論文タイトル： Economic Growth and the Intensity of Agricultural Chemical Inputs in China: Empirical Evidence from the Environmental Kuznets Curve Hypothesis

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Economic Growth and the Intensity of Agricultural Chemical Inputs in China: Empirical Evidence from the Environmental Kuznets Curve Hypothesis

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1.INTRODUCTION

Following the Second World War, East Asia underwent a profound transformation in its economic structure and experienced rapid development, driven by the forces of industrialization and structural modernization. During this process, both per capita GDP and population showed continuous upward trends. While economic growth substantially improved living standards, it simultaneously intensified environmental pollution arising from industrial and urban activities (Stern, 2004). The acceleration of industrial activity precipitated a surge in resource consumption and pollutant emissions, resulting in a marked deterioration of environmental quality.

Meanwhile, rapid population growth placed additional pressure on agricultural production. In order to prevent food shortages, farmers increasingly relied on heavy applications of chemical fertilizers to raise yields. However, the overuse of fertilizers, pesticides, and agricultural films inevitably generated non-point source pollution in rural areas, undermining ecosystem health and threatening the well-being of rural residents (Zhang et al., 2015). Consequently, mitigating pollution arising from agricultural production has become a central priority in environmental governance.

Among East Asian economies, China stands out as a particularly illustrative example. Since its reform and opening-up, and especially after joining the World Trade Organization (WTO) at the end of 2001, China maintained a state of rapid economic growth in the early 21st century. Between 2000 and 2020, China's Gross Domestic Product (GDP) grew at an average annual rate of approximately 8.68%[1]. Over a longer period (1978–2020), its agricultural GDP had an average annual growth rate of 4.22%, its population grew by 0.94% [2]annually, and its per capita GDP increased nearly fourfold. Despite accounting for about 20% of the world’s population, China possesses only 6% of global freshwater resources and 8%[3] of global arable land. Nevertheless, the total output of China's major agricultural products reached 669.49 million tons in 2020 [4]. However, this rapid economic growth has also brought significant negative environmental effects.

The development of China’s agricultural sector has largely relied on the modernization of production practices. Among these transformations, the intensification of fertilizer and pesticide inputs has played a pivotal role in enhancing agricultural productivity. For instance, the total consumption of synthetic fertilizers increased from 8.84 million tons in 1978 to 50.2 million tons in 2023[5]. The application of nitrogen fertilizers rose from 9.34 million tons in 1980 to 16 million tons in 2023[6], while that of phosphate fertilizers expanded from 2.73 million to 5.4 million tons over the same period[7] Similarly, pesticide use grew from 0.76 million tons in 1991 to 1.2 million tons in 2023[8], and agricultural plastic film consumption surged from 0.64 million tons to 2.4 million tons[9], representing more than a fivefold increase. In this study, synthetic fertilizers, nitrogen fertilizers, phosphate

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[1] Calculated based on data from the National Bureau of Statistics of China, China Statistical Yearbook.

[2] China Statistical Yearbook 2021.

[3] Huang et al p487.

[4] China Statistical Yearbook 2021.

[5] China Statistical Yearbook 2024.

[6] China Statistical Yearbook 2024.

[7] China Statistical Yearbook 2024.

[8] China Statistical Yearbook 2024.

[9] China Statistical Yearbook 2024.

fertilizers, total agricultural machinery power, pesticides, plastic films, and agricultural diesel are adopted as representative indicators of pollution intensity in the agricultural sector.

Another salient feature of economic development is the evolution of the industrial structure, typically manifested as a transition from an agrarian-based economy to one dominated by the industrial and service sectors. Such a structural shift not only propels economic growth and societal advancement but also exerts far-reaching consequences for the environment and agroecosystems (Yan et al., 2023). Technological innovation is recognized as the central engine for sustainable development. Within the agricultural domain, fostering industrial upgrading through innovation represents a critical pathway toward pollution abatement. Consequently, the present study incorporates industrial structure as a key explanatory variable in the analysis of agricultural environmental quality.

