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RESEARCH ARTICLE

Agricultural environmental total factor productivity in China under technological heterogeneity: characteristics and determinants

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Abstract

With limited resources, growing environment constraints and downward pressure on the economy, increasing agricultural environmental total factor productivity (AETFP) and its contribution to agricultural growth is significant for transforming agricultural development to make it more resource efficient and environment-friendly. This paper considered technological heterogeneity in different regions of China and measured AETFP in 30 provinces from 1997 to 2015 using the Metafrontier Malmquist-Luenberger (MML) productivity index. Multi-dimensional analysis was made on temporal and spatial characteristics, evolution patterns, and influencing factors of AETFP in China. The results showed that: (1) AETFP increased in the Ninth, Tenth, Eleventh, and Twelfth Five-Year Plan periods, with average annual growth rates of 0.76%, 0.88%, 1.17%, and 0.87%, respectively. (2) The average annual growth rate of AETFP in the eastern, central, and western regions decreased successively. The eastern region generally had played a leading role. The central region had a catch-up effect on environmental production technologies from the eastern region, while the western region lacked the catch-up effect. (3) The dynamic evolution of AETFP had prominent features. For the whole nation, the kernel density curve of AETFP continuously moved to the right. The main peak value continuously decreased and the width of the main peak continuously increased. The internal differences of AETFP in the eastern and western regions exhibited an increasing trend, while the internal differences of AETFP in the central region showed little change. (4) There was an inverted U-shaped relationship between agricultural economic growth and AETFP. Both the disaster rate and planting structure had a negative impact on AETFP with varying degrees of significance. Income gaps between urban and rural areas can partially offset the role of urbanization in promoting the growth of AETFP. The greater the income differences between urban and rural areas, the weaker the role of urbanization in promoting the growth of AETFP. These findings can help the government determine policies to change the agricultural development mode and formulate effective measures to improve AETFP.

Keywords Technological heterogeneity · Agricultural environmental total factor productivity · Metafrontier Malmquist-Luenberger productivity index · Influencing factors

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Introduction

Rapid agricultural growth in China has been accompanied by high levels of resource consumption and pollution (Liang et al. 2015; Wei et al. 2017). More pesticides and fertilizers are used in China than any other country. The total amount of pesticides and fertilizers used is 15% higher than that in developed countries and the use of chemical fertilizers is 20% higher than that in developed countries. Due to the excessive, and often inappropriate, use of agrochemical inputs, environmental pollution problems have become severe. In 2015, the emissions of chemical oxygen demand (COD_{Cr}) from China's industrial sources and agricultural sources were 2.935 and 10.686 MT, respectively. The emissions of NH_3-H from industrial and agricultural sources were 0.217 and 0.726 MT, respectively (MEP 2015). Agriculture has surpassed industry as an emission source of COD_{Cr} and NH_3-H. In June 2018, the Central Committee of the Communist Party of China and the State Council made the deployments to enhance ecological environment protection. One important goal, by 2020, is to reduce at least 10% of the emissions of COD_{Cr} and NH_3-H as that in 2015. In addition, as a developing country, China has always made development its top priority (Su et al. 2016). The outline of China's Thirteenth Five-Year Plan established targets such as consolidation and improvement of grain production capacity by 2020 and a doubling of the per capita income of rural residents by 2020 compared to 2010. Agriculture in China faces the multiple pressures of energy conservation, emissions reduction, and sustainable growth. Therefore, the following issues in China agriculture must be dealt with: (1) determining the proper relationship between agricultural growth and environmental resources, (2) reducing agricultural pollutant emissions while maintaining agricultural growth, and (3) achieving sustainable agricultural growth.

In the context of tight constraints on resources and environment management and the increasing downward pressure on the economy, the choices for solving the multiple challenges facing agricultural development in China involve changing the mode of agricultural development, increasing the agricultural total factor productivity (ATFP), and constructing a resource-conserving and environmentally friendly mode of agricultural development (Song 2016). Much research has been published concerning ATFP (Chen et al. 2008; Nin-Pratt and Yu 2010; Hoang 2011; Peng et al. 2013; Yin et al. 2014; Gao 2015).

Unlike the parameter model, the data envelopment analysis (DEA) model can avoid function-specification errors (Guo et al. 2018; Yin 2017). For this reason, the DEA model is widely used to measure the ATFP. However, the traditional measurement of the ATFP ignores the effects of environmentally harmful by-products. If the constraint of environmental factors is not considered, the measurement results may be inaccurate (Han and Zhao 2013). Chung et al. (1997) established the Malmquist-Luenberger (ML) productivity index based on the directional distance function. Unlike the traditional total factor productivity, which did not consider the effect of environmentally harmful by-products, the ML index did consider these effects. Since its introduction, the ML productivity index has been widely used to measure the total factor productivity considering undesirable outputs such as environmentally harmful by-products. For example, Zhang et al. (2011) evaluated the total factor productivity of China's 30 provincial regions incorporating undesirable outputs using the ML productivity index. Shao and Wang (2016) studied productivity growth of China's nonferrous metal industry using the ML productivity index. They found that the total factor productivity of the nonferrous metal industry would be overestimated if the undesirable output was disregarded. Maziotis et al. (2017) used the ML index to assess changes in the productivity of the water industry in England and Wales with poor service quality as an undesirable output. Yu et al. (2016) used the ML index to evaluate the total factor productivity of the pulp and paper industry in China considering wastewater emissions, COD_{Cr}, and NH_3-H as undesirable outputs.

There have been attempts to integrate agricultural pollutant emissions as undesirable outputs into the evaluation model of ATFP, and several studies have examined agricultural environmental total factor productivity (AETFP).[1] For example, Ye and Hui (2016) and Pan (2014) included agricultural non-point source pollution as an undesirable output in the ATFP evaluation model. Other studies have included agricultural carbon emissions as undesirable outputs in the ATFP evaluation model (Tian et al. 2015; Zhang et al. 2015; Fei and Lin 2017). However, most studies considered only one aspect of the undesirable output of agriculture when measuring AETFP. Few studies have considered both agricultural non-point source pollution and agricultural carbon emissions. Thus, the real agriculture production process has not been comprehensively fitted to the model.

In measuring AETFP, existing studies usually assume that different decision-making units (DMUs) have the same or similar production technology.[2] Under the assumption of technology homogeneity, all DMUs are evaluated based on the same set of benchmark technologies (production frontier).

However, due to the differences between internal characteristics and the external environment of DMUs belonging to different groups, the set of benchmark technologies available for different groups may not be the same (Wang et al. 2017a). We recognize significant differences in resource endowments, climatic conditions, cropping structure, and agricultural systems among the eastern, central, and western regions of China (Du et al. 2014). Therefore, the potential optimal production technology that can be achieved by different regions varies due to the diversity of production frontiers. The heterogeneity of production technologies in different regions must be considered because provinces located in different regions may have different production frontiers with technological heterogeneity. Without this consideration, the measurement results of AETFP in each province may deviate from their actual values (Fei and Lin 2016). If provinces in different regions are placed under different production fronts for comparison, the lack of uniform standards can lead to the incomparability of AETFP between provinces in different regions.

[1] In this paper, the agricultural total factor productivity, which takes into account the environmental factors, is called the agricultural environmental total factor productivity. There is also literature that calls it the agricultural green total factor productivity.

[2] Production technology, as defined herein, is a generalized production technology term that refers to the knowledge and ability to convert inputs into outputs.

