frontiers | Frontiers in Environmental Science

ORIGINAL RESEARCH
published: 03 June 2022
doi: 10.3389/fenvs.2022.909321

RETRACTED: Efficiency Measurement and Spatial Spillover Effect of Green Agricultural Development in China

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Green agriculture is mainstream for the sustainable development of agriculture. Based on the Chinese provincial agriculture panel data from 2010 to 2019, we adopted the slack-based measure (SBM) super-efficiency model, sales force automation (SFA) model, and global malmquist–luenberger (GML) production index to measure the efficiency of agricultural green development (AGD). Moreover, Moran's I and spatial econometric model were applied to analyze factors influencing AGD. The threshold model was used to analyze the relationship between the scale of AGD and gross domestic product (GDP). The results show that **1)** Chinese green agricultural development efficiency is on a rising trend, reducing the impact of environmental factors and random interference on the AGD. 2) The analysis of AGD in the spatial effect showed a direct positive effect from agricultural mechanization, science and technology innovation, industrial agglomeration, income level, and environmental rule and a direct negative effect from agricultural yield structure, farmland pollution, and agricultural disasters. Furthermore, industrial structure optimization and environmental rule evoke a demonstration effect, but technical innovation, income level, and agricultural industrial agglomeration triggered a siphonic effect. 3) The threshold model was used to analyze the scale of AGD to realize sustainable development between agriculture and economy.

Keywords: sustainable development, agriculture's green efficiency, slack-based measure-global malmquist–luenberger, spatial spillover effect, threshold effect

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Specialty section:
This article was submitted to Environmental Economics and Management,
a section of the journal Frontiers in Environmental Science

Received: *31 March 2022*
Accepted: *12 April 2022*
Published: *03 June 2022*

Citation:
Xu P, Jin Z, Ye X and Wang C (2022) Efficiency Measurement and Spatial Spillover Effect of Green Agricultural Development in China. Front. Environ. Sci. 10:909321. doi: 10.3389/fenvs.2022.909321

HIGHLIGHTS

Research has focused on the level of agricultural sustainable development. The article first constructs an evaluation index system for the level of agricultural green development (AGD) from three dimensions to reduce the impact of environmental factors and random interference on the AGD and then we analyze the spatial spillover effect of factors influencing AGD. Moreover, the threshold model was used to describe the relationship between AGD and economic development. The results provide a reference for understanding the status of China's AGD and policy recommendations for realizing sustainable development between agriculture and economy.

1 INTRODUCTION

With increased financial support for agriculture, implementation of balanced urban and rural development, and promotion of rural revitalization, agriculture plays a central role in sustainable development (Adewuyi, 2016). In the 5th plenary session of the 18th Communist Party of China

(CPC) Central Committee, the concept of green agriculture development was proposed (Kanter et al., 2018); and China's Central Government in 2021 repeatedly stated that efforts should be made to build a demonstration county superior in the comprehensive governance of agricultural non-point source pollution and focus on the sustainable development of agriculture (Godfray et al., 2010). Chinese agriculture has since developed rapidly. For example, the mechanized cultivation of farm crops exceeded 65% (Li et al., 2019), the advance contribution rate in agricultural science and technology reached over 57%; and agriculture's total-factor contribution rate increased from a negative value to 60% (Stoll-Kleemann and Schmidt, 2017). However, the long-term extensive development of agriculture has increasingly resulted in ecological and environmental problems, including constraints on land and water resources and a degraded agricultural ecosystem (Firbank, 2020; Zhao et al., 2022a). Further improvement of efficient green agricultural development is critical for coordinating production, life, and ecology and realizing sustainable development (Azadi et al., 2015).

The efficiency of AGD is referred to as agricultural ecological efficiency. It can reflect the capacity of achieving maximal agricultural output while consuming minimal resources and causing minimal environmental impacts after various agricultural elements are used under specific output conditions. This is a significant indicator for the sustainable development capacity of green agriculture. Many scholars have investigated the green agriculture development indicator system. For example, Bergius et al. (2018); Zhao et al. (2022b) established relevant indicators from the perspective of economical utilization of resources, environment-friendly agriculture, stable ecological systems, and high efficiency of green supply based on the green agriculture development goal (Bergius et al. (2018)). Gagan et al. (2006) appraised the level of green agriculture development from the perspective of agricultural production, agricultural ecology, and economic development, without the use of an external environmental variable (Sharma et al., 2021). Typically, studies have used the entropy method (Vo and Le, 2021), analytic hierarchy process (AHP) (Chopra et al., 2022), comprehensive evaluation method (Chi et al., 2021a), and data envelopment analysis (DEA) (Chen et al., 2021a). Some studies have considered the external environment and used the data envelopment analysis-slack-based measure (DEA-SBM) model (Chen et al., 2022a), SBM-Undesirable model (Berk et al., 2020; Zhao et al., 2022c), and Geographic Markup Language-Geographic Information System (GML-GIS) (Guo et al., 2020a) to investigate the regional difference in Chinese green agriculture production efficiency and various influencing factors. The existing research has provided different evaluation methods for the efficiency of AGD, but the aforementioned research has three shortcomings. First and foremost, most of the existing literature focuses on evaluating regional or provincial AGD efficiency; it lacks relevant research on evaluating AGD from the perspective of national level. Second, the difference in measuring the efficiency of AGD among existing scientific literature should be considered not only as the output indicator but also as the external environmental variables. It makes the evaluation results more objective and accurate. Finally, there is lack of relevant research on the grounded theory to construct an analytical framework from three aspects: resource input, economic growth, and environmental impact.

Research on the spatial effect of influencing factors in AGD is necessary to quantitatively evaluate the current agricultural development level (Altarhouni et al., 2021). Previously, the main factors affecting green agriculture efficiency have been analyzed based on a grounded theory from various aspects, including resource investment, economic growth, and environmental influence (Liu et al., 2013). Some studies have also shown that green agriculture efficiency is subject to the impact of production factors (Hristov et al., 2020), industrial structure, scientific and technological level, income level, environmental rule, and other factors (Davies and Shen, 2020). By changing the farming structure and boosting the transfer of agricultural labor forces, agricultural mechanization could indirectly impact green agriculture efficiency (Ahmad et al., 2016; Zhao et al., 2022d). An inverted bell curve relationship could be observed between income level and green efficiency. Industrial structure, urbanization level, and environmental pollution have a negative impact (Shahbaz et al., 2018). Shahbaz et al. (2017) reported that urbanization would positively influence green agricultural production efficiency, while damaged crop area would cause a significant negative impact. Wei et al. (2018) applied the spatial error model to analyze various factors affecting green efficiency and found that agricultural industrial agglomeration, residential income level, and scientific and technological level would exert significant positive impacts on green agriculture development, while the impacts of urbanization were insignificant (Wei et al., 2018; Kanter et al., 2018). Through sorting and reviewing existing research, a theoretical model of factors influencing green agriculture efficiency is concluded and shown in **Figure 1**.

