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The Impact Mechanism of the Agricultural Input Price Index on Water Quality at River Monitoring Sections: Evidence from Provincial Panel Data

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Abstract. This study examines the impact of agricultural input prices on river water quality in China, using provincial panel data and high-frequency monitoring records for chemical oxygen demand (COD) and ammonia nitrogen (NH_3-N). In our own research, we have collected data from 30 provinces from 2010 to 2020.Employing a two-way fixed effects model, we find significant heterogeneity across input types. Rising fertilizer prices reduce pollution through cost constraints and input substitution, supporting a price-induced reduction effect. Pesticide prices show no statistically significant effect, reflecting their inelastic demand as essential crop protection inputs. In contrast, higher mechanization costs are associated with increased pollution, as they discourage the use of efficient machinery and prompt a return to less precise traditional practices, thereby exacerbating nutrient runoff. These results suggest that price-based policies are not uniformly effective. We therefore propose a three-pronged strategy: reforming fertilizer pricing to curb overuse, providing targeted subsidies for green mechanization to lower adoption barriers, and establishing cross-regional governance frameworks to address spatial spillovers in water quality management.

Keywords: River Water Quality, Agricultural Non-point Source Pollution, Farmer Behavior, Environmental Sustainability, Water Pollution

1. Introduction

China has set up policy plans like the 14th Five-Year Plan and the Beautiful China program to deal with environmental problems, but farm non-point source pollution is still a big threat to water quality. Data from the Ministry of Ecology and Environment show that surface water quality improved from 2020 to 2025, but we do not fully know how these changes happened, especially how farm input prices played a part.

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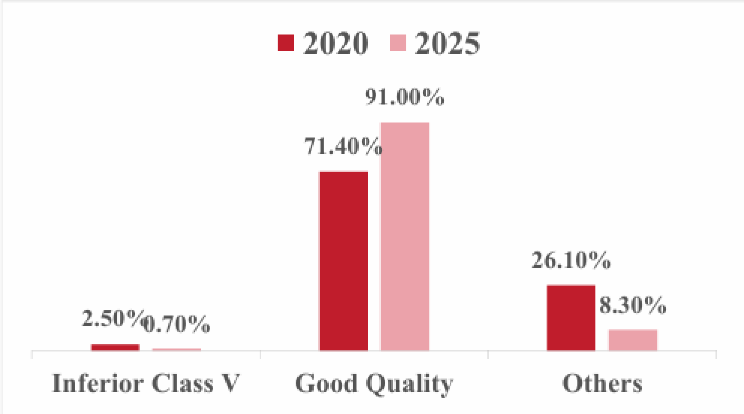

Figure 1. Comparison of national surface water assessment sections in 2020 and Q1 2025

But these improvements do not mean China's water ecology is safe, because its natural conditions are weak and risks still exist. Human activities, especially farm pollution from crop cultivation, have changed water and nutrient cycles, and this has become a main driver of river water quality decline.

Farm pollution from surface runoff is a major cause of this decline [1]. Pollutants from fertilizers, pesticides, and animal manure enter water bodies through runoff, drainage, or underground flow, and high levels of TP, TN, and COD lead to eutrophication and poor water quality.

The main types of farm pollution in China are fertilizer runoff, livestock waste, and solid waste from farmland [2]. These pollutants do not come from fixed discharge points, and they are spread over large areas. Unlike pollution from factories or cities, farm pollution is more scattered, so we need to change farming methods early on to stop pollution at the source. Following Steve R. et al. [3], the causes of farm pollution can be direct or indirect. Direct causes change the ecosystem through physical and chemical processes, and indirect causes—like population, economic development, social systems, technology, and culture—affect the direct ones and shape how the ecosystem changes. This paper looks at how economic factors affect water quality, and we use the farm input price index as the main measure in a microeconomic view.