To overcome the heterogeneity among different groups of samples, the meta-production function was proposed by Hayami (1969) and further described by Battese and Rao (2002) and by Battese et al. (2004). Rambaldi et al. (2007) defined the meta-production function using the distance function and established the Metafrontier-Malmquist (MM) productivity index using the DEA method. In this way, the concept of meta-production function was extended to the field of total factor productivity index measurement. However, the MM productivity index does not account for the effects of environmentally harmful by-products. To overcome the shortcomings of the MM productivity index, Oh (2010) proposed a MML productivity index that incorporates undesirable outputs into the MM productivity index. The MML productivity index not only deals with the heterogeneity of different groups but also considers the effect of environmentally harmful by-products. Since the report by Oh (2010), the MML productivity index has been widely used to measure the total factor productivity of DMUs. For applications at the national level, Lin et al. (2013) provide guidance. Choi et al. (2015) provided background and direction for the province level, Chung and Heshmati (2015) for the industrial level, Juo et al. (2015) for Taiwanese credit departments, and Yu et al. (2017) for the regional transport sector. However, little attention has been given to using the MML productivity index on Chinese agriculture.

In the context of previous research on these productivity indexes, we focused on three areas: (1) measuring AETFP, considering both the undesirable outputs of agricultural non-point source pollution and agricultural carbon emission simultaneously to produce more accurate results. (2) AETFP in all of the China provinces was measured based on the MML productivity index under the framework of technological heterogeneity. The technology gap among different regions was determined and the comparability of AETFP among different provinces was also determined.

(3) Under technological heterogeneity, multidimensional analysis was conducted for the AETFP in China. The temporal and spatial characteristics and evolution patterns of AETFP in China were explored and empirical tests were performed on the influencing factors of AETFP using the DIF-GMM method (Arellano and Bond 1991) and SYS-GMM (Blundell and Bond 1998) method of dynamic panel data.

The remainder of this paper is structured as follows. In section "Methodology", we introduce the MML productivity index. The details of the agricultural input and output index as well as the data description are presented in section "Variables and data". Section "Results and analysis" reports and discusses the main results. We present our conclusions and policy implications in section "Conclusions and implications".

Methodology

Environmental production technology

Agriculture produces desirable outputs such as food and generates undesirable outputs that pollute water, air, and soil. These outputs result from large inputs of fertilizers, pesticides, and other production materials. To comprehensively and objectively model the agricultural production process, a set of production possibilities that include both desirable and undesirable outputs was constructed. Each province is considered to be a DMU. Suppose there are $k = 1, \ldots, K$ DMUs within the time period of $t = 1, \ldots, T$ that use N types of inputs $x = (x_1, \ldots, x_N) \in R_+^N$, and obtain M types of desirable outputs $y = (y_1, \ldots, y_M) \in R_+^M$ and J types of undesirable outputs $b = (b_1, \ldots, b_J) \in R_+^J$. Then, the set of production possibilities, $P(x)$, can be expressed as (Munisamy and Arabi 2015):

$$P(x) = \left\{(y, b) : x \ can \ produce \ (y, b), x \in R_+^N\right\} \tag{1}$$

$P(x)$ is assumed to satisfy three axioms.

$$if \ (y, b) \in P(x) \quad and \ b = 0, \qquad then \ y = 0 \tag{2a}$$

$$if \ (y, b) \in P(x) \quad and \ y' \leq y, \qquad then \ \left(y', b\right) \in P(x) \tag{2b}$$

$$if \ (y, b) \in P(x) \quad and \ 0 \leq \theta \leq 1, \quad then \ (\theta y, \theta b) \in P(x) \tag{2c}$$

The first axiom in Eq. (2a) is known as null jointness. The second axiom in Eq. (2b) means that the desirable outputs are strongly disposable. The third axiom in Eq. (2c) suggests that the undesirable and desirable outputs are jointly weakly disposable (Chung and Heshmati 2015; Miao et al. 2016).

MML productivity index

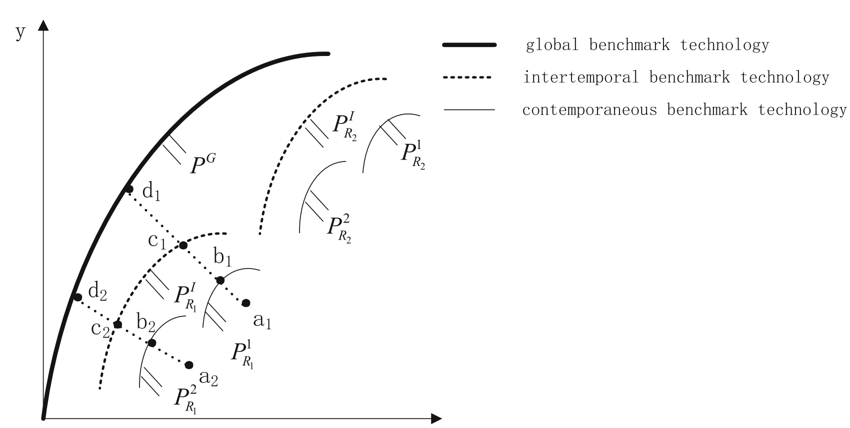
Due to technological heterogeneity, it is assumed that there are H different sample groups $R_h (h = 1, \ldots, H)$. To analyze the MML productivity index, three benchmark technology sets need to be introduced: the contemporaneous, the intertemporal, and the global benchmark technology set (Tulkens and Eeckaut 1993). The contemporaneous benchmark technology set is defined as $P_{R_h}^t(x^t) = \{(y^t, b^t) : x^t \ can \ produce \ (y^t, b^t)\}$, where $t = 1, \ldots, T$, represent the set of production possibilities for the group R_h at time t. The intertemporal benchmark technology set is defined as $P_{R_h}^I = conv\left\{P_{R_h}^1 \cup P_{R_h}^2 \cup \ldots \cup P_{R_h}^T\right\}$, indicating the set of production possibilities for the group R_h over the entire period ($t = 1, \ldots, T$). It is difficult for a DMU of a certain intertemporal benchmark technology set to reach the production technology of other intertemporal benchmark technology sets. The global benchmark technology set is defined as $P^G = conv\left\{P^I_{R_1} \cup P^I_{R_2} \cup \ldots \cup P^I_{R_H}\right\}$, indicating the set of production possibilities for all groups over the entire period ($t = 1, \ldots, T$), and represents the maximum limit on the output for DMUs. Figure 1 shows the relationship between the three benchmark technology sets using two groups and two periods as examples. The intertemporal benchmark technology set is the envelope curve of the contemporaneous benchmark technology set of the group, and the global benchmark technology set is the envelope curve of the intertemporal benchmark technology set of the group (Fig. 1).

