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SPATIOTEMPORAL DISTRIBUTION OF THE IMPACT OF ENVIRONMENTAL REGULATIONS ON AGRICULTURAL POLLUTION

Environmental regulation is crucial for reducing agricultural pollution. This study quantified agricultural non-point source pollution (ANSP) in China from 2007 to 2023 using the pollution discharge coefficient method. It analyzed the spatiotemporal distribution of agricultural pollution and applied a geographically and temporally weighted regression (GTWR) model to explore the dynamics of influencing factors. The findings revealed that China's ANSP initially increased and then decreased, characterized by a decelerating growth rate and notable fluctuations. The southern region exhibited significantly higher ANSP levels than the northern region. Moreover, the impact of each factor on agricultural pollution exhibited significant spatiotemporal heterogeneity. Specifically, local government attention to agricultural pollution (LGA), local fiscal allocation for agricultural environmental protection (LFEA), total power of agricultural machinery (TPOAM), investment completed for wastewater treatment projects (WWI), and domestic waste clearance volume (DWCV) positively influenced ANSP. Conversely, investment completed for waste gas treatment projects (WGI) had a negative effect. Notably, the influence of DWCV on ANSP was consistent across regions. LGA primarily affected Northwest China, while LFEA and WWI influenced Northwest and North China. TPOAM impacted East China, and WGI affected North China, Central South China, and East China. The results offer a basis for region-specific strategies.

1. INTRODUCTION

With the rapid growth of China's agricultural economy, environmental pollution problems have become increasingly prominent. The *2023 China Ecological Environment Statistics Annual Report* indicates that agricultural sources contributed 21.357 million tons of water pollutants, including chemical oxygen demand, ammonia nitrogen, total nitrogen, and total phosphorus, accounting for 61.8% of the nation's total water pollutant discharge. A key driver of this pollution is the excessive use of agricultural inputs, such as chemical

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fertilizers and pesticides. Although there has been some progress in addressing agricultural pollution in recent years, with reduced application of chemical fertilizers and pesticides and improved resource utilization efficiency, pollution remains a pressing issue [1, 2]. Strengthening the prevention and control of agricultural pollution is essential for promoting the green transformation of agriculture and ensuring the sustainable development of the ecological environment.

Environmental regulation is a crucial tool for controlling agricultural pollution. It not only directly reduces pollution but also fosters technological innovation and industrial structural adjustments, thereby improving environmental conditions [3]. Given the complex sources of agricultural pollution, establishing a comprehensive evaluation system for agricultural pollution and exploring how to control it through environmental regulation have emerged as key issues in environmental science. In China, the uneven development across provinces necessitates the formulation and implementation of targeted agricultural pollution control policies that account for regional differences to enhance the ecological environment. This challenge is central to China's current environmental agenda and serves as the foundation for this study.

Compared with existing research, the innovations of this study mainly lie in two aspects. First, it introduces a new research perspective. Previous studies have mostly focused on the agricultural pollution situation in individual regions, often neglecting regional differences and a comprehensive national analysis. Second, it innovates in research content. Most existing studies assess the impact of environmental regulation on agricultural pollution using single pollution sources or chemical input indicators, failing to conduct a comprehensive assessment of agricultural pollution from the pollutant discharge perspective. This results in an insufficient quantification of actual pollution emissions. Moreover, in selecting environmental regulation indicators, this study goes beyond merely considering environmental governance investment. It also incorporates indicators such as government attention and environmental governance capacity, providing a more comprehensive assessment framework.

Agricultural pollution. Agricultural pollution is intrinsically linked to human health, and the existing literature predominantly centers on its measurement and influencing factors. A common way to assess agricultural pollution is to examine fertilizer use. For instance, nitrogen pollution has been utilized to evaluate the ecological environment of rice in the Jinxi River Basin, leading to the development of a framework for assessing agricultural pollution risk [4]. Similarly, the levels of nitrogen and phosphorus fertilizer loss have been employed to study agricultural pollution on smallholder farms under new agricultural models. These studies have demonstrated that new agricultural practices can significantly enhance fertilizer use efficiency and mitigate pollution [5]. Other studies have also quantified the level of agricultural pollution through chemical fertilizer and pesticide residues, and explored the role of precision management technology in the relationship between agricultural pollution and farmers' income [6]. In addition, research has measured agricultural pollution indicators based on land use types, crop management, and the attenuation of pollutants with distance. For example, a quantitative assessment model of agricultural pollution was constructed for the Mun River Basin in Thailand [7]. Another comprehensive study established an integrated agricultural pollution index, encompassing four potential pollution pathways: soil heavy metal contamination, soil acidification, surface water pollution, and air pollution. This index was employed to conduct an in-depth analysis of the impact of potential agricultural pollution on food security and human health in economically developed regions [8].