Price mechanisms link supply and demand, and economic agents are divided into consumers, producers, and factor owners. Farmers are key players in farming and economic choices, and they can either protect or harm the environment. Their fertilizer use is affected by things like economic, psychological, and social factors [4]. Agricultural inputs like seeds, fertilizers, pesticides, film, labor, and machinery are a big part of costs, and they affect output and farmer income [5]. This paper looks at how farmers respond to changes in input prices as producers. Specifically, farmers change their input and output decisions based on changes in output and factor prices [6]. Rational farmers try to maximize profits, and price signals guide their behavior [7]. When output prices go up, farmers increase supply; when input costs go up, they cut production. If output stays the same, higher input prices create production and substitution effects, and in this situation farmers are both demanders of factors and decision-makers in production.

The production effect shows in farmers' buying behavior in two ways. Seed price changes affect farmers' crop choices and so change planting patterns. China's past "price scissors" policy left farmers with low profits, so they are very sensitive to price rises in seeds and other inputs [5]. When the price of a specific seed goes up, farmers switch to cheaper options, and this changes planting patterns. Zheng et al. [8] find that changes in cropping structure, especially the growth of cash crops, are the main cause of worse non-point source pollution from farming in the Xingyun Lake basin.If

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cash crop seed prices go above grain crop prices, farmers plant more cash crops, and this raises fertilizer and pesticide use and makes farm pollution worse and harms local water quality.Also, higher fertilizer prices, especially for nitrogen and compound ones, have made some farmers buy cheaper and lower-quality replacements [9]. And because farmers have low to middle incomes and demand for farm inputs does not change much, their planned production costs stay the same when prices change.In this situation, when input prices go up, farmers buy cheaper and lower-quality fertilizers. These have less active ingredients and are not used as well by crops, so more nutrients stay in the soil or go into the environment, and these fertilizers lose much more nitrogen and phosphorus than high-quality ones. Such fertilizers often contain heavy metals, industrial waste, and undecomposed organic matter, and crops cannot absorb these substances, and they also break down slowly. This causes mixed pollution, and it raises nitrogen, phosphorus, and other harmful substances in water and makes farm pollution worse.

The substitution effect shows how farmers change their actions to save costs when budgets are tight, and this is shown in two ways. On one hand, farmers may switch from machines to labor, for example by giving up mechanized farming. This change comes from the high costs of machinery, like buying, maintaining, and repairing it, and these machines improve efficiency but also raise production costs.When input prices go up a lot, production costs may be higher than revenues, so farmers may use manual labor instead of machines. This change in inputs can raise the risk of farm pollution. Take fertilizing as an example. Manual fertilizing does not use measuring tools, and it depends on farmers' experience, which is not very precise [10] and quite random. This often leads to applying too much or too little fertilizer, and extra nitrogen and phosphorus stay in the environment. Spreading fertilizer on the surface means it is exposed to rain and runoff, and water carries nutrients into nearby rivers and harms water quality. Also, farmers may give up some farmland in response to price changes, and cutting down planted area is also a useful way to control costs. When input prices change, farmers may give up plots that are not profitable. Longer fallow periods change soil nutrients, plant growth, and water flow, and other human activities also affect the ecosystem. Farmland left unused for a long time [11] can cause soil erosion and release leftover pesticides through soil and water movement, and this creates pesticide-based pollution that weakens the ecosystem's ability to regulate itself, slows down pollutant breakdown, and keeps water quality poor for a long time. Misused abandoned farmland, such as for livestock, waste dumping, or unplanned farming, can create new pollution sources. This paper uses the agricultural input price index as a measure of economic conditions. Under microeconomic theory, price changes cause farmers to adjust their behavior, and this affects pollution through farming activities and finally changes river water quality. The core transmission mechanism is shown below.

