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Analysis on the Evolution Characteristics of County Carbon Total Factor Productivity in the Yellow River

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Abstract

Climate change has become a global non-traditional security issue. As an important ecological security barrier in China, the comprehensive management of the Yellow River basin with carbon emission reduction as the core is of great significance to the high-quality development of the Yellow River basin. In this paper, by calculating the level of carbon total factor productivity in the Yellow River basin from 2000 to 2017, the spatial correlation analysis model and geographic detector model are used to analyze the spatio-temporal dynamic evolution characteristics of carbon productivity in the Yellow River basin. The results show that: 1) the average annual growth rate of county carbon total factor productivity in the Yellow River Basin from 2000 to 2017 is 14.98%. From the source of carbon total factor productivity growth, scale technological progress is the main driving force to promote the growth of county carbon total factor productivity in the Yellow River Basin. 2) from the perspective of spatio-temporal trend, the growth of carbon total factor productivity in counties in the Yellow River Basin from 2000 to 2017 showed obvious periodic fluctuations and spatial imbalance. 3) from the point of view of the decomposition items of carbon total factor productivity in each province, the driving situation of total carbon factor productivity in the counties of nine provinces in the Yellow River Basin is mainly divided into two kinds: the first situation is "two-track drive". It mainly includes 8 provinces of Gansu, Henan, Inner Mongolia, Ningxia, Shandong, Shanxi, Shaanxi and Sichuan. The second case is "monorail drive", which represents the province as Qinghai. 4) the regional gap of county total carbon factor productivity in the Yellow River basin shows a narrowing trend, has the characteristics of dynamic convergence, and its growth shows the phenomenon of overall disparity. From the distribution of each province, the convergence characteristic is obvious, but the level of carbon total factor productivity fluctuates greatly.

Keywords

Yellow River Basin, Carbon Total Factor Productivity, County, SBL-ML Model, Kernel Density Estimation

1. Introduction

Global warming has posed a serious threat to the earth's ecology and human life, and this major global security hazard has become an issue of common concern to governments and people of all countries. In the context of global warming, the development model of low-carbon economy begins with the goal of "high efficiency, low emission and low pollution", which has attracted the attention of countries all over the world.

As an important ecological security barrier in China, the Yellow River Basin has a core strategic position in national development and socialist modernization. The contradiction between environmental protection and economic and social development hinders the high-quality development of the Yellow River basin, and the green transformation and development of the Yellow River basin in the new era still has a long way to go.

In order to deeply study and implement the spirit of the General Secretary's important speech on ecological protection and high-quality development of the Yellow River Basin, and implement the decision-making arrangements of the Central Committee of the Communist Party of China and the State Council, the Outline for Ecological Protection and High-Quality Development of the Yellow River Basin was issued in October 2021 to comprehensively promote ecological protection and high-quality development of the Yellow River Basin. On October 16, 2022, the report of the 20th National Congress of the Communist Party of China pointed out that it is necessary to promote green and low-carbon development and achieve sustainable economic, social and ecological environment development. How to balance the relationship between economic development and sustainability has become a major issue that urgently needs to be solved in the Yellow River Basin at present.

To achieve the dual-carbon goals without causing significant negative impacts on the economy, it must rely on low-carbon technological innovation and the improvement of energy utilization efficiency, that is, taking the improvement of total factor productivity of carbon as the basic route to achieve the dual-carbon goals. Therefore, it is very necessary to objectively assess and analyze the current situation and evolution characteristics of total factor productivity in various regions of the Yellow River Basin. Due to the differences in economic basis, development paths, endowment characteristics and development paths in different regions, what kind of differences will exist in their total factor productivity of carbon? How does this difference change? The external characteristics of environmental pollution itself and economic correlations among regions determine that the total factor productivity of carbon may have spatial dependence characteristics.

Therefore, accurately measuring the total factor productivity of carbon in various regions of the Yellow River Basin, and analyzing the spatio-temporal evolution characteristics and dynamic convergence effect of total factor productivity of carbon in each region are of great significance for promoting the low-carbon transformation, upgrading and coordinated development of various regions in the Yellow River Basin

2. Research Review

This paper mainly discusses the measurement and analysis based on the total factor productivity of carbon. The methods for measuring total factor productivity include the growth accounting method, the Solow residual method, and non-parametric and parametric methods (Zhang, 2022). Among them, the Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) methods have developed rapidly and are widely used in the academic community. The traditional DEA methods are deficient in both model setting and measurement content. In terms of model setting, such as the CCR and BCC models, they are radial efficiency models that increase or decrease values in the same proportion. While the SBM method is a non-radial efficiency model in DEA, which improves the radial efficiency model and can better estimate the efficiency value and conduct decomposition. In terms of measurement content, the past DEA models measured total factor efficiency and ignored environmental impacts, which led to the consequence of underestimating the true productivity. Due to the importance of environmental protection, the academic community has begun to incorporate undesired pollutant outputs, such as wastewater, waste gas and solid waste, into the SBM model. Due to the proposal and promotion of carbon peak and carbon neutrality, China's social production model is undergoing tremendous changes, and more and more literature has begun to incorporate carbon emissions as undesired outputs into the SBM model (Jia et al., 2022).

