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RESEARCH ARTICLE

Impact of China's water pollution on agricultural economic growth: an empirical analysis based on a dynamic spatial panel lag model

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Abstract
The average annual growth rate of China's waste emissions from 2007 to 2017 was 2.3%. The main pollutants in the wastewater are chemical oxygen demand, ammonia nitrogen, total ammonia, total phosphorus, and so on which pollute groundwater and destroy ecosystems. Poor water quality reduces the edible value of agricultural products and has an impact on human health. Based on the panel data of 31 provinces in China from 2007 to 2017, this paper uses a dynamic spatial panel lag model to study the impact of China's water pollution on agricultural economic growth. The results show that the impact of China's water pollution on agricultural economic growth is significant. If the intensity of wastewater discharge is taken as an input factor in the process of agricultural production, the growth of agricultural economy tends to decline with the increase of water pollution. In the effect analysis, the short-term and long-term effects are significant. The absolute value of the long-term total effect is far greater than the short-term total effect, indicating that the inhibitory effect of water pollution on agricultural economic growth is more obvious. The cumulative effect of water pollution on agricultural economic growth continues to expand, resulting in more and more economic losses. The central and local governments should take various measures to reduce water pollution, guide the green development of agriculture, and increase farmers' income to realize the rural revitalization plan.

Keywords Water pollution · Agricultural economic growth · Dynamic spatial panel lag model

Introduction

The sources of wastewater discharge in China mainly include industrial sources, agricultural sources, urban living sources, motor vehicles, and centralized pollution control facilities. The main pollutants in the wastewater are chemical oxygen demand, ammonia nitrogen, total ammonia, total phosphorus, and so on. In 2007, the amount of wastewater discharged was 55.7 billion tons. In 2017, the amount of wastewater discharged in China reached almost 70 billion tons, with an average annual growth rate of 2.3%.Wastewater discharge not only pollutes groundwater and destroys ecosystems (Desimone and Howes 1996; Vesna et al. 2015; Srinivas and Singh 2018) but also affects rivers, lakes, and coastal waters (Reopanichkul et al. 2010). The Environmental Protection Law of the People's Republic of China and the Water Pollution Prevention and Control Law of the People's Republic of China have published a series of local wastewater discharge standards, and various regions have adopted different measures in environmental governance (Li et al. 2019; Xu et al. 2020; Li et al. 2020), jointly to control water pollution.

All kinds of plants need water for growth (Brown et al. 2010; Herath et al. 2013). Poor water quality will affect plants and change their metabolic pathways (AbouAli and ElAyouti 2014; Margenat et al. 2017). The growth of agricultural crops in China requires large amounts of groundwater irrigation. However, the 2018 China Eco-Environmental Bulletin announced that among the 10,168 national groundwater quality monitoring points in China, inferior V water quality monitoring points reached 15.5%. The 2833 shallow groundwater monitoring wells with inferior water quality accounted for 46.9%. Manganese, iron, turbidity, total dissolved solids, iodide, etc. exceeded the standard, and the overall water quality was poor. Poor water quality will make crops prone to malnutrition and quality deterioration and will cause a decline in

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agricultural production. These will cause losses to the agricultural economy. China is a large agricultural country. In 2018, 560 million people lived in rural areas, accounting for 40% of the total population. Agricultural economic growth has an important strategic status for a country's overall development and stability.

This paper uses a dynamic spatial panel lag model to study the impact of China's water pollution on agricultural economic growth. This paper makes the following theoretical and empirical contributions. The study offers a new perspective about China's water pollution on agricultural economic growth. The impact of water pollution on agricultural economic growth is significant, which is a huge obstacle to China's rural revitalization plan. The cumulative effect of China's water pollution on agricultural economic growth continues to expand in time and space, destroying the agricultural ecosystem. The research can provide empirical support for the government to formulate agricultural policies. Therefore, research of China's water pollution on agricultural economic growth is conducive to guiding agricultural green development, increasing farmers' income, and realizing rural revitalization and other strategic plans.

The structure of this paper is organized as follows. In the "Literature review" section, we provide literature review which mainly includes research progress in this field. In the "Methodology" section, we introduce the methodology which includes data source, variable description, and research methods. In the "An empirical analysis of China's water pollution on agricultural economic growth" section, we present the research results which include the impact and effect decomposition of China's water pollution on agricultural economic growth. Finally, we present the conclusions in the "Conclusion" section.