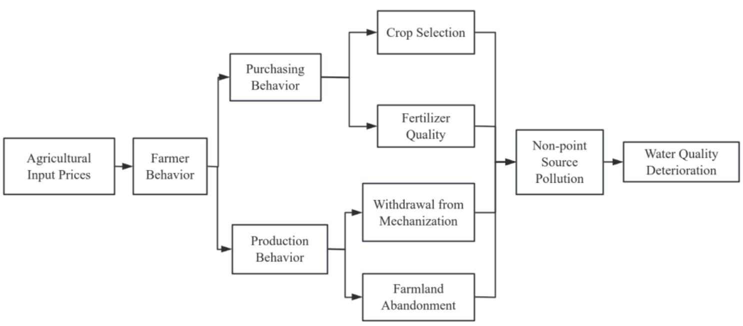

Figure 2. Mechanism of the agricultural input price index on water quality

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This study makes four contributions: (1) quantifying the link between agricultural input prices and pollution intensity; (2) using large-scale micro-level data for micro-econometric analysis; (3) identifying farmers' behavioral adjustments as an intermediate mechanism; and (4) revealing the transmission mechanism from input prices to river water quality.

2. Literature review

This paper looks at how farm input prices affect river water quality. The related studies have three main groups. One group is about what causes farm pollution. Another group is about how farmers act when market prices change. And the third group is about what factors affect river water quality. Farm pollution is an important research topic because it connects to farm output, farmers' income, environmental rules, and policy.

Liang et al. [2] find that too much and improper fertilizer use leads to surface water eutrophication and nitrate pollution in groundwater. They use an inventory method and divide the factors into direct and indirect ones, and this shows that economic development affects pollution through indirect pathways like changes in industrial structure. Song et al. [12] say that farming, livestock, regional development, and technical and policy support all add to non-point source pollution in an indirect way, and they also find that agricultural technical progress weakens the effect of local fiscal support on pollution.

Liu et al. [13] show that land transfer cuts down non-point source pollution indirectly by making farms bigger and increasing grain planting, and this effect also spreads to nearby areas. He and Yu [14] show that urbanization changes farming inputs and methods, and pollution goes up then down, but this pattern varies a lot by region. Hou, Lyu, and Yin [15] say that farmer behavior affects environmental risks, and differences in farmers' knowledge about fertilizer and farm size cause different amounts of farm waste.

Farmers are the main decision-makers, and their preferences, budget limits, and expectations shape their production choices. So farmer behavior is the basic building block of agricultural economics and an important factor for looking at how resources are used. Chi [7] says that farmers' supply decisions are affected by price and non-price factors, and how sensitive they are depends on how strong those non-price factors are. Because farmers care about profits and have fixed assets, they often react to price signals in ways that go against typical producer behavior. When prices are bad, they may grow food only for themselves or stop farming, and this can lower productivity. Jiang and Yang [16] talk about "cognitively rational small-scale farmers" in a two-stage game: the first stage is about cognitive balance, and the second is about game balance. They show that small farmers' rational actions depend on the situation, and this shows up as context locking and context adaptation. So farmers in small markets adjust their behavior mainly around price signals. Huang, Luo, and Zhang [17] use an adaptive theory approach, and they include household head traits and family resources as farmer variables, and production costs and market prices as market environment measures. They find that two forces drive farmers' scale decisions: price expectations and production control ability, and price swings are the biggest worry. For example, higher production costs or an older household head tend to make farmers reduce their scale.

River water quality is a complex system that changes over time and space and is affected by many factors, including human pollution, water flow changes, pollutant release from sediments, and changes in self-cleaning ability. Zhai et al. [18] studied pollution sources and water management in rural and urban rivers in the Dengsha River basin, Dalian. They used the output coefficient method and the QUAL2K model to measure how much NH_3-N and TP came from four sources: industrial point sources, rural sewage, livestock farming, and agricultural cultivation. Livestock farming and

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agricultural cultivation were the top sources, and their contributions varied a lot by season and location.Zhang et al. [19] studied the gap between water quality goals and pollution loads in urban rivers. They used a one-dimensional model and divided the river into control units to work out environmental capacity and find each unit's quality level and excess level, and this made predictions more accurate. Then they suggested different ecological measures like grass swales and floating wetlands. Ren et al. [20] dealt with the high cost of TN monitoring in urban rivers by using machine learning to build an inversion model, and they found that NH_3-N, water temperature, pH, and electrical conductivity were key indicators for TN prediction. The random forest model gave accurate TN values every minute.Wang et al. found that season and rainfall have a clear effect on water quality in the Maoming [21] section of the Jianjiang River. Urban pollution is the main source in dry periods, but during heavy rain, farm pollution, internal release, and industrial pollution go up quickly.

