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Evaluation and Influence Factor of Green Efficiency of China's Agricultural Innovation from the Perspective of Technical Transformation

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Abstract: Agricultural innovation is important for the green transformation of agriculture. Based on the perspective of technology transformation, this paper builds a theoretical analysis framework and evaluation index system for green efficiency of agricultural innovation, and discusses the evolution laws and influencing factors of the green efficiency of China's agricultural innovation from 2005 to 2017 utilizing the DEA model, Malmquist index, and Tobit regression analysis. The results show that: 1) The overall green efficiency of China's agricultural innovation is not high, the green efficiency of agricultural innovation in eastern China is mainly driven by pure technical efficiency, while that in central and western China is mainly driven by the scale efficiency. The green efficiency of agricultural innovation shows significant spatial differences, and the low efficiency and relatively low-efficiency regions moved to central and southeastern China. 2) Technical progress is the main force affecting the change of green total factor productivity of China's agricultural innovation, seeing a trend of decrease followed by an increase. Pure technical efficiency and scale efficiency exhibit an increasing-decreasing trend, and gradually transform into key factors that restrict the improvement of the green total factor productivity of agricultural innovation. 3) Agricultural technologies' diffusion, absorption, and implementation are three influencing factors of the green efficiency of agricultural innovation. The local level of informatization, the number of agricultural technicians in enterprises and institutions, average education level of residents, and the level of agricultural mechanization have positive impacts on the promotion of the green efficiency of agricultural innovation, promoting the diffusion, absorption and implementation of agricultural innovation technology can significantly improve the green efficiency of agricultural innovation.

Keywords: the green efficiency of agricultural innovation; Data Envelopment Analysis (DEA); Malmquist index; Tobit regression; China

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1 Introduction

Since the 20th Century, 'green' and 'innovation' have gradually evolved into the themes of global economic development (Sala et al., 2015; Li and Liu, 2017). Agriculture is an important component of the world's eco-

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nomics. With the rapid growth of agriculture, agricultural environmental problems have become of great concern to society. Coordination between agricultural environmental protection and agricultural growth, as well as the mechanisms of agricultural green transformation, have become hot issues in academic circles. As a largely agricultural country, China urgently needs agricultural green transformation. Since the 18th National Congress of the Communist Party of China, it has been mentioned in many No. 1 Central Documents that more efforts should be made in terms of governance of agricultural non-point source pollution and that agricultural fertilizer and pesticide saving measures should be executed. No. 1 Central Document 2020 further reiterates that resource protection and ecology recovery should be strengthened to promote the green development of agriculture. As an important way to control and reduce agricultural pollution, agricultural technology innovation has received increasing attention. Constructing an agricultural innovation system has become an important policy tool for governments to solve the problems of agricultural growth and agricultural environmental pollution. To this end, it is important to clarify the green efficiency of agricultural innovation and its development law in different areas as soon as possible to accelerate China's transformation to green agriculture.

At present, the interaction between innovation and green development is not very clear. Some scholars believe that innovation is triggered by regional environmental regulation (Gray and Shadbegian, 1998; De Azevedo and Pereira, 2010), and regard innovation as a process of passive adaptation in a region; others regard innovation as a necessity for regional development, focus on the positive impact of innovation on the environment and discuss regional green innovation ability from the perspective of the innovative value chain (Olson, 2014; Chen and Lei, 2018). Existing literature mainly focuses on green agriculture and agricultural innovation; it overlooks agricultural innovation for green development. Research on green agriculture has mainly focused on green agriculture evaluation (Liu et al, 2020), policies (OECD, 2011; Mouysset, 2014), efficiency (Hoang and Rao, 2010; Ray and Ghose, 2014), *etc*., and research on agricultural innovation has mainly focused on innovation diffusion (Turaeva and Hornidge, 2013; Cavallo et al., 2014; Spielman and Ma, 2016) and innovation networks (Hermans et al., 2015; Reed and Hickey, 2016; Gava et al., 2017; Li et al., 2018).

Innovation efficiency highlights the operational level and quality of a regional innovation system (Liu and Guan, 2002). Cao et al. (2015) analyzed the spatial differentiation characteristics of the technical research and development efficiency of city clusters in the Yangtze River Delta with the DEA method and Malmquist index. Sheng et al. (2020) discussed the innovation efficiency and influence factor of five major city clusters in China's eastern coastal area by using the Stochastic Frontier Approach. Han et al. (2017) researched the efficiency of the whole process from innovation input to innovation transformation of three provinces in northeastern China from the perspective of the innovation system. Qin et al. (2017) thought that research of the innovation efficiency from the perspective of the whole process of innovation may cover the efficiency characteristic of one link of innovation and researched the evolution characteristics of the innovation efficiency of Chinese universities from three aspects, including knowledge access, technical innovation and achievement transformation. These researches revolve around non-agricultural fields, with little research on the green efficiency of agricultural innovation. China's technologies have taken a good lead in the world, but China's achievement transformation rate is far lower compared to developed countries; this is attributable to the poor industry-university-research cooperation that makes it difficult to transform and elevate science and technologies to advanced productivity (Li et al., 2018). Therefore, researching the green efficiency of regional agricultural innovation from the perspective of agricultural innovation technology transformation will better explore the efficiency characteristics of each link of innovation. However, such research has been scarcely conducted in previous literature.

In this case, what is the green efficiency of agricultural innovation? What is the nature of the green efficiency of China's agricultural innovation? What are its spatial differences? What are its influencing factors? To approach these questions, this paper builds an evaluation index system of the green efficiency of agricultural innovation based on definitions and theoretical discussions, explores the pattern and evolution of the green efficiency of agricultural innovation using the DEA model and Malmquist index, and analyzes the influencing factors on the green efficiency of agricultural innovation through Tobit regression. As a result, the evolution laws of the green efficiency of China's agricultural innovation are summarized, providing references for agricultural green transformation in different regions of China.