Literature review

Environmental quality and agricultural economic growth constitute a dynamic and complex open system that is interrelated, interactive, and mutually restrictive (Jiang and Wang 2019). In research on the relationship between environmental pollution and economic growth, most scholars focus on the impact of economic growth on environmental pollution, and believe that the impact of economic growth on environmental pollution has an inverted "U" relationship (Ma and Li 2006; Usama et al. 2015; Kong et al. 2017; Xu 2018; Rao and Yan 2020). The research on environmental pollution caused by agricultural economic growth can be divided into two categories. The first category is to decompose the impact of economic growth on environmental pollution into multiple effects (Hu 1993; Grossman and Krueger 1995; Liang et al. 2013) based on the principle of structural decomposition. The second category is based on the classical environmental Kuznets curve (EKC), which studies the relationship between agricultural economic growth and agricultural pollution (Tsuzuki 2006; Managi 2006; Li and Zhang 2009; Aziz et al. 2020). Because of its own "illusory nature" (Zhong 2005), the EKC method has been controversial and criticized (Zhao and Wen 2004; Liu and He 2009; Feng and Zhao 2011). But this method is still advocated by some scholars (Shang et al. 2017; Qiao et al. 2019; Kong et al. 2019; Şentürk et al. 2020).

The above research believes that economic growth brings pollution. If economic development reaches a critical position, economic growth will improve environmental quality and achieve coordinated development (Cole 2003; Gavrilova et al. 2010; Le and Sarkodie 2020). Environmental pollution will not only cause economic losses but also affect residents' health. The impact of environmental pollution on economic growth cannot be ignored. Scholars have relatively little research on the impact of environmental pollution on economic growth. From the perspective of input and output, some scholars use environmental pollution as a factor in production input (Hailu and Veeman 2000), and find that environmental pollution has a huge impact on economic growth (Dai et al. 2015; Anser et al. 2020). Yan and Cao (2020) used the Gauss-Newton iterative method to estimate the economic losses caused by environmental pollution. Empirical research results show that environmental pollution will hinder economic growth. Ji et al. (2013) proved that when untreated wastewater is discharged into the sea, it will pose a major threat to water quality. The impact of water pollution is significant not only on the ecological environment and economic development level but also on the health of residents.

In summary, from the research content, in the study of the relationship between environmental pollution and economic growth, most scholars analyzed the impact of economic growth on the environment, and only a small number of scholars studied the impact of environmental pollution on economic growth. There are few relevant references on the impact of water pollution on the economic growth of the agricultural industry. From research methods, most scholars use the general panel model or the spatial panel model. Although the spatial panel model considers the spatial correlation more than the general panel model, it ignores the inertia and time lag of economic development. The economic growth of the previous period will affect the current period more or less. Therefore, this paper adopts the dynamic spatial panel lag model to solve two problems. The first is the impact of water pollution on agricultural economic growth. The second is the decomposition of the short-term and long-term effects of water pollution on agricultural economic growth due to the cumulative effect of water pollution.

Methodology

Data source

In order to ensure the uniformity of the sample data, the research object of this article is 31 provinces of China except Hong Kong, Macau, and Taiwan from 2007 to 2017. The gross agricultural product and fiscal agricultural expenditure come from the *China Rural Statistical Yearbook 2008–2018*. The total amount of wastewater discharge, the urbanization level, and the proportion of secondary industry come from the *China Statistical Yearbook 2008–2018*. The software used for data analysis is Stata 16.0.

Variable description

The explained variable, agricultural economic growth (Aeg) Referring to the literatures of Yu et al. (2019) and Yan and He (2019), this paper uses the gross agricultural product (100 million yuan) to represent agricultural economic growth. It can better reflect the economic level of the development of the primary industry, and the data are objective and true.

Core explanatory variable, water pollution (Wpo) Water pollution is a serious threat to the safety of water resources in China, which will have an impact on the surface water environment, soil, groundwater, offshore waters, and even the atmosphere. The deterioration of water quality will affect the safety of drinking water and agricultural products, and ultimately threaten human health. In this paper, the intensity of wastewater discharge (10,000 tons/100 million yuan) is used to represent water pollution, which is calculated by dividing the total amount of wastewater discharge by the total agricultural production value. The greater the intensity of wastewater discharge, the greater the impact on agricultural products, and the quality of agricultural products will decline.

Referring to the research ideas of Wei (2007), Yao et al. (2016), and Xin and Chen (2017), this paper uses the intensity of fiscal agricultural expenditure (Iae), the urbanization level (Url), and the proportion of secondary industry (Psi) as control variables. The intensity of fiscal agricultural expenditure is calculated by using the fiscal agricultural expenditure (100 million yuan) divided by the gross agricultural product. The greater the intensity of fiscal agricultural expenditure, the better the agricultural economic growth. The urbanization level is calculated by using the urban population (10,000 people) divided by the total population (10,000 people). The stronger the urbanization level, the more developed the economy, and the better the agricultural economic growth. The proportion of secondary industry is a percentage (%). The higher the proportion of the secondary industry, the more developed the mechanical power, and the more beneficial it is to the growth of the agricultural economy.