The research related to low carbon in the Yellow River Basin started relatively late. With the ecological protection and high-quality development of the Yellow River Basin rising as a major national strategy, the academic community has concentrated on conducting research in the past three years. The existing literature, starting from different perspectives and methods, has made beneficial contributions to the research related to the low-carbon economy in the Yellow River Basin, including the measurement of carbon emissions (Mo & Wang, 2021), carbon emission efficiency in the Yellow River Basin, and the impact of carbon emissions on other aspects of the basin (Du et al., 2021). It mainly focuses on the provincial, municipal and urban agglomeration levels, while county-level research is relatively lacking. At the provincial level, scholars have explored the characteristics of implicit carbon emissions in each province and region and their spatial transfer paths (Kang & Ma, 2022), and evaluated that the provinces and regions in the Yellow River Basin present a distribution characteristic of carbon emission reduction potential of "high in the northwest and low in the southeast" (Song & Zou, 2022). At the municipal level, based on the perspective of prefectural-level administrative divisions, scholars have analyzed and concluded that 91.2% of the cities in the Yellow River Basin have achieved a relative decoupling of carbon emissions and economic growth (Zhang et al., 2022). Carbon emissions in the Yellow River Basin grew rapidly at first and then slowly, while carbon sinks generally showed a slow growth trend. Regional economic growth level, energy structure, industrial structure, and technological level are important factors affecting carbon emission intensity. At the urban agglomeration level, the influencing factors of industrial pollution reduction and carbon reduction (Kang et al., 2023) and the coupling relationship between industrial growth, energy consumption and carbon emissions (Liu et al., 2023) have been investigated around the three major urban agglomerations of Hohhot-Baotou-Ordos-Yulin, Guanzhong Plain and Central Plains.

To sum up, there is certain room for improvement in the research on total factor productivity of carbon. Based on this, this paper has the following marginal contributions: 1) Counties are important supporting units for the low-carbon transformation of the Yellow River Basin and are the key to implementing the national strategy of ecological protection and high-quality development of the Yellow River Basin. Existing studies have focused more on regions such as the Yangtze River Delta and the Beijing-Tianjin-Hebei region, lacking research on the Yellow River Basin. Most studies have concentrated at the provincial level, and analyses using county-level data are even rarer. The research object of this paper is further microscopically refined, which is conducive to capturing the productivity characteristics of regional total factor productivity and its change mechanism more clearly, providing a more detailed theoretical basis for proposing more targeted regional low-carbon transformation paths in the context of regional coordination. 2) Incorporating carbon emissions into the total factor productivity framework of the Yellow River Basin is of great significance for promoting the low-carbon transformation, upgrading and coordinated development of various regions in the Yellow River Basin. 3) Using the kernel density estimation method for dynamic analysis, and striving to combine spatio-temporal evolution and dynamic convergence, is conducive to promoting the overall positive development of the basin.

3. Research Design

3.1. Index Selection and Regional Definition

According to the regional boundaries delineated in the "Outline for Ecological Protection and High-Quality Development of the Yellow River Basin", this paper determines the research area as the counties (including districts and county-level cities) of nine provincial administrative regions of Shanxi, Shaanxi, Henan, Shandong, Qinghai, Sichuan, Gansu, Ningxia, and Inner Mongolia as the research units. Due to the lack of data in some districts and counties, after elimination, 897 districts and counties remain, and some missing data are filled by interpolation. Considering the latest update years of the existing data, this paper selects the data of regional GDP, employed population per unit, and common cultivated land area in the county areas of the Yellow River Basin from 2000 to 2017, and calculates the capital stock based on fixed asset investment. The data are from the provincial statistical yearbooks and China County (City) Socio-economic Statistical Yearbook, China County Statistical Yearbook, and CEADs China Carbon Accounting Database.

In terms of output indicators, based on the experience of existing literature, this paper selects regional GDP as the expected output variable and adds carbon emissions as the undesired output indicator. In terms of input indicators, this paper follows the three-factor input hypothesis and incorporates the three factors of labor, capital, and land into the input indicator framework to comprehensively consider the input factors. First, quantify the capital indicators. Scholars have different methods to estimate the capital stock. Based on the assumption by (Zhang et al., 2009) that the capital-output ratio in China is 3, the perpetual inventory method is used to calculate the capital stock of each county over the years. Regarding the selection of the depreciation rate, this paper refers to the depreciation rates and selects 9.6% (Zhou et al., 2009). Second, quantification of the labor force indicator. For the labor force factor, this paper, based on existing literature, selects the employed population of the unit as the labor force variable. Third, the selection of the land indicator. Since the land factor also occupies an important position in economic development, this paper draws on existing literature and selects the common cultivated land area within the county as the indicator to measure the land factor. The descriptive statistics are shown in **Table 1**.

Table 1. Explanation of input and output indicators.

