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Original Research

Research on the Supervision Mechanism and Effect of Environmental Regulation – Re-Estimation Based on China's Corn Planting Fertilizer Pollution

Yuzhuo Shen[1], Pan Hu[1,3], Yizhu Hou[1], Zhiyu Ying[1], Gangyi Wang[1,2]*

[1]School of Economics and Management, Northeast Agricultural University, Harbin 150030, China
[2]Chongqing Rural Revitalization Research Institute, Chongqing 402100, China
[3]Postdoctoral Research Station of Heilongjiang Property Rights Exchange Group

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Abstract

Environmental regulation is an important means of agricultural governance of agricultural non-point source pollution, and environmental supervision, as an important supplement to it, plays a key role in pollution governance. The relationships between environmental regulation and environmental supervision and the pollution of agricultural facial sources are of great theoretical and practical significance in achieving ecological livability and governance effectively, optimizing the theory of environmental separation, and promoting green development in agriculture. A theoretical model between environmental regulation and environmental supervision and the behavior of farmers‘ facial source pollution was constructed based on risk expectation theory, the fertilizer pollution equivalents during maize cultivation were estimated using the data of Maize Cultivation in each province of China from 2006 to 2018, and the relationships between environmental regulation and environmental supervision and agricultural non-point source pollution were analyzed by the dynamic panel model and the threshold effect model.

The study found that: firstly, fertilizer pollution equivalents increased year by year with corn planting, and in addition to planting benefits, the increase in production costs would also exacerbate fertilizer pollution through interelement substitution; secondly, the impacts of environmental regulation on the pollution equivalents of maize fertilizers are inverted U-shaped, and reasonable environmental regulation is helpful to effectively restrain the growth of agricultural non-point source pollution; thirdly, the environmental supervision will linearly regulate the inverted U-shaped relationship between environmental regulation and agricultural non-point source pollution, and strengthen the inhibitory effect of environmental regulation on pollution growth; fourthly, the impacts of environmental

*e-mail: awgy@cau.edu.cn

supervision on agricultural facet source pollution will exhibit two threshold characteristics as the intensity of environmental regulation changes, from insignificant effects to promoting effects, and turn to inhibiting effects after surpassing the second threshold. To propose differentiated and environmental supervision measures against regional environmental regulation intensity, strengthening environmental regulation, then separating the two-step go and conquer pollution model of regulation and regulation.

Keywords: environmental regulation, environmental supervision, non-point source pollution, chemical fertilizer pollution equivalent

Introduction

China is a largely agricultural country, but there is also serious agricultural non-point source pollution caused by excessive fertilizer application. In this regard, the relevant departments have attached great importance to it, but the results have not been good. Since 2011, the Chinese government has continuously improved its agricultural environmental regulations to promote agricultural intensive, efficient, safe, and sustainable development [1]. However, according to the ”Communiqué on the State of the Ecological Environment in China (2019)”, China, where the total application amount ranks first in the world, uses only 39.2% of fertilizers for the three major food crops of rice, corn, and wheat, and the effects of agricultural environmental regulations are not satisfactory [2]. Existing research and practical results show that local governments have greater discretion in environmental governance. However, in the goal selection of ”promoting growth” and ”protecting the environment”, influenced by factors such as promotion incentives, it is more inclined to sacrifice non-economic function goals to promote short-term economic growth. This leads to deviations between environmental protection incentives and targets, induces incomplete implementation of environmental regulations, and results in a decline in pollution control effects [3, 4]. Some research pointed out that improving the probability and ability of the central government‘s supervision is an important means to eliminate local government behavior deviations under the decentralized system and achieve environmental regulation policy objectives [5, 6]. It can be seen that under the environmental decentralization system, supervision has become a bottleneck factor in improving the effectiveness of environmental regulation [7].

The public choice theory believes that the government will pursue the maximization of its interests. And there are ”economic man” characteristics in the political market, and the possibility of being captured by polluting companies [8, 9]. The theory of environmental decentralization based on fiscal decentralization provides a direction to solve this problem. It believes that decentralization of power helps to improve residents‘ direct supervision of local government behavior, and achieves the best environmental governance effect through ”voting with feet” [10]. Central governments in various countries generally adopt de facto environmental decentralization governance models in their management practices. However, due to restrictions such as local government behavior preference [11], information transmission efficiency [12], empirical research results usually deviate from the theoretical hypothesis that decentralization governance is effective, leading to regulatory failure.

The core issue of the theory of environmental decentralization is the setting of environmental standards at all levels of government and the improvement of implementation efficiency. Focusing on this core issue, a large number of scholars have analyzed the power setting [13], regional overflow [14], and external supervision [15]. Some scholars hope to solve the problem of inconsistency between the environmental protection goals of the central and local governments through incentive compatibility [16, 17], and suggest using indicators such as green GDP to consider resource and environmental factors for performance evaluation [18]; some scholars also hope to restrain local governments and polluting enterprises and improve the effectiveness of environmental regulation through environmental supervision [19], non-governmental organizations [20] and public participation [21]. Some studies have pointed out that in the context of environmental decentralization, environmental supervision investment will crowd out government investment in pollution control, weakening the effect of pollution control [22, 23]. Another part of the research believes that environmental supervision can effectively correct the deviations in the policy implementation process, thereby effectively improving the effect of environmental regulations [24].

Affected by the characteristics of extensiveness, dispersion, and concealment, agricultural non-point source pollution has become an important factor threatening the ecological environment. Existing studies on the influencing factors of agricultural non-point source pollution are mostly limited to two aspects: one is the analysis of the influencing factors of micro-will. It is believed that through government propaganda, technical training, and other methods, farmers' awareness can be improved and agricultural non-point source pollution can be reduced [25]; the second is the analysis of external economic factors, and it is believed that agricultural non-point source pollution is related to the intensity of fertilizer application [26], economic development level [27], industrial structure [28], urban-rural income gap [29], etc. Because economic factors need to be based on institutional factors, coupled with market failures in pollution control, environmental regulation has become an important means to control agricultural non-point source pollution. However, limited by the dual structure of urban and rural areas and the intensity of environmental supervision, the effect of agricultural non-point source pollution control has never been able to meet expectations [30]. In terms of analysis methods, the index substitution method is mainly used to estimate agricultural non-point source pollution. This method is relatively simple to obtain data, but it lacks consideration of factors such as regional differences and environmental absorption capacity, and the reliability of the indicators is insufficient [31]. Some scholars also use methods such as AGNPS and output coefficients to estimate agricultural non-point source pollution, but due to the availability of data, they have not been widely used [32].

In summary, previous studies have laid a good theoretical foundation and methodological reference for this article, but there is still room for improvement. First, the research on agricultural non-point source pollution mostly focuses on the analysis of external economic factors and individual behavioral factors. The analysis of system design needs to be in-depth, and the domestic research is mostly based on the theoretical analysis of multi-party games, and the relevant empirical studies are slightly insufficient [33]; second, existing studies mostly use index substitution methods to analyze non-point source pollution, and insufficient consideration of regional soil fertility differences, and the reliability of index selection needs to be improved [34]; third, when some scholars analyze the impact of environmental regulations, environmental decentralization, and agricultural non-point source pollution, they treat administrative decentralization, supervision decentralization and supervision decentralization as the same level of analysis, and the inspection of the effective operation of supervision and protection of environmental regulations needs to be in-depth [35]. It can be seen that agricultural non-point source pollution is different from industry and city pollution and is greatly affected by natural resources and crop varieties. It needs to be analyzed in combination with specific crops and production links. Rice, corn and wheat are the three major grain crops in China, among which corn has the largest annual output and the largest planting area. The planting difference between the south and the north of China is small, so it is better to analyze agricultural non-point source pollution nationwide. Therefore, this paper takes corn as an example to analyze the impact of environmental regulation and environmental supervision on agricultural non-point source pollution. Therefore, we analyze farmers‘ responses to environmental regulation and supervision from the perspective of risk expectation theory and farmers‘ behavior theory, identify the pollution control mechanisms of environmental regulation and supervision, and then conduct an empirical test with China‘s provincial panel data from 2006 to 2018.

Our main contributions are as follows: First, we fully respect the farmers‘ production rationality and introduce the expected utility model to analyze the farmers‘ production behavior in the face of environmental regulation, which provides a new way of thinking for the research of regulation theory, conducted an empirical test with the provincial panel data in China; Secondly, we estimated the pollution in the production process of specific crops, fully considered the differences in soil fertility between regions, and put forward a fertilizer pollution estimation method that is more in line with the pollution level. Finally, the effectiveness of environmental regulation and environmental supervision was discussed based on the actual situation of fertilizer use in the maize planting process in China, and further policy recommendations were put forward, which are helpful to control agricultural non-point source pollution.