The marginal contributions of this study are as follows: 1) with external environmental variables, this study introduces the 3-stage SBM model and GML index to objectively measure the efficiency of AGD, avoiding the interference of environmental factors effectively. 2) Moran's I index and spatial econometric model were adopted to analyze various factors affecting AGD efficiency. Specifically, a direct positive effect from agricultural mechanization, science and technology innovation, industrial agglomeration, income level, and environmental rule and a direct negative effect from agricultural yield structure, farmland pollution, and agricultural disasters. 3) From the perspective of spatial spillover effect, technical innovation, income level, and agricultural industrial agglomeration have a negative spatial spillover effect, while industrial structure optimization and environmental rule have a positive spatial spillover effect. 4) Moreover, the threshold regression model is rarely used in the limited relevant literature. This study used the 2010–2019 panel data of 31 provinces to explore the relationship between ADG and economic growth based on the threshold regression model. Some meaningful results were discovered. For example, AGD has a significant threshold effect on the growth of the economy in a single-threshold effect. In the short term, AGD has a negative effect on the increase of GDP. However, when the green development scale exceeded the threshold value, AGD will promote high-quality economic development. Therefore, it is necessary to formulate AGD policies suitable for the characteristics of China. Among them, how to balance economic growth and

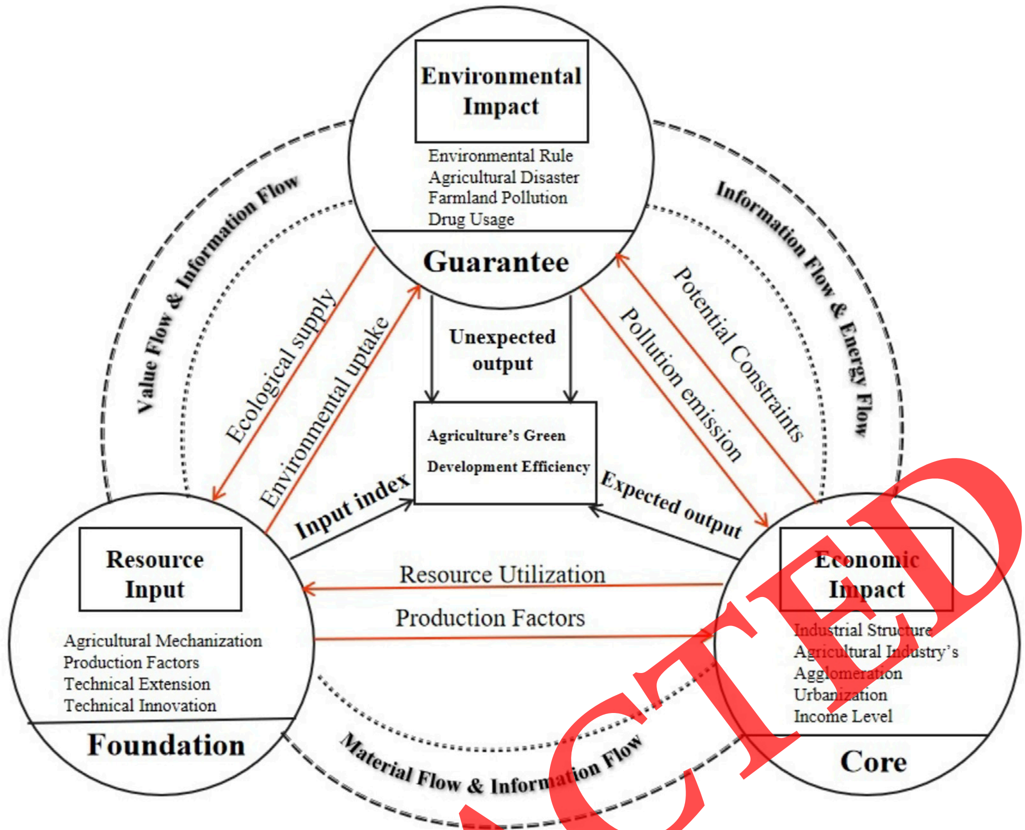

FIGURE 1 | Theoretical model of factors influencing green agriculture development.

agricultural sustainable development should be considered in the first place. Therefore, the government should fully consider the regional relevance of the efficiency of AGD and formulate comprehensive spatial planning for the agricultural sustainable development as a whole.

2 MEASUREMENT OF GREEN AGRICULTURE DEVELOPMENT EFFICIENCY

2.1 Selection of Indicators and Data Sources

According to the definition of the level of green agricultural development and that in previous studies, this study selected 17 indicators from three perspectives, namely, input indicators, output indicators, and the external environmental indicator for the level of green agricultural development in China (**Table 1**). All data were sourced from the *China Statistical Yearbook*, *China Statistical Yearbook on Environment, and China Rural Statistical Yearbook*. The panel data from 31 provinces (cities; districts) in China (excluding Taiwan, Hong Kong, and Macau) from 2010 to 2019 were used as the empirical research sample. SPSS 2.0, Stata14.0, and MAXDEA were adopted to complete the data processing.

Input indicators were taken from the study by Wei Qi et al. (2018) for the establishment of the green agricultural development assessment indicator system and selected based on the evaluation indicators adopted by the United Nations Environment Program (UNEP) and Organization for Economic Co-operation and Development (OECD) Wei et al. (2018). Output indicators were quoted from Guo et al. (2020b), including the desirable output and non-desirable output indicators (Zhang et al., 2022). The standardized pesticide usage, chemical fertilizer loss, and agricultural film usage amounts were multiplied with the corresponding weights. The sum was then calculated to determine the agricultural non-point source pollution (Guo et al., 2020c), and the agricultural carbon emission calculation formula was used according to the *PICC2006 Guidelines for National Greenhouse Gas Inventory*. The external environment indicator was based on the study by Ji Xueqiang (2021) (Liu et al., 2021), and various indicators were selected to set up the Chinese Green Agriculture Development Assessment Indicators System (**Table 1**), including agricultural modernization, public service system in rural areas, and farmer quality.

2.2 Efficiency Measurement Method

The green agriculture development efficiency is the premise to ensure the desirable output and inputs of agricultural elements, resource consumption, and undesirable outputs which need to be reduced as much as possible. By constructing the green

TABLE 1 | Green agriculture development assessment Indicator system.

Assessment stage	DEA indicator type	Assessment indicators	Unit	Variable	Source	Indicator nature
Stage 1	Input indicator	Agricultural labor force	Ten thousand	$i1$	Wei et al. (2018)	Input indicator
		Agricultural land area	1000 ha	$i2$	Wei et al. (2018)	Input indicator
		Total power of agricultural machinery	100 million kw	$i3$	Wei et al. (2018)	Input indicator
		Chemical fertilizer usage amount	Ten thousand tons	$i4$	Wei et al. (2018)	Input indicator
		Pesticide usage amount	Ten thousand tons	$i5$	Wei et al. (2018)	Input indicator
		Agricultural film usage amount	Ten thousand tons	$i6$	Wei et al. (2018)	Input indicator
	Output indicator	Gross output value of agriculture, forestry, animal husbandry, and fishery	100 million yuan	$o1$	Zhang et al. (2022)	Desirable output
		Agricultural carbon emission	Ten thousand tons	$o2$	Zhang et al. (2022)	Undesirable output
		Agricultural non-point source pollution index		$o3$	Guo et al. (2020c)	Undesirable output
	Agricultural modernization	National financial support in agriculture	100 million yuan	$a1$	Liu et al. (2021)	External environment
		Main agricultural machinery holding quantity at the end of the year	Ten thousand pieces	$a2$	Liu et al. (2021)	External environment
Stage 2	Public service system in rural areas	Township health center in rural areas	Unit	$r1$	Liu et al. (2021)	External environment
		Quantity of medical personnel	Person	$r2$	Liu et al. (2021)	External environment
		Quantity of elderly care institutions in rural areas	Unit	$r3$	Liu et al. (2021)	External environment
		Quantity of rural residents eligible for subsistence allowances	Ten thousand	$r4$	Liu et al. (2021)	External environment
	Farmer quality	Disposable income of rural residents	Yuan	$f1$	Liu et al. (2021)	External environment
		Average years of education of working population in rural areas	Years	$f2$	Liu et al. (2021)	External environment

agricultural development indicator system, applying the super-efficiency SBM model, adding the SFA model (the environment variable included), and the GML production function, the green agricultural development efficiency in three stages is measured.