In addition to constructing agricultural pollution measures and their distribution, there are many results on the factors affecting agricultural pollution. For instance, one study examined the relationship between agricultural pollution and various factors, including emission intensity, production scale, labor intensity, urbanization, and population size. The findings indicated that emission intensity is the primary limiting factor for pollution levels, whereas production scale has the most significant impact on increasing pollution loads. Additionally, research has highlighted the dual-edged nature of policy interventions. While agricultural subsidies have been shown to effectively incentivize emission reductions, the expansion of government financial expenditures may conversely lead to increased emissions [9]. In terms of spatial analysis, studies have constructed basic agricultural environmental indices based on cultivated land area and soil fertility quality. Through qualitative analysis, China has been divided into 10 distinct agricultural pollution regions [10]. Furthermore, land use patterns and fertilizer application have been identified as key determinants of agricultural non-point source pollution [11].

The above findings highlight the complexity of agricultural pollution and show the important role played by policy and spatial factors in mitigating it. In recent years, governments and international organizations have introduced a series of environmental regulatory measures aimed at reducing agricultural pollution and improving the environmental Sustainability-Basel of agricultural production by means of policy guidance, technology promotion, and economic incentives [12, 13]. The Chinese government has also introduced a series of measures, but agricultural pollution management still faces many challenges due to the complexity and diversity of agricultural production [14, 15].

Impact of environmental regulation on agricultural pollution. Environmental regulation is a crucial tool in the fight against agricultural pollution. In recent years, various countries have been actively exploring effective strategies to address agricultural pollution through the formulation and implementation of agricultural policies and government interventions. For instance, the European Union has been promoting the transformation of agricultural practices via the European Green Deal and the reform of the Common Agricultural Policy. One notable measure proposed is the limitation of livestock density to mitigate the negative impacts of livestock farming [12]. Green finance, as an emerging financial paradigm, has also played a significant role in reducing agricultural pollution and carbon emissions by optimizing resource allocation [16]. Green investments have the potential to spur technological innovation and industrial optimization, thereby decreasing agricultural pollution and carbon dioxide emissions [17]. In China, the full-cost insurance policy has effectively reduced nitrogen and phosphorus emissions by lowering fertilizer application intensity and enhancing fertilizer use efficiency [18]. Furthermore, Luan et al. [19] highlighted the importance of the ecological compensation mechanism in encouraging farmers to adopt arable land protection measures. They also pointed out that factors such as capital endowment, social networks, and education significantly influence farmers' willingness to accept compensation. These findings provide a basis for designing more precise and effective compensation policies.

The adoption of sustainable agricultural technologies and digital precision management has proven to be effective in mitigating agricultural pollution. Innovations in agro-technology, for instance, have significantly enhanced water use efficiency in agriculture [20]. Biochar, as a soil amendment and a means of carbon sequestration, offers potential advantages in agricultural pollution management. It can improve soil quality, reduce nutrient runoff, and have positive impacts on human health and the environment [21]. Additionally, digital technologies have optimized the allocation of agricultural resources, increased crop yields, and reduced the use of chemical fertilizers, thereby contributing positively to pollution management [22, 23].

Effective agricultural pollution management extends beyond technological innovation to encompass social factors, including farmers' behavior and cognition. There are notable disparities in agricultural practices and environmental awareness among farmers across different regions [24]. Government regulations play a crucial role in bridging the gap between farmers' intentions and actual behaviors regarding green production [25]. When promoting agro-environmental measures, it is essential to consider the psychological and behavioral factors of farmers [26]. Enhancing farmers' education levels and strengthening their connections with management agencies can increase their awareness of environmental risks and promote the recycling of agricultural plastic waste [27]. Moreover, social norms and environmental regulations can effectively guide farmers' environmental behaviors and reduce agricultural pollution [28].

Fiscal environmental protection expenditure (FEPE) has been shown to significantly reduce agricultural carbon emissions (ACEs), with notable regional heterogeneity in its impact [29]. Financial development also plays a crucial role in mitigating the negative effects of pollution emissions on agricultural production [26]. A study constructed a three-party evolutionary game model involving local governments, village collectives, and farmers. This research explored the strategic choices and influencing factors of these different stakeholders, providing theoretical guidance for the government to develop differentiated intervention mechanisms [13]. Another study discussed the potential for reducing agricultural pollution through policy interventions, focusing on supply chain management. It highlighted that single environmental governance measures are insufficient for effectively controlling agricultural non-point source pollution [30]. To address this, an integrated model was designed to promote fertilizer reduction, the return of manure and straw to the fields, and rural sewage treatment. Additionally, engineering measures such as the establishment of buffer zones in high-risk pollution areas were proposed. These strategies aim to achieve green and sustainable agricultural development in the Yangtze River Economic Belt [31].

In summary, most scholars only focus on individual regions without considering the issue of uneven development in different parts of China, but instead analyze it from a national perspective. Moreover, when studying the impact of environmental regulations on agricultural pollution, a comprehensive assessment of agricultural pollution from the perspective of pollution discharge has not been conducted. Therefore, it is important to consider regional differences, calculate the comprehensive level of agricultural pollution from the perspective of pollution discharge, analyze the temporal and spatial distribution characteristics of the impact of environmental regulation on agricultural pollution, and give prevention and control policies that are adapted to local conditions.

