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Exploration of Hybrid Modeling and Computational Methods for Structural Adjustment of Agricultural Economy under Environmental Changes

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Abstract The adjustment of agricultural economic structure under environmental change has become a key path to realize sustainable agricultural development. The purpose of this paper is to construct an analytical model to provide theoretical basis and practical guidance for agricultural economic restructuring. The model reflects the dynamic process of agricultural economic restructuring under environmental change by introducing indicators such as environmental technology efficiency and green total factor productivity. The model adopts the SBM directional distance function (SBM-DDF) and combines it with the Malmquist-Luenberger (ML) productivity indicators to measure the intertemporal dynamic changes of environmental technical efficiency and green total factor productivity in Chinese agriculture. The empirical analysis shows that the effect of environmental regulation on agricultural productivity in China has a distinct geographical nature. Currently, the environmental regulation construction in Chinese agriculture is relatively weak in general, and there is a great potential to improve the technical efficiency of agriculture, and the western part of the country should be a key area of concern for the future construction of environmental regulation in agriculture.

Index Terms Agricultural economic structure, SBM-DDF, Green total factor productivity, ML

I. Introduction

With the development of society, environmental change has a far-reaching impact on our lives, and environmental change is not only the change of nature, but also includes the adjustment of the structure of agricultural economy [1], [2].

First of all, environmental change has an important impact on agricultural resource allocation. Resources are the basis for the operation of agricultural economy, and environmental changes will directly affect the availability and distribution of resources [3], [4]. For example, the reduction of water sources can lead to the restriction of agricultural production, resulting in insufficient food production, which can lead to economic turmoil [5]. Meanwhile, energy scarcity can also trigger structural adjustments in the agricultural economy, prompting the search for alternative energy sources and new ways of energy utilization [6]-[8]. These adjustments will inevitably affect the structure of the agricultural economy, changing the original industrial layout and resource allocation pattern [9]. Secondly, environmental changes have produced adjustments in consumption habits on the structure of agricultural economy [10]. In the case of environmental problems becoming more and more prominent, people have put forward higher requirements for lifestyle and consumption habits [11], [12]. Environmental protection and low carbon have become fashionable and social trends, which has prompted the adjustment of the consumption structure [13]. For example, consumers are more and more inclined to buy environmentally friendly products, green food, etc., which also promotes the corresponding industrial development and economic structure adjustment [14], [15]. The adjustment of consumption habits by environmental change not only reflects people's concern for environmental protection, but also has a far-reaching impact on social and economic structure [16]-[18]. In addition, environmental change has a significant impact on industrial structure and employment structure [19].

In this paper, we adopt the SBM directional distance function and combine it with the ML index to measure the green total factor productivity of 31 provinces in China. The model is based on the perspective of combining planting and raising, considering factors such as livestock and poultry manure, crop straw return to the field and nutrient uptake by crops, and selecting the nitrogen surplus intensity of agricultural land as a non-expected output indicator, and measuring the effect of environmental regulation intensity on China's agricultural technological efficiency from 2005 to 2024 at three levels of non-regulation, weak regulation, and strong regulation, and the ML index and its decomposition are used to The driving and inhibiting factors of agricultural efficiency in China as a whole and in the three regions are analyzed, so as to clarify the direction of future efforts in building agricultural environmental regulations in different regions.

II. The significance of the restructuring of the agricultural economy

Adjustment of agricultural economic structure is a key path to realize sustainable agricultural development, and timely adjustment of agricultural economic structure has the following significance in the context of environmental change:

(1) Ease the pressure on resources and environment. Optimizing the agricultural structure can reduce agricultural surface source pollution, improve the quality of arable land, and reduce the excessive dependence on natural resources and environmental damage.

(2) Promote the improvement of the quality of agricultural products to meet the needs of the market. Adjusting the quality, types and consumption demand for specific uses of agricultural products and increasing the supply of high-quality and diverse agricultural products can better enhance the market competitiveness of agricultural products.

(3) The degree of benefit to the agricultural industry chain will be enhanced. The close convergence of planting and raising links to promote the increase in the comparative efficiency of agriculture can extend the industrial chain, which in turn promotes the improvement of the level of farmers' income and increases the added value of agricultural products [20].

(4) It is conducive to giving full play to the comparative advantages of agricultural regions. It is conducive to the formation of agricultural industries with local characteristics, promoting the improvement of the overall efficiency of agriculture, thus optimizing the regional layout of agriculture and giving full play to the comparative advantages of various regions.