2.2.1 Stage 1: Slack-Based Measure Super-efficiency Model

The SBM super-efficiency model takes the non-difference variable impact into consideration, and the optimal efficiency frontier is reached based on the minimal rate (Liu et al., 2021). This was carried out to reduce the impact of agricultural production chain inefficiencies, differentiate the feasibility of scale, and evaluate the rationality of resource allocation. The model is expressed as follows:

$$Min \quad h = \frac{1 + \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1 - \frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{s_r^-}{y_{rk}} + \sum_{t=1}^{q_2}\frac{s_i^{b-}}{b_{rk}}\right)},$$

$$s.t. \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j - s_i^- \le x_{ik},$$

$$\sum_{j=1, j\neq k}^{n} y_{rj}\lambda_j - s_r^+ \ge y_{rk},$$

$$\sum_{j=1, j\neq k}^{n} b_{tj}\lambda_j - s_t^{b-} \le b_{tk},$$

$$1 - \frac{1}{q_1+q_2}\left(\frac{\sum_{r=1}^{q_1} s_r^+}{y_{rk}} + \frac{\sum_{t=1}^{q_2} s_t^{b-}}{b_{rk}}\right) > 0,$$

$$\lambda, s^+, s^- \ge 0, \sum_{j=1}^{n}\lambda_j = 1. \quad (1)$$

In **Formula (1)**, s^+ and s^-, respectively, means the slack variable of the output and input, x_{ik} and y_{ik} are the input and output variable, h refers to the regional agricultural production efficiency, and the super-efficiency model means that the ranking comparison would be conducted when all decision-making units under k are valid to select all units greater than 1.

2.2.2 Stage 2: Sales Force Automation Model

The SFA model was established by referring to the study by Yu et al. (2020) to analyze the relationship between slack variables and newly added environmental variables in the first stage (Muscolo et al., 2021). Therefore, the estimated value of the corrected green agricultural production input could be calculated. The SFA model was expressed as follows:

$$s_{ni} = f^n\left(z_i, \beta^n\right) + v_{ni} + u_{ni}, \tag{2}$$

$$\hat{E}\left[v_{ni} | v_{ni} + u_{ni}\right] = s_{ni} - z_i \hat{\beta}^n - \hat{E}\left[u_{ni} | v_{ni}\right], \tag{3}$$

$$\hat{x}_{ni} = x_{ni} + \left\{\max\left[z_i, \hat{\beta}^n\right] - z_i \hat{\beta}^n\right\} + \left\{\max\left[\hat{v}_{ni}\right] - \hat{v}_{ni}\right\}, \tag{4}$$

where **Formula (2)** denotes the theoretical model relating to slack variables and environment variables; $f^n(z_i, \beta^n)$ was the slack frontier concluded on the first stage, namely, the optimal resource allocation; and $v_{ni} + u_{ni}$ was the mixed error. **Formula (3)** denotes the homozygous model by separating the random fluctuation; $\hat{E}[v_{ni}|v_{ni} + u_{ni}]$ was the estimated homozygous value. **Formula (4)** denotes the adjusted green agricultural development input variable, of which, $\{\max[z_i, \hat{\beta}^n] - z_i\hat{\beta}^n\}$ referred to the industry's internal operation status after adjustment and $\{\max[\hat{v}_{ni}] - \hat{v}_{ni}\}$ referred to the industry's external policy control after adjustment. The two items were the minimum value with consistent status.

2.2.3 Stage 3: The Slacks-Based Measure Model is the Framed Global Malmquist–Luenberger Production Function

Compared with the traditional total-factor productivity index method, the GML production function technology set included observation samples throughout all stages to avoid the possibility of unachievable solutions in linear planning, constructing the non-circumferential geometry, and resolving the transitivity problem existing in traditional production functions (Yu, 2020). The calculation formula is shown as follows:

$$GML = \frac{1 + \vec{D}^G\left(x^t, y^t, b^t, y^t, -b^t\right)}{1 + \vec{D}^G\left(x^{t+1}, y^{t+1}, b^{t+1}, y^t, -b^{t+1}\right)}. \tag{5}$$

$$GML = GEC \times GTC. \tag{6}$$

$$GPC_t^{t+1} = \frac{1 + \vec{D}_v^t\left(x^t, y^t, b^t, y^t, -b^t\right)}{1 + \vec{D}_v^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}, y^t, -b^{t+1}\right)}. \tag{7}$$

$$GEC_t^{t+1} = \frac{\frac{1+\vec{D}_c^G\left(x^t, y^t, b^t, y^t, -b^t\right)}{1+\vec{D}_v^G\left(x^t, y^t, b^t, y^t, -b^t\right)}}{\frac{1+\vec{D}_c^G\left(x^{t+1}, y^{t+1}, b^{t+1}, y^t, -b^{t+1}\right)}{1+\vec{D}_v^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}, y^t, -b^{t+1}\right)}}. \tag{8}$$

$$GTC_t^{t+1} = \frac{\frac{1+\vec{D}_c^G\left(x^t, y^t, b^t, y^t, -b^t\right)}{1+\vec{D}_v^{t+1}\left(x^t, y^t, b^t, y^t, -b^t\right)}}{\frac{1+\vec{D}_v^G\left(x^{t+1}, y^{t+1}, b^{t+1}, y^t, -b^{t+1}\right)}{1+\vec{D}_v^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}, y^t, -b^{t+1}\right)}}. \tag{9}$$

The global directional distance function $\vec{D}_0^G(x^\tau, y^\tau, b^\tau, -b^\tau) = \max\{\beta\colon (y^\tau, -b^\tau,) + \beta g^\tau \in P^G(x^\tau)\}$, GML, GEC, GPC, and GTC greater than 1, respectively, indicate the improvement of environmental total factor productivity, pure technical efficiency, scale efficiency, and technological progress. The current and GML productivity indexes are calculated and decomposed by the linear programming method, and the four directional distance functions are calculated.

