.20944/preprints202311.0820.v1

emissions. (6) The regression coefficient of government intervention in the middle reaches is negative and passes the significance test at 1% level, while the regression results in the upstream and downstream are not significant, among which the regression coefficient in the downstream is positive. The possible reason 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 in fertilizer, pesticides and other aspects, and the improvement of the ecological environment is not paid enough attention, which has a significant negative impact on the low-carbon efficiency of agriculture.

4.4.4. Robustness test

In order to test the accuracy of the empirical results of the Tobit model, this paper 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 Table 8 and Table 9. In the overall test results of the Yellow River Basin, the sub-sample regression results of 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 during 2000-2010 are not significant, but the regression coefficient is still negative. The sample regression results of urbanization level, multiple cropping index, agricultural scale level and government intervention during 2011-2020 are not significant, but the regression coefficients are consistent with the full sample regression results. In 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 2000-2010.

variable/region	totality	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)

Table 9. Test results 2000-2010.

variable/region	totality	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)

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government intervention	-0.008 (0.019)	0.032 (0.038)	0.007 (0.032)	-0.014 (0.022)

5. Conclusion and Suggestion

5.1. Research conclusions

In this paper, the super-DEA model is used to measure the agricultural low-carbon 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 low-carbon efficiency. On this basis, the panel Tobit model is used to explore the relationship between urbanization and agricultural low-carbon efficiency. Finally, the following conclusions are drawn:

First, the overall level of agricultural low-carbon 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 low-carbon efficiency in the lower reaches > middle reaches > upper reaches showed a downward trend from 2000 to 2015, and gradually rebounded after 2016.

Second, the internal differences of the overall agricultural low-carbon 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 low-carbon efficiency has a negative trend of transferring to a low level on the whole, and tends to maintain the original state level, 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 low-carbon 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.

Third, in the Yellow River Basin as a whole, urbanization level, multiple cropping index and agricultural economic development level all have significant positive impacts on agricultural low-carbon efficiency, while the level of energy-saving technology in agricultural production, agricultural industrial structure, agricultural scale level and government intervention have significant inhibitory effects on agricultural low-carbon efficiency. The influencing factors and directions of agricultural low-carbon efficiency in the upper, middle and lower reaches are different from those in the Yellow River Basin.

5.2. Policy suggestion

Based on the above research conclusions, this paper puts forward the following policy recommendations:

First, we will promote green and modernized agriculture. The overall agricultural low-carbon 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, change the previous extensive agricultural production mode, use organic fertilizers and low-carbon agricultural machinery and equipment, and use green high-tech to improve resource utilization efficiency and reduce environmental pollution.

Second, strengthen inter-regional cooperation and exchanges. Cities with high agricultural low-carbon 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 low-carbon efficiency, and narrow the gap between them and neighboring cities.

Third, we should pay more attention to the significant influencing factors of agricultural low-carbon efficiency. Promote the level of urbanization 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, improve the level of energy-saving technology in agricultural production, and promote the improvement of low-carbon efficiency in agriculture.

5.3. Research limitation

There are still the following shortcomings in this paper: First, 75 cities in the Yellow River Basin from 2000 to 2020 were studied in this paper, and the scale of analysis is still relatively macro. If more detailed and specific county-level data can be used for future research, it will be able to more pertinently reflect the spatio-temporal change characteristics of local agricultural low-carbon efficiency, and corresponding countermeasures and suggestions will be put forward. Secondly, this paper only uses a single population urbanization to represent the level of urbanization. Under the background that China, especially the Yellow River Basin, keeps accelerating the process of new-type urbanization and promoting high-quality agricultural development, a more diversified and comprehensive indicator system needs to be established in the future to evaluate the level of urbanization more accurately. Finally, due to the availability and operability of data, this paper only selected some indicators to evaluate agricultural low-carbon efficiency, and with the continuous enrichment and change of the connotation of agricultural low-carbon efficiency, its index system needs to be further improved and amended in the future.

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