Oh and Lee (2010) defined the MML productivity index as

$$\begin{aligned} MML\left(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}\right) &= \frac{1+\overrightarrow{D_G}\left(x^t, y^t, b^t\right)}{1+\overrightarrow{D_G}\left(x^{t+1}, y^{t+1}, b^{t+1}\right)} = \frac{1+\overrightarrow{D^t}\left(x^t, y^t, b^t\right)}{1+\overrightarrow{D^{t+1}}\left(x^{t+1}, y^{t+1}, b^{t+1}\right)} \\ &\times \frac{\left(1+\overrightarrow{D^I}\left(x^t, y^t, b^t\right)\right)/\left(1+\overrightarrow{D^t}\left(x^t, y^t, b^t\right)\right)}{\left(1+\overrightarrow{D^I}\left(x^{t+1}, y^{t+1}, b^{t+1}\right)\right)/\left(1+\overrightarrow{D^t}\left(x^{t+1}, y^{t+1}, b^{t+1}\right)\right)} \\ &\times \frac{\left(1+\overrightarrow{D_G}\left(x^t, y^t, b^t\right)\right)/\left(1+\overrightarrow{D^I}\left(x^t, y^t, b^t\right)\right)}{\left(1+\overrightarrow{D_G}\left(x^{t+1}, y^{t+1}, b^{t+1}\right)\right)/\left(1+\overrightarrow{D^I}\left(x^{t+1}, y^{t+1}, b^{t+1}\right)\right)} \\ &= \frac{TE^{t+1}}{TE^t} \times \frac{BPG^{t+1}}{BPG^t} \times \frac{TGR^{t+1}}{TGR^t} = EC \times BPC \times TGC \end{aligned} \tag{3}$$

where $\overrightarrow{D^s}(x, y, b) = \inf\{\beta : (x, y+\beta y, b-\beta b) \in P^s_{R_h}\}$, $s = t$, $t+1$ denotes the contemporaneous directional distance function defined on the contemporaneous benchmark technology set; $\overrightarrow{D^I}(x, y, b) = \inf\{\beta : (x, y+\beta y, b-\beta b) \in P^I_{R_h}\}$ denotes the intertemporal directional distance function defined on the intertemporal benchmark technology set; and $\overrightarrow{D_G}(x, y, b) = \inf\{\beta : (x, y+\beta y, b-\beta b) \in P^G\}$ denotes the global directional distance function defined on the global benchmark technology set. In addition, EC is the index of environmental efficiency change, reflecting the catch-up effect of the decision-making unit to the contemporaneous frontier of the group. BPC is the index of the change in the best practice gap ratio between the contemporaneous frontier and the intertemporal frontier during two periods (Choi et al. 2015). BPC reflects environmental technical change. When BPC is greater than (or less than) 1, it indicates that the contemporaneous frontier of the group of the DMU at $t+1$ is closer to (or further away from) the group's intertemporal frontier than at t, reflecting the environmental technology progress (or regression) of the group. TGC is the index of environmental technology gap ratio change, reflecting the change of the gap between the intertemporal

Fig. 1 Diagram of the MML productivity index



frontier and the global frontier of the group during two periods. When *TGC* is greater than (or less than) 1, it indicates that the intertemporal frontier of the group at $t+1$ of the DMU is closer to (or further away from) the global frontier than that of the group at t, reflecting the further narrowing (or widening) of the gap between the environmental production technologies of the group and the global environmental production technologies (Wang et al. 2015).

Figure 1 depicts the MML productivity index and its decomposition. It assumes that a_1 is the DMU with a period of 1 in group R_1, and a_2 is the DMU with a period of two in group R_1. Then, using the directional distance function, the MML productivity index can be expressed as (Li et al. 2018):

$$MML\left(x^t,y^t,b^t,x^{t+1},y^{t+1},b^{t+1}\right)=\frac{1+a_1d_1}{1+a_2d_2}=\frac{1+a_1b_1}{1+a_2b_2}\times\frac{(1+a_1c_1)/(1+a_1b_1)}{(1+a_2c_2)/(1+a_2b_2)}\times\frac{(1+a_1d_1)/(1+a_1c_1)}{(1+a_2d_2)/(1+a_2c_2)} \tag{4}$$

Oh (2010) demonstrated that the MML productivity index of the k' DMU can be obtained by solving six directional distance functions ($\overrightarrow{D^s}(x^s,y^s,b^s)$, $\overrightarrow{D^I}(x^s,y^s,b^s)$ 和 $\overrightarrow{D^G}(x^s,y^s,b^s)$, $s=t,t+1$). The linear programming formula of these directional distance functions can be uniformly expressed as

$$\begin{aligned}
&\overrightarrow{D^d}\left(x^{k',s},y^{k',s},b^{k',s}\right)=\max\beta\\
&s.t.\ \sum_{con}\lambda^{k,s}y_m^{k,s}\geq(1+\beta)y_m^{k',s},m=1,\ldots,M\\
&\sum_{con}\lambda^{k,s}b_j^{k,s}=(1-\beta)b_j^{k',s},j=1,\ldots,J\\
&\sum_{con}\lambda^{k,s}x_n^{k,s}\leq x_n^{k',s},n=1,\ldots,N\\
&\lambda^{k,s}\geq 0
\end{aligned} \tag{5}$$

where d represents the type of directional distance function; $\lambda^{k,s}$ is the weight vector; and *con* is the type of benchmark technology set. These are the contemporaneous, intertemporal, and global benchmark technology sets.

Econometric model

Due to the inertia of AETFP growth, its growth in a previous period can affect the contemporaneous growth (Han et al. 2014). Therefore, the dynamic panel regression model was used to empirically test the driving factors of AETFP. According to the characteristics of agricultural production and the availability of data, the preliminary influential factors of AETFP growth selected in this study are the agricultural economic growth level, the disaster rate, and the planting structure. The main reasons of selection are as follows: (1) improvement of the agricultural economic growth level can usually improve agricultural infrastructure and increase agricultural production input. However, the impact of agricultural economic growth level on agricultural production usually occurs in stages. Therefore, the impact of the agricultural economic growth level and its square term on AETFP growth are examined at the same time in this study. (2) Agricultural production is greatly influenced by the natural environment. A harsh natural environment can affect crop growth and natural disasters can seriously harm agricultural development. (3) China is in a critical period of economic transformation and structural adjustment. Exploring the influence of agricultural structure, especially the planting structure, is significant to the growth of AETFP. Considering the above factors, the following dynamic panel regression model is established in this study:

$$\begin{aligned}
\ln MML_{i,t}^a=&\beta_0+\beta_1\ln MML_{i,t-1}^a+\beta_2\ln agri_{i,t}\\
&+\beta_3\left(\ln agri_{i,t}\right)^2+\beta_4\ln nature_{i,t}\\
&+\beta_5\ln struc_{i,t}+u_i+\varepsilon_{i,t}
\end{aligned} \tag{6}$$

Here, ln represents the natural logarithm, i and t represent the region and time, u represents the individual fixed effect, and ε is the random disturbance. *MML* is the index of AETFP, and the superscript a indicates its cumulative value. $\ln MML_{i,t-1}^a$ is the lag phase of the explained variables; *agri* is the growth level of the agricultural economy represented by the per capita net income of rural residents. To verify the existence of Kuznets Curve of AETFP, the square term of the natural logarithm of agricultural economy growth level, $(\ln agri_{i,t})^2$, was added to the model. The *nature* term is the disaster rate, represented by the ratio of the disaster affected area and total sown crop area. The *struc* term is the planting structure, represented by the ratio of the grain sown area and the total sown crop area.

In order to further explore the impact of urbanization and the urban-rural income gap on AETFP, model (6) was expanded as follows:

$$\begin{aligned}
\ln MML_{i,t}=&\beta_0+\beta_1\ln MML_{i,t-1}+\beta_2\ln agri_{i,t}\\
&+\beta_3\left(\ln agri_{i,t}\right)^2+\beta_4\ln nature_{i,t}+\beta_5\ln struc_{i,t}\\
&+\beta_6\ln urban_{i,t}+\beta_7\ln urid_{i,t}+\beta_8\ln urban_{i,t}\\
&\times\ln urid_{i,t}+u_i+\varepsilon_{i,t}
\end{aligned} \tag{7}$$

Here, *urban* is the urbanization level, represented by the proportion of urban population to the total population; *urid* is the income gap between urban and rural areas, expressed as the ratio of per capita disposable income of urban residents to per capita net income of rural residents; and $\ln urban \times \ln urid$ is the cross term between the natural logarithm of urbanization level and the natural logarithm of the urban-rural income gap. The other variables are the same as in model (6). The data of the explained variables were calculated from the next sections. The data of other explanatory variables are from the "Compilation of Statistical Data for Sixty Years in New China," the "Statistical Yearbook of China" of each year, and the statistical yearbook of each province.

