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Xiaodan Zhang
Tongji University School of Economics and Management
Kaicheng Liao
Tongji University School of Economics and Management
Xianghong Zhou (xhztongji0927@163.com)
Tongji University School of Economics and Management

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Analysis of Regional Differences and Dynamic Mechanisms of Agricultural Carbon Emissions Efficiency in China's Seven Agricultural Regions

Xiaodan Zhang[1], Kaicheng Liao[1], Xianghong Zhou[1,2]

[1] School of Economics and Management, Tongji University, Shanghai, China, 200092;

Address: Building A, No.1 Zhangwu road , Yangpu district, Shanghai City, China.

[2] corresponding author: Xianghong Zhou. E-mail: xhztongji0927@163.com Tel: +86 19121805801, Fax: +86 021 6598 3383.

Abstract:

A profound understanding of the present status and regional characteristics of China's agricultural carbon emissions (ACE) is the basic prerequisite for exploring a pathway to ACE reduction that is compatible with China's national conditions. This study uses the inter-provincial agricultural industry panel data from 2001 to 2017, and selects the three-stage slack-based measure data envelope analysis (SBM-DEA) model and Malmquist Luenberger (ML) index model to measure the dynamic efficiency of agricultural carbon emission (ACE). Additionally, this study uses the Dagum Gini coefficient and the panel vector auto-regression (PVAR) model to analyze the sources of regional differences in dynamic efficiency and the internal structure, respectively. The empirical results reveal the following: (i) The dynamic efficiency of China's ACE is in a state of "efficiency optimization." Although both technological change and technological efficiency change are in an "efficient" state, they also show a decline in technological efficiency change, and a regression in technological change, respectively. (ii) The overall Dagum Gini coefficient of China's ACE dynamic efficiency, technological change, and technological efficiency change all demonstrate upward trends. The gap between regions is the main reason for the long-term gap between the dynamic efficiency of China's ACE, technological change, and technological efficiency change. (iii) Regardless of the time horizon, technological change has always been the main driving force for the continuous growth of dynamic efficiency; the contribution of technological change to dynamic efficiency is far greater than that of technological efficiency change. This conclusion has been verified in samples from different regions of China.

Keywords: dynamic efficiency; technological change; technological efficiency change; Dagum Gini coefficient; PVAR model

1. Introduction

As the global climate problem has become increasingly serious, the "low-carbon economy" has become

a new schema for global development. According to the IPCC (2018) report, Global warming is 1.5°C higher than pre-industrial levels. Moreover, Agriculture's share of greenhouse gases cannot be underestimated, approximately 1/4 of the total net artificial greenhouse gas emissions (GHG) and 14% of the total global carbon emissions are related to agricultural activities (IPCC 2007)[1,2]. However, due to the widespread and universal nature of agricultural activities suggest that carbon emissions from this sector are an important source of global carbon emissions that must be addressed. (Fei and Lin 2016 and Dogan and Sebri et al. 2016). China's agricultural sector accounts for approximately 17% of the country's total carbon emissions (Dong et al.2008). Reducing carbon emissions and improving unit carbon emission efficiency are important measures for achieving low-carbon economic development (Beinhocker et al. 2008). Due to the increasing severity of the global climate problem, achieving emission reductions and low-carbon economic development have become matters of concern.

Many studies on ACE have been conducted. Early literatures focused on the factors that influence ACE. For instance, West et al. (2002) conducted an in-depth examination of the factors that influence ACE. In contrast, research by Johnson et al. (2007) found that ACE are primarily derived from livestock and poultry gas emissions, manure management, rice cultivation, arbitrary disposal of agricultural waste, and biological combustion. More recently, He and Dai (2016) highlighted that both the agricultural economic structure and the level of agricultural mechanization are leading factors that lead to differences in the spatial structure of agricultural carbon emissions in China. Moreover, Tian and Zhang (2017) found that chemical fertilizers, agricultural lime, pesticides, agricultural irrigation, and seed cultivation were the main sources of ACE.

Decomposition analysis of China's ACE is another area of burgeoning inquiry. Li and Li (2010) measured the amount of carbon dioxide emissions from energy consumption in China's agricultural sector from 1981 to 2007. Furthermore, Han and Zhang (2013) found that the import effect contributes at the greatest rate to China’s current carbon emissions related to agricultural energy consumption, and followed by the export counter-effect, industrial scale effect, and energy efficiency effect. On this basis, they used the logarithmic mean Divisia index (LMDI) model to decompose carbon emissions, they found that economic growth was the most important driving factor for ACE. The comprehensive measurement of ACE has been used for calculating GHG emissions from energy crop cultivation based on carbon footprint (CFP) approaches. For example, Valin et al. (2013) investigated the effects of crop yield and livestock feed efficiency scenarios on GHG emissions from agriculture and land use change in developing countries. Besides that, Peter et al. (2017), have analyzed the available calculators and approaches according to the goal and scope of the calculator, the methodology used to account for GHG emissions from energy crop cultivation, energy crop cultivation management practices, and the ability to

[1] IPCC. Intergovernmental Panel on Climate Change. Switzerland: IPCC WGI Fourth Assessment Report, 2007.

[2] IPCC.Climate change 2007: mitigation of climate change. Contribution of working group III to the fourth assessment report of the intergovernmental panel on climate change .Cambridge, United Kingdom: Cambridge University Press: 63－67.

model crop rotation. In addition, Ismael et al. (2018) used annual data for the period 1970 to 2014 to examine the interaction between agricultural technology factors and the environment in terms of carbon emissions in Jordan. Recently, LMDI decomposition and decoupling analysis has been used by researchers such as Liu et al. (2019) to test the changing trends and regional differences in China's ACE.

As research on ACE continues to deepen, scholars have shifted from simple ACE calculations to more comprehensive research on total factor productivity that relies on input and output analysis. Among the representative studies, Guo et al. (2018) used the SBM-Undesirable model with undesirable outputs to evaluate the total agricultural carbon emissions and carbon emission efficiency of various provinces in western China, and they found that the total amount of ACE in western China is increasing, and that there are obvious spatial differences regarding carbon emissions. In addition, Wang (2020) used the undesired output super-efficiency SBM model to empirically test the agricultural efficiency level and its spatial pattern in Anhui Province, China. Moreover, Lei et al. (2020) empirically tested the non-linear relationship between agricultural technological change and ACE efficiency by constructing a panel-threshold model .

Collectively, the aforementioned studies provide a wealth of theoretical value for exploring the ACE reduction. However, as the understanding of China’s agricultural development continues to deepen, research on carbon emissions must move beyond the static level of index calculation and regional difference feature analysis. It is necessary to explore the dynamic efficiency of ACE and the internal mechanism of its formation.

The findings from the existing research on ACE not only lay an important theoretical and methodological basis for this study, but also highlight the insufficiency of research on ACE efficiency. In the relevant research on the total factor carbon emission productivity, the parametric method (e.g. Färe et al., 2005; Marklund and Samakovlis, 2007) and the non-parametric method (e.g. Liu et al., 2011; Zhou and Nie, 2012; Xu and Luan, 2018) are mainly used to measure the carbon emission production efficiency. Among them, non-parametric models are widely used by scholars in the evaluation of total-factor carbon emission efficiency because they do not need to establish functional forms and prior conditions in advance (e.g.Song et al., 2012; Molinos-Senante et al., 2016）, and can effectively avoid the subjectivity of parameter weighting（e.g. Zhou et al., 2010; Dong et al., 2017). In previous studies on ACE efficiency, most of them adopted the traditional data envelope analysis (DEA) model or SBM-DEA model as their analytical approach. These approaches ignore the influence of the external environment and random interference to a certain extent, and only consider the decision-making unit (DMU). Therefore, the estimated result is quite different from the actual situation (e.g. Tone, 2001; Choi et al., 2012; Gómez-Calvet et al., 2014; Iftikhar et al., 2016; Chen et al., 2017; Wu et al., 2019). To compensate for this shortcoming, this study uses the framework of Fried et al. (2002) to propose a three-stage DEA model based on a combination of the traditional DEA model and the stochastic frontier analysis (SFA) method. In addition, to explore the dynamic changes of ACE efficiency, we refer to existing studies (e.g. Kortelainen, 2008; Wang et al., 2014), and adopt the DEA-Malmquist-Luenberger index method to analyze the dynamics of ACE efficiency. The decomposition analysis explores dynamic efficiency, technological efficiency change, and technological change, and uses PVARmodel to test the dynamic relationship of these three factors.

In summary, this paper divides China's 30 provincial-level administrative units into seven major agricultural emission regions, and uses the three-stage SBM-DEA model and the ML index method to measure the ACE efficiency from a dynamic perspective. In addition, the Dagum Gini coefficient and the PVAR model are used to empirically test the ACE in 30 provinces and regions of China from 2001 to 2017. The marginal contributions of this paper are as follows: first, the correct division of the study area according to the research question is an important prerequisite for exploring the road to carbon emission reduction in China's agricultural sector. Unlike previous studies, this study conducts an empirical analysis of the regional differences in the dynamic efficiency of ACE and its formation mechanism according to the division of the seven major agricultural regions[3]. Second, in contrast to existing studies on the static efficiency of ACE, this study uses the undesired output super-efficiency three-stage SBM-DEA model and the ML index decomposition method to measure the dynamic efficiency of ACE. Third, this study not only focuses on the regional differences and contribution sources of the dynamic efficiency of ACE in various regions, but also expands the research perspective to evaluate the internal structure of dynamic efficiency. The findings of this research can be used to diagnose the regional differences in the dynamic efficiency of ACE and their mechanisms, and to provide reference about ACE reduction for policy makers and planning of relevant government entities.

2. Research design

2.1 Dagum Gini coefficient and its subgroup decomposition method

With reference to existing research, the study area is divided into seven major agricultural regions: Northeast China, Huanghuaihai Region, The middle and lower reaches of the Yellow River, South China, Northwest and Areas along the Great Wall, Southwest and Qinghai-Tibet Region. Dagum (1997))'s methods empirically test the dynamic efficiency, technological efficiency change (EC) and technological change (TC) of ACE, and the regional differences among those three factors in China's seven major agricultural regions. Dagum defines Gini coefficient as:

$$G=\sum_{i=1}^{K}\sum_{j=1}^{K}\sum_{h=1}^{n_i}\sum_{r=1}^{n_j}\left|y_{ih}-y_{jr}\right|\Big/2n^2\mu \qquad (1)$$

In the formula (1), G represents the total Gini coefficient, which measures the total difference of ACE between all provinces. K represents the number of regions, including seven major agricultural regions. y_{ih} and y_{jr} represent the true levels of the dynamic efficiency of ACE of all provinces and cities, and

[3] According to the "National Agricultural Sustainable Development Plan (2015-2030)", the country is divided into seven major regions, namely the Northeast Region (Heilongjiang, Jilin, Liaoning), Huanghuaihai Region (Beijing, Tianjin, Hebei, Henan, Shandong), and the Yangtze River Middle and lower reaches (Jiangxi, Zhejiang, Shanghai, Jiangsu, Anhui, Hubei, Hunan), South China (Fujian, Guangdong, Hainan), Northwest and areas along the Great Wall (Xinjiang, NingXia, Gansu, Shaanxi, Shanxi,Inner Mongolia), Southwest Region (Guangxi, Guizhou, Sichuan, Chongqing, Yunnan), Qinghai-Tibet area (Qinghai, Tibet).

i=1,2,…,K; j=1,2,…,K. μ is the average value of the dynamic efficiency of ACE of all provinces and cities, n is the number of all provinces and cities, and n_i and n_j are the number of provinces and cities.

G can be decomposed into three parts: intra-regional gap G_w, inter-regional gap G_{rb}, and tansvariation intensity G_t. The three parts satisfy: $G=G_w+G_{rb}+G_t$. Among them, Gw represents the distribution gap of the dynamic efficiency of ACE in the $i(j)$ region. Grb represents the distribution gap of the dynamic efficiency of agricultural carbon emissions between regions $i(j)$. G_t represents the impact of the cross term of the dynamic efficiency of ACE between regions on the total Gini coefficient G. If G_t=0, it means that the cross term of the dynamic efficiency of ACE between regions does not exist. The specific decomposition formula is as follows:

$$G_w = \sum_{i=1}^{K} \lambda_i s_i G_{ii} \tag{2}$$

Fromula (2) measures the contribution of the difference of dynamic efficiency of ACE within region to the total Gini coefficient G;

$$G_{rb} = \sum_{i=2}^{K} \sum_{j=1}^{i-1} \left(\lambda_j s_i + \lambda_i s_j \right) G_{ij} D_{ij} \tag{3}$$

Formula (3) measures the net contribution of the extended difference of dynamic efficiency of ACE between regions to the total Gini coefficient G;

$$G_t = \sum_{i=2}^{K} \sum_{j=1}^{i=1} \left(\lambda_j s_i + \lambda_i s_j \right) G_{ij} (1 - D_{ij}) \tag{4}$$

Formula (4) measures the contribution of the transvariation intensity between regions to the total Gini coefficient G. $\lambda_i = n_i/n$ and $s_i = \lambda_i \mu_i/\mu$, μ_i and μ_j are the average of dynamic efficiency of ACE.