Indicator	Indicator Selection	Variables and Descriptions
Input	Labour	Employed population per unit (hundred thousand people)
	Capital	Capital stock (hundred million yuan)
	Land	Common cultivated land area (thousand hectares)
Expected Output	Economic Output	Regional GDP (hundred million yuan)
Undesired Output	Carbon Emission	Carbon emissions (ten thousand tons)

3.2. Research Methods

1) The SBM Model

Kaoru Tone proposed the SBM model based on slack variables, reducing the deviation caused by the selection of different angles and radial input and output indicators in the DEA model. Tone later incorporated undesired outputs into the SBM model, that is, the SBM model of undesired outputs. In this paper, carbon emissions are incorporated as a new undesired output variable into the model, and the SBM model of undesired outputs is used to measure the total factor productivity of carbon.

In the SBM model, it is assumed that there are K decision-making units in the production system, each unit contains M input variables, N expected output variables, and Q kinds of undesired outputs. λ_k^t is the weight vector. The formula is shown as follows:

$$\rho = \min \frac{1 - \frac{1}{M}\sum_{m=1}^{M}\frac{S_m^x}{x_m^k}}{1 + \frac{1}{N+Q}\left(\sum_{n=1}^{N}\frac{S_n^y}{x_n^k} + \sum_{q=1}^{Q}\frac{S_q^f}{f_k^q}\right)} \tag{1}$$

$$\begin{cases} \text{s.t } \sum_{k=1}^{K}\lambda_k^t y_{Mk}^t + S_m^x = x_{km}^t \\ \sum_{k=1}^{K}\lambda_k^t y_{Nk}^t - S_n^y = y_{kn}^t,\ \forall n \\ \sum_{k=1}^{K}\lambda_k^t f_{qk}^t - S_q^f = f_{kq}^t \\ S_m^x \ge 0,\ S_n^y \ge 0,\ S_q^f \ge 0,\ \lambda_k^t \ge 0 \end{cases} \tag{2}$$

In the above formulas (1) and (2), under the condition of constant returns to scale, ρ refers to the efficiency value of the decision-making unit, S_m^x represents the input quantity, S_n^y is the expected output, and S_q^f represents the undesired output. When the decision-making unit takes the optimal value, that is, $\rho = 1$, $S_m^x = S_n^y = S_q^f = 0$. At this time, the decision-making unit is effective and is on the production frontier, and there is no redundancy in input and output. When $0 < \rho < 1$, there is a loss of efficiency. At this time, the decision-making unit has not reached an effective state and can still be improved (Wei et al., 2023).

2) The ML Index Model

This study refers to available literature and directly uses the efficiency value calculated by the undesired output SBM to apply the M index calculation formula to calculate the ML index (Lin et al., 2022). Based on the above SBM function, this study constructs the ML index from period t to period $t + 1$, and the formula is as follows:

$$\mathrm{ML}\left(x_t, y_t, x_{t+1}, y_{t+1}\right) = \sqrt{\frac{D_0^t\left(x_{t+1}, y_{t+1}\right)}{D_0^t\left(x_t, y_t\right)} \times \frac{D_0^{t+1}\left(x_{t+1}, y_{t+1}\right)}{D_0^{t+1}\left(x_t, y_t\right)}} \tag{3}$$

Among them, ML is the total factor productivity of carbon in the county areas of the Yellow River Basin, $\left(x_t, y_t\right)$ is the input-output variable of the total factor productivity of carbon in period t, $\left(x_{t+1}, y_{t+1}\right)$ is the input-output variable of the total factor productivity of carbon in period $t + 1$, D_0^t is the directional distance function in period t, and D_0^{t+1} is the directional distance function in period $t + 1$.

For each decision-making unit, if the ML index is greater than 1, it indicates that the total factor productivity of carbon has increased during the period from t to $t + 1$, and if it is less than 1, it has decreased. It can be further decomposed into four indices: 1) The pure technical efficiency change index, which reflects the degree of relative technical efficiency change of the decision-making unit or the degree of catch-up change to the technical frontier under the fixed return to scale, that is, the "catch-up effect". 2) The scale efficiency change index, the change in the total factor productivity of carbon caused by the change in the scale factor, that is, the "scale effect". 3) The pure technical change index, which reflects the movement towards the pure technical frontier, that is, the "pure technical frontier movement effect". 4) The scale technical change index, which reflects the movement towards the scale technical frontier, that is, the "scale technical frontier movement effect".

3) Kernel Density Estimation

Kernel density estimation is a non-parametric estimation method. By smoothing the probability density estimation of a random variable, a distribution model of the random variable is obtained to estimate the probability density function of the random variable (Liu et al., 2021). This paper uses the kernel density estimation method to analyze the spatio-temporal evolution characteristics of the total factor productivity of carbon in the county areas of the Yellow River Basin, providing a theoretical basis for the government to formulate reasonable carbon emission reduction policies. The formula is:

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right) \tag{4}$$

Among them, $K(\cdot)$ is the kernel function, h is the bandwidth, n is the number of observations, X_i is the observation value, and x is the mean value of the observation values.

4. Analysis of the Evolution Characteristics of County-Level Carbon Total Factor Productivity in the Yellow River Basin

4.1. Measurement and Spatio-Temporal Evolution Characteristics of County-Level Carbon Total Factor Productivity in the Yellow River Basin

Using the MaxDEA software, the growth of county-level carbon total factor productivity in the Yellow River Basin during the period from 2000 to 2017 was measured respectively, and further decomposed into technical efficiency (PEC) index, scale efficiency (SEC) index, pure technology (PTC) index and scale technology (STC) index for analysis. The results are shown in Table 2.