Dynamic spatial panel lag model

Regional agricultural economic growth is affected not only by local factors but also by the previous period's agricultural economic growth in the region and other regions' previous and same period agricultural economic growth. This paper refers to the dynamic spatial panel lag model (Elhorst 2005; Yu et al. 2008) to study the impact of China's water pollution on agricultural economic growth. For simplicity, Y represents agricultural economic growth (Aeg). X represents water pollution (Wpo), fiscal agricultural expenditure (Iae), urbanization level (Url), and the proportion of secondary industry (Psi). The specific form of the dynamic space panel lag model is as follows:

$$Y_{it} = \tau Y_{it-1} + \rho \sum_{j=1}^{n} w_{ij} Y_{jt} + X_{it}^{'}\beta + a_i + \gamma_t + u_{it} \tag{1}$$

$$Y_{it} = \delta \sum_{j=1}^{n} w_{ij} Y_{jt-1} + \rho \sum_{j=1}^{n} w_{ij} Y_{jt} + X_{it}^{'}\beta + a_i + \gamma_t + u_{it} \tag{2}$$

$$Y_{it} = \tau Y_{it-1} + \delta \sum_{j=1}^{n} w_{ij} Y_{jt-1} + \rho \sum_{j=1}^{n} w_{ij} Y_{jt} + X_{it}^{'}\beta + a_i + \gamma_t + u_{it} \tag{3}$$

where $i = 1, 2, 3, \ldots, n$ represents the region and $t = 1, 2, 3, \ldots, T$ represents the time. Y_{it} represents the agricultural economic growth of period t in region i. Y_{it-1} represents the agricultural economic growth of period $t-1$ in region i. w_{ij} is an element in the spatial weight matrix. When region i is adjacent to j, w_{ij} is 1. When region i is not adjacent to$j$, w_{ij} is 0. $w_{ij}Y_{jt}$ represents the agricultural economic growth of a neighboring region in period t. $\mathbf{X}_{it}^{'} = (X_{1it}, X_{2it}, \ldots, X_{kit})$ represents water pollution and other influencing factors. $w_{ij}Y_{jt-1}$ represents the agricultural economic growth of the previous period in the neighboring region. τ, ρ, β, δrepresent the regression coefficients. α_i represents individual effects. γ_t represents time effects. u_{it} represents random error terms.

Spatial correlation test

Before estimating the coefficients of the models (1), (2), and (3), the paper carries out a spatial correlation test, mainly including the Moran index test (Moran 1950;Cliff and Ord 1972) and the LM test (Anselin 2006; Elhorst 2010). Although Moran's I may test whether the model has spatial correlation, it cannot judge the specific form of the spatial measurement model, and the LM test can determine the specific form of the model.

This paper uses the Moran index test to determine whether there is spatial autocorrelation. $H_0 : \mu_{it}$ is an independent distribution. $H_1 : \mu_{it}$ is the spatial distribution. The statistic used in the test is

$$I = \frac{e^{'} I_T \otimes We}{e^{'} e} \tag{4}$$

where **e** is the residual vector of the traditional panel model (regardless of spatial correlation). J and T_W are defined as follows:

$$J = \frac{1}{\widehat{\sigma}^2} \left[\left((I_T \otimes W) X \widehat{\beta} \right)^{'} \left(I_{nT} - X \left(X^{'} X \right)^{-1} X^{'} \right) \times (I_T \otimes W) X \widehat{\beta} + T T_W \widehat{\sigma}^2 \right]$$
$$T_W = tr \left(WW + W^{'} W \right)$$

This paper uses the test of the spatial panel lag model to determine the model form. $H_0: \tau, \delta, \rho$ are 0. $H_1: not\ all\ \tau, \delta, \rho$ are 0. The statistic used in the test is

$$LM = \frac{\left[e^{'} (I_T \otimes W) Y / \widehat{\sigma}^2 \right]^2}{J} \tag{5}$$

$$\text{Robust } LM = \frac{\left[e^{'} (I_T \otimes W) Y / \widehat{\sigma}^2 - e^{'} (I_T \otimes W) e / \widehat{\sigma}^2 \right]^2}{J - T T_W} \tag{6}$$

This paper uses the test of the spatial panel error model to determine the model form. $H_0: u_{it}$ has no spatial autocorrelation. $H_1: u_{it}$ has spatial autocorrelation. The statistic used in the test is

$$LM = \frac{\left[e^{'} (I_T \otimes W) e / \widehat{\sigma}^2 \right]^2}{T T_W} \tag{7}$$