In Eq. (10), $D_{ij}=(d_{ij}-p_{ij})/(d_{ij}+p_{ij})$ is the relative economic affluence between the *ith* and the *jth* region, and the gross economic affluence d_{ij} between the *ith* and the *jth* region, such as $\mu_i>\mu_j$, is

$$d_{ij} = \int_0^{\infty} \int_0^{y} \left(y - x \right) f_j(x) dx f_j(y) dy \tag{5}$$

Where d_{ij} is under the condition of $y_{ih}>y_{ir}$, the weighted average of the dynamic efficiency gap (y_{ih}-y_{ir}) of all ACE under the following conditions. For the continuous density distribution functions $f_i(y)$ and $f_j(y)$.

p_{ij} is the first-order moment of transvariation intensity between the *ith* and the *jth* region, such that $\mu_i>\mu_j$ is

$$p_{ij} = \int_0^{\infty} \int_0^{y} \left(y - x \right) f_j(x) dx f_j(y) dy \tag{6}$$

G_{ii} is the Gini coefficient within region and G_{ij} is the Gini coefficient between regions, i.e.,

$$G_{ii}=\sum_{h=1}^{n_i}\sum_{r=1}^{n_j}\left|y_{ih}-y_{jr}\right|\Big/2n_i^2\mu_i \tag{7}$$

$$G_{ij}=\sum_{h=1}^{n_i}\sum_{r=1}^{n_j}\left|y_{ih}-y_{jr}\right|\Big/n_in_j(\mu_i+\mu_j) \tag{8}$$

2.2 The Super-efficiency three-stage SBM-ML model of undesired output

The super-efficiency three-stage SBM-ML model of undesired output can be used to analyze the dynamic changes of carbon emission efficiency. The three-stage process is: the first stage uses the undesired output super-efficiency SBM-DEA model to analyze the changes in total factor productivity; the second stage uses the stochastic frontier method to adjust the input-output variables; the third stage will adjust the Input variables and original output variables are substituted into the undesired output super-efficiency SBM-ML model for measurement.

(1) The first stage: use the super-efficiency SBM-DEA model of undesired output to calculate the initial efficiency of each decision-making unit (DMU) and the slack variables of input-output. The SBM-DEA model is:

$$\rho=\min\frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1+\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g}+\sum_{r=1}^{s_2}\frac{s_r^b}{y_{r0}^b}\right)} \tag{9}$$

$$subject\quad to\begin{cases}x_0=X\lambda+S^-\\ y_0^g=Y^g\lambda-S^g\\ y_0^b=Y^b\lambda+S^b\\ S^-\geq 0,S^g\geq 0,S^b\geq 0,\lambda\geq 0\end{cases}$$

Where λ is the weight vector. x and y are matrixes that compose of the input and output of all DMU, which y^g is the expected output, y^b is the undesired output. m are the number of input indicators, S are the number of outputs indicators (S_1 represents expected output, S_2 represents undesired output). n is the number of DMU. S^-、S^g、S^b are the slack variables of input variables, expected output and undesired output, respectively. ρ is the carbon emission efficiency value, and $0\leq\rho\leq1$. When $\rho=1$, $S^-=S^g=S^b=0$. At this time, it is completely efficient for this particular DMU; when $\rho<1$, it means that the DMU is inefficient, and the input variables and output variables need to be improved to improve efficiency.

From observing formula , it can be found that input-output slack variables are directly substituted into the objective function for calculation. On the one hand, it solves the problem of slackness of input and output variables in the traditional DEA model, and on the other hand, it also effectively solve the problem of expected and undesired output in output variables. Therefore, the SBM model is more effective in evaluating carbon emission efficiency issues.

(2) The second stage: First, construct and use the stochastic frontier analysis (SFA) to decompose the input relaxation value obtained in the first order stage. The SFA regression model is:

$$S_{ij} = f\left(Z_j;\beta_i\right) + v_{ij} + \mu_{ij} \quad (i = 1,2,\mathrm{K}\ ,I;\ j = 1,2,\mathrm{K}\ ,J) \tag{10}$$

Where S_{ij} is the slack variable of the *ith* input of the *jth* DMU, Z_j is the environmental variable, β_i is the coefficient of the environmental variable, $v_{ij}+\mu_{ij}$ represents the mixed error term, v_{ij} is random error, and μ_{ij} is the managerial inefficiency, which means the influence of managerial factors on the input slack variable, assumed it follows the truncated half-normal distribution at the zero point, ie. $\mu \sim N^{+}\left(0,\sigma_{\mu}^{2}\right)$.

Using the SFA model, the input slack variables of the 30 provincial regions from 2001 to 2017 obtained in the first stage were used as the explanatory variables, economic development level, industrial structure, energy structure, government regulation, technological innovation level and degree of opening to the outside world which six environmental factors were used as explanatory variables for regression analysis. Frontier4.1 was used to obtain SFA regression results. In order to make the calculation results more precise, this paper adopts the method of year-by-year analysis and establishes a total of 54 regression equations.

The input-output slack variable calculated in the first stage is affected by managerial inefficiency, environmental factors and statistical noise. Therefore, it is necessary to isolate these three effects and eliminate environmental factors and random errors. The specific separation method is as follows: Separate environmental factors, managerial inefficiency, and random errors:

$$E\left(\mu/\varepsilon\right) = \sigma_{*}\left[\frac{f\left(\lambda\frac{\varepsilon}{\sigma}\right)}{\varphi\left(\lambda\frac{\varepsilon}{\sigma}\right)} + \frac{\lambda\varepsilon}{\sigma}\right] \tag{11}$$

Where: $\sigma_{*}=\frac{\sigma_{\mu}\sigma_{v}}{\sigma}$, $\sigma_{*}=\sqrt{\sigma_{\mu}^{2}+\sigma_{v}^{2}}$, $\lambda=\sigma_{\mu}/\sigma_{v}$, $\varepsilon=\mu_{ij}+v_{ij}$ In this way, the random error term can be separated from the mixed error term, and the separation equation is:

$$E\left[v_{ij}/\left(v_{ij}+u_{ij}\right)\right] = S_{ij} - f\left(Z_j;\beta_i\right) - E\left[u_{ij}/\left(v_{ij}+u_{ij}\right)\right] \tag{12}$$

Finally, adjust the input and output variables. Separating managerial inefficiency, environmental factors and random errors in slack variables in order to put all DMU in the same external environment for efficiency evaluation, so there are two adjustment methods. One is to adjust all DMU to a superior external environment, which can be adjusted by reducing the input and output of other DMU; the other is to adjust to a in-superior external environment and increase the input and output of other DMU. This paper chooses the second adjustment method in view of the operability of the data, and its equation is:

$$X_{ij}^{A} = X_{ij} + \left\{ \max\left[f\left(Z_j;\beta_i\right)\right] - f\left(Z_j;\beta_i\right)\right\} + \left[\max\left(v_{ij}\right) - v_{ij}\right] \qquad (13)$$

Above formula represent adjusted input variable and X_{ij} represent before adjusted input variable. In summary, all DMU will be placed in the same external environment.

(3) The third stage: The adjusted input value removes the external environment factors and random interference factors, then recalculate it with the initial output data using the undesired output super-efficiency SBM-ML model. The efficiency value at this time eliminated the influence of environmental factors and random errors, and can more accurately reflect the true efficiency of the internal management and investment scale of each DMU.

The undesired output super-efficiency SBM model can only be used to analyze the static environmental efficiency of regions, but it cannot effectively measure the dynamic environmental efficiency of regions. Färe et al. (1992) proposed the calculation method of Malmquist index which can be used to analyze the efficiency of dynamic environment. Chung et al. (1997) introduced the directional distance function into the Malmquist index to deal with the problem of undesired output, and called it The ML index, which has all the virtues of the Malmquist index model. On this basis, not only the undesired output is taken into account, but also the decrease of undesired output and the increase of expected output are taken into consideration simultaneously. Therefore, this paper adopts the super-efficiency SBM-ML index, which includes undesired output, to measure the dynamic total factor carbon emission efficiency of 30 provincial regions from 2001 to 2017. According to the ML index calculation method proposed by Chung et al. (1997), it is assumed that the "bad" output is weakly disposed and the "good" output is freely disposed. The direction vector $g^t = (y^t, -b^t)$, then the ML productivity index from t period to $t+1$ is:

$$ML_t^{t+1} = \sqrt{\frac{\left[1+\vec{D}_0^t\left(x^t, y^t, b^t; y^t, -b^t\right)\right]}{\left[1+D_0^t\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)\right]} \bullet \frac{\left[1+\vec{D}_0^{t+1}\left(x^t, y^t, b^t; y^t, -b^t\right)\right]}{\left[1+D_0^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)\right]}} \qquad (14)$$

ML measures the change in productivity from period t to period $t+1$. If $ML<1$, production efficiency decline, when $ML=1$, production efficiency remains unchanged, and if $ML>1$, production efficiency ascending. The ML index can be further decomposed into two parts: one part measures technological efficiency change (EC), and the other part measures technological change (TC). The expression is as follows:

$$ML_t^{t+1} = MLEFFCH_t^{t+1} \bullet MLTECH_t^{t+1} \qquad (15)$$

$$MLEFFCH_t^{t+1} = \frac{1+\vec{D}_0^t\left(x^t, y^t, b^t; y^t, -b^t\right)}{1+\vec{D}_0^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)} \qquad (16)$$

$$MLTECH_t^{t+1} = \sqrt{\frac{\left[1+\vec{D}_0^{t+1}\left(x^t, y^t, b^t; y^t, -b^t\right)\right]}{\left[1+D_0^t\left(x^t, y^t, b^t; y^t, -b^t\right)\right]} \bullet \frac{\left[1+\vec{D}_0^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)\right]}{\left[1+D_0^t\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)\right]}} \quad (17)$$

EC measures how close each observation value is to its respective production frontier, while *TC* measures the change in the production possibility boundary from period *t* to period *t+1*. Among them, when *EC>1* means that the technological efficiency is improved; EC<1 means that the technological efficiency is reduced. *TC>1*, indicating technological improved; TC<1, indicating technological regression. *ML>1*, indicating that the efficiency has increased; ML<1, indicating that the efficiency has decreased.

3. Data and variable selection

Based on the panel data of 30 provinces, municipalities, and autonomous regions in China from 2001 to 2017[4]. According to the classification standard of "National Economic Industry Classification"[5], this paper focuses on the dynamic efficiency of ACE and uses undesired output. The super-efficiency three-stage SBM-ML model. The required data mainly comes from the 2001-2017 China Statistical Yearbook, China Energy Statistical Yearbook, China Science and Technology Statistical Yearbook, local statistical yearbooks and bulletins. Part of the missing data is supplemented by research methods such as interpolation, exponential smoothing, and mean method. In order to test the interval difference in the dynamic efficiency of agricultural carbon emissions, the study divided the regions according to the seven major agricultural region, and conducted empirical analysis on samples from different regions. The specific variables are selected as follows:

(1) Selection of input-output variables. From the research of Li et al. (2020) , this paper takes labor, capital stock, and total energy consumption as input variables, and regional agricultural production and carbon dioxide emissions as output variables. The specific description of the variables is shown in Table 1.

(2) Selection of environment variables. For the selection of environmental variables in the three-stage DEA model, the main criterion is that the selection has a significant impact on the efficiency of carbon dioxide emissions, but it is also a factor that cannot be controlled by the DMU. Based on comprehensive consideration of data availability, representativeness of variable indicators and existing research (e.g. Chen et al., 2017; Huang and Bai, 2019), this study focuses on economic energy, institutional environment, and six indicators are selected as the environmental variables in this paper. They are economic development level, industrial structure, energy structure, government regulation, technological

[4] There are 34 provinces in China. For the reason of the lack of data, Tibet, Macau, Hong Kong and Taiwan are excluded from the sample.

[5] The "Classification of National Economic Industries" (GB/T4754-2003) divides my country into 3 major industries and 6 major industries. Among them, the three major industries include the primary, secondary and tertiary industries; and the six major industries cover agriculture, forestry, animal husbandry, and fishery; Agriculture; construction industry; transportation, storage, post and telecommunications industry; wholesale, retail and accommodation, catering industry; other industries.

innovation level, and degree of openness to the outside world. The level of economic development. This paper uses regional GDP per capita to express the level of regional economic development.