Table 2 shows the growth and decomposition of county-level carbon total factor productivity in the Yellow River Basin. As can be seen from Table 2, the average annual growth rate of county-level carbon total factor productivity in the Yellow River Basin from 2000 to 2017 was 14.98%. From the source of the

Table 2. The growth situation and decomposition of county-level carbon total factor productivity in the Yellow River Basin during the period from 2000 to 2017.

year	ML Index	PEC Index	SEC Index	PTC Index	STC Index
2000-2001	1.2501	3.7064	7.2349	0.3593	0.2920
2001-2002	1.0740	0.4834	0.6189	2.7197	2.2905
2002-2003	1.1986	0.9990	1.0329	1.0791	1.1377
2003-2004	1.2503	1.4277	0.8853	0.7565	1.4232
2004-2005	1.2224	1.2775	1.7291	0.9451	0.7565
2005-2006	1.1406	1.1423	0.7744	0.9645	1.6520
2006-2007	1.1496	0.9694	1.2977	1.0846	0.9437
2007-2008	1.1969	0.8329	0.9629	1.3102	1.2467
2008-2009	1.1209	0.6275	0.5974	1.8494	2.1622
2009-2010	1.0960	0.9841	0.9976	1.0502	1.1832
2010-2011	1.1304	1.0555	0.9355	1.0094	4.0510
2011-2012	1.1715	1.0601	0.9781	0.9753	1.1635
2012-2013	1.1196	1.0678	0.9780	0.9805	1.1535
2013-2014	1.0572	1.0744	0.9735	0.9552	1.0842
2014-2015	1.1497	1.0979	0.9648	0.9638	1.0849
2015-2016	1.0994	1.0532	1.0149	0.9915	1.0449
2016-2017	1.1186	1.0084	0.9225	1.0362	1.1616
average	1.1498	1.1687	1.3470	1.1195	1.4018

[a]The values in the table are the average values of all districts and counties in the corresponding year.

growth of carbon total factor productivity, the growth of county-level carbon total factor productivity in the Yellow River Basin comes from the combined effect of technical efficiency, scale efficiency, pure technology and scale technology. The growth rate of technical efficiency was 16.87%, the growth rate of scale efficiency was 34.7%, the growth rate of pure technology was 11.95%, and the growth rate of scale technology was 40.18%. This indicates that the progress of scale technology is the driving source affecting the growth of carbon total factor productivity, and also reflects the realistic reason for the insufficient potential of resource utilization and technology improvement in China's industrial development (Yin et al., 2022), especially the utilization efficiency of input factors needs to be improved.

From the perspective of the time trend, the growth of county-level carbon total factor productivity in the Yellow River Basin from 2001 to 2017 showed obvious phased fluctuations, which can be roughly divided into three stages: 2001-2010, 2010-2012, and 2012-2017. The growth rate of carbon total factor productivity varied little in different stages. In the first stage, both carbon total factor productivity and its decomposition factors fluctuated upward or downward. Carbon total factor productivity showed a steady upward trend, and its growth rate presented a fluctuating form of "decrease - increase - decrease - increase - decrease", and the fluctuations of technical efficiency (PEC), scale efficiency (SEC), pure technology (PTC), and scale technology (STC) were relatively intense and frequent. In the second stage, both carbon total factor productivity and its decomposition factors tended to be stable and showed a growth trend. In 2010, scale technology (STC) grew rapidly and fell back in 2012. The reason was the implementation of the "Twelfth Five-Year Plan", which led to the "scale technology frontier movement effect". In 2016, scale efficiency (SEC) showed a negative growth state, possibly due to the greater downward pressure on the economy and the macro impact brought by the supply-side reform.

Table 3. The growth situation and decomposition of county-level carbon total factor productivity in the Yellow River Basin during the period from 2000 to 2017.

region	The number of counties	ML Index		
		2001	2017	Growth rate
Gansu	85	0.9231	1.0335	0.65%
Henan	116	1.1815	1.1318	−0.29%
Inner Mongolia	99	0.8008	0.8317	0.18%
Ningxia	21	1.0939	0.9680	−0.74%
Qinghai	41	0.7847	1.0665	1.66%
Shandong	136	2.0422	1.9978	−0.26%
Shanxi	112	1.0167	0.9872	−0.17%
Shaanxi	107	1.2000	1.1651	−0.21%
Sichuan	180	1.3966	1.3936	−0.02%
Average		1.1599	1.1750	0.09%

[a]The values in the table are the cumulative indices of the total factor productivity of carbon in the counties of each province in the current year, and the growth rate is the average annual growth rate of the total factor productivity of carbon in the counties of each province in the Yellow River Basin. Due to limited space, the measurement results of the total factor productivity of carbon in all counties have not been listed.

