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Spatial-temporal characteristics and influencing factors of agricultural eco-efficiency in China in recent 40 years

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ABSTRACT

Chinese agricultural output has been multiple under the intensive input of production factors since the reform and opening-up. Such a growth pattern that realizes high output through high input results in increasingly prominent environmental pollution problems. Considering the provincial panel data in China during 1978–2017 as the research units and taking agriculture in broad sense as the study object, the agricultural eco-efficiency (AEE) was measured by the Super-SBM Model, and the influencing factors were screened out from agricultural basic condition, agricultural industrial structure, agricultural development potential and agricultural input strength. The findings indicated that agricultural expected output and unexpected output were synchronously increased, while the change of input factors was totally different and gradually transferred to materiality from resources. In 1978–2017, AEE was increased to 0.713 from 0.405, with an increase of about 76%. And it approximately underwent four stages, including free development, reform promotion, market regulation and policy incentives. Under the resource restraint and policy incentives, AEE showed that Northeast, East and South China were higher than the national average level. North and Central China basically fitted for the national average level, and Southwest and Northwest China were lower than the national average level. Also, it was successively present in some spatial characteristics including polarization, differentiation, agglomeration and reconstruction on the provincial scale. The magnitude and direction of influencing factors indicated that the introduction of subsidy policies for compound fertilizers, an increase of farmers' incomes, optimization of agricultural plantation structure, and maintenance of stable agricultural product prices could effectively improve AEE.

1. Introduction

China is the most populous country and also a big agricultural country (Liu et al., 2018a,2018b,2018c), whose agricultural development has achieved remarkable achievements (Deng and Gibson, 2019). The nation's total grain output, meat output and aquatic product output showed a 2-fold, 10-fold and 14-fold increase from 1978–2017, and the current outputs equaled about 1/5, 1/4 and 1/3 of world corresponding supplies. It is evident that China is well accomplished in its development of agriculture, which acted as a powerful support for the healthy and continuous development of the nation's economy as well as its society (Liu et al., 2019). However, the application of chemical fertilizers, agricultural plastic films and pesticides has increased by 6.6 times, 5.3 times and 2.3 times, respectively (Rural Social Economic Investigation Division, National Bureau of Statistics of China, 2018). The utilization rate of fertilizers and pesticides was less than 1/3 and the recovery rate of plastic film was less than 2/3, the effective treatment rate of livestock and poultry manure was less than 50%, and straw incineration and marine eutrophication are serious (Ministry of Agriculture et al., 2015). Thus, it could be seen that the agricultural growth mainly depends on the intensive input of production factors, and it is this kind of agricultural production pattern with high-yield, low-efficiency and high-input (Liu et al., 2019; Rao et al., 2012; Zou et al., 2020) that has caused the agricultural pollution to become more and more serious, even exceeding the industrial pollution as the main source of water pollution (Li et al., 2011; Liu et al., 2013). Therefore, it is of great importance for policymakers to investigate the agricultural performance and its influencing factors as making agricultural sustainable policies.

Eco-efficiency was originally introduced in the literature as a quantitative management tool for studying economic and environmental aspects by Schaltegger and Sturm (1990), and its concept, as a

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distance between a certain quantity of input and output of sustainability environmental performance, was proposed by the World Business Council for Sustainable Development (Verfaillie and Bidwell, 1991). Until 1998, the Organization for Economic Co-operation and Development (OECD) promoted eco-efficiency initiatives in the agricultural sector with the purpose of tackling the increasing concern on the relationship between environmental impacts and agricultural production (OECD, 1998). Since then, a growing number of international literatures about eco-efficiency assessment in agriculture sector have already been developed and made great achievements (Liu et al., 2019; Maia et al., 2016), many case studies at different scales are promoted in North America (Konefal et al., 2019; Reith and Guidry, 2003), Latin America (Rosano Peña et al., 2018), Europe (Gómez-Limón et al., 2012; Maia et al., 2016; Rybaczewska-Błażejowska and Gierulski, 2018), Asia (Bidisha et al., 2018; Halder, 2019; Huang and Jiang, 2019) and Africa (Nsiah and Fayissa, 2019), demonstrating the possible gains in the evaluation of the environmental impacts and economic aspects.

To quantify the eco-efficiency performance of agriculture, many methods were built and used, such as Ratio Method, Life Cycle Assessment (LCA), Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). These methods have their own advantages and disadvantages. Among them, SFA and DEA are the two most important methods achieving highly correlated results in most cases (Alene and Zeller, 2005; Todorovic et al., 2016; Wang and Zhang, 2018). SFA is a parametric method, although it can distinguish statistical error and management error and can avoid the influence of uncontrollable factors on inefficiency, by which make the results closer to reality (Aigner et al., 1977; Meeusen and Broeck, 1977), it is generally only suitable for single-output and multi-input production (Jin et al., 2019). DEA is a widely accepted non-parametric method to evaluate the eco-efficiency involved in multi-output and multi-input (Vlontzos et al., 2014). It can estimate the frontier production function in the form of material objects and overcome the influence of non-technical factors such as an unreasonable price system on the frontier production function (Angulo-Meza et al., 2019; Picazo-Tadeo et al., 2011; Toma et al., 2015).

There are numerous existing studies focusing on eco-efficiency in the agricultural sector of China in the recent period. Most of them mainly put emphasis on the changing trends of agricultural eco-efficiency (AEE) over a period of time. Notable among them are Deng and Gibson (2019), who estimated land productivity in Shandong Province during 1990–2010 using the Estimation System of Land Production (ESLP), and then analyzed the eco-efficiency for the sustainable agricultural production based on SFA. Wang and Zhang (2018) estimated the provincial AEE in 1996–2015 by DEA, and pointed out that the overall trend in China was on the rise and existed inter-provincial differences. Hou and Yao (2018) measured the inter-provincial AEE from 1978 to 2016 by the Super-SBM model, and predicted its long-term evolution trend by using the traditional and spatial Markov probability transfer matrices. Besides that, several of the studies also have sought to explain the observed variation of AEE in terms of a number of farm characteristics like local off-farm employment and migration (Yang et al., 2016), fertilizer overuse (Huang and Jiang, 2019), agricultural subsidy policies (Li et al., 2019a,2019b; Wagan et al., 2018), and agricultural mechanization (Zhou and Kong, 2019).