Experimental

Analysis on the Impact of Supervision Mechanism on Farmers' Pollution Behavior in Agricultural Environmental Regulation

Analysis of Farmers' Pollution Behaviors under Environmental Regulations

According to the theory of environmental decentralization, relying solely on the government for regulation will produce ”regulation captives”, so it is necessary to monitor the government‘s environmental regulation behavior. Jia F. et al. (2021) uses the principal-agent model to analyze the tripartite game between central government regulation, local government regulation and enterprise pollution behavior, and explains the necessity of environmental supervision with the information asymmetry theory [36]. This paper constructs a theoretical model to analyze the relationship between environmental supervision, environmental regulation and pollution from the perspective of risk. Firstly, it analyzes the production behavior of environmental regulation farmers. Based on the Cobb-Douglas production function, the production behavior of farmers can be described as $Y_t = AK_t^{\alpha}L_t^{\beta}$. Among them, K is capital input and L is labor input. When the output is Y_t, the pollution produced is W_t which means the pollution caused by the excessive application of chemical fertilizers by farmers during the planting process. Farmers who adopt cleaner production behaviors need to pay the marginal cost θ for pollution W_t. In actual production, θ can be regarded as reducing the additional cost of artificial weeding, purchase of improved seeds, and organic fertilizer treatment caused by the application of chemical fertilizers and pesticides. Since the above behaviors need to consume certain factors of production, assuming that the total cost of pollution W_t needs to be paid in proportion to the potential output F is $\gamma \in [0, 1)$ the production function becomes $Y_t = (1 - \gamma)\ AK_t^{\alpha}L_t^{\beta}$. Assuming that the pollution generation function of farmers is $f(\gamma) = l^{-1}(1 - \gamma)^{1/\varphi}$, the pollution amount $W_t = l^{-1}(1 - \gamma)^{1/\varphi} * AK_t^{\alpha}L_t^{\beta}$. The production function of farmers is rewritten as $Y_t = (l * W_t)^{\varphi}[AK_t^{\alpha}L_t^{\beta}]^{1-\varphi}$. Under the theory of rational smallholders, farmers' production decisions include two parts: One is to select the optimal combination of capital and labor allocation under the established capital price γ_t and labor price ω_t to make the unit potential output cost C_F the lowest; the second is to select the combination of optimal pollution emission and potential output F under the established marginal cost of pollution emission θ and unit potential output cost C_F so that the production cost C_X of the unit product X is the lowest.

Existing:

$$\mathrm{C}_F(\mathrm{K},\ \mathrm{L}\_) = \min\left\{\gamma_t \mathrm{K}_{+\omega_t \mathrm{L},\ \mathrm{F}(\mathrm{K},\ \mathrm{L}\_)} = 1\right\}$$
$$\mathrm{C}_{Q_t}(W_t,\ \mathrm{F}) = \min\{\theta W_t + \mathrm{C}_F \mathrm{F},\ \ W_t{}^{\varphi}[\mathrm{F}(\mathrm{L},\ \mathrm{K})^{1-\varphi}] = 1\}$$

Calculated as:

$$\frac{\partial \mathrm{F}}{\partial \mathrm{K}} \Big/ \frac{\partial \mathrm{F}}{\partial \mathrm{L}} = r/w$$
$$\frac{(1-\varphi) l W_t}{\varphi \mathrm{F}} = \frac{\mathrm{C_F}}{\theta}$$

At this time, the optimal cost of the farmer and the income and profit obtained are:

$$C(Q_0) = \omega_0{}^{\frac{\beta}{\alpha+\beta}} * \gamma_0{}^{\frac{\alpha}{\alpha+\beta}} * \left[\left(\frac{\beta}{\alpha}\right)^{\frac{\alpha}{\alpha+\beta}} + \left(\frac{\alpha}{\beta}\right)^{\frac{\beta}{\alpha+\beta}}\right] + \theta\left(l^{-1}(1-\gamma)^{1/\varphi} Q_0\right)$$
$$\pi_{Q_0} = PQ_0 - C(Q_0) = PQ_0 - \left\{\omega_0{}^{\frac{\beta}{\alpha+\beta}} * \gamma_0{}^{\frac{\alpha}{\alpha+\beta}} * \left[\left(\frac{\beta}{\alpha}\right)^{\frac{\alpha}{\alpha+\beta}} + \left(\frac{\alpha}{\beta}\right)^{\frac{\beta}{\alpha+\beta}}\right]\right\}$$

In the practice of agricultural environmental regulation, the government will guide farmers to clean production through taxes, subsidies, fines, and other forms. There is a one-time transfer payment T_{W_t}, and the income of farmers' production becomes $\pi_{Q_0} = \pi_{Q_t} - T_{W_t}$. The optimal pollution amount of a rational farmer is $W_t = \frac{[\varphi \mathrm{F}(\mathrm{C_F} - T'_{W_t})]}{[(1-\varphi) l\theta]}$. If at this time, the farmer does not carry out clean production and does not need to pay additional environmental costs θ, the total production cost will drop by $\theta(l^{-1}(1 - \gamma)^{1/\varphi}\ Q_0)$. In the case of the same product price, additional benefits will be obtained. The above analysis shows that in the absence of environmental regulations, farmers' pollution behavior will be encouraged and will not spontaneously carry out clean production. When the government implements environmental regulations, farmers need to weigh transfer payments and clean production costs. When the government's incentives for clean production or fines for pollution are greater than the cost of clean production, farmers will conduct clean production, and vice versa.

Based on the above analysis, hypothesis H1 is proposed: the impact of environmental regulations on agricultural non-point source pollution is inverted U-shaped.

Analysis of Farmers' Pollution Behaviors under Environmental Supervision

The existing agricultural environmental regulations are mainly based on rewarding clean behaviors, and no clear administrative penalty standards have been issued. However, in 2020, there have been restrictions on pollution behaviors. This article assumes that the government will deal with over-limit pollution behaviors through administrative penalties, and that the government conducts environmental supervision with intensity ξ. In environmental supervision, on the one hand, the government acts are controlled to directly punish the government of adverse selection; on the other hand, the polluting enterprises are also randomly selected to punish the polluters. For example, in the public information released by the central eco-environmental protection inspector on Xinhua Online, not only 218 cadres in Jilin, Shandong, Hubei and other places were held accountable [37], but also enterprises such as China Nonferrous Metals Group were notified for administrative punishment by local governments.

In the first case, the enterprise will not receive the punishment directly, but the local officials will increase the overall intensity of the regulation to reduce their own administrative departure. In the second case, environmental supervision will directly affect the polluters. This paper quantifies this behavior as the probability that the enterprise's pollution behavior will be detected, assuming that environmental supervision households will increase the probability that the farmers' pollution behavior will be detected, and the probability of farmers' pollution behaviors being investigated is $(P(\xi)|P \in (0, 1),\ P'>0)$. When a farmer's pollution behavior is investigated and punished, a fine ζW_t must be paid. Assuming that farmers' attitudes and preferences towards risks do not affect the amount of pollution produced, but only affect whether they carry out pollution control, according to the Neumann-Morgenstern function, to quantify the production behavior of farmers under risk, the profits are:

$$\pi_{Q_0} = PQ_0 - \left\{\omega_t{}^{\frac{\beta}{\alpha+\beta}} * \gamma_t{}^{\frac{\alpha}{\alpha+\beta}} * \left[\left(\frac{\beta}{\alpha}\right)^{\frac{\alpha}{\alpha+\beta}} + \left(\frac{\alpha}{\beta}\right)^{\frac{\beta}{\alpha+\beta}}\right]\right\} - T_{W_0},\ \ [1 - P(\xi)]$$
$$\pi_{Q_0} = PQ_1 - \left\{\omega_t{}^{\frac{\beta}{\alpha+\beta}} * \gamma_t{}^{\frac{\alpha}{\alpha+\beta}} * \left[\left(\frac{\beta}{\alpha}\right)^{\frac{\alpha}{\alpha+\beta}} + \left(\frac{\alpha}{\beta}\right)^{\frac{\beta}{\alpha+\beta}}\right]\right\} - \zeta\left(l^{-1}(1-\gamma)^{1/\varphi} Q_1\right) - T_{W_1},\ \ P(\xi)$$

The expected benefits of farmers who do not carry out cleaner production are:

$$E_{\pi_Q} = PQ - \left\{ \omega_t^{\frac{\beta}{\alpha+\beta}} * \gamma_t^{\frac{\alpha}{\alpha+\beta}} * \left[\left(\frac{\beta}{\alpha}\right)^{\frac{\alpha}{\alpha+\beta}} + \left(\frac{\alpha}{\beta}\right)^{\frac{\beta}{\alpha+\beta}} \right] \right\} - \zeta\left(l^{-1}(1-\gamma)^{1/\varphi} Q_1\right) P(\xi)$$

Popkin S. (1980) theory of rational small farmers holds that the behavior logic of farmers is to pursue the maximization of interests, and will weigh the participation cost and expected benefits of everything in economic, political and cultural life repeatedly as investors. This view not only emphasizes the farmers' rational production behavior, but also emphasizes the farmers' rationality of risk, that is, they will make production decisions through risk expectation. For example, Meyer-Aurich A. et al. (2016) when studying grain irrigation and nitrogen fertilizer application in Germany, regards risk and price expectation as the insult angle, and thinks that farmers' behavioral motivation is the lowest expected risk [38]. Based on this point of view, this paper introduces the expected utility model to analyze the farmers' cleaner production behavior under environmental regulation. Given the retention utility μ_2, the profit maximization conditions of farmers are:

$$\pi_{Q_2}(W_2,\ \xi) = \max\{ PQ_2 - C_F F,$$
$$W_2{}^{\varphi}[F(L,\ K)^{1-\varphi}] - E[\zeta P(\xi) W_2]\}$$

According to the prospect theory, the constraint condition of farmers' production is $EV(\pi_{Q_2}) \geq \mu_2$; $E[\zeta P(\xi)]>0$. Under environmental supervision, the utility difference of whether a farmer does cleaner production is $\Delta\pi_{Q_t} = [\theta - \zeta P(\xi)]\Delta W_1$. When the marginal cost θ of pollution treatment remains unchanged, the increase in fines ζ and government supervision ξ will reduce the expected utility of farmers and the pollution generated.

