

Does economic agglomeration improve agricultural green total factor productivity? Evidence from China's Yangtze river delta

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Abstract

Economic agglomeration plays an important role in China's social transformation process of industry feeding agriculture and urban supporting rural areas, and is one of the core weapons to promote agricultural economic growth and green and efficient development. Based on panel data of 41 cities in the Yangtze River Delta (YRD) from 2010 to 2020, this paper constructs an "environment-resource-energy-economy" agricultural input-output system, taking into account carbon emissions and surface pollution, and provides a more comprehensive accounting of agricultural green total factor productivity (AGTFP), the non-linear effects of economic agglomeration on AGTFP and shock responses were empirically analyzed using a panel threshold model and a panel vector autoregression (VAR), respectively. The findings show that: (1) during the period 2010–2020, the AGTFP in the YRD showed an overall rising trend with regional spatial agglomeration characteristics. (2) Economic agglomeration has a triple threshold effect on AGTFP, which was a weak facilitative effect in the early stage, inhibited by the siphoning effect of resource loss and arable land fragmentation in the growth stage, promoted by the radiation effect of external increasing return to scale in the form of sharing, matching and learning in the maturity stage, and finally tends to decline. (3) The shock response of economic agglomeration to AGTFP showed a continuous positive shock, peaking in the first period and then gradually converging to zero. (4)

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The heterogeneity analysis demonstrated that economic agglomeration has a considerable impact on boosting AGTFP in non-metropolitan areas and cities on the outskirts of YRD. In the future, China should effectively play a positive role in economic agglomeration on AGTFP and enhance the mutual coordination of economic agglomeration and agricultural green development in the process of urban cluster economic growth.

Keywords

Economic agglomeration, agriculture green total factor productivity, threshold effect, impulse response analysis, Yangtze river delta

Introduction

One of the major concerns for agricultural economic growth has been the topic of green development in agriculture.¹ Since the Green Revolution (GR), global agricultural yields and per capita food have grown substantially, especially in developing countries, where food production has achieved extraordinary growth, hunger and malnutrition have been effectively alleviated. However, its limitations have gradually been exposed: the high level of fertilizer and pesticide application brought about by GR has seriously damaged the ecological environment.^{2,3} In the 40 years since reform and opening up, China's rural and agricultural economies have witnessed profound transformations, with the primary sector's real value-added expanding at an average annual rate of 4.3% from 1978 to 2020. The percentage of employed employees in the primary sector declined from 70.5% in 1978 to 23.6% in 2020, as agriculture labor productivity and agricultural automation rates both increased rapidly.⁴ This signifies that Chinese agriculture's overall factor productivity has increased significantly. However, this shift was the result of China's long-term reliance on factor drive, which has been compounded by resource, energy, and environmental limits, putting pressure on long-term agricultural development. As a result, the environment was extensively contaminated, and significant greenhouse gas emissions were produced.^{5,6} Total Factor Productivity (TFP) has always been the core indicator of agricultural economic development, although it only considers labor and capital, and is less involved in agricultural pollution or greenhouse gas emissions. However, the use of contemporary agricultural production materials such as pesticides, agricultural films, fertilizers, and agricultural gear is rising, as is the total amount of agricultural carbon emissions, which makes the current Chinese agriculture show high carbon. Ignoring the environmental costs of agricultural production will inevitably distort the status quo of agricultural green development, exaggerate the performance of agricultural green development, and propose policies and measures that mislead agricultural green development. Therefore, it is necessary to incorporate environmental resource constraints into the analysis framework, fully consider undesired outputs, and achieve a scientific and systematic analysis of agricultural green total factor productivity (AGTFP), which can better grasp the development status of green agriculture in China and improve the level of agricultural greening in a more targeted manner.

As early as the early twentieth century, scholars have recognized that economic agglomeration can reduce costs, increase wages, and play an important role in increasing labor productivity.⁷ As China gradually enters the new normal of economy, the industrial

form has changed from agriculture-supporting industry to industry-supporting agriculture; from rural areas serving cities to urban driving rural areas. Meanwhile, the relationship between industry and agriculture, city and rural is undergoing an unprecedented historical transformation. Economic development is also shifting from a crude model of pursuing growth rate to a connotative model of pursuing structural adjustment and environmental efficiency, with economic agglomeration undoubtedly becoming one of the themes in China's green transformation and development.⁸ With the acceleration of urban-rural integration in China, economic agglomeration can produce an agglomeration effect through the redistribution of economic factors and affect the transformation of the agricultural development mode. Accordingly, studies have shown that food production is closely related to economic development.⁹ Countries have more capital ability to enhance fiscal spending on agriculture to sustain food production as a result of fast economic development.¹⁰

As a testing ground for ecological green integration in China, the problems of green agricultural development in the Yangtze River Delta (YRD) cannot be ignored. Because of its better geographical advantages, metropolitan clusters such as Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta have quickly concentrated their economic activity in the last three decades. As economic agglomeration accelerates, population agglomeration and industrial agglomeration promote each other, and land conversion from farmland to urban areas becomes increasingly intensive,^{11,12} resulting in a significant reduction in the number of available cultivated land, particularly in the YRD. Rapid urbanization has taken up a lot of fertile farmlands, among which the supply of cultivated land in Shanghai, eastern Zhejiang, and southern Jiangsu is currently unable to meet demand.¹³ During 2005–2015, the rate of farmland loss in 16 cities in the YRD reached 69.02 hm² during the 20-year period, of which 87.1% was caused by urban sprawl.¹⁴ Economic agglomeration also brings about a decline in the quality of cultivated land. More than half of China's cultivated land is thought to have been degraded in some way as a result of excessive chemical agricultural inputs such as fertilizers and pesticides. Similarly, the growth in production scale brought about by economic agglomeration is sure to result in greater energy consumption and carbon emissions, posing a serious challenge to the future sustainability of Chinese agriculture.^{15,16} Therefore, it is of great significance to fully understand the relationship between economic agglomeration and agricultural green development, and to systematically analyze the influence of economic agglomeration on AGTFP. However, there are still several questions that need to be addressed: What kind of impact does economic agglomeration play on AGTFP? Is there a non-linear relationship between them? What are the paths and mechanisms of the influence? The answers to the above questions not only provide rich empirical evidence for urban economic agglomeration supporting green agricultural development in China in the new era, but also provide experiences for green and efficient agricultural development in other developing countries.

The marginal contributions of this paper are as follows: (1) Focusing on the agricultural sector. Most of the existing literature on the effects of economic agglomeration on green total factor productivity (GTFP) mostly focuses on cities, and rarely on agriculture. Besides, it differs from previous research that solely focuses on agricultural carbon emissions in a narrow sense in terms of agricultural material inputs, agricultural energy, and so

on. By accounting for surface source pollution from fertilizer inputs during agricultural cultivation, this paper achieves a thorough characterization of AGTFP. (2) To better identify the interaction between Chinese industry and agriculture, urban and rural areas. This paper breaks through the previous perspectives of industrial agglomeration and urbanization, and innovatively explores the nonlinear effects of economic agglomeration on AGTFP from the perspective of economic agglomeration at the overall city level and based on the accounting of AGTFP. In addition, considering the development process of economic agglomeration with its resulting lagged effects, this paper captures the impact of economic agglomeration on AGTFP in terms of threshold effects and impulse responses. (3) This paper also compares the heterogeneous effect of economic agglomeration on AGTFP in two dimensions, namely, center-periphery, and metropolitan-nonmetropolitan.

Literature review

According to the conventional economic theory of agglomeration, compact economic activities can produce various agglomeration and spillover effects, which are conducive to improving the efficiency of factor use under the impact of positive externalities.¹⁷ Related studies also showed that the positive effects of economic agglomeration outweigh the negative effects. Zeng and Zhao,¹⁸ Dean et al.¹⁹ stated that economic agglomeration can alleviate pollution through externalities such as knowledge spillover effects and economies of scale. Zhou et al.²⁰ also came to the same conclusion with 339 cities in China, that is, under the background of economic agglomeration, the increase of economic activity can significantly enhance resource and energy usage efficiency, which is beneficial to curb water pollution, and this effect was more obvious in small-sized and medium-sized cities. Based on an ecological footprint model, Jin et al.²¹ discovered a positive correlation between economic agglomeration and eco-efficiency, and the improvement of the level of economic agglomeration can promote local resource utilization efficiency. Wang et al.²² conducted an empirical analysis from the perspective of spatial effects and found that economic agglomeration can affect labor productivity and thus had a considerable spatial spillover effect on haze pollution. In general, when economic agglomeration was at a mature level, it can play a self-purifying function, promoting pollution control.