Along with the existing studies, there are three important points should be noted. First, the objects mainly focused on agriculture in narrow sense, which means crop-plantation (Hou and Yao, 2018; Picazo-Tadeo et al., 2011). Generally, agriculture has broad sense and narrow sense. In the broad sense, it contains the crop-plantation, forestry, animal husbandry and fishery, while in the narrow sense, it only refers to the crop-plantation. In terms of Chinese agricultural output value, the current output value of crop-plantation accounts for about 50% of gross output value of agriculture, indicating that the traditional agricultural production pattern that gives priority to crop planting has been gradually replaced by the diversified agricultural production mode (Huang, 2016; Shen et al., 2014). Furthermore, the pollutant discharge proportion of the non-planting industry in agricultural pollutants is close to 75%, implying that if the eco-efficiency of the crop-plantation is used to represent China's AEE, the estimated results will have a great deviation with the physical truth (Wang and Zhang, 2018). Second, previous studies mainly analyzed the temporal changes of AEE, while were lacking in characterizing the spatial distribution and dynamic variation, and the explanation of spatial-temporal patterns was poor in institutional and policy environment (Chen and Zhang, 2019; Ray and Ghose, 2014). It has been widely proven that the AEE is closely associated with the agricultural development level and relevant macro-environment (Aznar-Sánchez et al., 2019; Liu et al., 2018a,2018b,2018c). Consequently, the agricultural performance should be judged not merely by the development level of inputs, but also by the system revolution and policy succession (Halder, 2019). Third, previous studies have paid less attention to the influencing factors, lacking the integration of human and natural factors, and the quantitative decomposition of each index was even less common (Aznar-Sánchez et al., 2019; Wang and Zhang, 2018). As we are facing resources restraints and increasing food demand, modern agricultural development should rely on precise implementation of agricultural reform policies, and thus a quantitative examination on the influencing factor of AEE is the foundation for the policy makers to design policies tailored to local conditions (Deng et al., 2016).

Since the 21 st century, the issue relating to agriculture, rural areas and farmers has become the top priority of Chinese agricultural modernization. The No. 1 central document focused on this theme for 17 consecutive years, especially for the introduction of a series of new agricultural policies, such as increasing agricultural subsidies, realizing agricultural modernization, and promoting the supply-side structural reform of agriculture, which activated the intrinsic vitality of rural and agricultural development (Cai et al., 2017; Zhao et al., 2016). As the most important industry of rural society in China, AEE not only reflects the stability, efficiency and sustainability of agricultural ecosystem, but also reveals the evolution of agricultural ecosystem and the change of interaction between human and land system (Liu et al., 2018a,2018b,2018c). Against this context, the paper concentrated on the following objectives: 1) to depict the spatial-temporal variation of agricultural output and input from 1978–2017, 2) to estimate the AEE involving multi-output and multi-input, 3) to analyze the variation mechanism of AEE combining the system revolution and policy succession aspects, 4) to identify the influencing factors of AEE and put forward some improvement suggestions. The remainder of this paper is organized as follows: Section 2 describes the research methods and materials, then Section 3 presents the empirical results and provides some policy implications, and then Section 4 concludes the paper.

2. Methods and materials

2.1. Estimation of agricultural eco-efficiency based on Super-SBM model

In the process of agricultural production, the input of production factors not only produces expected output, but also discharges various pollutants, that is, unexpected output (Färe and Grosskopf, 2009). According to the previous statement, the agriculture in broad sense is selected as the research object in this study, and by which the gross output of agriculture, forestry, animal husbandry and fishery (AFAF) is selected as the expected output index, which reveals the total scale and overall achievements of agricultural production. Agricultural unexpected output mainly comes from excessive input or low-efficient utilization of some production factors (Adu and Kumarasamy, 2018). To be specific, this paper considers the total pollution loads of chemical oxygen demand (COD), total nitrogen (TN) and total phosphorus (TP), discharged by farmland fertilizers, livestock breeding, aquaculture and farmland straw, as unexpected output indexes.

Referring to the summary of input indicators of AEE in existing literatures, four input variables are selected, including land, labor, capital, and technologies (Hou and Yao, 2019; Yang et al., 2016). The first one, *land*, has been measured by the "crop sown area", which is more accurate in measuring the actual utilization rate of land than "arable land area". The second one, *labor*, has been measured by the "agricultural labor force" directly obtained from the existing statistical data. The third one, *capital*, has been measured by the "agricultural capital stock", which is the currency replacement value of tangible fixed assets (such as machinery, construction, livestock, land improvement) that can be reused in the agricultural production process. The fourth one, *technologies*, has been measured by the "agricultural machinery power", refers to the total power of various power machinery mainly used in AFAF and expresses as an important feature of modern agriculture.

At present, DEA is an effective method to analyze the AEE, which was proposed as a mathematical programming for evaluating the relative efficiency of decision making units (DMUs) having multi-output and multi-input (Charnes et al., 1978). However, the basic DEA has shortcomings in two aspects: one is that the efficiency rating results in practice has a deviation for numerous strict assumptions in cone and radial direction. The other one is that negative external benefits or other unexpected output are not brought into consideration. Hence, Tone (2001) proposed a non-radial and non-angular SBM model, which gives an overall consideration to input and output of each DMU and directly puts the slack variable into the target function, so as to solve a problem of the slack input-output. The Super-SBM model based on unexpected output is adopted in this study. The model is constructed as:

$$Min\rho = \frac{\frac{1}{m}\sum_{i=1}^{m}(\overline{x}/x_{ik})}{\frac{1}{r_1+r_2}\left(\sum_{s=1}^{r_1}\overline{y^d}/y_{sk}^d + \sum_{q=1}^{r_2}\overline{y^u}/y_{qk}^u\right)} \tag{1}$$

$$\begin{cases} \overline{x} \geq \sum\limits_{j=1,\neq k}^{n} x_{ij}\lambda_i;\ \overline{y^d} \leq \sum\limits_{j=1,\neq k}^{n} y_{sj}^d\lambda_j;\ \overline{y^d} \geq \sum\limits_{j=1,\neq k}^{n} y_{qj}^d\lambda_j;\ \overline{x} \geq x_k;\ \overline{y^d} \leq y_k^d;\ \overline{y^u} \\ \leq y_k^u \\ \lambda_j \geq 0,\ i = 1, 2, \cdots, m;\ j = 1, 2, \cdots, n,\ j \neq 0;\ s = 1, 2, \cdots, r_1;\ q = 1, 2, \cdots, r_2 \end{cases} \tag{2}$$

In the formula, E assumes that there are n DMUs. Each DMU is composed of input (m), expected output (r_1) and unexpected output (r_2). x, y^d and y^u respectively represent the input matrix, expected output matrix and unexpected output matrix. ρ is the value of AEE. The estimation of efficiency scores is conducted using the DEA-SOLVER Pro12.0 software.