2.3 Result and Analysis

2.3.1 Regional Green Agriculture Development Index

The Global-Malmquist–Luenberger (GML) production function estimation was made by resorting to the next stage. MAXDEA software was adopted by separating the technical advance and technical efficiency. The analysis was carried out based on relevant results concluded in 2019 (**Table 2**). (limited to the length of the article, the results of 2019 are selected for analysis)

Based on **Table 2**, the following conclusion was made: the green agricultural development indices were all greater than 1 in various regions, revealing that the specific regional level varied despite a rise in the overall green development of Chinese agriculture between 2010 and 2019. First, environmentally, the average value of CO_2 increased to 409.7872 million tons, which proved China's weakness in processing agricultural pollution, and the upgrading into modernized ecological agriculture was curbed. Second, technically, advance in technology was the general trend as various provinces took effective measures to restrict the production of high-pollution agricultural products, including the agricultural environment supervision and pollution governance in rural areas. In particular, Zhejiang, Jiangsu, and Shanghai provinces made greater progress. After the year 2014, a special effort was made to develop the Yangtze River Economic Belt into a demonstration belt for agricultural ecology; emphasis was placed on the innovation and development of agricultural sciences and technologies, and advanced technologies were the core forces driving the green agricultural transformation. Yet, slight progress in technology was found in Henan, Guangxi, and Hainan provinces with a value below 1.05. These provinces were weak in their infrastructures, and their agricultural industrial structure was relatively rough and single. As a result, the industrial transformation of green agriculture development driven by technology lagged.

2.3.2 Chinese Agricultural Environment Efficiency Assessment

In the second stage, the aforementioned slack variable calculation results were annually averaged into the explained variables, while environmental variables were regarded as explaining variables. The frontier software was then added to the SFA model for regression (**Table 3**).

The slack variables, LR test, and Walds test all passed the 1% significance testing with the model's variation approximate to 1 (**Table 3**). Namely, the technical inefficiency was included in the difference between the actual output of agricultural production and the frontier, proving the applicability of the established random frontier production function. Based on the original index system, the input variables were adjusted and introduced into the SBM super-efficiency model again by calculating the adjusted input variables. It was then possible to conclude Stage-3 of the Chinese green agriculture development index and environmental efficiency evaluation score. To clearly describe the spatial distribution of Chinese green agricultural production efficiency, the green agricultural production efficiency

TABLE 2 | GML index and its factorization of China's green agriculture development in 2019.

Provinces	GML	GEC	GTC	GPC	Provinces	GML	GEC	GTC	GPC
Beijing	1.00	1.00	1.00	1.00	Hubei	1.11	1.12	0.97	1.02
Tianjin	1.22	1.08	1.06	1.07	Hunan	0.40	0.39	1.02	1.00
Hebei	0.97	1.07	0.91	1.00	Guangdong	0.91	1.14	0.79	1.01
Shanxi	1.03	1.17	0.88	1.00	Guangxi	0.30	0.36	0.93	0.82
Inner Mongolia	1.05	1.03	1.06	0.96	Hainan	1.26	1.42	0.89	0.99
Liaoning	0.98	1.08	0.90	1.00	Chongqing	0.98	1.00	1.04	0.94
Jilin	0.86	0.96	0.90	1.00	Sichuan	1.00	1.00	1.00	1.00
Heilongjiang	1.42	1.53	1.12	0.82	Guizhou	1.26	1.01	1.00	1.24
Shanghai	1.00	1.00	1.00	1.00	Yunnan	1.32	1.00	1.32	1.00
Jiangsu	1.02	1.26	1.00	0.81	Tibet	1.10	1.06	1.28	0.81
Zhejiang	1.04	1.00	1.05	0.99	Shaanxi	1.02	1.00	1.01	1.01
Anhui	0.96	1.20	0.80	1.00	Gansu	0.99	0.92	1.18	0.91
Fujian	0.97	1.01	0.96	1.00	Qinghai	1.34	1.26	1.33	0.80
Jiangxi	0.98	0.88	1.11	1.00	Ningxia	1.09	1.05	1.06	0.98
Shandong	1.14	0.98	1.16	1.00	Xinjiang	1.08	1.05	1.06	0.97
Henan	0.81	0.82	0.99	0.99	Average Value	1.02	1.03	1.01	0.98

TABLE 3 | Results of SFA analysis.

Variables	$s^-(i_1)$	$s^-(i_2)$	$s^-(i_3)$	$s^-(i_4)$	$s^-(i_5)$
Cons tan t Term	56.768*** (5.14)	249.347*** (3.287)	122.613*** (1.921)	32.924*** (7.243)	116.900*** (1.625)
v	0.452*** (0.017)	−0.117*** (0.090)	−0.135*** (-0.087)	0.236*** (0.046)	−0.128*** (0.073)
u	−0.450*** (0.014)	0.080*** (0.064)	0.112** (0.074)	−0.485*** (0.048)	0.103*** (0.059)
n	0.937*** (0.033)	0.468*** (0.038)	0.240*** (0.016)	0.418*** (0.099)	0.234*** (0.014)
δ^2	311.70*** (4.571)	687.251** (10.539)	203.464** (3.121)	357.908*** (5.322)	154.933*** (2.366)
γ	1.000*** (0.016)	1.000*** (0.012)	1.000*** (0.031)	1.000*** (0.069)	1.000*** (0.032)
Log_likelihood	39.890	86.369	80.734	51.158	79.467
Wald	21.444***	66.693***	77.157***	43.622***	49.240***

****, **, and *, respectively, mean that the significance testing was successful with the significance at 0.01, 0.05, and 0.1; the standard error was indicated in the bracket.*

in various provinces was divided into five levels: high (0.5–1.0), relatively high (0.4–0.5), medium (0.3–0.4), moderately low (0.2–0.3) and low (0.0–0.2). Using ArcGIS 9.3, the spatial distribution of Chinese green agricultural development efficiency in 2010 and 2019 was mapped (**Figure 2**). In addition, variations in Chinese green agricultural development efficiency indices in the first and third stages from 2010 to 2019 were reflected (**Figure 3**). According to these figures, Chinese green agricultural development efficiency was enhanced; however, significant differences were found in various regions. Provinces achieving high efficiency were mainly located in the southeastern coastal areas, featuring high economic development levels, and the western provinces, while low-efficiency provinces were found in the northern China plain, roughly increasing from central south China and north China.

Table 4 showed the environment efficiency score and green development indices after the agricultural production was adjusted in 2019, and the following conclusions were drawn. First, the overall efficiency scores indicated that the environment efficiency score in the third stage after adjustment was lower than that in the first stage, and the external environment severely influenced the agricultural production efficiency. Second, the environmental efficiency in the third stage was rising overall but then stagnated and declined between 2013 and 2016. As traditional agriculture was extensive, the increase in the earlier stage was attributed to the input of agricultural chemicals; after 2017, attention was paid to save resources and establish a demonstration area for ecological civilization. As a result, the green agricultural development efficiency largely increased; however, the efficiency did not achieve the frontier in 2019. Therefore, special effort was required to improve the upper legislation and system for green agricultural development. Third, the average value of the development efficiency in Fujian, Beijing, Shanghai, Zhejiang, Guangxi, and Gansu provinces sharply declined during the third stage, indicating that these provinces/cities benefited from favorable external environmental advantages, including the higher level of economy and human capital, strong government policy support for agriculture and farmers, subsidies granted to agricultural mechanization, and the establishment of demonstration area for ecological civilization.

3 ANALYSIS OF THE SPATIAL EFFECT OF AGRICULTURE'S GREEN DEVELOPMENT EFFICIENCY

Based on the measurement of Chinese green agricultural efficiency, further analysis would be made on its distribution pattern and spatial effect of efficiency to thoroughly identify key factors influencing the efficiency.