However, some scholars also advocated the negative externalities of economic agglomeration. While economic agglomeration might improve technical efficiency, it also produces additional resource consumption and demand, resulting in a rebound effect in which resource savings from improved technical efficiency were countered by increasing carbon emissions from economic expansion.²³ Furthermore, the extension of urbanization as a result of economic agglomeration will influence agricultural infrastructure in surrounding rural regions, increase agricultural costs and the degree of fragmentation of cultivated land, and adversely affect agricultural productivity.²⁴

The effect of economic agglomeration on environmental pollution depends on the combined effect of the above positive and negative effects, and therefore some empirical studies have found the relationship between the two to be uncertain or non-linear. For example, Wang et al.²² based on panel data from 74 cities in China's Yellow River

Basin, inferred an N-type relationship between economic agglomeration and haze pollution. Glaeser and Kahn²⁵ hold that increasing urban economic density was conducive to reducing carbon emissions, with a non-linear relationship between the two indicators. Shao et al.⁸ based on 22 years of panel data for 30 provinces in China and concluded that there is an inverted N curve relationship between economic agglomeration and carbon emission intensity and per capita carbon emission and that once the economic agglomeration level reaches a certain threshold, it can show significant energy-saving and emission reduction effects.

Based on the above literature review, it could be found that the existing literature on the effects of economic agglomeration on environmental pollution and resource utilization is rich, and the research mechanism is relatively mature, but there are still two limitations. On the one hand, previous literature about the effects of economic agglomeration on GTFP is less focused on agriculture. However, the process of urban-rural integration has accelerated since October 2003, when China explicitly proposed to integrate urban and rural development. The economic development of cities has also had a profound impact on local agriculture, and various economic, social, and environmental problems in the agricultural industry have occurred frequently, and the effect of economic agglomeration on green agricultural development deserves more attention. On the other hand, previous research mostly focused on the one-way linear relationship between economic agglomeration and green agricultural development, but the reality is often more complex, with differences in the impact of different stages of economic development on agriculture.

Accordingly, three marginal contributions of this paper are proposed, firstly, focusing on the agricultural sector; secondly, downscaling analysis. Using the YRD city cluster as a research scale to investigate the dynamic relationship between economic agglomeration and AGTFP, unlike the traditional sample of provincial economic regions, urban agglomerations are themselves a mapping of economic agglomeration in spatial organization. Thus, the findings of this paper are more pertinent to the sustainable development of regionally integrated agriculture. Thirdly, the life-cycle of economic agglomeration is introduced into the theoretical analytical framework and paired with a panel threshold model for empirical testing, building on the life-cycle theory of industrial agglomeration. This conclusion serves as a guide for policymakers working on high-quality agricultural development.

This paper is structured as follows: *Literature review* analyzes relevant studies on economic agglomeration and AGTFP. *Theoretical analysis and research hypothesis* introduce the life cycle theory of economic agglomeration and present the corresponding hypotheses. *Methods and materials* explain the measurement method of AGTFP and the setting of the empirical model. *Results* analyze the spatial and temporal distribution characteristics of AGTFP and also provide empirical results. *Discussion* provides conclusions, significant findings, study implications, and limitations.

Theoretical analysis and hypothesis

Previous research shows that the impact of economic agglomeration on resource efficiency and pollution has both promoting and inhibiting features. Similarly, the

Williamson hypothesis states that when economic agglomeration exceeds a particular threshold value, it causes agglomeration diseconomies, resulting in a loss of economic efficiency, and the two have an inverted U-shaped connection. In order to account for both environmental and economic benefits, AGTFP is used as an indicator to evaluate China's agricultural green development. Therefore, the first hypothesis is formulated:

Hypothesis 1: Economic agglomeration has an impact on AGTFP, and the two have a non-linear relationship.

Is the relationship between economic agglomeration and AGTFP just an inverted U shape? Does it have different effects with different developmental periods? Tichy, an Austrian economist, researched the dynamics of industrial agglomeration through time and created the industrial agglomeration life cycle theory.²⁶ Industrial agglomeration is one of the most visible forms of economic agglomeration, with varied life cycles corresponding to different stages of economic growth. Based on the life cycle theory of industrial agglomeration, economic agglomeration development is divided into four stages: infancy, growth, maturity, and decline. The level of externality manifested by the agglomeration effect varies in different stages of economic development,^{27,28} implying that the influence of economic agglomeration on AGTFP varies over time. Figure 1 depicts the theoretical analytical framework.

As shown in Figure 1, economic agglomeration can increase AGTFP during the infancy stage, although the effect is minor. As economic agglomeration grows, it may result in the formation of several economic uplands, resulting in more employment opportunities for farmers with higher income levels, which can benefit local farmers through trickle-down mechanisms,²⁹ cash and technology assistance are provided for agricultural production and the use of ecologically friendly technology. In reality, economic agglomeration in the true sense of the word has not yet been formed, and it is only at the stage of merging like items of some capital and industries in the region, and the organizational model is still in a disorderly state, and the benefits

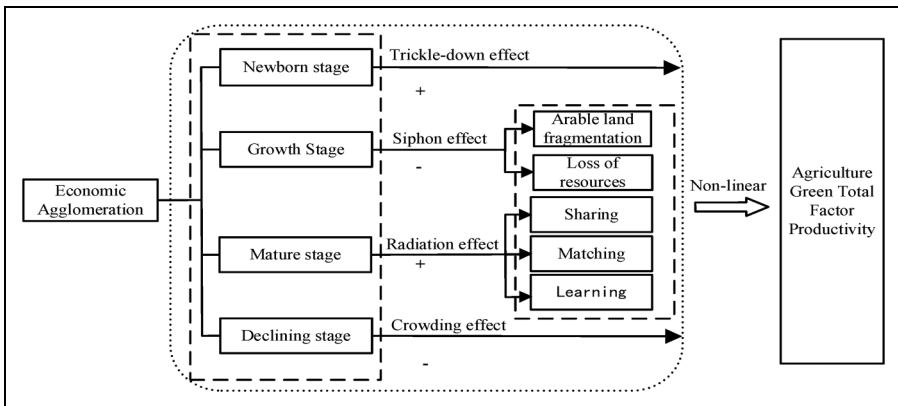


Figure 1. Mechanisms of economic agglomeration on AGTFP.

of agglomeration have not yet been fully realized. Despite the trickle-down effect that can influence farmers, it is unclear if it will have a substantial impact on the improvement of AGTFP.

In the growth stage, economic agglomeration plays a significant inhibiting role on AGTFP. The degree of economic agglomeration is expanding, the factor attraction of the urban center agglomeration region is increasing, and rapid production capacity growth will result in a dramatic increase in energy consumption. At this time, the siphon effect circle continued to expand, as production factors flow from periphery areas to central cities, and agriculture and rural regions are under tremendous pressure from the loss of resource factors, which are manifested in three levels: (1) Human capital level. Young and middle-aged rural labor force are migrating to cities, rural productivity is inadequate, and the elderly left behind in rural areas are unable to master modern production equipment and professional production technology; (2) Financial Capital Level. Currently, the level of financial product development in China's financial system for rural areas and agriculture lags behind the development of rural agriculture, resulting in financial institutions failing to meet the policy of benefiting farmers and instead allowing rural capital to be transferred to towns and big cities, causing a lack of financial resources needed in rural areas; (3) Technology and capital level. The results of scientific and technological progress in agriculture have limited economic benefits, and are more of public and social nature. Further, from an analysis of the investment return ratio, agricultural projects and agricultural technology equipment are characterized by long investment cycles and low returns, which are not conducive to the entry of social resources, and inherently have the risk of resource loss.

In the maturity stage, economic agglomeration plays a significant role in promoting AGTFP. Specifically, economic agglomeration provides for a radiation effect on rural regions to boost AGTFP through the following three mechanisms. Firstly, sharing mechanism. The improvement of infrastructure in agglomeration areas brought about by economic agglomeration enables urban and rural areas to effectively share inseparable services or facilities, share external risks, share specialization and diversification, and make farmers' lives more convenient. With the sharing mechanism, the economic agglomeration in the maturity stage can promote the development of the local economy and maximize the trickle-down effect to benefit farmers, which has a significant impact on agricultural income growth.³⁰ In addition, whether or not farmers obtain more income in an environment of economic agglomeration, they still benefit from a lower consumer price index and hence higher real wages owing to the price index effect. Secondly, the matching mechanism. Matching agricultural goods and markets minimize transaction costs, and allows for knowledge and technology exchange and innovation, thereby increasing labor productivity, which is critical for AGTFP. Thirdly, learning mechanism. The knowledge spillover effect from economic agglomeration is self-evident. The diffusion and creation of knowledge and technology promote the improvement of the cultural quality of agricultural producers so that they have the ability to reduce pollution emissions during agricultural production through the more rational use of chemical factors and more organic fertilizers and other environmentally friendly behaviors. Furthermore, owing to the rational use of elements, agricultural producers with high educational levels will also obtain

considerably high output efficiency and profitability. Under the dual action, AGTFP is significantly improved.

In the decline stage, economic agglomeration weakens AGTFP. When economic agglomeration reaches a certain level, resources will be scarce, rising factor prices, and intense competition for agglomeration, resulting in the crowding effect, also known as the density restriction, which states that additional labor and capital inputs on a given land would bring about a higher density of factor inputs per unit of land. Increasing crowding reduces the productivity of capital and labor, leading to diminishing marginal output. Based on this, this paper puts forward the second hypothesis:

Hypothesis 2a: In the infancy stage, economic agglomeration has a catalytic effect on AGTFP in the form of a trickle-down effect, but the effect is weak.