2.2. Identification of influencing factors based on regression analysis

The National Modern Agriculture Development Plan (NMADP) (2011–2015) advocates promoting Chinese modern agricultural development from eight aspects, such as agricultural science and talent support, agricultural infrastructure conditions, agroecological environment. Based on these, the influencing factors of AEE are inspected from the agricultural basic condition, agricultural production structure, agricultural development potential, and agricultural input strength in Table 1. To be specific, (1) precipitation is the primary natural factor to determine regional agricultural efficiency. On the one hand, the more abundant precipitation, the higher the agricultural productive competence (Wang et al., 2017). On the other hand, rainfall-runoff intensifies the migration of agricultural pollution (Chen et al., 2018). (2) The agricultural accessibility level reveals the transportation costs and agricultural marketization degree. The better regional transportation condition implies the lower agricultural product transportation cost, and the higher the marketization degree. (3) Irrigation facilities are basic conditions for high-efficient agricultural development. The bigger the irrigation area is, the stronger agricultural productive competence will be and the higher eco-efficiency will be Sun et al. (2019). (4) The crop sown area shows the agricultural plantation scale. The larger the agricultural plantation scale, the larger the potential expected output and unexpected output. Therefore, its impact on AEE is unknown. (5) Due to a big input-output efficiency difference between cash crops and grain crops, AEE also has a great difference. Studies have indicated that from the perspectives of the labor force and biological chemical input, the horticultural plants reaches the maximum, followed by cash crops and grain crops (Song and Li, 2019). Therefore, if cash crops have a bigger cultivated area than grain crops, AEE will be lower. (6) Livestock breeding now is the primary agricultural pollution source in China. More than 50% of livestock and poultry manure are directly discharged without disposal. Hence, the higher the proportion of livestock breeding in agriculture, the lower AEE (Yang et al., 2013). (7) The improvement in farmers' income levels will generate the income effect and substitution effect on AEE. In other words, high-income is expected to induce farmers to enlarge input of production factors to gain more and more agricultural products, so as to inevitably result in increased pollution emissions (Wang and Zhang, 2018). Besides, an increase in farmers' incomes may drive them to purchase and use high-quality production materials, so as to be a benefit for reducing agricultural pollution discharges (Xiao et al., 2014). (8) The rising agricultural product price would enhance farmers' willingness to enlarge the input of production factors (i.e. pesticides and fertilizer), which would result in increasing agricultural pollution discharges. (9) Agricultural resource endowment reveals the agricultural scale to some extent. It has been observed that per capita cultivated land is present in the positive correlation with the scale of agricultural operation (Wang et al., 2015a,2015b), while agricultural scale operation means high-strength input of pesticides and fertilizers. (10) If the farmers have a higher education, they have a stronger subjective initiative to use new technologies or accept pollution reduction policies (Bayyurt and Yılmaz, 2012; Chen and Zhang, 2019), which is conducive to AEE. (11) Agricultural mechanization is the main part of agricultural technology innovation in current days. The input of agricultural machinery would increase the input of petrifaction resources, while enhancing agricultural production efficiency, so its influence on AEE is unknown (Zhou and Kong, 2019). (12) China is the great power of fertilizer production and consumption, but the overall level of use ratio is not high, resulting in serious resource waste or even accumulating in nitrogen and phosphorus in soils (Huang and Jiang, 2019). (13) Agricultural films are mainly used for covering farmlands and develop a role of improving ground temperature, guaranteeing the quality of soil humidity, promoting seed germination and rapid growth, but traditional agricultural plastic films have low recovery and they are not easy to be decomposed. (14) Even if pesticides can effectively prevent insect disease and regulate plant growth, they would cause serious environmental pollution when they flow into the environment.

We used the Ordinary Least Squares (OLS), Fixed Effect Model (FEM) and Random Effect Model (REM) to analyze the influencing factors of AEE. Considering that AEE calculated by the Super-SBM model is a variable with a nonnegative truncated feature. For such a restricted dependent variable, OLS is often used to obtain biased estimation results. What's more, the explanatory variable of AEE is provincial panel data, so OLS estimation violates the basic assumptions of error serial correlation, error provincial horizontal correlation and error heteroskedasticity. As a result, FEM and REM of panel data are utilized in this paper. The FEM/REM is stated as follows:

$$AEE_{it} = \beta_0 + \sum_j \beta_j X_{j,it} + \mu_i + \varepsilon_{it} \tag{3}$$

In the formula (3), AEE_{it} represents the eco-efficiency of the agricultural sector, i and t respectively stand for the ith province and tth year. β_0 is the intercept term and β_j is the coefficient of the explanatory variable, $X_{j,it}$ is the explanatory variable, μ_i is the individual effect, and ε_{it} is the random error term. In addition to the explanatory variable, the above-mentioned models contain observable and unobservable variables that are not included in the regression models. If μ_i is related to a

Table 1
Explanatory variable, index description and symbol prognosis of agricultural eco-efficiency.

Primary variable	Secondary variable	Abbreviation	Index description	Direction
Agricultural basic condition	Precipitation	*RAINFALL*	Average annual rainfall of main cities	Unknown
	Agricultural accessibility level	*ROAD*	Mileage of highways*	+
	Agricultural irrigation conditions	*IRRIGATION*	Effective irrigation area	+
Agricultural industrial structure	Agricultural planting scale	*APA*	Total crop sown area	Unknown
	Agricultural planting structure	*APS*	Seeded area of grain crops/ seeded area of cash crops	–
	Livestock breeding proportion	*LIVESTOCK*	The proportion of animal husbandry in total agricultural output value	–
Agricultural development potential	Agricultural dependence degree	*INCOME*	Per capita disposable income of farmers	Unknown
	Market stability of agricultural products	*APPPI*	Agricultural products' price index	–
	Agricultural resource endowment	*ARE*	Cultivated land area per capita	–
	Farmers' education level	*EDUCATION*	The proportion of illiteracy population in rural areas above 15 years old	–
Agricultural input strength	Technological innovation strength	*TECHNOLOGY*	Total power of agricultural machinery/output of planting industry	Unknown
	Fertilizer use intensity	*FERTILIZER*	The pure application of fertilizers/ output of planting industry	–
	Film use intensity	*MPF*	The application of agricultural plastic film /output of planting industry	–
	Pesticides use intensity	*PESTICIDES*	The application of pesticides/output of planting industry	–

* The mileage of highways refers to the length of highways that has actually reached the specified grade in the Technical Standard of Highway Engineering (JTJ01-88) and have been formally accepted and delivered for use by the highway authorities.

certain explanatory variable, it is called the FEM. If μ_i is not related to all explanatory variables, it is called the REM. The FEM can solve the endogenous problem caused by individual differences, while the REM enables individual observation to show a certain correlation, so as to fit for data including dependent observation. The selection of two models is inspected by Hausman. In order to overcome the heteroscedasticity problem of the data and reduce the single integer order, all variables are logarithmic, except for *APS*, *LIVESTOCK*, and *EDUCATION*. The statistical significance is defined from the p-value of a two-tailed Student's *t*-test. Besides, R^2 is used to measure the goodness of fit of regression models. The closer the value is to 1, the better the fitting degree of the model to the observed value will be; otherwise, the smaller the value is, the worse the fitting degree of the model to the observed value will be.