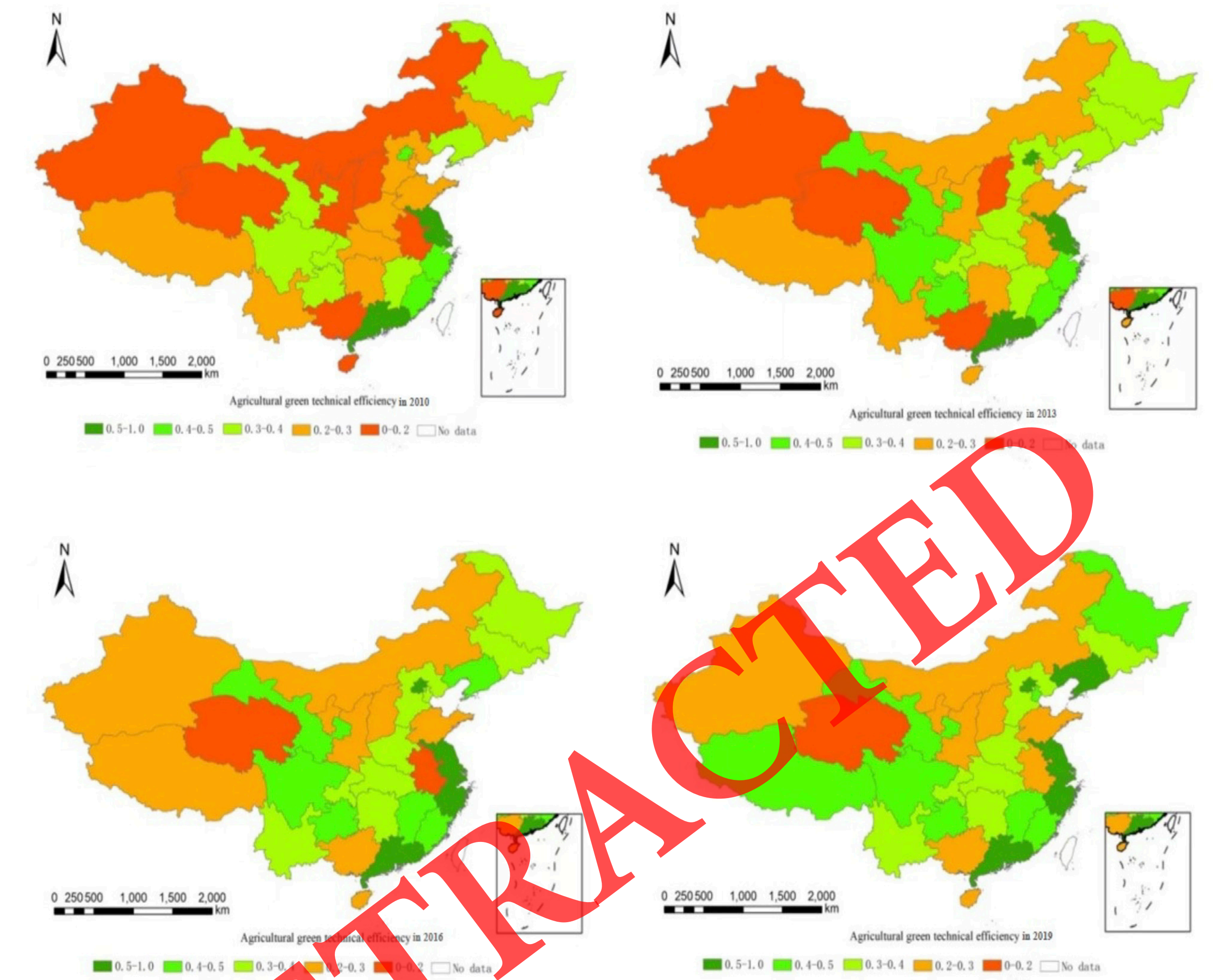

FIGURE 2 | Spatial distribution of the agricultural green development index (AGDI) in crucial years in China.

3.1 Spatial Econometric Model

The Moran's I was applied to conduct the spatial correlation test for Chinese green agricultural efficiency. The result showed that Moran's I value fluctuated between 0.149 and 0.025 and proved an obvious spatial correlation existing in regional efficiency. At present, scholars have frequently applied the SEM, SDM, and SLM (Yu, 2020; Chi et al., 2021b). To perform the robustness test, geographic characteristics and economic characteristics were introduced and three spatial weight matrices were selected to achieve a better analysis.

$$\text{The SDM}: Y = \rho WY + X\beta + WX\gamma + \delta. \tag{10}$$

$$\text{The SLM}: Y = \rho WY + X\beta + \phi. \tag{11}$$

$$\text{The SEM}: Y = X\beta + \theta W\varepsilon + \mu. \tag{12}$$

In **Formulae (10)**, **(11)**, and **(12)**, Y means the agriculture's green efficiency in the region i during the period t; W was the spatial weight matrix; X means the independent variable vector in the region i during the period t; β was the parameter vector pending for estimation; ρ was the spatial autoregressive coefficient; γ was the spatial lag explaining variable's coefficient; and $\varepsilon, \phi, \delta, \mu$ were random disturbances.

The spatial weight matrix with geographic characteristics included the adjacency and distance spatial weight matrixes as shown in **Formula (13)** and **Formula (14)**:

$$W_{ij}^{01} = \begin{cases} 1, \text{province i adjacent to province j}\,{}_{(i\neq j)} \\ 0, \text{otherwise}\,{}^{(i=j)} \end{cases}. \tag{13}$$

$$W_{ij}^{d} = e^{-adij} \tag{14}$$

i and j refer to geographic units and d_{ij} the geographic distance between i and j. The Euclidean distance between provincial capitals was adopted for measurement. α was the reciprocal of the shortest distance between provincial capitals, which was used to eliminate the impact of the distance measurement unit on the estimated result.

The spatial weight matrix, with geographic characteristics, was used to analyze the spatial relationship using the economy and

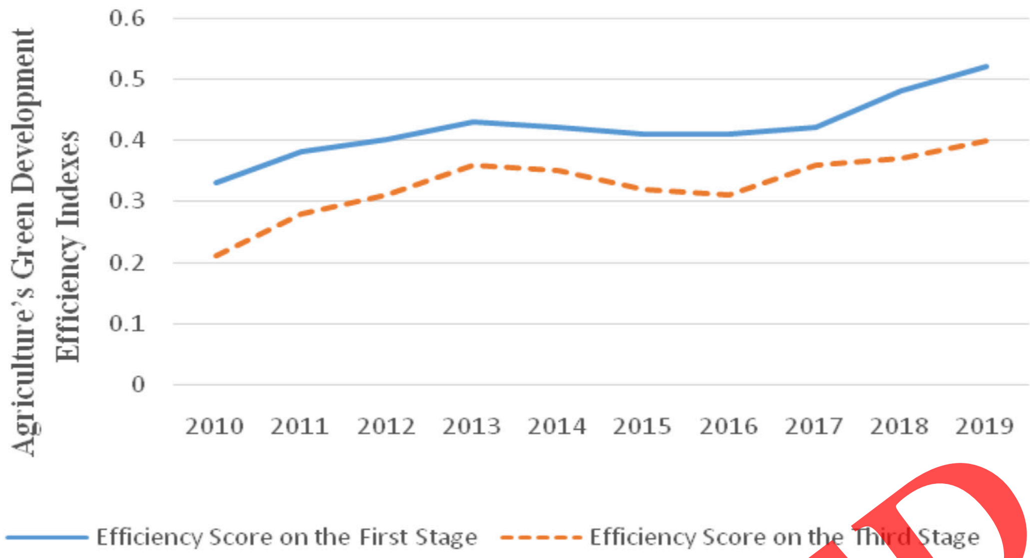

FIGURE 3 | Indexes of Chinese agricultural green development efficiency from 2010 to 2019.

