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Provincial Low-carbon Emission Efficiency Measurement and Spatial-temporal Evolution in China Based on Super-SBM Model and GML Analysis#

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ABSTRACT

This paper analyzes China's provincial low-carbon efficiency using the super-SBM model, GML index, and ridge regression. Results reveal that enhancing energy structure, promoting renewable energy, and increasing carbon sequestration benefit the efficiency. Eastern and western regions' renewable energy use significantly impacts efficiency, while vegetation construction is vital in central and northeastern regions. Efficiency initially decreased, hitting a low in 2011-2012, then rose since 2013. Spatially, efficiency declines from periphery to center, with the order: east, west, northeast, and central. Technological progress notably influences low-carbon efficiency. Findings inform carbon mitigation strategies, guiding China's path to carbon neutrality.

Keywords: Low-carbon emission efficiency, renewable energy, carbon sequestration, super-SBM model

NONMENCLATURE

Abbreviations	
Super-SBM	Super slack based measure
GML index	Global Malmquist-Luenberger

1. INTRODUCTION

In recent years, China's economy has developed rapidly. At the same time, carbon dioxide emissions have increased, creating some environmental problems. China has become the country with the highest carbon emissions in the world [1]. China has undertaken an extremely important social responsibility and adopted a series of energy conservation and emission reduction policies to actively address climate change [2, 3]. In 2020, China further proposed to "reach carbon peaking by 2030 and achieve carbon neutrality by 2060" in response to climate change[4, 5]. Improving low-carbon emission efficiency (LCEE) is an effective way to help China's low-carbon development. In 2019, China's renewable energy generation accounted for 27.9% of the total[6]. Compared with fossil energy, renewable energy has zero emissions and can effectively reduce CO_2 emissions. Meanwhile, carbon sequestration of vegetation has the effect of increasing sink and reducing emissions, which is another effective way to improve low-carbon efficiency[7, 8].

Many literature have studied regional carbon emission efficiency[9], energy efficiency[10], and green development efficiency[11] in China. However, there are few studies on low-carbon efficiency[12]. Most of the selected indicators focus on total energy consumption and carbon emissions[13]. Renewable energy and carbon sequestration factors have rarely been considered. With the increasing proportion of renewable energy consumption and the construction of a green ecosystem, it is an inevitable trend to consider renewable energy and carbon sequestration in the measurement of LCEE. It is difficult to go through the same path to achieve low-carbon development in different regions.

So far, the data envelopment analysis model (DEA) and its extensions have made some progress in the study of carbon emission efficiency[14, 15], energy efficiency[16], environmental efficiency[17, 18], and so on. The GML index is further used to analyze the dynamic change of efficiency from technical efficiency and scale progress [19]. Among them, the super-SBM model not only considers the maximization of desirable output but also the minimization of undesired output when measuring efficiency. This is more in line with the concept of low-carbon development. Combined with the existing literature, it can be seen that the SBM model still has certain limitations, which cannot clarify the degree of influence of each factor on efficiency. Ridge regression model is widely used in multi-index impact assessment [20].

In summary, this paper included renewable energy consumption and carbon sequestration as evaluation indicators, super-SBM model was used to measure the low-carbon emission efficiency of 30 provinces in China from 2007 to 2017, GML index analyzed the spatio-temporal distribution characteristics of efficiency from technical efficiency and scale progress. The Ridge regression model analyzed the degree to which factors

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such as renewable energy consumption, carbon sequestration, GDP and fossil energy consumption affect the low carbon emission efficiency in different regions. This study is expected to provide a reference for China's low-carbon development path.

2. MATERIAL AND METHODS

2.1 Super-SBM model with undesirable outputs

In this paper, the super-SBM model with undesirable outputs is used to measure the low-carbon emission efficiency (LCE) of Chinese provinces[21]. Because improving low carbon efficiency is to responding to China's carbon emission challenges, while also to achieving sustainable development[22]. Therefore, the measurement of LCE does not only reflect changes in economic-social inputs and energy consumption structures, but also considers the carbon sequestration and the degree of carbon emission in each province. The formula of this model can be constructed as Eq. (1), Eq. (2), Eq. (3) and Eq. (4).