Robust LM

$$= \frac{\left[e^{'} (I_T \otimes W) e / \widehat{\sigma}^2 - T T_W / J \times e^{'} (I_T \otimes W) Y / \widehat{\sigma}^2 \right]^2}{T T_W [1 - T T_W / J]} \tag{8}$$

Model estimation and effect decomposition

To estimate the parameters τ, ρ, β, δ of models (1), (2), and (3), the method used is the maximum likelihood estimation, and the estimated equation is

$$LogL = -\frac{nT}{2} \log(2\pi\sigma^2) + T \log|I_n - \rho W| - \frac{1}{2\sigma^2} \sum_{i=1}^{n} \sum_{t=1}^{T} \left[Y_{it} - \tau Y_{it-1} - \delta \left(\sum_{j=1}^{n} w_{it} Y_{jt-1} \right) - \rho \left(\sum_{j=i}^{n} w_{ij} Y_{jt-1} \right) - X^{'}_{it} \beta \right]^2 \tag{9}$$

When δ is equal to 0, formula (9) can be transformed into model (1). When τ is equal to 0, formula (9) can be transformed into model (2). When δ and τ are not equal to 0, formula (9) can be transformed into model (3). $\mathbf{I_n} - \boldsymbol{\rho} \mathbf{W}$ is the matrix representation of $Y_{it} - \rho \sum_{j=1}^{n} w_{ij}\ Y_{jt}$ without Y_{jt}.

By calculating the maximum likelihood function value of formula (9), the estimated value of the unknown parameter τ, ρ, β, δ can be obtained.

Model (1) is expressed in matrix form: $\mathbf{Y_t} = \tau \mathbf{Y_{t-1}} + \rho \mathbf{W} \mathbf{Y_t} + \mathbf{X}^{'}_{\mathbf{t}} \boldsymbol{\beta} + \boldsymbol{\varepsilon}_{\mathbf{t}}$, and this model can be rewritten as

$$Y_t = (I - \rho W)^{-1} \tau Y_{t-1} + (I - \rho W)^{-1} \left(X^{'}_{it} \beta \right) + (I - \rho W)^{-1} \varepsilon_t \tag{10}$$

Model (2) is expressed in matrix form: $\mathbf{Y_t} = \delta \mathbf{W} \mathbf{Y_{t-1}} + \rho \mathbf{W} \mathbf{Y_t} + \mathbf{X}^{'}_{\mathbf{t}} \boldsymbol{\beta} + \boldsymbol{\varepsilon}_{\mathbf{t}}$, and this model can be rewritten as

$$Y_t = (I - \rho W)^{-1} \delta W Y_{t-1} + (I - \rho W)^{-1} \left(X^{'}_{it} \beta \right) + (I - \rho W)^{-1} \varepsilon_t \tag{11}$$

Model (3) is expressed in matrix form: $\mathbf{Y_t} = \tau \mathbf{Y_{t-1}} + \delta \mathbf{W} \mathbf{Y_{t-1}} + \rho \mathbf{W} \mathbf{Y_t} + \mathbf{X}^{'}_{\mathbf{t}} \boldsymbol{\beta} + \boldsymbol{\varepsilon}_{\mathbf{t}}$, and this model can be rewritten as

$$Y_t = (I - \rho W)^{-1} (\tau I + \delta W) Y_{t-1} + (I - \rho W)^{-1} \left(X^{'}_{it} \beta \right) + (I - \rho W)^{-1} \varepsilon_t \tag{12}$$

After models (1), (2), and (3) are converted into matrix forms (10), (11), and (12), the short-term direct effects, short-term indirect effects, long-term direct effects, and long-term indirect effects are shown in Table 1.

An empirical analysis of China's water pollution on agricultural economic growth

Temporal and spatial characteristics of water pollution and agricultural economic growth

Figure 1 is a graph showing the temporal and spatial characteristics of the total amount of wastewater discharged and the gross agricultural production. Four red lines in Fig. 1 represent the average wastewater discharge and the average gross agricultural production in the end of the 11th and 12th 5-year plan. The end year of the 11th and 12th 5-year plan is 2010 and 2015. In 2010 and 2015, the average wastewater discharge of 31 provinces in China was 1958.892 and 2372.008 million tons, and the average gross agricultural product is 98.7455 and 176.682 billion yuan. The provinces with the total wastewater discharge from 2007 to 2017 which exceeded the average wastewater discharge of 31 provinces in China in 2010 and 2015 include Guangdong, Henan, Hubei, Hunan, Jiangsu, Shandong, Sichuan, and Zhejiang. The 8 main provinces

Table 1 The short-term, long-term, direct, and indirect effects of the dynamic spatial panel lag model (spatial spillover effect)