Hypothesis 2b: In the growth stage, economic agglomeration has a negative impact on AGTFP, mainly through the siphoning effect to suppress AGTFP.

Hypothesis 2c: In the maturity stage, economic agglomeration has a positive impact on AGTFP, mainly through the radiation effect to promote AGTFP.

Hypothesis 2d: In the decline stage, economic agglomeration has a suppressive effect on AGTFP, manifested as a crowding effect.

Study area

YRD is located in the heart of mainland China's eastern shore, with a regional area of 356,700km². It is one of China's most dynamic, open, and inventive economic zones, as well as a model location for ecological and green integrated development. Besides, YRD is also a significant agricultural zone. In 2020, YRD generated a total value added in agriculture of roughly 999.397-billion-yuan, accounting for more than 12% of the national agricultural economy, and played an essential role in the country's agricultural economic development. The rapid growth of YRD's agricultural economy is also accompanied by a high dependence on agrochemicals, showing serious surface source pollution problems and an urgent need for green transformation in agricultural development. The study area includes three provinces and one municipality in YRD, with 13 prefecture-level cities in Jiangsu, 11 prefecture-level cities in Zhejiang, 16 prefecture-level cities in Anhui, and 1 municipality directly under the Central Government in Shanghai. Therefore, there are 41 basic units in the study area. Figure 2.

Methods and materials

Measurement of green total factor productivity of China's agriculture

AGTFP is the inclusion of resource and environmental factors in the measurement of agricultural productivity, which is used to examine the effectiveness of agricultural green development, and this paper mainly adopts the SBM-GML method. The traditional TFP measurement methods mainly include Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA), and SFA is limited in application because it requires

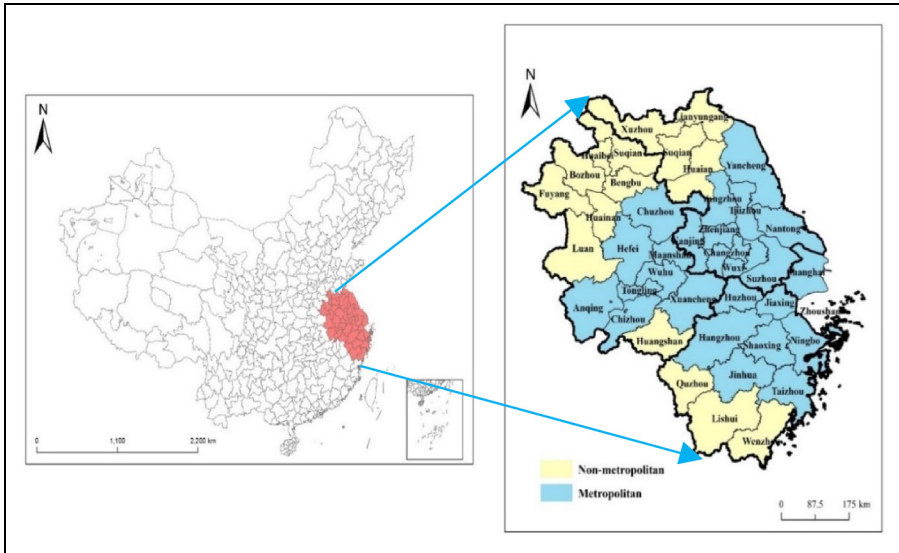


Figure 2. Location of the study area in the YRD.

pre-defined production functions and technical inefficiency term distribution forms. DEA overcomes these drawbacks, but considering the non-angular, non-radial characteristics of traditional DEA models, Tone³¹ proposed a standard efficiency model for SBM. The SBM standard efficiency model cannot rank two or more active cells when they exist in the same period. For this reason, Tone³² further proposed the super-efficient SBM model, however, this model also fails to take into account undesired outputs. Ultimately, referencing Tone³³ a super-efficient SBM model capable of incorporating undesired output was chosen. In addition, in order to reflect the inter-annual variation of AGTFP, the most widely used methods are the Malmquist-Luenberger (ML) index. However, ML indexes are often not circular and often suffer from problems such as linear programming insolvability. Oh³⁴ further proposed the Global Malmquist-Luenberger (GML) index. Nowadays the combination of the super-efficient SBM model and the GML index has been widely used as an estimation method to measure GTFP. Liu and Xin³⁵ measured GTFP in major provinces along the Belt and Road and found an overall upward trend, but with significant regional differences. Wang et al.³⁶ considered three types of non-desired outputs, wastewater, waste gas and solid waste, and found that GTFP in the Central Plains urban agglomeration of China exhibited a fluctuating upward trend, but productivity levels remained low.

Super-SBM model. The inputs of agricultural production components yield desired outputs such as food and economic advantages in the agricultural production process. Excessive use of agrochemicals, on the other hand, might result in undesirable outputs such as agricultural pollution emissions. This paper chooses the Super-SBM model to measure

AGTFP to thoroughly and truly portray the agricultural production process.^{33,37} The model can take undesirable outputs and slack into account as well as fully consider the environmental benefits.³⁸ The model assumes that YRD has n cities and that each city serves as a decision unit on the production frontier. m inputs are used by each decision unit, $x \in R^m$. Suppose the model has s_1 desired outputs, $y^g \in R^{s_1}$. And s_2 undesirable outputs, $y^b \in R^{s_2}$. Defining the matrices X, Y^g, Y^b as:

$$\begin{cases} X = [x_1, x_2, \dots, x_n] \in R^m \times n, \\ Y^g = [y_1^g, \dots, y_n^g] \in R^{s_1} \times n, \\ Y^b = [y_1^b, \dots, y_n^b] \in R^{s_2} \times n. \end{cases} \tag{1}$$

Assuming $X > 0, Y^g > 0, Y^b > 0$, then the set of production possibilities is:

$$P = \{(x, y^g, y^b) | x \geq X\lambda, y^g \leq Y^g\lambda, y^b \geq Y^b\lambda, \lambda \geq 0\} \tag{2}$$

Based on Equation (1), it is assumed that $DMU_k(x_k, y_k^g, y_k^b)$ is SBM effective, and the corresponding Super-SBM model is set below:

$$\rho^* = \min = \frac{1 + \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{ik}}}{1 - \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{rk}^g} + \sum_{t=1}^{s_2} \frac{s_t^b}{y_{tk}^b} \right)}$$

$$s. t. \begin{cases} \sum_{j=1, j \neq k}^n y_{rj} \lambda_j - s_i^- \leq x_{ik} \\ \sum_{j=1, j \neq k}^n y_{rj} \lambda_j + s_r^g \geq y_{rk}^g \\ \sum_{j=1, j \neq k}^n y_{tj} \lambda_j - s_t^b \leq y_{tk}^b \\ 1 - \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{rk}^g} + \sum_{t=1}^{s_2} \frac{s_t^b}{y_{tk}^b} \right) > 0 \\ \lambda, s^g, s^b, s^- \geq 0 \end{cases} \tag{3}$$

In equation (3), the average inefficiency of input is represented by $\frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{ik}}$, while the average inefficiency of output is represented by $\frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{rk}^g} + \sum_{t=1}^{s_2} \frac{s_t^b}{y_{tk}^b} \right)$. λ is the weight vector, s_i^-, s_r^g, s_t^b is the slack variable, ρ^* is the super-efficiency value of the decision unit, i.e. the GTFP value of agriculture in k city in the YRD. When $\rho^* \geq 1$, the evaluated decision unit is relatively valid; when $\rho^* < 1$, it is relatively invalid.

Global malmquist-luenberger Index. The Super-SBM model can only measure the annual AGTFP level of YRD cities, and cannot reflect the dynamic changes between this year

and the previous year, or this year and the next year. The GML index will be used in this paper. Referring to Oh³⁴ the GML index is defined as:

$$GML_t^{t+1}(x, y, b; x_{t+1}, y_{t+1}, b_{t+1}) = \frac{1 + D^G(x, y, b)}{1 + D^G(x_{t+1}, y_{t+1}, b_{t+1})} \quad (4)$$

If $GML_t^{t+1} < 1$, it means that desired output decreases, non-desired output increases, and AGTFP is lower than the level of the previous year; conversely, $GML_t^{t+1} > 1$, it means that AGTFP increases at this time.

Model setting

Baseline regression model. This paper focuses on the effect of economic agglomeration on AGTFP. Considering the possible non-linear relationship between economic agglomeration and AGTFP, the squared term of economic agglomeration is added to the regression model, and the empirical model is as follows:

$$AGTFP_{i,t} = \alpha_0 + \beta_1 AGG_{i,t} + \beta_2 AGG_{i,t}^2 + \gamma X_{i,t} + \mu_i + v_t + \varepsilon_{i,t} \quad (5)$$

In equation (5), $AGTFP$ is the GTFP of agriculture, i represents the region, t represents time, $AGG_{i,t}$ represents economic agglomeration, and X is a set of control variables, Digital Inclusive Finance Index (DIF), economic level ($PGDP$), urbanization (URB), industrial structure ($STRU$), industrialization (IND), income gap (GAP), environmental regulation (ER). Individual and time-fixed effects are represented by μ_i and v_t , respectively, whereas $\varepsilon_{i,t}$ is a random disturbance term.