$$\rho^* = min\frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}}{x_{i0}}}{\frac{1}{n_1+n_2}(\sum_{\mathrm{r}=1}^{n_1}\frac{\bar{y}}{y_{\mathrm{r}0}}+\sum_{\mathrm{r}=1}^{n_2}\frac{\bar{z}}{z_{\mathrm{r}0}})} \tag{1}$$

$$\text{s.t.}\ \ \bar{x} \geq \sum_{j=1,j\neq 0}^{n}\lambda_j \mathrm{x}_{ij} \qquad x_0 = \mathrm{x}\lambda + \varsigma^- \tag{2}$$

$$\bar{y} \leq \sum_{j=1,j\neq 0}^{n}\lambda_j\, y_{rj} \qquad y_0 = y_r\lambda - \varsigma^y \tag{3}$$

$$\bar{z} \geq \sum_{j=1,j\neq 0}^{n}\lambda_j\, \mathrm{z}_{rj} \qquad z_0 = \mathrm{z}_r\lambda + \varsigma^z \tag{4}$$

where x_{ij}, y_{ij} and z_{ij} are the inputs, desirable outputs, and undesired outputs, respectively; ς^-, ς^y and ς^z are the input and output slack matrices; X, Y, and Z are the input and output matrices, respectively; λ is the weight vector; ρ^* is the efficiency evaluation. If and only if $\rho^* \geq 1$, the DMU is considered effective. Otherwise, the DMU is in an inefficient state and needs to be further improved in terms of inputs, outputs, production scale, or industrial structure.

For the scenario analysis of renewable energy consumption and carbon sequestration capacity, we take control of the input and output variables of the SBM-DEA model to achieve this.

2.2 GML index

The Malmquist index is widely used in efficiency analysis. Oh [23] proposed a model with high continuity to estimate the growth of total factor efficiency, namely, GML index. This model realizes the possibility of cross-period comparison of efficiency and can reflect the contribution of technical efficiency and scale progress to the change of environmental efficiency.

$$\begin{aligned} GML_k^{t,t+1} &= \frac{1+D^G(x_k^t,y_k^t,p_k^t)}{1+D^G(x_k^{t+1},y_k^{t+1},p_k^{t+1})} \\ &= \frac{1+D^t(x_k^t,y_k^t,p_k^t)}{1+D^{t+1}(x_k^{t+1},y_k^{t+1},p_k^{t+1})} \\ &\times \left[\frac{1+D^G(x_k^t,y_k^t,p_k^t)}{1+D^t(x_k^t,y_k^t,p_k^t)} \times \frac{1+D^{t+1}(x_k^{t+1},y_k^{t+1},p_k^{t+1})}{1+D^G(x_k^{t+1},y_k^{t+1},p_k^{t+1})}\right] \\ &= EC_k^{t,t+1}\times TC_k^{t,t+1} \end{aligned} \tag{5}$$

Where, GM $L_K^{t,t+1}$ represents the change of low-carbon emission efficiency (LCEE) in the two-phase of DMU; $\mathrm{E}C_K^{t,t+1}$ represents the change of technical efficiency; and $\mathrm{T}C_K^{t,t+1}$ represents the technological scale progress. Among them, GML>1 (<1) represents the improvement (decrease) in LCEE; EC > 1 (<1) represents the improvement (decrease) in technical efficiency; and TC > 1(<1) represents technological progress (regression).

2.3 Ridge regression model

Multiple collinearities among factors of production, so a series of problems will arise in analyzing the impactions. The ridge regression estimation is a least squares regression with a two-norm penalty, which can effectively solve the problems of collinearity. Furthermore, as coefficients estimated using ridge regression are more realistic. So, the ridge regression is used to solve this problem.

2.4 Variables and data

Considering the feasibility of data acquisition, 30 provinces in China from 2007-2017 were selected for this study, and Tibet was not considered. The input and output variables are shown in Table 1.

Input variables： (1) Socioeconomic factors: capital and labor were selected as input variables. Among them, capital input was measured by the perpetual inventory method proposed by Jun Zhang[24], as in Eq (6). The labor input variable was measured by the number of employees at the end of the year in each province. Data were obtained from the China Provincial Statistical Yearbook (2008-2018).

$$K_{it} = K_{it-1}(1-\delta) + I_{it} \tag{6}$$

Where, K_{it} is the capital stock of the province i in year t; K_{it-1} is the capital stock in year t-1; δ is the depreciation rate, typically 9.6%[24]; I_{it} is the fixed asset investment in year t.