Based on the above analysis, hypothesis H2 is put forward: Strengthening environmental supervision will help curb agricultural non-point source pollution.

Choice of Environmental Regulation and Environmental Supervision under Cost Constraints

The previous analysis shows that both environmental supervision and environmental regulation can suppress agricultural non-point source pollution. Due to the limitation of environmental protection costs, there is an optimal combination of environmental regulation and environmental supervision. Assuming that the government is a welfare government, its environmental regulation goal is to maximize social welfare. Rewritten according to the social welfare function given by classical economics, the social welfare function of environmental regulation is:

$$SW = \sum U\left(\hat{\pi}_{Q_t},\ \check{T}_{W_t}\right) + \sum U\left(\check{D}\right) + \sum U\left(\hat{T}_{(W_t,\ \rho)}\right)$$

Among them, $\Sigma U(\hat{\pi}_{Q_t}, \check{T}_{W_t})$ are the sum of the utility of farmers, $\Sigma U(\check{D})$ is the social welfare loss caused by non-point source pollution emissions, $\Sigma U(\hat{T}_{(W_t,\ \rho)})$ is the government transfer payment for social welfare compensation, ρ is the marginal cost of the government to raise public revenue. Its microform is:

$$SW = n\left(\pi_{Q_t} - T_{W_t}\right) - nW_t + (1-\rho)n T_{W_t} = (1-\rho)n\pi_{Q_t} - nW_t - n\rho U_{Q_t}$$

To ensure the normal production of farmers, the lower limit of the farmers' utility is introduced, and there is $U(Q_t) \geq \mu_t$. At this time, the conditions for maximizing social welfare are:

$$\delta SW/\delta Q_t = (1-\rho)n\pi_t' - D_t'(nW_t) = 0$$

Simplify to have:

$$\pi_t' = [D_t'(nW_t)]/[(1-\rho)n]$$

The pollution function brought into the farmers is:

$$\zeta P(\xi) = \frac{(1-\rho)nl\zeta P(\xi) + \lambda lEV'D_t'(nW_t)}{(1-\rho)n(1-\gamma)^{1/\varphi}}$$

To ensure the optimal level of social welfare, when the government's operating costs are reduced by $\Delta\rho|\Delta\rho \in (0, \rho)$, the intensity of environmental regulations needs to be increased $\Delta\rho\lambda lEV'D'_t(nW_t)/[1 - \rho + \Delta\rho)(1 - \rho)n(1 - \gamma)^{1/\varphi}]$, the change in the amount of pollution discharged by farmers $\Delta W_2 = C + [(\rho - 1)/(1 - \rho + \Delta\rho)]>0$. It can be seen that reducing government operating costs is an important way to improve the efficiency of environmental regulations, and environmental regulations and environmental supervision need to be carried out while controlling government operating costs. The government operating cost C_G is divided into pollution technology limit cost C_θ, illegal punishment cost C_ζ, and environmental supervision cost C_ξ and there is $C_\theta + C_\zeta + C_\xi \leq C_G$. When the government operating cost C_G is limited, there is a crowding-out effect between the intensity of environmental supervision and the intensity of environmental regulations.

Based on the previous analysis, hypothesis H3 is proposed: Environmental supervision can adjust the impact of environmental regulations on non-point source pollution.

Re-estimation of China's Corn Planting Fertilizer Pollution Considering the Difference of Soil Fertility

Estimation Methods and Data Sources of Fertilizer Pollution

"Dictionary of Ecological Civilization Construction" shows that agricultural non-point source pollution is the pollution to the ecological system caused by chemical fertilizers, pesticides, poultry manure and other organic or inorganic pollutants in agricultural production activities through farmland surface runoff, farmland drainage and underground leakage. Among them, poultry pollution is also called "half-point source pollution". Considering the relatively small amounts of pesticides used, this paper takes fertilizer pollution as an example to estimate the non-point source pollution of corn cultivation. Nutrient balance method. It is believed that the purpose of fertilizer application is to achieve a balance of nutrient supply and demand between crops and soil and to make up for the difference between the amount of fertilizer required by the crop and the amount of fertilizer supplied by the soil. Under this theory, the part of the fertilizer application that exceeds the actual demand of the crop is pollution. Based on this theory, Yang Jun (2020) uses the total amount of excess nitrogen in the soil per unit area to measure agricultural non-point source pollution, and gives the following calculation formula: $\vartheta = \Sigma X_j Y_j + E_k - S$. Where ϑ is the total amount of excess nitrogen, X_j and Y_j are the nitrogen content and application amount of organic fertilizer applied by farm household j, respectively, E_k is the amount of pure nitrogen fertilizer applied in k years, and S is the basic nitrogen content of the land [39]. This estimation method can partially reflect agricultural non-point source pollution, but ignores the consumption of other elements during the growth of crops, and does not consider the differences in soil fertility between different regions. Therefore, this article introduces the regional fertilizer input limit to reflect the difference in soil fertility in different regions, and estimate the fertilizer pollution in the process of corn planting.

$$W_{xi} = \begin{cases} {}_{xi} - {}_{xi}, \quad {}_{xi} - {}_{xi} > \\ 0, \; , \; (F_{xi} - F_{xi}^{*}) < 0 \end{cases}$$

$$F_{xi} = \sum_{j=1}^{m} \theta_{ij} \left[\sum_{q=1}^{4} \eta_{xj} * Mix_{ijq} + Oth_{xi} \right]$$

$$F_{Ni}^{*} = \sum_{j=1}^{m} \theta_{ij} \left[\sum_{q=1}^{4} \left(\eta_{Nj} * Mix_{ijq}^{*} \right) + 0.467 Czrb_i^{*} \right]$$

$$F_{Pi}^{*} = \sum_{j=1}^{m} \theta_{ij} \left[\sum_{q=1}^{4} \left(\eta_{Pj} * Mix_{ijq}^{*} \right) \right]$$

$$F_{Ki}^{*} = \sum_{j=1}^{m} \theta_{ij} \left[\sum_{q=1}^{4} \left(\eta_{Kj} * Mix_{ijq}^{*} \right) \right]$$

$CaPO_i$ Among them, W_{xi} is the pollution amount of element x in chemical fertilizers in province i; F_x is the actual application amount of pollution element x; F_x^{*} is the recommended application amount of pollutant element x, including the recommended application amount of compo und fertilizer in corn planting area j Mix^{*}_{ijq} and urea dose $Czbr^{*}_i$, m is the total number of corn planting areas in the province i, θ_{ij} is the proportion of the province i corn planting area j, q is the province i middle j area output level, η is the corn planting area j recommended to use the proportion of the elements in the fertilizer formula x, Mix is the application amount of compound fertilizer, Oth_x is the amount of element x contained in non-compound fertilizer. $Oth_{Ni} = 0.467Czrb_i + 0.177CN_i + 0.3Noth_i$, among them, $Czrb_i$, CN_i and $Noth_i$ are the application rates of urea, ammonium bicarbonate and other nitrogen fertilizers per mu in province i, respectively; $Oth_{Pi} = 0.0859CaPO_i + 0.2148(FP_i - CaPO_i)$, where and FP_i are the amount of phosphorus peroxide and phosphate fertilizer applied per hectare in province i, respectively. Other phosphate fertilizers are calculated based on 20% effective P_2O_5; $Oth_{Ki} = 0.5235KCl_i + 0.4483(FK_i - KCl_i)$, where KCl_i and FK_i are the average potassium chloride and potassium fertilizer application rates per hectare in province i, and other phosphate fertilizers are calculated based on K_2O.

Fertilizer application rates in different corn planting areas are shown in Table 1.

Due to the difference in the degree of harm of different pollutants to the environment, a direct comparison of the emissions of different pollutants cannot directly reflect the true impact of fertilizer pollution. This article uses the "Environmental Protection Tax Law" as a reference to estimate the pollution equivalent of fertilizer pollution in the process of corn planting. Since element K is usually not calculated as pollution, when calculating fertilizer pollution equivalent, only N and P pollution elements are considered.

$$W_{Ai} = \Sigma \left(\frac{W_{xi}}{\varphi_x} \right)$$

Among them, W_{Ai} is the chemical fertilizer pollution equivalent of corn planting in province i, φ_x is the pollution equivalent coefficient of pollutant element x, and the pollution equivalent values of nitrogen pollution and organic phosphorus pollution in the "Taxable Pollutants and Equivalent Value Table" are 0.8 and 0.05, respectively.

According to the above method, the data of 20 major corn-growing provinces in China from 2006 to 2018 are selected to estimate the fertilizer pollution of corn planting in China.

The statistical description is shown in Table 2.

