Environmental Engineering and Management Journal December 2020, Vol.19, No. 12, 2255-2261
http://www.eemj.icpm.tuiasi.ro/; http://www.eemj.eu

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STUDY ON THE TEMPORAL-SPATIAL EVOLUTION RULES OF INTER-PROVINCIAL ECO-EFFICIENCY IN CHINA

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Abstract

To study the inter-provincial eco-efficiency in China from multiple perspectives and various aspects, this paper built the super-efficiency data envelopment analysis (US-DEA) model of undesirable outputs, σ convergence model, spatial correlation model and Malmquist index. The model constructed was used to analyze the convergence of inter-provincial eco-efficiency of different years based on the inter-provincial panel data from 2008 to 2017 in China. The spatial correlation of inter-provincial eco-efficiency was measured as well. Then this paper carried out the dynamic analysis of the inter-provincial total factor productivity. The results show that: ① The dynamic analysis indicates that the overall eco-efficiency in China has not changed much and the eco-efficiency does not have convergence; the horizontal analysis shows that the eco-efficiency of each province differs greatly; ② The analysis of the global Moran's I index in China shows that the absolute value of this index is relatively small, indicating that there is no spatial correlation between the eco-efficiency of all provinces in China; ③ According to the analysis of the Malmquist index in different years, it can be known that the year-on-year rise of this index is quite significant, resulting from the increasing inter-provincial production technological efficiency change TC. The inter-provincial technical efficiency change EC is not significant.

Keywords: convergence model, inter-provincial eco-efficiency, Malmquist index, Moran's I index, super efficiency DEA model

Received: January, 2020; Revised final: April, 2020; Accepted: June, 2020; Published in final edited form: December, 2020

1. Introduction

Since the reform and opening up, China's economy has been developing rapidly, but at the huge cost of energy and environment. Especially over the past ten years, the proportion of hazy days in China has increased, water quality has been polluted, and industrial waste has increased, reflecting the severity of environmental pollution and ecological vulnerability in China. To this end, the fourth plenary session of the 18th Central Committee of the Communist Party of China (CPC) clearly pointed out that it is necessary to protect the ecological environment and establish a legal system for ecological civilization. Therefore, how to obtain the maximum economic and social benefits with the least resource loss is an important issue for all regions in the process of economic development and environmental protection. The efficiency of regional input and output can be quantitatively measured through the evaluation of eco-efficiency. German scholars Schaltegger and Sturn first proposed the concept of eco-efficiency in 1990 as a practical approach of expressing sustainability, the ratio of increased value to increased environmental impact (Schaltegger and Sturm, 1990). In 1998, the Organization for Economic Co-operation and Development (OECD) expanded and promoted the concept of eco-efficiency (Kuosmanen, 2010) to the sectors in rural cultivated land (Bonfiglio et al., 2017), agriculture (Maia et al., 2016) and small and medium-sized enterprises (Charmondusit et al., 2014). In general, eco-efficiency refers to the production

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process with smaller ecological input, greater economic output and less environmental pollution (e.g. wastewater, waste gas and solid waste) generated during economic development (Mengyang and Shunbo, 2018). With the deepening of the research, a variety of approaches are applied in the evaluation of eco-efficiency. The main approaches are comprehensive index evaluation method (Danyang et al., 2016), ecological footprint method (Yi et al., 2017), participatory method (Mickwitz et al., 2006), energy value-material flow method (Chuanglin and Yufei, 2017; Yongbin et al., 2015) and data envelopment method (Chengyu et al., 2018; Yeh et al., 2020) with evaluating objects being diverse.

From the analysis of the current research data, it can be known that the data envelopment analysis (DEA) is the main method used to evaluate the eco-efficiency. Its advantage lies in the use of professional statistical methods to automatically assign reasonable weights to each indicator rather than traditional methods based on subjective experience, which can avoid the uncontrollable impact from the arbitrariness of subjective weighting on the calculation (Jun, 2014). The application of DEA to study eco-efficiency is not comprehensive.