(5) Promote the integration of primary, secondary and tertiary industries. Through agricultural structural adjustment, it promotes the deep integration of agriculture with industry and service industry, forms a diversified system of agricultural industry, expands agricultural functions and taps agricultural potential, and injects new vitality into the sustainable development of agriculture.

III. Decision-making study on structural adjustment of the agricultural economy

Owing to the nature of the stage of agricultural development, the role of influencing factors changes over time. Studying and understanding the influencing factors of agricultural structural change can recognize the current situation of agricultural structure, the trend and law of change of agricultural structure, and the inherent causes of agricultural structural change, which in turn can provide a basis for promoting agricultural structural adjustment and formulating corresponding agricultural policies, and promote the evolution of agricultural structure towards rationalization and heightening. Strategies for adjusting agricultural economic structure under environmental change can be explored by analyzing the relationship between environmental regulation and agricultural technical efficiency.

III. A. Measurement techniques and methods

III. A. 1) Environmental technologies

In this paper, Chinese provinces are used as decision-making units (DMUs) to construct agricultural production frontiers. We introduce period t and compare the actual production points of DMUs with the mapping points of the frontier to measure technical efficiency and technical progress. Set k DMUs to produce M desired outputs y and J undesired outputs b in period t using N input factors x, and denote the environmental technology $P(x)$ by the production possibilities set (PPS), which can produce a combination (y,b) of desired and undesired outputs for each input vector x. The set of production possibilities is described as follows:

$$P(x)=\left\{(y,b)\middle|x \text{ able to produce } (y,b)\right\}, x\in R_+^N, y\in R_+^M, b\in R_+^J \tag{1}$$

In equation (1), the ET production function is subject to the following conditions:

(1) For all $x\in R_+^N$, there is $(0,0)\in P(x)$, denoting the case of neither input nor production.

(2) For any $x\in R_+^N$, $P(x)$ is a tight set, denoting the production of a finite number of outputs subject to a finite number of factor inputs.

(3) If $x'\geq x$, then $P(x')\supseteq P(x)$, indicating that the inputs are strongly disposable, i.e., it is impossible for outputs to decrease as a result of an increase in inputs.

(4) If $(y,b)\in P(x)$ and $0\leq\theta\leq 1$, then $(\theta y,\theta b)\in P(x)$, indicates that a decrease in non-desired output must be accompanied by a proportional decrease in desired output, i.e., there is a cost associated with lowering non-desired output.

(5) If $(y,b)\in P(x)$ and $y'\leq y$, then $(y',b)\in P(x)$, indicating that desired output is strongly disposable.

(6) If $(y,b)\in P(x)$ and $b=0$, then $y=0$, indicating that both desired and nondesired outputs must be produced. Reducing non-desired outputs is additionally costly, and the environmental technology requires all inputs and desired outputs to be strongly disposable and desired outputs to be weakly disposable jointly with non-desired outputs.

This paper introduces the environmental directional distance function. Set the direction vector $g=(g_y,g_b)$, where $g\in R_+^M\times R_+^J$, and the DDF is defined as follows:

$$D(x,y,b;g_y,g_b)=max\left\{\beta\,|\,(y+\beta g_y,b-\beta g_b)\in P(x)\right\} \tag{2}$$

III. A. 2) Environmental technical efficiency and environmental total factor productivity

Theoretically, in calculating the productivity index, the productivity change is measured by first constructing the production frontier based on the benchmark of the current period, then constructing the directional distance function and calculating the productivity of the decision-making units in each period accordingly, and finally solving the geometric mean of the productivity indices of the two neighboring periods. In this paper, we propose a global index that uses all the periods examined for each decision unit as a benchmark to construct the production frontier, which satisfies the circularity without generating an unsolvable situation and allows for a technological backward step in the calculation of the index. The reference set of the set of production possibilities for period t is constructed from the current benchmark, which is defined as follows:

$$P_C^t(x^t)=\left\{\left(y^t,b^t\right)\middle|x^t \text{ able to produce } \left(y^t,b^t\right)\right\} \tag{3}$$

Unlike the current benchmark, the global benchmark is defined as $P_G=P_C^1\cup P_C^2\cup\cdots\cup P_C^S$, with the subscripts C and G representing the current benchmark and global benchmark, respectively, and all the current benchmarks are fully enveloped to form a single global production possibilities set of references to which all the other periods can be Comparison. The ML index of decision unit i is calculated based on the current reference set:

$$ML^S\left(x^t,y^t,b^t,x^{t+1},y^{t+1},b^{t+1}\right)=\frac{1+D_C^S(x^t,y^t,b^t)}{1+D_C^S(x^{t+1},y^{t+1},b^{t+1})} \tag{4}$$