Table 1 Indicators for Measuring and Calculating the China's ACE efficiency

Index	variable	Index composition	Unit
Input	Labor Input	Number of employment at the end of the year by region	(10,000 people)
	Capital Input	Capital stock[6]	(100 million yuan)
	Total energy consumption	The total energy consumption of each province over the years.	(10,000 tons)
Output	Gross agricultural production	The gross agricultural production value of each region is regarded as the expected output.	(100 million yuan)
	Carbon dioxide emissions	CO2 emissions in various regions as undesired output。	(10,000 tons)
Environment	The level of economic development	GDP per capita	
	Industrial structure	The ratio of agricultural production to GDP	(%)
	Energy structure	The ratio of agricultural carbon emissions to total energy consumption.[7]	(%)
	Government environmental regulation	The ratio of government investment in environmental governance to GDP.	(%)
	The level of technological innovation	The ratio of R&D expenditure to GDP.	(%)

6 Calculation method: First, based on the construction method of Zhang (2004) and Shan (2008) about capital stock, the price deflator of the investment data of various industries in this article is calculated by Xu (2007)'s deflation index construction method. Then, Drawing on the provincial depreciation rate and base period capital stock data calculated by Zong (2014) method, according to the perpetual inventory method, the provincial capital stock data of the three industries in this paper are obtained. Finally, through the calculation of the amount of capital in the base period and the selection of depreciation rates and current investment indicators, the total investment in fixed assets of the whole society is then deflated.

7 Calculation method: According to the calculation formula in the "Guidelines for National Greenhouse Gas Inventories" compiled by the United Nations Intergovernmental Panel on Climate Change in 2006 (IPCC, 2006)

Degree of openness	The ratio of total import and export to GDP.	(%)

4. Decomposition of regional differences in agricultural carbon emission efficiency in China

4.1 Overview of china's ACE efficiency

Figures 1–3 show the temporal and spatial evolution of the ACE dynamic efficiency (ML), EC, and TC in China from 2001 to 2017, respectively.

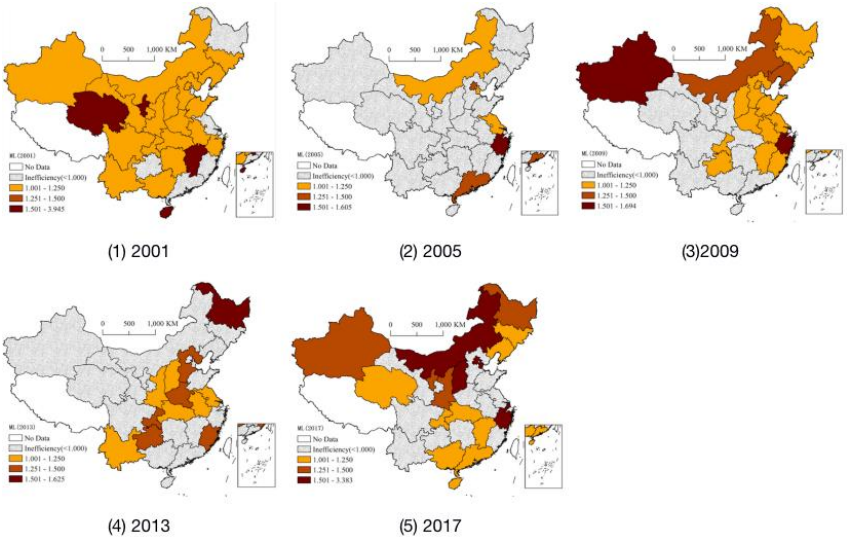

Fig. 1 Distribution of the dynamic efficiency of China's ACE efficiency

In Figure 1, in 2001, ML exhibited a spatially distributed orderly pattern, with higher values in western regions and lower in eastern regions, and an overall average efficiency of 1.199. Among the 30 regions, 23 regions had ML>1 (efficiency growth areas) and 7 regions had ML<1 (efficiency decline areas), most of which were agglomerated in the middle and lower reaches of the Yangtze River and the Huanghuaihai region. By 2005, ML was distributed in a point-like space, and the overall average efficiency decreased to 0.885, whereas the efficiency growth area was mainly clustered in economically developed areas. By 2009, the spatial distribution of ML showed higher values in eastern and northern regions and lower values in western and southern regions, and the overall average efficiency increased to 1.034. Efficiency decline areas reduced, with 13 regions in total, whereas efficiency growth areas were mainly distributed in the Northeast, Huanghuaihai region, and the middle and lower reaches of the Yangtze River. By 2013, the overall average efficiency decreased to 0.994; the number of efficiency decline regions increased, and the efficiency growth areas were mainly located in the middle and lower reaches of the Yangtze River. By 2017, the overall average efficiency increased to 1.321; efficiency growth regions also further increased, the distribution was more dispersed, and the efficiency of economically developed regions and agricultural-based regions was higher.

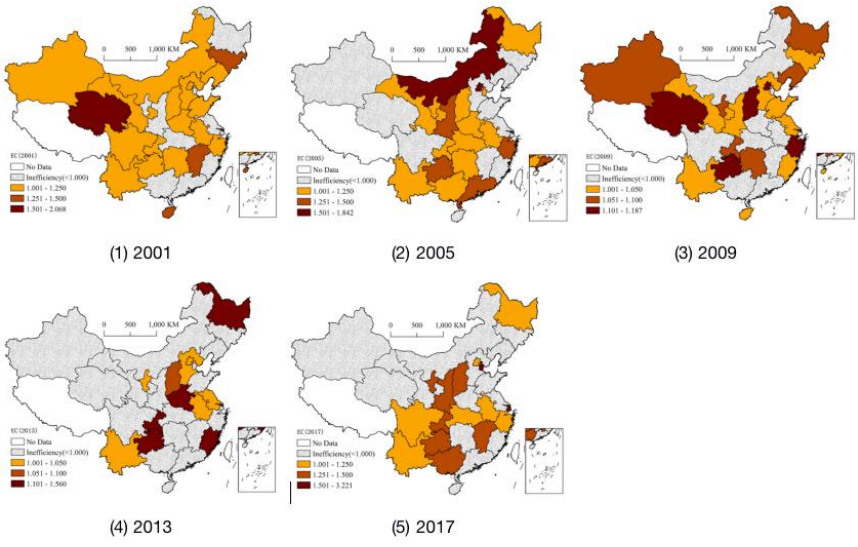

Fig. 2 Distribution of the technological efficiency change of China's ACE efficiency

In Figure 2, in 2001, the overall average EC was 1.065; from the total area, two-thirds were EC growth areas (EC>1), and one-third were efficiency decline areas (EC<1). In 2005, the overall average EC was 1.124, whose spatial distribution showed higher values in central regions and lower values in eastern and western regions. The number of EC decline regions did not considerably change. However, the overall EC of the Northwest and Southwest regions declined. By 2009, EC showed a horizontal band distribution, with an overall average efficiency of 1.013. The areas of EC growth were mainly concentrated along the Yellow River Belt, Northeast China, and Southwest China. The EC decline areas decreased to one-third, and were mainly concentrated in the middle and lower reaches of the Yangtze River and the southern coastal regions. By 2013, EC was distributed in a small-scale block-like spatial structure, with an overall average efficiency of 0.946; technology decline areas further expanded, mainly distributed in the Northwest and areas along the Great Wall, middle and lower reaches of the Yangtze River, Northeast China, South China, and Southwest China. By 2017, the overall average EC was 1.146, the number of decline areas of EC reduced, and the spatial distribution of increasing efficiency areas moved to the Southwest.

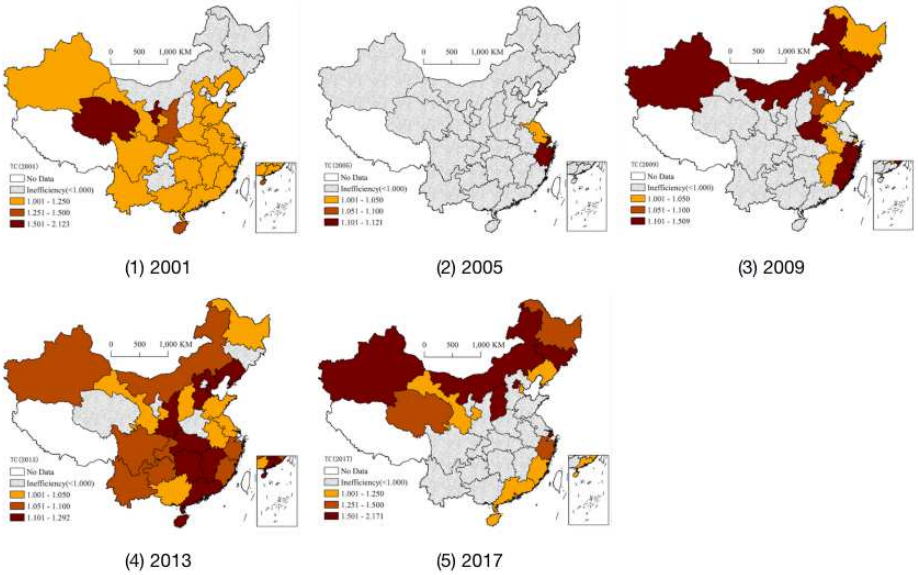

Fig. 3 Distribution of the technological change of China's ACE efficiency

It can be seen from Figure 3 that in 2001, TC in most of the China regions showed a growing tendency, being evenly distributed in the eastern and western regions. The declining areas of TC were distributed in a dot-like pattern, and regions of inefficiency of TC in parts of the middle and lower reaches of the Yangtze River and the southwestern region expanded. By 2005,Only three regions remained with TC>1, all of which were agglomerated in the middle and lower reaches of the Yangtze River. By 2009, the number of regions with TC growth gradually expanded, mainly in the Northeast and Huanghuaihai regions. Until 2013, the TC growth type areas showed an orderly pattern of high TC in the middle and low TC in the East. In South China, TC degraded from growth type to decline type. In 12 regions, concentrated in the Southwest, Huanghuaihai region, and the middle and lower reaches of the Yangtze River, TC upgraded from decline to growth. Finally, by 2017, the growth area of TC showed a flaky type distribution pattern in the North and South.

4.2 Decomposition of regional differences of China's ACE efficiency

The dynamic tendencies of the sources of regional differences in China's ACE are illustrated in Figure 4.

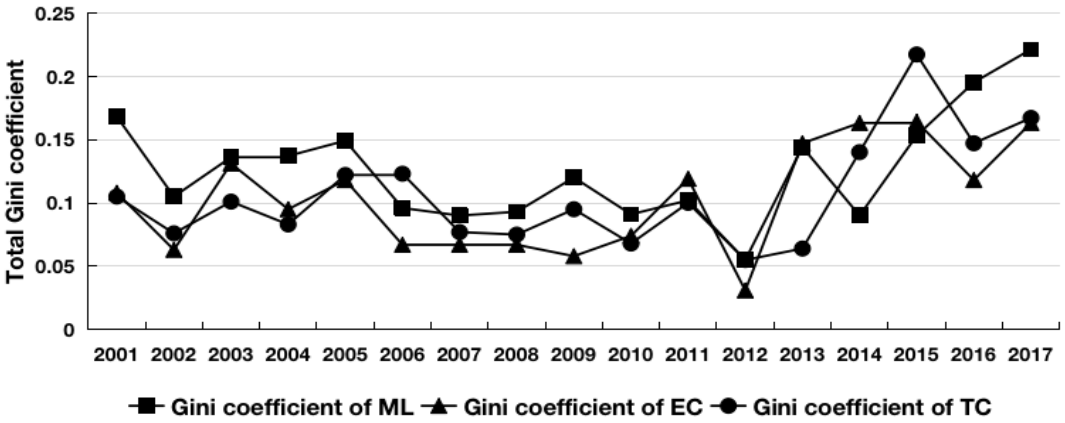

Fig. 4 The total Gini coefficient of the China's ACE dynamic efficiency, technological efficiency change, and technological change

By analyzing the Gini coefficient of ML (GML), from 2001 to 2017, GML showed an upward tendency of volatility, with an average annual growth rate of 1.729%, which indicates that the gap of ML across China was gradually expanding, and the Gini coefficient of EC (GEC) and TC (GTC) also showed an upward tendency, with average annual growth rates of 2.606% and 2.943%, respectively. In terms of inter-annual changes, GML, GEC, and GTC showed W-shaped fluctuations. It can be observed that the changes in GML were mainly due to the effects of GEC and GTC. However, in different periods, considerable differences were observed between the two contributions to GML fluctuations.