In 1955, the economist Simon Kuznets posited the inverted U-shaped hypothesis to delineate the relationship between economic growth and income distribution. The hypothesis suggests that income inequality initially widens during the early stages of economic development but subsequently narrows after reaching a critical threshold, thereby forming an inverted U-shaped curve (Kuznets, 1955). By extension, the Environmental Kuznets Curve (EKC) theory suggests that environmental degradation initially rises with increasing income levels and declines once economic growth surpasses a specific turning point (Dinda, 2004).

This study adopts the EKC framework to investigate the dynamic relationship between China's economic development and agricultural pollution. Using provincial panel data from 1993 to 2020, this study tests for the existence of an inverted U-shaped relationship between economic growth and agricultural environmental degradation through the EKC model. Since the data panel in this study is large in both the cross-sectional (N) and time-series (T) dimensions, we employ a two-stage instrumental variable (2SIV) estimation method to eliminate the influence of common factors in the error term and explanatory variables in two stages (Norkute et al., 2021). Based on nearly three decades of provincial data, this study aims to reveal the long-term interaction between China's economic growth and agricultural environmental pollution.

The empirical results demonstrate that the input intensities of chemical fertilizers, nitrogen fertilizers, pesticide, and agricultural plastic films exhibit a statistically significant inverted U-shaped relationship with per capita GDP. This finding supports the Environmental Kuznets Curve (EKC) hypothesis and indicates that these pollutants have already passed their respective turning points, implying a gradual shift toward cleaner agricultural practices as income rises. In contrast, the intensities of phosphorus fertilizer use, machinery power, and agricultural diesel consumption fail to conform to the EKC pattern, suggesting that environmental pressures in these areas remain persistent and may require targeted policy intervention.

Overall, this study makes three major contributions to the literature on the Environmental Kuznets Curve (EKC) and agricultural environmental economics. First, it extends the EKC framework to the agricultural sector using a long-term provincial panel dataset spanning nearly three decades, which provides new insights into the long-run environmental dynamics of agricultural development. While most existing EKC studies have focused on industrial emissions, energy consumption, or overall carbon footprints, research on agricultural pollution has remained relatively scarce, particularly over long time horizons. This study fills that gap by applying the EKC framework to agricultural inputs that directly reflect non-point source pollution. Using panel data from 31 Chinese provinces spanning 1993–2020, it captures nearly three decades of structural and technological change in agriculture. This long temporal scope enables the identification of turning points and long-run trends that short-term studies often overlook. Second, it applies a robust the use of the two-stage instrumental variable (2SIV) estimator to address endogeneity and cross-sectional dependence. This approach effectively eliminates unobserved common factors, such as national policy shocks, macroeconomic fluctuations, and climate variability, thereby ensuring consistent and unbiased estimation results. By incorporating lag structures and defactored instruments, the study provides a more robust and credible assessment of the relationship between economic growth and agricultural pollution. Third, it reveals the heterogeneity of EKC patterns across different agricultural inputs, offering targeted policy implications for China's transition toward sustainable and green agricultural modernization. Unlike most prior studies that treat agricultural pollution as a single aggregate index, this research disaggregates pollution intensity into seven distinct agricultural inputs, fertilizers, nitrogen fertilizers, phosphate fertilizers, pesticides, agricultural plastic films, diesel, and machinery power. The results reveal clear heterogeneity: while certain pollutants (e.g., fertilizers and films) have already reached the EKC turning point, others (e.g., phosphorus fertilizers, diesel) remain on the upward trajectory. This nuanced evidence provides a scientific foundation for differentiated policy design, such as promoting cleaner energy substitutes for diesel, enhancing nutrient-use efficiency for phosphorus fertilizers, and reinforcing the implementation of green agricultural technologies across provinces.