Variables and data

Variables

Input variables

Land, labor, agricultural machinery, and fertilizer were selected as agricultural input variables. (1) Land input. Arable land area and sown area are the two main variables related to land input available from the statistical yearbook. However, the arable land area does not provide information on multiple cropping and interplanting. Therefore, the total sown area of crops was used to represent the land input variable. (2) Labor input. The primary industry employees were used to represent the labor input variable. The 1997–2010 data were from the "China Statistical Yearbook." The 2011–2015 data were from the statistical yearbooks of the provinces, and some of the data with disagreement of statistical caliber had been adjusted. (3) Agricultural machinery input. The agricultural machinery gross power was used to represent the agricultural machinery input variable. (4) The amount of chemical fertilizer. The amount of chemical fertilizer used for agricultural production was used to represent the chemical fertilizer variable.

Output variables

Agricultural output variables should include both desirable outputs and undesirable outputs. Desirable outputs are represented here by the gross output value of agriculture in 1997 at constant prices. There are no direct data for the agricultural undesirable output variable and it required correct measurement methods. The agricultural undesirable output refers to injuries to the agro-ecological environment caused by excess application of pesticides and fertilizers, releases of livestock and poultry manure, and the inappropriate disposal of farmland wastes during agricultural production. This undesirable output mainly occurs as agricultural non-point source pollution[3] and agricultural carbon emissions.[4]

The unit survey and evaluation method were used to calculate agricultural non-point source pollution, and the sources of pollutants are identified as farmland fertilizer, animal husbandry, and farmland solid waste. The calculation formula is $E_w = \sum EU\rho(1-\eta)C$, where E_w is the amount of agricultural non-point source pollutant emissions into water, specifically referring to the emissions of COD_{Cr}, total nitrogen(TN), and total phosphorus (TP). *EU* is the statistical indicator of the pollution unit. ρ is the pollutant production intensity coefficient, η is the resource utilization efficiency coefficient, and C is the pollutant emission coefficient. Among these, all the parameters were obtained from the literature (Lai 2004; Liang 2009). To facilitate the analysis, we converted the COD_{Cr}, TN, and TP types of agricultural non-point source emissions into agricultural non-point source standard equivalent pollution load based on the class III standard in the surface water environmental quality standard (GB3838-2002).

To calculate agricultural carbon emissions, we constructed a formula based on the research of Tian and Zhang (2013): $E_a = \sum (T_i \times \delta_i)$, where E_a is the amount of agricultural carbon emissions; i is the ith type of agricultural carbon emission source; T is the characterization data of agricultural carbon emission sources; and δ is the carbon emission coefficient of agricultural carbon emission sources. We mainly investigated CO_2 gas emissions caused by the use of agricultural materials and agricultural energy consumption in the use of agricultural land; CH_4 gas emissions from rice cultivation; and CH_4 and N_2O emissions from livestock and poultry farming. The carbon emission coefficients of the agricultural carbon emission sources were based on the research of Li et al. (2011) and Tian et al. (2012). To facilitate the analysis, greenhouse gases such as CO_2, CH_4, and N_2O were converted into a standard C equivalent to unify the measurement unit. According to the Fourth Assessment Report of the IPCC (United Nations Intergovernmental Panel on Climate Change), the greenhouse effect produced by 1 t of CO_2, CH_4, and N_2O is equivalent to the greenhouse effect produced by 0.2727 t, 6.8175 t, and 81.2646 t of C, respectively.

[3] The concept of agricultural non-point source pollution came from an amendment of the Clean Water Act of the United States in 1997. The amendment addresses non-point source pollution as pollutants entering the surface water and groundwater bodies in a multi-source, diffused, and trace form.

[4] The concept of agricultural carbon emissions used in this paper is a general term for agricultural greenhouse gas emissions.

Data description

Panel data of 30 provincial administrative units (= provinces) in Mainland China from 1997 to 2015 were studied. Tibet has special resource endowment conditions, so this study excluded Tibet. Unless otherwise specified, the original data for each variable came from the "China Statistical Yearbook," "China Rural Statistical Yearbook," "China Agricultural Statistical Report," and the "China Animal Husbandry Yearbook."

Table 1 shows a simple statistical description of the input-output variable of AETFP in the eastern, central, and western regions. It shows large differences in the input and output of agricultural production in different regions of China form Table 1. Using the land input variable as an example, the average total sown area of crops in the central region of China was 7929.47 thousand ha during the study period. This was nearly twice the average total sown area of crops in the eastern region. In addition, the minimum total sown area of crops was 173.70, 3653.15, and 466.80 thousand ha, in the eastern, central, and western regions, respectively. The ratio of the three was 1:21.0:2.69.

Due to the variation in resource endowments among regions and differences in the scale and pace of economic development, there are large differences in production technology levels and production frontiers in the regions. It was necessary to divide provinces into different groups based on certain criteria. Li et al. (2013) considered that geographical location is a key factor affecting knowledge spillover and technology diffusion speed. Therefore, based on data from the National Bureau of Statistics, the provinces of China were divided into eastern, central, and western groups having different production technology levels. The eastern group included Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central group included Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. The western group included Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

Results and analysis

Temporal characteristics of AETFP of China under technological heterogeneity

China's agricultural MML productivity index and its decomposition were calculated for each year of the survey period (Table 2). For comparison, the ML productivity index and

Table 1 Statistical description of input and output variables of agricultural environmental TFP in the three regions

Regions	Variables description	Observed value	Average value	Standard deviation	Maximum value	Minimum value
Eastern region	Total sown area of crops (thousand hm^2)	209	3970.45	3552.68	11,266.12	173.70
	Employees in the primary industry (ten thousand people)	209	813.33	694.01	2510.50	36.35
	Agricultural machinery gross power (ten thousand kW)	209	2757.26	3321.81	13,353.00	95.32
	Amount of chemical fertilizer (ten thousand t)	209	157.59	143.67	500.34	9.90
	Gross output value of agriculture (hundred million yuan)	209	1536.60	1189.66	5008.60	148.83
	Agricultural non-point source standard equivalent pollution load (10^6 m^3)	209	390,146.27	346,090.61	1,315,877.35	32,865.36
	Agricultural carbon emission (ten thousand t)	209	947.59	737.00	2466.82	71.83
Central region	Total sown area of crops (thousand hm^2)	152	7929.47	3136.87	14,425.00	3653.15
	Employees in the primary industry (ten thousand people)	152	1324.53	798.61	3569.04	510.96
	Agricultural machinery gross power (ten thousand kW)	152	3485.15	2397.25	11,710.10	750.00
	Amount of chemical fertilizer (ten thousand t)	152	239.88	145.15	716.10	82.60
	Gross output value of agriculture (hundred million yuan)	152	1576.51	822.18	4339.86	340.77
	Agricultural non-point source standard equivalent pollution load (10^6 m^3)	152	388,615.46	231,164.05	1,185,104.38	98,916.69
	Agricultural carbon emission (ten thousand t)	152	1531.42	639.42	2722.31	411.51
Western region	Total sown area of crops (thousand hm^2)	209	4606.49	2442.17	9717.70	466.80
	Employees in the primary industry (ten thousand people)	209	951.97	664.43	2872.40	115.09
	Agricultural machinery gross power (ten thousand kW)	209	1525.29	938.24	4404.50	207.90
	Amount of chemical fertilizer (ten thousand t)	209	119.52	74.16	259.90	6.57
	Gross output value of agriculture (hundred million yuan)	209	860.96	653.19	3101.72	59.01
	Agricultural non-point source standard equivalent pollution load (10^6 m^3)	209	191,171.17	111,864.30	514,902.78	35,193.37
	Agricultural carbon emission (ten thousand t)	209	916.99	555.53	2287.13	119.15