Among them, the average amount of fertilizer input per hectare and the average output per hectare are from the "Compilation of National Agricultural Product Costs and Benefits". Due to the lack of statistical data in Guangxi Province in 2007, a total of 259 data were obtained. In actual estimation, moving average method is used to deal with missing values.

China's Corn Planting Fertilizer Pollution

(1) Estimation results of nitrogen, phosphorus, and potassium pollution of chemical fertilizers planted in corn.

Estimating the pollution equivalent of chemical fertilizer for corn planting needs to be based on the pollution amount of each element, and the pollution

Table 1. Fertilizer application rate in different corn planting area.

I-1Northeast cold spring corn area			I-2Northeast subhumid spring corn area			I-3Northeast semiarid spring corn area		
Yield level kg/ha	Compound fertilizer kg (14-18-13)	Urea kg	Yield level kg/ha	Compound fertilizer kg (15-18-12)	Urea kg	Yield level kg/ha	Compound fertilizer kg (13-20-12)	Urea kg
<7500	345	165	<8250	360	195	<6750	375	150
7500-9000	420	195	8250-10500	465	240	6750-9000	495	210
9000-10500	480	240	10500-12000	525	270	9000-10500	570	240
>10500	555	270	>12000	600	315	>10500	660	270
I-4 Northeast warm and wet spring corn area			II-1 North China north-central summer corn area			II-2 North China south summer corn area		
Yield level kg/ha	Compound fertilizer kg (17-17-12)	Urea kg	Yield level kg/ha	Compound fertilizer kg (18-12-15)	Urea kg	Yield level kg/ha	Compound fertilizer kg (18-15-12)	Urea kg
<7500	360	210	<6750	300	195	<6000	405	165
7500-9000	435	240	6750-8250	375	240	6000-7500	495	210
9000-10500	510	285	8250-9750	450	285	7500-9000	600	255
>10500	585	330	>9750	525	330	>9000	705	300
III-1 Northwest rain-feddryland spring corn area			III-2 North irrigation spring corn area			III-3 Northwest oasis irrigation spring corn area		
Yield level kg/ha	Compound fertilizer kg (15-20-10)	Urea kg	Yield level kg/ha	Compound fertilizer kg (13-22-10)	Urea kg	Yield level kg/ha	Compound fertilizer kg (17-23-6)	Urea kg
<6750	345	180	<7500	390	195	<8250	405	225
6750-9000	450	240	7500-9750	510	240	8250-10500	525	285
9000-10500	525	285	9750-12000	630	300	10500-12000	600	315
>10500	600	330	>12000	705	345	>12000	675	360
IV-1 Sichuan Basin corn area			IV-2 Southwest mountains and hills corn area			IV-3 Southwest plateau corn area		
Yield level kg/ha	Compound fertilizer kg (17-16-12)	Urea kg	Yield level kg/ha	Compound fertilizer kg (20-15-10)	Urea kg	Yield level kg/ha	Compound fertilizer kg (19-15-11)	Urea kg
<6000	420	165	<6000	360	150	<6000	360	150
6000-7500	525	195	6000-7500	450	165	6000-8250	495	165
7500-9000	630	240	7500-9000	540	240	8250-10500	630	255
>9000	720	285	>9000	630	270	>10500	720	300

amount of each element is estimated according to (Equation 1), and the result is shown in Fig. 1.

Analyzed from the time trend, phosphorus and potassium pollution continue to grow rapidly, and nitrogen pollution is growing in an N-type, and the total pollution is far more than phosphorus and potassium pollution. Before 2012, China's corn planting fertilizer nitrogen pollution showed an upward trend, and reached the highest level in 2012. The average nitrogen pollution per hectare in each province was 22.73 kg. From 2013 to 2016, the amount of nitrogen pollution per hectare has been reduced. However, in 2017 and 2018, fertilizer nitrogen pollution has a ”rising” trend. As of 2018, the amount of nitrogen pollution per hectare in each province has reached 19.36kg, which is close to the second-highest level in previous years. From 2006 to 2018, the amount of phosphorus and potassium pollution per hectare increased year by year, reaching the highest

Table 2 . Description of statistical rows of China‘s corn planting fertilizer pollution estimation data.

	Symbol	Unit	Count	Maximum	Minimum	Average	Variance
Unit production value	*F*	Kg/ ha	3885	11228.85	3448.2	6994.95	1755799.065
Urea	*Czrb*	Kg/ha	3885	1482.45	129.9	612.3	60266.845
Ammonium bicarbonate	*CN*	Kg/ha	3885	559.35	0	110.55	20537.64
Other nitrogen	*Noth*	Kg/ha	3885	74.1	0	3.3	85.41
Phosphatic fertilize	*FP*	Kg/ha	3885	307.8	0	65.85	416.3535
Superphosphate	*CaPO*	Kg/ha	3885	304.95	0	60.3	5716.5075
Potash fertilizer	*FP*	Kg/ha	3885	314.55	0	21.15	1863.945
Potassium chloride	*KCl*	Kg/ha	3885	314.55	0	15.3	1516.95
Compound fertilizer	*Mix*	Kg/ha	3885	2266.65	131.4	1028.417	244791.585

levels of 4.17 kg and 5.27 kg respectively in 2018. The average annual growth rates are 27.34% and 24.91%, which are 3.60 times and 3.28 times the average annual growth rates of nitrogen pollution.

From the analysis of inter-provincial differences, nitrogen, phosphorus, and potassium pollution have obvious inter-provincial differences. The five provinces with the most nitrogen pollution per hectare were Yunnan, Gansu, Xinjiang, Guangxi, and Jiangsu, with average nitrogen pollution of 363.6 kg per hectare. The five provinces with the least nitrogen pollution per hectare of chemical fertilizer were Sichuan, Shanxi, Hebei, Heilongjiang, and Chongqing. The average nitrogen pollution per hectare was 151.65 kg, less than 50% of the provinces with higher pollution. The five provinces with the most phosphorus pollution per hectare are Jilin, Liaoning, Shandong, Shanxi, and Ningxia, and the average of the five provinces is 2.04 times the national average. The five provinces with the most potassium pollution per hectare are Shandong, Jilin, Liaoning, Henan, and Hebei, and the average of the five provinces is 2.19 times the national average.

(2) Estimation of the equivalent of fertilizer pollution in corn planting.

Based on the pollution amount of nitrogen, phosphorus, and potassium (Formula 2), the equivalent

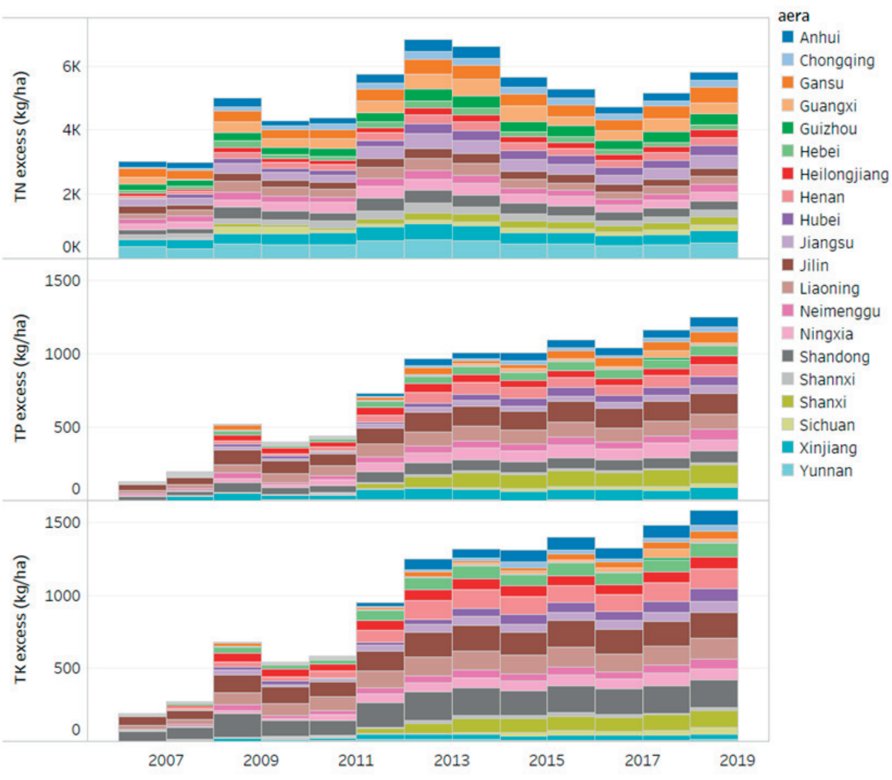

Fig. 1. 2006-2018 China’s corn planting fertilizer pollution trends.