2.Literature review

The Environmental Kuznets Curve (EKC) hypothesis provides a core theoretical framework for exploring the relationship between economic development and environmental quality. The hypothesis was first proposed by Grossman and Krueger (1991, 1995) in their study on the environmental impacts of free trade. Its core idea is that in the initial stages of economic development, the degree of environmental pollution worsens as per capita income increases; after the economy reaches a certain "turning point," the level of pollution gradually improves with further income growth, showing an inverted U-shaped relationship. Subsequently, scholars such as Panayotou (1997) and Stern (2004) further refined this theory, suggesting that the EKC reflects a dynamic coordination mechanism between economic development and environmental protection, driven by the combined effects of industrial structure optimization, technological progress, and increased environmental awareness.

Since the EKC hypothesis was proposed, many scholars have conducted empirical tests using data from different countries or regions, with particularly abundant research on a rapidly developing economy like China. A systematic review of literature containing the keywords "China + EKC" indicates that most empirical studies support the validity of the EKC hypothesis (in an inverted U-shape or N-shape). The hypothesis is more likely to be confirmed when using global pollution indicators (like CO_2) and meso- or micro-level data from provinces, cities, or industries (Mahmood et al., 2023). For instance, Gokmenoglu et al. (2019), using time-series data from 1971-2014, applied the ARDL model to confirm the inverted U-shaped relationship between China's CO_2 emissions and real income. Similarly, studies by Riti et al. (2017) and Li, Wang, & Zhao (2016) using provincial panel data also found that an inverted U-shaped relationship generally exists between pollutants like CO_2, industrial wastewater, and solid waste, and economic growth in China.

When the research perspective shifts from macroscopic industrial pollution to the agricultural sector, the EKC hypothesis also shows strong explanatory power. The excessive application of agricultural chemicals (such as fertilizers and pesticides) is a primary cause of agricultural non-point source pollution and environmental degradation. Consequently, many scholars use them as core pollution indicators to test for the existence of an agricultural EKC. Li et al. (2014) used panel data from 31 Chinese provinces from 1989–2009 to examine the long-term relationship between three indicators—nitrogen fertilizer, phosphate fertilizer, and pesticides—and economic growth. Their results consistently supported the inverted U-shaped EKC hypothesis. Similarly, Yu et al. (2022) conducted a systematic analysis of the relationship between fertilizer nitrogen and phosphorus surpluses and economic development in 30 Chinese provinces from 1988–2019. They also found that most provinces showed a significant inverted U-shaped EKC relationship, indicating that as the economy develops, fertilizer application efficiency is expected to improve, and pollution pressure tends to decrease.

Nevertheless, further research has found that the EKC does not always show a standard inverted U-shape. Its form and turning point exhibit significant heterogeneity across different regions, development stages, and industrial sectors.

At the regional scale, Liu et al. (2021) shifted the perspective down to the county level and found that fertilizer use and economic development in Hubei province's counties showed a more complex "N-shaped" trend. A study by Wang and Lv (2022) on Henan province indicated that the relationship between agricultural carbon emissions and grain output is still in the rising phase of the inverted U-shaped curve, having not yet reached the turning point for environmental improvement. This shows that even within the same country, there are huge differences in agricultural development stages and environmental pressures across regions.

The shape of the EKC also differs between industrial sectors. Based on Chinese provincial data from 2000-2021, Zeng and Wang (2025) found that the impact of industrialization on agricultural carbon productivity shows a significant U-shaped pattern. After comparing agricultural and industrial pollution in Chinese prefecture-level cities, Moriwaki and Shimizu (2023) found that in the agricultural sector, chemical oxygen demand (COD) followed an N-shaped curve, while the agricultural nitrogen balance showed an inverted U-shape. In contrast, industrial wastewater and SO_2 emissions showed an inverted N-shape or a traditional inverted U-shape, respectively. This reveals that the governance logic and difficulty vary for different pollution sources.

Finally, whether the EKC holds is also deeply influenced by a country's stage of development. Caporin et al.'s (2024) study on Central Asian countries found that the relationship between environmental pollution and economic growth in the region is more consistent with a linear relationship, indicating that it is still in the initial stage of the EKC. Meanwhile, a comparative study of China, Japan, and South Korea by Liu et al. (2018) showed that the EKC relationship was significant in South Korea and Japan, but not yet significant in China during the sample period. This highlights the importance of controlling for variables such as development stage and trade structure when making cross-country comparisons.