2 Theoretical Analysis Framework

2.1 Definition of the green efficiency of agricultural innovation

There are mainly two views on understanding the definition of innovation in the academic circle. One view is exploring the relationship between subjects during the technical research and development process based on the Theory of Knowledge Production (Jiao et al., 2019; Zhou et al., 2019), and such research mainly focuses on the production end of innovation knowledge; the other view is exploring the diffusion, adoption and economic benefits of innovation achievements based on the Theory of Diffusion of Innovations (Li and Luo, 2016; Shi et al., 2016), and such research mainly focuses on the application end of innovation knowledge. The innovation theory of Schumpeter points out that innovation is establishing a new 'production function' to introduce the 'new combination' of production elements and production conditions into the production system (Miao et al., 2011). This paper is more inclined to understand agricultural innovation from the knowledge application end and thinks that agricultural innovation is a process where regional rural households change the original agricultural production relations with new agricultural technologies (OECD, 2013). Rural households are the subject in this process, and the innovation behavior of regional rural households will ultimately drive the innovation of the entire agricultural level. Regional technology achievement is the basis of innovation as well as the source of agricultural innovation technologies. Green development of agriculture cannot be separated from agricultural innovation. The significance of agricultural innovation for green development of agriculture lies in that rural households change the traditional agricultural production modes, optimize the input-output relation of agricultural production and realize a win-win situation of agricultural economic benefits and environmental benefits with new agricultural technologies and new achievements (Fig. 1). Thus, the essence of green efficiency of agricultural innovation is a new-type input-output relation formed by incorporating agricultural technical innovation into the agricultural production system.

2.2 Evaluation indexes of green efficiency of agricultural innovation

The input-output relationship is used to determine the green efficiency of agricultural innovation. The lesser the input and non-expected output, and the greater the expected output, the higher the efficiency (Fig. 1). The green efficiency of agricultural innovation is mainly reflected in economic efficiency and environmental efficiency: 1) Economic efficiency is an important goal for both traditional agriculture and green agriculture; however, green agriculture pursues more green economic benefits. The economic connotation of green efficiency of agricultural innovation is to maximize the green economic benefits under the given investment level. 2) Agricultural green production should ensure both economic benefit and eco-environmental protection. The environmental connotation of green efficiency of agricultural innovation is to minimize agricultural environmental pollution at the given input and economic output levels. Based on input and output processes, this paper creates an evaluation index system for the green efficiency of agricultural innovation (Table 1). Input in-

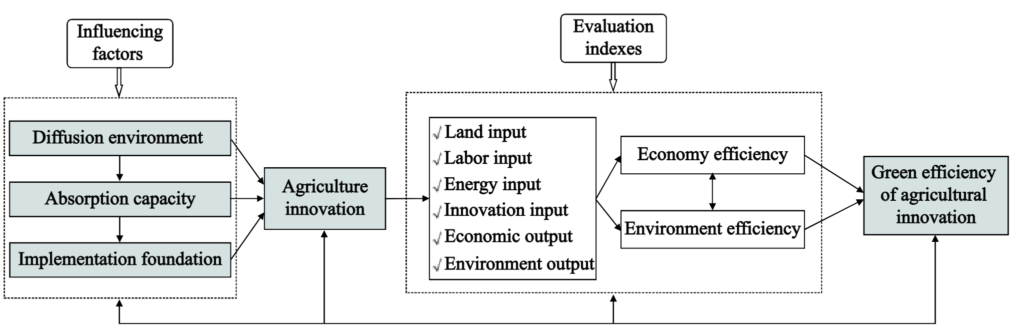

Fig. 1 Theoretical analytical framework for green efficiency of agricultural innovation

Table 1 The evaluation indexes of green efficiency of agricultural innovation

Index type	Consideration	Selected index
Input	Land input	Sown area of farm crops / 1000 ha
	Labor input	Number of agricultural, forestry, animal husbandry, and fishery employees / 10000 people
	Energy input	Energy consumption of agriculture, forestry, animal husbandry, and fishery / 10000 t standard coal); Pesticide usage (t); Application amount of chemical fertilizer / 10000 t; Agricultural water consumption / 100 million m^3
	Innovation input	Number of patents and technology achievements in agriculture, forestry, animal husbandry, and fishery
Desirable output	Economic output	Agricultural green GDP / 10000 yuan (RMB)
Unexpected output	Environment output	Agriculture COD, TP, and TN emissions / 10000 yuan (RMB)

dexes comprise land, labor, energy and innovation, and expected output indexes comprise economic output (measured by agricultural green GDP), and non-expected output indexes mainly refer to environmental output (measured by agricultural pollutants, such as Chemical Oxygen Demand (COD), total phosphorus (TP), and total nitrogen emissions (TN)). The agriculture in this paper refers to general agriculture (agriculture, forestry, animal husbandry, and fishery). It should be noted that agricultural green GDP is calculated mainly from the perspective of ecological value and carbon emissions, while COD, TP, and TN emissions focus on the negative impact introduced by organic pollution during agricultural production. Essentially, they complement each other.

2.3 Influencing factors of green efficiency of agricultural innovation

The diffusion, absorption, and transformation of agricultural technology directly impact agricultural innovation, which, in turn, will alter the input-output relationship of agricultural production, further affecting the green efficiency of agricultural innovation. Based on the Regional Innovation Theory and Technology Diffusion Theory, we have built a multi-stage theoretical analysis framework of influencing factors of green efficiency of agricultural innovation featuring 'diffusion environment-absorption capacity-implementation foundation' from the technology transformation perspective (Fig. 1). 'Diffusion environments' affect the flow of new agricultural technologies; 'Absorption capacity' reflects the potential of farmers to learn new technologies; 'Implementation foundation' provides conditions for the transformation of new agricultural technologies. The three factors affect the ability of agricultural scientific and technological achievements to metamorphose into agricultural green productivity and have a significant impact on the green efficiency of agricultural innovation. The quantitative indexes are shown in Table 2. Innovation diffusion is correlated with the local development of information technology and expressed in the throughput of postal and telecommunication services per capita, as the better the development of information technology, the stronger the flow capacity of new knowledge and new technology in a region. The extension of agricultural technology is conducive to the diffusion of new agricul-

Table 2 The influence factors and descriptive statistics of green efficiency of agricultural innovation

Influencing mechanism	Specific index	Average value	Standard deviation	Min.	Max.
Diffusion environment	Total postal and telecommunication services/total population / (yuan (RMB)/person (X_1))	1682.28	1036.42	454.54	6255.56
	The number of agricultural technicians in enterprises and institutions/the number of employees in agriculture, forestry, animal husbandry and fishery / (person/10000 person (X_2))	34.824	21.362	104.802	7.808
Absorption capacity	Average years of schooling / yr (X_3)	8.61	1.22	3.74	12.50
	Rural per capita net income / yuan (RMB) (X_4)	7994.64	4673.01	1876.96	27825.00
Implementation foundation	Total power of agricultural machinery/sown area of farm crops / (kW/ha (X_5))	6.22	3.39	2.08	24.63
	Fiscal expenditure for agriculture, forestry and water conservancy/total output value of agriculture, forestry, animal husbandry and fishery / % (X_6)	0.20	0.24	0.02	1.68

tural technology. Agricultural technicians of enterprises and institutions undertake the task of agricultural technology extension, playing an important role in the diffusion of agricultural technology. Innovation absorption ability is represented by average years of education and rural per capita net income, as the higher the education level of rural people, the greater their ability to learn new technologies (Abebe et al., 2013); the higher the rural income level, the more capable rural people will become to bear the opportunity costs and innovation risks inherent in the adoption of new technologies (Wegren, 2008). The foundation for innovation implementation is expressed by the agricultural mechanization level and financial support for agriculture, as the implementation of new agricultural technologies sets higher requirements for local agriculture. The higher the level of agricultural mechanization and the more complete the agricultural infrastructure construction, the more conducive the environment for the implementation of new technologies.