The research objects should be studied from a spatial perspective to investigate the correlation of each research object in space as well as the correlation degree. At the same time, changes in the total factor productivity should be analyzed from a dynamic perspective to analyze the influence degree and direction of each factor affecting the total factor productivity so that the spatial condition and evolution law of regional eco-efficiency can be understood comprehensively from multiple perspectives and various aspects. This paper will quantitatively measure the eco-efficiency of each province in different years in China by constructing the super efficiency data envelopment model with undesirable outputs; apply the convergence model to investigate the convergence of eco-efficiency and use the spatial correlation model to measure the eco-efficiency spatial correlation between different provinces; use the Malmquist index to measure the total factor productivity, analyse the influence degree and direction of each factor affecting the total factor productivity.

2. Research methods and index data selection

2.1. Research methods

2.1.1. Super efficiency DEA model

Many different models for DEA have been constructed with its research and application. In 1978, Charnes, Cooper and Rhodes proposed the first DEA method to measure the relative efficiency of decision-making units (Charnes et al., 1978). This model is called the CCR model. It assumes that the scale returns of the production function are constant, or that all the measured units are in the optimal production scale stage despite of the variable scale returns of the production technology. However, in actual production, many production units are not in the optimal production state. Therefore, in 1984, Banker, Charnes and Cooper W. proposed the BCC model based on variable scale returns (Banker et al., 1984). The above two models are most applied to the evaluation of eco-efficiency in areas such as regions, industries and enterprises. However, the two models calculate the relative efficiency between 0 and 1, that is, the maximum efficiency value is 1. If values are the same, the efficiency of the effective decision-making units (DMUs) cannot be further compared and analyzed. Therefore, Andersen and Petersen (1993) proposed an approach for further distinguishing the effective DMUs. The approach is called the "Super Efficiency Model" (Andersen and Petersen, 1993), and the calculated efficiency value of the model can be greater than 1, which allows for a comparative analysis of effective decision-making units. In practical applications, output variables are sometimes undesired variables such as exhaust gas, solid waste and wastewater that occur during production. Scholars constructed models with undesired outputs based on the characteristics of non-undesired output.

In this paper, the super efficiency model with undesired output is applied to comprehensively evaluate the inter-provincial eco-efficiency based on the characteristics of the research objects. Suppose there are *n* DMUs and *m* inputs, and the *i* input of the *k* DMU is recorded as x_{ik} ($i = 1, 2, \ldots, m$); there are *q* outputs, of which there are q_1 desired outputs and q_2 undesired outputs. The *r* desired output of the *k* DMU is recorded as y_{rk} ($r = 1, 2 \ldots, q_i$); the *t* undesired output of the *k* decision-making unit is recorded as $b_{tk}(t = 1,2,\cdots,q_2)$; defining the US-DEA model with undesired output (Gang, 2014) (Eq. 1):

$$\min \rho = \frac{1+\frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{ik}}{1-\frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1} s_r^+ / y_{rk} + \sum_{t=1}^{q_2} s_t^{b-} / y_{tk}\right)}$$

$$s.t. \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j - s_i^- \leq x_{ik}$$

$$\sum_{j=1, j\neq k}^{n} y_{rj}\lambda_j - s_r^+ \geq y_{rk}$$

$$\sum_{j=1, j\neq k}^{n} b_{tj}\lambda_j - s_t^{b-} \leq b_{tk}$$

$$1-\frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1} s_r^+ / y_{rk} + \sum_{t=1}^{q_2} s_t^{b-} / y_{tk}\right) > 0$$

$$\lambda, s^-, s^+ \geq 0$$

$$i = 1,2,\cdots,m;\ j = 1,2,\cdots,q;\ j = 1,2,\cdots,n(j \neq k) \qquad (1)$$

where s_i^- is the input slack variable, s_r^+ is the desired output slack variable, s_t^{b-} is the non-desired output slack variable, and λ is the combined ratio in the effective decision making unit.