In Eq. (4), the superscripts $S=t$, $t+1$, denote two adjacent periods, the subscript C denotes the current benchmark, and $D\left(x,y,b\right)$ is the simplified directional distance function $D\left(x,y,b;g_y,g_b\right)$. If the productive activity produces more desired output and less undesired output, then $ML^S>1$, indicating an increase in productivity. If it produces less desired output and more undesired output, then $ML^S<1$, indicating lower productivity. In the empirical analysis, the ML-index is defined as the geometric mean of the productivity indices ML^t and ML^{t+1} for two consecutive periods, and the ML-index can be further decomposed into the change in efficiency $\left(EC\right)$ and the technological progress $\left(TC\right)$:

$$\begin{aligned}
&ML^{t,t+1}\left(x^t,y^t,b^t,x^{t+1},y^{t+1},b^{t+1}\right)\\
&=\left[\frac{1+D_C^t(x^t,y^t,b^t)}{1+D_C^t(x^{t+1},y^{t+1},b^{t+1})}\times\frac{1+D_C^{t+1}(x^t,y^t,b^t)}{1+D_C^{t+1}(x^{t+1},y^{t+1},b^{t+1})}\right]^{1/2}\\
&=\frac{1+D_C^t(x^t,y^t,b^t)}{1+D_C^{t+1}(x^{t+1},y^{t+1},b^{t+1})}\\
&\times\left[\frac{1+D_C^{t+1}(x^t,y^t,b^t)}{1+D_C^t(x^t,y^t,b^t)}\times\frac{1+D_C^{t+1}(x^{t+1},y^{t+1},b^{t+1})}{1+D_C^t(x^{t+1},y^{t+1},b^{t+1})}\right]^{1/2}\\
&=\frac{TE^{t+1}}{TE^t}\times\left[TG_t^{t+1}\times TG_{t+1}^{t+1}\right]^{1/2}=EC^{t,t+1}\times TC^{t,t+1}
\end{aligned} \tag{5}$$

The GML index is defined below:

$$GML^{t,t+1}\left(x^t,y^t,b^t,x^{t+1},y^{t+1},b^{t+1}\right)=\frac{1+D_G^t(x^t,y^t,b^t)}{1+D_G^t(x^{t+1},y^{t+1},b^{t+1})} \tag{6}$$

In equation (6), $D_G^T(x,y,b)=\max\{\beta \mid (y+\beta y, b-\beta b)\in P_G(x)\}$, given according to the reference set of the global set of production possibilities P_G. If more desired outputs and fewer undesired outputs are produced, then $GML^{t,t+1}>1$, indicating an increase in productivity. If fewer desired outputs and more undesired outputs are produced, then $GML^{t,t+1}<1$, indicating a decrease in productivity.The GML index is further decomposed as follows:

$$\begin{aligned} &GML^{t,t+1}\left(x^t,y^t,b^t,x^{t+1},y^{t+1},b^{t+1}\right)=\frac{1+D_G^t(x^t,y^t,b^t)}{1+D_G^t(x^{t+1},y^{t+1},b^{t+1})} \\ &=\frac{1+D_C^t(x^t,y^t,b^t)}{1+D_C^{t+1}(x^{t+1},y^{t+1},b^{t+1})} \\ &\times\left[\frac{(1+D_G^t(x^t,y^t,b^t))/(1+D_C^t(x^t,y^t,b^t))}{(1+D_G^t(x^{t+1},y^{t+1},b^{t+1}))/(1+D_C^{t+1}(x^{t+1},y^{t+1},b^{t+1}))}\right] \\ &=\frac{TE^{t+1}}{TE^t}\times\left[\frac{BPG_t^{t+1}}{BPG_{t+1}^{t+1}}\right]=EC^{t,t+1}\times BPC^{t,t+1} \end{aligned} \tag{7}$$

In equation (7), TE and EC denote technical efficiency and efficiency change, respectively. BPG_t^{t+1} is the "Best Practitioner Gap (BPG)" between the current period and the global technological frontier, $BPC^{t,t+1}$ measures the change of the "Best Practitioner Gap" (i.e., the technological change) in two periods, $BPC^{t,t+1}>1$ indicates technological progress and $BPC^{t,t+1}<1$ indicates technological regression.