3. Data definition and model specification

3.1. Data definition

3.1.1 The dependent variable is river water quality, measured by ammonia nitrogen and chemical oxygen demand. The data come from three public datasets put together by Cai Yanpeng's team [22] using R and Python, and these datasets have daily (3,588), weekly (217,751), and monthly (114,954) records of surface water quality from 1980 to 2022. They also cover 18 indicators from 2,384 monitoring sites—244 daily, 149 weekly, and 1,991 monthly—across inland, coastal, and marine areas.

3.1.2 Explanatory variable: Agricultural input price index, represented by fertilizer price index, pesticide price index, and mechanization level. All data are from the National Bureau of Statistics without further calculation.

3.1.3 Control Variables: Technological development level, year-end population, number of patent grants, industrialization level, environmental regulation intensity, and climate change index.

(1) Technological development level – domestic patent grants divided by year-end population (provincial panel data from the National Bureau of Statistics).

(2) Industrialization level – industrial added value divided by gross regional product (data from the National Bureau of Statistics).

(3) Environmental regulation intensity – measured as the proportion of sentences containing environmental protection keywords in government work reports, following Shao et al. (2024).

(4) Climate change index (CPRI) – based on daily average temperature, rainfall, and dew point temperature (for relative humidity). Using 1973–1992 as the baseline, extreme events are defined as: low temperature days (LTD, daily temperature < 10th percentile, Ti10); high temperature days (HTD, daily temperature > 90th percentile, Ti90); extreme rainfall days (ERD, daily rainfall > 95th percentile, Ri95); and extreme drought days (EDD, daily relative humidity < 5th percentile, Hi5). Each sub-index is standardized to [0,100] using (observed − min) / (max − min) × 100, and aggregated into CPRI with equal weights (25% each).

The calculation formula is as follows:

$$CPRI = 0.25 \times L\bar{T}D + 0.25 \times H\bar{T}D + 0.25 \times E\bar{R}D + 0.25 \times E\bar{D}D \tag{1}$$

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3.2. Model specification

We estimate the following two-way fixed effects model to examine the impact of agricultural input prices on water pollution, controlling for time-invariant individual characteristics and region-invariant time trends:

$$pollution_{it} = \alpha_1 + \alpha_2 index_{it} + \alpha_2 X_{it} + \mu_i + \zeta_t + \varepsilon_{it} \quad (2)$$

The dependent variable is the average water quality (ammonia nitrogen or COD) for river sections in province i in year t, and the core explanatory variable is the agricultural input price index (for fertilizers, pesticides, and machinery). Control variables include technology level, year-end population, number of patents, industrialization level, environmental regulation, and climate change. Province fixed effects control for time-invariant provincial factors, while year fixed effects capture common shocks that affect all provinces in the same period, and the error term is random. Also, to deal with heteroskedasticity and serial correlation, all regression standard errors are clustered at the provincial level.

4. Empirical results

4.1. Descriptive statistics

The sample data show a lot of spread and differences. For the dependent variables, the mean values of COD and NH_3-N are 4.52 and 0.80. But their standard deviations are much larger than their means, and the extreme values are not evenly spread (for example, COD has a maximum of 57.50 and a minimum of just 1.00). So there are big differences in pollution levels across samples. So the data are adjusted by trimming the upper and lower values. For the main independent variables, the mean values of the price indices are around 100. Among these, the fertilizer price index has the largest standard deviation (10.14), and this shows that its prices change the most, so it is a main source of change that affects farmers' input choices. But the distributions of the mechanization and pesticide price indices are more concentrated.