Table 1 Input-output index system

Variable	Index	Representation and unit
Input	Capital input	Investment stock of fixed assets (current billion yuan)
	Labor input	Employed workers (million people)
	Traditional fossil energy consumption	Traditional fossil energy consumption (million tons of coal)
	RE	Renewable energy generation capacity (billion kw·h)
Desirable output	GDP	Constant GDP in 2000 (100 million yuan)
	CSV	Carbon Sequestration Value of Terrestrial Vegetation (million tons)
Undesirable output	CO_2 emissions	CO_2 emissions (million tons)

(2) Energy consumption structure factors: energy consumption in each province was divided into traditional fossil energy and renewable energy consumption. As there were no direct renewable energy consumption statistics in China. According to the method of dividing the total energy consumption by the statistical yearbook, the total primary energy consumption was divided into fossil energy consumption (including coal, oil, natural gas, etc.) and primary electricity and other energy sources. According to the statistical yearbook, "primary electricity" included nuclear power, hydropower, wind power, and solar power. These were all renewable and clean energy sources. In addition, electricity was the most widely consumed form of non-fossil energy. Therefore, this paper used "primary electricity and other energy generation" to represent renewable energy consumption. The data were obtained from China Energy Statistical Yearbook (2007-2018).

Output variables: (1) Desirable output included GDP and carbon sequestration capacity of each province. Among them, in order to eliminate the influence of price factors on GDP, this paper took 2000 as the base period, then calculated the constant GDP in 2000. The data were obtained from the China Provincial Statistical Yearbook (2008-2018). Meanwhile, in order to consider the significance of vegetation construction on LCE improvement, the carbon sequestration capacity of each province was included as the expected output. It was obtained by summing up the county-level carbon sequestration value of terrestrial vegetation during 2007-2017 according to CEADs. (2) Undesirable output was CO_2 emissions. The data were obtained from CEADs.

3. RESULTS

3.1 Spatial- Temporal distribution

As shown the Fg.1, it can be found that the efficiency values of several provinces change significantly after considering renewable energy consumption and carbon sink benefits. This indicates that the transformation of the energy structure and the construction of the ecological environment have an important impact on the evaluation of low carbon emission efficiency, which is important for the improvement of low carbon emission efficiency. And the Fig.2 shows that the number of effective provinces was lowest in the early years of the 11th Five-Year Plan. From the mid to late 12th Five-Year Plan to the late 13th Five-Year Plan, the number of provinces with effective low-carbon emission efficiency gradually increased, breaking into single digits in 2016, reaching 13 provinces with effective efficiency. Further The Fig.3 show that the relative ranking of LCEE efficiency in each province at different periods have no major fluctuations in China's provinces, and the development is relatively stable. Guangdong, Hainan, Jiangsu, Qinghai, Zhejiang and Fujian are more efficient, while Shanxi, Shaanxi, Guizhou and Liaoning are less efficient. In addition, it is worth noting that since the middle and late stages of the 12th Five-Year Plan, the efficiency values of Beijing and Tianjin have increased significantly and their rankings have risen.

Notes： LCEE is the Low-Carbon Emission Efficiency considering RE and CSV; CEE is the Low-Carbon Emission Efficiency considering energy no RE and CSV