2.1.2. σ convergence model

In order to evaluate the temporal-spatial eco-efficiency fluctuations, a convergence model can be applied for measurement. Sun Hui and Deng Xiaole measured the convergence of regional carbon productivity in China by the σ convergence method and the β convergence method (Hui and Xiaole, 2018). Hou Mengyang and Yao Shunbo applied the α convergence method and the β convergence method to evaluate the convergence of China's agroecological efficiency (Mengyang and Shunbo, 2019). Liang Shuang and Zhang Yanhua constructed a bivariate Moran's Index to study the spatial distribution characteristics and the convergence of the urban human capital in China (Shuang and Yanhua, 2019). Nowadays, the σ convergence method is more often applied to evaluate convergence. It can be applied when the data has different means. Therefore, in this paper the σ convergence method is selected to evaluate the convergence of eco-efficiency. The calculation equation of the σ convergence method is (Eq. 2):

$$\sigma = \sqrt{n^{-1}\sum_{i=1}^{n}\left\{y_i - \left[n^{-1}\sum_{i=1}^{n} y_i\right]\right\}^2} \tag{2}$$

$$v_\sigma = \frac{\sigma}{\bar{y}} \tag{3}$$

where σ is the standard deviation of eco-efficiency, v_σ is the convergence coefficient of eco-efficiency, y_i is the eco-efficiency of the *i* period, $\bar{y}$ is the average of eco-efficiency, and *n* is the number of periods of eco-efficiency.

If the convergence coefficient v_σ of dynamic eco-efficiency is getting smaller and smaller, it indicates that the fluctuation of eco-efficiency becomes smaller and is converging; otherwise, the eco-efficiency is not converging.

2.1.3. Moran's I index model of eco-efficiency

To analyze the spatial correlation between the inter-provincial eco-efficiency, this paper used the global Moran's I index to measure the spatial correlation of inter-provincial eco-efficiency. The global Moran's I index can quantitatively measure the spatial correlation degree of regional eco-efficiency. The calculation equation is (Eq. 4):

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}(e_i - \bar{e})(e_j - \bar{e})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} \cdot \sum_{i=1}^{n}(e_i - \bar{e})^2} (i \neq j) \tag{4}$$

$$Z = \frac{(I - E(I)}{\sqrt{Var(I)}} \tag{5}$$

$$Var(I) = \frac{1}{S_0^2(n-1)}(n^2 S_1 - nS_2 + 3S_0^2) - \frac{1}{(n-1)^2},$$

$$E(I) = -\frac{1}{n-1}$$

$$S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij} \text{ , } S_1 = 2\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}^2 \text{ , } S_2 = 4\sum_{i=1}^{n} W_{i\cdot} \text{ , } W_{i\cdot} = \sum_{j=1}^{n} W_{ij}$$

where W_{ij} is the correlation coefficient between the *i*-th province and the *j*-th province. When the *i*-th province is correlated to the *j*-th province, $W_{ij} = 1$; otherwise, $w_{ij} = 0$.

2.1.4. Total factor productivity index model of eco-efficiency

The Malmquist total factor productivity (TFP) index model can be used to study the dynamic evolution characteristics of eco-efficiency in different periods. The model can be decomposed into the technological changes (TC) and the technical efficiency changes (EC) within two periods. The calculation equation of the fixed reference Malmquist index is given by Eq. (6):

$$MI(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{E^f(x^{t+1}, y^{t+1})}{E^f(x^t, y^t)}$$

$$= \frac{E^{t+1}(x^{t+1}, y^{t+1})}{E^t(x^t, y^t)} \times \frac{E^f(x^{t+1}, y^{t+1}) / E^f(x^t, y^t)}{E^{t+1}(x^{t+1}, y^{t+1}) / E^t(x^t, y^t)} = EC \times TC \tag{6}$$

where $E^f(x^t, y^t), E^f(x^{t+1}, y^{t+1})$ indicates the total factor productivity index of the $t, t+1$ period with a fixed period as own reference frontier. $E^t(x^t, y^t), E^{t+1}(x^{t+1}, y^{t+1})$ indicate the total factor productivity index of the $t, t+1$ period with the current period as own reference frontier.

2.2. Index data selection

2.2.1. Index selection

▪ *Input indexes*

The number of employed people, total water consumption and total energy consumption are selected as input indexes to study the inter-provincial eco-efficiency. The important determinant of the output of a region is the number of people employed. The consumption of water and energy resources in the output process is also considered. The total energy consumption is the conversion of the energy consumption of coal, oil and natural gas in each province into the total energy consumption as an input index.