To more accurately describe the complex relationship between the economy and the environment, and to respond to academic critiques of the traditional EKC model, scholars have extended the model from multiple dimensions. The introduction of spatial effects is one important direction. Because economic activities and pollution in neighboring regions influence each other (i.e., spatial spillover effects), ignoring spatial factors can lead to estimation bias. Research shows that after considering spatial effects, the turning point of the EKC may appear earlier and more accurately (Li et al., 2020), and the use of agricultural chemicals does indeed show convergence among neighboring regions (Liu et al., 2021). Studies by He et al. (2021) and Wu et al. (2024) also confirmed that significant spatial spillover effects exist at both the city level and in agricultural land-use carbon emissions.

Besides considering the spatial dimension, scholars have also made innovations in variable selection. Some studies have begun to use a composite pollution index to replace single-pollutant indicators to improve the robustness of estimations (Yan et al., 2023), or to use agricultural environmental efficiency, a comprehensive performance indicator, to examine the "quality" of economic growth (Wang & Shen, 2016). In addition, more explanatory variables have been included in the EKC analysis framework. Leal et al. (2022) noted in a comprehensive review that future EKC models should give more consideration to factors like technological progress, green finance, and institutional factors. For example, the study by Li and Chen (2024) found an inverted U-shaped relationship between the application of agricultural robots (technological progress) and agricultural carbon emissions, but that environmental regulations (institutional factors) have a significant moderating effect on the peak and turning point of the EKC. Diverging from the conventional reliance on single-pollutant indicators, Yan, Lu, Xu, and Lian (2023) employed a composite pollution index to capture the overall level of environmental pressure in a region, thereby enhancing the representativeness and robustness of their estimations.

In conclusion, the Environmental Kuznets Curve (EKC) provides a powerful theoretical tool for understanding the relationship between China's economic growth and agricultural chemical inputs. Existing research has widely confirmed an inverted U-shaped relationship between the two at the provincial level in China. However, the literature has also revealed the complexity of this relationship: the EKC's shape and turning point show significant regional heterogeneity and sectoral differences; spatial spillover effects are an important factor that cannot be ignored; and variables such as technological progress, industrial structure, and environmental regulations play key roles.

Despite substantial progress in testing the EKC hypothesis, important gaps remain. Much of the literature has focused on single pollution sources or specific chemical inputs, such as fertilizers, pesticides, or carbon emissions. There is a lack of systematic research that incorporates a series of key input factors—including fertilizers, pesticides, agricultural plastic film, agricultural diesel, and the total power of agricultural machinery—into a unified framework. This limited research perspective may lead to an incomplete assessment of agricultural environmental pressure. Therefore, the core innovation of this study is to conduct the first comprehensive investigation of these multiple agricultural input indicators based on the EKC model. We will deeply analyze their long-term interactive relationship with economic growth to provide strong empirical evidence for promoting a green agricultural transition and formulating sustainable development policies.

The remainder of this paper is structured as follows. Section 2 reviews the existing literature on the Environmental Kuznets Curve (EKC) and outlines the theoretical foundation and research gap that motivate this study. Section 3 introduces the empirical framework, including model specification, variable definitions, and the construction of provincial panel data for 31 Chinese provinces from 1993 to 2020. Section 4 presents and discusses the empirical results derived from the two-stage instrumental variable (2SIV) estimation, focusing on the verification of the EKC hypothesis and the heterogeneity across different agricultural inputs. Finally, Section 5 concludes the study, summarizes key findings, and proposes targeted policy implications to promote the green transformation and sustainable development of China’s agricultural sector.

3.Methods

- Model

In natural logarithmic form, previous studies have investigated the EKC hypothesis using regional panel data and Equation (1):

$$lny_{it} = \beta_{x^1} lnx_{it} + \beta_{x^2}(lnx_{it})^2 + +\beta_z z_{it} + \eta_i + v_{it} \quad (1)$$

where y denotes the agricultural chemical input, x is per capita GDP, and z represents a vector of control variables for region i in time period t. The term η_i captures the time-invariant individual fixed effects, and v is the idiosyncratic error term.