III. B. Hybrid modeling

This paper draws on the SBM directional distance function method (SBM-DDF) [21] and combines it with the Malmquist-Luenberger (ML) index [22] to measure green total factor productivity. Assume that x represents N input factors used by each decision unit, $x=(x_1,x_2,\cdots,x_N)\in R_N^+$. y denotes M kinds of desired output, $y=(y_1,y_2,\cdots,y_M)\in R_M^+$. b denotes I kinds of undesired outputs, $b=(y_1,y_2,\cdots,y_I)\in R_I^+$, (x^{tk},y^{tk},b^{tk}) denotes the vector of inputs, the vector of desired outputs and the vector of undesired outputs of the decision making unit, (g^x,g^y,g^b) denotes the vector of inputs respectively compression, desired output expansion, and undesired output compression direction vectors, and (s^x,s^y,s^b) denote input-output, desired-output, and undesired-output slack variables, respectively. The SBM directional distance function used in this paper is:

$$\begin{aligned} &S_V^t\left(x^{t,k'},y^{t,k'},b^{t,k'},g^x,g^y,g^b\right) \\ &=\max\frac{\frac{1}{N}\sum_{n=1}^{N}\frac{s_n^x}{g_n^x}+\frac{1}{M+I}\left[\sum_{m=1}^{M}\frac{s_m^y}{g_m^y}+\sum_{i=1}^{I}\frac{s_i^b}{g_i^b}\right]}{2} \\ &s.t.\sum_{k=1}^{K}\lambda_k^t x_{kn}^t+s_n^x=x_{k'n}^t,\forall n;\sum_{k=1}^{K}\lambda_k^t y_{km}^t-s_m^x=y_{k'm}^t,\forall m \\ &\sum_{k=1}^{K}\lambda_k^t b_{ki}^t+s_i^b=b_{k'i}^t,\forall i;\sum_{k=1}^{K}\lambda_k^t=1,\lambda_k^t\ge 0,\forall k \\ &s_n^x\ge 0,\forall n;s_m^y\ge 0,\forall m;s_i^b\ge 0,\forall i \end{aligned} \tag{8}$$

The ML from the $t+1$ period to the t period is:

$$ML_t^{t+1}=\frac{1+D^G(x^t,y^t,b^t,g^x,g^y,g^b)}{1+D^G(x^{t+1},y^{t+1},b^{t+1},g^x,g^y,g^b)} \tag{9}$$

Where if the ML index is greater than 1, it indicates a rise in green total factor productivity. The opposite is true for a decline.

The ML index can be used to measure total factor productivity and can be further decomposed into the product of the efficiency change index $(effch)$ and the technological progress index $(tech)$, which, given variable returns to scale, can be decomposed into the product of the purely technical efficiency index $(pech)$ and the scale efficiency index $(sech)$:

$$ML=tech\times effch=tech\times pech\times sech \tag{10}$$

$$tech = (\frac{1+D_0^t(x^{t+1},y^{t+1},b^{t+1})}{1+D_0^{t+1}(x^{t+1},y^{t+1},b^{t+1})} \times \frac{1+D_0^t(x^t,y^t,b^t)}{1+D_0^{t+1}(x^t,y^t,b^t)})^{\frac{1}{2}} \tag{11}$$

$$pech = \frac{1+D_0^{t+1}(x^{t+1},y^{t+1},b^{t+1} \sim VRS)}{1+D_0^t(x^{t+1},y^{t+1},b^{t+1} \sim VRS)} \tag{12}$$

$$sech = \frac{1+D_0^{t+1}(x^{t+1},y^{t+1},b^{t+1} \sim CRS)}{1+D_0^{t+1}(x^{t+1},y^{t+1},b^{t+1} \sim VRS)} \times \frac{1+D_0^t(x^t,y^t,b^t \sim VRS)}{1+D_0^t(x^t,y^t,b^t \sim CRS)} \tag{13}$$

where VRS represents variable returns to scale and CRS represents constant returns to scale. $tech$ characterizes the advancement of the technological production frontier, and $tech > 1(<1)$ represents technological progress (regression). $effch$ characterizes the relative change in technological efficiency, $effch > 1(<1)$ represents relative efficiency increase (decrease). $pech$ characterizes the change in managerial efficiency, $pech > 1(<1)$ represents an increase (decrease) in managerial level. $sech$ characterizes the gap between the current production scale and the optimal production scale, $sech > 1(<1)$ represents close to (deviation from) the optimal production scale. Through the ML index decomposition, the drivers and inhibitors of agricultural production efficiency can be judged, in order to clarify the focus points for different regions to strengthen environmental regulation and improve agricultural production efficiency in the future.