Fig. 1 The two scenarios

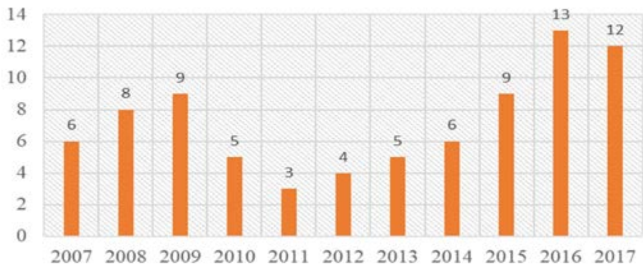

Fig. 2 Number of provinces with effective efficiency

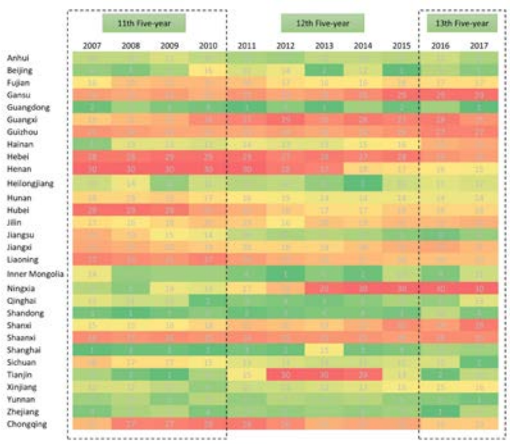

Fig. 3 The relative ranking

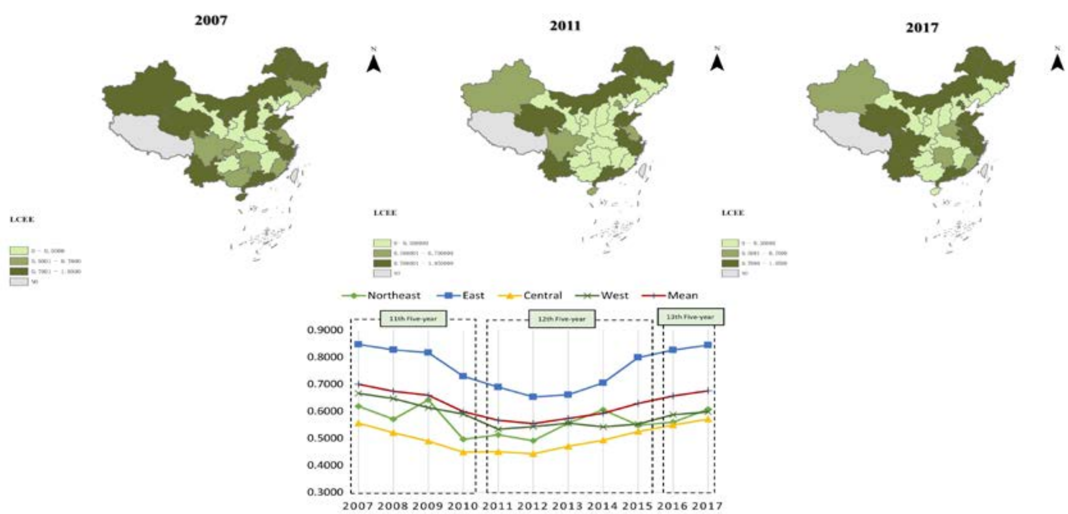

Fig. 4 Spatial- Temporal characteristics

The low carbon emission efficiency of 30 provinces in China is divided into three groups (high-medium-low). From the Fig. 4, the efficiency value gradually decreases from the surrounding to the center. High-efficiency provinces first decreased and then increased from the 11th Five-Year Plan to the 13th Five-Year Plan. From different regions, the order of efficiency values from high to low is east, west, northeast and central. Among them, the low-carbon emission efficiency of the eastern region is higher than the national average. During the study period, the overall value first decreased and then increased. Efficiency values were lowest in 2011 and 2012. However, it has increased since 2013. The national average efficiency increased from 0.5542 in 2012 to 0.6755 in 2017. The low-carbon environmental efficiency value in the eastern region has increased significantly, from 0.6530 in 2012 to 0.8446 in 2017.

To sum up, in the "Eleventh Five-Year Plan" period and the early "Twelfth Five-Year Plan" period, with the acceleration of industrialization and urbanization, the contradiction between the rapid development of China's energy demand and the resources and environment has become more prominent, resulting in low energy consumption during this period. The efficiency has declined. In the 12th Five-year Plan, China's central government first proposed the green development target. Accordingly, China's governments at all levels began to attach importance to the improvement of their regional green development level. Thus, from 2013 promote. During the 13th Five-Year Plan period, China began to advocate the development of a low-carbon economy and announced a series of policies. The efficiency has rapidly improved.

3.2 GML index decomposition

As shown in Table 2, from 2007 to 2017, the GML index of most provinces in China was greater than 1, indicating that their low-carbon emission efficiency showed an overall increasing trend. Ten provinces of Gansu, Guangxi, Guizhou, Hainan, Jilin, Ningxia, Shanxi, Shaanxi and Xinjiang declined slightly. It can be found that during the "13th Five-Year Plan" period, the provinces that achieved efficiency growth were significantly more than other periods, indicating that China's provinces have improved in low-carbon emission efficiency in recent years.