TABLE 4 | Comparison of the three-stage in 2019.

Provinces	Efficiency index in the first stage	Efficiency index on the third stage	Adjusted GML index	Provinces	Efficiency index in the first stage	Efficiency index on the third stage	Adjusted GML index
Beijing	1.02	0.54	0.53	Hubei	0.39	0.33	0.87
Tianjin	0.40	0.33	1.01	Hunan	0.65	0.32	0.54
Hebei	0.35	0.35	0.97	Guangdong	0.51	0.54	0.90
Shanxi	0.29	0.23	0.82	Guangxi	0.96	0.25	0.27
Inner Mongolia	0.37	0.29	0.82	Hainan	0.53	0.29	0.59
Liaoning	0.63	0.57	0.89	Chongqing	0.56	0.40	0.74
Jilin	0.28	0.36	1.11	Sichuan	0.83	0.48	0.70
Heilongjiang	0.47	0.42	1.27	Guizhou	0.42	0.47	1.26
Shanghai	1.04	0.53	0.51	Yunnan	0.32	0.34	1.28
Jiangsu	0.52	0.80	1.57	Tibet	0.50	0.42	0.88
Zhejiang	1.00	0.62	0.64	Shaanxi	0.33	0.25	0.80
Anhui	0.30	0.25	0.80	Gansu	0.70	0.47	0.96
Fujian	1.02	0.48	0.46	Qinghai	0.31	0.13	0.47
Jiangxi	0.45	0.46	1.00	Ningxia	0.37	0.24	0.71
Shandong	0.46	0.29	0.72	Xinjiang	0.41	0.21	0.55
Henan	0.50	0.37	0.76	Average Value	0.52	0.40	0.86

geography nested matrices (Chi et al., 2021b). The economic space weight matrix and the resource space weight matrix are expressed in **Formula (15)**:

$$W_{ij}^{e} = W_{ij}^{d} diag\left(\bar{Y}_1/\bar{Y}, \bar{Y}/\bar{Y}_2 \ldots \bar{Y}_n/\bar{Y}\right), \tag{15}$$

of which, $\bar{Y}_i$ was the average GDP of the province i between 2009 and 2019; $\bar{Y}$ was the average GDP of all regions.

3.2 Selection of Variables

By referring to the practice of Ren et al. (2021) and Chi et al. (2021a), agricultural resource inputs mainly included agricultural mechanization (*mech*), production factors (*fact*), technical extension (*exte*), and technological innovation (*tech*) Chi et al. (2021a); Ren and Yu (2021); **Table 5**. First, the value of various factors was subject to the Min–Max standardization; then, the production factor variable data were identified through totaling and summation. Based on the research made by Wang et al. (2021a), the number of agricultural patents was used to embody the technological innovation; for the technical extension, expenditure and the number of trainees were selected to depict the level of green agricultural technical extension Wang et al. (2021a). According to Guo et al. (2020a), various economic factors affecting the efficiency mainly included industrial structure (*stru*), economic development (*econ*), agricultural industrial agglomeration (*idl*), income level (*inco*), and urbanization (*urban*) Guo et al., (2020a). In fact, agricultural industrial agglomeration provoked the scale economy effect (Deng et al., 2022). The improvement of labor

TABLE 5 | Variable description and descriptive statistical results.

Primary indicators	Secondary indicators	Variable symbol	Calculation method	Source	Average value	Standard difference
Explained variable	Agriculture's green efficiency	*effi*	The agriculture's green efficiency was measured previously	(Guo et al., 2020b; Wang et al., 2021a; Chi et al., 2021b; Ren and Yu, 2021)	0.860	0.197
	Agricultural mechanization	*mech*	Total power of agricultural machinery (100 million kw)	(Guo et al., 2020b; Wang et al., 2021a; Chi et al., 2021b; Ren and Yu, 2021)	0.807	0.619
	Production factors	*fact*	Sum of the standardized value of seeded area, labor, offspring, and intermediate consumption	(Cui et al., 2019; Zhang and Chen, 2021; Deng et al., 2022)	0.713	0.181
Resource input	Technical extension	*exte*	Sum of the standardized value of the number of agricultural trainees and the technical extension expenditure	(Cui et al., 2019; Zhang and Chen, 2021; Deng et al., 2022)	0.914	1.072
	Technical innovation	*tech*	The number of patents related to agriculture (100)	(Cui et al., 2019; Zhang and Chen, 2021; Deng et al., 2022)	4.031	0.374
	Industrial structure	*stru*	The proportion of increases in regional 2nd industry and 3rd industry in GDP	(Feng et al., 2021; Zhang and Chen, 2021; Chen et al., 2022a)	0.829	0.344
Economic impact	Agricultural industry's agglomeration	*idl*	The proportion of the number of agricultural employees in the total quantity of employees	(Feng et al., 2021; Zhang and Chen, 2021; Chen et al., 2022a)	0.296	0.493
	Urbanization	*urban*	The permanent population's urbanization rate	(Feng et al., 2021; Zhang and Chen, 2021; Chen et al., 2022a)	0.527	0.128
	Income level	*inco*	The disposable income of rural residents (ten thousand yuan)	(Feng et al., 2021; Zhang and Chen, 2021; Chen et al., 2022a)	2.631	0.805
Environmental Impact	Environmental rule	*rule*	The quantity of environment-friendly agricultural policies	Chen et al. (2022a)	3.821	0.596
	Agricultural disaster	*disa*	The proportion of crops damaged areas in the total seeded areas	Chen et al. (2022a)	0.103	1.569
	Farmland pollution	*poll*	Comprehensive value calculated from chemical fertilizer, pesticide, and agricultural film used per unit crop area	Chen et al. (2022a)	0.322	0.159
	Drug usage	*drug*	Weight of crops damage areas in the total seeded areas	Chen et al. (2022a)	0.417	0.752

productivity was conducive to the enhancement of the production efficiency (Cui et al., 2019); urbanization was beneficial to attracting the high-level talents, accelerating agricultural industrial agglomeration and promoting innovation in green technology (Zhang and Chen, 2021; Chen et al., 2021b). The main environmental factors affecting the efficiency included farmland pollution (*poll*), environmental rule (*rule*), drug usage (*drug*), and agricultural disaster (*disa*) (Feng et al., 2021). Substantially, command and control rules predominated in regulating the environment (Chen et al., 2022b). The number of environmental protection policies related to agriculture executed by various provinces at the end of each year was added up and then subject to logarithmic analysis.