IV. Empirical analysis

IV. A. Data sources and selection of indicators

In accordance with the requirements of the methodology and model described above, this paper uses data from the China Statistical Yearbook, the China Rural Statistical Yearbook, the China Agricultural Products Cost and Benefit Information Compendium and some local statistical bureaus for the period 2005-2024. Some indicators are indirectly accounted for by statistical data.

(1) Agricultural production input indicators.

a) Labor input, using the number of employees in the primary industry as the benchmark, discounting the output value of planting and animal husbandry according to the proportion of the output value of planting and animal husbandry to that of the primary industry, and estimating the number of employees in the agricultural and animal husbandry industry.

b) Agricultural land input, using the area of agricultural land, taking into account the direction of input of chemical fertilizer and livestock manure, the agricultural land in this paper only includes arable land, garden land and grassland. Considering the crop replanting index, the arable land is replaced by the sown area of crops, and the pasture area and the provinces in the agricultural and pastoral areas are added to the area of available grassland.

c) Livestock and poultry farming inputs, in view of the complexity of the composition of input costs in livestock and poultry farming, using the product of unit livestock and poultry product costs and total output of livestock and poultry products, unit livestock and poultry product costs from previous years, “China's agricultural products cost and benefit data compilation” relevant data projections.

d) Agricultural machinery inputs, using the total power of agricultural machinery.

e) Agricultural inputs, using agricultural fertilizer application of pure volume.

(2) Agricultural output indicators.

a) Desired output, i.e., “good” output, using the gross value of agricultural and animal husbandry products.

b) Non-desired output, i.e. “bad” output. In this paper, taking into account factors such as fertilizer inputs, livestock and poultry manure and crop residues, sewage discharges from rural areas, nitrogen fixation by leguminous crops, and nutrient uptake by crops and grasslands, we take the nitrogen surplus intensity of agricultural land as a “bad” output indicator, which can more scientifically reflect and compare the level of regional green development of agriculture. The formula for calculating the nitrogen surplus intensity of agricultural land is as follows:

$$f_{SO} = F_{SO} / S_{CA}, F_{SO} = Y_{FE} + Y_{LM} + Y_{ST} + Y_{RM} + Y_{LN} - Y_{CA} - Y_{GA} \tag{14}$$

$$Y_{LM} = \sum_{i=1}^{m} Q_i \times r_i \times \rho_i \times v, Y_{ST} = \sum_{j=1}^{n} C_j \times \varepsilon_j \times \eta_j \times \kappa, \tag{15}$$

$$Y_{RM} = P \times \varphi \times \omega \tag{16}$$

$$Y_{LN} = B \times b, Y_{CA} = \sum_{j=1}^{n} C_j \times \theta_j, Y_{GA} = S_{GA} \times \delta \tag{17}$$

where, f_{SO}: soil nitrogen surplus intensity in agricultural land, unit: kg / hm^2. F_{SO}: soil nitrogen nutrient surplus of agricultural land. S_{CA}: area of agricultural land. Y_{FE}: Nitrogen nutrient discount in fertilizer. Y_{LM}: Nitrogen nutrient content of livestock and poultry manure returned to the land. Y_{ST}: Nitrogen nutrient content of crop residues returned to the field. Y_{RM}: Nitrogen nutrient content of rural manure returned to the field. Y_{LN}: Nitrogen fixation nutrient content of legume crops. Y_{CA}: Nitrogen nutrient content of crop uptake. Y_{GA}: Nitrogen nutrient content absorbed by pasture. Q_i: stocking or slaughtering of the i th species of livestock**. r_i: fecal excretion coefficient of i type of livestock and poultry. ρ_i: fecal nitrogen content of the i th species of livestock and poultry. v: proportion of livestock and poultry manure returned to the field, take $v = 0.425$. C_j: crop yield of j category. ε_j: crop grass to grain ratio. η_j: crop straw nitrogen nutrient content. κ: crop straw return ratio, take $\kappa = 0.625$. P: the number of rural population. φ: per capita manure emission, take $\varphi = 0.4$ kg/day. ω: Proportion of manure returned to the field from rural habitats, take $\omega = 0.88$. B: legume crop yield. b: coefficient of nitrogen fixation of legume crops, take $b = 0.667$. θ_j: nitrogen content of j crop. S_{GA}: pasture grassland area. δ: the amount of nitrogen required for the growth of pasture grass per unit area, taking $\delta = 40$ kilograms/hectare.

The excretion coefficient and nitrogen content of livestock and poultry feces per unit feeding cycle are shown in Table 1.