Model	Short-term direct effect	Short-term indirect effect	Long-term direct effect	Long-term indirect effect
1	$[(I-\rho W)^{-1}\ (\beta_k\ I_n)\ ]^{\overline{d}}$	$[(I-\rho W)^{-1}\ (\beta_k\ I_n)\ ]^{\overline{rsum}}$	$\{[(1-\tau)\ \ \mathrm{I}-\rho \mathrm{W}]^{-1}\ (\beta_k\ I_n)\ \}^{\overline{d}}$	$\{[(1-\tau)\ \ \mathrm{I}-\rho \mathrm{W}]^{-1}\ \overline{(\beta_k}\ I_n)\ \}^{rsum}$
2	$[(I-\rho W)^{-1}\ (\beta_k\ I_n)\ ]^{\overline{d}}$	$[(I-\rho W)^{-1}\ (\beta_k\ I_n)\ ]^{\overline{rsum}}$	$\{[\mathrm{I}-(\rho+\delta)\ \ \mathrm{W}]^{-1}\ (\beta_k\ I_n)\ \}^{\overline{d}}$	$\{[\mathrm{I}-(\rho+\delta)\ \ \mathrm{W}]^{-1}\ \overline{(\beta_k}\ I_n)\ \}^{rsum}$
3	$[(I-\rho W)^{-1}\ (\beta_k\ I_n)\ ]^{\overline{d}}$	$[(I-\rho W)^{-1}\ (\beta_k\ I_n)\ ]^{\overline{rsum}}$	$\{[(1-\tau)\ \mathrm{I}-(\rho+\delta)\ \mathrm{W}]^{-1}\ (\beta_k\ I_n)\ \}^{\overline{d}}$	$\{[(1-\tau)\ \mathrm{I}-(\rho+\delta)\ \mathrm{W}]^{-1}\ \overline{(\beta_k}\ I_n)\ \}^{rsum}$

$\overline{d}$ represents the operator that calculates the mean value of the diagonal elements of the matrix, and $\overline{rsum}$ represents the operator that calculates the row and average value of the non-diagonal elements of the matrix

which fluctuated around the average are Anhui, Chongqing, Fujian, Guangxi, Hebei, Jiangxi, Liaoning, and Shanghai. The other 15 provinces did not exceed the average from 2007 to 2017. On the whole, the top three provinces with total wastewater discharge are Guangdong, Jiangsu, and Shandong, which are located in China's coastal provinces and have relatively developed economies. Xizang, Qinghai, and Ningxia are the last three provinces in terms of total wastewater discharge. They are located in the western region of China, and their economies are relatively backward.

The provinces with gross agricultural production from 2007 to 2017 that exceeded the average agricultural production of China's 31 provinces in 2015 include Henan and Shandong. Provinces exceeding the average gross agricultural product of China's 31 provinces in 2010 include Guangdong, Hebei, Hubei, Hunan, Jiangsu, and Sichuan. Except Anhui (2007), Heilongjiang, and Guangxi (2007 and 2008), the agricultural production in other years exceeded the average of 2010. The gross agricultural product of Chongqing, Fujian, Guizhou, Gansu, Jiangxi, Jilin, Liaoning, Neimonggu, Shaanxi, Xinjiang, Yunnan, and Zhejiang fluctuated around the average value in 2010. The gross agricultural product of Xinjiang from 2014 to 2017, Shaanxi and Yunnan from 2015 to 2017, Guizhou and Liaoning from 2016 to 2017, and Fujian in 2017 exceeded the average value in 2015. The provinces which from 2007 to 2017 have lower than the average values in 2010 include Tibet, Beijing, Hainan, Ningxia, Qinghai, Shanghai, Shanxi, and Tianjin. Xizang, Ningxia, and Qinghai are located in the west, and the land is relatively barren.

Beijing, Shanghai, and Tianjin are municipalities with less land. Hainan is an isolated island, and the land area of Shanxi is small and scattered.