Panel threshold regression model. The preceding theoretical research reveals that, depending on the agglomeration effect, the influence of economic agglomeration on AGTFP differs over the four stages. That is, at distinct threshold intervals, there are fundamental abrupt shifts in the influence of economic agglomeration on AGTFP, and there may be more than one such threshold effect. This paper uses a multiple threshold model based on panel data to measure the nonlinear relationship between economic agglomeration and AGTFP.³⁹ The model is set up as follows:

$$AGTFP_{i,t} = \alpha_0 + \beta_1 AGG_{i,t} \times I(AGG \leq \gamma_1) + \beta_2 AGG_{i,t} \times I(\gamma_1 < AGG \leq \gamma_2) + \dots + \beta_n AGG_{i,t} \times I(\gamma_{n-1} < AGG \leq \gamma_n) + \beta_{n+1} AGG_{i,t} \times I(AGG > \gamma_n) + \eta X_{i,t} + \varepsilon_{i,t} \quad (6)$$

In equation (6), i denotes the region, t denotes the period, α_0 represents the constant term, $\beta_1, \beta_2, \dots, \beta_{n+1}$ is the coefficient to be estimated, and $AGG_{i,t}$ indicates the core explanatory variable, namely economic agglomeration, which is also employed as the threshold variable in this paper. The indicative function is $I(\cdot)$, the control variable impacting AGTFP is $X_{i,t}$, the estimated control variable coefficient is η , and the threshold value is $\gamma_1, \gamma_2 \dots \gamma_n$.

Panel vector autoregressive model. To better understand the dynamic relationship between economic agglomeration and AGTFP, this paper employs a panel vector autoregressive

(VAR) model that incorporates lags, endogenous variables, and individual heterogeneity while maintaining the benefits of time-series characteristics, as represented by the model as:

$$y_{i,t} = \beta_0 + \sum_{l=1}^p \beta_l y_{i,t-l} + f_t + d_t + \varepsilon_{i,t} \tag{7}$$

In equation (7), $y_{i,t} = (AGTFP, AGG)$ is a column vector with two endogenous variables: agricultural green total factor production and economic agglomeration. The lag order is p , β_0 denotes the intercept term vector, β_l denotes the parameter matrix of lagged variables, i denotes region, t denotes time, f_t and d_t are individual fixed effects and time fixed effects, respectively, and $\varepsilon_{i,t}$ is the random disturbance term.

Variable selection

Dependent variable. Agricultural green total factor productivity (AGTFP) is the dependent variable, and it is measured with the super-SBM model and GML index. The inputs and outputs indicators are shown in Table 1.

Labor, land, mechanical power, fertilizer, pesticide, and film were used as input indicators. In contrast to previous literature, draft animals were not taken into account. There are two reasons. On the one hand, China’s mechanization has been continuously improved since the twenty-first century, and animal husbandry as a driving force has become increasingly rare; on the other hand, most yearbooks no longer include statistical

Table 1. Input-output indicators of AGTFP.

Type	Variable	Source	Coef	Reference
Input	Labor, Land, Mechanical, Power, Fertilizer, Pesticide, Film			China Urban Statistical Yearbook
Desirable output	Added value of agriculture			
Undesired output	Carbon emission	Fertilizer	0.8956 kg·kg ⁻¹	West and Marland ⁴⁰ Oak Ridge National Laboratory
		Pesticide	4.9431 kg·kg ⁻¹	Oak Ridge National Laboratory
	Agricultural film	5.18 kg·kg ⁻¹	Institute of Agricultural Resources and Ecological Environment, Nanjing Agricultural University	
	Agricultural diesel	0.5927 kg·kg ⁻¹	IPCC	
	Ploughing	312.6 kg·km ⁻²	School of Biology and Technology, China Agricultural University	
	Irrigation	20.476 kg·Cha ⁻¹	Dubey and Lal, Li et al. ^{41,42}	
	TN	N:P:C*	1:0:0.3	Lai et al, Tao et al ^{43,44}
TP		0:0.44:0.15		
NH ₃ -N		0.083		

*N:P:C = Phosphate fertilizer: Nitrogen fertilizer: Compound fertilizer.

indicators for draft animals, considering the availability of data, draft animals are not included in the input indicators.

Agricultural value added is selected as the desirable output indicator. In the current study, gross output and added value of agriculture are most widely used as the desirable outputs. However, the gross output value is often affected by intermediate consumption and does not reflect the real output. Therefore, it is more reasonable to use agricultural value added to represent the desirable output.

Agricultural carbon emissions and fertilizer pollution^a were chosen as undesirable output variables. Agricultural non-point source pollution has several origins, and their definitions are quite different. Generally speaking, agricultural non-point source pollution mainly refers to chemical pollution caused by chemical fertilizer, livestock and poultry breeding, solid waste, and rural life are all examples of. To begin with, there is worldwide agreement on nitrogen and phosphorus contamination caused by chemical fertilizer use. Secondly, while livestock and poultry breeding pollution are mainly related to manure, livestock and poultry manure has long been utilized as a fertilizer, and the pollution is still open to question. Straw is the most common type of solid waste, in China, the government has strictly regulated the burning of straw in the fields, and by 2020, China has reached a complete utilization rate of over 90% of straw; hence, straw should not be included in undesirable outputs. Finally, although human emissions account for the majority of rural home pollution, agriculture is not the only source of pollution.

Therefore, this paper primarily uses fertilizer-related surface source pollution as a measurement index of agricultural non-point source pollution, that is, the total nitrogen, total phosphorus, and ammonia nitrogen pollution caused by chemical fertilizer application.

Core independent Variable. Economic agglomeration (AGG), as measured by economic density,³⁰ is the core independent variable in this paper, and it has a high level of recognition. The reason for this is that economic agglomeration mainly refers to the density of economic activities in a unit space, which is the process and phenomena of concentration of diverse economic activities in an area. Its common measurement indicators include the spatial Gini coefficient, the Herfindahl index, but these indicators ignore the differences of small geographical units, whereas output density, namely the amount of economic activity carried per unit area, is considered a good indicator of economic agglomeration in a region.⁴⁵ It has been widely used.^{8,20}

Control variables. The following variables were selected to control for unobservable factors to more accurately estimate the influence of economic agglomeration on AGTFP. (1) The digital inclusive finance index (DIF) is a measurement of the digital financial level (DIF).⁴⁶ The popularity and growth of digital inclusive finance in rural regions is a general trend in China's digital countryside, and some research has demonstrated that digital inclusive finance has a heterogeneous impact on agro-ecological efficiency.⁴⁷ (2) Economic level (PGDP), as measured by GDP per capita. For the purpose of controlling differences in regional economic development levels. (3) Level of urbanization, expressed as a share of the non-farm population in the total population. Increased urbanization brings losses of agricultural land and makes agricultural activities more

Table 2. Statistical description of variables.

Variable	Definition	Obs	Mean	S. D.	Min	Max
AGTFP	Agricultural green total factor productivity	451	1.081	0.148	0.456	3.008
AGG	Economic agglomeration	451	0.617	0.834	0.032	5.664
DIF	Digital inclusive financial	451	181.231	78.396	27.080	334.480
PGDP	GDP per capita	451	6.792	3.782	0.972	18.506
URB	Urbanization rate	451	0.604	0.121	0.307	0.898
STRU	Agricultural industry structure	451	0.646	0.157	0.206	0.950
IND	Level of industrialization	451	2.770	1.610	0.303	7.898
GAP	Income gap	451	2.210	0.388	1.555	3.547
ER	Environmental regulation	451	36.127	16.703	2.821	103.952

difficult. The pressure on farmers is multiplied.⁴⁸ (4) Industry structure, expressed as food sown area/total crop sown area.⁴⁹ (5) Industrialization level (IND), expressed in terms of regional industrial value-added and the resident population at the end of the year.⁴⁹ The notion of industry nurturing agriculture is a policy concept with Chinese features, as well as the stage of agricultural growth that China is going through. (6) Income gap (GAP), expressed as the ratio of urban per capita disposable income to rural per capita disposable income. Agricultural carbon emissions are influenced by the optimization of urban-rural income distribution patterns.⁵⁰ (7) Environmental controls (ER). Learning from the study of Chen et al., the frequency of 15 keywords related to green development and agricultural non-point source pollution that occurs in the year's local government work report is calculated.⁵¹ Statistics description of variables is shown in Table 2.

Date sources

From 2010 to 2020, panel data was collected for 41 prefecture-level cities in the YRD. The data came from the China Urban Statistical Yearbook, China Urban and Rural Construction Statistical Yearbook, China Agricultural Yearbook, and yearly statistical yearbooks of Chinese prefecture-level cities. For missing values in the data source, this paper uses interpolation to fill in. In all subsequent models, except for AGTFP, the data of the rest variables are processed with a natural logarithm. The data processing and statistical analysis software used in this paper were MaxDEA6.7, Stata16.0, and ArcMap10.8.