Table 3 shows the growth of total factor productivity of carbon in the counties of the Yellow River Basin exhibited spatial imbalance from 2001 to 2017. Among the nine provinces, Qinghai had the highest growth rate of total factor productivity of carbon at 1.66%, while Ningxia had the lowest at -0.74%. The total factor productivity of carbon increased in Gansu, Inner Mongolia, and Qinghai, while it showed negative growth in Henan, Ningxia, Shandong, Shanxi, Shaanxi, and Sichuan. Among them, by 2017, the total factor productivity of carbon in Inner Mongolia, Ningxia, and Shanxi still had not achieved growth, possibly because the per capita carbon emissions in Inner Mongolia, Ningxia, and Shanxi have always been among the highest in the country, and the eco-nomic growth of these three provinces overly relied on energy consumption.

From the perspective of counties, the top three counties with the highest growth in total factor productivity of carbon were Pinglu District in Shanxi Province, Jimo District in Shandong Province, and Shibei District in Shandong Province, with growth rates of 61.75%, 50.47%, and 40.62% respectively. The three counties with the slowest growth were Anju District in Sichuan Province, Juancheng County in Shandong Province, and Yutai County in Shandong Province, all showing negative growth. Generally speaking, there were obvious regional differences in the growth of total factor productivity of carbon among counties.

Table 4. The growth situation and decomposition of the total factor productivity of carbon in the counties of each province in the Yellow River Basin from 2000 to 2017.

region	ML Index	PEC Index	SEC Index	PTC Index	STC Index	ranking
Gansu	1.0402	1.0720	1.5642	1.0351	1.3101	8
Henan	1.1343	1.2197	1.1049	1.1516	1.1278	4
Inner Mongolia	1.0330	1.1143	1.4097	1.1152	1.2468	9
Ningxia	1.1326	1.1621	1.3829	1.1169	1.2380	5
Qinghai	1.1488	1.1098	1.7589	1.0507	5.0616	3
Shandong	1.3041	1.3843	1.1731	1.2608	1.1430	1
Shanxi	1.0866	1.1047	1.4257	1.0694	1.2648	7
Shaanxi	1.2822	1.1582	1.3348	1.1317	1.2684	2
Sichuan	1.1217	1.1059	1.3575	1.0742	1.2528	6

[a]Ranking is carried out based on the ML index of each province.

Table 4 shows the total factor productivity of carbon in the counties of the Yellow River Basin all achieved growth from 2000 to 2017. The ranking from high to low is as follows: Shandong (1.3041), Shaanxi (1.2822), Qinghai (1.1488), Henan (1.1343), Ningxia (1.1326), Sichuan (1.1217), Shanxi (1.0866), and Gansu (1.0402).

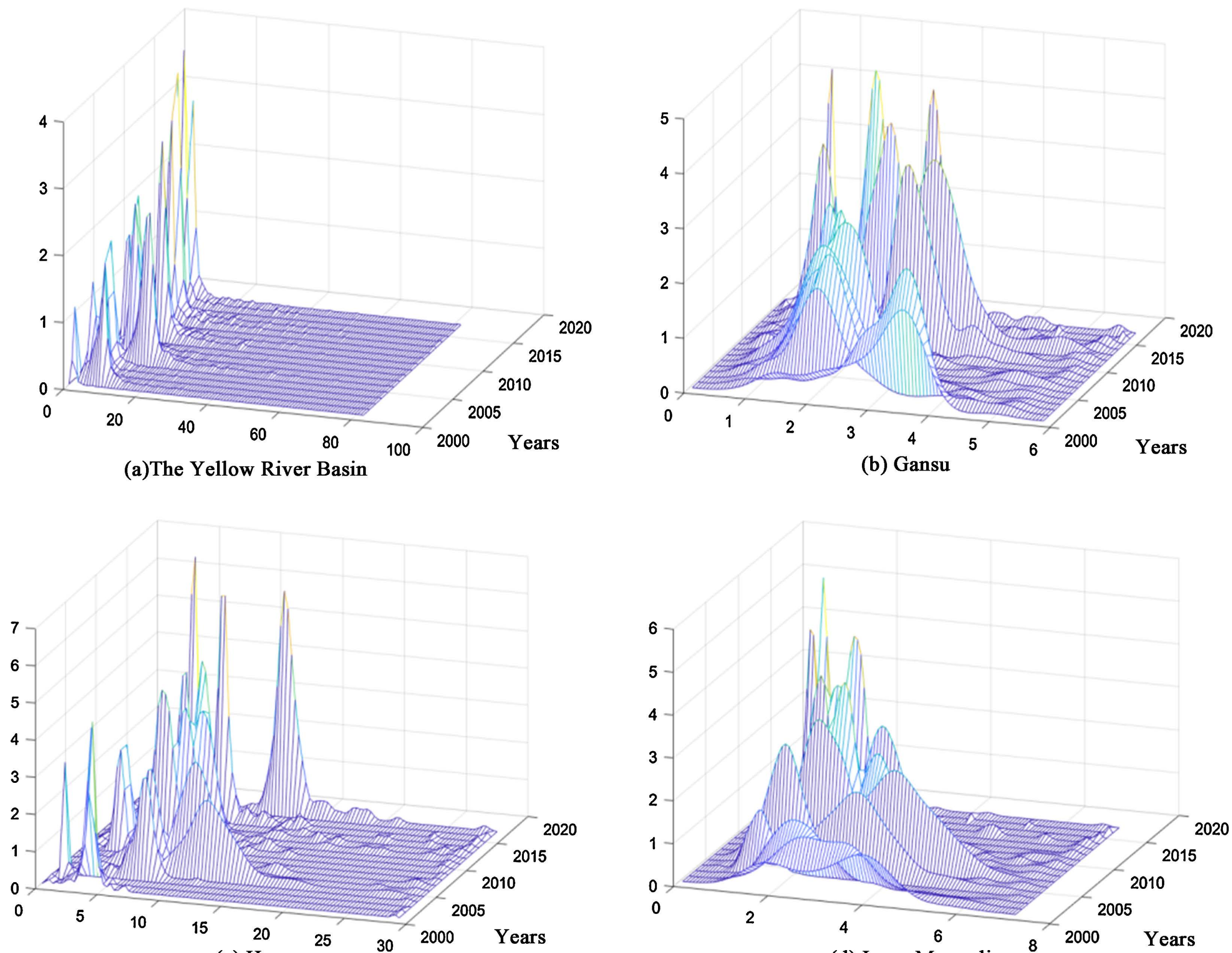
From the decomposition items of the total factor productivity of carbon in each province, the driving situations of the total factor productivity of carbon in the counties of the nine provinces in the Yellow River Basin are mainly divided into two types: The first type is "dual-track driving", mainly including eight provinces such as Gansu, Henan, Inner Mongolia, Ningxia, Shandong, Shanxi, Shaanxi, and Sichuan. Among them, Gansu, Inner Mongolia, Ningxia, Shanxi, Shaanxi, and Sichuan mainly rely on scale efficiency (SEC) and scale technology (STC), that is, the two-way driving of the "scale effect" and the "scale technology frontier movement effect”. Henan and Shandong mainly rely on technical efficiency (PEC) and pure technology (PTC), that is, the combined effect of the “catch-up effect” and the “pure technology frontier movement effect”. The second type is “single-track driving”. The main driving factor of Qinghai is scale technology (STC), and the “scale technology frontier movement effect” is significant, promoting the improvement of the total factor productivity of carbon in Qinghai.