Table 2 The results of GML

	11th Five-year			11th Five-year			11th Five-year			The study stage		
	GML	EC	TC	GML	EC	TC	GML	EC	TC	GML	EC	TC
Anhui	0.86	1.12	0.77	1.24	0.99	1.25	1.06	1.00	1.07	1.13	1.11	1.02
Beijing	0.63	1.04	0.61	1.58	1.15	1.37	1.02	1.03	0.99	1.02	1.23	0.83
Fujian	0.69	0.60	1.15	1.24	1.01	1.22	1.09	1.04	1.06	0.93	0.63	1.48
Gansu	0.75	1.00	0.75	0.93	1.03	0.90	0.97	1.01	0.95	0.68	1.05	0.65
Guangdong	1.00	0.98	1.02	0.99	0.99	1.01	1.03	1.01	1.02	1.03	0.98	1.04
Guangxi	0.58	0.62	0.93	1.09	1.03	1.06	1.02	0.98	1.04	0.64	0.63	1.02
Guizhou	0.79	1.08	0.73	0.95	1.12	0.85	1.00	1.06	0.94	0.75	1.29	0.59
Hainan	0.58	1.05	0.55	0.68	0.54	1.25	1.00	0.99	1.01	0.39	0.57	0.69
Hebei	0.78	0.91	0.85	1.22	1.06	1.14	1.02	0.97	1.05	0.96	0.94	1.02
Henan	0.96	1.03	0.93	2.03	1.41	1.45	1.01	0.98	1.04	1.97	1.41	1.39
Heilongjiang	0.90	1.03	0.87	1.15	1.03	1.11	1.14	1.01	1.13	1.18	1.08	1.09
Hunan	0.86	1.06	0.81	1.18	1.07	1.10	1.10	1.06	1.04	1.12	1.20	0.93
Hubei	1.02	1.24	0.83	1.30	1.29	1.01	1.02	0.99	1.04	1.36	1.58	0.86
Jilin	0.72	0.75	0.97	0.94	1.40	0.67	1.01	1.02	0.99	0.69	1.07	0.65
Jiangsu	1.27	1.01	1.26	1.53	1.03	1.49	1.01	0.99	1.02	1.97	1.03	1.91
Jiangxi	0.87	0.73	1.19	0.89	0.82	1.08	1.06	1.07	0.99	0.82	0.64	1.28
Liaoning	0.83	0.96	0.87	1.15	0.97	1.18	1.03	0.99	1.04	0.98	0.93	1.06
Inner Mongolia	1.13	0.97	1.17	1.17	1.00	1.17	1.00	1.00	1.00	1.33	0.97	1.37
Ningxia	0.52	1.03	0.51	0.33	0.98	0.34	0.89	1.00	0.89	0.15	1.00	0.15
Qinghai	0.96	0.94	1.03	1.23	1.02	1.21	1.00	0.99	1.01	1.19	0.95	1.25
Shandong	1.00	0.65	1.53	0.97	0.86	1.13	1.06	1.01	1.05	1.02	0.56	1.82
Shanxi	0.51	0.87	0.58	0.95	0.99	0.96	0.92	1.01	0.92	0.44	0.87	0.51
Shaanxi	0.73	0.98	0.75	1.07	1.07	1.00	0.99	0.97	1.02	0.77	1.02	0.76
Shanghai	0.95	1.00	0.95	1.00	0.92	1.09	1.02	0.99	1.03	0.97	0.90	1.07
Sichuan	1.08	1.59	0.68	1.59	1.04	1.53	1.11	1.00	1.10	1.90	1.65	1.15
Tianjin	0.56	0.63	0.90	1.96	0.66	2.96	1.00	0.92	1.08	1.10	0.38	2.86
Xinjiang	0.77	1.06	0.72	0.85	0.88	0.97	0.97	0.99	0.98	0.64	0.92	0.69
Yunnan	0.84	0.91	0.92	1.25	0.95	1.32	1.03	1.02	1.01	1.08	0.89	1.22
Zhejiang	0.80	0.98	0.82	1.27	1.00	1.27	0.99	0.98	1.02	1.01	0.96	1.05
Chongqing	0.56	0.80	0.70	1.38	1.22	1.13	1.07	1.08	0.99	0.83	1.06	0.79
National average	0.82	0.95	0.88	1.17	1.02	1.17	1.02	1.01	1.02	1.00	0.98	1.07

In the Fig.5, on the national average, the contribution of technological progress to low-carbon emission efficiency is significantly greater than that of technological efficiency. From 2007 to 2017, the national average low-carbon emission efficiency increased at a rate of 0.2%, of which technological progress contributed 7%, while the technical efficiency declined, slowing down the improvement of the national average low-carbon emission efficiency.

Similarly, from the perspective of the 30 provinces, the contribution rate of technological progress in most provinces is greater than that of technological efficiency. Among them, jiangsu, heilongjiang, bejing, henan, Sichuan, hunan. These six provinces have improved in technological progress and technical efficiency. However, Hainan, xinjiang and shanxi all declined during the study period.