Results

Temporal and spatial characteristics of the AGTFP

Considering that the AGTFP measured above was a chain index, it mainly represented the change of AGTFP of the current year compared with the previous year. As a result, the index is turned into a fixed-base index in Figure 3 to show AGTFP's cumulative trend, which is convenient for analyzing its geographical and temporal variation characteristics.

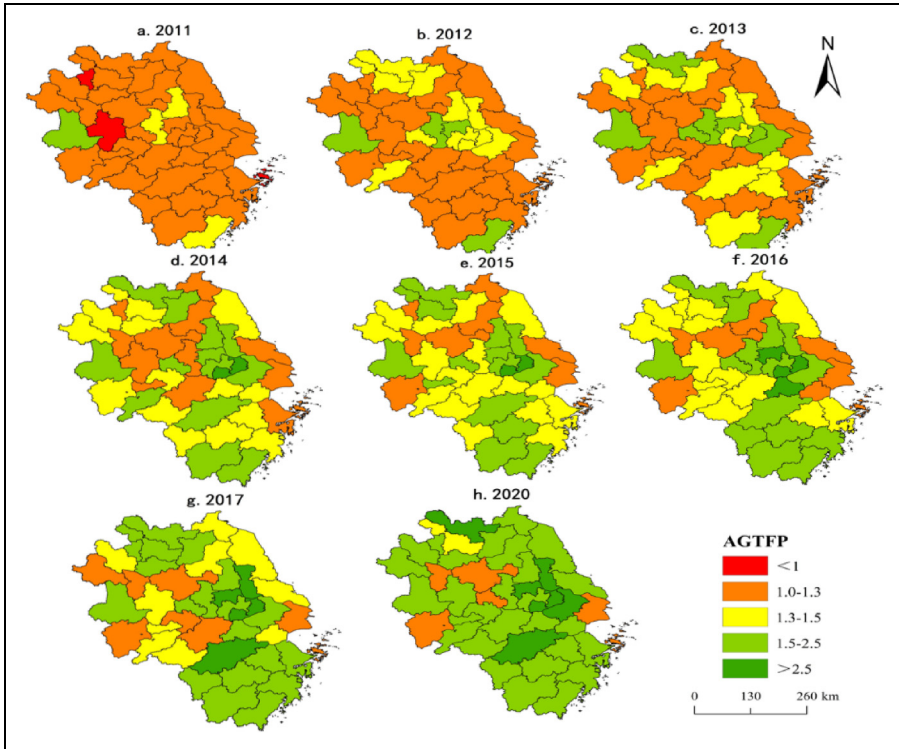


Figure 3. AGTFP of the YRD from 2011 to 2020.

That is, taking the AGTFP of 2010 as the base period and making it equal to 1. The actual value of the AGTFP for 2011 is the product of the AGTFP for the current year and the AGTFP for 2010, and the estimated value of AGTFP in other years was deduced by analogy. As demonstrated in Figure 2, the AGTFP showed an upward trend year by year from 2011 to 2020. In terms of the time period, in the early period (2011–2013), the improvement of AGTFP showed a form of diffusion from the center to the surrounding area, in the mid-to-late period (2014–2020), the trend of AGTFP growth showed a concentration from northern and southern cities to central cities. Regionally, there were significant differences and spatial agglomeration characteristics of AGTFP among cities. Specifically, Shanghai, is the city with the lowest AGTFP average value (1.09) and Wuxi (3.01), with a difference of 3 times. Wuxi actively developed high-quality, high-efficiency and green agriculture, focusing on agricultural science and technology means driven. Since 2010, Wuxi has made biological and intelligent agriculture a new growth point for the city's modern agricultural development. As of 2020, the application of Wuxi's chemical fertilizer and pesticide has been maintaining zero growth compared to 2015, and the straw utilization rate was stable at over 95%. From these indicators, Wuxi's AGTFP level was in the leading position in China. However, Shanghai's urban agriculture model

has produced the typical phenomenon of the Inverse Thunen Circle, that is, Shanghai's suburban cities were prone to the excessive pursuit of short-term land transfer added-value benefits, resulting in extensive land management or low utilization, which resulted in a significant increase in agricultural carbon emissions and non-point surface pollution, leading to a low level of AGTFP development.

Baseline regression results

A fixed effects model was used to estimate the model parameters. As shown in model (1) of Table 3, the coefficients of the primary and quadratic terms of economic agglomeration were significant at the 1% and 5% levels, respectively, and were positive and negative in turn, showing an inverted U-shaped curve. Combined with the characteristics of economic agglomeration, a possible explanation was that the economies of scale, and spillover effects from economic agglomeration can promote AGTFP. According to Marshall's concept of externalities, spatial agglomeration was a result of the snowball effect, as the level of economic agglomeration rises, more and more labor and industry converge on urban centers to share the benefits of economic diversification and specialization. Furthermore, the lag of rural modernization has prompted a large number of peasants to leave their land and their hometowns to flock to cities disorderly, making the phenomenon of empty nests in rural areas increasingly serious; the number of idle village houses and contracted land abandoned continued to rise; the phenomenon of urban-rural polarization has intensified, and the Matthew effect appeared, namely the weak getting weaker and the strong getting stronger. On the one hand, farmers' agricultural labor productivity was declining, while on the other side, farmers were opting for the easy way out by increasing fertilizer inputs to equal historical yields. Under the combined action of various factors, it made sense that the AGTFP would decline. However, the actual

Table 3. Benchmark regression and robustness checks.

	(1)	(2)	(3)	(4)
Variables	FE	Replacing core variable	Removing extreme values	Delete capital city
AGG	0.036***(0.010)	0.079***(0.020)	0.037***(0.010)	0.036***(0.011)
AGG^2	-0.026***(0.010)	-0.027***(0.011)	-0.027***(0.010)	-0.023*(0.012)
DIF	-0.164*** (0.034)	-0.164*** (0.035)	-0.166*** (0.034)	-0.159*** (0.037)
PGDP	0.237***(0.110)	0.233***(0.111)	0.216***(0.101)	0.224(0.139)
URB	-0.385***(0.187)	-0.371*(0.186)	-0.368***(0.170)	-0.374*(0.218)
STRU	-0.053(0.094)	-0.058(0.095)	-0.046(0.084)	-0.037(0.112)
IND	0.021(0.021)	0.020(0.020)	0.022(0.019)	0.024(0.022)
GAP	-0.090(0.097)	-0.080(0.098)	-0.104(0.083)	-0.073(0.110)
ER	-0.032*(0.016)	-0.032*(0.016)	-0.029***(0.013)	-0.027(0.017)
Constant	1.537*** (0.213)	1.499*** (0.209)	1.596*** (0.190)	1.514*** (0.263)
Obs	451	451	451	407
R ²	0.078	0.077	0.150	0.077

Notes: Robust standard errors in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01.

situation was often more complicated, given that the relationship between economic agglomeration and AGTFP is not a simple inverted U-shaped relationship, there may be multiple thresholds, so a further threshold is required.

In terms of control variables, digital inclusion finance was significantly negative at the 1% level, indicating that the dividends of digital inclusion financial development were mainly reflected in the cities and remained negative for agricultural production. The level of economic development was significantly positive at the 5% level, showing that the higher the level of regional economic development, the stronger the public awareness of environmental protection, while the greater the government's financial support for agricultural development was conducive to AGTFP. Urbanization was significantly negative at the 5% level. In terms of economic trends, urbanization has more advantages than disadvantages, as small towns can create new jobs and divert some of the surplus farmers. Then, through farmland renovation and farmer training, conditions were created for future large-scale industrialization of agriculture and professionalization of farmers. However, nature was different in a country like China, which has a long-standing dualistic economic structure. China's economic progress has been built on the sacrifices of generations. Although a few people became wealthy, the bulk did not. If we merely chase the appearance of riches through town construction, the peasants will lose even their most basic land. Environmental regulation was significantly negative at 10%, indicating that for weak agriculture, too strong environmental regulation can instead inhibit AGTFP.

Robustness test

Models (2)-(4) in Table 3 provided the three methods of robustness testing: replacing core independent variables, removing extreme values, and removing provincial capitals or municipalities. Economic agglomeration indicators were recalculated using the locational entropy approach and introduced as core independent variables in the benchmark regression model. In addition, the baseline regression results were re-estimated by removing the 1% extreme values. Due to the unique political and locational conditions of provincial capital cities (municipalities directly under the central government), economic agglomeration has an inherent advantage, which may also affect the empirical results. Therefore, cities such as Shanghai, Hangzhou, Nanjing, and Hefei were excluded from the total sample. Under all three methods, the primary and quadratic terms of economic agglomeration remain significant, and the coefficients were in the same direction. As a consequence, the findings of this paper were robust.

Threshold effect of economic agglomeration on AGTFP

The non-linear relationship between economic agglomeration and AGTFP has been confirmed above. To further investigate whether there were multiple thresholds, this paper used economic agglomeration as a threshold-dependent variable, and minimized the sum of squares to determine the threshold of economic agglomeration, and then assumed that a single threshold was known to search for other thresholds. Because the threshold value cannot be identified under the original threshold effect assumption,

Table 4. Results of the threshold effect.