2. EXPERIMENTAL

Variables. Agricultural non-point source pollution in China mainly comes from pesticides and fertilizers applied during agricultural production, as well as from livestock and poultry farming activities. Given the dominance of cultivation in agricultural production, this study chose to use cultivation-related pollutants of agricultural origin as an indicator of agricultural pollution. According to the *Method and Coefficient Manual of Pollutant Discharge Accounting for Statistical Survey of Emission Sources* issued by the Ministry of Ecology and Environment of China in 2021, the pollution discharge coefficient method is used to measure the level of agricultural non-point source pollution (ANSP). The annual discharge of pollutants from the planting industry is related to the local types of crops grown, the acreage planted, and the amount of fertilizer used per unit area. The calculation formula is as follows:

$$Q_j = \left(A_g e_{gj} + A_y e_{yj}\right)\frac{q_j}{q_0} \times 10^{-3} \tag{1}$$

where Q_j, tons, refers to the emission of pollutant j in the plantation industry in a province, A_g, ha, refers to the total sown area of crops in a province, e_{gj}, kg/ha, refers to the loss coefficient of water pollutant j in the process of crop cultivation in a province, A_y, ha, refers to the area of gardening land in a province, e_{yj}, kg/ha, refers to the loss coefficient of water pollutant j in gardening land, q_j, kg/ha, refers to the amount of nitrogenous fertilizers (including phosphorus fertilizers) used per unit area for cultivation in a province in the survey year, q_0, kg/ha, refers to the amount of nitrogenous fertilizers (including phosphorus fertilizers) used per unit area for cultivation in a province in 2017.

Selection of indicators for environmental regulation: Local government attention to agricultural pollution (LGA), local fiscal allocation for agricultural environmental protection (LFEA), investment completed for waste gas treatment projects (WGI), investment completed for wastewater treatment projects (WWI), and domestic waste clearance volume (DWCV). LGA is measured using the number of government work reports that involve agricultural pollution control, agroecology, and rural ecology. In addition, considering the impact of agricultural technology on the level of agricultural pollution, this study also introduces the total power of agricultural machinery (TPOAM) as an indicator of agricultural technology. The definitions of the variables and the descriptive statistics are shown in Tables 1 and 2. As can be seen from Table 2, the range of ANSP is from 0.007 to 10.487×10,000 tons/year, with a mean of 2.73×10,000 tons/year.

Table 1

Agricultural pollution and environmental regulation variables

Variable	Definition
ANSP, 10,000 tons/year	agricultural non-Point source pollution
LGA	local government's attention to agricultural pollution
LFEA, 100 million CNY	local fiscal allocation for agricultural environmental protection
TPOAM, 10000 kW	total power of agricultural machinery
WGI, 100 million CNY	investment completed for waste gas treatment projects
WWI, 100 million CNY	investment completed for wastewater treatment projects
DWCV, 10,000 tons/year	domestic waste clearance volume

Table 2

Descriptive statistics of the initial indicators by provinces

Variable	Min	Lower quartile	Median	Mean	Upper quartile	Max
ANSP	0.007	0.236	1.392	2.730	5.094	10.487
LGA	0.000	11.000	19.000	26.975	34.000	225.000
LFEA	0.150	5.658	10.910	11.649	15.933	55.660
TPOAM	93.970	1,340.720	2,523.765	3,316.072	4,286.505	1,3353.020
WGI	0.014	3.677	7.400	11.802	14.806	128.135
WWI	0.001	0.796	2.371	3.638	4.988	29.554
DWCV	63.600	330.375	530.650	659.496	824.275	3,389.500

Research methods. In order to study the spatiotemporal heterogeneity of the impact of environmental regulation on agricultural pollution, this study used a geographically and temporally weighted regression (GTWR) model. Geographically weighted regression (GWR) and time-weighted regression (TWR) are commonly used in existing studies to address issues of spatial and temporal heterogeneity. Huang et al. [32] proposed the GTWR model, which is an improvement on the GWR and TWR models. It applies panel data regression and can simultaneously analyze spatiotemporal heterogeneity. The GTWR method is represented by:

$$y_i = \beta_0\left(u_i, v_i, t_i\right) + \sum_{k=1}^{P} \beta_k\left(u_i, v_i, t_i\right) x_{ik} + \varepsilon_i \tag{2}$$

where y_i refers to the dependent variable, which in this article represents the degree of air pollution, i.e., the value of sulfur dioxide, u_i and v_i are the longitude and latitude coordinates of the observation point, respectively, (u_i, v_i, t_i) is the space-time coordinate of the ith sample point, β_0 is the regression constant of sample point i, that is, the constant term of GTWR, β_k is the kth regression parameter of point i, and x_{ik} is the value of independent variable x_k at point i, that is, the value of each explanatory variable in the GTWR model. ε_i is the random error term for observation i, which captures the unexplained variance by the model and is assumed to be independently and identically distributed.