Table 1. Descriptive statistics

Variable	Mean	Std. dev.	Min	Max
nh4	0.80	1.12	0.04	8.36
cod	4.52	4.86	1.00	57.50
Fertilizer Price Index	103.03	10.14	0.00	145.76
Mechanization Tools	100.72	5.73	0.00	122.20
Agricultural Means of Production Price Index	103.52	7.22	0.00	128.05
Pesticide Price Index	101.07	5.64	0.00	129.67
Technological Development Level	8.66	14.14	0.03	92.82
Environmental Regulation Intensity	0.00	0.00	0.00	0.02
Year-End Population	4340.04	2806.63	258.00	12706.00

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Table 1. (continued)

Industrialization Level	0.34	0.10	0.07	0.57
Number of Patent Grants	43.66	93.81	0.01	872.21
Climate Change Index	26.05	6.64	9.89	78.15

Table 2 shows how the overall farm input price index affects farm pollution. The coefficient for COD is -0.0644 ($p < 0.1$), and for ammonia nitrogen it is -0.0262 ($p < 0.05$). So there is a clear negative link between farm input prices and pollutant emissions. When prices of seeds, film, and other inputs go up, farmers' operating costs rise. And because farm product prices stay the same, farmers tend to plant less or use inputs more carefully to avoid losing money. This behavioral change cuts pollution.

Table 2. Regression results of the comprehensive agricultural means of production price index on agricultural non-point source pollution

variable	Chemical Oxygen Demand	Ammonia Nitrogen
Agricultural Means of Production Price Index	-0.0644* (0.0356)	-0.0262** (0.0105)
Pesticide Price Index	-0.0399*** (0.0114)	-0.0051*** (0.0012)
Technological Development Level	-35.4494*** (12.8176)	-31.2371*** (10.4051)
Environmental Regulation Intensity	0.0014* (0.0008)	0.0007*** (0.0001)
Year-End Population	5.4887*** (1.1722)	1.5808*** (0.0608)
Industrialization Level	0.0225 (0.0211)	-0.0043*** (0.0003)
Number of Patent Grants	-0.0011*** (0.0003)	-0.0088* (0.0064)
Constants	-9.4368 (10.8229)	-5.4932* (3.2006)
Id	yes	yes
Time	yes	yes
R2	0.6467	0.5694

Note: The numbers in parentheses are robust standard errors of the regression coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3 looks at how changes in fertilizer price affect the two main water pollutants. The regression results show that the fertilizer price index has a coefficient of -0.0384 on COD, significant at 10%, and a coefficient of -0.0130 on ammonia nitrogen, significant at 5%. Because fertilizer is the most direct source of farm pollution, farmers' fertilizer use directly affects pollution

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levels. The results support the idea that higher fertilizer prices cause two effects. The first is a direct "reduction effect," where farmers reduce the amount used per unit area. The second is a "substitution effect," and it makes farmers look for bio-fertilizers or more accurate application methods.

Table 3. Regression results of fertilizer price index on agricultural non-point source pollution

variable	Chemical Oxygen Demand	Ammonia Nitrogen
Fertilizer Price Index	-0.0384* (0.0205)	-0.0130** (0.0061)
Environmental Regulation Intensity	-26.8322** (13.0006)	-35.0088*** (6.6399)
Year-End Population	0.0014 (0.0019)	0.0006*** (0.0001)
Industrialization Level	37.2037*** (7.0098)	2.3668 (2.0817)
Number of Patent Grants	0.0247 (0.0210)	-0.0033*** (0.0005)
Climate Change Index	-0.0007 (0.0352)	-0.0082* (0.0054)
Constants	-7.0211 (10.5065)	-4.2728* (2.2202)
Id	yes	yes
Time	yes	yes
R2	0.6469	0.5639

This table shows how the pesticide price index affects pollutant emissions. The results indicate that the coefficients on COD(-0.0781) and ammonia nitrogen(-0.0108) are both negative, but neither is statistically significant. This means that the effect of pesticide prices on non-point source pollution is not strong in statistics. The economic reason is that pesticides act as an "insurance reserve" against pest and disease risks, so their demand is not very sensitive to price changes. Farmers' demand for pesticides is less affected by price changes and more by crop damage or prevention needs.