2.3. Data source and processing

This paper regarded agricultural input-output data of 31 provinces in China from 1978 to 2017 as samples excluding Hong Kong, Taiwan and Macao. Due to the adjustment of administrative division, data of Chongqing in 1978–1996 were included in Sichuan. Data in Hainan in 1978–1987 were contained in Guangdong. The gross value of AFAF came from the *China Rural Statistical Yearbook* (1985–2018) and Statistic Yearbook (1978–1984) in each province, which conducted the price deflator with the base period of 1978. Since there is lack of provincial statistical data of agricultural pollutant loads, pure application of fertilizers, numbers of livestock and poultry, output of aquatic products, and crop yield were gained from *China Rural Statistical Yearbook, Agricultural Statistical Compilation for 30 years of Reform and Opening-up, Agricultural Statistics for 50 years in New China, Agricultural Statistics for 60 years in New China, China Statistical Yearbook, China Fishery Statistical Yearbook, China Marine Statistical Yearbook, China Agricultural Machinery Industry Yearbook, Chinese Agricultural Statistical Compilation*. An inventory analysis is adopted to estimate the pollutant loads of COD, TN and TP (Chen et al., 2006; Lai, 2004; Zou et al., 2020), which are the main components of agricultural pollutants. Crop sown area, farmers engaged in AFAF, agricultural mechanical power, rainfall, road mileages and valid irrigation area are also collected from the above-mentioned statistical data. The agricultural capital stock is measured by the perpetual inventory method taking 1978 as the base year (Chow, 1993).

In order to increase the model explanatory, Variance Inflation Factor (VIF) was used to do multicollinearity analysis for all variables, finding that VIF of valid irrigation area and crop sown area are greater than 10. It showed the multicollinearity between them. Considering the uncertainty of crop sown area on the influence of AEE, it was excluded. The remaining 13 variables were used as the explanatory variables into the model.

3. Results

3.1. Descriptive analysis of agricultural input and output

It was showed that Chinese agricultural output and input in 1978–2017 ha d a larger amplitude and totally different change rule, indicating that the agricultural production mode was constantly adjusted under the impacts of economic development, social structural change and policy evolution. To be specific in Fig. 1, the overall growth trends of expected output and unexpected output were obvious, but there were slight fluctuations during the period. Land input (crop sown area) maintained an upward trend as a whole, but the amplitude of fluctuations was great. Labor input (agricultural labor force) was present in the inverted "U" type. Capital input (agricultural capital stock) showed rapid exponential growth. Technical input (agricultural machinery power) was climbing straightly. These change characteristics implied that since the reform and opening policy, Chinese agricultural production has been transformed into substance dependence (e.g. capital, technologies and fertilizers) from resource dependence (e.g. land and labor) under the guidance of urbanization, industrialization and agricultural modernization. Such a transformation brought the multiple growth of agricultural economic output and resulted in the increasingly prominent agricultural pollution problem (Huang and Jiang, 2019).

In 2017, Chinese agricultural output and input showed obvious regional, and it revealed the spatial pattern of "high in the east and low in the west" in Fig. 2, which was basically consistent with the agricultural regional pattern drawn by Liu et al. (2018a,2018b,2018c). To be specific, the percent contributions of expected output and unexpected in Central and East China are relatively high, while that of North China and Northwest China are relatively low. The percent contributions of land input in Central and Northeast China, and that of labor input in Central and Southwest China are higher than in other regions. Capital input in Central and North China, and that of technical input in Central and Eastern China take up larger percent contributions. The results are consistent with the fact that these provinces were major agricultural areas with a large rural population (Chen et al., 2006). The spatial-temporal features of agricultural output and input indicated that

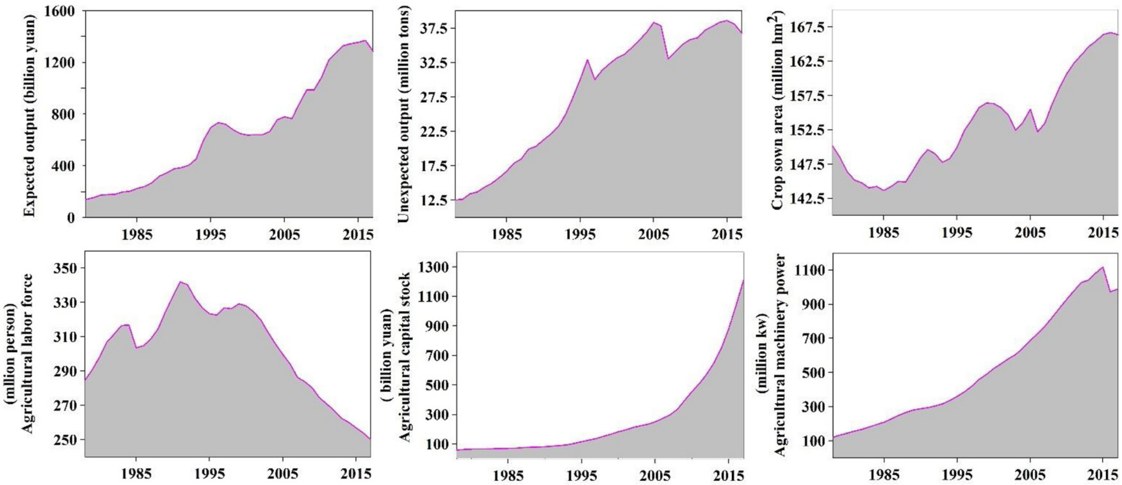

Fig. 1. The changing trend of agricultural input and output in China from 1978 to 2017.

due to different geographic spatial patterns, resource endowment and agricultural economic development level, Chinese agricultural development had the obvious provincial differentiation and asynchronism, which would result in differences of AEE.