Data sources. This study examines agricultural pollution across 30 provinces (including autonomous regions and municipalities directly under the central government) in China. Regions such as Hong Kong, Macao, Taiwan, and Tibet were excluded due to substantial data gaps. The dataset spans from 2007 to 2023 and is sourced from the *China Statistical Yearbook*, *China Rural Statistical Yearbook*, *China Statistical Yearbook of Environment*, and the *Peking University Treasure Law Database*. To ensure data integrity, missing values were interpolated using the mean method.

3. RESULTS AND DISCUSSION

3.1. SPATIOTEMPORAL DISTRIBUTION OF AGRICULTURAL POLLUTION

The chain growth rate of ANSP was calculated using ANSP values for different years, with 2007 as the base period. The time evolution of ANSP and its growth rate is illustrated in Fig. 1.

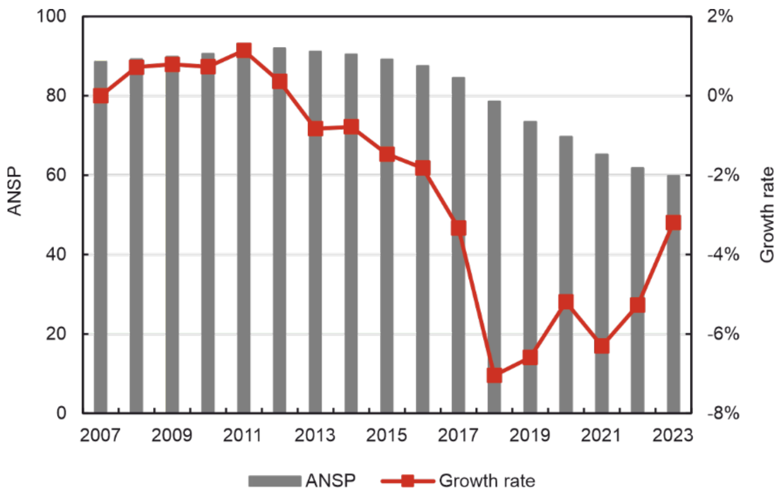

Fig. 1. Statistical chart of ANSP from 2007 to 2023

The overall trend of ANSP first increases and then decreases. From 2007 to 2011, ANSP exhibited an upward trend, reaching its peak at 91.554 ×10,000 tons/year in 2011. Afterward, ANSP began to decline gradually, particularly after 2017, with a more pronounced drop to 59.814×10,000 tons/year by 2023. When analyzing the growth rate of ANSP, it is evident that fluctuations have occurred over time. Between 2007 and 2011, the growth rates were all positive, indicating an increase in agricultural pollution. However, starting from 2012, the growth rates became negative, reaching a low of –7.04 in 2018, signaling a decline in agricultural pollution levels. Although there was a slight recovery in the growth rates in 2019, 2020, 2022, and 2023, the overall trend remains downward.

To explore the spatial distribution characteristics of agricultural pollution levels, based on the size of ANSP, it was further divided into five categories by quartiles: low [0.007, 0.178], lower (0.178, 0.820], middle (0.820, 2.782], (2.782, 5.668] and ANSP high-value zone (5.668, 10.487], and plotted the spatial distribution of ANSP for the years 2007, 2015, 2023, and 2007–2023 mean values as shown in Fig. 2.

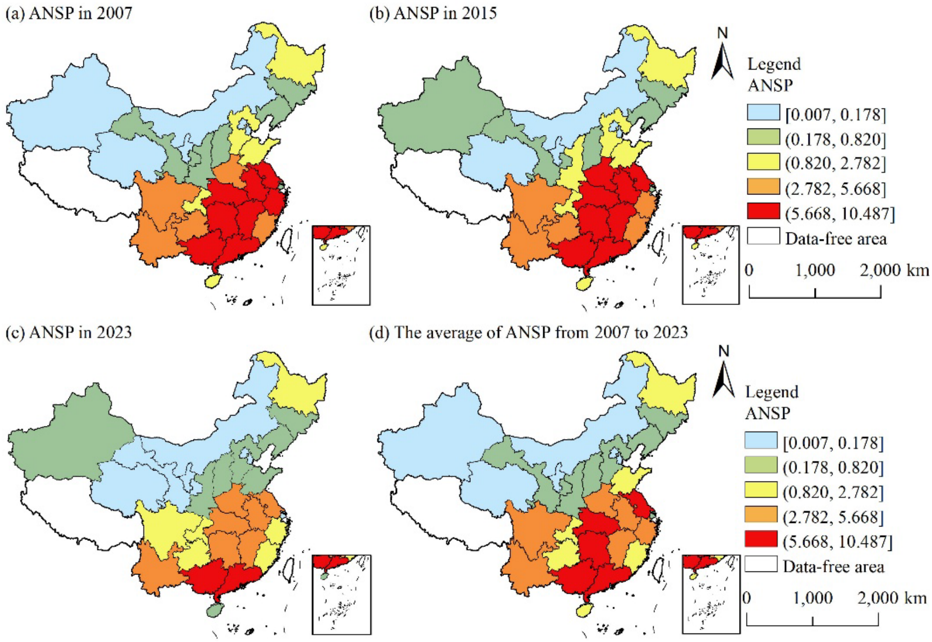

Fig. 2. Spatial distribution map of ANSP, map review number: GS (2024) 0650

The overall trend in ANSP shows that changes from high to low over time. From the perspective of regional differences, ANSP distribution varies greatly in different regions, and ANSP distribution has spatiotemporal heterogeneity. In 2007, the spatial distribution of ANSP showed a gradient pattern of high in the southeast and low in the northwest.