Figure 5a-5c presents the differences in China's ACE dynamic efficiency, technological efficiency change, and technological change among the regions from 2001 to 2017, respectively. It can be seen that the GML changes in various regions were considerably different. Among them, the GML in Northeast and South China showed a downward tendency, and South China had the maximum decrease (6.993%). Furthermore, the GML in the other regions showed an upward tendency. The GML in the Huanghuaihai region exhibited the largest increase (10.582%). The GEC of South China and Southwest China showed a downward tendency from 2001 to 2017. In addition, South China had the largest decline (7.207%), GEC in other regions showed an upward tendency, and the overall gap gradually widened. For the GTC, from 2001 to 2017, it showed a downward tendency in the Northeast, South China, Northwest, and areas along the Great Wall, whereas in the remainder regions, an overall upward tendency was observed, with the largest increase (11.973%) in the Huanghuaihai region.

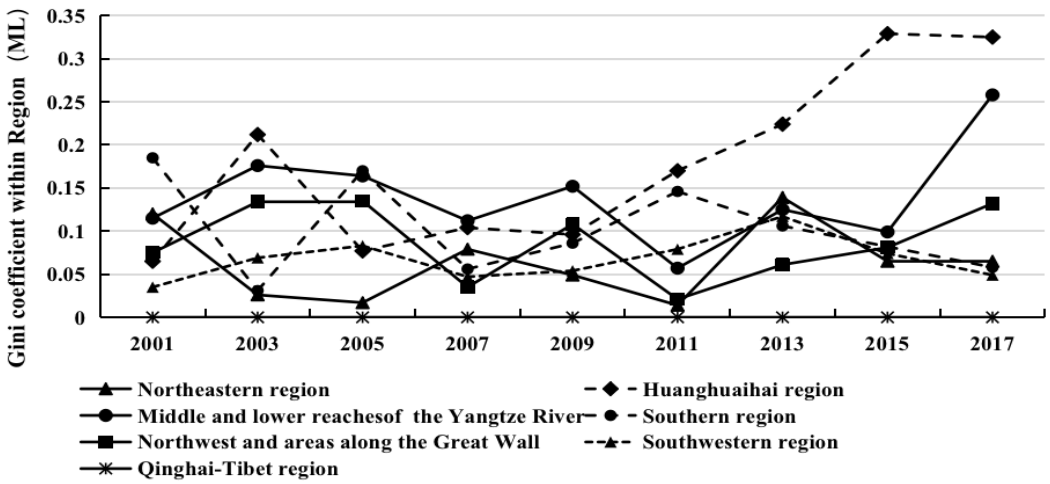

Fig. 5a Tendency of differences in China’s ACE dynamic efficiency

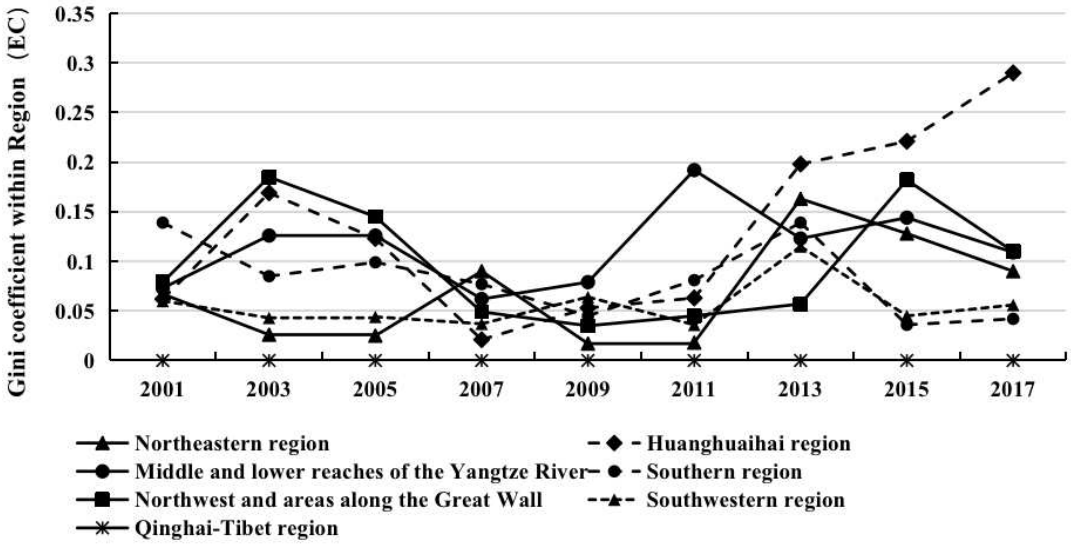

Fig. 5b Tendency of differences in China’s ACE technological efficiency change

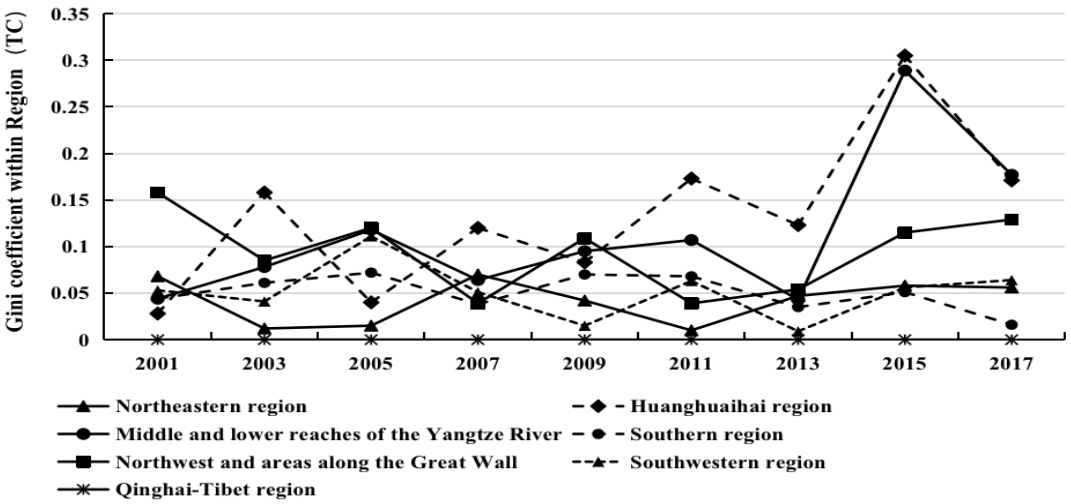

Fig. 5c Tendency of differences in China’s ACE technological change

Note: Since there is only Qinghai in Qinghai-Tibet area, the intra-group difference is 0.

Table 2 Results of inter-group differences

Region	ML of ACE（*GML*）					EC of ACE（*GEC*）					TC of ACE（*GTC*）				
	2001	2009	2017	Average	Annual Growth rate	2001	2009	2017	Average	Annual Growth rate	2001	2009	2017	Average	Annual Growth Rate
1→2	0.092	0.088	0.280	0.134	7.174%	0.069	0.045	0.253	0.111	8.483%	0.052	0.076	0.163	0.105	7.370%
1→3	0.121	0.135	0.218	0.112	3.764%	0.074	0.063	0.121	0.097	3.140%	0.065	0.087	0.168	0.095	6.145%
1→4	0.170	0.090	0.098	0.083	-3.417%	0.115	0.039	0.071	0.079	-2.908%	0.092	0.067	0.095	0.066	0.217%
1→5	0.102	0.096	0.123	0.085	1.210%	0.082	0.030	0.122	0.088	2.541%	0.153	0.097	0.115	0.086	-1.743%
1→6	0.076	0.078	0.079	0.082	0.289%	0.068	0.051	0.108	0.072	2.989%	0.073	0.052	0.163	0.077	5.122%
1→7	0.359	0.094	0.058	0.086	-10.791%	0.168	0.021	0.091	0.071	-3.723%	0.194	0.099	0.051	0.066	-8.055%
2→3	0.098	0.137	0.300	0.145	7.206%	0.071	0.070	0.210	0.114	7.018%	0.041	0.094	0.179	0.118	9.571%
2→4	0.131	0.104	0.296	0.141	5.206%	0.103	0.052	0.239	0.110	5.425%	0.050	0.084	0.130	0.107	6.137%
2→5	0.076	0.117	0.254	0.133	7.803%	0.073	0.047	0.221	0.108	7.155%	0.115	0.109	0.162	0.119	2.153%
2→6	0.053	0.087	0.262	0.133	10.499%	0.062	0.060	0.213	0.101	8.033%	0.045	0.062	0.160	0.108	8.240%
2→7	0.292	0.109	0.311	0.168	0.404%	0.156	0.055	0.283	0.118	3.776%	0.122	0.102	0.175	0.124	2.270%
3→4	0.146	0.139	0.228	0.118	2.822%	0.101	0.072	0.111	0.097	0.566%	0.051	0.092	0.147	0.094	6.789%
3→5	0.100	0.140	0.219	0.113	5.023%	0.079	0.061	0.113	0.096	2.245%	0.111	0.106	0.167	0.104	2.570%
3→6	0.087	0.118	0.200	0.111	5.335%	0.070	0.076	0.094	0.088	1.869%	0.051	0.073	0.162	0.094	7.513%
3→7	0.280	0.150	0.241	0.131	-0.929%	0.145	0.076	0.124	0.102	-0.967%	0.112	0.112	0.176	0.106	2.856%
4→5	0.127	0.114	0.160	0.098	1.457%	0.108	0.045	0.108	0.088	0.024%	0.130	0.103	0.121	0.087	-0.457%
4→6	0.115	0.071	0.056	0.083	-4.353%	0.101	0.061	0.098	0.074	-0.207%	0.058	0.044	0.082	0.064	2.130%
4→7	0.344	0.084	0.069	0.096	-9.562%	0.224	0.054	0.054	0.079	-8.529%	0.124	0.100	0.081	0.069	-2.641%
5→6	0.064	0.103	0.145	0.093	5.272%	0.073	0.051	0.094	0.080	1.580%	0.122	0.083	0.167	0.086	2.003%
5→7	0.254	0.123	0.132	0.094	-4.005%	0.162	0.035	0.123	0.089	-1.681%	0.176	0.129	0.122	0.088	-2.285%
6→7	0.274	0.060	0.053	0.085	-9.773%	0.157	0.061	0.097	0.071	-2.991%	0.130	0.046	0.138	0.069	0.360%

Average	0.160	0.107	0.180	0.111	0.983%	0.108	0.054	0.140	0.092	1.611%	0.099	0.086	0.139	0.092	2.679%

Note: 1, 2, 3, 4, 5, 6, and 7 in the table correspond to the Northeast, Huanghuaihai, Middle and Lower Yangtze River, South China, Northwest and areas along the Great Wall, Southwest, and Qinghai-Tibet region, respectively.

From table 2, it can be seen that during the research period, the inter-region differences of GML, GEC, and GTC were at different levels, and the overall tendency of fluctuations was evident. The overall average annual growth rate of the inter-region difference of GML ranged from 10.79% to 10.50%. Moreover, the inter-region difference of GML in most regions showed an upward tendency. Among them, the largest increase occurred between Northeast China and the middle and lower reaches of the Yangtze River, with a rate of 10.50%, and the smallest increase occurred between the middle and lower reaches of the Yangtze River and Southwest China (0.40%). The largest decrease was between the Huanghuaihai District and Southwest China, at 10.79%, whereas the Northwest and the areas along the Great Wall and Southwest Region had the smallest decline of 0.93%.

In contrast to GML, the overall average annual growth rate of the inter-region difference of GEC ranged from 8.529% to 8.483%, and GEC also showed an upward tendency in most regions. Moreover, the average annual increase between South China and the Northwest and the Great Wall was the smallest (0.024%), whereas the Northeast and Huanghuaihai regions had the largest average annual increase (8.483%). Moreover, South China and Southwest China had the largest average annual decrease (8.529%), whereas South China and Southwest China had the lowest average annual decrease (0.207%).

Considering the GTC, the overall average annual growth rate of the inter-region difference ranged from 8.055% to 9.571%. Similarly, most regions showed an upward tendency. The Huanghuaihai region and the middle and lower reaches of the Yangtze River had the largest average annual increase (9.571%), whereas the Northeast and South China had the smallest average annual increase (0.217%). Furthermore, the Northeast and Qinghai-Tibet regions had the largest average annual decrease (8.055%), whereas South China, Northwest, and along the Great Wall had the smallest average annual decrease (-0.457%).

4.3 Research on the source decomposition and contribution rate of regional differences of China's ACE efficiency

Figure 6a-6c exhibit sources of differences between ML, EC, and TC and their contribution rate from 2001 to 2017, respectively.

Considering GML, the contribution to the gap of GML in various parts of China were 46.743%, 39.419%, and 13.840%, for Grb (the inter-region gap), Gt (transvariation intensity), and Gw (the intra-region gap), respectively. Grb is the main responsible for the gap of GML in China. From the perspective of inter-annual changes, Grb and Gt have considerably different contributions to the gap of GML in different periods. Among the years analyzed, for 2003, 2007, 2009, 2012, 2013, 2015, and 2017, the contribution rates of Gt to GML were higher than those of Grb, ranging from 42.638% to 59.338%. Gt is mainly used to describe the phenomenon of overlap between regions.