Table 2 Timing characteristics of China's agricultural MML productivity index and its decomposition

Year	Global benchmark technology set				Contemporaneous benchmark technology set		
	MML	EC	BPC	TGC	ML	EC	TC
1997–1998	1.0049	0.9996	1.0027	1.0026	1.0126	0.9919	1.0209
1998–1999	1.0092	1.0035	0.9972	1.0085	1.0116	1.0004	1.0112
1999–2000	1.0087	1.0009	1.0042	1.0037	1.0192	1.0044	1.0148
Average of the Ninth Five–year Plan period	1.0076	1.0013	1.0014	1.0049	1.0145	0.9989	1.0156
2000–2001	1.0102	0.9974	1.0127	1.0002	1.0218	0.9924	1.0296
2001–2002	1.0112	0.9907	1.0232	0.9976	1.0216	0.9932	1.0286
2002–2003	1.0104	0.9958	1.0168	0.9979	1.0183	0.9932	1.0252
2003–2004	1.0063	0.9989	1.0113	0.9962	1.0170	0.9927	1.0245
2004–2005	1.0060	0.9986	1.0069	1.0006	1.0108	1.0039	1.0069
Average of the Tenth Five–year Plan period	1.0088	0.9963	1.0142	0.9985	1.0179	0.9951	1.0229
2005–2006	1.0086	0.9963	1.0138	0.9987	1.0143	0.9940	1.0203
2006–2007	1.0300	1.0072	1.0256	0.9972	1.0351	1.0002	1.0349
2007–2008	1.0066	0.9994	1.0085	0.9987	1.0114	0.9979	1.0136
2008–2009	1.0059	0.9976	1.0087	0.9996	1.0106	0.9956	1.0151
2009–2010	1.0077	1.0038	1.0020	1.0018	1.0105	0.9996	1.0109
Average of the Eleventh Five-year Plan period	1.0117	1.0008	1.0117	0.9992	1.0163	0.9975	1.0189
2010–2011	1.0109	1.0014	1.0123	0.9972	1.0115	0.9973	1.0142
2011–2012	1.0063	0.9979	1.0081	1.0003	1.0113	0.9965	1.0149
2012–2013	1.0092	0.9954	1.0167	0.9973	1.0150	0.9921	1.0231
2013–2014	1.0135	0.9982	1.0192	0.9963	1.0177	0.9925	1.0255
2014–2015	1.0036	0.9917	1.0147	0.9974	0.9945	0.8960	1.1100
Average of the Twelfth Five-year Plan period	1.0087	0.9969	1.0142	0.9977	1.0100	0.9740	1.0369
Overall average	1.0094	0.9986	1.0113	0.9995	1.0147	0.9905	1.0244

Note: (1) Due to the data limitations, the Ninth Five-Year period only includes 3 years of data. (2) The average values in this table are geometric mean values. (3) Due to paper length restrictions, we did not provide the measurement results based on the intertemporal benchmark technology set

its decomposition, without considering technological heterogeneity, are also given.

Table 2 shows the following: (1) China's agricultural MML productivity index and ML productivity index differ. Except for 2014–2015, the MML productivity indexes of other periods were less than the ML productivity index. Therefore, when the ML productivity index is used, the AETFP may be overestimated. This is because the ML productivity index uses the contemporaneous benchmark technology set. It uses the contemporaneous potential best technology as a reference and ignores the group technology heterogeneity. (2) Under the global benchmark technology set, the AETFP index (MML) of China increased by 0.94% annually from 1997 to 2015. This estimate is significantly lower than the estimate of Li (2014), which was referenced to the contemporaneous benchmark technology set. From 1997 to 2015, the index of agricultural environmental efficiency change (EC) decreased by 0.14% annually, indicating that the underdeveloped provinces did not catch up with the advanced provinces and receded from the contemporaneous frontier of the group. The average annual growth rate of the agricultural environmental technology change index (BPC) was 1.13%, indicating that the contemporaneous frontier of the group gradually approached the intertemporal frontier of the group. The gap in environmental production technologies among the different provinces continued to shrink. The environmental production technologies in the underdeveloped provinces appeared to provide a "catch-up" effect on the potential best environmental technologies in the group. The index of the environmental technology gap ratio change (TGC) decreased by an average of 0.05% annually indicating that the intertemporal frontier of the group continued to deviate from the global frontier. The gap between the potential optimal environmental production technologies of the three groups gradually increased. The agricultural environmental technology change appears to be the major driving force behind the growth of agricultural environmental total factor productivity. (3) AETFP increased, to varying degrees, in the Ninth, Tenth, Eleventh, and Twelfth Five-Year Plan periods, with average growth rates of 0.76%, 0.88%, 1.17%, and 0.87%, respectively. The growth rate during the Eleventh Five-Year Plan period was the highest and it exceeded the average growth rate of the entire study period. This period is an important window for promoting the new socialist countryside and agricultural modernization. During this period, China established agriculture, rural areas, and farmers as the focus for a series of policies introduced to improve agriculture and benefit farmers. The government adopted a series of measures to promote the sustainable development of agriculture and rural areas (Song 2010). In the first year of the Eleventh Five-Year Plan period, the government abolished the agricultural tax that had existed, nationwide, for millennia. This greatly reduced the burden on farmers and enhanced agricultural competitiveness. In 2007, "Law of the People's Republic of China on Farmers' Professional Cooperatives" was implemented and related policies have since been carried out to promote rapid development of farmer professional cooperatives. The Ministry of Agriculture has implemented the "Overall Framework of National Agricultural and Rural Information Construction (2007–2015)" and planned the development of agricultural informatization. By 2009, more than 80% of the county level agricultural departments had information services and regulatory agencies. The implementation of these policies and measures has improved AETFP, transformed the agricultural development mode, and promoted sound and rapid agricultural development.

Spatial characteristics of AETFP of China under technological heterogeneity

The spatial characteristics of AETFP in China were analyzed by calculating the agricultural MML productivity index and its decomposition in various regions and provinces (Table 3).