3 Research Method and Data Sources

3.1 Research method

3.1.1 Calculation of agricultural green GDP

Green GDP is regarded as an important index to measure the coordinated development of the economy and environment (Wang, 2016). Based on the emergy analysis, the accounting method of green GDP was put forward (Zhang et al., 2010; Kunanuntakij et al., 2017), where Li et al. (2016) introduced it to calculate agricultural green GDP. The formula is as follows:

$$GDP_g = GDP_t - GDP_e = V_p - C_p + V_{es} - C_e \tag{1}$$

where GDP_g represents agricultural green GDP, GDP_t and GDP_e stand for general agriculture GDP and agro-ecology GDP, respectively, V_p stands for the total output of farming, forestry, animal husbandry, and fishery, C_p represents the intermediate consumption of farming, forestry, animal husbandry, and fishery, V_{es} represents the value of agro-ecosystem services, and C_e represents the agriculture ecological environmental cost. Data on the total output of farming, forestry, animal husbandry and fishery, and the intermediate consumption of the same, are extracted from the statistical yearbook. Next, this paper will next deal with calculating the service value of the agro-eco system and agriculture ecological environmental cost.

(1) V_{es} is calculated by the following formula:

$$V_{es} = I \times V = \frac{K}{1 + ae^{-b(1/En^{-3})}} \times \sum_{i=1}^{m}\sum_{j=1}^{n} A_j E_{ij} \tag{2}$$

where I represents public acceptance of agro-ecological value at the given stage, and V represents the total ecological service value of the regional agricultural system. To facilitate calculation, we regard K, a, and b as 1, the development stage index as the pearl growth curve, and En as the Engel coefficient (Li, 2002). A_j represents the area of j-type agricultural resources. The value of agro-ecological services represents the ecological value produced during agricultural activities in farmlands, forests, and water areas; therefore, $n = 3$. In this paper, the value produced by tea gardens, orchards, and aquiculture stands for the value produced by forest and water areas. E_{ij} represents the price unit of ecological service i regarding agricultural resource j. According to Xie et al. (2003) research, there are nine types of ecological service; therefore, $m = 9$.

The formula for E_{ij} is as follows:

$$E_{ij} = e_{ij} \times E_a = e_{ij} \times \frac{1}{7}\sum_{t=1}^{k}\frac{m_t q_t p_t}{M} \tag{3}$$

where e_{ij} represents the value equivalent to ecological service i of agricultural resource j, according to the value equivalence scale provided by Xie et al. (2003), E_a represents the value of food production per unit area, t represents a type of grain crop (this paper only includes the most widely grown crops in China, such as wheat, paddy, corn, and soybean; therefore, $k = 5$), m_t represents the growing area of the t-type crop, q_t represents the per unit yield of the t-type crop, p_t represents the average price of the t-type crop, and M represents the sum of the growing area of the t-type crop.

(2) The formula for C_e is given below:

$$\begin{aligned} C_e &= L_s + L_g + L_f + L_r = A_1(E_1 S_1 + E_2 S_2) + \\ &\quad P_c(a_1 T_1 + a_2 T_2) + A_3 V_p + L_r \end{aligned} \tag{4}$$

where L_s, L_g and L_f are the environmental cost of farming, animal husbandry and aquaculture respectively, L_r is ecological value loss caused by the decrease of agriculture area due to the adjustment of agriculture resources (it is the accounting result of formulas (2) and (3)), A_1 is farmland area, E_1 and E_2 are ecological service price regarding biodiversity protection and food production, S_1 and S_2 are the loss rates of farm biodiversity and food production respectively (we take S_1 and S_2 as 35.4% and 2.04% (Li et al., 1999)), T_1 and T_2 are the emissions of two greenhouse gases respectively (Hu and Wang, 2010), as animal husbandry will emit greenhouse gas of CH_4 and N_2O, a_1 and a_2 are conversion coefficients from the two greenhouse gases and CO_2 (Cao, 1998), P_c is economic loss per unit of greenhouse gas, which is almost 150 yuan (RMB)/t according to the 2007 World Bank report, A_3 is the area of aquaculture, and V_p is the eutrophication cost per unit of aquaculture area, which is taken as 4192 yuan (RMB)/ha (Yang et al., 2012).

3.1.2 List analysis

We calculate chemical oxygen demand, total phosphorus and total nitrogen emissions of agriculture by list analysis. The formula (Chen et al., 2006) is as follows:

$$E_{ij} = EU_{ij} \times \rho_{ij}(1-\eta_i)C_{ij}\left(EU_{ij}, S\right) \tag{5}$$

where E_{ij} is the emission of contaminant j in district i, EU_{ij} is the statistical index of contaminant j in district i, ρ_{ij} is the pollutant-producing coefficient of contaminant j in district i, η_i is the utilization rate of the related resource in district i, and C_{ij} is the emission coefficient of contaminant j in district i, which depends on the characteristics of the contaminant and the district, ρ_{ij}, η_i and C_{ij} can be decided according to the relevant literature (Lai et al., 2004; Liang et al., 2010).