4.2. The Spatio-Temporal Dynamic Evolution of the Total Factor Productivity of Carbon in the Counties of the Yellow River Basin

The three-dimensional kernel density estimation method was used to analyze the spatio-temporal evolution pattern of the total factor productivity of carbon in the counties of the Yellow River Basin and its provinces from 2000 to 2017, as shown in Figure 1.

The overall regularity of the spatio-temporal evolution of industrial total factor productivity of prefecture-level cities in China can be obtained from Figure 1.

Figure 1(a) is the kernel density curve of the total factor productivity of



(a)The Yellow River Basin (b) Gansu (c) Henan (d) Inner Mongolia

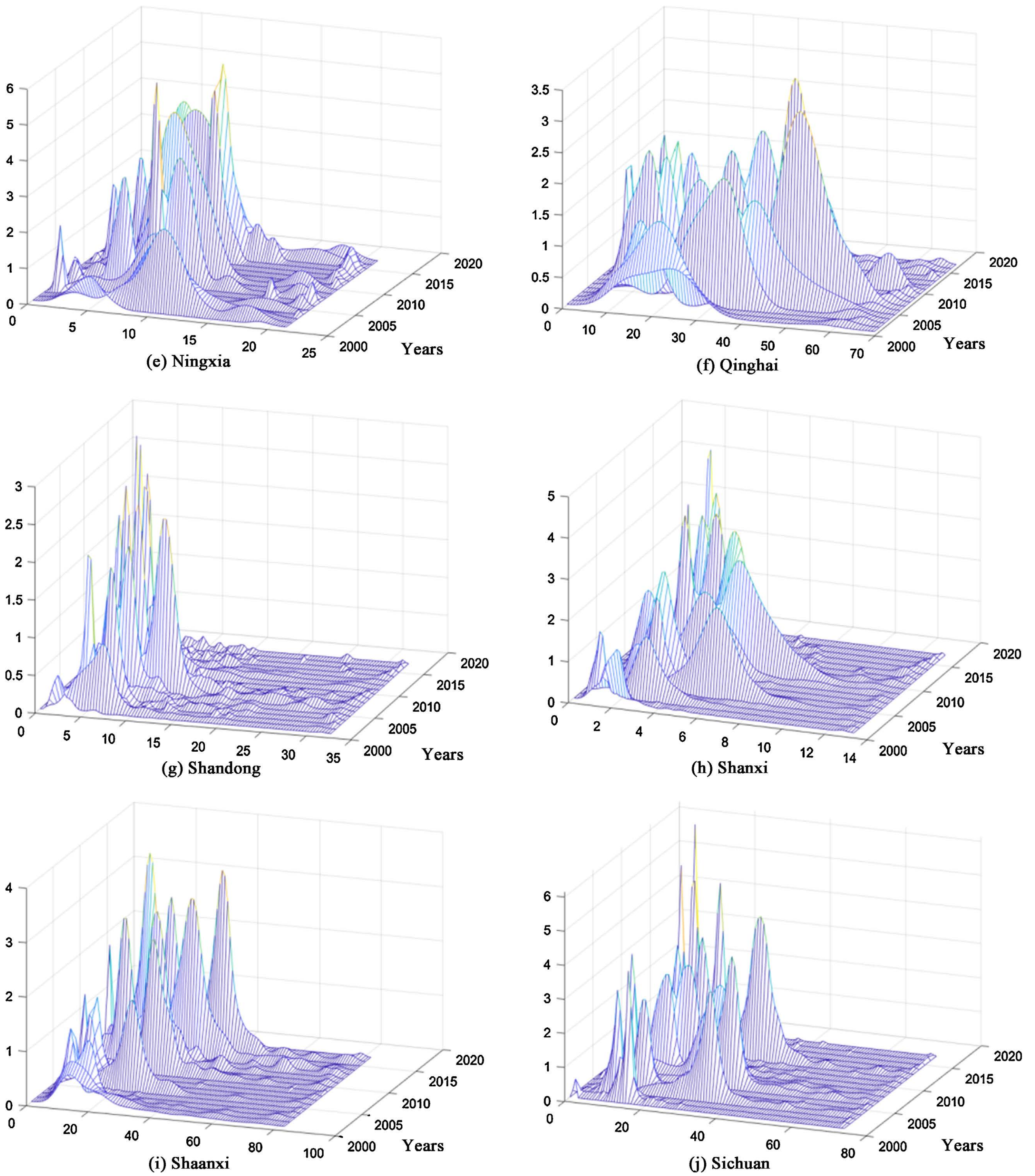


Figure 1. Kernel Density Estimation Map of Total Factor Productivity of Carbon in the Counties of the Yellow River Basin and Its Provinces from 2000 to 2017.

carbon in the counties of the Yellow River Basin, used to analyze the dynamic evolution of the total factor productivity of carbon in the counties of the Yellow River Basin. Overall, the kernel density curve shows a distinct "single peak" distribution. The waveform shifts to the left, presenting a right-skewed distribution.

The peak value increases in vertical height and decreases in horizontal width, indicating that the kernel density tends to move in the direction of decreasing values. That is, the regional differences in the total factor productivity of carbon in the counties of the Yellow River Basin tend to narrow, presenting the convergent characteristic of dynamic convergence. The growth of total factor productivity of carbon shows an overall deterioration phenomenon.

As shown in Figure 1(b), the main peak of the kernel density distribution curve of the total factor productivity of carbon in the counties of Gansu keeps rising and contracting, showing a fluctuating leftward shift trend, and starts to move to the right in 2017 with a slightly lower main peak. This indicates that the internal differences in the total factor productivity of carbon in Gansu have decreased, showing dynamic convergence. The total factor productivity of carbon improved significantly in 2017, and the monopolarization slightly weakened.

As shown in Figure 1(c), the kernel density distribution curve of the total factor productivity of carbon in the counties of Henan is mainly divided into three stages. From 2001 to 2002, the main peak shifted to the left, the peak value rose, and the peak shape narrowed. This indicates that the total factor productivity of carbon in Henan decreased and the differences narrowed during this period. From 2003 to 2016, the kernel density curve of