▪ *Output indexes*

GDP, financial revenue, industrial wastewater discharge, the industrial waste gas emissions and the total amount of industrial solid waste production are selected as output indexes. The first two are desired outputs; the latter three are undesired outputs. In terms of output, most scholars choose GDP as the output index because the eco-efficiency analysis is dynamic, where the GDP calculated at the current price is converted into the GDP calculated at the constant price of 2008. In this paper financial revenue is also used as an output index to reflect the output results more completely, allowing the output indexes to be more comprehensive. A region has the desired output and also produces the undesired output. The industrial wastewater discharge, the industrial waste gas emissions and the total amount of industrial solid waste production are selected in this paper as the undesired output indexes.

2.2.2. Data selection

In this paper, the data of 30 provinces, autonomous regions and municipalities directly under the Central Government (Hong Kong, Macao, Taiwan and Tibet are not included in the analysis due to lack of data) from 2008 to 2017 are selected as a research sample with a total of 300 observed values. All data are derived from the "China Statistical Yearbook", "China Environment Yearbook" and "China Energy Statistics Yearbook" over the years.

3. Calculation results and analysis

3.1. Static analysis of inter-provincial eco-efficiency

The MaxDEA7 was used to perform the eco-efficiency calculation based on China's input-output indicator data from 2008 to 2017. The eco-efficiency of 30 provinces in China with different years as the reference sets was obtained. The specific data is shown in Table 1. From the analysis of dynamic average data, it can be seen that the eco-efficiency of each province is quite different. The four provinces with the highest eco-efficiency are Beijing, Shandong, Guangdong and Shanghai whose eco-efficiency is 2.536, 1.446, 1.417, and 1.263, respectively. These provinces are all economically developed regions; the four provinces with the lowest eco-efficiency are Guangxi, Yunnan, Jiangxi, and Xinjiang whose eco-efficiency is 0.695, 0.734, 0.751 and 0.756, respectively. These provinces are economically underdeveloped regions. From the analysis of China's average annual eco-efficiency in different years, it can be known that the average value in 2008 was 0.967, which was 0.993 in 2017. It can be found that the inter-provincial eco-efficiency in China has no uptrend.

Table 1. Static eco-efficiency values of 30 provinces in China from 2008 to 2017

Province	*2008*	*2009*	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*	*Average*
Anhui	0.774	0.769	0.791	0.728	0.745	0.741	0.743	0.750	0.786	0.790	0.762
Beijing	2.067	1.974	2.106	2.230	3.034	3.099	2.612	2.500	2.616	3.120	2.536
Fujian	0.794	0.792	0.810	0.779	0.814	0.825	0.848	0.866	0.893	0.868	0.829
Gansu	0.852	0.832	0.855	0.796	0.826	0.817	0.832	0.833	0.844	0.855	0.834
Guangdong	1.423	1.396	1.361	1.384	1.403	1.385	1.452	1.423	1.461	1.482	1.417
Guangxi	0.640	0.645	0.651	0.682	0.685	0.701	0.720	0.729	0.754	0.743	0.695
Guizhou	0.821	0.799	0.827	0.755	0.777	0.778	0.742	0.746	0.782	0.737	0.776
Hainan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Hebei	0.867	0.862	0.885	0.868	0.861	0.862	0.868	0.885	0.877	0.921	0.876
Henan	0.865	0.854	0.878	0.833	0.835	0.832	0.840	0.868	0.873	0.883	0.856
Heilongjiang	0.894	0.875	0.890	0.840	0.827	0.837	0.836	0.838	0.849	0.841	0.853
Hubei	0.778	0.786	0.809	0.788	0.804	0.810	0.819	0.825	0.864	0.840	0.812
Hunan	0.808	0.809	0.815	0.825	0.812	0.819	0.845	0.863	0.875	0.857	0.833
Jilin	0.825	0.805	0.819	0.802	0.821	0.814	0.825	0.797	0.871	0.812	0.819
Jiangsu	1.016	1.034	1.038	1.053	1.085	1.107	1.132	1.134	1.149	1.154	1.090
Jiangxi	0.792	0.783	0.765	0.729	0.733	0.731	0.736	0.727	0.751	0.766	0.751
Liaoning	0.870	0.880	0.926	0.925	0.930	0.942	0.891	0.884	0.854	0.833	0.894
Inner Mongolia	1.075	1.072	1.013	0.975	1.025	0.999	0.991	1.004	1.004	1.002	1.016
Ningxia	1.195	0.909	0.872	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.998
Qinghai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Shandong	1.391	1.408	1.419	1.425	1.441	1.464	1.494	1.542	1.436	1.443	1.446
Shanxi	0.837	0.808	0.806	0.798	0.796	0.783	0.767	0.754	0.744	0.762	0.786
Shaanxi	0.844	0.822	0.842	0.837	0.852	0.848	0.835	0.807	0.795	0.791	0.827
Shanghai	1.457	1.385	1.431	1.224	1.238	1.248	1.105	1.130	1.224	1.191	1.263
Sichuan	0.804	0.825	0.843	0.840	0.856	0.857	0.860	0.890	0.879	0.848	0.850
Tianjin	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Xinjiang	0.794	0.756	0.745	0.737	0.747	0.741	0.749	0.756	0.770	0.768	0.756
Yunnan	0.818	0.787	0.802	0.691	0.713	0.714	0.713	0.703	0.691	0.704	0.734
Zhejiang	0.976	0.973	0.970	0.978	0.974	0.982	0.993	0.989	1.008	1.010	0.985
Chongqing	0.743	0.748	0.772	0.787	0.806	0.793	0.800	0.803	0.765	0.755	0.777
Average	0.967	0.946	0.958	0.944	0.981	0.984	0.968	0.968	0.981	0.993	0.976