3.1.3 DEA model

Data Envelopment Analysis (DEA) is a nonparametric method for analyzing relative input-output efficiency (Cao et al., 2015). Suppose we wish to evaluate the green efficiency of agricultural innovation in K regions and there are L input indexes and M output indexes; we assume that X_{ij} stands for the input of factor i in unit j, and y_{jm} stands for the output of factor m in unit j. The following are the DEA models for unit n (n=1, 2,..., K) (Wang et al., 2012):

$$\begin{cases} min\left[\theta - \varepsilon\left(e_1^T s^- + e_2^T s^+\right)\right] \\ s.t. \sum_{j=1}^{K} X_{jl}\lambda_j + s^- = \theta X_1^n \quad l = 1,2,\ldots,L \\ \sum_{j=1}^{K} y_{jm}\lambda_j - s^+ = y_m^n \quad m = 1,2,\ldots,M \\ \lambda \geqslant 0 \quad n = 1,2,\ldots,K \end{cases} \tag{6}$$

In the formula, θ ($0 < \theta \leq 1$) is the combined efficiency index, λ_j ($\lambda_j \geq 0$) is the weight variable, s^- ($s^- \geq 0$)(is the slack variable, s^+ ($s^+ \geq 0$) is the surplus variable, and ε is Archimede's infinitely small quantity. $e_1^T = (1, 1, \ldots, 1) \in E_m$ and $e_2^T = (1, 1, \ldots, 1) \in E_m$ are the unit vector space of dimension m and dimension k. The closer θ is to 1, the higher the efficiency; the closer θ is to 0, the lower the efficiency. $\theta = 1$ indicates that the green efficiency of agricultural innovation is at the forefront of optimal production with the highest combined efficiency. The constraint $\sum_{j=1}^{K} \lambda_j = 1$ is added to formula (6) to transform it into a model with variable returns to scale (VRS). The VRS model is used to break the combined efficiency into pure technical efficiency and scale efficiency.

The DEA model can only be used to compare the relative efficiency of different assessment units, not efficiency at different times. As such, it is necessary to introduce the Malmquist Index to study the dynamic change of efficiency at different times. According to the rational exponent theory, the geometric mean between two periods is the change of the total factor productivity exponent. Under the VRS assumption, the change of the Malmquist exponent can be divided into technological change (*techch*), pure technical efficiency change (*pech*), and scale efficiency change (*sech*).The formula is as follows (Kortelainen, 2008; Guo et al., 2009):

$$tfpch = techch \cdot effch = techch \cdot pech \cdot sech \tag{7}$$

$$tfph = \frac{D_v^t\left(x^{t+1}, y^{t+1}\right)}{D_v^t\left(x^t, y^t\right)} \cdot \left[\frac{D_v^t\left(x^t, y^t\right)}{D_c^t\left(x^t, y^t\right)} \times \frac{D_c^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_v^t\left(x^{t+1}, y^{t+1}\right)}\right] \cdot \left[\frac{D_c^t\left(x^{t+1}, y^{t+1}\right)}{D_c^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{D_c^t\left(x^t, y^t\right)}{D_v^{t+1}\left(x^t, y^t\right)}\right]^{\frac{1}{2}} \tag{8}$$

$$\begin{cases} techch = \dfrac{D_v^t\left(x^{t+1}, y^{t+1}\right)}{D_v^t\left(x^t, y^t\right)} \\ pech = \dfrac{D_v^t\left(x^t, y^t\right)}{D_c^t\left(x^t, y^t\right)} \times \dfrac{D_c^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_v^t\left(x^{t+1}, y^{t+1}\right)} \\ sech = \left[\dfrac{D_c^t\left(x^{t+1}, y^{t+1}\right)}{D_c^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \dfrac{D_c^t\left(x^t, y^t\right)}{D_v^{t+1}\left(x^t, y^t\right)}\right]^{\frac{1}{2}} \end{cases} \tag{9}$$

where *tfph* is the change of green total factor productivity of the agricultural innovation; (x_t, y_t) and (x_{t+1}, y_{t+1}) is taken as the relation between the input and output at the t and $t + 1$ stages, the change in the relation between input and output from (x_t, y_t) to (x_{t+1}, y_{t+1}) is the change in total factor productivity; $D_c^{\,t}(x^t, y^t)$ and $D_c^{\,t+1}(x^{t+1}, y^{t+1})$ are distance functions between real output and optimal output based on constant returns to scale; $D_v^{\,t}(x^t, y^t)$ and $D_v^{\,t+1}(x^{t+1}, y^{t+1})$ are distance functions between real output and optimal output based on variable returns to scale. When *tfph techch*, *pech*, and *sech* are greater than 1, it indicates that total factor productivity, technological progress, pure technical efficiency, and scale efficiency tend to increase; else, it decreases.

3.1.4 Tobit regression

As the efficiency resulting from the DEA model is between 0 and 1, the dependent variable of the regression formula is cut off. If we use the normal least-square theory in regression, the regression parameter will be biased (Greene, 1981). To solve this problem, we used the Tobit regression model to analyze the influence factors of the green efficiency of agricultural innovation (Adesina and Zinnah, 1993).

$$Y_i = \begin{cases} Y_i^* > 0 \\ 0, Y_i^* \end{cases} \quad Y_i^* = \sum_{i=1}^{n} a_i X_i + b_i \quad (i = 1,2,3,\ldots,n) \quad (10)$$

where Y_i^* is the dependent variable, Y_i is the green efficiency of agricultural innovation, X_i is an independent variable, a_i is the coefficient of association, and b_i is an error term.

3.2 Data sources

The statistical data in this paper mainly comes from the *China Agriculture Yearbook* (China Agricultural Yearbook Editorial Committee, 2006–2018), *China Rural Statistical Yearbook* (National Statistical Bureau of China, 2006–2018a), *Yearbook of Science and Technology of China* (National Statistical Bureau of China, 2006–2018b), and *China Statistical Yearbook* (National Statistical Bureau of China, 2006–2018c). The numbers of agricultural technology patents and technological achievements in agriculture, forestry, animal husbandry, and fishery are from the CNKI (https://www.cnki.net/). Since agricultural COD, TP, and TN are non-expected output indexes, they were positively transformed by adopting the inverse in the calculation (Cheng et al., 2016; Xie et al., 2017). After transformation, these indicators can be treated as expected indicators. Additionally, considering that the DEA model has certain requirements for input and output quantity, that is, the total number of input and output indicators is less than or equal to one-third of the number of decision units (Liu et al., 2018), we take the environmental output as a comprehensive index and calculate it by the entropy method (Zhang et al., 2008; Wu and Wu, 2009; Ren et al., 2017). In this paper, the scope of China's three major zones is based on the classification of *China Statistical Yearbook*, and eastern China includes Liaoning, Beijing, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Guangxi, and Hainan; central China includes Shanxi, Inner Mongolia, Heilongjiang, Jilin, Anhui, Henan, Jiangxi, Hubei, and Hunan, and the western China includes Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Sichuan, Chongqing, Yunnan, Guizhou, and Tibet. The missing data of Tibet for individual years are fixed using the interpolation method. *Statistical Yearbook* does not contain Hong Kong, Macao, and Taiwan data, so they are not considered in this study.