Spatial correlation test results

According to formulas (4), (5), (6), (7), and (8), the spatial correlation test is carried out. The test results are shown in

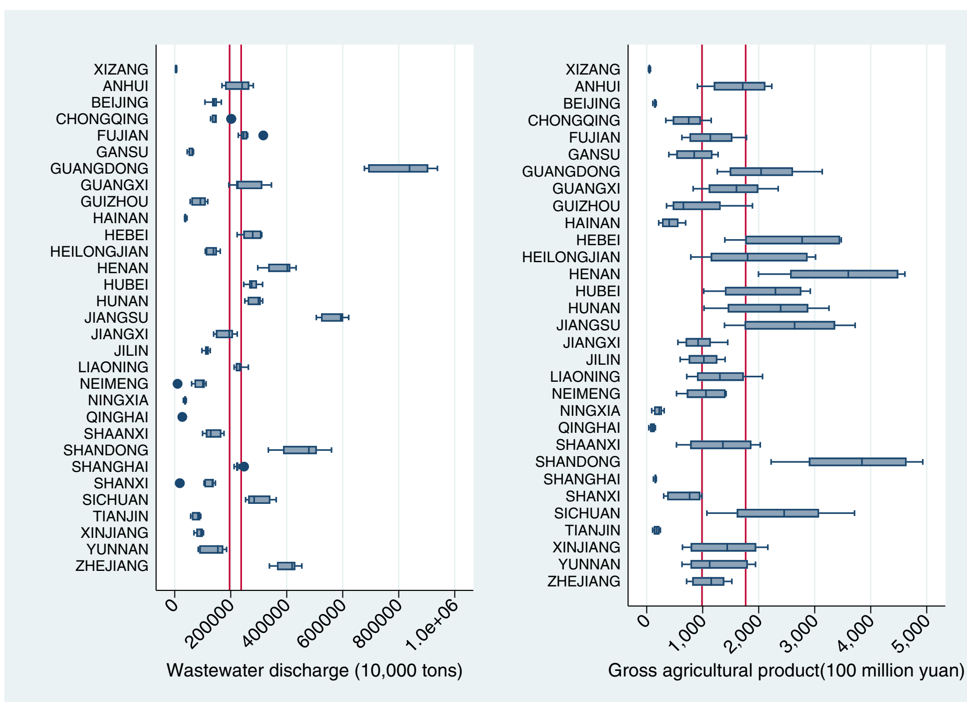

Fig. 1 Temporal and spatial characteristics of wastewater discharge and gross agricultural production

Table 2. It can be seen from Table 2 that Moran's statistic is 18.621, and the corresponding P value is 0 less than 0.05, indicating that the sample data has a spatial correlation. The LM statistics of the spatial panel lag model and the spatial panel error model are 326.382 and 271.948, and the corresponding P values are 0, which is less than the significance level of 0.05, indicating that both the spatial panel lag model and the spatial panel error model can be used. However, the robust LM statistic of the spatial panel error model is 0.098, and the corresponding P value is 0.754, which is greater than the significance level of 0.05. The robust LM statistic of the spatial panel lag model is 54.533, and the corresponding P value is 0, which is less than the significance level of 0.05. Therefore, it can be determined that the model used in the analysis should be the spatial panel lag model.

Analysis of the impact of China's water pollution on agricultural economic growth

Using formula (9) to estimate the models (1), (2), and (3), the estimation results are shown in Table 3. For comparison purposes, the regression results of the static spatial panel lag model are included in Table 3. When wastewater discharge intensity increases by 1 unit, it will increase the gross agricultural production by 0.595 units. It shows that the more the water pollution increases, the more the gross agricultural production increases, which is similar to the conclusion of Huang (2010). If agricultural economic growth follows this path, China's water environment will continue to deteriorate.

If water pollution is an influencing factor, the increase of water pollution will restrain the regional agricultural economic growth to a certain extent. This should be paid attention to by the government departments in various regions. In dynamic spatial panel lag model 1, the regression coefficient of wastewater discharge intensity is −7.958, and its absolute value is much smaller than 27.994. Although this model considers dynamic effects, using the results of this model to analyze the impact of water pollution on agricultural economic growth will underestimate the inhibitory effect of water pollution on agricultural economic growth. In dynamic spatial panel lag model 2, the regression coefficient of wastewater discharge intensity is 0.637. Although this model considers the dynamic space effect, there will be that the more pollution, the more growth will occur if we used this model to analyze the impact of water pollution on agricultural economic growth.

Table 2 Spatial correlation test results

Test	Statistic	df	P value
Spatial error			
Moran's I	18.621	1	0
Lagrange multiplier	271.948	1	0
Robust Lagrange multiplier	0.098	1	0.754
Spatial lag			
Lagrange multiplier	326.382	1	0
Robust Lagrange multiplier	54.533	1	0

Dynamic spatial panel lag model 3 considers both dynamic and dynamic spatial effects. According to the regression results, China's water pollution significantly reduced the agricultural economic growth from 2007 to 2017. Under other conditions unchanged, for China's wastewater discharge intensity increase by 1 unit, agricultural economic growth decreased by an average of 27.994 units. The corresponding t statistic was −237.39, and the impact of water pollution was significant. If the intensity of wastewater discharge is taken as an input factor in the process of agricultural production, the growth of agricultural economy tends to decline with the increase of water pollution. The effect of water pollution on agricultural economy is negative, which is consistent with the conclusion of Lei and Wang (2020). They used panel regression to find that environmental pollution has a significant inhibitory effect on high-quality economic development. The empirical results show that the impact of water pollution on agricultural economic growth is very significant, while Cai et al. (2020) pointed out that the reduction of water pollution will not occur automatically and water pollution has become a major obstacle to agricultural economic growth. With green development becoming the main theme of China's social and economic development, water pollution control should become a long-term issue for governments at all levels.