3.2. Convergence analysis of inter-provincial eco-efficiency

The standard deviation σ and the convergence coefficient v_σ of different inter-provincial eco-efficiency can be calculated based on equations (2) and (3), as well as the data of Table 1. The specific data is shown in Table 2. From Table 2, it can be seen that the convergence coefficient in 2008 was 0.294, which was 0.440 in 2017. There was no downtrend during the period, indicating that the inter-provincial eco-efficiency in China was not convergent. The eco-efficiency fluctuation did not decrease during the period, reflecting that the inter-provincial eco-efficiency fluctuation during the period is unstable.

3.3. Spatial correlation analysis of inter-provincial eco-efficiency

To analyze the spatial correlation between the inter-provincial eco-efficiency, the global Moran's I index measurement model was applied to calculate the inter-provincial Moran's I index in different periods in China. The specific data is shown in Table 3. According to the corresponding relationship in Table 4, the P values corresponding to different Z can be determined. It can be seen from the data in Table 3 that the index is relatively small. The data in Table 4 shows that the corresponding P values are all zero, indicating that there is no spatial correlation between the inter-provincial eco-efficiency in China.

3.4. Dynamic analysis of inter-provincial total factor productivity

To study the dynamic evolution characteristics of the total factor productivity in different periods, 2008 was used as the fixed reference set to calculate the Malmquist index in different years. The specific data is shown in Table 5. According to the data in Table 5, it can be found that the Malmquist index is increasing year by year. In 2008, the arithmetic average of the index was 0.967, which rose to 1.752 in 2017. The year-on-year increase is very significant.

Table 2. Convergence coefficient of inter-provincial eco-efficiency in China from 2008 to 2017

Indicator	*2008*	*2009*	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*
σ	0.284	0.267	0.282	0.300	0.422	0.434	0.357	0.342	0.355	0.437
$\overline{e}$	0.967	0.946	0.958	0.944	0.981	0.984	0.968	0.968	0.981	0.993
v_σ	0.294	0.283	0.294	0.317	0.431	0.441	0.369	0.353	0.362	0.440

Table 3. Spatial Moran's I index of each inter-provincial eco-efficiency in China from 008 to 2017

Indicator	*2008*	*2009*	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*
I	-0.001	-0.002	0.002	0.004	-0.011	-0.009	-0.014	-0.011	-0.016	0.002
Z	0.303	0.293	0.332	0.350	0.215	0.232	0.189	0.215	0.208	0.327