Henan roughly presents a change process of "widening - convergence", shifting from moving to the right to moving to the left. This indicates that the total factor productivity of carbon in Henan increased and the differences narrowed. In 2017, the kernel density curve moved to the right and the main peak slightly decreased. This indicates that the total factor productivity of carbon in Gansu improved significantly during this period, and the monopolarization weakened.

As shown in Figure 1(d), the main peak of the kernel density distribution curve of the total factor productivity of carbon in the counties of Inner Mongolia keeps rising and contracting, showing a fluctuating leftward shift trend. The main peak starts to move to the right in 2017, the peak value decreases, and the peak shape widens. This indicates that the total factor productivity of carbon in Inner Mongolia decreases year by year and the internal differences among districts and counties decrease, but it improves significantly in 2017 and the internal differences increase.

As shown in Figure 1(e), the kernel density distribution curve of the total factor productivity of carbon in the counties of Ningxia roughly presents a change process of "widening - convergence - widening - convergence - widening". The main peak moves to the left as a whole, there is a multipolar distribution but the monopolar distribution is obvious, and the peak value shows a fluctuating upward trend. This indicates that the total factor productivity of carbon in Ningxia decreases year by year, and the internal differences have a certain degree of narrowing trend.

As shown in Figure 1(f), the kernel density distribution curve of the total factor productivity of carbon in the counties of Qinghai fluctuates greatly. The movement of the main peak roughly presents a change process of "right shift - left shift - right shift", which indicates that the total factor productivity of carbon shows a trend of "increase - decrease - increase"; the peak value first increases and then decreases, and the width increases, indicating that the differences in the total factor productivity of carbon among districts and counties increase.

As shown in Figure 1(g) and Figure 1(h), the kernel density distribution curves of the total factor productivity of carbon in the counties of Shandong and Shanxi are similar. The main peak shows a fluctuating leftward shift, the peak value rises, and the peak shape narrows. This indicates that the total factor productivity of carbon in Shandong and Shanxi decreases year by year, and the gap among districts and counties shows a narrowing trend, with the characteristic of dynamic convergence.