4 Results

4.1 Lateral static evaluation of green efficiency of agricultural innovation

4.1.1 Green efficiency measures for the agricultural innovation

The score of green efficiency of agricultural innovation of 31 areas in China in 2005, 2010, and 2017 (Table 3) were calculated with DEAP2.1 software, and presented the following features:

First, the overall green efficiency of agricultural innovation was low, while the green efficiency of agricultural innovation in most areas did not reach the optimum level. The average green efficiency of China's agricultural innovation in 2005, 2010, and 2017 was 0.856, 0.907, and 0.751, respectively, which means that they only accounted for 85.6%, 90.7%, and 75.1% of the optimum level, leaving much room for improvement. The numbers of areas that reached an efficiency level of 1 in 2005, 2010, and 2017 were 9, 14, and 7, respectively, accounting for 29.0%, 45.2%, and 22.6%. The efficiency levels of Beijing, Shanghai, Liaoning, Hainan, and Tibet in the selected years were about 1, indicating that in these regions agricultural innovation to green development was efficient, without redundant input or insufficient output, whilst the efficiency levels of most areas were relatively low, suggesting fluctuation.

Second, the impact of pure technical efficiency and scale efficiency on comprehensive efficiency were quite different across various regions. During the investigat-

Table 3 The score of green efficiency of agricultural innovation in different areas from 2005–2017

DUM	2005				2010				2017			
	crste	*vrste*	scale	*rts*	*crste*	*vrste*	*scale*	*rts*	*crste*	*vrste*	*scale*	*rts*
Beijing	1.000	1.000	1.000	–	1.000	1.000	1.000	–	1.000	1.000	1.000	–
Tianjing	1.000	1.000	1.000	–	1.000	1.000	1.000	–	0.537	0.538	0.998	irs
Hebei	0.850	1.000	0.850	drs	0.925	1.000	0.925	drs	0.625	0.819	0.764	drs
Shanxi	0.501	0.501	0.999	–	0.622	0.781	0.796	drs	0.464	0.465	0.998	drs
Inner Mongolia	0.926	1.000	0.926	drs	0.970	0.971	0.999	irs	0.841	0.854	0.984	drs
Liaoning	1.000	1.000	1.000	–	1.000	1.000	1.000	–	1.000	1.000	1.000	–
Jilin	0.862	0.938	0.919	drs	0.907	0.908	0.998	irs	0.662	0.697	0.951	drs
Heilongjiang	0.802	1.000	0.802	drs	0.736	0.743	0.991	drs	0.834	1.000	0.834	drs
Shanghai	1.000	1.000	1.000	–	1.000	1.000	1.000	–	1.000	1.000	1.000	–
Jiangsu	0.825	1.000	0.825	drs	1.000	1.000	1.000	–	0.900	1.000	0.900	drs
Zhejiang	0.984	1.000	0.984	drs	1.000	1.000	1.000	–	0.581	1.000	0.581	drs
Anhui	0.942	0.978	0.963	drs	0.883	0.903	0.978	drs	0.462	0.575	0.803	drs
Fujian	0.962	1.000	0.962	drs	1.000	1.000	1.000	–	0.902	1.000	0.902	drs
Jiangxi	1.000	1.000	1.000	–	0.967	0.967	1.000	–	0.552	0.556	0.993	drs
Shandong	0.865	1.000	0.865	drs	0.917	1.000	0.917	drs	0.628	1.000	0.628	drs
Henan	0.853	1.000	0.853	drs	0.941	1.000	0.941	drs	0.608	1.000	0.608	drs
Hubei	0.856	0.981	0.873	drs	0.944	1.000	0.944	drs	0.733	1.000	0.733	drs
Hunan	0.849	0.930	0.913	drs	1.000	1.000	1.000	–	0.496	0.562	0.883	drs
Guangdong	0.845	1.000	0.845	drs	0.787	1.000	0.787	drs	0.600	1.000	0.600	drs
Guangxi	0.914	1.000	0.914	drs	0.837	0.895	0.934	drs	0.603	0.925	0.652	drs
Hainan	1.000	1.000	1.000	–	1.000	1.000	1.000	–	1.000	1.000	1.000	–
Chongqing	0.771	0.842	0.916	drs	0.672	0.822	0.818	drs	0.815	0.905	0.900	drs
Sichuan	1.000	1.000	1.000	–	1.000	1.000	1.000	–	0.802	1.000	0.802	drs
Guizhou	0.670	0.743	0.902	drs	1.000	1.000	1.000	–	1.000	1.000	1.000	–
Yunnan	0.645	0.645	1.000	–	0.653	0.654	0.998	irs	0.651	0.662	0.984	drs
Tibet	1.000	1.000	1.000	–	1.000	1.000	1.000	–	1.000	1.000	1.000	–
Shaanxi	0.778	0.778	0.999	–	1.000	1.000	1.000	–	0.942	1.000	0.942	drs
Gansu	0.403	0.405	0.994	drs	0.451	0.556	0.812	drs	0.330	0.385	0.858	drs
Qinghai	1.000	1.000	1.000	–	1.000	1.000	1.000	–	0.793	0.799	0.992	irs
Ningxia	0.485	0.500	0.970	drs	0.901	0.919	0.980	drs	1.000	1.000	1.000	–
Xijiang	0.960	1.000	0.960	drs	1.000	1.000	1.000	–	0.935	0.950	0.984	drs
Average of the eastern	0.937	1.000	0.937		0.956	0.991	0.964		0.781	0.940	0.835	
Average of the central	0.843	0.925	0.916		0.886	0.919	0.961		0.628	0.745	0.865	
Average of the western	0.771	0.791	0.974		0.868	0.895	0.961		0.827	0.870	0.946	
Average of whole country	0.856	0.911	0.943		0.907	0.939	0.962		0.751	0.861	0.880	

Notes: DUM represents the area, *crste*, *vrste* and *scale* represents comprehensive efficiency, pure technical efficiency, and scale efficiency, respectively; *rts* represents the change of scale efficiency; –, irs and drs represents the same scale efficiency, increasing scale efficiency and decreasing scale efficiency

ive years, the mean value of pure technical efficiency in eastern China was higher than that of scale efficiency. At the provincial level, except in 2017 when the scale efficiency in Tianjin was a little higher than the pure technical efficiency, the pure technical efficiency was either larger or equal to the scale efficiency in all the other regions of eastern China in other years; the mean value of pure technical efficiency in central China was lower than that of scale efficiency, except 2005 when it was a little higher than that of scale efficiency. At the provincial level, the number of regions where the scale efficiency was higher than the pure technical efficiency in central China surpassed the number of regions where the pure technical efficiency was higher than scale efficiency, except 2005; In western China, the mean value of scale efficiency was higher than that of the pure technical efficiency in all years, and the number of regions where the scale efficiency was higher than pure technical efficiency surpassed the number of regions where pure technical efficiency was higher than scale efficiency. In conclusion, the green efficiency of agricultural innovation in eastern China is mainly driven by pure technical efficiency, while in central and western China; scale efficiency is the main driver.