High-value areas are concentrated in the main grain-producing areas in the central and eastern parts of the country, while low-value areas are mainly distributed in the western region. In 2015, the overall spatial pattern was similar to that of 2007, but there were changes in localized regions, with higher ANSP values in Xinjiang, Shaanxi, and Henan, and lower ANSP values in Zhejiang. In 2023, the overall level of ANSP declines nationwide, with significant decreases in ANSP in eastern and central China, as well as in Shanxi, Gansu, Sichuan, and Guizhou in the western region. From the average perspective of ANSP in China from 2007 to 2023, the low ANSP areas are mainly distributed in North China and Northwest China, and the high ANSP areas are mainly distributed in East China and Central South China. The unbalanced distribution of ANSP highlights the importance of studying regional differences in ANSP and the factors influencing them.

3.2. GTWR MODEL EVALUATION

To account for regional development disparities across China, the GTWR model is employed to examine the spatiotemporal distribution of environmental regulation's impact on agricultural pollution. A comparison of the fitting performance of OLS, TWR, and GWR models reveals that the GTWR model offers superior accuracy and applicability in analyzing the factors influencing ANSP in China. The data were standardized for model construction, and the evaluation results are presented in Table 3. AICc refers to the corrected Akaike information criterion. Lower AICc values indicate a better model fit. These results indicate that the AICc values for the ordinary least squares (OLS), TWR, GWR, and GTWR models decrease sequentially, with adjusted R-squared values of 0.32, 0.51, 0.86, and 0.90, respectively. When considering temporal non-smoothness, the TWR model outperforms Globe OLS, while the GWR model excels in addressing spatial non-smoothness. Thus, the GTWR model, which incorporates both temporal and spatial non-stationarity, demonstrates higher accuracy and applicability than the other models.

Table 3

Goodness-of-fit results
for the OLS, TWR, GWR, and GTWR models

Model	AICc	R^2
OLS	–54.04	0.32
TWR	–159.94	0.51
GWR	–749.49	0.86

Figure 3 illustrates the GTWR model's fitting performance by presenting the mean ANSP values over time, comparing the fitted and observed values. The high degree of alignment between the actual data and the model's predictions, along with the adjusted R-squared and model effect plots, confirms the effectiveness of the GTWR model in this study.

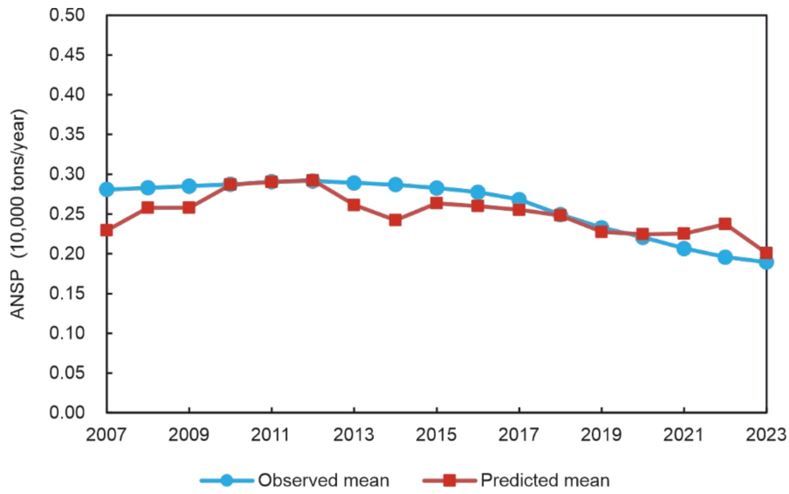

Fig. 3. GTWR model fitting effect

3.3. SPATIOTEMPORAL DISTRIBUTION OF FACTORS INFLUENCING AGRICULTURAL POLLUTION

Table 4 presents the descriptive statistics of the estimated regression coefficients calculated by the GTWR model. For instance, on average, LGA, LFEA, TPOAM, WWI, and DWCV exhibit positive impacts, while WGI shows a negative impact. The range of the coefficients indicates that the minimum value of each variable is negative and the maximum value is positive. This variation suggests that the impact of environmental regulation on ANSP exhibits spatial and temporal heterogeneity, necessitating further investigation into these differences.