3.3 Spatial Spillover Effect

The Hausman test shows that explaining variables were not endogenous. Stata14.0 software was used to estimate the SLM, SEM, and SDM simultaneously (Guo et al., 2020c; Guo et al., 2020b; Chen et al., 2022a; Zhang et al., 2022); using three spatial weight matrices (adjacency, distance, and economy), analysis was made on factors influencing the efficiency and spatial spillover effect (**Table 6**).

The fitting result showed that the space autoregression coefficient ρ was significant in the SEM under the adjacency space weight matrix and resource space weight matrix and in the SDM under the adjacency space weight matrix. By combining the test of goodness of fit (R^2) and log likelihood, this study selected the SDM estimation result under the adjacency space weight matrix for further analysis. The model space autoregression coefficient was 0.1898 and the 5% significance test was successful, which indicated that a significant correlation was present between the green agricultural efficiency and space.

3.3.1 Resource Input

The agricultural mechanization and green technology extension had a positive impact on efficiency. The agricultural mechanization promoted the traditional labor to be replaced by agricultural machines, mitigating the risks of missing the season caused by labor shortage, improving the low agricultural efficiency, boosting the reallocation of agricultural factors and resources, and driving Chinese agricultural development in an economical way. In addition, advanced agricultural production

TABLE 6 | Model comparison estimation results of SLM, SEM, and SDM.

Variable	Adjacency spatial matrix			Distance spatial matrix			Economy spatial matrix		
	SLM	SEM	SDM	SLM	SEM	SDM	SLM	SEM	SDM
mech	0.2310***	0.0211***	0.0238***	0.0228***	0.0217***	0.0219***	0.0229***	0.0248***	0.0269***
fact	0.0518	0.1491	0.0034	0.0316	0.1019	0.2104	0.0322	0.1159	0.1299
exte	0.0349	0.0213	0.1064**	0.0412	0.0391	0.0572	0.0423	0.0419	0.0871**
tech	−0.1745	−0.3102	−0.0059	−0.2119	−0.2312	−0.0169	−0.2310	−0.2698	5.7214
stru	0.2917	0.4763**	0.1152	0.2664	0.4469**	0.0490	0.3138	0.4057*	2.2140***
idl	1.2461***	1.2156***	1.2334***	1.2307***	1.2061***	1.2498***	1.3947***	1.7022***	1.4290***
inco	0.4911**	0.4420**	2.1536***	0.5491***	0.4627**	2.6910***	0.5493***	0.4529**	2.2301***
rule	0.1229	0.1238	0.1316	0.1267	0.1303	0.1412	0.1269	0.1346	0.1411
disa	−0.0273	−0.0246	−0.0338*	−0.0271	−0.0266	−0.0337**	−0.0268	−0.0274	−0.0331**
poll	−0.1572	−0.0699	−0.2910**	−0.1763	−0.0726	−0.4572***	−0.1851	−0.0728	−0.3044**
drug	−0.0332	−0.0314	−0.0387	−0.0328	−0.0305	−0.0321	−0.0337	−0.0297	−0.0369
ρ	0.0511	0.2714***	0.1898**	−0.0074	0.2016	0.0648	−0.0189	0.2154	0.1344
R^2	0.4528	0.4476	0.6433	0.4601	0.4537	0.7215	0.4681	0.4377	0.6341
Log_ likelihood	57.5863	60.5422	74.8293	57.3370	58.4551	76.3361	57.4298	57.9810	79.8853

technologies increased the desirable output, reduced undesirable output, and realized the improvement of green agricultural efficiency.

3.3.2 Economic Growth

Agricultural industrial agglomeration and income level had a significantly positive impact on the efficiency in this region. From the perspective of agglomeration economy, the scale economics effect brought down the production cost, input of factors, and energies. The agglomeration of talents and industries stimulated the knowledge effect which effectively promoted agricultural research and development; new equipment application, production, and circulation; and the rise in the development efficiency. The higher income level triggered the consumer's demand for high-quality agricultural products and expedited the agricultural conversion and upgrading into the resource-saving and environment-friendly model. The yield structure exerted a significantly negative impact on the efficiency in this region. As the current agricultural yield structure was not reasonable and was largely restricted by the unfavorable environmental resources with weak abilities to mitigate risks, the unbalanced yield structure resulted in the decline of efficiency. Unfortunately, this was exacerbated by an excessively large proportion of the planting industry, a small proportion of animal husbandry and deep grain processing, and worsened water pollution caused by aquaculture.

3.3.3 Environmental Impact

The agricultural disaster and farmland pollution exerted a significantly negative influence on the efficiency. A disaster in any form would trigger decline in desirable output, and farmland pollution would compromise the agriculture product yield, quality, and damage to the efficiency. Stronger carbon sequestration ability would stimulate higher desirable output, and environmental rules could increase efficiency.

While various factors affected efficiency in this region, their action was transferred to adjacent regions by means of the spatial spillover mechanism involving the flow of factors, technology spillover, and policy spillover. A significant spatial spillover effect (triggered by technical extension, income level, industrial structure, environmental rule, and agricultural industry's agglomeration) affected the efficiency by using the partial differential effect decomposition method (**Table 7**). First, optimization of industrial structure and the environmental rule would stimulate a demonstration effect. As the advanced planting, processing, and service technology would penetrate the surrounding areas, the technology spillover mechanism could be applied to improve the efficiency in surrounding areas; the region's yield structure optimization policy could set an example for surrounding areas; various agricultural enterprises would be guided to initiate material optimization and equipment upgrading based on the policy spillover mechanism. Eventually, green development was realized. Second, technical innovation, income level, and agricultural industry's agglomeration would form the siphonic effect. Specifically, the input of science and technology funds could create a favorable environment for scientific research; a higher level of income and industrial agglomeration would encourage the consumption market's expansion, pose diversified employment and investment opportunities, and attract various production factors in surrounding areas including capital, talents, technology, and equipment; in this way, the factor flow mechanism could enable the balanced flow of resources involved in the agriculture's green development in surrounding areas.

4 OPTIMAL SCALE FOR GREEN AGRICULTURE DEVELOPMENT

Based on the earlier analysis, further effort was made to explore the impact of green agricultural development on economic growth. By setting the green agricultural development index as the threshold variable, it was possible to determine the optimal scale (Liu et al., 2021). The model can be expressed as follows:

$$A_{i,t} = \alpha + \beta_1 Y_{i,t} + \beta_2 GML_{i,t} + \beta_3 GML_{i,t} l(q_{i,t} \le \rho) + \beta_4 GML_{i,t} l(q_{i,t} > \rho) + \gamma X + \varepsilon, \quad (16)$$

TABLE 7 | Spatial effect of Chinese agricultural green development.

Variables	Direct effect		Spatial spillover effect		Gross effect	
	Elastic coefficients	t value	Elastic coefficients	t value	Elastic coefficients	t value
mech	0.0312	0.83	−0.0131	−0.43	−0.3823	−1.07
fact	−0.0284	−0.17	−0.0116	−0.14	0.0182	0.16
exte	0.2053**	2.11	−0.0449	0.46	0.0611	0.51
tech	−0.0519	−1.07	−0.6738**	−1.98	−0.6373**	−2.01
stru	−2.2416***	−4.12	2.0811***	2.97	−0.1698	−1.19
idl	0.0629	0.26	−0.6687*	−1.72	-0.5894	1.61
inco	2.0911***	3.81	−1.5012**	−2.44	0.5811	1.54
rule	0.3128	2.53	1.4981**	2.06	0.5216*	1.89
disa	−0.0305	−1.37	0.0318	1.10	0.0049	0.12
poll	0.2891**	2.04	0.2013	1.02	0.0614	0.52
drug	0.0258***	3.51	0.0003	0.05	0.0029	0.17

TABLE 8 | Threshold effect test.