Third, although scale efficiency shows a high level, we see the same returns to scale and diminishing returns to scale in most areas. In 2005, 2010, and 2017, the average value of scale efficiency of agricultural innovation to green development in China was 0.943, 0.962, and 0.880, respectively, which were higher than the average value of pure technical efficiency in the same period; except for Inner Mongolia, Jilin, and Yunnan in 2010, Tianjin and Qinghai in 2017, others show the characteristics of same returns to scale and diminishing returns to scale, which indicates that scaling up alone will fail to continually promote the efficiency of scale during the investigation period. Therefore, the focus of regional agricultural green development needs to shift from the 'heavy investment' to 'structural adjustment' in the future, and the allocation of agricultural innovation resources must be optimized continuously, with much attention channeled to the promotion and application of new agricultural technology in the green transformation of agricultural. This suggests that it is only when pure technical efficiency and scale efficiency are brought into full play that can they promote the continued improvement of green efficiency of China's agricultural innovation.

4.1.2 Spatial pattern of green efficiency of China's agricultural innovation

Using the Arc GIS10.2 software, the comprehensive efficiency of China's agricultural innovation to green development in 2005, 2010, and 2017 was divided between areas of high efficiency, relatively high efficiency, relatively low efficiency, and low efficiency through the Jenks Nature Breaks method (Fig. 2).

Fig. 2 indicates that the green efficiency of China's agricultural innovation has an obvious spatial variation where low efficiency and relatively low-efficiency areas move to central and southeast China. In 2005, high efficiency and relatively high-efficiency areas were mainly concentrated in the northwest, central, and east China and areas of low efficiency and relatively low efficiency were mainly distributed in mid-western China, especially in Gansu, Ningxia, and Shanxi. In 2010, high-efficiency areas expanded to Hunan, Yunnan, and Shaanxi, with Guangxi and Guangdong changing from high-efficiency areas to low-efficiency areas. The low-value areas of green efficiency of agricultural innovation show a tendency of moving to southeast China. In 2017, high-efficiency areas decreased sharply, and low-efficiency areas and relatively low-efficiency areas expanded rapidly to central and southeast China. Low efficiency and relatively low-efficiency areas, except for Hubei cover the central areas. The low-value areas of green efficiency of agricultural innovation show concentrated distribution in central and southeast China.

Central China has a large agricultural production scale but insufficient industry-university-research cooperation in the aspect of agriculture, thus resulting in

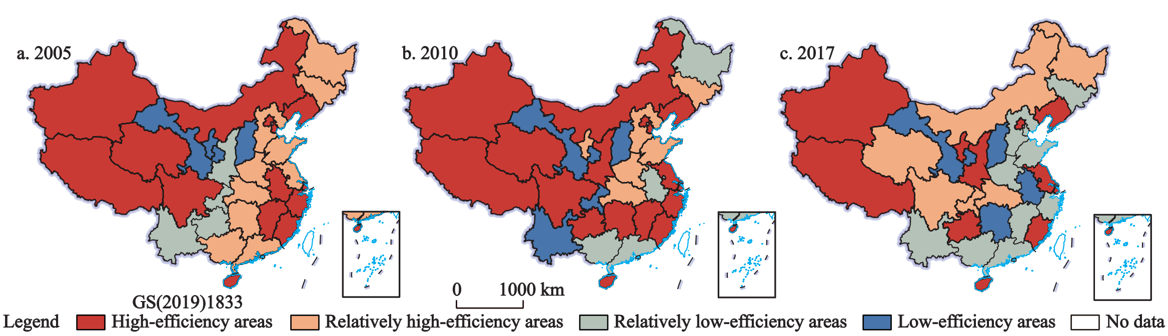

Fig. 2 Spatial differences in green efficiency of agricultural innovation in 2005 (a), 2010 (b), and 2017 (c)

low contributions of agricultural innovation to the green development of agriculture (Qin et al., 2017). During the years where the national agricultural innovation level was low, the green efficiency of agricultural innovation in central China was still at a medium-high level because of the huge agricultural economic output. However, with the transformation of traditional agriculture to green agriculture, this disadvantage has become more prominent. During the transformation to green agriculture, central China may experience a risk of 'locked low-end paths'; thus, steadily promoting the improvement of the green efficiency of agricultural innovation in China's large agricultural production provinces is vital for the transformation to green agriculture. In southeastern China, urbanization and industrialization levels are high, so urban and industrial development leaves few opportunities for agricultural development. Li et al. (2012) carried out research and found that the crop yield in southeastern China was on the decline; hence, its position of the 'land of fish and rice' was gradually replaced. Meanwhile, in southeastern China, technical research and development levels are high, a plethora of agricultural technology achievements have been made, and innovation input in agricultural green production in this region is redundant. Therefore, promoting the cross-regional transformation of agricultural innovation achievements can improve the entire green level of China's agriculture to some extent.

4.2 Vertical dynamics evaluation of green efficiency of agricultural innovation

To analyze the dynamic changes in the green efficiency of China's agricultural innovation from 2005–2017 more precisely, the Malmquist Total Factor Productivity Index was applied to resolve the change of green efficiency of agricultural innovation into the changes of technical progress, pure technical efficiency, and scale efficiency (Table 4). The calculation results have the following features:

First, technical progress is the main force affecting the green total factor productivity of agricultural innovation. From 2005 to 2010, the total factor productivity dropped by 0.6%, wherein technical progress dropped by 1.9%, pure technical efficiency increased by 1.0%, and scale efficiency increased by 0.4%, indicating that technical progress had the most impact on total factor productivity and determined the change direction of total factor productivity. From 2010 to 2017, the total factor productivity increased by 3.2%, wherein technical progress increased by 6.4%, pure technical efficiency dropped by 1.5%, scale efficiency dropped by 1.4%, indicating that technical progress still contributed the most to total factor productivity. In the three major zones, from 2005 to 2010, technical progress in eastern, central, and western China dropped by 2.0%, 1.4%, and 2.2%, pure technical efficiency increased by –0.2%, 0.2%, and 3%, and scale efficiency increased by 0.6%, 1%, and –0.3%. Total factor productivity dropped by 1.7% in eastern China and 0.2% in central China but increased by 0.4% in western China. From 2010 to 2017, technical progress in eastern, central, and western China increased by 7.6%, 7.0%, and 4.3%, pure technical efficiency dropped by 0.9%, 3.3%, and 0.6%, scale efficiency dropped by 2.3%, 1.6%, and 0.2%, and total factor productivity increased by 4.2%, 1.8%, and 3.4%. The above analysis reveals that technical progress is the most important factor affecting the change of total factor productivity, except from 2005–2010 when the impact of technical progress on the total factor productivity was a little lower than those of pure technical efficiency in western China. In terms of provinces, where technical progress contributed the most to total factor productivity, was 18 from 2005 to 2010, and 25 from 2010 to 2017, suggesting the pivotal role of technical progress in the growth of the green total factor productivity of agricultural innovation.