Similarly, in terms of GEC, we found that Grb, Gt, and Gw, respectively, provided the major contributions to the gap of GML in various parts of China, and Grb contributed the most to the gap of GEC

differentiation in various parts of China. However, in the years 2001, 2002, 2005, 2009, 2010, 2013, and 2015, the contribution rate of Gt was ranked first, ranging from 43.384% to 58.049%. The contribution rate of Gw to GEC fluctuated between 11.297% and 16.398%, with an average annual growth rate of 1.125%.

For GTC, the major contribution to the gap of GTC in various parts of China was still due to Grb, followed by Gt and Gw. From the perspective of inter-annual changes, Grb and Gt alternately became the main contributors for the regional gap of GTC. Moreover, in the two stages of 2007–2008 and 2011–2014, the contribution rates of Gt to GTC were higher than those of Grb. Therefore, Gt was the main responsible for the regional gap of GTC. In contrast, the contribution rate of Gw was stable from 11.808% to 16.113%.

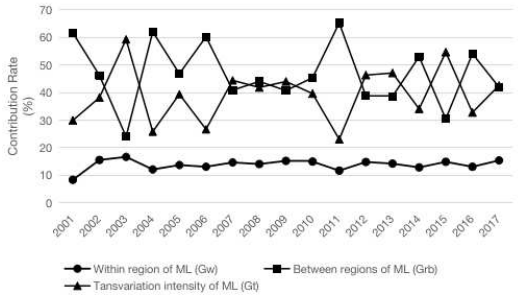

Fig. 6a Trend of CR of ML

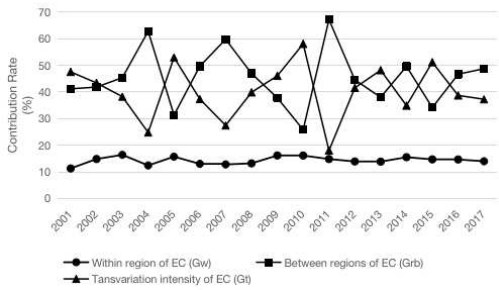

Fig. 6b Trend of CR of EC

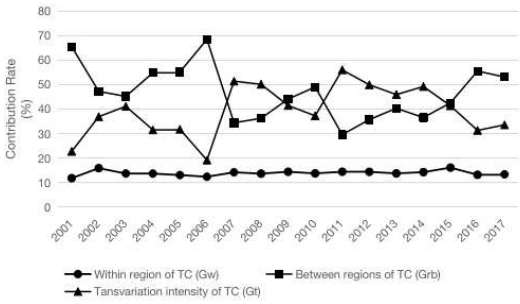

Fig. 6c Trend of CR of TC

5. Expansion analysis: quantitative analysis of the sources of regional differences in China's ACE

5.1 Stationarity test of variables

The analysis provided explains the static relationship between ML, EC, and TC; however, it does not explain the dynamic relationship between these three factors, which requires a model. As EC and TC are generated by the decomposition of the ML index, there must be an internal connection between the three factors. The vector auto-regression (VAR) model allows each component to be an endogenous variable, and the time span of the data is 17 years, which meets the requirements of time series samples. Therefore, we used the PVAR model to test the dynamic relationships between the three factors. Before analyzing

the PVAR model, it is necessary to test the stationarity of each variable and define the optimal post-order. The test results are presented in Table 3[8]. The study found that the variables of each regional sample showed a stationary series. Therefore, a direct model and analysis of the original data could be performed.

Table 3 Results of Stationarity test

Region	Index	Mode (C,T,L)	*LLC*	*IPS*	*ADF*	*PP*	Result	Region	Index	Mode (C,T,L)	*LLC*	*IPS*	*ADF*	*PP*	Result
Northeast China	*ML*	(C,0,1)	-8.837***	-7.546***	47.315***	50.791***	stationary	Northwest and areas along the Great Wall	*ML*	(C,0,0)	-13.751***	-13.715***	133.832***	137.427***	stationary
			[0.000]	[0.000]	[0.000]	[0.000]					[0.000]	[0.000]	[0.000]	[0.000]	
	EC	(C,0,1)	-8.396***	-6.742***	42.370***	46.638***	stationary		*EC*	(C,0,0)	-12.752***	-10.217***	91.113***	111.157***	stationary
			[0.000]	[0.000]	[0.000]	[0.000]					[0.000]	[0.000]	[0.000]	[0.000]	
	TC	(C,0,0)	-10.934***	-10.327***	65.104***	66.478***	stationary		*TC*	(C,0,0)	-15.258***	-16.071***	149.640***	388.981***	stationary
			[0.000]	[0.000]	[0.000]	[0.000]					[0.000]	[0.000]	[0.000]	[0.000]	
Huanghuaihai region	*ML*	(C,0,0)	-7.269***	-6.220***	50.627***	53.668***	stationary	South-west China	*ML*	(C,0,0)	-12.253***	-10.719***	88.069***	105.472***	stationary
			[0.000]	[0.000]	[0.000]	[0.000]					[0.000]	[0.000]	[0.000]	[0.000]	
	EC	(C,0,0)	-10.073***	-8.247***	67.023***	111.584***	stationary		*EC*	(C,0,0)	-7.169***	-5.883***	48.109***	49.570***	stationary
			[0.000]	[0.000]	[0.000]	[0.000]					[0.000]	[0.000]	[0.000]	[0.000]	
	TC	(C,0,0)	-8.008***	-7.797***	63.161***	73.409***	stationary		*TC*	(C,0,0)	-10.915***	-9.205***	74.624***	106.661***	stationary
			[0.000]	[0.000]	[0.000]	[0.000]					[0.000]	[0.000]	[0.000]	[0.000]	

[8] In the stationarity test, we selected the Levin, Lin, and Chu (LLC), Im, Pesaran, and Shin (IPS), augmented Dickey-Fuller (ADF), and Phillips–Perron (PP) test statistics to test whether each variable belonged to a stationary series.

Middle and lower reaches of the Yangtze River	*ML*	(C,0,0)	-11.866***	-10.592***	101.494***	219.296***	stationary
			[0.000]	[0.000]	[0.000]	[0.000]	
	EC	(C,0,0)	-12.324***	-11.119	107.601***	139.902***	stationary
			[0.000]	[0.000]	[0.000]	[0.000]	
	TC	(C,0,0)	-12.526***	-12.567***	122.554***	126.709***	stationary
			[0.000]	[0.000]	[0.000]	[0.000]	
South China	*ML*	(C,0,0)	-6.075***	-5.092***	32.165***	33.022***	stationary
			[0.000]	[0.000]	[0.000]	[0.000]	
	EC	(C,0,0)	-6.069***	-6.243***	39.203***	55.523***	stationary
			[0.000]	[0.000]	[0.000]	[0.000]	
	TC	(C,0,0)	-5.674***	-7.440***	46.735***	46.667***	stationary
			[0.000]	[0.000]	[0.000]	[0.000]	

Results of VAR Stationarity test

Region	Index	Mode (C,T,L)	ADF	Test Level 1% level	5% level	10% level	Result
Qinghai-Tibet region	*ML*	(C,0,0)	-13.413***	-3.920	-3.066	-2.673	stationary
			[0.000]				
	EC	(C,0,0)	-7.370***	-3.920	-3.066	-2.673	stationary
			[0.000]				
	TC	(C,0,0)	-5.321***	-3.920	-3.066	-2.673	stationary
			[0.001]				

Note: "*", "**", and "***" all indicate passing the test at the significance level of 10%, 5%, and 1%; the P value in square brackets; the empirical results retain three decimal places.

5.2 Granger causality test

The above research shows that the data of ML, EC, and TC were stationary series. Thus, in this study, a direct test was performed to evaluate whether there was Granger causality among the three factors. Before the Granger causality test, the optimal lag order must be determined. To ensure the accuracy of the research results, the optimal lag order was determined by adopting the test value that passed the most. The results are listed in Table 4. The results of the Northeast China show that the changes in EC were affected by changes in ML and TC, and their combined effects; the results in the Huanghuaihai region show that there was a two-way Granger causality relationship between TC and ML, EC and TC, manifested as the interaction between the two; EC and ML had a one-way Granger causality relationship, manifested as changes in EC, which were affected by changes in ML; results in the middle and lower reaches of the Yangtze River showed that ML and TC had a two-way Granger causality relationship. However, there was only a one-way Granger causality relationship between EC and TC, which shows that the change in TC was affected by the change in EC. Moreover, there was a two-way Granger

causality relationship between ML, EC, and TC in South China, and there was a two-way Granger causality relationship between TC and EC in the northwest and areas along the Great Wall; the relationship between ML, TC, and EC was only manifested in that the changes in TC and EC were all affected by changes in ML. The results in the Qinghai-Tibet region show that there was no interaction between ML, EC, and TC.

Table 4 Result of Granger causality test

Null hypothesis	Northeast China		Huanghuaihai region		Middle and lower reaches of the Yangtze River		South China		Northwest and areas along the Great Wall		Southwest China		Qinghai-Tibet region	
	Ratio	Result	Ratio	Result	Ratio	Result	Ratio	Result	Ratio	Result	Ratio	Result	Ratio	Result
The change in EC is not the cause of the change in ML（*df*_A）	0.642 [0.423]	NO	0.041 [0.980]	NO	4.128 [0.127]	NO	14.552*** [0.000]	YES	0.903 [0.637]	NO	12.754*** [0.000]	YES	2.145 [0.342]	NO
The change in TC is not the cause of the change in ML（*df*_A）	0.008 [0.929]	NO	9.596*** [0.008]	YES	32.832*** [0.000]	YES	12.310*** [0.001]	YES	0.561 [0.755]	NO	11.394*** [0.001]	YES	0.865 [0.649]	NO
The Changes in EC and TC are not the cause of changes in ML, Simultaneously（*df*_B）	5.105* [0.078]	YES	15.882*** [0.003]	YES	66.247*** [0.000]	YES	15.106*** [0.001]	YES	9.496** [0.050]	YES	12.780*** [0.002]	YES	3.627 [0.459]	NO
The Changes in ML are not the cause of changes in EC（*df*_A）	3.733* [0.053]	YES	10.582*** [0.005]	YES	0.644 [0.725]	NO	4.823** [0.028]	YES	7.873** [0.020]	YES	0.027 [0.869]	NO	0.853 [0.653]	NO
The change in TC growth is not the cause of the change in EC（*df*_A）	6.849*** [0.009]	YES	24.218*** [0.000]	YES	0.151 [0.927]	NO	6.110** [0.013]	YES	7.780** [0.021]	YES	0.011 [0.918]	NO	1.005 [0.605]	NO
The Changes in ML and TC are not the cause of changes in EC, Simultaneously（*df*_B）	8.278** [0.016]	YES	25.536*** [0.000]	YES	1.823 [0.768]	NO	7.263** [0.027]	YES	8.154* [0.086]	YES	0.121 [0.940]	NO	1.072 [0.899]	NO
The change in ML is not the cause of the change in TC（*df*_A）	0.125 [0.724]	NO	27.363*** [0.000]	YES	20.442*** [0.000]	YES	4.042** [0.044]	YES	15.997*** [0.000]	YES	21.839*** [0.000]	YES	0.280 [0.870]	NO
The Changes in EC are not the cause of changes in TC（*df*_A）	0.013 [0.908]	NO	62.528*** [0.000]	YES	45.186*** [0.000]	YES	6.465** [0.011]	YES	13.518*** [0.001]	YES	17.650*** [0.000]	YES	0.369 [0.831]	NO
The Changes in ML and EC are not the cause of changes in TC, Simultaneously（*df*_B）	0.338 [0.845]	NO	62.615*** [0.000]	YES	54.769*** [0.000]	YES	10.598*** [0.005]	YES	16.039*** [0.003]	YES	22.490*** [0.000]	YES	0.951 [0.917]	NO
N	48		75		105		48		90		80		15	
*df*_A	1		2		2		1		2		1		2	

*df*_B	2	4	4	2	4	2	4

Note: "*", "**" and "***" all indicate that the test passed the test at the significance level of 10%, 5%, and 1%; the P value in brackets; YES and NO respectively indicate whether the test passed or not . The empirical results retain three decimal places.