3.2. Measurement and divisional discussion of agricultural eco-efficiency

Through comparative analysis, the Super-SBM Non-Oriented (VRS) model was adopted to measure the Chinese AEE. It was shown that the national AEE had increased from 0.405 in 1978 to 0.713 in 2017, increased by about 76%. It illustrated that the AEE was remarkably improved under the restriction of a series of agricultural pollution control measures and policies. However, the AEE in 2017 was lower than the maximum of 0.764 in 2016. Moreover, AEE in Northwest China was only 0.495, implying that there is a large space for resource-saving and environmental protection in the development of Two-oriented Agriculture.

The evolution of AEE overall underwent four stages in Fig. 3: the first one was the free development stage in 1978 − 1985. Due to the lack of market mechanisms and national policy, the AEE fluctuated slightly. The second one was the reform promotion stage in 1986 − 1995. Due to the promotion of household contract responsibility system, and the nation gradually reformed the central procurement dispatching system of agricultural and sideline products into the system with the priority of planning and assistance of market regulation, the enthusiasm of agricultural producers was fully mobilized (Wagan et al., 2018). Furthermore, considering the scale effect of production factor input, the growth amplitude of agricultural expected output exceeded unexpected output,

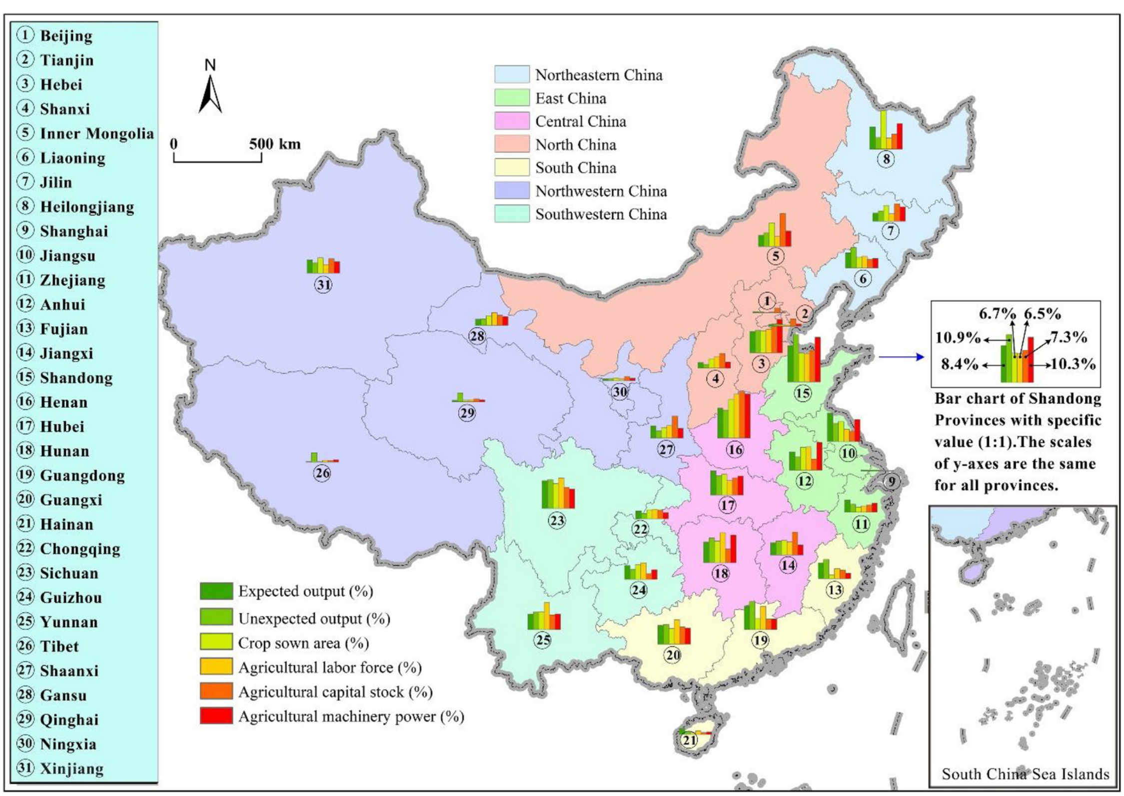

Fig. 2. Spatial pattern of agricultural output and input in 2017 in China. The length of bars in different colors stand for the percent contributions of output and input factors in national totals.

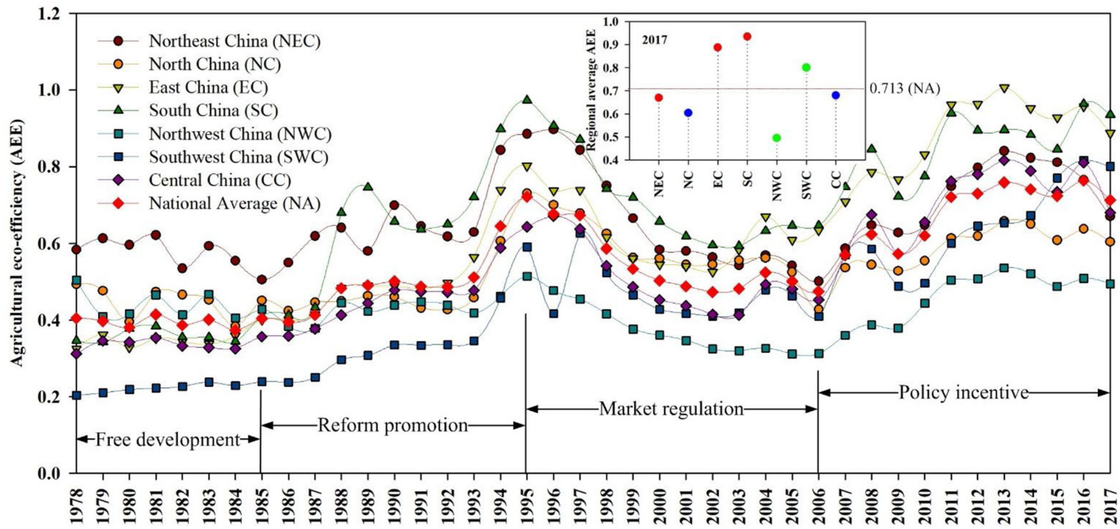

Fig. 3. Agricultural eco-efficiency in different regions of China from 1978 to 2017.

showing the rapid growth of AEE. The third one was the market regulation stage in 1996–2006, which was featured with protecting agricultural production, supporting the increase of farmers' incomes, promoting rural development, abolishing agricultural taxes, and re-feeding agriculture by industry. AEE was slowly reduced under the self-regulation of the market mechanism. The fourth one was the policy incentive stage in 2007 – 2017. Publication of a series of agricultural new policies in this stage motivated the internal vitality of agriculture and rural development, including an increase of agricultural subsidies, the realization of agricultural modernization, and promotion of structural reform at the agricultural supply side (Liu et al., 2015).