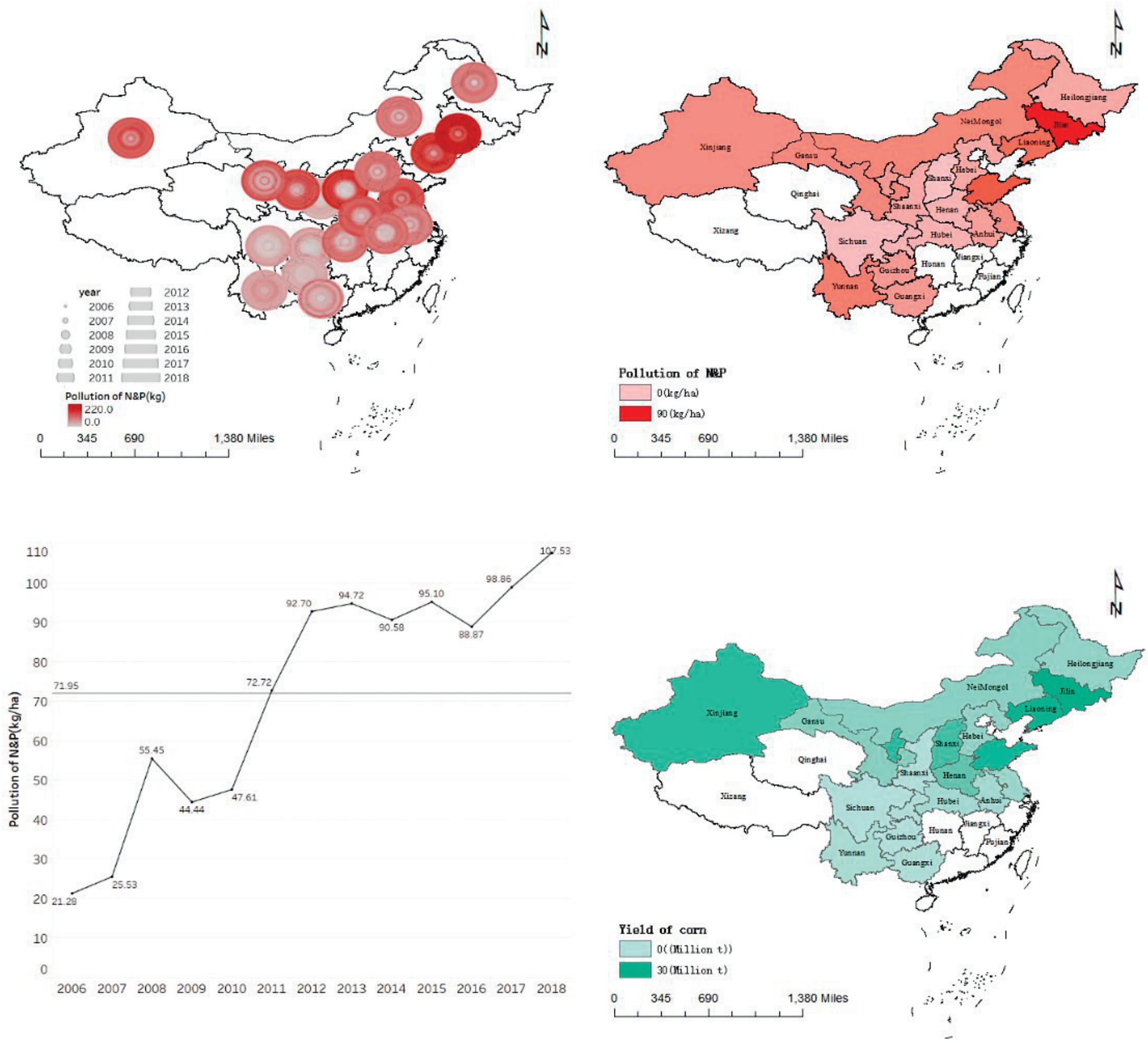

Fig. 2. Pollution equivalent of corn planting fertilizer in China from 2006 to 2018.

of fertilizer pollution in corn planting in China was estimated, and the result is shown in Fig. 2.

It can be seen from the figure that the equivalent of fertilizer pollution in corn planting in China presents an overall upward trend, and there are significant differences in the equivalent of pollution and growth rate among different provinces. In terms of time trend, the equivalent of fertilizer pollution in corn planting in China was generally at a high level after 2012 and reached the maximum value of 1466.25kg in 2018, 1.44 times the average value of previous years. From the perspective of growth rate, the growth of the equivalent of fertilizer pollution in corn planting in China can be divided into four stages: before 2010, it was in the stage of low-level fluctuation; from 2010 to 2012, it was in the stage of rapid growth; from 2012 to 2016, it was in the stage of high-level fluctuation; after 2016, it was in the stage of new growth. In terms of inter-provincial differences, the excess amount of fertilizer pollution in maize planting in northern provinces is higher than that in southern provinces, and the top five provinces in terms of the equivalent of fertilizer pollution are Jilin, Liaoning, Shandong, Xinjiang, and Ningxia, with an average of 2999.4 kg per hectare of pollution equivalent, 2.93 times more than the average of the bottom five provinces. In addition to the equivalent of pollution, the growth rate of the equivalent of pollution also has obvious inter-provincial differences. From 2006 to 2018, Shanxi, Sichuan, Henan, Hubei, Heilongjiang, Chongqing, and Hebei saw a faster growth rate of pollution, which was 25.09% higher than the national average. Shanxi Province had the fastest annual growth rate of 117.73%, which was 4.69 times the average growth rate.

By comparing the equivalent of fertilizer pollution in corn planting with the amount of the pollution of nitrogen, phosphorus, and potassium, the severity of each element pollution was analyzed, and the results were shown in Fig. 3.

As can be seen from the figure, the negative impact of phosphorus pollution from the fertilizer in corn planting on the environment is stronger than that of nitrogen pollution, and phosphorus pollution is serious in Jilin, Shenyang, and other northern provinces. According to the average pollution amount

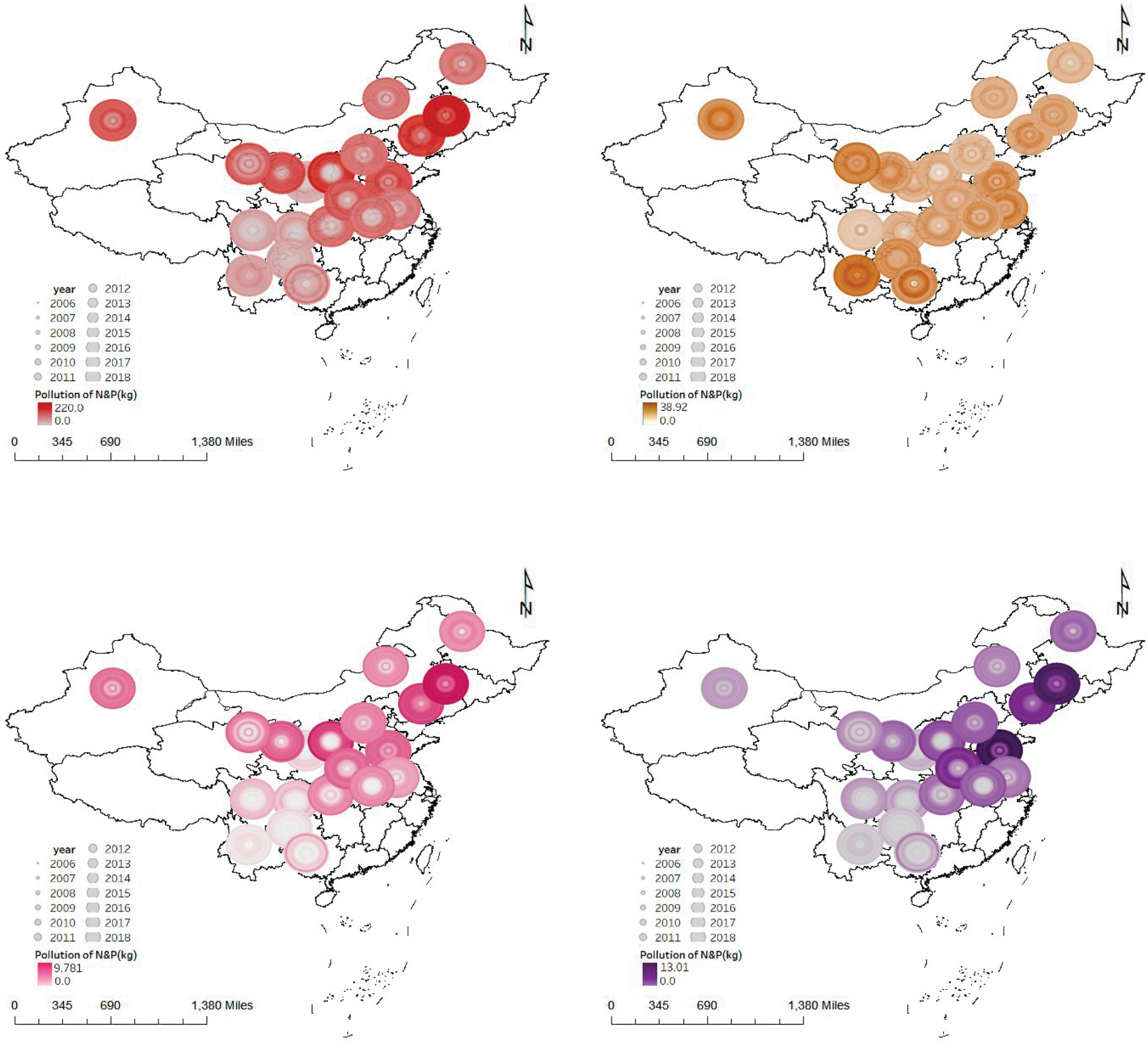

Fig. 3. Change trend of the equivalent of chemical fertilizer pollution and pollution of various elements in corn planting in China from 2006 to 2018.

of N, P, and K per hectare, nitrogen pollution is the main pollution of fertilizer in corn planting in the south, while P and K pollution is the main pollution in the northern provinces. The possible reason is that the promotion of maize and soybean rotation systems in the higher northern latitudes can reduce the amount of the pollution of nitrogen applied by farmers through the nitrogen-fixing effect of rhizobia [32]. Combined with the variation trend of the equivalent of chemical fertilizer pollution, it was found that the inter-provincial difference and growth of the equivalent of chemical fertilizer pollution in corn planting were consistent with phosphorus pollution. Combined with the analysis of nitrogen and phosphorus the amount of pollution, it can be seen that: In the process of corn planting, the total amount of organophosphorus pollution is less, but the harm to the environment is greater, so it should be regarded as an important direction to control non-point source pollution.