Table 3 shows the following: (1) the annual growth rate of AETFP in the eastern, central, and western regions decreased by 1.38%, 0.72%, and 0.66%, respectively, and numbers in the central and western regions were lower than the national average. In addition, the average annual growth rate of AETFP in more than 60% of the provinces was lower than the national average. Most of these provinces are located in the central and western regions. There were only 10 provinces above the national average, and all of these, except for Shaanxi, were in the eastern region. (2) For the index of agricultural environmental efficiency change, the central region index increased by 0.04% annually, while the index values of the eastern and western regions decreased by 0.34 and 0.08% annually. This indicated that only the agricultural environmental efficiency change in the central region had a positive contribution to the growth of AETFP, while the improvement of agricultural environmental efficiency change in the eastern and western regions reduced AETFP growth in these areas. Among single provinces, the index of agricultural environmental efficiency change of Henan, Ningxia, Hainan, Shanxi, Yunnan, and Jiangsu provinces increased in varying degrees while the index of the agricultural environmental efficiency change of the other provinces either remained the

Table 3 Spatial characteristics of China's agricultural MML productivity index and its decomposition

Province	MML	EC	BPC	TGC	Province	MML	EC	BPC	TGC
Beijing	1.0187	1.0000	1.0187	1.0000	Hunan	1.0070	1.0000	1.0046	1.0024
Tianjin	1.0070	0.9952	1.0118	1.0000	Guangdong	1.0130	0.9944	1.0187	1.0000
Hebei	1.0110	0.9965	1.0146	1.0000	Guangxi	1.0083	1.0000	1.0053	1.0031
Shanxi	1.0078	1.0025	1.0096	0.9957	Hainan	1.0242	1.0018	1.0224	1.0000
Inner Mongolia	1.0034	0.9934	1.0197	0.9905	Chongqing	1.0063	1.0000	1.0010	1.0053
Liaoning	1.0093	0.9904	1.0191	1.0000	Sichuan	1.0069	1.0000	1.0000	1.0069
Jilin	1.0068	1.0000	1.0025	1.0043	Guizhou	1.0064	0.9960	1.0020	1.0085
Heilongjiang	1.0072	1.0000	1.0054	1.0018	Yunnan	1.0086	1.0034	1.0094	0.9958
Shanghai	1.0097	0.9952	1.0145	1.0000	Shaanxi	1.0106	1.0000	1.0130	0.9976
Jiangsu	1.0203	1.0085	1.0117	1.0000	Gansu	1.0049	0.9978	1.0108	0.9963
Zhejiang	1.0139	0.9932	1.0209	1.0000	Qinghai	1.0055	0.9994	1.0216	0.9848
Anhui	1.0073	1.0000	1.0108	0.9965	Ningxia	1.0062	1.0008	1.0137	0.9918
Fujian	1.0136	0.9926	1.0212	1.0000	Xinjiang	1.0058	1.0000	1.0090	0.9968
Jiangxi	1.0053	1.0000	1.0000	1.0053	The eastern region	1.0138	0.9966	1.0172	1.0000
Shandong	1.0111	0.9954	1.0157	1.0000	The central region	1.0072	1.0004	1.0057	1.0011
Henan	1.0077	1.0003	1.0129	0.9945	The western region	1.0066	0.9992	1.0096	0.9979
Hubei	1.0087	1.0000	1.0002	1.0085	The whole nation	1.0094	0.9986	1.0113	0.9995

Note: The values in the table are the geometric mean values from 1997 to 2015 same or declined. Liaoning province had the largest decline. (3) The average annual growth rate of agricultural environmental technology change in the eastern, central, and western regions was 1.72%, 0.57%, and 0.96%, respectively, and the index of agricultural environmental technology change in all provinces was ≥ 1, with no regression of agricultural environmental technology. This shows that, in comparison to the agricultural environmental efficiency change, agricultural environmental technology change was the dominant factor promoting the growth of AETFP in all regions. The communist party and government consider innovation of agricultural science and technology to be of great importance. They have publicly supported and promoted the foundation, and social status of agricultural science and technology innovation is the No. 1 document of the Central Committee. China has made considerable progress in the cultivation of new crop varieties, integrated pest management, research and development of new agricultural facilities and equipment, efficient utilization of agricultural resources, and environmental remediation. However, the loss of talented individuals promoting agricultural science and technology and the inadequate level of farmer training and knowledge has produced a situation where new agricultural environmental technologies are not transferred to farmers and the implementation of current agricultural research is low. Thus, the agricultural environmental efficiency change cannot be coordinated and unified with agricultural environmental technology changes. (4) The indexes of the agricultural environmental technology gap ratio in the eastern, central, and western regions were 1, 1.0011, and 0.9979, respectively.[5] This shows that all provinces in the eastern region are at the global production frontier, play leading roles, and represent the best environmental production technologies in China. The gap between the production frontier of the central region and the production frontier of the eastern region has gradually narrowed, showing the catch-up effect on the EPT in the eastern region. However, the gap between the production frontier of the western region and the production frontier of the eastern region has gradually increased, indicating no catch-up effects on environmental production technologies in the eastern region.

The dynamic evolution of AETFP of China under technological heterogeneity

Although a previous study conducted statistical analysis on the temporal characteristics and spatial characteristics of the AETFP in China, it did not examine the dynamic evolution of AETFP. The distribution of the AETFP appears to be random and complex. Its distribution function is difficult to determine. To adequately describe and analyze the dynamic evolution characteristics of AETFP, we used the kernel density estimation method, which does not require the prescribed function. Kernel density estimation is a nonparametric estimation method and is mainly used to estimate the probability density of random variables. The distribution of random variables is described by continuous density curves. This method is widely used to estimate unknown distributions because it does not require a preset function form.

To ensure study integrity and continuity, the entire study period was divided into three intervals: 1998–2003, 2004–2009, and 2010–2015. The Gaussian kernel function was used to draw the kernel density curve of AETFP in the whole county and in the eastern, central, and western regions (Wang et al. 2017b) (Fig. 2). In Fig. 2, the horizontal axis shows the cumulative AETFP and the vertical axis represents the kernel density.

Figure 2a illustrates the dynamic evolution of AETFP in all provinces of China. (1) The kernel density curve of AETFP moved to the right, indicating that AETFP had a continuous upward trend. The average AETFP values in 1998–2003, 2004–2009, and 2010–2015 were 1.0293, 1.0935, and 1.1594, respectively. The average AETFP in the third and second stages increased by 12.65 and 6.24% compared to the first stage. (2) The main peak value of the kernel density curve of AETFP continued to decrease, width of the main peak continued to increase, and the difference of AETFP among all provinces showed an expansion trend. Specifically, comparing 2004–2009 with 1998–2003, the main peak value of the kernel density curve dropped sharply and the width of the main peak increased. This indicated that the distribution of AETFP in this stage had become more dispersed and the regional differences had increased. Comparing 2010–2015 with 2004–2009, the main peak value of the kernel density curve continued to decline and the width of the main peak slightly increased. Meanwhile, the center of the kernel density function shifted to the right. The two forces promoting the changes in regional differences of AETFP offset each other and no obvious changes in the regional differences of the provinces occurred in this stage. Compared to 1998–2003, the main peak of the kernel density curve of 2010–2015 dropped sharply, the width of the main peak increased sharply, and the right tail of the distribution increased. Although the center of the density function shifted to the right, the force from the latter driving smaller regional differences of AETFP among the provinces was weaker than the force from the former promoting larger regional differences among the provinces. The differences of AETFP among the provinces during the entire study period show an overall expansion trend. (3) During the entire study period, the kernel density curve of AETFP consisted of one main peak and two flanking peaks. Specifically, the kernel density curve of 1998–2003 consisted of one main peak and two flanking peaks. From 2004 to 2009, the left flanking peak of the kernel density curve disappeared and two obvious flanking peaks appeared on the right. This shows that, over time, significant multi-level

[5] The index of agricultural environmental technology gap ratio of the provinces in the eastern region is also 1.