Table 4

Description statistics of GTWR results

Variable	Min	Q1	Median	Mean	Q3	Max
Intercept	–0.140	–0.017	0.031	0.066	0.107	0.438
LGA	–0.580	0.0478	0.595	0.610	0.965	2.860
LFEA	–1.425	–0.104	0.053	0.219	0.406	2.842
TPOAM	–1.207	0.039	0.188	0.415	0.595	3.737
WGI	–0.840	–0.442	–0.157	–0.119	0.018	1.449
WWI	–0.377	0.001	0.229	0.294	0.415	1.465
DWCV	–0.651	–0.224	–0.026	0.122	0.239	3.805

Figure 4 illustrates the temporal trends in the impact of environmental regulations on ANSP, as represented by their regression coefficients (vertical axis). Overall, the effects of the various variables exhibit fluctuations, with WGI showing the most significant variation. WGI has a predominantly negative and declining effect on ANSP, with its values ultimately approaching zero over time. In contrast, the other variables exert a positive influence on ANSP. The effects of LGA, DWCV, and LFEA initially decline before rising again, while TPOAM, WGI, and WWI show an increasing effect followed by a decrease. Among these variables, WWI exhibits the least fluctuation.

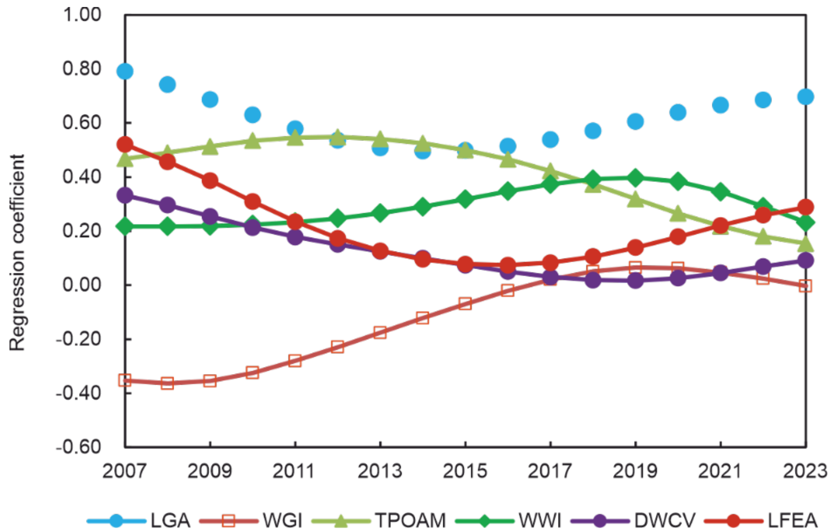

Fig. 4. Temporal evolution of environmental regulation factors on the impact of ANSP

As shown in Fig. 5a, the regression coefficients for the effect of LGA on ANSP are predominantly positive and fluctuate over time. In 2007, areas with high positive values were primarily concentrated in North China and the northern part of East China, while areas with negative values were concentrated in Northeast, Central South, and the southern part of East China. By 2015, the impact of LGA on ANSP shifted from negative to positive in Central South China, whereas the opposite trend occurred in Qinghai and Gansu in Northwest China. In 2023, the negative value area in Northwest China expanded into Xinjiang, and all other regions in China transitioned to positive value areas. These trends indicate that, for most regions in China, the influence of government policy support for agricultural environmental protection on ANSP governance has gradually increased. However, in Xinjiang, Qinghai, and Gansu, insufficient grassroots supervisory capacity may lead to limited awareness among farmers regarding the dangers of agricultural pollution and a lack of environmental consciousness. As a result, the government may find it difficult to effectively oversee agricultural pollution behaviors, and the implementation of policies at the grassroots level may be challenging.

As depicted in Fig. 5b, the regression coefficients of the effect of LFEA on ANSP exhibit a pattern of initial decline followed by an increase.