According to Akaike information criterion (AIC) and Bayesian information criterion (BIC), if explanatory variables are added to the model and the values of AIC and BIC become smaller, the model is the optimal model. Among the four models in Table 3, the values of AIC and BIC in dynamic space panel lag model 3 are 3672.649 and 3702.542, which are the smallest values among the four models. Therefore, this model is the optimal model, and its regression coefficients can better reflect the actual situation of China. The following analysis of control variables and effect results focuses on the regression coefficient of dynamic space panel lag model 3.

As fiscal agricultural expenditure intensity increased by 1 unit, the agricultural economic growth increased by an average of 6301.67 units. This indicates that local governments have played a positive role in correcting agricultural market failures and supporting agricultural production and services. When urbanization level increased by 1 unit, agricultural economic growth increased by an average of 289.39 units. With the development of urbanization, the expanding urban production and life have increased the demand for agricultural products, thus providing a broader market for the development of agriculture. For the proportion of the second industry increase by 1 unit, agricultural economic growth increased by an average of

Table 3 Regression results of the spatial panel lag model

Variable	Static spatial panel lag model	Dynamic spatial panel lag model		
		Model 1	Model 2	Model 3
AegL1		2.801***		3.475***
		(132.97)		(169.12)
WAegL1			0.31**	68.067***
			(2.45)	(954.87)
Wpo	0.595**	− 7.958***	0.637**	− 27.994***
	(2.17)	(− 65.57)	(2.07)	(− 237.39)
Iae	− 285.69***	6654.274***	− 317.896***	6301.607***
	(− 5.09)	(290.99)	(− 5.42)	(276.87)
Url	82.129***	257.055***	68.286***	289.39***
	(13.4)	(82.78)	(9.44)	(94.26)
Psi	− 13.556***	− 12.66***	− 10.013**	427.763***
	(− 3.33)	(− 7.46)	(− 2.2)	(242.19)
Spatial rho	0.296***	− 6.356***	0.128	− 76.351***
	(4.85)	(− 209.12)	(1.24)	(− 1129.88)
Number	341	310	310	310
AIC	4759.118	3681.647	4276.256	3672.649
BIC	4782.109	3707.803	4302.412	3702.542

The value in parentheses is the *z* value. "**" indicates significant at 5% level, and "***" indicates significant at 1% level

427.67 units, indicating that the driving effect of the second industry on the first industry is relatively obvious.

Analysis of the effect decomposition of China's water pollution on agricultural economic growth

Table 4 is the effect analysis of the dynamic space panel lag model 3, which includes short-term effects and long-term effects. Short-term effects and long-term effects are decomposed into direct and indirect effects, and the total effects are the sum of direct and indirect effects. From the total effect, the short-term total effect of water pollution is − 0.362, the long-term total effect is − 4.821, and the short-term and long-term effects are significant. The absolute value of the long-term total effect is far greater than that of the short-term total effect, indicating that the inhibitory effect of water pollution on agricultural economic growth is more obvious in the long run. This has a lot to do with the cumulative effect of water pollution.

It can be seen from the direct effect that the short-term direct effect of water pollution is − 3.052 and the long-term direct effect is − 0.456, and the short-term direct effect and the long-term direct effect are significant. This shows that the short-term inhibitory effect of water pollution on agricultural economic growth is higher than the long-term inhibitory effect. It can be seen from the indirect effects that the short-term indirect effect of water pollution is 2.69, the long-term indirect effect is − 4.365, and the short-term indirect effect and the long-term indirect effect are significant, which shows that the spatial spillover effect of water pollution in neighboring areas has changed from positive to negative influences. Overall, this has a lot to do with the mobility of water pollution.