Results and Discussion

An Empirical Analysis of the Effect of Supervision Mechanism in Agricultural Environmental Regulation

Model Construction and Variable Selection

According to theoretical analysis, when the government implements environmental regulations with the goal of maximizing social welfare, the optimal fertilizer pollution amount for corn growers is:

$$W_t = \frac{\varphi \mathrm{FC_F}(1-\rho)n(1-\gamma)^{1/\varphi}}{(1-\varphi)l[(1-\rho)nl\zeta P(\xi)+\lambda lEV'D_t'(nW_t)]}$$

Among them, W_t is the optimal pollution emission of corn growers, and EV'', is the risk preference adjustment variable. When the individual factors of farmers and the

Table 3. Selection and statistical description of variable indicators.

Variable	Symbol	Mean	Variance	Variable	Symbol
Fertilizer Pollution	W_A	3250.65	0	1034.85	515073.758
Potential output	F	10720.35	3448.20	6967.935	1676962.80
Cost of production	C_F	28242.30	4641.90	12706.65	24676665.3225
The intensity of environmental regulation	R	63.60	7.80	22.35	116.3925
Technique level	l	171.00	66.60	109.35	447.705
Environmental supervision level	τ	71190.00	0	8664.60	248649591.0825

inherent attributes of the industry are not considered, a measurement model can be constructed:

$$\ln W_A = \ln \varphi F + \ln C_F + \ln(1-\rho) - \ln l - \ln \zeta P(\xi) + \mu$$

In the measurement model, W_A is the amount of pollution, F is the potential output, C_F is the cost of production, l is the level of green production technology of farmers, and $\zeta P(\xi)$ represents the comprehensive impact of the intensity of environmental regulation and environmental supervision. The research of Qi Yu et al. (2014) believes that the staffing of government agencies is the carrier to realize public services and functions [40]. Therefore, in papers on environmental decentralization, the ratio of the number of employees in the environmental protection department to the total number of employees is often used to measure environmental decentralization, and it is weighted by the total population of the region. Since the core issue studied in this paper is environmental supervision, this indicator is simplified, and the ratio of the number of environmental supervision units at the provincial level to the total population of the region is used as the proxy variable for environmental supervision. In addition, since the ”China Environmental Statistical Yearbook” does not count the number of environmental inspectors in 2018, this article only uses data from 2006 to 2017 for empirical analysis. The selection of each variable index and the description of its statistical row are shown in Table 3.

Among them, the average output value per mu, total cost, and fertilizer input per unit output are from the ”Compilation of Costs and Benefits of National Agricultural Products”, and the relevant data related to prices were reduced based on 2008. The percentage of environmental regulation inputs and the number of environmental supervisors from the ”China Environmental Statistics Yearbook”. The average N and P pollution equivalent per mu are calculated from the previous section.

Table 4. The test result of variable unit root.

Original Variables	IpsTest	Variable Of Feasible Region	IpsTest
W_A	0.3745	dW_A	0.0000
R	0.0878	dR	0.0000
τ	1.0000	dp	0.0002
F	0.0169	dF	0.0000
C_F	0.8140	dC_F	0.0000
l	0.0000	dl	0.0000

Model Inspection and the Results

Unit Root Test and Cointegration Test

The unit root test of Panel Data usually includes HT, LLC, IPS, among them, the test of HT is usually applicable for the short panel, the test of LLC is applicable for the long panel, and the test of Ips works for lack of data and less data. The paper selects Ips to check whether the variable is stable, specific results are shown in Table 4.

Judging from the table, the original data failed the unit Root Test and cannot be used directly for empirical analysis. Thus, processing feasible region on the original data and the data of the feasible region pass the Unit root test, that is the variable after the feasible region has no unit root, which is applicable for the analysis of the metrology model. Before the empirical analysis, var variables need to be tested for cointegration relationships, specific results are shown in Table 5.

The test results of Kao show that both the variables of the feasible region after processing and the original variables have cointegration relations. The empirical analysis of time series data requires data is stable. However, if there is a cointegration relationship between the variables, a regression can be performed even if the data is not stable, considering that the feasible region data will lose the original features, the paper presents an empirical analysis with the original data.

The Impact of Environmental Regulation and Environmental Supervision on Pollution

Because the decomposition of the chemical fertilizer in the soil is persistent, excessive application of fertilizer leaves fertilizer in the soil due to inadequate

Table 5. The results of the Cointegration Kao test.

Cointegration Kao Test	Original Variables		Variable Of Feasible Region	
	Stat.	P-value	Stat.	P-value
Modified Dickey-Fuller t	-1.9670	0.0246	-7.5425	0.0000
Dickey-Fuller t	-4.3141	0.0000	-13.3943	0.0000
Augmented Dickey-Fuller t	-2.3772	0.0087	-8.5876	0.0000
Unadjusted modified Dickey-Fuller t	-2.0878	0.0184	-10.3123	0.0000
Unadjusted Dickey-Fuller t	-4.3688	0.0000	-13.9987	0.0000

Table 6. Empirical regression results of environmental regulation and environmental supervision on agricultural non-point source pollution.

Variable		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$W_A(-1)$	Coef.	0.3435***	0.3134***	0.3887***	0.2692***	0.0846	0.2054***
	z(p)	4.93	4.21	8.82	5.99	1.14	3.1
$W_A(-2)$	Coef.	-0.1763***	-0.1874***	-0.1762***	0.0869*	0.0266	0.0696
	z(p)	-3.73	-3.4	-4.25	1.89	0.49	1.41
$W_A(-3)$	Coef.	0.2832***	0.2751***	0.2953***			
	z(p)	10.12	11.47	14.41			
R^3	Coef.		-0.0775				
	z(p)		-0.54				
R^2	Coef.	1.6899***	-0.5153*		-0.2856***	-0.6346***	-0.4707***
	z(p)	3.21	-1.73		-3.43	-3.08	-7.17
R	Coef.	-0.6591***	0.9769***		0.1866*	0.5054*	0.2880***
	z(p)	-3.35	3.39		1.74	1.79	2.9
τ	Coef.			1.0602***	-0.1146***	-0.0791***	-0.0751***
	z(p)			5.29	-7.39	-3.96	-3.75
F	Coef.	1.0002***	1.5716***	-0.1080***	2.2683***	1.4394***	1.9450***
	z(p)	3.57	3.33	-6.77	6.14	5.11	4.06
C_F	Coef.	0.3565***	0.4378***	0.5702***	0.7338***	1.1017***	0.8014***
	z(p)	3.45	3.58	4.81	4.82	7.48	4.49
l	Coef.	-0.1844*	-0.1604	-0.6985***	-1.2866***	-1.1266***	-1.1390***
	z(p)	-1.83	-1.49	-4.04	-7.84	-6.1	-6.44
$\tau * R^2$	Coef.					-0.0907	
	z(p)					-1.22	
$\tau * R$	Coef.					0.0398	-0.0657***
	z(p)					0.47	-2.44
Sargan	chi2(62)	11.9334	11.1861	17.4921	16.6902	13.1979	16.0748
Test	Prob	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Abond	AR2	0.1277	0.1619	0.0973	0.0037	0.1895	0.0406
Test	Prob	0.1258	0.1420	0.1138	0.1491	0.3197	0.1238

[1]In the result of regression, *, **, *** was significant at 10%, 5% and 1% significance levels.

decomposition and other reasons, causing fertilizer pollution of corn planting exists autocorrelation. Thus, traditional estimation of OLS cannot guarantee the reliability of results, using the method of GMM. The GMM estimates include the differential GMM estimates and the system GMM estimates because the system GMM can effectively solve the problem of the variables of the weak tool, the disappearance of individual effects, and so on, the paper chooses the method of system GMM estimates. Moreover, because the two-step method of GMM estimates can better eliminate the interference of heteroscedasticity, the paper chooses a two-step method of GMM estimates, specific results are shown in Table 6.

According to the requirements of the system GMM model, the Sargan test and A-Bond test shall be conducted. According to the result of A-Bond, choosing the lag order of the regression, getting the model 1. To further test whether there is an N-type impact between environmental regulation and agricultural non-point source pollution, building regression model 2, the results show that the N-type relationship does not exist. Model 1, Model 3, and Model 4 use the method of successive entry to analyze the impact of environmental regulations and environmental supervision on agricultural non-point source pollution, the results show that when environmental regulation and environmental supervision are considered at the same time, the lagging order of agricultural non-point source pollution's impact on itself has decreased, indicating the complexity of environmental supervision by the environmental supervision committee, and verifying the interaction effect between environmental regulation and environmental supervision.