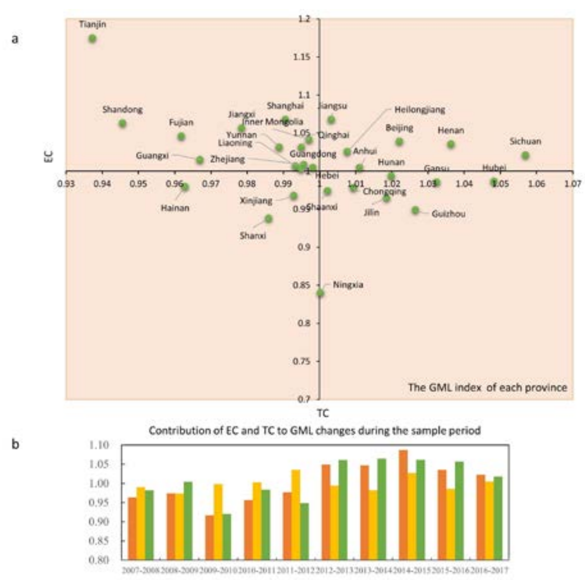

Fig. 5 The GML decomposition

Table 3 The influence of indexes

Northeast		East		Central		West	
k	0.0400	k	0.0600	k	0.0800	k	0.0500
Adjusted R^2	0.6968	Adjusted R^2	0.6780	Adjusted R^2	0.7069	Adjusted R^2	0.6780
Standard error	0.0420	Standard error	0.0251	Standard error	0.0248	Standard error	0.0251
F-statistic	5.5954	F-statistic	5.2118	F-statistic	5.8235	F-statistic	5.2118
Sig.F	0.0410	Sig.F	0.0471	Sig.F	0.0379	Sig.F	0.0471
Variable	Normalized coefficient	Variable	Normalized coefficient	Variable	Normalized coefficient	Variable	Normalized coefficient
E	-0.0278	E	-0.1039	E	-0.0122	E	-0.0079
RE	0.6444	RE	0.4155	RE	0.1103	RE	0.1405
GDP	0.0073	GDP	0.0465	GDP	0.0045	GDP	0.0046
TH	0.3024	TH	-0.3578	TH	0.8698	TH	0.8234
C	-0.0180	C	-0.0763	C	-0.0033	C	-0.0236

3.3 Influence of multiple indexes

The impact of GDP, traditional energy consumption (E), renewable energy consumption (RE), carbon sink income (CSV) and carbon dioxide emissions (CO_2) on low-carbon emission efficiency in four regions of China is shown in the Table 3. In the Eastern China, RE, GDP and CSV are positive effects on LCEE, but the contribution of RE is larger than that of CSV, and the contribution of GDP is not significant. The traditional energy consumption and carbon dioxide emissions are disadvantageous. In the western China, RE and GDP are positive effects on LCEE, but the contribution of GDP is not significant. However, traditional energy consumption, vegetation CSV and carbon dioxide emissions are unfavorable. In the northeast China, RE, GDP and CSV are positive effects on LCEE, but the contribution of CSV is larger than that of RE and the contribution of GDP is not significant. The traditional energy consumption and carbon dioxide emissions are disadvantageous. In the central China, RE, GDP and CSV are positive effects on LCEE, but the contribution of CSV is larger than that of RE and the contribution of GDP is not significant. The traditional energy consumption and carbon dioxide emissions are disadvantageous.

4. RESULTS

Through this paper used super-SBM model, GML index and ridge regression model to estimate the low-carbon emission efficiency of different provinces and regions in China, and evaluated the impact of renewable energy development and carbon sequestration construction in each province. The main conclusions are follows:

(1) Improving energy structure, increasing renewable energy consumption and increasing vegetation construction is all beneficial to improve low-carbon emission efficiency. However, the consumption of renewable energy in the eastern and western regions has a significant impact, while the effect of vegetation construction in the central and northeastern regions is more significant.

(2) During the study period, the low-carbon emission efficiency first decreased and then increased. Efficiency values were lowest in 2011 and 2012. However, it has increased since 2013. From the spatiotemporal distribution, the efficiency value gradually decreases from the surrounding to the center.

(3) From different regions, the order of efficiency values from high to low is east, west, northeast and central. Among them, the low-carbon emission efficiency of the eastern region is higher than the national average.

(4) From the driving factors, the contribution of technological progress to low-carbon emission efficiency is significantly greater than that of technological efficiency.

The research results are expected to provide inspiration for the comprehensive implementation of China's low-carbon transition, and comprehensively promote provincial actions to implement China's "dual carbon" goals.

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