Table 4. Regression results of pesticide price index on agricultural non-point source pollution

variable	Chemical Oxygen Demand	Ammonia Nitrogen
Pesticide Price Index	-0.0781 (0.0814)	-0.0108 (0.0243)
Technological Development Level	-0.0644*** (0.0001)	-0.0199*** (0.0000)
Environmental Regulation Intensity	-199.5356 (103.5397)	-29.9413* (16.6765)

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Table 4. (continued)

Year-End Population	0.0016 (0.0018)	0.0006* (0.0004)
Industrialization Level	38.2380*** (7.0164)	2.8048 (2.0911)
Number of Patent Grants	-0.0248 (0.0213)	-0.0026*** (0.0003)
Climate Change Index	-0.0005* (0.0003)	-0.0069 (0.0106)
Constants	-10.7745 (13.3218)	-3.9234 (3.9703)
Id	yes	yes
Time	yes	yes
R2	0.6432	0.5526

Table 5 shows different results from the inputs above. The coefficients for the mechanization tool price index on COD (0.0584) and ammonia nitrogen (0.0222) are positive and significant at the 10% and 5% levels. This shows that higher mechanization costs are linked to more pollution. The main reason is technology substitution. Modern farm machines often have green features like deep tillage, precision fertilizing, and precision spraying, and they raise input use efficiency. When mechanization costs go up, farmers use fewer machines and go back to old manual ways. This backward shift in farming makes fertilizer and pesticide loss rates rise again, and at the macro level, pollutant emission intensity increases.

Table 5. Regression results of mechanization tool price index on agricultural non-point source pollution

variable	Chemical Oxygen Demand	Ammonia Nitrogen
Mechanization Tool Price	0.0584* (0.0310)	0.0222** (0.0100)
Technological Development Level	-0.0664*** (0.0009)	-0.0151*** (0.0000)
Environmental Regulation Intensity	-25.6750** (12.0000)	31.3302 (30.7904)
Year-End Population	0.0016 (0.0018)	0.0006*** (0.0000)
Industrialization Level	37.9792*** (7.0586)	2.5994* (1.4800)
Number of Patent Grants	0.0263 (0.0212)	-0.0028*** (0.0003)
Climate Change Index	-0.0003 (0.0358)	-0.0083 (0.0106)

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Table 5. (continued)

Constants	-8.5283 (12.6004)	-5.0304 (3.7466)
Id	yes	yes
Time	yes	yes
R2	0.6428	0.5549

5. Conclusions and recommendations

5.1. Conclusions

Provincial panel data and river water quality data from 2007 to 2018 show that farm input prices affect water pollution differently by input type. Rising fertilizer prices cut NH_3-N and COD emissions through cost pressure, so market prices can help reduce fertilizer use. But pesticides are like an "insurance" for pest control, so price changes do not have a big effect on pesticide pollution. Also, higher mechanization costs are linked to more pollution, because mechanized farming improves fertilizing and spraying and lowers nutrient runoff. When mechanization is harder, pollution gets worse.

5.2. Recommendations

First, market-based ways should cut fertilizer use. Governments should adjust fertilizer prices to guide resource use and curb overuse. Move subsidies to organic fertilizers and soil testing, lowering the cost for switching to greener practices. For pesticides, price rules should also have administrative controls, like packaging recycling, use reduction, and tighter toxic restrictions.

Second, promote mechanization for environmental benefits. Because rising mechanization costs worsen pollution by reducing efficiency, increase subsidies for green and precise machinery. Focus on deep tillage and precise spraying equipment. Expand service groups to help small farmers access mechanization.

Finally, combine technology and regulation for water management. Give farm pollution more weight in reviews and allocate resources to key areas. Boost R&D for green technologies and ensure patents yield emission cuts.

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