In model 4, the regression coefficients of variablesand R^2 and R are -0.2856 and 0.1866 respectively, and significant at the 1% and 10% levels, it shows that the impact of environmental regulation on fertilizer pollution of corn planting is in an inverted U-type, assuming H1 is proved. Calculations show that the extreme point is reached when the value of R is 0.3267. On the left side of the extreme point, the fertilizer pollution of corn planting will increase with the increase in the intensity of environmental regulations, on the right side of the extreme point, the fertilizer pollution of corn planting will decrease as the intensity of environmental regulation increases.

The regression coefficient of the variable τ is -0.1146, and it is significant at the 1% significance level. It shows that for every 1% increase in the staff of the government's environmental protection department, the unit equivalent of fertilizer pollution produced by corn planting will be reduced by 0.11%, thus, assuming H2 is proven. Compare and analyze the impact of variables τ and variables R on fertilizer pollution. When R is greater than 0.3267 and less than 0.5273, the suppression effect of environmental regulations on pollution is less than that of environmental supervision. When R is greater than 0.5273, the suppression effect of environmental regulations on pollution is better than that of environmental supervision.

The regression coefficient of the variable ι is -1.2866, and it is significant at the 1% significance level. It shows that for every 1% increase in unit output of fertilizer input, fertilizer pollution during corn planting will decrease by 1.29%. Comparing the coefficients of variables ι and variables ρ, it can be seen that the effect of improving the technical level is significantly better than environmental supervision in the treatment of the equivalent of fertilizer pollution in corn planting. Comparing the impact of variables ι and variables R on the fertilizer pollution in corn planting. When R is greater than 0.4160 and less than 2.5791, the suppression effect of environmental regulation on pollution is less than the technical level, and when R is greater than 2.5791, the suppression effect of environmental regulation on pollution is better than the improvement of the technical level.

The regression coefficients of the variables F and C_F are 2.2683 and 0.7338, respectively, and they are significant at the 1% significance level. It shows that for every 1% increase in unit output and cost, farmers will cause 2.27% and 0.74% more fertilizer pollution during corn planting. To increase yields, reasonable farmers will use additional fertilizers in addition to the limited amounts of fertilizers. However, the empirical results show that the application of chemical fertilizer is not only related to income but also positively related to corn planting costs. This may be since chemical fertilizers are a relatively low-cost production factor for the corn planting process. Farmers will increase the amount of fertilizer applied to replace the input of other elements in the planting process, resulting in a positive correlation between fertilizer pollution and corn planting costs [33].

To further verify and study assuming H3, introducing interactive items $\tau * R^2$ and $\tau * R$ based on Model 4, and building model 5 and model 6. The results show that environmental supervision can linearly adjust the inverted U-type relationship between environmental regulation and agricultural non-point source pollution, which will move the inverted U-type curve to the lower left, lowering the threshold at which environmental regulation starts to inhibit agricultural non-point source pollution.

Further Analysis Based on the Threshold Model

Found in empirical analysis, environmental supervision not only has a better effect on pollution control when the intensity of regulation is low, but it can also effectively lower the critical threshold at which environmental regulation starts to suppress pollution. When conducting environmental regulation, the effectiveness of environmental supervision should be fully ensured. To further analyze how to use environmental supervision under environmental regulation, the article constructs a threshold effect

Table 7. The test of the number of thresholds.

Inspection Type	The number of thresholds	RSS	MSE	Fstat	Prob
$R \rightarrow \tau$	Single	176.1948	0.7728	3..29	0.8600
	Double	115.0992	0.5048	121.02	0.0086
	Triple	113.9607	0.4998	2.28	0.9400

Table 8. Empirical results of the effectiveness of environmental supervision under the threshold of regulatory intensity.

Model 7	F	C_F	I	$\tau(th_0)$	$\tau(th_1)$	$\tau(th_2)$
Coef.	1.4209*	1.8373***	-1.3008***	-0.1251*	0.7491***	-0.1123**
t	1.70	8.28	-2.99	-1.78	5.61	-2.02
Threshold	th_1			th_2		
Threshold value	0.0953			0.0677		

[1]In the result of regression, *, **, *** was significant at 10%, 5% and 1% significance levels

model to analyze the effect of environmental supervision under the threshold of the intensity of environmental regulation, respectively denoted as model 7. Because the panel threshold model requires the data to be balanced panel data, and there are some missing values in the original data, the article uses the moving average method to supplement data and construct balanced panel data. Before analyzing the threshold model, the number of thresholds needs to be tested, specific results are shown in Table 7.

As shown in Table 7, the article uses RSS, MSE, and Fstat to test the number of thresholds, and carry out double-threshold and three-threshold tests respectively. The results show that there is a double threshold effect of environmental regulation in Model 7. According to the results of the threshold test, the three toolkits in Stata15 is used for double threshold analysis, specific results are shown in Table 8.

In Model 7, variable $\tau(th_0)$, variable $\tau(th_1)$, and variable $\tau(th_2)$ are respectively the impact of environmental supervision on fertilizer pollution of corn planting in the three sections between the two thresholds. According to the values of variable th_1 and variable th_2, the two threshold values of variable R are 0.0677 and 0.0953 respectively. Analyzing the significance level of the variables τ in each region shows that, the coefficients of variables $\tau(th_1)$ and variables $\tau(th_2)$ are significant at the 1% and 5% levels, and their regression coefficients are 0.7491 and -0.1123, respectively, when the value of the variable R is between 0.0677 and 0.0953, the improvement of the level of environmental supervision will not directly inhibit agricultural non-point source pollution; when the value of the variable R exceeds 0.0953, every 1% increase in environmental supervision level will reduce the fertilizer pollution of corn planting by 0.11%; when the value of the variable R is less than 0.0677, environmental supervision has no significant direct impact on the fertilizer pollution of corn planting. It can be seen that only after the level of environmental regulation has reached a certain level can environmental supervision be strengthened to effectively inhibit agricultural non-point source pollution. The reason is that environmental supervision can reduce the uncertainty in the process of environmental regulation and ensure that the effect of environmental regulation is consistent with the regulatory goals.

Discussion

Discussion on the Level of Environmental Regulation

In the empirical analysis, the chemical fertilizer pollution equivalent considering regional soil fertility differences was used as a substitute index to analyze the impact of environmental regulations on non-point source pollution, and a consistent conclusion was obtained with the predecessors [41]. To formulate a targeted environmental regulation policy, the difference between the actual situation of environmental regulation in each province and the critical threshold is analyzed, and the specific results are shown in Fig. 4.

It can be seen from the figure that from 2006 to 2013, the difference between the average environmental regulation level of each province and the critical threshold gradually narrowed, but after 2013, the investment in environmental regulation gradually decreased. A comparative analysis of the differences between the provinces' environmental regulations and the optimal level of environmental regulations in 2006, 2013 and 2017, the province's investment in environmental regulations can be divided into three types: One is the pollution control type represented by Inner Mongolia, Ningxia and Xinjiang. The intensity of environmental regulation in these provinces is