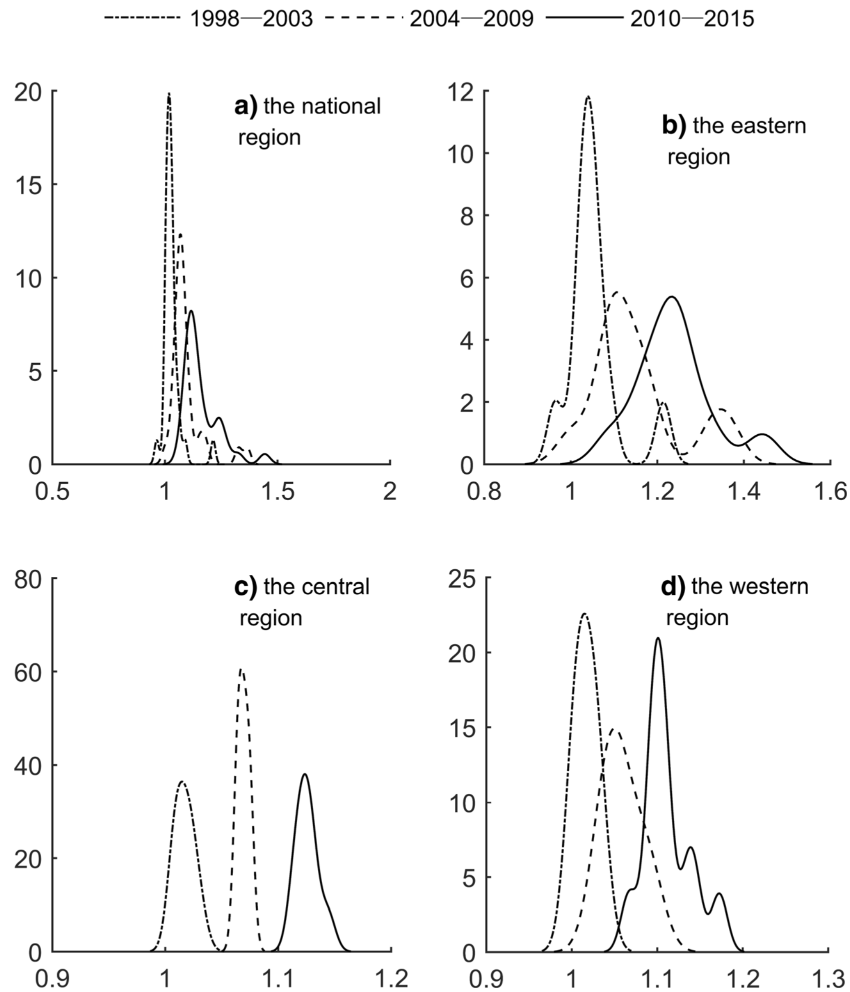


Fig. 2 Kernel density estimates of agricultural environmental TFP in China and in its eastern, central, and western regions

differentiation phenomena occurred in the distribution of AETFP in China, and two "clubs" with relatively fast development and a high index of AETFP were formed.

Figure 2b–d illustrates the dynamic evolution of AETFP in the eastern, central, and western regions. (1) The kernel density curve of AETFP in the eastern, central, and western regions continuously moved to the right, indicating that AETFP in all regions showed a continuous upward trend. (2) During the entire study period, the overall distribution of AETFP in eastern China showed a decrease in the main peak value and an increase in the width of the main peak. This indicated that the internal differences of AETFP in eastern China tended to expand. The main peak of the kernel density curve of AETFP in the central region first increased and then decreased and the width of the main peak first decreased and then increased. However, no significant change occurred in the whole. This shows that the internal differences of AETFP in the central region had little change. The main peak of the kernel density curve of AETFP in western China decreased first and then rose and the width of the main peak first increased and then decreased. In general, the main peak decreased, the width of main peak increased, and the distribution range increased. This indicates that the internal differences of AETFP in the western region had an increasing trend. (3) The kernel density curve of AETFP in the eastern region showed an evolving trend from three peaks to two peaks, indicating that AETFP in eastern China evolved from multi-level differentiation to polarization. The kernel density curve of AETFP in the central region always showed a single peak distribution, indicating that AETFP in central China did not show polarization during the study period. The kernel density curve of AETFP in the western region evolved from a single peak to a double peak, indicating that AETFP in western China was polarized in the latter part of the study period.

Analysis of factors influencing AETFP under technological heterogeneity in China

The temporal and spatial characteristics and evolution patterns of AETFP in China were previously discussed, but the formation of such characteristics and patterns was not analyzed. To this end, the dynamic panel regression model was used to test the factors driving AETFP growth. The results help illuminate the internal mechanisms that affect AETFP growth.

Table 4 Estimation of factors affecting agricultural environmental TFP in China

Variables	Mixed OLS	Fixed effect	DIF-GMM	SYS-GMM			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln MML_{i, t-1}$	0.9934***	0.8312***	0.9000***	0.9538***	0.9573***	0.9729***	0.9697***
	(0.1367)	(0.0248)	(0.0257)	(0.0180)	(0.0181)	(0.0209)	(0.0212)
$\ln agri_{i, t}$	0.0112**	0.0112**	0.0093*	0.0113***	0.0072*	0. 0131***	0.0157***
	(0.0053)	(0.0055)	(0.0051)	(0.0038)	(0.0041)	(0.0040)	(0.0050)
$(\ln agri_{i, t})^2$	−0.0038**	−0.0001	−0.0015	− 0.0033***	− 0.0031**	− 0.0046***	− 0.0060***
	(0.0017)	(0.0018)	(0.0017)	(0.0013)	(0.0013)	(0.0015)	(0.0017)
$\ln nature_{i, t}$	− 0.0043***	− 0.0054***	− 0.0057***	− 0.0053***	− 0.0052***	− 0.0052***	− 0.0047***
	(0.0012)	(0.0013)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
$\ln struc_{i, t}$	− 0.0035	− 0.0141	− 0.0207*	− 0.0126*	− 0.0079	− 0.0078	− 0.0029
	(0.0041)	(0.0113)	(0.0116)	(0.0075)	(0.0077)	(0.0080)	(0.0081)
$\ln urban_{i, t}$					0.0108***		0.0617***
					(0.0041)		(0.0166)
$\ln urid_{i, t}$						− 0.0100*	− 0.0513***
						(0.0053)	(0.0154)
$\ln urid_{i, t} \times \ln urban_{i, t}$							− 0.0520***
							(0.0158)
Const.	− 0.0046	− 0.0072	− 0.0097*	− 0.0084**	0.0079	0.0037	0.0543***
	(0.0042)	(0.0054)	(0.0052)	(0.0036)	(0.0071)	(0.0073)	(0.0155)
Wald P value	–	–	0.0000	0.0000	0.0000	0.0000	0.0000
AR (2) P value	–	–	0.7411	0.8015	0.8777	0.8185	0.8813
Sargan P value	–	–	1.0000	1.0000	1.0000	1.0000	1.0000
Observed value	510	510	480	510	510	510	510

Note: ***, **, and * indicate statistical significances at the level of 1%, 5%, and 10%, respectively; standard deviation is in the bracket

The explanatory variables of model (6) and model (7) all contain the lag phase of the explained variables, so endogenous problems remain. In addition, there may be a causal relationship between AETFP and the level of agricultural economic growth. The level of agricultural economic growth may have an impact on AETFP and the improvement of AETFP may also contribute to the growth of the agricultural economy. Therefore, the natural logarithm of agricultural economic growth and its square terms are regarded as endogenous explanatory variables. The DIF-GMM method and the SYS-GMM method were used to manage the endogenous problems in model (6) and model (7). In addition, as a comparison, the estimation results of mixed OLS and fixed-effect methods are also shown (Table 4).