Threshold's quantity	Threshold value	95% confidence interval	RSS	MSE	F Value	*p* Value	Critical value		
							10%	5%	1%
Single threshold	0.7300	[0.7100,0.7400]	23.3508	0.2595	15.2500	0.0600	12.5190	15.5560	19.0966
Dual threshold	0.5400	[0.5200,0.5500]	19.6981	0.2189	16.6900	0.0300	11.6257	14.3915	19.2254
Triple threshold	0.4700	[0.4600,0.5000]	18.3690	0.2041	6.5100	0.6567	20.9585	25.8419	41.1538

of which, $A_{i,t}$ was the first industry's increase rate in this region; $Y_{i,t}$ was the regional GDP increase rate; $GML_{i,t}$ was the agriculture's green development index; X was the controlling variable, including the resident's disposable income (X_1) and the region's consumption level (X_2). $q_{i,t}$ was the threshold variable, $l(.)$ the indicative function, β_1 the coefficient of various evaluation indicators, ρ the threshold value, α the constant term, and ε the random error. First, the model's Hausman test coefficient was 67.215, and the calculation result was within the rejection region, based on which, the conclusion could be drawn that a fixed effect existed in the panel model. The bootstrap method could be applied to verify the number of thresholds between agriculture's green development scale and economic growth.

The threshold value under the single-threshold model was 0.7300, and the confidence interval was 0.7100–0.7400 when the significance level achieved 95% (**Table 8**). The threshold value under the dual-threshold model was 0.5400, and the confidence interval was 0.5200–0.5500 when the significance level achieved 95%. The single-threshold model and the dual-threshold model, respectively, passed the 5% and 10% significance level test. According to the linear distribution of estimated results under the single-threshold model and the dual-threshold model (**Figure 4**), the estimation interval of the single-threshold model was narrower than that of the dual-threshold model, indicating that the estimated single-threshold value was precise. In the short term, the green agricultural development hindered the increase in the industry's added value and contained the overall agricultural development. However, in the long term, when the green development scale exceeded the threshold value of 0.7300, sustainable agricultural development was feasible despite the limitation in the capacity of ecological environment and resource carrying capacity. The economy's high-quality development could, therefore, be materialized.

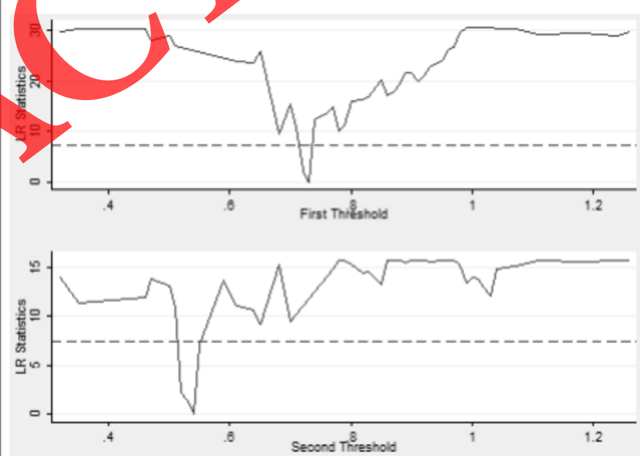

FIGURE 4 | Confidence interval diagram of the dual-threshold model.

5 CONCLUSION AND RECOMMENDATIONS

In this study, the GML production function with the 3-stage SBM model was used as the framework to measure the green agricultural development efficiency, and the spatial econometric model was adopted to analyze various factors affecting the green agricultural development and spatial spillover effect. The threshold model was involved in determining the relationship between the green agricultural development scale and economic growth. Therefore, the following conclusions were drawn. First, Chinese green agricultural development efficiency was on a rise, and the development efficiency was higher than that in reality; owing to external environmental impacts, it is necessary to improve the upper legislation and system suggested for the protection of ecological resources and sustainable development of agriculture, expand the green agricultural development scale, promote the coordinated development of agricultural sustainability, and maintain the high-quality economy after crossing the threshold value. Second, effort was made to analyze the spatial effect triggered by the efficiency and revealed key factors that influenced the green agricultural development. A direct positive effect was triggered by agricultural mechanization, green technology extension, agricultural industrial agglomeration, residential income level, and environmental rule. A direct negative effect was triggered by agricultural yield structure, farmland pollution, and agricultural disaster. The industrial structural optimization and the environmental rule generated a demonstration effect, and technical innovation, income level, and agricultural industrial agglomeration formed the siphonic effect. Third, considering that the environmental rule would exert a positive impact on the efficiency and provoke a demonstration effect, the central government should act more vigorously to publish and implement relevant environmental policies.

Therefore, based on the aforementioned research conclusions, we can draw the following policy enlightenment: First, it needs to cultivate agricultural industrialization construction demonstration areas and make full use of resource space in view of the positive spillover effect from the output structure on agricultural green efficiency. The government also needs to actively promote modern green agricultural production methods, optimize the agricultural structure, and reduce the use frequency of pesticides. Only in this way can we promote the development of energy conservation, efficiency of resource utilization, and emission reduction to a higher level (Shuang et al., 2021). Second, governments need to build an agricultural technology platform of communication in view of the negative spillover effect of agricultural science and technology and income level, and the local government should actively cooperate with university research institutions to solve the scientific and technological problems. Governments need to increase the investment in scientific research and technological invention funds in areas with relatively weak agricultural science (Wang et al., 2021b). With the local government strengthening the human capital to promote the transformation of agricultural scientific and technological achievements, it will drive the core areas of green agriculture to achieve large-scale development and promote the improvement of agricultural green efficiency in the surrounding. Third, with the introduction of high-level talents, through a series of preferential policies and continuously optimizing the structure of agricultural talents, it will develop new agricultural varieties with a high carbon sequestration rate, stimulate agricultural ecological dividends, and optimize the trading platform to promote high-quality economic development.

Due to the short time of putting forward AGD, most regions are still in the exploratory stage, and the research results are not sufficient. In the future, we can try to use the nonlinear model to research the impact of factors on AGD. Furthermore, the study only gives the spatial spillover effect of some factors on AGD. How to accurately identify other influencing factors and possibly other mechanisms needs to be studied further.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: http://www.stats.gov.cn/tjsj/ndsj/.

AUTHOR CONTRIBUTIONS

PX: conceptualization, methodology, formal analysis, data management, writing—original draft, and writing—review and editing; ZJ: conceptualization and supervision; XY: writing—original draft and writing—review and editing; CW: conceptualization, methodology, formal analysis, and data management.

FUNDING

This work has been financially supported by the Philosophy and Social Science Program Youth Project in Anhui Province of China, "Research on the mechanism and policy of environmental rule and green development's efficiency promoting the High-quality Development of Economy in Anhui" (No: AHSKQ 2021D177).

ACKNOWLEDGMENTS

The author is grateful to the editor and anonymous reviewers for their insightful and helpful comments.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.