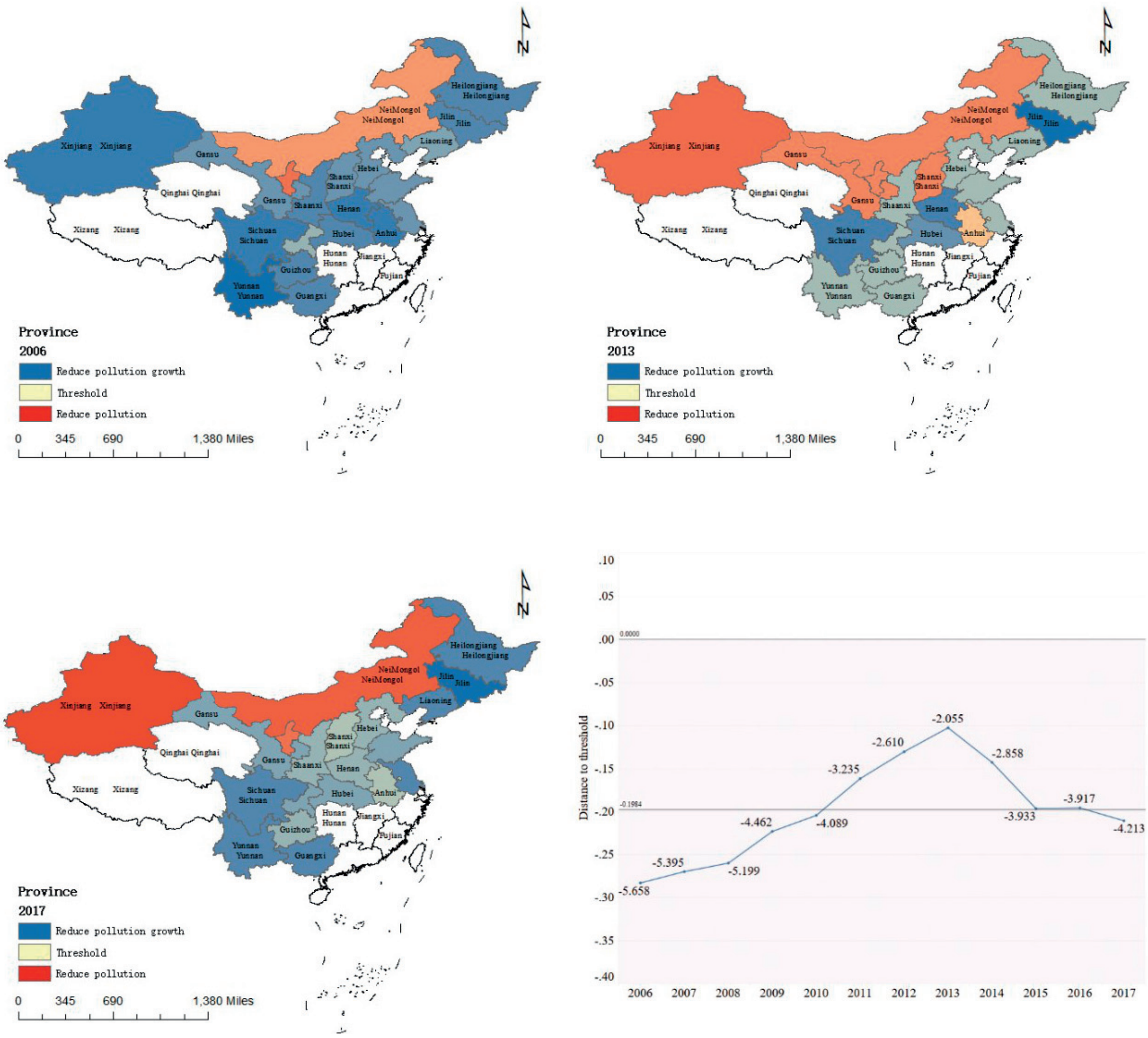

Fig. 4. Schematic diagram of the gap between environmental regulation and optimal regulation in various provinces from 2006 to 2017.

sufficient to effectively reduce agricultural non-point source pollution, and the regulation effect is good; the second is the incremental control type represented by Heilongjiang, Gansu, Yunnan and Guangxi. The intensity of environmental regulations in these provinces around 2013 was sufficient to reduce agricultural non-point source pollution, but after 2013, the investment in environmental regulations has gradually decreased. The intensity of environmental regulations can only achieve the suppression of the increase in pollution, and the intensity of environmental regulations needs to be improved; the third is the weak type of regulation represented by Sichuan, Jilin and Henan. The intensity of environmental regulation in such provinces has always been low, and the intensity of environmental regulation should be continuously improved.

Discussion on the Effectiveness of Environmental Supervision

In the analysis of the threshold model, environmental supervision is only effective under specific environmental regulatory intensity, combined with the number of environmental supervision personnel in each province in China, analyze the environmental supervision situation of each province, as shown in Fig. 5.

As can be seen from the figure, the level of environmental supervision in China‘s provinces in 2017 was not satisfactory, and environmental supervision in 9 provinces did not have a significant impact on pollution. Combining historical trends, it can be seen that China's environmental supervision is mostly located in the range of no significant impact and with both direct and regulatory effects. Only the environmental supervision of individual provinces suppresses pollution through regulatory effects. Based on the previous analysis, the provinces where environmental supervision has no significant impact on pollution are mainly incremental control provinces and weak regulation provinces. There is an urgent need to increase the intensity of environmental regulations to achieve effective treatment of agricultural non-point source pollution.

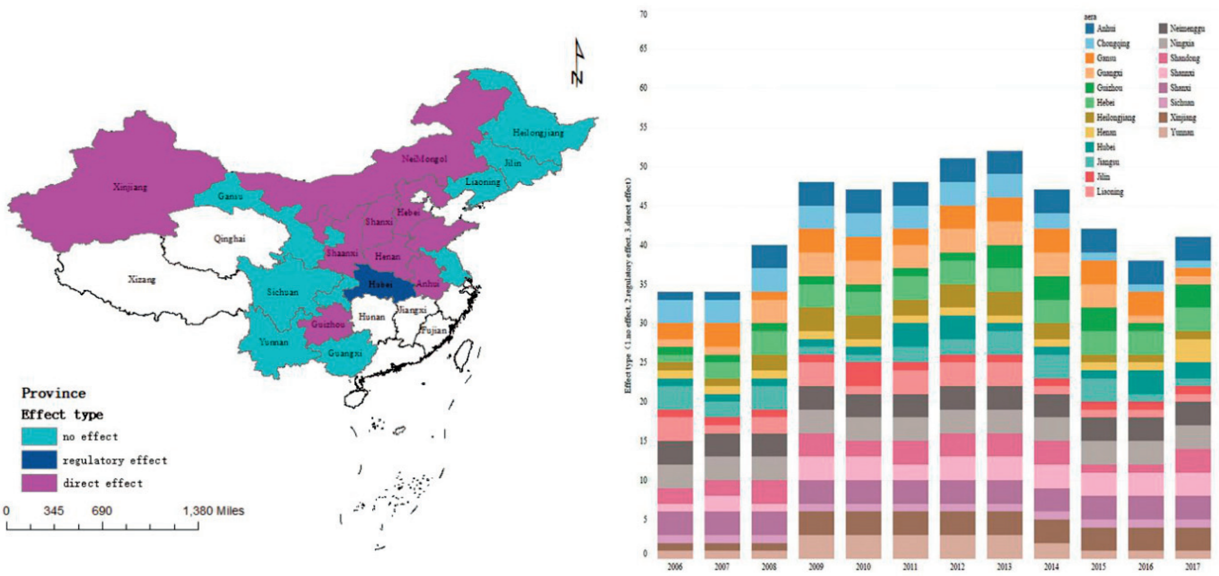

Fig. 5. Environmental supervision in various provinces in China.

Conclusions

In this paper, environmental regulation, environmental supervision and agricultural non-point source pollution are included in the same analysis framework, and a dynamic panel model and a panel threshold model are constructed. Using data from China's 20 major corn-growing provinces from 2006 to 2018, the fertilizer pollution equivalent was estimated, and then the supervision mechanism and effect in the process of agricultural environmental regulation were analyzed. The main conclusions are as follows: (1) The fertilizer pollution equivalent of corn planting is increasing year by year. In addition to planting benefits, the increase in production costs will also aggravate fertilizer pollution through the substitution of elements; (2) The impact of environmental regulations on corn fertilizer pollution equivalent is in an inverted U-shaped, and reasonable environmental regulation is helpful to effectively restrain the growth of agricultural non-point source pollution; (3) The Environmental Supervision Commission linearly adjusts the inverted U-shaped relationship between environmental regulations and agricultural non-point source pollution, and strengthens the inhibitory effect of environmental regulations on pollution growth; (4) The impact of environmental supervision on agricultural non-point source pollution will appear as a dual threshold feature with changes in the intensity of environmental regulations, turning from no significant impact to promoting effect, and turning into a restraining effect after exceeding the second threshold.

Based on the research conclusions, the following policy implications can be drawn: (1) government departments should improve the level of environmental supervision. The core conclusion of this paper shows that environmental supervision can not only strengthen the effect of environmental regulation on pollution control, but also directly participate in agricultural non-point source pollution control. When strengthening environmental supervision, the government should formulate differentiated environmental supervision measures according to different environmental regulation intensities. We should not only give full play to the strengthening effect of environmental supervision on the existing environmental regulations, improve the consistency of the objectives and behaviors of local governments' environmental regulations, and avoid the adverse selection behavior caused by local governments' self-interest, but also take into account the direct impact of environmental supervision on agricultural non-point source pollution, and adapt to a reasonable level of environmental regulations. (2) Formulate differentiated environmental regulation objectives. The results of pollution estimation show that nitrogen pollution is the main pollution of maize fertilizer in the southern provinces, while phosphorus pollution is the main pollution in the northern provinces. There are obvious pollution differences among different provinces. When formulating the objectives and intensity of environmental regulation, it is necessary to give full consideration to the local conditions, give full play to the "present management" features of local governments, and appropriately increase the environmental autonomy of local governments. For the regions where the intensity of environmental regulation is lower than the second threshold, the emphasis should be placed on strengthening environmental regulation, strengthening the number of environmental protection personnel in grass-roots areas, clarifying the regulation function of environmental departments, and increasing the transfer payment range of agricultural non-point source pollution; For regions where the intensity of environmental regulation is higher than the second threshold, both environmental regulation and supervision should be taken into account to reduce the risk preference of grass-roots environmental protection personnel and farmers for environmental damage behavior. (3) Agricultural non-point source pollution has regional heterogeneity and path dependence, which not only requires each region to establish a long-term dynamic agricultural non-point source pollution supervision system to achieve the normalization of pollution data monitoring, but also requires the central government to dredge feedback channels, coordinate the sharing of non-point source pollution control resources, form a trans-regional pollution control joint defense mechanism, and realize the coordination of agricultural pollution control. In addition, combined with the second national survey of agricultural pollution sources, monitoring points for agricultural non-point source pollution should be encrypted and fixed, and cross-level supervision and reporting systems and public opinion analysis systems should be provided to achieve high efficiency in the detection and handling of pollution problems.

Acknowledgments

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Conflict of Interest

The authors declare no conflict of interest.

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