Table 4. Correspondence between Z value and P value

No.	*1*	*2*	*3*	*4*	*5*	*6*	*7*
Z	<-2.58	-2.58~-1.96	-1.96~-1.65	0	1.65~1.96	1.96~2.58	>2.58
P	0.01	0.05	0.10	—	0.10	0.05	0.01

Table 5. Malmquist indexes of 30 provinces in China from 2008 to 2017

Province	*2008*	*2009*	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*
Anhui	0.774	0.800	0.841	0.811	0.873	0.927	0.967	1.024	1.143	1.209
Beijing	2.067	2.244	2.622	3.300	4.310	4.105	4.527	6.320	7.595	7.977
Fujian	0.794	0.821	0.854	0.843	0.931	0.996	1.067	1.130	1.225	1.266
Gansu	0.852	0.863	0.880	0.866	0.884	0.918	0.947	0.977	1.009	1.042
Guangdong	1.423	1.490	1.701	2.080	2.359	2.689	3.063	3.557	3.956	4.312
Guangxi	0.640	0.664	0.676	0.754	0.764	0.819	0.857	0.886	0.974	0.996
Guizhou	0.821	0.843	0.901	0.906	0.931	0.994	0.958	0.991	1.074	1.000
Hainan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Hebei	0.867	0.892	0.918	0.956	0.993	1.058	1.124	1.223	1.323	1.466
Henan	0.865	0.882	0.916	0.886	0.942	1.063	1.251	1.335	1.404	1.499
Heilongjiang	0.894	0.929	0.963	0.935	0.953	1.014	1.044	1.090	1.176	1.214
Hubei	0.778	0.813	0.854	0.843	0.905	0.979	1.066	1.156	1.257	1.317
Hunan	0.808	0.838	0.859	0.886	0.926	0.960	1.023	1.085	1.157	1.217
Jilin	0.825	0.848	0.882	0.918	0.969	1.020	1.044	1.066	1.245	1.174
Jiangsu	1.016	1.093	1.293	1.628	1.853	2.077	2.287	2.539	2.569	2.584
Jiangxi	0.792	0.810	0.825	0.806	0.835	0.873	0.937	1.018	1.021	1.105

Liaoning	0.870	0.924	1.006	1.141	1.317	1.423	1.406	1.330	1.333	1.405
Inner Mongolia	1.075	1.169	1.144	1.207	1.286	1.329	1.365	1.453	1.573	1.634
Ningxia	1.195	0.919	0.977	1.000	1.105	1.166	1.182	1.276	1.237	1.346
Qinghai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Shandong	1.391	1.560	1.740	1.922	2.123	2.351	2.579	2.799	3.002	3.264
Shanxi	0.837	0.864	0.887	0.957	0.959	0.998	1.006	1.006	1.043	1.112
Shaanxi	0.844	0.874	0.924	0.993	1.032	1.083	1.091	1.080	1.101	1.142
Shanghai	1.457	1.490	1.698	1.827	1.990	2.176	2.335	2.813	3.263	3.379
Sichuan	0.804	0.854	0.875	0.950	1.046	1.112	1.157	1.226	1.233	1.311
Tianjin	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Xinjiang	0.794	0.788	0.772	0.860	0.883	0.927	0.969	1.001	1.029	1.043
Yunnan	0.818	0.845	0.889	0.799	0.838	0.889	0.920	0.938	0.947	0.979
Zhejiang	0.976	1.052	1.134	1.307	1.422	1.558	1.703	1.958	2.161	2.360
Chongqing	0.743	0.771	0.839	0.913	0.965	0.973	1.030	1.105	1.123	1.205
Average	0.967	0.998	1.062	1.143	1.246	1.316	1.397	1.546	1.672	1.752

Table 6. Changes in Malmquist indexes of 30 provinces in China between 2017 and 2018