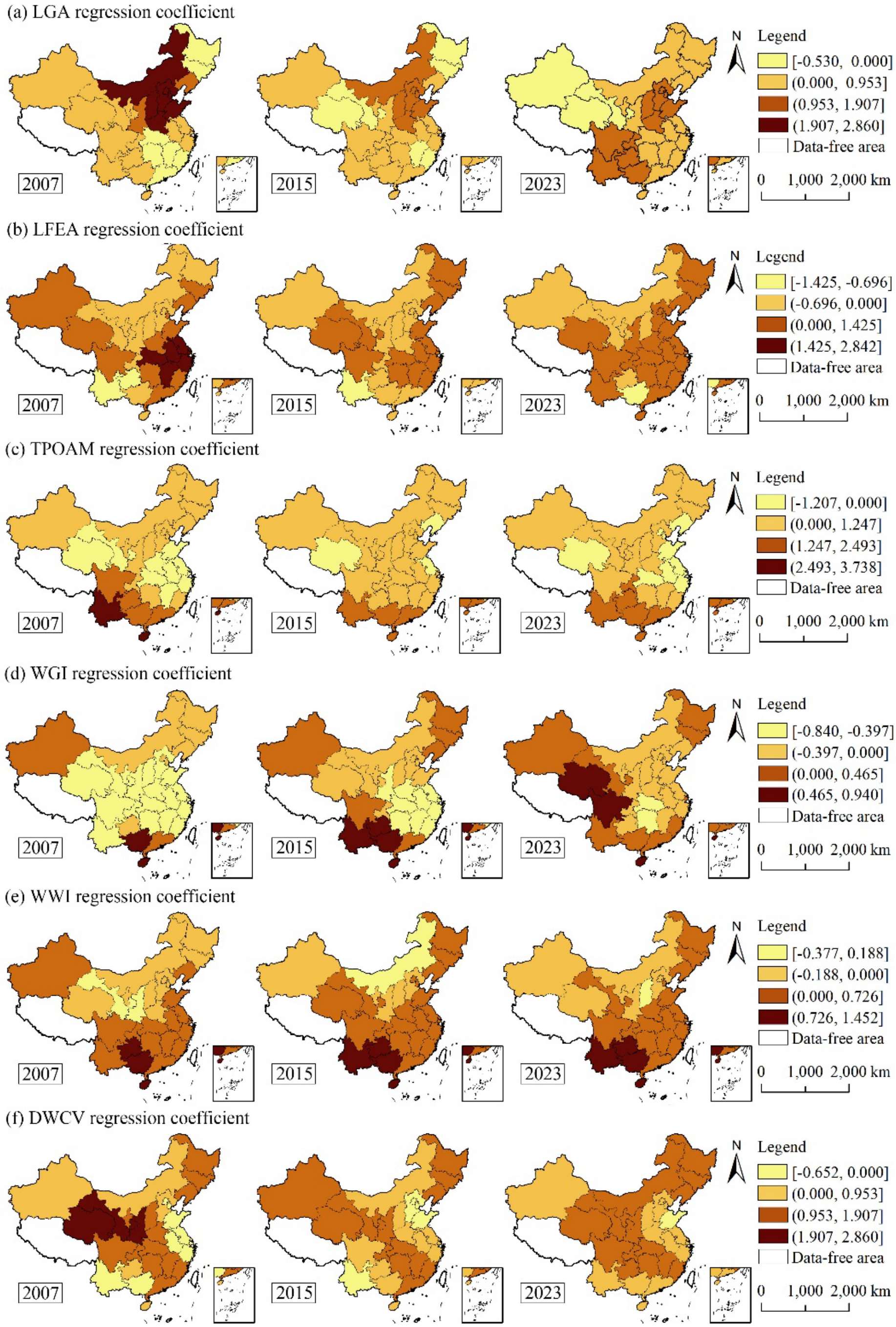

Fig. 5. Spatial evolution of environmental regulation factors on the impact of ANSP, map review number: GS (2024) 0650

In 2007, regions with high positive values were primarily concentrated in Central South and East China, while negative values were concentrated in North China. Notably, significant negative impacts were also observed in Yunnan and Guizhou in Southwest China. By 2015, the influence of LFEA on ANSP in Xinjiang, Tianjin, Henan, and Guangdong shifted from positive to negative, while the negative impacts in Gansu, Guizhou, and Heilongjiang diminished. By 2023, positive value areas expanded, indicating that LFEA inputs are increasingly contributing to ANSP governance. However, regions such as Xinjiang, Gansu, Ningxia, Inner Mongolia, Shanxi, Guizhou, and Guangxi remain in negative value areas, highlighting the need for continued enhancement of local financial resources for agricultural environmental protection. The temporal heterogeneity in the impact of LFEA on ANSP can be attributed to China's implementation of the *Zero-growth action of chemical fertilizer and pesticide use by 2020* since 2015. This policy has significantly bolstered the green development of agriculture, promoting the reduction of chemical fertilizers and pesticides and fostering high-quality development in the planting industry. These measures have effectively mitigated agricultural pollution, thereby influencing the observed trends in LFEA's impact on ANSP governance.

As shown in Fig. 5c, the negative effect of TPOAM on ANSP shows a tendency pattern of first weakening and then strengthening. In 2007, regions with negative impacts were predominantly located in the Northwest, Central South, and East China. By 2015, the negative impact area had contracted, with only Qinghai, Liaoning, and Jiangsu retaining negative effects. However, by 2023, the negative impact area expanded to include Beijing, Tianjin, Shandong, Anhui, Zhejiang, and Hubei. This trend can be attributed to the threshold effect of agricultural technology inputs on pollution management. When technology inputs surpass a certain threshold, they may exert a negative influence on controlling agricultural pollution. Excessive technological inputs may increase agricultural production costs while providing limited environmental benefits. Therefore, to achieve sustainable agricultural development, it is essential to make rational choices regarding technological inputs based on specific regional contexts.

As depicted in Fig. 5d, the regression coefficients for the effect of WGI on ANSP exhibit a diminishing negative influence over time, suggesting that ANSP decreases with increasing WGI inputs, albeit at a decreasing rate. In 2007, only Xinjiang, Guangdong, Guangxi, and Hainan achieved full capacity in WGI inputs, while other regions required further measures to enhance air quality through improved exhaust gas treatment. By 2015, China's nationwide efforts in exhaust gas management had proven effective, significantly reducing the negative impact of WGI on ANSP in Shandong, Hebei, Shanxi, and the Northeast and Western regions. By 2023, the negative impact area had further contracted, primarily in North, Central South, and East China, with only Hubei and Hunan remaining as high-negative-value regions.