As shown in Figure 1(i), the main peak of the kernel density distribution curve of the total factor productivity of carbon in the counties of Shaanxi keeps rising and contracting, showing a fluctuating rightward shift trend. The main peak starts to move to the left in 2017, and the peak value decreases. This indicates that the total factor productivity of carbon in Shaanxi increases year by year and the internal differences among districts and counties decrease, but it decreases significantly in 2017 and the internal differences increase.

As shown in Figure 1(j), the kernel density distribution curve of the total factor productivity of carbon in the counties of Sichuan roughly presents a moving process of "left shift - right shift - left shift - right shift - left shift", the peak value rises, and the peak shape narrows. This indicates that the total factor productivity of carbon in Sichuan changes greatly during this period, and no unified trend is formed. The gap among districts and counties shows a narrowing trend, with the characteristic of dynamic convergence.

5. Conclusions and Suggestions

Based on the data of human resources, land and capital stock in the counties of the nine provinces of the Yellow River Basin, this paper constructs a spatial model of total factor productivity of carbon in the Yellow River Basin. The SBM-ML index is used to calculate and decompose the total factor productivity of carbon in the Yellow River Basin at the county scale, and the spatio-temporal evolution characteristics are analyzed by the kernel density estimation method. The main conclusions are as follows:

1) From 2000 to 2017, the average annual growth rate of total factor productivity of carbon in the counties of the Yellow River Basin was 14.98%. From the source of the growth of total factor productivity of carbon, the progress of scale technology is the main driving force for the growth of total factor productivity of carbon in the counties of the Yellow River Basin.

2) From the perspective of spatio-temporal trends, the growth of total factor productivity of carbon in the counties of the Yellow River Basin from 2000 to 2017 showed obvious phased fluctuations, which can be roughly divided into

three stages: 2000-2010, 2010-2012, and 2012-2017. The growth rate of total factor productivity of carbon in different stages changed slightly and had spatial imbalance.

3) From the decomposition items of total factor productivity of carbon in each province, the driving situations of total factor productivity of carbon in the counties of the nine provinces in the Yellow River Basin are mainly divided into two types: The first type is "dual-track driving", mainly including eight provinces such as Gansu, Henan, Inner Mongolia, Ningxia, Shandong, Shanxi, Shaanxi and Sichuan. The second type is "single-track driving", and the representative province is Qinghai.

4) The regional gap of total factor productivity of carbon in the counties of the Yellow River Basin is narrowing, showing the characteristic of dynamic convergence, and its growth shows an overall deterioration phenomenon. From the perspective of the distribution of each province, the convergence characteristics are more obvious, but the level of total factor productivity of carbon fluctuates greatly.

Based on the above conclusions, the following policy suggestions are put forward:

1) Adapt measures to local conditions and strengthen regional coordinated governance. According to the unique geographical allocation of resources, market-oriented, establish forward-looking industries, accelerate industrial structure adjustment and leapfrogging. Use the geographical correlation between regional total factor productivity of carbon to jointly plan and formulate carbon dioxide emission reduction plans, minimize costs and improve the efficiency of emission reduction technologies, and establish a common prevention and control cooperation zone to collaboratively manage carbon dioxide emissions and share achievements. Give full play to the radiation effect of provinces with high total factor productivity of carbon to drive the common development of surrounding and underdeveloped areas and provide a good impetus for coordinated development.

2) Adjust and optimize the industrial structure. Focus on reducing industrial carbon dioxide emissions in high-carbon industries such as electricity, steel, non-ferrous metals, cement, petrochemicals, coal and coke, and vigorously promote the green development of high-carbon industries. Accelerate the development of emerging industries such as modern service industry, high-tech industry, advanced manufacturing industry and digital economy. Rely on technological progress and innovation to promote the effective growth of industries, promote the low-carbon transformation of traditional industries, vigorously develop new low-carbon and green economy, promote the adjustment and upgrading of industrial structure, reduce industrial energy consumption and carbon emissions, and gradually achieve decoupling of economic growth and carbon emissions.

3) Strengthen technological innovation. To establish a complete green and

low-carbon technological innovation path, it is necessary to take enterprises as the innovation subject of the green and low-carbon technology system, and give full play to the advantages of funds, technology, R&D centers and industrial laboratories, as well as industrial scale. Take private enterprises as the innovation subject of emerging green and low-carbon technologies, and make good use of the advantages of private enterprises in policy flexibility, innovation vitality, talent aggregation, etc. Deploy the exploration of technologies applicable to multiple industries in key fields to lay a foundation for the establishment of industrial innovation platforms.

4) Provide carbon reduction guarantees. To achieve the goals of carbon peak and carbon neutrality, not only top-level design support such as the national overall strategic plan is needed, but also it is necessary to establish and improve safeguard measures. With the help of loans, transfer payments or other means, support the research and development of emission reduction technologies and subsidize low-carbon costs. Improve carbon emission reduction policies through laws or regulations to increase the enthusiasm of companies and industries for carbon emission reduction. Coordinate the relationship between the government and the market and promote the market absorption of low-carbon technologies. Promote the establishment of the "government guidance + company cooperation" model, give full play to market orientation, accelerate the construction of the carbon market, and continuously improve the capacity of ecological carbon sinks.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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