The results of the AR (2) test and Sargan test of DIF-GMM method and SYS-GMM method in Table 4 show a lack of second-order correlation among the error terms of the model. The tool variables used in the model are reasonable and there was no over-identification problem. Both the DIF-GMM and SYS-GMM methods can be used to estimate the model. In the dynamic panel regression model, both the mixed OLS estimators and the fixed-effect estimators of the lag phase of the explained variables were biased up and biased down around the true value, respectively (Bond 2002). Thus, the estimated coefficient of $\ln MML_{i,\,t-1}$ was estimated to be within the range of 0.8312 to 0.9934. Table 4 shows that both coefficients of the lag phase of the explained variables estimated by DIF-GMM method and SYS-GMM method are within a reasonable range. Therefore, the estimation results of these two methods appear to be reliable. Although both the DIF-GMM and SYS-GMM methods can effectively solve the endogenous problem in the econometric model, the SYS-GMM method can overcome the small sample bias problem compared to the DIF-GMM method, and this study mainly focuses on the estimated results of the SYS-GMM method in the following discussion.

Based on the estimation results of column (4) in Table 4, we reached the following conclusions: (1) the coefficient of the natural logarithm of agricultural economic growth level is significantly positive, while the coefficient of its square term is significantly negative, indicating an inverted U-shaped relationship between agricultural economic growth and AETFP. When the level of agricultural economic growth exceeds the turning point of the inverted U-shaped curve, AETFP decreased as the level of agricultural economic growth increased. This verifies the existence of the Kuznets Curve of AETFP and reflects the catch-up effect of the underdeveloped agriculture areas on the developed areas. This conclusion is consistent with the findings of Du et al. (2016). (2) The coefficient of the natural logarithm of the disaster rate was significantly negative ($p < 0.01$) and an increase of 1% in the disaster rate could cause a decrease of 0.53% in AETFP. Agriculture belongs to the natural inferiority industry. This is because it is largely dependent on the natural environment and is unable to withstand natural disasters. Natural disasters seriously affect normal agricultural production. (3) The coefficient of the natural logarithm of planting structure was −0.0126, and the significance level was 10%. This shows that the planting structure has a slight negative effect on AETFP, but the effect was not significant.

Table 4, columns (5)–(7) show results of the SYS-GMM method based on model (7), mainly examining the impacts of urbanization level and the urban-rural income gap on AETFP. The main conclusions are: (1) after the new explanatory variables are added to model (6), the sign and significance of the variables such as $\ln MML_{i,\,t-1}$, $\ln agri_{i,\,t}$, $(\ln agri_{i,\,t})^2$, $\ln nature_{i,\,t}$, and $\ln struc_{i,\,t}$ did not significantly change, indicating the robustness of the estimation results. (2) The level of urbanization has a significant positive effect on AETFP. Increasing the proportion of urban population can increase the demand for agricultural products, raise the prices of agricultural products, promote the enthusiasm for agricultural production, and ultimately improve AETFP. (3) The widening income gap between urban and rural areas can speed up the transfer of the rural labor force. In particular, the rural labor force, with high human capital, may shift from agriculture to non-agricultural industry and from rural areas to urban areas. This results in the loss of important rural labor and inhibits AETFP growth. (4) The cross term between the natural logarithm of the urbanization level and the natural logarithm of the urban-rural income gap was significantly negative ($p < 0.01$) indicating that the urban-rural income gap can partially offset the urbanization contribution to the growth of AETFP. The greater the income gap between urban and rural areas, the weaker the contribution of urbanization to the growth of AETFP.

Conclusions and implications

Conclusions

The MML productivity index, which considers the heterogeneity of regional technology, was used to empirically measure AETFP including both agricultural non-point source pollution and agricultural carbon emissions as undesirable outputs. On this basis, the temporal and spatial characteristics, evolution patterns, and influencing factors of AETFP were studied. Our primarily findings are as follows.

(1) When the traditional ML productivity index is used to measure AETFP, it may overestimate the actual AETF*P* value. This is because the ML productivity index uses a contemporaneous benchmark technology set and is based only on the potentially best technology of the contemporaneous period. It thus ignores the technological heterogeneity of the study group. Under the global benchmark technology set, AETFP increased during the Ninth, Tenth, Eleventh, and Twelfth Five-Year Plan periods.

Agricultural environmental technology change is the major driving force behind the growth of AETFP. The average annual growth rate of AETFP in the eastern, central, and western regions decreased successively. The rate in the eastern region was higher than the national average while the rate in both central and western regions was lower than the national average. In addition, the provinces in the eastern region were at the global production frontier. The central region has a catch-up effect on environmental production technologies in the eastern region, while the western region has no catch-up effect on environmental production technologies in the eastern region.

(2) The dynamic evolution of AETFP throughout the nation and in the eastern, central, and western regions has unique characteristics. For the whole nation, with the continuous rise of AETFP, the values of AETFP among all provinces show an overall expansion trend. For a long time, the distribution of AETFP in China has shown a multi-level differentiation phenomenon. The internal differences of AETFP within the eastern and western regions have an increasing trend while the internal differences of AETFP in the central region show no obvious change. During the study period, AETFP in eastern China evolved from multi-level differentiation to polarization. However, in the latter part of the study period, AETFP in the western region also became more polarized. During the study period, the central region did not show polarization.

(3) An inverted U-shaped relationship exists between agricultural economic growth and AETFP. This verifies the existence of the Kuznets Curve of AETFP and reflects the catch-up effect of underdeveloped agricultural areas on these developed areas. The disaster rate and the planting structure have negative effects on AETFP, but the latter effect on AETFP was not significant in this study. Furthermore, the income gap between urban and rural areas can partially offset the promoting effect of urbanization on the growth of AETFP. Notably, the larger the urban-rural income gap, the weaker the contribution of urbanization to the growth of AETFP.

Policy implications

Based on the results and conclusions, several policy implications are proposed.

(1) Due to the heterogeneity of technology in different regions, a "one size fits all" policy should not be adopted to formulate regional agricultural green development. All regions should implement differentiated development paths according to their local characteristics. As the leader of agricultural environment technology, the eastern region should focus on independent research development and innovation of technologies while continuing to introduce advanced external agricultural production technologies, energy-saving and emission-reduction technologies. The central and western regions should strengthen their technological exchanges and cooperation with the eastern region to promote the flow of agricultural production information between regions. The gap between the frontiers of agricultural production in the eastern and western regions is gradually widening so the government should focus on the western regions in formulating relevant policies and increase financial support for agriculture in these areas.

(2) Agricultural environmental technological change is the major driving force behind the growth of AETFP, while agricultural environmental efficiency change has not played a significant role. Therefore, while continuing to maintain environmental technological advances in agriculture, more attention should be paid to optimizing the allocation of agricultural production resources and improving the operation and management of agricultural production. This will help improve agricultural environmental efficiency and make up the shortfall in the growth of AETFP.

(3) Based on the analysis of the influencing factors of AETFP growth, the effective measures for promoting the growth of AETFP include the following: under the premise of ensuring food security, reduce the grain production area and optimize the planting structure; strengthen the construction of agricultural disaster prevention systems and improve the capacity of agricultural disaster prevention and reduction; and reduce the urban-rural income gap, raising the level of urbanization and promoting the gradual transfer of rural surplus labor forces to urban areas.

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Compliance with ethical standards

Disclosure of potential conflicts of interest

Conflict of interest The authors declare that they have no conflict of interest.

Research involving human participants and/or animals Not applicable.

Informed consent Not applicable.

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