The influence of WGI on ANSP displays significant spatiotemporal heterogeneity. According to data from the *China Statistical Yearbook*, the average total sulfur dioxide emissions from 2007 to 2023 in Northeast, North, Northwest, East, Central South, and Southwest

China were 902.27, 1195.14, 708.97, 1044.68, 1002.28, and 950.61 thousand tons for each region. The likely reason for this pattern is that North China, as a major industrial hub, experiences high industrial emission intensity. Meanwhile, Central South and East China have undergone rapid economic development and have dense populations, leading to substantial emissions from industrial, agricultural, and domestic sources. The pollutants in these exhaust gases enter the soil and water bodies through atmospheric deposition, significantly affecting the surrounding agricultural environment. To effectively address exhaust gas pollution, it is crucial to identify pollution sources and intensify treatment and regulatory measures.

As shown in Fig. 5e, the regression coefficients for the effect of WWI on ANSP fluctuate relatively little over time. In 2007, negative value areas were mainly concentrated in Northeast, North, and Northwest China, while positive value areas were mainly distributed in East, Central South, and Southwest China. In 2015, the positive value area expanded northward, adding Qinghai, Gansu, Beijing, Tianjin, Henan, and Northeast China, and Xinjiang shifted to the negative value area. In 2023, the negative value area added Qinghai and Beijing, mainly concentrated in North and Northwest China. One explanation for the spatial heterogeneity of WWI's impact on ANSP is the ecological differences across regions. Water resources are relatively scarce in North China and Northwest China, and agricultural activities are highly dependent on limited water resources. The repeated use of water resources can easily lead to pollution problems. At the same time, wastewater from domestic, agricultural, and industrial sources can lead to environmental pollution if not properly treated. Therefore, these two regions should strengthen their policy support and financial investment and carry out special actions to combat wastewater pollution.

As depicted in Fig. 5f, the regression coefficients for the effect of DWCV on ANSP are predominantly positive, with the negative influence diminishing over time. In 2007, regions with negative values were primarily located in Yunnan, Guangxi, Anhui, and the eastern region. By 2015, the negative value area had contracted to Yunnan, Beijing, Tianjin, Hebei, and Shandong. By 2023, the negative value area was confined solely to Shandong province.

DWCV is the domestic waste clearance volume, which reflects the government's ability to treat domestic waste. The data from 2023 indicate that, except for Shandong, further increases in DWCV no longer result in reductions in ANSP. This suggests that current investments in domestic waste management are sufficient. Alternative governance methods need to be explored to further reduce environmental pollution.

4. CONCLUSIONS

This study examines the impact of environmental regulation on agricultural pollution using data from 30 Chinese provinces (excluding Hong Kong, Macau, Taiwan, and Tibet) spanning 2007 to 2023. The key findings are as follows: First, agricultural pollution in

China exhibits a general trend of initial growth followed by a decline. However, the growth rate has fluctuated significantly, and since 2012, it has been negative. Regionally, ANSP pollution levels are notably higher in the southern provinces than in the northern ones. Second, the impacts of various influencing factors on agricultural pollution differ across periods. Among these factors, WGI exhibits the most fluctuation and consistently hurts ANSP, while the remaining variables all exert a positive influence. WWI shows the least fluctuation. Third, significant spatiotemporal heterogeneity exists in the effects of certain variables. Specifically, the influence of DWCV on ANSP remains consistent across regions. LGA primarily affects Northwest China, while LFEA and WWI predominantly impact Northwest and North China. TPOAM has its main effect in East China, while WGI impacts North, Central South, and East China.

Based on these findings, the following practical policy recommendations are made for different regions. In Northwest China, policies should be refined to enhance grassroots enforcement. This can be achieved by systematically training regulatory personnel and establishing a village-level pollution reporting and response system. A pilot environmental credit mechanism for farmers should link subsidies to environmental compliance. Additionally, public awareness campaigns need strengthening to ensure effective policy implementation. In East China, agricultural mechanization should be rationally adjusted toward sustainability. Key measures include promoting precision sowing and variable-rate fertilization machinery to optimize inputs and reduce pollution based on soil data, providing subsidies for low-emission and new-energy agricultural machinery, and establishing an environmental protection standard system for agricultural machinery. In addition, in Northwest and North China, it is necessary to increase the investment in agricultural environmental protection funds, optimize the structure of the use of funds, focus on supporting water conservation projects and the construction of wastewater treatment facilities, and synchronize the special treatment of wastewater pollution actions. At the same time, the green development of agriculture has been boosted by improving the compensation mechanism for ecological protection and strengthening green financial support. North, East, and Central South China all need to continue to strengthen the treatment of exhaust gases and should identify the sources of pollution and increase treatment and regulation.

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