5.3 PVAR model analysis of the dynamic efficiency of China's ACE

Based on the above evaluation, the PVAR model system OLS of ML, EC, and TC, and the test results are shown in Table 5. The results in Northeast China show that ML significantly inhibited the development of EC during lag phase 1, whereas TC promoted the development of EC. In South China, ML had a self-weakening mechanism, and EC and TC had significant positive effects on ML. Furthermore, ML had an inhibitory effect on the development of EC, whereas TC had a promoting effect. In addition, ML had an inhibitory effect on TC development. In the middle and lower reaches of the Yangtze River, ML and EC had a self-weakening mechanism, but EC had a long-term self-weakening mechanism, whereas TC had a self-reinforcing mechanism. In the Huanghuaihai zone, TC had a significant positive impact on ML in the lag phase 2. In addition, EC had a self-weakening mechanism, whereas TC had a non-linear change mechanism, which was manifested as a self-enhancement at the initial stage and a self-weakening mechanism at the later stage. In the Northwest and areas along the Great Wall, both ML and EC had a self-weakening mechanism, but the self-weakening mechanism of EC lasted for a long time, whereas TC had a lagging self-enhancement mechanism. In addition, ML had a continuous weakening inhibitory effect on TC, and the promotion effect of ML on EC had a long hysteresis effect. In Southwest China, ML had a self-weakening mechanism, and both TC and EC that lagged in the first stage had a significant positive impact; moreover, TC had a self-reinforcing mechanism, which could effectively inhibit the development of TC, but the growth of EC drove the growth of TC. In the Qinghai-Tibet region, there was no correlation between ML, EC, and TC.

Table 5 Results of OLS

Region	Index	ML	EC	TC	Region	Index	ML	EC	TC
Northeast China	ML(-1)	-0.449	**-0.646***	-0.148	South China	ML(-1)	**-2.408*****	**-1.221****	**-1.203****
		(0.359)	(0.334)	(0.418)			(0.653)	(0.556)	(0.598)
	EC(-1)	0.312	0.523	0.052		EC(-1)	**2.604*****	**0.987***	**1.590****
		(0.389)	(0.363)	(0.453)			(0.683)	(0.581)	(0.625)
	TC(-1)	-0.029	**0.796*****	-0.517		TC(-1)	**2.442*****	**1.463****	1.019
		(0.326)	(0.304)	(0.380)			(0.696)	(0.592)	(0.637)
	C	1.279***	0.305	1.773***		C	**-1.614****	-0.235	-0.364
		(0.405)	(0.377)	(0.472)			(0.747)	(0.635)	(0.684)

Middle and lower reaches of the Yangtze River	ML(-1)	**-0.274****	-0.086	-0.949***
		(0.137)	(0.13798)	(0.225)
	ML(-2)	-0.111	-0.053	-0.160
		(0.149)	(0.150)	(0.245)
	EC(-1)	**0.205***	**-0.468*****	**1.264*****
		(0.115)	(0.115)	(0.188)
	EC(-2)	-0.142	**-0.352****	-0.073
		(0.142)	(0.143)	(0.233)
	TC(-1)	0.038	-0.031	**0.312****
		(0.092)	(0.093)	(0.152)
	TC(-2)	**0.431*****	0.024	0.212
		(0.081)	(0.082)	(0.133)
	C	0.891***	2.010***	0.481
		(0.221)	(0.222)	(0.363)

Results of VAR Test

Region	Index	ML	EC	TC
Qinghai-Tibet region	ML(-1)	0.007	-0.812	1.079
		(1.384)	(1.123)	(2.377)
	ML(-2)	0.741	0.166	0.422
		(0.621)	(0.504)	(1.067)
	EC(-1)	0.362	0.916	-0.977
		(1.506)	(1.222)	(2.586)
	EC(-2)	-1.504	-0.181	-1.100
		(1.139)	(0.924)	(1.957)
	TC(-1)	-0.094	0.648	-0.983
		(1.063)	(0.863)	(1.826)

Huanghuaihai region	ML(-1)	-0.297	-0.024	**-1.001*****
		(0.255)	(0.171)	(0.192)
	ML(-2)	-0.117	**-0.468*****	**0.583*****
		(0.256)	(0.171)	(0.193)
	EC(-1)	0.043	**-0.553*****	**1.369*****
		(0.231)	(0.154)	(0.173)
	EC(-2)	-0.049	0.027	**-0.754****
		(0.394)	(0.263)	(0.296)
	TC(-1)	0.031	-0.043	**0.796*****
		(0.320)	(0.214)	(0.241)
	TC(-2)	**0.571*****	**0.631*****	**-0.285***
		(0.215)	(0.143)	(0.161)
	C	0.885**	1.469***	0.354
		(0.398)	(0.266)	(0.299)
Northwest and areas along the Great Wall	ML(-1)	**-0.742***	0.353	**-1.323*****
		(0.397)	(0.346)	(0.418)
	ML(-2)	-0.033	**0.851****	**-0.769***
		(0.414)	(0.361)	(0.436)
	EC(-1)	0.344	**-0.599***	**1.136*****
		(0.366)	(0.319)	(0.386)
	EC(-2)	-0.117	**-0.895*****	0.651
		(0.377)	(0.329)	(0.397)
	TC(-1)	0.186	-0.263	0.552
		(0.380)	(0.332)	(0.400)
	TC(-2)	0.155	**-0.738****	**0.715***
		(0.345)	(0.303)	(0.369)
	C	1.254**	2.361***	0.051

	TC(-2)	-0.588	-0.255	-0.148			(0.488)	(0.426)	(0.514)
		(0.637)	(0.517)	(1.094)	Southwest China	ML(-1)	**-2.142*** **	0.066	**-2.678*** **
	C	2.011	0.432	2.762			(0.501)	(0.398)	(0.573)
		(1.860)	(1.509)	(3.195)		EC(-1)	**1.987*** **	-0.134	**2.674*** **
							(0.556)	(0.442)	(0.636)
						TC(-1)	**1.575*** **	-0.038	**2.004*** **
							(0.467)	(0.371)	(0.534)
						C	-0.364	**1.144*** **	-0.970
							(0.544)	(0.432)	(0.622)

Note: "*", "**", and "***" all indicate that they passed the test at the significance level of 10%, 5%, and 1%; the standard errors are in parentheses.

5.4 Impulse analysis and variance decomposition of the dynamic efficiency of China's ACE

Figures 7–13 show the results of impulse response between ML, EC, and TC in seven major agricultural zones in China, where the abscissa is the number of response periods of impact action, which was set to 10. The ordinate represents the degree of influence of the variables. The curve in the figure represents the impulse response function, and the curves on both sides represent the estimated values of the 95% and 5% quantile points, respectively.

Figure 7 shows that in the Northeast China, there were significant differences in the response of ML to EC and TC shocks. The response to EC shocks showed an initial positive effect, followed by a negative effect, and the intensity of volatility was weakened. In contrast, the impact of EC on ML and TC was also different. Moreover, the response to ML shock exhibited a continuously weakened positive effect at the initial stage, then turned to a negative effect, and then rebounded. The response to the TC shock showed a continuously increasing positive effect at the initial stage, followed by some small fluctuations. In contrast, in the impulse response analysis of TC, the impacts of ML and EC on TC exhibited severe fluctuations, and the fluctuation directions were completely opposite.

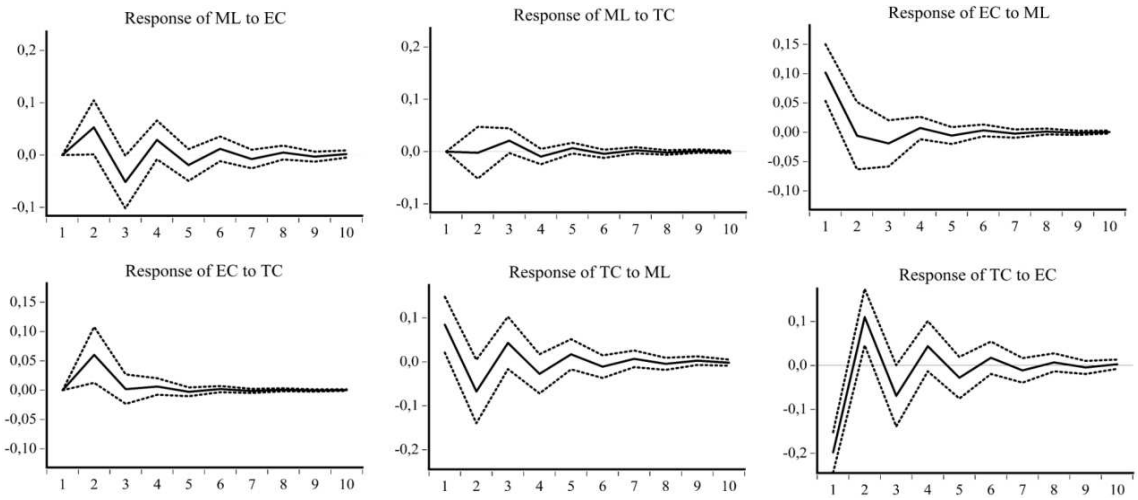

Fig. 7 Impulse response results of ML, EC, and TC of AEC emissions in Northeast China

Figure 8 shows that in the Huanghuaihai region, the ML response to EC and TC shocks had a large lag; at the same time, there were opposite fluctuations. In the second period, the ML response to EC shocks showed an initially negative followed by a positive effect, the intensity first increased, then decreased, and finally increased again. The reaction of ML to TC shock was the opposite, and the reaction intensity was weak. In the analysis of EC impulse response, the EC response to ML shock showed an initially positive effect followed by a negative effect. Furthermore, the EC response to TC shock had a large hysteresis, which first manifested in the second phase, and showed an initially positive followed by a negative effect. In addition, in the TC impulse response analysis, the TC response to ML and EC shocks was severe. The response to ML shock showed an initially positive effect followed by a negative effect, and the intensity gradually weakened. However, the response to the EC shock showed an initially negative followed by a positive effect, and the weakening of the intensity was not evident; finally, it remained as a positive effect.

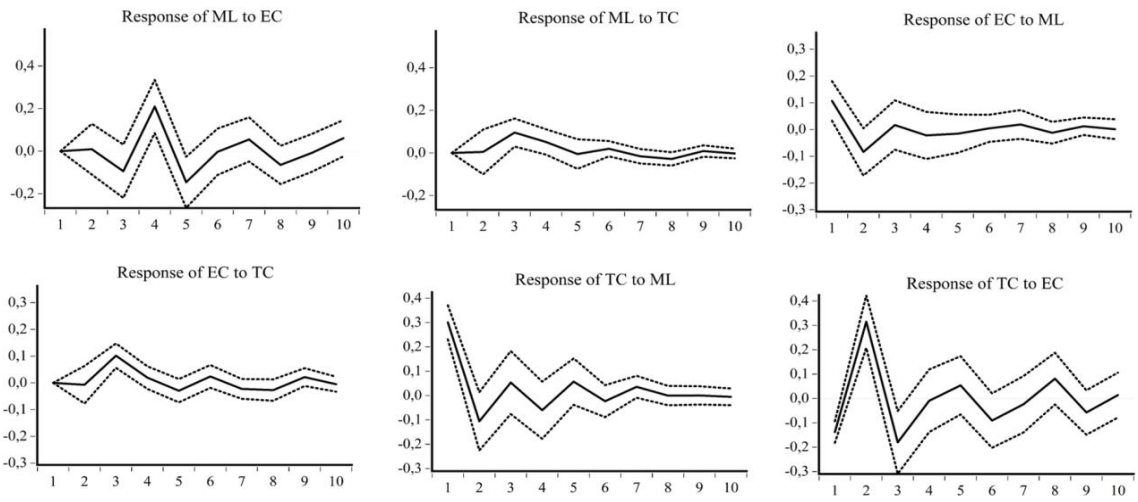

Fig. 8 Impulse response results of ML, EC, and TC of AEC emissions in the Huanghuaihai region

Figure 9 shows that in the middle and lower reaches of the Yangtze River, the response of ML to EC shocks showed an initially positive followed by a negative effect, and the intensity first increased and then decreased. In addition, the response to TC shocks showed an initially positive followed by a negative effect, and the intensity gradually weakened. Moreover, in the analysis of EC impulse response, the EC response to ML shock showed an initially positive followed by a negative fluctuation, whereas the response to TC shock was weak. Furthermore, in the impulse response analysis of TC, the response of TC to the shock of ML and EC was severe. In contrast, the reaction to ML shock showed an initially positive effect followed by a negative effect, and the intensity gradually weakened, whereas the reaction to EC shock showed an initially negative followed by a positive effect, and the intensity gradually weakened as well.