The initial stage of wastewater discharge is mainly concentrated in this area, which has a greater impact on the agricultural economic growth of this area. However, as part of the wastewater that seeps underground or flows into rivers and lakes, it will enter another area from one area. With the flow of wastewater, it will affect the agricultural economy of this area. The impact of growth is reduced, but the flow into neighboring areas will have a spatially negative effect on the agricultural economic growth of neighboring areas. At the initial stage of wastewater discharge, it is mainly concentrated in this region, which has a great impact on the agricultural economic growth of this region. However, as part of the wastewater that seeps into the ground or into rivers and lakes, it will flow from one region to another. With the flow of wastewater, the impact on the agricultural economic growth of this region will be reduced, but the impact on the agricultural economic growth of another region will be negative if it flows into the neighboring region. Li and Lu (2020) pointed out that water pollution had transboundary mobility, but the degree of impact of transboundary pollution on other provinces had not

Table 4 Effect analysis of the dynamic spatial panel lag model

	Variable	Short-term effect	Long-term effect
Direct	Wpo	− 3.052***	− 0.456*
		(− 208.89)	(− 1.72)
	Iae	687.311***	102.737*
		(257.5)	(1.71)
	Url	31.563***	4.715*
		(96.22)	(1.71)
	Psi	46.663***	6.972*
		(208.56)	(1.71)
Indirect	Wpo	2.69***	− 4.365***
		(199.84)	(− 20.29)
	Iae	− 605.837***	983.01***
		(− 264.04)	(20.68)
	Url	− 27.821***	45.144***
		(− 95.24)	(19.89)
	Psi	− 41.132***	66.741***
		(− 199.68)	(20.3)
Total	Wpo	− 0.362***	− 4.821***
		(− 250.71)	(− 88.16)
	Iae	81.474***	1085.741***
		(275.55)	(82.99)
	Url	3.742***	49.859***
		(99.88)	(68.9)
	Psi	5.531***	73.713***
		(248.18)	(87.71)

The value in parentheses is the z value. "*" indicates significant at 10% level, "**" indicates significant at 5% level, and "***" indicates significant at 1% level

been reflected. Through data analysis, this paper calculates the degree of impact of transboundary water pollution on agricultural economic growth in other regions.

Conclusion

Based on China's provincial panel data from 2007 to 2017, this paper uses a dynamic spatial panel lag model to study the impact of water pollution on agricultural economic growth and draws the following conclusions. First, China's water pollution has a significant inhibitory effect on agricultural economic growth. As China's wastewater discharge intensity increased by 1 unit, agricultural economic growth decreased by an average of 27.994 units. Second, the short-term direct effect of water pollution on agricultural economic growth is − 3.052, the long-term spatial spillover effect is − 4.365, and the impact is significant. Based on the above conclusions, this article proposes the following countermeasures.

Open and transparent water pollution information. In the total amount of wastewater discharge, the discharge of industrial wastewater in China is not only decreasing year by year in quantity, but also decreasing in quality. The standard rate of industrial wastewater discharge has reached 95.3% in 2010 (Zhang 2014). The impact of industrial wastewater discharge on agricultural economic growth has shown a downward trend. Rural wastewater discharge has a direct impact on agricultural economic growth, but rural wastewater discharge has always been an unpublished data. It is recommended to open the data and set up departments to supervise rural water pollution. On this basis, we can calculate the impact of industrial wastewater pollution and rural water pollution on agricultural economic growth, so that the consequences of the two kinds of pollution can be compared. The state will have a clearer tendency to formulate policies.

Strict water pollution control policy. The impact of water pollution on the agricultural economic growth is cumulative. In the short term, the wastewater discharge in this region has a greater impact on the agricultural economic growth in this region. In the long term, water pollution in other regions has a greater impact on the agricultural economic growth in this region. The supervision of wastewater discharge can rely not only on the unilateral actions of individual regions but also on the basis of mutual coordination between different regions to take common treatment measures. The integration policy of water pollution control should be the basic policy that all provinces adhere to. Even in provinces with lighter water pollution, strict pollution control policies must also be implemented.

Regional integration of water pollution control. China is a country with fiscal decentralization, and economic levels vary greatly among regions. Due to economic factors, water pollution control efforts and results will be different. Breaking the regional boundaries and implementing the integration of water pollution control can eliminate the imbalance brought about by the regional economy. The central government should set up water pollution supervision departments in all regions. These departments do not belong to the local area and should be directly under the central government. These departments are equipped with advanced technology and equipment and given certain law enforcement capabilities. As long as the trace of water pollution is found, it is necessary to trace its source. Regardless of the province in which it is located, it can be administratively punished or submitted to the central government for treatment.

This paper uses the spatial dynamic panel lag model to study the mean regression of explanatory variables to the explained variables. However, at the same pollution level, the impact of different quantiles on agricultural economic growth has not been fully reflected. In future research, we plan to use the spatial dynamic panel quantile model, which will more comprehensively analyze the impact of China's water pollution on agricultural economic growth.

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Data availability The data and materials used to support the findings of this study are shared by the requesting author.

Compliance with ethical standards

Competing interests The authors declare that they have no conflicts of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Consent to participate All authors consent to participate.

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