Second, total factor productivity, technical progress, pure technical efficiency, and scale efficiency all display stage characteristics, and decreasing pure technical efficiency and scale efficiency have gradually become key factors restricting the growth of total factor productivity. From 2005 to 2010, from the perspective of the average level of the country and the three major areas, technical progress indicated a downtrend; pure technical efficiency and scale efficiency display an increase, except with pure technical efficiency in eastern China and scale efficiency in western China. From the perspective of provinces, the number of provinces with decreased technical progress was 21, accounting for 67.7%. The number of provinces with increased pure technical efficiency and scale efficiency was 8 and 15 respectively, more than the number of areas with decreased pure technical efficiency (6) and scale efficiency (4). Within this period, the improvement of total

Table 4 Dynamic decomposition of green efficiency of China's agricultural innovation from 2005 to 2017

DUM	2005–2010				2010–2017			
	techch	*pech*	*sech*	*tfpch*	*techch*	*pech*	*sech*	*tfpch*
Beijing	0.826	1.000	1.000	0.826	1.000	1.000	1.000	1.000
Tianjing	0.940	1.000	1.000	0.940	1.189	0.915	1.000	1.088
Hebei	0.989	1.000	1.017	1.005	1.074	0.972	0.973	1.016
Shanxi	0.999	1.093	0.956	1.043	1.090	0.929	1.033	1.045
Inner Mongolia	1.001	0.994	1.015	1.010	1.104	0.982	0.998	1.081
Liaoning	0.999	1.000	1.000	0.999	1.083	1.000	1.000	1.083
Jilin	0.959	0.994	1.017	0.968	1.056	0.963	0.993	1.010
Heilongjiang	0.963	0.942	1.043	0.947	1.041	1.043	0.976	1.060
Shanghai	1.081	1.000	1.000	1.081	1.153	1.000	1.000	1.153
Jiangsu	0.979	1.000	1.039	1.017	1.042	1.000	0.985	1.026
Zhejiang	0.994	1.000	1.003	0.998	1.103	1.000	0.925	1.020
Anhui	0.997	0.984	1.003	0.984	1.066	0.938	0.972	0.972
Fujian	0.994	1.000	1.008	1.002	1.047	1.000	0.985	1.032
Jiangxi	0.958	0.993	1.000	0.952	1.061	0.924	0.999	0.979
Shandong	1.006	1.000	1.012	1.018	1.039	1.000	0.947	0.984
Henan	0.986	1.000	1.020	1.006	1.066	1.000	0.940	1.002
Hubei	1.008	1.004	1.016	1.028	1.080	1.000	0.965	1.042
Hunan	1.007	1.015	1.018	1.041	1.069	0.921	0.982	0.967
Guangdong	0.993	1.000	0.986	0.979	1.046	1.000	0.962	1.006
Guangxi	0.997	0.978	1.004	0.979	1.044	1.005	0.950	0.997
Hainan	0.956	1.000	1.000	0.956	1.097	1.000	1.000	1.097
Chongqing	0.998	0.995	0.978	0.971	1.073	1.014	1.014	1.103
Sichuan	1.008	1.000	1.000	1.008	1.018	1.000	0.969	0.986
Guizhou	1.001	1.061	1.021	1.084	1.038	1.000	1.000	1.038
Yunnan	0.994	1.003	1.000	0.996	1.035	1.002	0.998	1.034
Tibet	0.903	1.000	1.000	0.903	1.000	1.000	1.000	1.000
Shaanxi	1.009	1.051	1.000	1.061	1.036	1.000	0.992	1.028
Gansu	0.996	1.065	0.960	1.019	1.076	0.949	1.008	1.029
Qinghai	1.008	1.000	1.000	1.008	0.999	0.969	0.999	0.966
Ningxia	0.886	1.129	1.002	1.002	1.083	1.012	1.003	1.099
Xijiang	0.978	1.000	1.008	0.986	1.072	0.993	0.998	1.061
Average of the eastern	0.980	0.998	1.006	0.983	1.076	0.991	0.977	1.042
Average of the central	0.986	1.002	1.010	0.998	1.070	0.967	0.984	1.018
Average of the western	0.978	1.030	0.997	1.004	1.043	0.994	0.998	1.034
Average of whole country	0.981	1.010	1.004	0.994	1.064	0.985	0.986	1.032

Notes: DUM represent the area, *techch*, *pech*, *sech* and *tfpchf* represent the changes of technical progress, pure technical efficiency, scale efficiency and total factor productivity

factor productivity depended on the improvement of pure technical efficiency and scale efficiency. From 2010–2017, the technical progress of the country and three major areas appeared to be increasing, while pure technical efficiency and scale efficiency displayed a downtrend. From the perspective of provinces, the number of areas with increased technical progress was 28, accounting for 90.3%. The number of areas that reduced pure technical efficiency and scale efficiency was 11 and 20, far more than the number of areas with increased pure technical efficiency (5) and scale efficiency (4). Within this period, the improvement of total factor productivity depended on the improvement of technical progress, and decreasing pure technical efficiency and scale efficiency were the main cause restricting the growth of total factor productivity.

4.3 Influencing factors of the green efficiency of China's agricultural innovation

To further investigate the influencing factors of the green efficiency of agricultural innovation, the comprehensive efficiency obtained from the DEA analysis for 2005 to 2017 is taken as the dependent variable (Y), and X_1, X_2, X_3, X_4, X_5 and X_6 in Table 2 are taken as the independent variables to build a panel Tobit regression model. It is found through collinearity diagnostics that the VIF values of the whole variables and individual variables are less than 5, indicating that there is no obvious collinearity between the variables (Chen, 2014; Wang et al., 2016). The Tobit model is chosen to estimate the impact of each variable (Table 5).