Table 1: The coefficient of excretion and nitrogen content of livestock and poultry

Serial number	Type of animal and poultry	Excrement amount (ton/day)	Total nitrogen content (%)
1	Pig	1.0536	0.232
2	Draft cow	10.3	0.355
3	Beef cattle	7.9	0.355
4	Cow	19.8	0.355
5	Horse	5.6	0.371
6	Donkey/Mule	4.8	0.371
7	Sheep	0.86	1.016
8	Poultry	0.039	1.255

The values of grass to grain ratio taken for major crops and nitrogen nutrient contents are shown in Table 2.

Table 2: The main crop grass valley ratio and nitrogen nutrient content

Crops	Grass valley ratio	Straw nitrogen nutrient content (%)
Rice	1	0.83
Wheat	1.2	0.63
Corn	2.1	0.87
Beans	1.7	1.63
Cotton	3	1.24
Hemp	1.7	1.32
Sugarcane	0.2	0.29
Beet	0.1	0.4
Groundnut	1.4	1.66
Cole	2	0.83
Sesame	3.1	1.29
Tobacco	1.1	2.4
Rice	0.5	2.39
Wheat	1	0.83
Corn	1.2	0.63

Nitrogen nutrient contents of major crops are shown in Table 3.

Table 3: Nitrogen nutrient content of main crops

Crops	Nitrogen content (%)	Crops	Nitrogen content (%)
Grain	2.67	Rapeseed	5.88
Fruit	0.53	Sesame seed	8.24
Vegetable	0.44	Sugarcane	0.34
Beans	5.13	Beet	0.41
Potato	0.47	Tobacco leaf	4.13
Cotton	5.03	Tea	6.45
Groundnut	6.74	Rapeseed	

IV. B. Measurement results and analysis

IV. B. 1) Environmental regulation and technical efficiency in agriculture

The impact of environmental regulation on agricultural productivity in Chinese provinces from 2005 to 2024 is shown in Table 4. Reflecting the fact that agricultural productivity (D^s) under weak environmental regulation will increase considerably compared to the case without environmental regulation $(D*)$, the average level for the whole of China increases from 0.732 to 0.794, roughly an increase of 8.5%. The eastern, central, and western regions increased by 9.4%, 12.1%, and 8.9%, respectively, with the highest level in the east and the largest increase in the center, indicating that the necessity and importance for production entities to consider the elements of pollution and carbon emissions in their production decisions, and the neglect of environmental factors will surely lead to generalized inefficiency.

Compared with the case of weak environmental regulation, the technical efficiency of agriculture under strong environmental regulation (D^w) would increase from 0.794 to 0.899, an increase of about 13.2 percentage points, which shows that the current environmental regulation is relatively weak and unable to adapt to the requirements of productivity development. In terms of regions, the increases are, in descending order, in the west (9.8%), the center (8.3%), and the east (2.6%).

In terms of the environmental efficiency index EEI, the average value for the whole of China is 0.923, and except for Shanghai and Shanxi, where the EEL value is greater than 1, production efficiency under strong environmental regulation increases to varying degrees in all regions, with the most sensitive to increased levels of environmental regulation in Xinjiang (0.761), Yunnan (0.768), and Shaanxi (0.784), all of which are in the central and western provinces and regions. The least sensitive are Fujian (0.985), Guangdong (0.984) and Liaoning (0.986), which are mainly eastern provinces and regions.

Through the above analysis, it can be found that the effect of environmental regulation on the efficiency of Chinese agricultural production has a distinct geographical nature. The eastern region has superior climate, soil and other natural conditions, complete infrastructure, sufficient funds, and supported by high scientific and technological strength, which is conducive to the improvement of agricultural farming efficiency, and agricultural production is gradually showing the characteristics of mechanization, scale, industrialization and refinement. Agricultural production efficiency is generally high, with less potential for further growth through environmental regulation. The central region is at an intermediate level in terms of both agricultural output efficiency and room for growth. Although the western region has a vast land area, it has harsh climatic conditions, weak economic foundation, poor disaster resistance, low level of science and technology, transportation, market and other aspects of the limitations of agricultural output efficiency compared with the east and central regions is obviously low, but it also means that there is a lot of room for its efficiency to improve, if moderately improve the environmental regulation, from all aspects of the improvement of the conditions of agricultural production, will surely be able to stimulate its production potential, so as to improve the overall level of China's agricultural production efficiency. The overall level of production efficiency in China's agriculture. Therefore, the western part of the country is the focus of future agricultural environmental regulation.