Variable	Model	F	BS	10%	5%	1%	Threshold value	95% CI
AGG	Single threshold	17.97*	500	11.430	13.747	19.165	-0.860	[-0.862, -0.858]
	Double threshold	7.22	500	10.987	12.577	16.958	-0.285	[-0.360, -0.263]
AGG _{t-1}	Single threshold	16.86**	500	10.571	12.726	18.458	-0.424	[-0.579, -0.383]
	Double threshold	13.34*	500	11.833	14.574	22.065	-0.204	[-0.602, -0.196]
	Triple threshold	19.66**	500	13.608	17.594	59.061	-0.196	[-0.357, -0.187]

Notes: F denotes the F statistic; BS denotes the number of Bootstrap.

that is, the F statistic was non-normal distribution, this paper adopted the Bootstrap method, sets the number of 500 self-sampling to obtain the asymptotic distribution of F values, and then constructed the corresponding P values. As shown in Table 4, economic agglomeration passed only the single threshold test. The possible reason was that the impact of economic agglomeration on AGTFP had a path-dependent characteristic in time, that is, time effect, and there was a bidirectional causal relationship between them. In this regard, the one-period lag of the economic agglomeration variable was introduced as the core independent variable in the panel threshold model, which also alleviated the model endogeneity problem and ensured the robustness of the empirical results. The findings revealed that the p-values of AGG_{t-1} of single threshold, double threshold, and triple threshold were significant at the 5%, 10%, and 5% levels, respectively. Hence the threshold number was set to three, then specific thresholds were determined, and the maximum likelihood function was used to estimate the triple threshold values of economic agglomeration.

As shown in Table 5, the estimation results of the AGTFP triple threshold model of economic agglomeration with one lag period showed that its four threshold intervals correspond to the four periods of the life cycle of economic agglomeration, which confirms Hypothesis 2.

1. When the degree of economic agglomeration was low and less than the first threshold value ($\ln AGG \leq -0.424$), the coefficient of economic agglomeration was significantly positive. However, in terms of the magnitude of the regression coefficient, the small value implied a weak facilitation effect. The infancy stage was represented by this. The number and scale of various industries in the agglomeration area were relatively small, and they were frequently in the stage of an agriculture-supporting industry. Economic development, technology level, and agglomeration degree were relatively low, and although there was a certain trickle-down effect, the effect was weak.
2. Crossing the first threshold and reaching the second threshold value ($-0.424 < \ln AGG \leq -0.204$), it was significantly negative at the 1% level, and economic agglomeration presented a significant inhibitory effect on AGTFP (-0.334). This interval corresponded to the growth stage, China's initial rapid economic development was undoubtedly based on the blood-sucking of the scissors in

Table 5. Result of threshold regression.

Variables	Coefficient	Std. Err.	P	T
AGG-1	0.090**	0.039	0.020	2.344
AGG-2	-0.334***	0.109	0.002	-3.072
AGG-3	4.569***	0.698	0.000	6.546
AGG-4	-0.081	0.053	0.123	-1.545
DIF	-0.150***	0.033	0.000	-4.558
PGDP	0.212**	0.095	0.026	2.231
URB	-0.346**	0.165	0.036	-2.104
STRU	-0.060	0.062	0.334	-0.967
IND	0.025	0.038	0.509	0.660
GAP	-0.045	0.094	0.635	-0.475
ER	-0.021	0.019	0.271	-1.103
Constant	1.461***	0.236	0.000	6.187
Obs			451	
R ²			0.203	

Notes: *p < 0.1, **p < 0.05, ***p < 0.01.

the rural areas. Rapid urbanization led to the outflow of the rural population, and the siphoning effect of cities left a large number of rural areas in ruins.

3. Crossing the second threshold ($-0.204 < \ln \text{AGG} \leq -0.196$), it was significantly positive at the 1% level, that is, economic agglomeration showed a promoting effect and has a strong positive effect on AGTFP (4.569). This interval corresponded to the maturity stage, higher economic density implied the spillover effects of sharing, matching, and learning in agglomeration economies were greater.²⁸ At this time, the localized and urbanized economies were prominent, and the externalities generated by the higher level of economic agglomeration promoted AGTFP through the radiation effect. In a real sense, it has entered the stage of industry back-feeding agriculture and urban supporting rural areas.
4. With the increasing degree of economic agglomeration greater than the third threshold ($\ln \text{AGG} \geq -0.196$), economic agglomeration presented a weak but insignificant inhibitory effect on AGTFP. This interval corresponded to the decline stage, the crowding effect was manifested by the shortage of resources, rising factor prices, and intense competition for agglomeration. The reason for the insignificant effect may be that the economic agglomeration in YRD was mostly in its infancy and rapid development stages, and has not yet reached the decline stage.

Impulse response of economic agglomeration on AGTFP

The impulse response analysis employing a panel VAR model is more suited for determining the degree of dynamic influence of economic agglomeration. The LLC, IPS and ADF-Fisher tests were chosen to perform unit root checks of the data to test the stationarity of the data, as shown in Table 6.

Table 6. Test for stationarity of variables.

Variable	LLC test	IPS test	ADF-Fisher test
AGTFP	-17.091***	-3.754***	12.660***
AGG	-12.562***	-5.901***	2.034**

Table 7. The choice of lag order of variables.

Lag period	AIC	BIC	HQIC
1	-1.993*	-1.082*	-1.631*
2	-1.767	-0.727	-1.352
3	-1.570	-0.371	-1.089
4	-1.347	0.050	-0.784
5	-1.228	0.425	-0.559

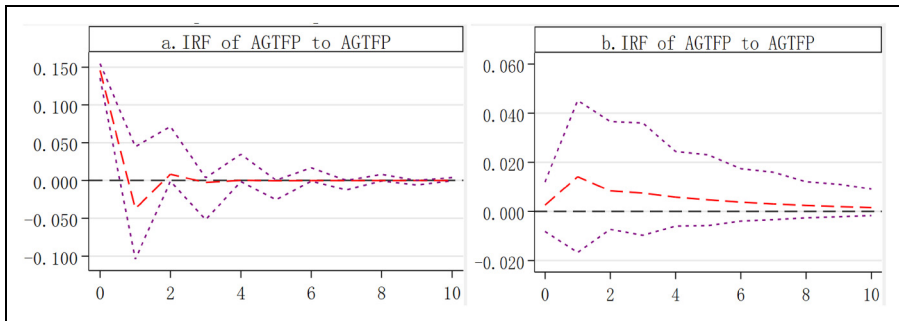


Figure 4. Results of impulse response analysis.

The model’s optimal lag order was then determined, as shown in Table 7, and the results of the three determination criteria, AIC, BIC, and HQIC, indicated that the choice of lag order-1 was appropriate.

Finally, impulse response function analysis was performed to summarize the impulse response plots of the Monte-Carlo simulation 500 times. The results of the impulse response analysis were as follows:

1. Figure 4(a) represents the response of AGTFP to its own shocks. Specifically, the peak of AGTFP on self-shock was in period 1, indicating that the value of AGTFP in the current period was closely related to that of AGTFP in the previous period, and had a weak negative effect initially. As the number of periods increases, the impact effect of AGTFP on itself gradually diminishes and basically converges to zero in period 4. It showed that agricultural resource inputs and outputs from the

previous period have a positive impact on the subsequent AGTFP, and that the high-quality development trend of agriculture must be maintained to reduce undesirable outputs, which was conducive to agricultural green development in the next phase.

2. Figure 4(b) represents the shock response of economic agglomeration (AGG) to AGTFP. The effect of economic agglomeration on AGTFP showed a continuous effect after being influenced by one standard deviation of economic agglomeration. After reaching the peak in the second period, it began to decrease slowly and lasted for a long time, and still maintained a positive effect in the tenth period. That is, it showed a positive effect trend of rising first and then falling, and tends to be stable in the long run.

Regional heterogeneity analysis

Because cities differ in terms of economic emphasis, financial support for agriculture, and rural human capital, distinct effects of economic agglomeration on local AGTFP may occur. As a consequence, this paper divided the 41 cities in the YRD region into two types of samples: center cities and peripheral cities, metropolitan coordinating region and non-metropolitan coordinating region. And then explored the regional heterogeneity of the impact of economic agglomeration on AGTFP.

(1) Center-peripheral cities.

The municipalities directly under the central government and provincial capitals of the YRD's 41 cities were regarded as center cities. At the same time, since Ningbo was a sub-provincial city and Suzhou was the city in Jiangsu Province with the largest GDP, both Ningbo and Suzhou were also categorized as central cities, while other prefecture-level cities were classified as peripheral cities. Comparing model (1) and model (2) in Table 8, it can be seen that economic agglomeration showed a negative but insignificant effect on AGTFP for the central cities, while the AGTFP for peripheral cities was significantly positive at the 1% level. The crux of the problem was the rising cost of urban and rural mobility. In coastal locations, housing cost has become a significant expense of life, while the cost of housing in center cities was out of reach for most farmers. If the rural labor force is free to relocate to cities, rural regions can better achieve the growth of agricultural scale and modernization, which was conducive to rural revitalization, and also helped to reduce the production cost of Chinese agricultural products and improve agricultural international competitiveness,⁵² which had a substantial impact on AGTFP growth.