Fig. 3 also showed that Northeast, East and South China were higher than the national average level. North and Central China basically fitted for the national average level, while Southwest and Northwest China were lower than the national average level. With the vast land and high soil organic matter in Northeast China, agricultural production was relatively sensitive to climate, policies, and economy, showing the higher fluctuations of AEE. With the economic development in Eastern China, the agricultural modernization process was fast and had stricter ecological environmental control. AEE had a faster speed of improvement. Because of agroclimatic resources and the social-economic environment changed obviously, the AEE in South China had a faster growth speed. Due to flat regional terrain, good water-soil conditions and adequate labor force, agricultural production level and agricultural modernization progress in North China and Central China were basically synchronous. Considering the less per capita cultivated land and a high degree of land fragmentation in Southwest China (Wang et al., 2015a,2015b), AEE was relatively lower and had slower growth. Due to the poor natural conditions and agricultural input, the agricultural production mode in Northwest China was relatively extensive and AEE was kept at the minimum level. The regional difference of AEE indicated that agricultural production was directly affected by light, heat, water and soil and also suffered from the comprehensive impacts of agricultural productivity, industrial policies, market demands and regional economic level under different economic social development conditions (Li et al., 2018; Liu et al., 2018a,2018b,2018c).

3.3. The spatial-temporal pattern of agricultural eco-efficiency

In order to reveal the spatial-temporal pattern of AEE, the average values of AEE within each Five-Year Plan (FYP), were adopted for analysis. With the natural breakpoint, all the value of AEE was subdivided into four grades in Fig. 4. During the period of 5th FYP and 6th FYP, the grade of AEE in more than 2/3 provinces belonged to the first grade or second grade. The spatial distribution is characterized by obvious "core-periphery", that is, the AEE of the central provinces is generally lower than that of the southeast coastal and northeast provinces. During the period of 7th FYP and 8th FYP, AEE was slightly improved, and the grade of AEE in over 1/2 provinces belonged to the first grade or second grade. The spatial differentiation feature was obvious. During the period of 9th FYP and 10th FYP, AEE had a higher amplitude of variation. Particularly, during the 10th FYP, the grade of AEE in 20 provinces was reduced. The spatial agglomeration features gradually appeared. During the period of 11th FYP and 12th FYP, AEE was remarkably improved. The grade of AEE in over 1/2 provinces was the fourth grade, showing the relatively remarkable club convergence. During the period of 13th FYP, the grade of AEE in more than 24 provinces belonged to the third grade or fourth grade. However, owing to regional differences in agricultural policy execution, spatial agglomeration features of AEE were slightly weakened.

From 1978–2017, AEE had a phasic feature with a national economic plan in time and space. During the period of 5th FYP and 6th FYP, the nation adopted the fewer agricultural incentive policies and the grade of AEE was lower. During the period of 7th FYP and 8th FYP, stimulated from the agricultural product market to the plan-oriented market transformation, AEE was evidently increased with the increase of the expected output. During the period of 9th FYP and 10th FYP, the national policy incentives were weakened and AEE was decreased. During the period 11th FYP and 12th FYP, the nation paid more attention to the problem of "agriculture, rural areas, and rural residents". Also, agricultural development entered into the post-agricultural tax period. In this way, AEE has improved again. During the period of 13th FYP, agricultural energy-saving and discharge reduction measures were further reinforced. The regional variation of AEE was higher. Evidently, national policy incentives have become the indicators of Chinese AEE evolution (Wagan et al., 2018). Particularly, implementation of the agricultural product market mechanism, removal of agricultural tax and increase of agricultural subsidies, AEE was constantly changed in time and space (Rao et al., 2012). It was worth noting that even if AEE was constantly improved with the increase of expected output, unexpected output was present in the increasing trend as a whole. The environmental pollution problem caused by agricultural development absolutely couldn't be ignored with the improvement of AEE.

3.4. Influencing factor analysis of agricultural eco-efficiency

The comparative analysis of the estimation results of three models showed that although there were two insignificant factors in each

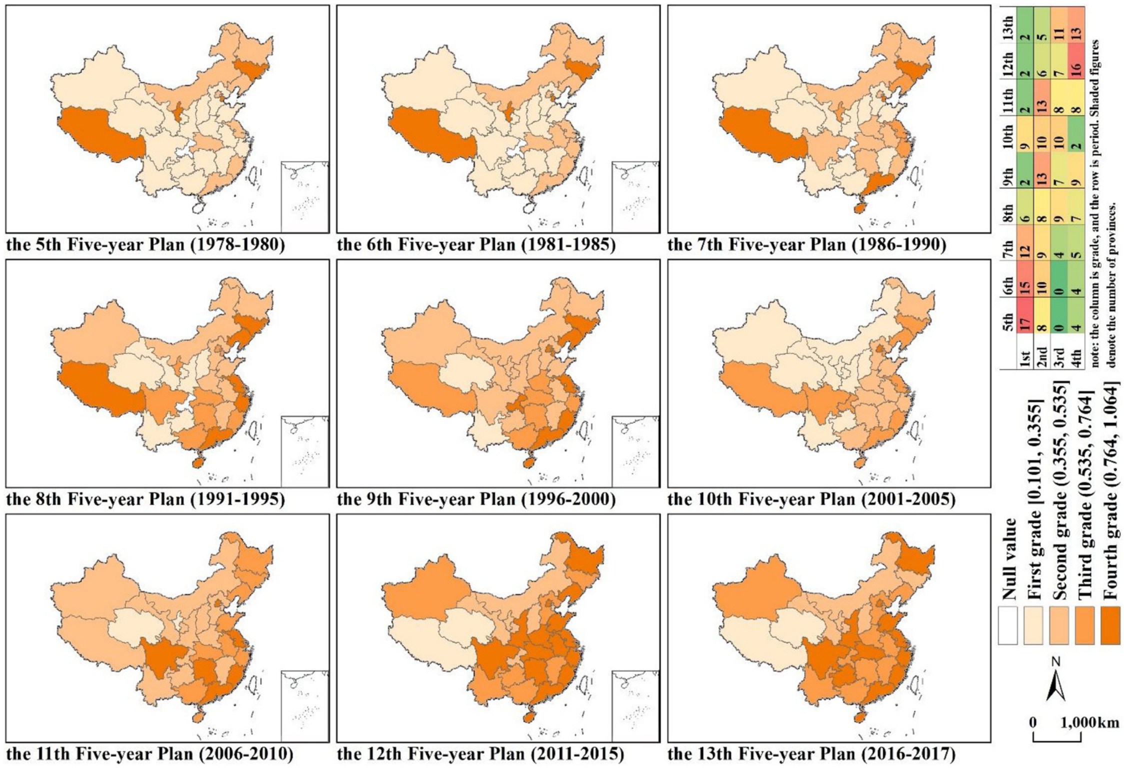

Fig. 4. Spatial-temporal pattern of agricultural eco-efficiency in different stages of China.