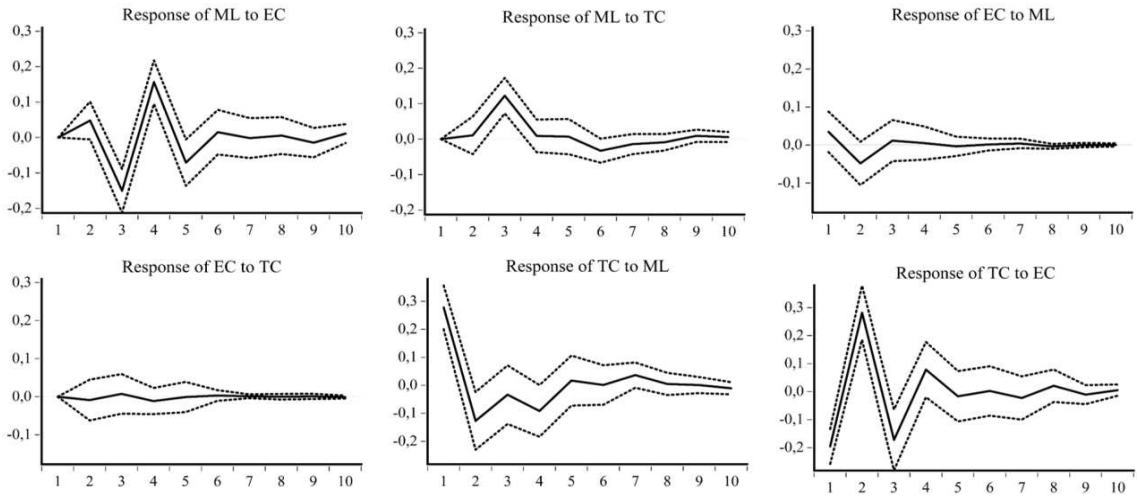

Fig. 9 Impulse response results of ML, EC, and TC of AEC emissions in the middle and lower reaches of the Yangtze River

Figure 10 shows that in South China, the response of ML to EC shocks showed an initially positive followed by a negative effect, with the intensity first increasing and then decreasing. At the same time, the response to TC shocks showed a continuous positive effect, the intensity first increased and then decreased. Moreover, in the analysis of EC impulse response, the EC response to ML shock showed a continuous weakening positive effect, whereas the response to TC shock showed a continuous positive effect, with the intensity first increasing and then decreasing. Furthermore, in the impulse response analysis of TC, the response of TC to ML shock showed a continuously weakening positive effect, whereas the response to EC shock was very severe, showing an initially negative followed by a positive effect, and the intensity gradually weakened.

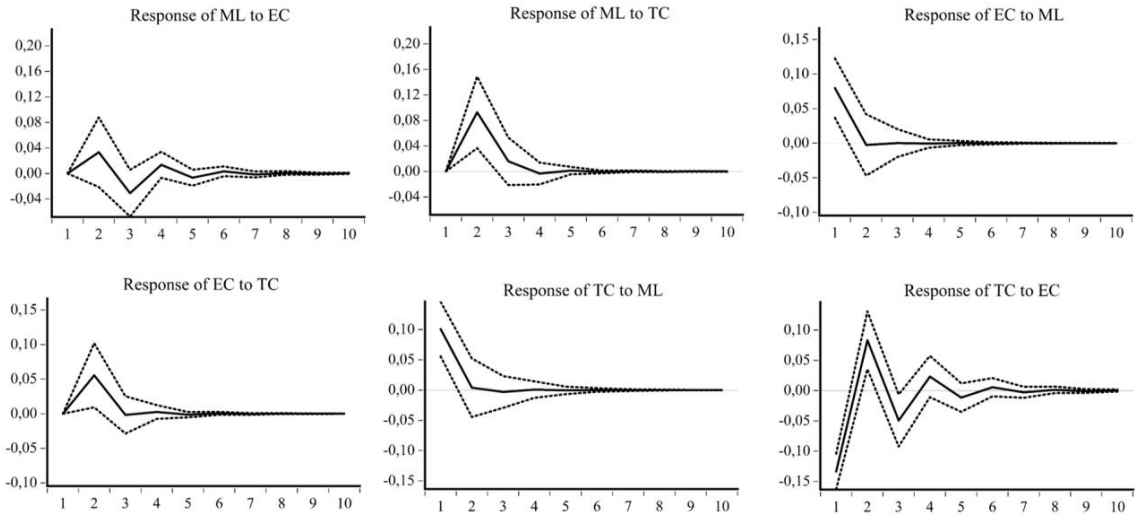

Fig. 10 Impulse response results of ML, EC, and TC of AEC emissions in South China

Figure 11 shows that in the Northwest and along the Great Wall, ML reacted violently to EC shocks, showing a fluctuating pattern of alternating positive and negative effects. Although the intensity weakened, it was not evident. In addition, the response to the TC shock was not significant. In the analysis of EC impulse response, EC showed a continuously weakening positive effect on ML shock. The response to TC shock showed a continuously increasing negative effect at the initial stage, and then rebounded to its peak in the fourth period, showing a positive effect. Furthermore, in the impulse response analysis of TC, the response of TC to ML and EC shocks was severe. Moreover, the response to the ML shock showed an initially positive followed by a negative effect, and the intensity gradually weakened, whereas the response to the EC shock showed an initially negative followed by a positive effect, the intensity gradually weakened, and finally the shock effect remained positive.

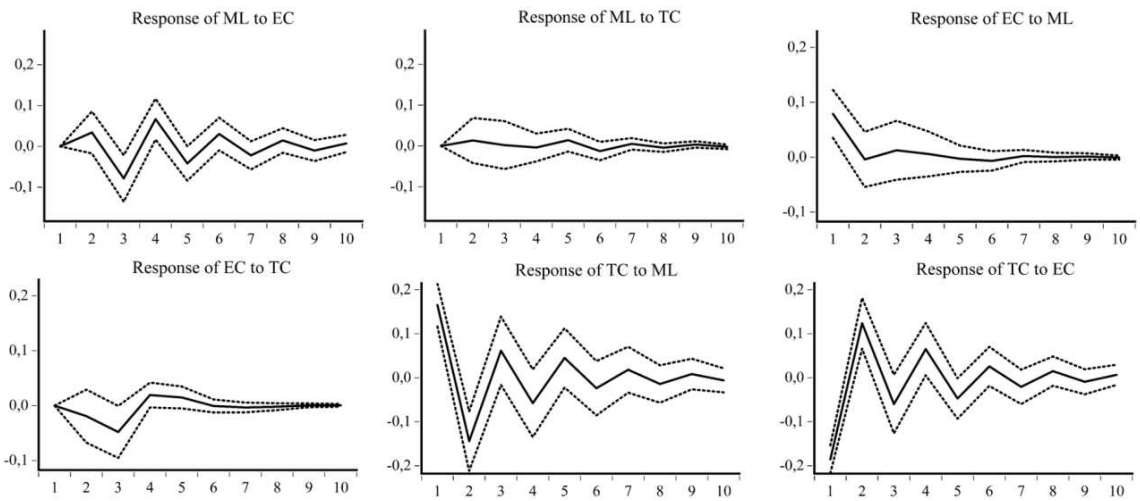

Fig. 11 Impulse response results of ML, EC, and TC of AEC emissions in the Northwest and along the Great Wall

Figure 12 shows that in the Southwest China, the response of ML to EC shocks showed a continuous positive effect, with the intensity first increasing and then decreasing. At the same time, the response to the TC shock showed an initially positive followed by a negative effect, and the intensity first increased and then decreased. Moreover, in the analysis of EC impulse response, the response of EC to ML shock showed a continuously weakening positive effect, whereas the intensity of response to TC shock was around zero. In contrast, in the impulse response analysis of TC, the response of TC to the shock of ML and EC was severe. Furthermore, the response to ML shock showed an initially positive followed by a negative effect, and the intensity first decreased, then increased, and decreased again, whereas the response to the EC shock showed an initially negative followed by a positive effect, and the intensity first increased and then decreased.

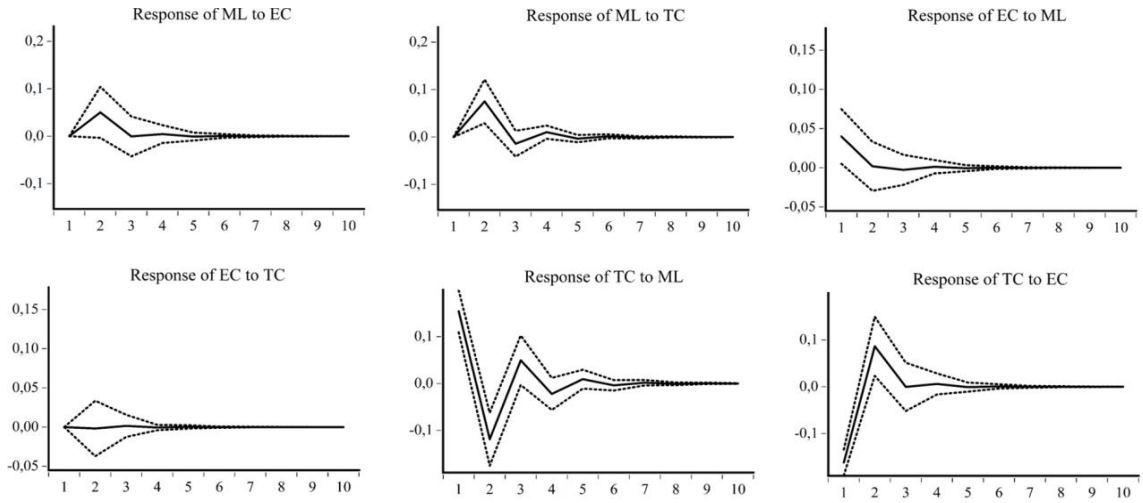

Fig. 12 Impulse response results of ML, EC, and TC of AEC emissions in Southwest China

Figure 13 shows that in the Qinghai-Tibet region, the response of ML to EC shocks showed an initially positive followed by a negative effect, and the intensity first increased and then decreased. In addition, the response to TC shocks was weaker, there was a large hysteresis effect, and the negative effect was first identified in the third period. Moreover, in the analysis of EC impulse response, the EC response to ML shock showed an initially positive followed by a negative effect, and the intensity first increased and then decreased, whereas the response to TC shock showed a steady positive effect at the initial stage, and then showed a positive effect. In contrast, in the impulse response analysis of TC, the response of TC to ML and EC shocks was severe. Moreover, the response to the ML shock showed an initially positive followed by a negative effect, and the intensity gradually weakened, whereas the response to EC shocks showed an initially negative followed by a positive effect, and the intensity gradually weakened.

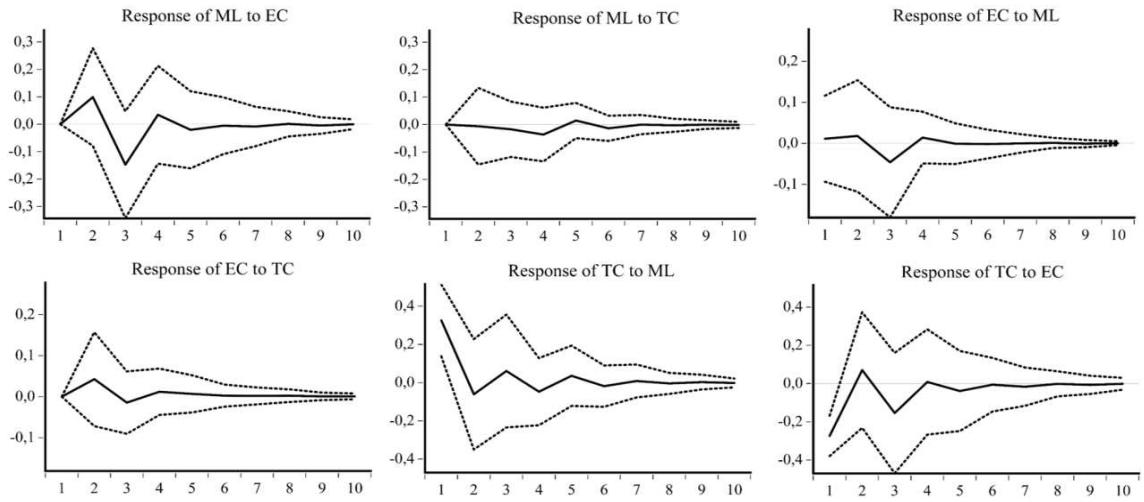

Fig. 13 Impulse response results of ML, EC, and TC of AEC emissions in the Qinghai-Tibet region

Table 6 shows that for the variance decomposition of the ML of ACE in the seven major agricultural regions of China, ML was 100% affected by its own fluctuation shock in the first period, and the impact of EC and TC on ML was first identified in the second period. Except for the Southwest region, the impact of EC on ML in other regions was higher than the impact of TC on ML, and the impact strength continued to increase, indicating that the impact of EC on ML was lagging, long-term, and continuous. In the variance decomposition of EC and TC, each region also had certain commonalities. First, the impact of ML on EC was manifested in the first period, and the impact of TC on EC was first identified in the second period. Second, the impact strength of TC to EC was very small, ranging from 0.013% to 9.654%. Third, the impact of ML and EC on TC was first identified in the first period. Fourth, except for certain periods, the impact of TC on itself was considerably smaller than the impact of ML and EC on TC, which indicates that the development of TC depends on changes in ML and EC.