According to Table 5, the regression coefficients of X_1, X_2, X_3, and X_5 are positive; that is, the level of regional informatization, regional agricultural technology promotion level, average education attainment of residents, and level of agricultural mechanization have positive impacts on the green efficiency of agricultural innovation. The level of regional informatization paves the way for the diffusion of agricultural scientific and technological achievements, which, in turn, helps agriculture operators to learn advanced agricultural technologies and improve the green efficiency of agricultural innovation. Agricultural technicians play a very important role in the absorption, publicity, and promotion of new agricultural technologies. They make up the cognitive gap between rural households and agricultural researchers (Klerkx et al., 2010), can help rural households absorb and utilize new agricultural technologies to improve rural households' innovation abilities, and further promote the improvement of green efficiency of regional agricultural innovation. Agriculture operators with a higher educational level can learn new agricultural technologies faster, and they will be more likely to apply new technologies to agricultural production to make agriculture develop in a greener way, thus improving the green efficiency of agricultural innovation. Whether new agricultural technologies are implemented depends on the agricultural foundation. The areas of higher levels of agricultural mechanization provide conditions for the implementation of new agricultural technologies and achievements, which can also effectively improve the green efficiency of agricultural innovation. More specifically, improving the green efficiency of agricultural innovation depends on the combination of agricultural innovation from generation to implementation. Only by steadily enhancing the 'capabilities' in each stage can agricultural innovation be made to better serve agricultural green development, and ultimately improve the green efficiency of agricultural innovation.

The regression coefficient of X_4 is negative, that is, the net income per capita of rural residents is negatively related to the green efficiency of agricultural innovation. Li et al. (2008) found that non-agricultural income accounts for a great proportion of Chinese farmers' income, and those rural residents with a higher net income often leave agricultural activities behind to engage in non-agricultural activities. Gao et al. (2015) also found that the income of migrant workers is generally higher than that of agriculture, thus compelling some farmers to abandon agricultural activities and seek non-agricultural activities to engage in. Under the special background of China's rural areas, the increase of the number of people engaged in non-agricultural activities might trigger actual investment in agricultural labor to be lower than the statistical input, which would not be conducive to the improvement of green efficiency of agricultural innovation. On the other hand, the regression coefficient of X_6 is positive but not significant, because financial support for agriculture is currently focused on

Table 5 Panel Tobit regression results of green efficiency of agricultural innovation

Variable	Regression coefficient	Standard error	Z value
X_1	$8.93\times10^{-5***}$	1.80×10^{-5}	4.97
X_2	$1.66\times10^{-3*}$	8.82×10^{-4}	1.88
X_3	$2.42\times10^{-2**}$	1.50×10^{-2}	2.12
X_4	$-1.84\times10^{-5***}$	5.20×10^{-6}	−3.54
X_5	$1.29\times10^{-2**}$	5.26×10^{-3}	2.49
X_6	0.184	0.115	1.60
Cons	0.544^{***}	0.148	3.67

Notes: *, ** and *** represent significance at confidence levels of 90%, 95% and 99%

casting off poverty and becoming prosperous, while the effect on the green efficiency of agricultural innovation is not fully exerted. Fang (2011) found that China's financial support for agriculture is mainly used for agricultural science and technology research and development, rural infrastructure construction and rural relief, and the financial support for farmers' technical training and agricultural technology promotion are very limited. Financial support for agriculture should focus on the promotion of agricultural innovation technology and the governance of the agricultural environment as the subsequent step.

5 Conclusions and Suggestions

Based on the perspective of technology transformation, this paper defines the connotation of the green efficiency of agricultural innovation and constructs a theoretical analysis framework and evaluation index system of the green efficiency of agricultural innovation. The DEA model and Malmquist index are applied to calculate the green efficiency of agricultural innovation in China's provinces (cities) from 2005 to 2017, and Tobit regression is used to analyze the influencing factors. The main conclusions are as follows: 1) the lateral state performance evaluation indicates that the overall green efficiency of China's agricultural innovation is low and that the efficiency level in most provinces is not optimal. The green efficiency of agricultural innovation in eastern China is mainly driven by pure technical efficiency, while in central and western China; it is mainly driven by scale efficiency. The green efficiency of agricultural innovation shows significant spatial differences, and low efficiency and relatively low-efficiency regions moved to central and southeast China. 2) the vertical dynamic performance evaluation indicates that the green total factor productivity of China's agricultural innovation, technical progress, pure technical efficiency, and scale efficiency all exhibit stage characteristics from 2005 to 2017; technical progress has always been the most important force that affects the green total factor productivity of agricultural innovation. The contribution of pure technical efficiency and scale efficiency to total factor productivity alternates from positive to negative, and have gradually become the main factors restricting the growth of total factor productivity. 3) the local level of informatization, the number of agricultural technicians in enterprises and institutions, average educational level of residents, and level of agricultural mechanization have positively impacted the promotion of green efficiency of agricultural innovation. This indicates that the improvement of green efficiency of agricultural innovation is closely related to the diffusion, absorption, and implementation of innovation, which is the result of the combined action of multiple stages. Therefore, skills training at multiple stages should be strengthened, as well as the transformation of innovation results, to allow agricultural innovation to better serve the development of green agriculture. The main contribution of this paper is to establish a theoretical analysis framework and evaluation index system of the green efficiency of agricultural innovation from the perspective of agricultural technology conversion innovatively, which will contribute to promoting the green transformation of agriculture in developing countries.

Based on the research results of the paper, several suggestions on green development of China's agricultural innovation were posited: First, ramp up agricultural technology training to improve rural households' innovation skills. Research indicates that a significant positive correlation exists between the literacy level of farmers and the green efficiency of agricultural innovation; however, in most regions, farmers' literacy level is not high, coupled with their prevalence of low skills to proactively learn new agricultural technologies and carry out agricultural innovation. Therefore, it is imperative and urgent to offer training on new agricultural technologies to farmers to elevate their innovation abilities. Second, construct an industry-university-research cooperation network and refine the agricultural innovation system. Agricultural innovation is a systematic process and involves many links. Research has proven the positive impacts of innovation diffusion, absorption, and implementation on the green efficiency of agricultural innovation. Therefore, we should keep polishing the agricultural innovation environment in agricultural areas, make more efforts to build the agricultural industry-university-research cooperation network, use the network as the carrier to promote the spread and feedback of agricultural information, and gradually form an agricultural innovation system featuring close contacts of subjects and promote innovation achievement transformation. Third, strengthen the cross-regional transformation of agricultural technology achievements. Research shows that innovation input in eastern China is redundant, with central China inundated with insufficient agricultural innovation capabilities. Therefore, we should strengthen the cross-regional flow of agricultural technologies and achievements to realize mutual complementarity of regions and accelerate the green transformation of agriculture in China.

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