(2) Metropolitan cities and non-metropolitan cities

The metropolitan cities were the 26 cities listed in the *Yangtze River Delta City Cluster Development Plan*, which was formally accepted by the executive meeting of the State Council in May 2016, and Non-metropolitan cities referred to the remaining 15 cities. The results of model (3) and model (4) in Table 8 showed that economic agglomeration was significantly positive at the 5% level for non-metropolitan cities, but not for metropolitan cities. The reason for this was that as the metropolitan region continued to

Table 8. Analysis of heterogeneity in YRD.

Variables	(1) Central	(2) Peripheral	(3) Metropolitan	(4) Non-metropolitan
AGG	-0.105*(0.047)	0.037***(0.011)	-0.030(0.081)	0.039**(0.017)
AGG ²	-0.066(0.060)	-0.028**(0.013)	-0.047***(0.014)	0.005(0.016)
DIF	-0.182**(0.048)	-0.158***(0.037)	-0.208***(0.030)	-0.085(0.055)
PGDP	0.559**(0.181)	0.177(0.129)	0.370***(0.111)	-0.095(0.165)
URB	0.209(0.781)	-0.296(0.241)	-0.688***(0.198)	0.583*(0.316)
STRU	-0.176(0.120)	-0.054(0.111)	-0.046(0.082)	0.093(0.114)
IND	-0.260(0.188)	0.024(0.022)	0.093*(0.046)	-0.006(0.014)
GAP	-0.037(0.122)	-0.056(0.117)	-0.173(0.135)	0.089(0.092)
ER	-0.044*(0.022)	-0.023(0.017)	-0.043*(0.023)	-0.007(0.016)
Constant	1.260**(0.473)	1.617***(0.269)	1.299***(0.240)	2.027***(0.449)
Obs	66	396	286	165
R ²	0.206	0.074	0.083	0.262

Notes: Robust standard errors in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01.

urbanize, the agricultural circle continued to migrate outward. Suburban agriculture was impacted by the large market in the urban region, which must fulfill the consumption demand of the urban population in the metropolitan area while also competing with the income of the urban inhabitants. As a result, suburban agriculture had the development direction of mechanization, intensification, facility and high efficiency.

Interestingly, in the metropolitan cities, as shown in model (3), industrialization was significantly positive. The reason was that Peigang Zhang defined industrialization in *Agriculture and Industrialization* in a new way: not only the increase of the proportion of industrial production but also the mechanization and modernization of agriculture. When industrialization reached a mature stage, if the market law was allowed to continue to work, it will inevitably lead to changes in the structure of agricultural production, the expansion of agricultural markets and the improvement of agricultural production technology. This was the time to officially enter the stage of industry nurturing agriculture, which was conducive to the improvement of AGTFP. In the non-metropolitan area, as shown in model (4), a significant positive effect of urbanization was observed for the first time. This suggested that non-metropolitan locations had lower living costs than metropolitan areas, as well as reduced human resource flow costs between urban and rural areas. As a result, social capital may be diverted to rural regions, and new energy can be pumped into agriculture's green development.

Discussion and conclusion

Based on the above empirical results, the following three conclusions were obtained:(1) From 2010 to 2020, the YRD's overall AGTFP increased steadily over time, while the spatial pattern showed a synergistic increase around the core cities (Nanjing, Hangzhou, and Hefei), with the northern and southern cities having distinct spatial clustering characteristics. (2) Economic agglomeration has a non-linear effect on AGTFP.

Specifically, the infancy stage exerted a weak promotion effect on AGTFP through the trickle-down effect; the growth stage suppressed AGTFP through the siphoning effect; the maturity stage significantly promoted AGTFP through the radiation effect; and the decline stage showed a crowding effect, which was detrimental to AGTFP. Overall, economic agglomeration has a positive impact on AGTFP, but the effect lagged. (3) Economic agglomeration can promote AGTFP in peripheral cities and non-metropolitan area cities, while it showed a suppressive effect in central cities.

Some important findings deserve special attention. This paper verified that the non-linear effect of economic agglomeration in the YRD region on AGTFP was consistent with life-cycle theory through a threshold model, the growth and maturation stages were of particular interest. To begin, in the growth stage, economic agglomeration can inhibit AGTFP through the siphoning effect. Industrialization and urbanization were typical paths of economic development in developing countries, and early accumulation that lacked external resources had to rely on the low cost of its resources such as land and human resources. Thus, in the early stage of economic growth, acquiring a large number of cheap land and cheap labor from rural areas was a shortcut to the economic miracle. In the case of China's reality, the urbanization brought about by rapid economic agglomeration has not essentially absorbed the rural population, but rather served as a casualty of urban development. Many rural laborers went to cities but struggled to afford the high cost of living, and as they aged, the final destination was still the countryside. However, since the main labor forces of the countryside flowed to the cities, it was difficult for the countryside to develop, which was a vicious circle. Then, in the maturity stage, economic agglomeration can promote AGTFP through the radiation effect. The high concentration of economic activities effectively reduced barriers to capital factor mobility by amplifying the effects of sharing, matching and learning, which in turn optimized capital allocation and improved AGTFP. Last, digital financial inclusion was not conducive to AGTFP improvement, this result was different from existing studies.^{47,53,54} The reason for this may be that, on the one hand, due to a lack of agricultural production factors and a scarcity of financial products that truly correspond to "agriculture, rural areas, farmers", many platforms were directly moved from the city back to the rural, which was not only ineffective but also wasteful of resources, making it difficult to promote and implement digital financial inclusion products. On the other hand, farmers' lack of financial literacy and traditional conservative thinking has led to insufficient awareness of financial services and low Internet participation, such as loans, payments, and wealth management through digital financial service platforms. Farmers and rural businesses have difficulty in taking advantage of the third-party financial support provided by digital financial inclusion to increase productivity.⁵⁵

This paper has both theoretical and practical implications. In the theoretical sense, on the one hand, it breaks through the limitations of existing agricultural green transformation from the perspective of economic agglomeration research. On the other hand, the life cycle theory is introduced to further expand the theoretical mechanism of the impact of economic agglomeration on AGTFP. In a practical sense, this study helps to understand the relationship between economic agglomeration and AGTFP in the social context of urban support for rural areas and industrial support for agriculture in China. It has important implications on how to coordinate the two and thus promote green and

high-quality agricultural development. Therefore, the following two recommendations are made: (1) Economic agglomeration has a substantial direct impact on the enhancement of AGTFP, and a green development path for agriculture induced by economic agglomeration should be established. However, since economic agglomeration has a non-linear effect on AGTFP, the government should accurately grasp the critical point at which the positive externalities of economic agglomeration come into play and objectively view the impact of economic agglomeration on rural farmers in agriculture. (2) The influence of economic agglomeration on AGTFP tends to lag, and agricultural inputs and outputs differ significantly across urban regions. Accordingly, agricultural development and environmental protection strategies are designed with a long-term vision on the one hand. Government, on the other hand, the government should formulate differentiated regional development policies to guide local agricultural production on the actual situation.

There are still limitations in this paper, and two points deserve improvement. The first point is that some studies have shown that the spatial diffusivity of economic agglomeration is consistent with spatial spillover effects in spatial econometric analysis.^{8,45} So, is there a spatial correlation between economic agglomeration and green agricultural development? Given the space limitation and outside the theoretical framework of this study, but is well worth exploring in future research. Another point is that pesticides are not considered in the calculation of agricultural non-point source pollution. The reason for this is the difficulty of quantifying pesticide pollution sources and the unavailability of discounted data. The measurement of pesticide contamination deserves further analysis in future studies.

Author statement

Fengting Wang: Conceptualization, Writing-Original draft preparation, Writing-Reviewing and Editing. Hao Wang: Methodology, Software, Visualization, Resources. Cong Liu: Data curation. Lichun Xiong: Resources, Software, Validation. Fanbin Kong: Writing-Reviewing and Editing, Supervision, Project administration.


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Note

- a. The absence of pesticide effluent coefficients makes it difficult to quantify pesticide pollution. The undesired output in this paper do not consider pesticides.