Province	***2008***	***2017***	MI	EC	TC
Anhui	0.774	1.209	1.562	1.022	1.528
Beijing	2.067	7.977	3.859	1.509	2.558
Fujian	0.794	1.266	1.594	1.093	1.458
Gansu	0.852	1.042	1.223	1.002	1.220
Guangdong	1.423	4.312	3.030	1.042	2.908
Guangxi	0.640	0.996	1.556	1.160	1.341
Guizhou	0.821	1.000	1.218	0.897	1.358
Hainan	1.000	1.000	1.000	1.000	1.000
Hebei	0.867	1.466	1.691	1.063	1.591
Henan	0.865	1.499	1.733	1.020	1.699
Heilongjiang	0.894	1.214	1.358	0.940	1.444
Hubei	0.778	1.317	1.693	1.080	1.567
Hunan	0.808	1.217	1.506	1.061	1.420
Jilin	0.825	1.174	1.423	0.983	1.448
Jiangsu	1.016	2.584	2.543	1.135	2.241
Jiangxi	0.792	1.105	1.395	0.965	1.445
Liaoning	0.870	1.405	1.615	0.957	1.687
Inner Mongolia	1.075	1.634	1.520	0.933	1.630
Ningxia	1.195	1.346	1.126	0.836	1.347
Qinghai	1.000	1.000	1.000	1.000	1.000
Shandong	1.391	3.264	2.347	1.039	2.258
Shanxi	0.837	1.112	1.329	0.912	1.458
Shaanxi	0.844	1.142	1.353	0.938	1.443
Shanghai	1.457	3.379	2.319	0.818	2.835
Sichuan	0.804	1.311	1.631	1.056	1.545
Tianjin	1.000	1.000	1.000	1.000	1.000
Xinjiang	0.794	1.043	1.314	0.970	1.355
Yunnan	0.818	0.979	1.197	0.860	1.392
Zhejiang	0.976	2.360	2.418	1.036	2.335
Chongqing	0.743	1.205	1.622	1.017	1.595
Average	0.967	1.752	1.673	1.011	1.637

To further analyze the changes and influencing factors of the Malmquist index for the dynamic total factor productivity, the 2008 and 2017 Malmquist indexes were listed in Table 6. The Malmquist index of 2017 was divided by that of 2008 to obtain *MI*, which can reflect the changes in the dynamic total factor productivity. Provinces with *MI* greater than 2.000 are Beijing, Guangdong, Jiangsu, Shandong, Zhejiang and Shanghai, which are all economically developed regions. Provinces with *MI* remaining 1.000 are Hainan, Qinghai, and Tianjin. Both provinces are economically underdeveloped regions except Tianjin. The change in the total factor productivity index MI can be decomposed into the efficiency change (EC) and technological change (*TC*), the relationship is: *MI* = *EC* x *TC*. It can be known from Table 6 that except for Beijing, the *EC* values of other provinces are all around 1, indicating that the efficiency of these provinces has not changed much during the period; the *TC* values of all provinces are greater than or equal to 1, indicating that the increasing *MI* values of provinces during the period result from by the increasing *TC* values. The influences of *EC* changes on *MI* are not significant.

4. Research conclusions and inspirations

This paper used the super efficiency DEA model with undesirable outputs, the σ convergence model, the spatial correlation model and the Malmquist index model to study the eco-efficiency of inter-provincial regions in China from 2008 to 2017. The eco-efficiency spatial correlation of different provinces and the dynamic evolution were analyzed comprehensively. The following conclusions can be drawn:

From the analysis of the average eco-efficiency of each province, it can be found that the eco-efficiency of each province is quite different. Provinces with high eco-efficiency are economically developed regions; while provinces with the lowest eco-efficiency are almost economically underdeveloped areas, indicating that the eco-efficiency is related to the economic development level.

From the convergence coefficient analysis of inter-provincial eco-efficiency in China from 2008 to 2017, it can be seen that there is no trend for the value to become smaller during this period, indicating that the inter-provincial eco-efficiency in China does not have convergence, reflecting that inter-provincial eco-efficiency fluctuations are unstable.

Based on the global Moran's I index measurement analysis in China, it can be known that the index is relatively small and most of values are negative, indicating that there is no spatial correlation between China's inter-provincial eco-efficiency, and each inter-provincial eco-efficiency is specifically independent.

The analysis of the Malmquist index in different years shows that there is a significant year-on-year rise trend of the index, resulting from the increasing inter-provincial production technological efficiency change *TC*. The inter-provincial technical efficiency change *EC* is not significant.

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