IV. B. 2) ML index and its decomposition

In order to further analyze the influencing factors of agricultural total factor productivity, the ML index and the values of each decomposition term were obtained using equations (10) to (13) as shown in Table 5.

From the overall level of China as a whole, the average total factor productivity of agriculture in China as a whole is 1.017 from 2005 to 2024, indicating that the overall agricultural productivity has improved by about 1.7 percentage points in ten years, and there is still a lot of room for progress. The only decomposition term greater than 1 is $tech$, with an average value of 1.061, indicating that the overall “frontier shifting effect” is significant, and that agricultural technology is advancing at a faster rate, which is worth recognizing. The average value of $effch$ is 0.979, less than

1, which shows that the “catching-up effect” of agricultural technology efficiency in various provinces and regions is not obvious in the past ten years, indicating that China's agricultural production efficiency has a distinctive regional nature. The average value of $pech$ is 0.995, and the level of agricultural management needs to be further improved. The average value of $sech$ is 0.998, which is very close to 1, indicating that the scale efficiency of China's agriculture has remained almost unchanged in the past ten years.

Table 4: The effect of environmental regulation on agricultural production efficiency

Region	$D*$	D^s	D^w	EEI
Beijing	0.849	0.857	0.944	0.896
Fujian	0.824	0.828	0.839	0.985
Guangdong	0.817	0.87	0.873	0.984
Hainan	0.853	0.925	0.958	0.974
Hebei	0.695	0.778	0.849	0.91
Jiangsu	0.758	0.827	0.924	0.958
Liaoning	0.796	0.923	0.96	0.986
Shandong	0.689	0.79	0.86	0.932
Shanghai	0.914	0.965	0.944	1.019
Tianjin	0.778	0.873	0.92	0.938
Zhejiang	0.768	0.874	0.94	0.908
Anhui	0.682	0.773	0.836	0.921
Henan	0.644	0.746	0.829	0.927
Heilongjiang	0.796	0.851	0.948	0.902
Hupei	0.674	0.853	0.892	0.966
Hunan	0.801	0.84	0.882	0.934
Jiangxi	0.783	0.752	0.861	0.874
Jilin	0.787	0.829	0.951	0.894
Shanxi	0.685	0.882	0.88	1.009
Chongqing	0.719	0.715	0.873	0.824
Kansu	0.629	0.717	0.884	0.816
Guangxi	0.714	0.697	0.841	0.855
Guizhou	0.717	0.784	0.835	0.943
Inner Mongolia	0.706	0.799	0.881	0.919
Ningxia	0.676	0.711	0.851	0.853
Qinghai	0.756	0.82	0.854	0.957
Shaanxi	0.5	0.671	0.784	0.854
Sichuan	0.823	0.729	0.861	0.846
Xinjiang	0.613	0.588	0.761	0.783
Tibet	0.869	0.812	0.936	0.866
Yunnan	0.536	0.673	0.768	0.863
East	0.802	0.877	0.9	0.94
Middle	0.729	0.817	0.885	0.932
West	0.693	0.755	0.829	0.859
Whole country	0.732	0.794	0.899	0.923

In terms of sub-variables, ML mean value is the highest in the east at 1.068, followed by 1.045 in the center, both of which have seen some growth in agricultural total factor productivity over the decade, while the west is only 0.951, an overall decline of about 4.9 percentage points, and there is a pressing need to improve the efficiency of agricultural production.

From the perspective of driving and inhibiting factors, agricultural production efficiency in the whole of China is significantly driven by $tech$, i.e., technological progress, while the other factors are lagging behind in the construction of the relevant environmental regulations, and thus their effects are not significant. The drivers of agricultural production efficiency in the eastern region are $effch$ and $pech$, i.e., the improvement of relative efficiency and management efficiency, and the inhibiting factor is $tech$, while the role of $sech$ is insignificant, i.e., the scale efficiency remains almost unchanged. The driving factors in the center are $tech$ and $sech$, with faster technological progress and significantly stronger scale effects, a stronger inhibiting effect of $pech$, and the need to strengthen the construction of environmental regulations in terms of improving managerial efficiency, in addition to the fact that $effch$ also creates a certain impediment to the improvement of efficiency. The driving factor in the west is $tech$, and the inhibiting effect of the rest of the factors are more obvious, seriously hindering the improvement of agricultural production efficiency, and the environmental regulation construction is facing a comprehensive challenge.