Table 2
The estimation results of agricultural eco-efficiency in China.

Variables	OLS	FEM	REM
ln *(RAINFALL)*	−0.015** (−2.55)	−0.013** (−2.46)	−0.014** (−2.41)
ln *(ROAD)*	−0.040*** (−9.28)	0.000 (0.04)	−0.036*** (−8.2)
ln *(IRRIGATION)*	0.033*** (8.40)	0.011*** (2.67)	0.031*** (7.78)
APS	−0.061*** (−7.73)	−0.039*** (−5.04)	−0.057*** (−7.24)
LIVESTOCK	0.000 (−0.36)	−0.001*** (−2.65)	0.000 (−0.92)
ln *(INCOME)*	0.020*** (4.12)	0.095*** (10.51)	0.024*** (4.58)
APPPI	0.000*** (−4.28)	−0.001*** (−6.54)	−0.001*** (−5.56)
ln *(ARE)*	−0.038*** (−8.53)	−0.015*** (−3.20)	−0.035*** (−7.79)
EDUCATION	−0.001*** (−3.73)	−0.001*** (−4.28)	−0.001*** (−4.3)
ln *(TECHNOLOGY)*	−0.088*** (−14.93)	−0.076*** (−13.64)	−0.086*** (−14.74)
ln *(FERTILIZER)*	−0.354*** (−3.48)	−0.180* (−1.85)	−0.306*** (−3.02)
ln *(MPF)*	−0.027*** (−8.19)	−0.027*** (−8.88)	−0.027*** (−8.22)
ln *(PESTICIDES)*	0.006 (1.38)	−0.003 (−0.63)	0.007 (1.45)
CONSTANT	1.673*** (13.80)	0.653*** (4.30)	1.580*** (12.64)
F-statistic	95.59***	101.11***	
F-statistic (P value)	0.000	0.000	
R^2	0.636		
Adjust R^2	0.629		
R^2 *(within)*		0.656	0.615
Hausman (P-value)		0.000	

Notes: Value out of the bracket is the parametric estimation value; value in the bracket is *t*-test value; *, **, *** represent significance at 10%, 5% and 1%, respectively.

model, the goodness of fit in FEM reached the maximum of 0.656, and the influence directions were the same as the prediction. The P-value of Hausman was 0.000, strongly refusing the null hypothesis. Furthermore, to explore the influence of different variables on the estimation results, based on the study of Wang et al. (2015a,2015b), the gross freight and GDP per capita were respectively used to replace the total length of road and per capita disposable incomes of farmers in the explanatory variables for the robustness test. The results had no substantive changes with the above-mentioned ones, indicating that the above-mentioned models and estimated results were stable. To sum up, this study chose the estimation results of FEM to analyze the influencing factors of AEE in Table 2.

The results indicated that all the variables have passed the significant test except for *ROAD* and *PESTICIDES*. Among these, *IRRIGATION* and *INCOME* had positive impacts on AEE, implying that the increase of agricultural irrigation facilities and the increase in farmers' incomes could effectively improve AEE. What' s more, the estimated coefficient of *INCOME* was 0.095, indicating that when the average disposable income of farmers was increased ¥100 yuan, AEE was increased by 9.5%. Besides of *IRRIGATION* and *INCOME*, all the other significant factors had negative impacts on AEE. Among which, the estimated coefficient of *FERTILIZER* was the maximum as −0.180. On the one hand, it showed that Chinese agriculture constantly enhanced the dependency on fertilizers, which developed an important role in improving the grain output. However, excessive application of fertilizers resulted in serious pollution in soil and water. On the other hand, structural adjustment of fertilizer application and testing soil for formulated fertilization could measure the soil nutrition, showing that the compound fertilizer subsidy policy to be published could reduce nitrogen and phosphorus in farmland soil. The coefficient of *TECHNOLOGY* was −0.076, indicating that agricultural mechanization would be the inevitable direction of modernized agricultural development. However, how to change the traditional labor-intensive production mode and reduce the investment in agricultural petrochemical resources is a problem that must be solved in the development of modern agriculture. Besides, the coefficients of *APS*, *MPE* and *ARE* were large, showing that moderate guidance of agricultural plantation structure transferred to cash crops from grain crops, and reduction of plastic film utilization could reduce agricultural pollutant discharge and improve AEE.

4. Discussion and policy implications

This paper has explored the spatial-temporal variation of AEE as well as its influencing factors. Although relevant researches have been carried out (Gancone et al., 2017; Hou and Yao, 2018; Rybaczewska-Błażejowska and Gierulski, 2018), there are still some innovations made in our study. Firstly, the unexpected output in our study has been estimated by an inventory analysis, which has a good performance indirectly and accurately reflecting the agricultural pollution discharges in national-scale (Chen et al., 2006); Secondly, the agriculture in broad sense is selected as the research object in this study, while the agriculture in narrow sense is selected by Hou and Yao (2018), and by which the estimated results would have a great deviation with the physical truth (Wang and Zhang, 2018); Thirdly, we provided an integrating study on the nature and humanity factors affecting AEE, which is great of significance for providing support for agricultural policies making (Deng and Gibson, 2019). Through these innovative explorations, we could gain some insights into the Chinese agricultural sector.