Table 6 Results of Variance decomposition

Period	Northeast China											
	Variance decomposition of ML				Variance decomposition of EC				Variance decomposition of TC			
	S.E.	ML	EC	TC	S.E.	ML	EC	TC	S.E.	ML	EC	TC
1	0.196	100.000	0.000	0.000	0.182	31.251	68.749	0.000	0.228	13.772	75.191	11.037
2	0.211	93.703	6.286	0.011	0.208	24.205	67.350	8.446	0.265	16.660	72.978	10.362
3	0.220	87.820	11.263	0.918	0.209	24.731	66.917	8.353	0.278	17.525	72.345	10.130
4	0.223	86.257	12.665	1.077	0.210	24.675	66.943	8.382	0.284	17.816	72.130	10.055
5	0.224	85.596	13.249	1.155	0.210	24.684	66.938	8.378	0.286	17.928	72.047	10.025
6	0.224	85.340	13.476	1.184	0.210	24.685	66.937	8.378	0.286	17.972	72.014	10.014

7	0.225	85.238	13.566	1.196	0.210	24.685	66.937	8.378	0.287	17.990	72.001	10.009
8	0.225	85.196	13.603	1.201	0.210	24.685	66.937	8.378	0.287	17.997	71.996	10.007
9	0.225	85.180	13.617	1.203	0.210	24.685	66.937	8.378	0.287	17.999	71.994	10.007
10	0.225	85.173	13.623	1.203	0.210	24.685	66.937	8.378	0.287	18.001	71.993	10.006
Period	Huanghuaihai region											
	Variance decomposition of ML				Variance decomposition of EC				Variance decomposition of TC			
	S.E.	ML	EC	TC	S.E.	ML	EC	TC	S.E.	ML	EC	TC
1	0.491	100.000	0.000	0.000	0.328	10.599	89.401	0.000	0.369	66.331	13.937	19.732
2	0.509	99.957	0.033	0.010	0.377	12.935	87.031	0.035	0.514	38.493	44.850	16.656
3	0.545	93.875	3.016	3.109	0.391	12.219	80.987	6.794	0.549	34.695	50.102	15.203
4	0.592	81.496	15.105	3.399	0.441	9.887	84.558	5.555	0.554	35.188	49.153	15.659
5	0.610	76.901	19.898	3.201	0.479	8.468	86.457	5.075	0.560	35.497	49.051	15.452
6	0.612	76.884	19.821	3.295	0.480	8.454	86.236	5.310	0.570	34.437	49.896	15.667
7	0.615	76.309	20.373	3.318	0.491	8.233	86.481	5.287	0.572	34.639	49.783	15.578
8	0.620	75.346	21.178	3.477	0.504	7.863	86.837	5.300	0.578	33.942	50.770	15.288
9	0.620	75.345	21.163	3.492	0.505	7.889	86.650	5.461	0.581	33.604	51.243	15.152
10	0.623	74.623	21.917	3.460	0.510	7.742	86.890	5.369	0.581	33.546	51.198	15.256
Period	Middle and lower reaches of the Yangtze River											
	Variance decomposition of ML				Variance decomposition of EC				Variance decomposition of TC			
	S.E.	ML	EC	TC	S.E.	ML	EC	TC	S.E.	ML	EC	TC
1	0.272	100.000	0.000	0.000	0.273	1.614	98.386	0.000	0.446	38.982	19.273	41.745
2	0.282	96.940	2.912	0.148	0.303	3.846	96.070	0.085	0.550	30.964	38.928	30.108
3	0.353	67.806	19.993	12.200	0.308	3.850	96.010	0.140	0.581	28.055	43.631	28.314
4	0.391	57.789	32.240	9.971	0.322	3.558	96.187	0.255	0.597	28.898	43.017	28.085
5	0.398	55.973	34.350	9.678	0.324	3.527	96.220	0.253	0.600	28.730	42.727	28.543
6	0.400	55.773	34.018	10.209	0.324	3.521	96.218	0.262	0.601	28.612	42.552	28.835
7	0.401	55.788	33.912	10.301	0.325	3.521	96.217	0.262	0.603	28.822	42.464	28.714

8	0.401	55.750	33.907	10.342	0.325	3.531	96.208	0.262	0.603	28.773	42.503	28.723
9	0.402	55.691	33.942	10.367	0.325	3.529	96.209	0.262	0.603	28.740	42.485	28.776
10	0.402	55.637	33.985	10.378	0.325	3.527	96.209	0.263	0.604	28.759	42.475	28.766
Period	South China											
	Variance decomposition of ML				Variance decomposition of EC				Variance decomposition of TC			
	S.E.	ML	EC	TC	S.E.	ML	EC	TC	S.E.	ML	EC	TC
1	0.187	100.000	0.000	0.000	0.159	25.002	74.998	0.000	0.172	34.523	60.577	4.900
2	0.212	78.337	2.466	19.197	0.179	19.860	70.485	9.654	0.195	26.863	65.378	7.759
3	0.214	76.287	4.475	19.238	0.180	19.539	70.953	9.508	0.201	25.098	67.015	7.887
4	0.215	75.966	4.853	19.181	0.181	19.452	71.063	9.485	0.203	24.751	67.401	7.848
5	0.215	75.891	4.944	19.166	0.181	19.431	71.089	9.480	0.203	24.669	67.493	7.838
6	0.215	75.872	4.966	19.162	0.181	19.426	71.096	9.479	0.203	24.649	67.515	7.835
7	0.215	75.868	4.971	19.162	0.181	19.424	71.097	9.478	0.203	24.645	67.521	7.835
8	0.215	75.866	4.972	19.161	0.181	19.424	71.098	9.478	0.203	24.643	67.522	7.835
9	0.215	75.866	4.972	19.161	0.181	19.424	71.098	9.478	0.203	24.643	67.522	7.835
10	0.215	75.866	4.973	19.161	0.181	19.424	71.098	9.478	0.203	24.643	67.522	7.835
Period	Northwest and areas along the Great Wall											
	Variance decomposition of ML				Variance decomposition of EC				Variance decomposition of TC			
	S.E.	ML	EC	TC	S.E.	ML	EC	TC	S.E.	ML	EC	TC
1	0.245	100.000	0.000	0.000	0.214	13.556	86.444	0.000	0.259	40.819	51.278	7.903
2	0.277	98.261	1.502	0.237	0.226	12.166	87.120	0.714	0.323	45.907	47.492	6.602
3	0.297	91.509	8.279	0.212	0.233	11.820	83.245	4.935	0.336	45.775	47.063	7.162
4	0.310	87.524	12.267	0.209	0.233	11.794	82.617	5.589	0.349	45.275	47.210	7.515
5	0.315	85.999	13.595	0.406	0.234	11.760	82.273	5.967	0.355	45.362	47.375	7.263
6	0.318	85.198	14.250	0.552	0.234	11.827	82.213	5.960	0.357	45.335	47.410	7.255
7	0.320	84.835	14.590	0.574	0.234	11.832	82.190	5.978	0.358	45.292	47.425	7.283
8	0.320	84.673	14.738	0.589	0.234	11.831	82.184	5.985	0.358	45.294	47.442	7.264

9	0.321	84.589	14.811	0.601	0.234	11.833	82.182	5.985	0.359	45.292	47.447	7.261
10	0.321	84.549	14.847	0.605	0.234	11.833	82.181	5.985	0.359	45.289	47.449	7.262
Period	Southwest China											
	Variance decomposition of ML				Variance decomposition of EC				Variance decomposition of TC			
	S.E.	ML	EC	TC	S.E.	ML	EC	TC	S.E.	ML	EC	TC
1	0.200	100.000	0.000	0.000	0.159	6.339	93.661	0.000	0.228	45.541	50.088	4.371
2	0.243	86.167	4.278	9.555	0.159	6.299	93.688	0.013	0.288	45.690	40.510	13.800
3	0.247	86.305	4.137	9.559	0.159	6.324	93.654	0.022	0.292	47.137	39.250	13.613
4	0.248	86.206	4.137	9.657	0.159	6.329	93.647	0.024	0.294	47.333	38.976	13.690
5	0.248	86.204	4.133	9.663	0.159	6.331	93.645	0.024	0.294	47.377	38.932	13.691
6	0.248	86.202	4.133	9.665	0.159	6.331	93.645	0.024	0.294	47.384	38.924	13.692
7	0.248	86.202	4.133	9.666	0.159	6.331	93.645	0.024	0.294	47.385	38.922	13.692
8	0.248	86.202	4.133	9.666	0.159	6.331	93.645	0.024	0.294	47.386	38.922	13.692
9	0.248	86.201	4.133	9.666	0.159	6.331	93.645	0.024	0.294	47.386	38.922	13.692
10	0.248	86.201	4.133	9.666	0.159	6.331	93.645	0.024	0.294	47.386	38.922	13.692
Period	Qinghai-Tibet region											
	Variance decomposition of ML				Variance decomposition of EC				Variance decomposition of TC			
	S.E.	ML	EC	TC	S.E.	ML	EC	TC	S.E.	ML	EC	TC
1	0.251	100.000	0.000	0.000	0.203	0.302	99.698	0.000	0.430	57.261	40.410	2.329
2	0.271	86.528	13.420	0.052	0.209	1.026	94.813	4.162	0.445	55.414	40.303	4.283
3	0.309	66.599	33.050	0.351	0.214	5.612	89.979	4.408	0.475	50.330	45.894	3.776
4	0.314	65.241	33.072	1.687	0.216	5.928	89.439	4.633	0.480	50.261	44.971	4.768
5	0.317	65.259	32.873	1.869	0.217	5.907	89.380	4.713	0.483	50.201	45.075	4.724
6	0.318	65.259	32.697	2.044	0.217	5.913	89.363	4.724	0.484	50.198	44.959	4.843
7	0.319	65.232	32.726	2.042	0.217	5.908	89.365	4.726	0.484	50.155	45.008	4.837
8	0.319	65.228	32.723	2.049	0.217	5.910	89.354	4.736	0.484	50.151	44.998	4.851
9	0.319	65.215	32.737	2.048	0.217	5.910	89.353	4.737	0.484	50.142	45.007	4.850

10	0.319	65.213	32.736	2.051	0.217	5.910	89.352	4.738	0.484	50.141	45.006	4.853

6. Conclusion

This study examines the regional differences in the dynamic efficiency of ACE from 2001 to 2017 in China, and empirically analyzes the dynamic effects of the internal structure of dynamic efficiency by using the Dagum Gini coefficient and the PVAR model. The results of this study found that: (i) the overall dynamic efficiency of China's ACE is in a state of "efficiency optimization", but most provinces in the Southwest and Huanghuaihai regions are in a state of "inefficiency"; numerically, the dynamic efficiency was higher in 2017 than in 2001. Technological change and technological efficiency change are in a state of "inefficiency" in most areas, and "regions of efficiency decline" present a clustering phenomenon in the spatial structure of emissions in the region. In addition, in the early period of the study (2001–2009), technological change was found to be the main factor leading to dynamic efficiency change, while in the later period (2010–2017), technological efficiency change dominated the dynamic efficiency. (ii) In terms of regional differences, the overall Dagum Gini coefficient of China's ACE dynamic efficiency, technological change, and technological efficiency change all show upward trends; this indicates that the domestic gap is gradually widening. Among the differences within and between regions, the contribution of technological efficiency change and technological change to the dynamic efficiency of China's ACE varies greatly between regions. In economically developed regions, technological efficiency change drives dynamic efficiency, whereas technological change is the main driver of dynamic efficiency in underdeveloped regions. In terms of the performance of the contribution rate, we found that the gap between regions and the transvariation intensity are the main reasons for the gap between dynamic efficiency, technological change, and technological efficiency change in China's ACE. These two factors perform differently in different samples and during different time periods. (iii) In the analysis of the internal formation of dynamic efficiency, we found that the technological change, technological efficiency change, and dynamic efficiency interacted with one another in terms of intensity, direction, and continuity.

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Author information

Affiliations

Xiaodan Zhang, Kaicheng Liang, Xianghong Zhou

School of Economics and Management, Tongji University, Shanghai, China, 200092

Corresponding author

Correspondence to Xianghong Zhou.

School of Economics and Management, Tongji University, Shanghai, China, 200092

xhztongji0927@163.com

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Not applicable.

Consent to Participate

Not applicable.

Consent to publication

Not applicable.

Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Competing interests

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