Table 5: The value of the ML index and the decomposition items

Region	ML	$tech$	$effch$	$pech$	$sech$
Beijing	0.932	0.955	0.978	1.035	0.965
Fujian	0.978	0.923	1.061	1.08	0.98
Guangdong	1.359	0.866	1.595	1.695	0.933
Hainan	1.315	0.95	1.39	1.444	0.957
Hebei	0.812	0.891	0.924	0.937	1.003
Jiangsu	1.121	0.934	1.211	1.33	0.919
Liaoning	0.967	0.969	0.995	0.974	1.029
Shandong	0.862	0.906	0.958	1.104	0.88
Shanghai	1.342	0.894	1.476	1.526	0.999
Tianjin	0.933	0.913	1.027	1.119	0.914
Zhejiang	1.029	0.971	1.06	1.113	0.948
Anhui	1.273	1.314	0.967	1.004	0.988
Henan	0.823	1.323	0.621	0.629	0.978
Heilongjiang	1.145	1.082	1.08	0.809	1.34
Hupei	1.057	0.96	1.095	1	1.095
Hunan	0.926	0.987	0.939	0.972	0.975
Jiangxi	1.089	0.988	1.088	1.012	1.075
Jilin	1.064	1.224	0.889	0.624	1.439
Shanxi	0.924	0.937	0.962	1.1	0.87
Chongqing	0.88	1.106	0.804	0.934	0.858
Kansu	0.847	1.051	0.836	0.882	0.903
Guangxi	0.955	1.352	0.718	0.763	0.931
Guizhou	0.878	1.214	0.714	0.824	0.88
Inner Mongolia	0.876	0.98	0.886	0.923	0.982
Ningxia	0.982	1.255	0.764	0.647	1.221
Qinghai	1.126	1.389	0.834	0.828	0.991
Shaanxi	0.896	0.959	0.925	0.954	0.964
Sichuan	0.915	0.96	0.948	0.991	0.955
Xinjiang	0.947	1.201	0.799	0.867	0.912
Tibet	1.2	1.432	0.834	0.896	0.929
Yunnan	0.949	1.028	0.928	1.057	0.863
East	1.068	0.924	1.138	1.208	0.971
Middle	1.045	1.1	0.963	0.897	1.105
West	0.951	1.177	0.84	0.89	0.955
Whole country	1.017	1.061	0.979	0.995	0.998

In conclusion, the structural adjustment of China's agricultural economy should focus on the central and western regions, especially the western region. Different regions should strengthen their environmental regulations on the basis of identifying their own driving and inhibiting factors, and fully explore the potential of each factor to improve the efficiency of agricultural technology. While continuing to maintain its advantages in agricultural development and playing an advanced demonstration role, the eastern part of the country should focus on strengthening the introduction and popularization of international advanced agricultural technologies, encouraging self-innovation, and improving the agricultural technology service system to make up for technological deficiencies. The central part of the country should focus mainly on the construction of environmental regulations to improve the level and efficiency of production management. The western part of the country should actively learn from the advanced experience of the eastern part of the country in agricultural development, strengthen production management, improve the efficiency of resource utilization, optimize the scale of production, and comprehensively strengthen agricultural environmental regulations from multiple perspectives.

V. Conclusion

This paper uses the SBM-DDF model and ML index to analyze the growth of agricultural environmental technical efficiency and green total factor productivity in 31 Chinese provinces from 2005 to 2024, and draws the following conclusions:

(1) The current environmental regulation construction in China's agriculture is generally weak, and there is a large potential for agricultural technical efficiency improvement. Compared to the case of weak environmental regulation, agricultural technical efficiency under strong environmental regulation would increase the average level by 8.5% across China, with growth of 9.4%, 12.1%, and 8.9% in the eastern, central, and western regions, respectively.

(2) The effect of environmental regulation on the efficiency of agricultural production in China is distinctly geographical. No environmental regulation, weak environmental regulation and strong environmental regulation of the three cases of technical efficiency are east, center and west of the order of decreasing, while the east, center and west of the efficiency loss due to insufficient regulation in order of increasing, that is, the three regions for the improvement of the intensity of environmental regulation of the sensitivity of the order of increasing. The western part should be the key region to pay attention to the construction of agricultural environmental regulation in the future.

(3) The decomposition of ML index shows that the national agricultural production efficiency is obviously driven by technological progress, and the effect of other factors is not significant.

Based on the above analysis, this paper proposes that the current structural adjustment of the agricultural economy should focus on the western region, and should actively learn from the advanced experience of agricultural development in the east, strengthen production management, improve resource utilization efficiency, and optimize the scale of production. The eastern region can continue to play an advanced demonstration role. The central region should focus on the construction of environmental regulations to improve the level and efficiency of production management.

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