Since the reform and opening-up, Chinese society and economic structure had a huge variation (Liu et al., 2018a,2018b,2018c). Chinese official statistics showed that the urbanization rate increased from 17.9% in 1978 to 58.52% in 2017, while the proportion of primary industry in GDP dropped from 28.2%–7.9% (National Bureau of Statistics of China, 2019). It indicates that China has transitioned from traditional agriculture society to modern society and from a planned economy to a modern market system (Bai et al., 2014). In this process, agricultural product output and input factors were dramatically changed, while AEE showed the trend of stable improvement with the time variation under the incentives and constraints of reform and policies. However, due to different regional resource endowment, agricultural productivity and industrial policies, the spatial-temporal evolution of AEE had the obvious provincial difference. For example, the AEE of Shanghai was significantly increased from 0.206 in 1978 to 1.154 in 2017, while Inner Mongolia was slightly increased from 0.325 to 0.643. Thus indicated that the agricultural modernization still faced the arduous tasks of resource-saving and environmental protection (Huang and Jiang, 2019). As a result, the future national agricultural policy should be based on motivating the agricultural development vitality, depending on the strategies of targeted poverty alleviation and rural revitalization (Liu and Li, 2017) to compensate for regional disadvantages of agricultural development, and give play to the advantage of backwardness in agricultural backward areas.

Future Earth Plan and Sustainability Science focus on the integration of nature and humanity elements (Wang et al., 2015a,2015b). Throughout the existing studies, it can be found that nature and social-economic factors are primary variables to affect AEE (Aznar-Sánchez et al., 2019; Liu et al., 2018a,2018b,2018c; Wang and Zhang, 2018). This paper inspected the influencing factors of AEE from the agricultural basic condition, agricultural industrial structure, agricultural development potential and agricultural input strength. The results showed that *IRRIGATION* and *INCOME* had positive impacts on AEE. Therefore, it is proposed to further strengthen the protection of agricultural ecology, promote the comprehensive consolidation of rural land, and accelerate the development of high-efficiency agriculture, as a major strategy to achieve high-quality national agricultural development and improve the modern agricultural governance system (Liu, 2018). In addition, the results also showed that an increase of substantial productive factor input including fertilizers, machinery and plastic films were the important factor to restrict improvement on AEE. China is the largest producer and consumer of fertilizer in the world (Huang and Jiang, 2019), and there is significant evidence of overuse and inefficient use of fertilizer in agriculture (Huang and Jiang, 2019; Zhu et al., 2016). Besides, more than 1 million tons of plastic films are used each year in agricultural production to promote or protect crop growth (Chen et al., 2013), and a relatively large amount of plasticizers may be released into the environment (Navarro et al., 2010). Hence, to issue compound fertilizer subsidies and waste agricultural film recycling would be useful for further improvement of AEE. However, as the key influencing factor of grain output, agricultural mechanization showed a negative correlation with AEE, indicating that current agricultural mechanization aimed to increase production, instead of improving quality (Zhou and Kong, 2019). Also, it might be urgent for Chinese agricultural policies' orientation to transform from the increase production to quality improvement.

The long-term evolution trend and the influencing factors indicated that Chinese AEE is a complicated problem of comprehensive influence including nature, society, economy and policies. Agricultural change is not simply determined by market and (or) technology, or property right system and other factors that people pay more attention to today, but by the interaction between these factors and human land relationship resource endowment, urban-rural relationship, state behavior, and historical coincidence (Li et al., 2019a,2019b). Therefore, the formulation of agricultural policies should be based on the requirements of Two-oriented Agricultural development. Namely, in policy planning as well as management decisions, our attention should always be paid not only to the maximization of agricultural production, but also to the environmental resource overexploitation (Li et al., 2019a,2019b; Toma et al., 2017). Besides, the agricultural sector should improve the quality and efficiency of agricultural supply through structural reforms on the agricultural supply side, and think deeply about how to improve overall agricultural efficiency and international competitiveness in the context of economic globalization (Kong, 2016). Furthermore, the transformation of the agricultural development model should be centered on improving the land output rate, resource use rate and labor productivity, reduce dependency on petrifaction agriculture, decrease discharge of agricultural pollutants, greatly cultivate the concept of the resource-saving and environmental protection of agricultural subjects (Deng and Gibson, 2019), and explore the new idea and new mode of circulative agriculture, ecological agriculture, and intensive agriculture.

This paper measured Chinese AEE and analyzed its influencing factors in 1978–2017, finding that Chinese AEE is the concurrent result of multiple factors. Exploring the differential contributions from multiple factors is helpful for improving our understanding of the effects of human activities on the agriculture sector (Liu et al., 2018a,2018b,2018c). With the global economic integration, changing global climate, changing international agricultural plantation structure, and foreign direct investment, the influence on agricultural production is increasingly valued (Ma and Feng, 2013). However, this study was a lack of corresponding analysis and discussion. Even if from the perspective of quantitative analysis results, AEE not just had a simple linear relationship with its influencing factor. For instance, previous studies indicated that per capita cultivated land was present in the "U" correlation with AEE (Rybaczewska-Błażejowska and Gierulski, 2018; Wang et al., 2015a,2015b). Overall, AEE is a useful index to evaluate the stability and sustainability of agricultural ecological system. To improve the AEE is the goal orientation of agricultural development, the key of which is to take measures in light of local conditions and make scientific decisions based on the agricultural regional types. At the same time, it is proposed to strengthen the governance and management of agricultural system and promote the establishment of agricultural management engineering system. In addition, AEE should be placed on the evolution of agricultural ecosystem and the interaction of human-land system with consideration of the physiographic conditions, regional ecological environment, large-scale climatic changes, international trade, and national ecological civilization construction. Our results provide reference for scientifically promoting Chinese rural revitalization, modernization of agriculture and rural areas, and national territorial space planning in the new era.

5. Conclusions

Considering the provincial panel data in China from 1978 to 2017 as the research units and taking agriculture in broad sense as the study object, the AEE was measured by the Super-SBM Model, and the influencing factors were screened out by the FEM. During the period of 1978–2017, expected output and unexpected output of Chinese agriculture were synchronously increased, while the change of input factors was totally different and gradually transferred to materiality from resources. The estimated results revealed that Chinese AEE increased from 0.405 in 1978 to 0.713 in 2017, with an increase of about 76%. However, the current AEE had a declining trend and efficiency in some provinces was still lower. In addition, AEE had remarkable staging features and overall underwent four stages, including free development, reform promotion, market regulation and policy incentives. Affected by the land system, economic environment and agricultural policies, AEE had the obvious provincial difference. The spatial-temporal pattern of AEE was present in the features including spatial polarization, spatial differentiation, spatial agglomeration and spatial reconstruction in time order. During this period, national policy incentives have become indicators of AEE. FEM estimation results indicated that there were eleven variables had significant impacts on AEE. Among those, *IRRIGATION* and *INCOME* developed the positive impacts on AEE, while the other nine variables caused the negative impacts. Our results indicated that Chinese agriculture still faces the arduous tasks of resource-saving and environmental protection, the agricultural policies should avoid from falling into the trap of profit-seeking, and actively change agricultural production mode and explore new agricultural management mode.

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