References

1. Liu Y, Sun D, Wang H, et al. An evaluation of China's agricultural green production: 1978–2017. *J Cleaner Prod* 2020; 243: 118483.
2. Pingali PL. Green revolution: impacts, limits, and the path ahead. *Proc Natl Acad Sci USA*. 2012; 109: 12302–12308.
3. Sinha E, Calvin KV, Kyle PG, et al. Implication of imposing fertilizer limitations on energy, agriculture, and land systems. *J Environ Manage*. 2022; 305: 114391.
4. Luo S, He K and Zhang J. Re-discussion on China's agricultural total factor productivity since the reform and opening up——based on the perspective of production factor quality and infrastructure. *Chinese Rural Economy* 2022; 2: 115–136. (In Chinese).
5. Xu B and Lin B. Factors affecting CO₂ emissions in China's agriculture sector: evidence from geographically weighted regression model. *Energy Policy* 2017; 104: 404–414.
6. Qu Y, Zhang Q, Zhan L, et al. Understanding the nonpoint source pollution loads' spatio-temporal dynamic response to intensive land use in rural China. *J Environ Manage*. 2022; 315: 115066.
7. Marshall. *Principles of Economics*. London: Macmillan, 1920.
8. Shao S, Zhang K and Dou J. Energy conservation and emission reduction effect of economic agglomeration: theory and Chinese experience. *Manage World* 2019; 35: 36–60 + 226. (In Chinese).
9. Marques AC, Fuinhas JA and Pais DF. Economic growth, sustainable development and food consumption: evidence across different income groups of countries. *J Cleaner Prod* 2018; 196: 245–258.
10. Sokolova E, Kirovski P and Ivanov B. The Role of Eu Direct Payments for Production Decision-Making in Bulgarian Agriculture. *The Journal "Agriculture and Forestry"* 2015; 61: 145–152.
11. Tao Y, Wang H, Ou W, et al. A land-cover-based approach to assessing ecosystem services supply and demand dynamics in the rapidly urbanizing Yangtze river Delta region. *Land Use Policy* 2018; 72: 250–258.
12. Wu H, Fang S, Zhang C, et al. Exploring the impact of urban form on urban land use efficiency under low-carbon emission constraints: a case study in China's Yellow River basin. *J Environ Manage*. 2022; 311: 114866.
13. Guo J, Zhu T, Ou M, et al. A Framework of Payment for Ecosystem Services to Protect Cropland: A Case Study of the Yangtze River Delta in China. *Sustainability* 2018; 10: 178.
14. Yu M, Yang Y, Chen F, et al. Response of agricultural multifunctionality to farmland loss under rapidly urbanizing processes in Yangtze river Delta, China. *Sci Total Environ* 2019; 666: 1–11.
15. Li H, Liu Z, Li Z, et al. Resilience analysis for agricultural systems of north China plain based on a dynamic system model. *Sci Agric* 2011; 68: 8–17.
16. Lu Y, Jenkins A, Ferrier RC, et al. Addressing China's grand challenge of achieving food security while ensuring environmental sustainability. *Sci Adv* 2015; 1: e1400039.
17. Glaeser EL. Triumph of the city: how our greatest invention makes us richer, smarter, greener, healthier, and happier (an excerpt) (translated by Inn0 Kushnareva). *Economic Sociology* 2011; 14: 75–94.
18. Zeng DZ and Zhao L. Pollution havens and industrial agglomeration. *J Environ Econ Manage* 2006; 58: 141–153.
19. Dean JM, Lovely ME and Wang H. Are foreign investors attracted to weak environmental regulations? Evaluating the evidence from China. *J Dev Econ* 2009; 90: 1–13.
20. Zhou K, Liu H and Wang Q. The impact of economic agglomeration on water pollutant emissions from the perspective of spatial spillover effects. *J Geog Sci* 2020; 29: 2015–2030.

21. Jin X, Li X, Feng Z, et al. Linking ecological efficiency and the economic agglomeration of China based on the ecological footprint and nighttime light data. *Ecol Indic* 2020; 111: 106035.
22. Wang X, Zhang Q and Chang W-Y. Does economic agglomeration affect haze pollution? Evidence from China's Yellow River basin. *J Cleaner Prod* 2022; 335: 130271.
23. Liu W, Xu R, Deng Y, et al. Dynamic Relationships, Regional Differences, and Driving Mechanisms between Economic Development and Carbon Emissions from the Farming Industry: Empirical Evidence from Rural China. *Int J Environ Res Public Health*. 2021; 18: 2257.
24. Wu J. Agglomeration: economic and environmental impacts. *Annu Rev Resour Economics* 2019; 11: 419–438.
25. Glaeser EL and Kahn ME. The greenness of cities: carbon dioxide emissions and urban development. *J Urban Econ* 2010; 67: 404–418.
26. Tichy G. *Clusters: less dispensable and more risky than ever clusters and regional specialization*. London: Pion Limited, 1998, pp.226–237.
27. Jiřčikova E, Pavelkova D, Bialic-Davendra M, et al. The age of clusters and its influence on their activity preferences. *Technological and Economic Development of Economy* 2013; 19: 621–637.
28. Ingstrup MB and Damgaard T. Cluster facilitation from a cluster life cycle perspective. *European Planning Studies* 2013; 21: 556–574.
29. Timmer MP and Szirmai A. Productivity growth in Asian manufacturing: the structural bonus hypothesis examined. *Structural Change and Economic Dynamics* 2000; 11: 371–392.
30. Wu J, Ruan J and Xu G. Economic agglomeration, economic distance and Farmers' income increase: direct effects and spatial spillover effects. *China Economic Quarterly* 2017; 16: 297–320. (In Chinese).
31. Tone K. A slacks-based measure of efficiency in data envelopment analysis. *Eur J Oper Res* 2001; 130: 498–509.
32. Tone K. A slacks-based measure of super-efficiency in data envelopment analysis. *Eur J Oper Res* 2002; 143: 32–41.
33. Tone K. Dealing with Undesirable Outputs in DEA: A Slacks-based Measure(SBM) Approach. *GRIPS Research Report Series* 2003; 44–445.
34. Oh D-h. A global Malmquist-Luenberger productivity index. *Journal of Productivity Analysis* 2010; 34: 183–197.
35. Liu Z and Xin L. Has China's belt and road initiative promoted its green total factor productivity? —evidence from primary provinces along the route. *Energy Policy* 2019; 129: 360–369.
36. Wang F, Li R, Yu C, et al. Temporal-Spatial Evolution and Driving Factors of the Green Total Factor Productivity of China's Central Plains Urban Agglomeration. *Frontiers in Environmental Science* 2021; 9: 686–725.
37. Zhang J, Zeng W, Wang J, et al. Regional low-carbon economy efficiency in China: analysis based on the super-SBM model with CO2 emissions. *J Cleaner Prod* 2017; 163: 202–211.
38. Sueyoshi T and Goto M. World trend in energy: an extension to DEA applied to energy and environment. *J Econ Struct* 2017; 6: 13.
39. Hansen BE. Threshold effects in non-dynamic panels: estimation, testing, and inference. *J Econom* 1999; 93: 345–368.
40. West TO and Marland G. A synthesis of carbon sequestration, carbon emissions, and net carbon flux in agriculture: comparing tillage practices in the United States. *Agric Ecosyst Environ* 2002; 91: 217–232.
41. Dubey A and Lal R. Carbon footprint and sustainability of agricultural production systems in Punjab, India, and Ohio. *USA. Journal of Crop Improvement* 2009; 23: 332–350.
42. Li B, Zhang J and Li H. Spatiotemporal characteristics of China's agricultural carbon emissions and decomposition of influencing factors. *China Population, Resources and Environment* 2011; 21: 80–86. (In Chinese).

43. Lai s-y, Du P-f and Chen J-n. Evaluation of non-point source pollution based on unit analysis. *Journal of Tsinghua University(Science and Technology)* 2004; 9: 1184–1187. (In Chinese).
44. Tao Y, Wang S, Guan X, et al. Analysis on characteristics of agricultural non-point source pollution sources in Qinghai province. *Transactions of the Chinese Society of Agricultural Engineering* 2019; 35: 164–172.
45. Ciccone A and Robert EH. Productivity and the density of economic activity. *Am Econ Rev* 1996; 86: 54–70.
46. Guo F, Wang J, Wang F, et al. Measuring the development of digital inclusive finance in China: index compilation and spatial characteristics. *China Economic Quarterly* 2020; 19: 1401–1418. (In Chinese).
47. Ma J and Li Z. Does Digital Financial Inclusion Affect Agricultural Eco-Efficiency? A Case Study on China. *Agronomy* 2021; 11: 1949.
48. Beckers V, Poelmans L, Van Rompaey A, et al. The impact of urbanization on agricultural dynamics: a case study in Belgium. *J Land Use Sci* 2020; 15: 626–643.
49. Liu D, Zhu X and Wang Y. China's agricultural green total factor productivity based on carbon emission: An analysis of evolution trend and influencing factors. *J Cleaner Prod* 2021; 278: 123692.
50. Chen J, Cheng S and Song M. Changes in energy-related carbon dioxide emissions of the agricultural sector in China from 2005 to 2013. *Renewable Sustainable Energy Rev* 2018; 94: 748–761.
51. Chen Z, Kahn ME, Liu Y, et al. The consequences of spatially differentiated water pollution regulation in China. *J Environ Econ Manage* 2018; 88: 468–485.
52. Lu M. From scattering to agglomeration: theory, misunderstanding and reform of rural urbanization. *Issues in Agricultural Economy* 2021; 09: 27–35.
53. Chang J. The role of digital finance in reducing agricultural carbon emissions: evidence from China's provincial panel data. *Environ Sci Pollut Res Int.* 2022; 11: 1–16.
54. Gao Q, Cheng C, Sun G, et al. The Impact of Digital Inclusive Finance on Agricultural Green Total Factor Productivity: Evidence From China. *Front Ecol Evol* 2022; 10: 905644.
55. Li T and Liao G. The Heterogeneous Impact of Financial Development on Green Total Factor Productivity. *Frontiers in Energy Research* 2020; 8: 29.

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