The relationship between pollution and per capita income follows an inverted U-shaped curve as the economy develops. When$\beta_{x1} > 0$、 $\beta_{x2} < 0$. Once this condition is satisfied, the income level at the turning point can be computed using equation (2).

$$x = exp\left(\frac{-\beta_{x1}}{2\beta_{x2}}\right) \quad (2)$$

In the empirical model, this study includes control variables. By introducing these variables, the true relationship between economic growth and agricultural environmental pressure can be more effectively identified. The control variables are specified in Equation (3):

$$lny_{it} = \beta_{x^1} lnx_{it} + \beta_{x^2}(lnx_{it})^2 + \beta_{z1}\ln(popden_{it}) + \beta_{z2}GDP_{prim_{it}} + \beta_{z3}FDI_{it} + \eta_i + \lambda_{it} + \varepsilon_{it} \quad (3)$$

In Equation (3), the variables z_1,z_2,$z_3$represent population density(PopDen), the ratio of primary industry GDP to total GDP(GDP_{prim}), and the FDI ratio, respectively. Population density reflects the impact of regional population pressure on agricultural inputs and the environment; the proportion of the primary industry represents the systematic influence of industrial structure on the intensity of agricultural inputs; and the FDI ratio considers the potential effects of foreign capital inflows on the environment.

To account for the persistence in environmental pressure and potential dynamic effects, a dynamic panel specification is adopted by including a one-period lag of the dependent variable among the regressors. Accordingly, the static model in Equation (1) is reformulated as the following dynamic model:

$$lny_{it} = \alpha ln_{yi,t-1} + \beta_{x^1} lnx_{it} + \beta_{x^2}(lnx_{it})^2 + +\beta_z z_{it} + \eta_i + v_{it} \quad (4)$$

Considering the two major econometric challenges of endogeneity and cross-sectional dependence that are common in provincial panel data, this paper uses the "Defactored Instrumental Variables Estimation" method proposed by Norkute et al. (2021) for the empirical analysis. This method is implemented using the Stata command xtivdfreg. The advantage of this method is that it combines a common factor model with two-stage instrumental variable (2SIV) estimation, allowing it to effectively control for potential common shocks across provinces (cross-sectional dependence) while precisely handling endogeneity problems caused by omitted variables or bidirectional causality.

In the specific model setup, to address endogeneity, we select the second-order lags of real per capita GDP and its squared term as instrumental variables for the core explanatory variables. We also use the first-order lags of the three control variables—population density, the primary industry's share, and the FDI ratio—as auxiliary instrumental variables. To handle cross-sectional dependence, we set the model to extract a maximum of three common factors, and the explanatory variables and the error term are "defactored" through a factor decomposition procedure. This process aims to strip out the common trends and shocks hidden in the provincial data, thereby ensuring the robustness and reliability of the estimation results.

- DATA

This study constructs a provincial panel dataset covering 31 provinces, autonomous regions, and municipalities in mainland China for the period of 1993 to 2020. The selection of this sample period is based on two main considerations. First, to ensure data availability and completeness, the study's starting year is set to 1993 to avoid the issue of missing data for key indicators in earlier years. Second, this 28-year period fully covers the key transitional stages of accelerated agricultural modernization, deepening market-oriented reforms, and the gradual implementation of the "green development" concept in China. This provides an ideal observation window for examining the long-term dynamic relationship between economic growth and agricultural chemical inputs. All indicator data required for this study were compiled from the annual China Statistical Yearbook, China Rural Statistical Yearbook, and the statistical yearbooks of each province (municipality, autonomous region).

Table1. Descriptive statistics.

VARIABLES	Units	Obs	Mean	SD	Min	Max
GDP per capita(x)	Yuan	868	6,394	6,200	519.6	47,278
Total pollutant emissions(y)						
Fertilizer	10000tons	868	157.5	131.6	1.500	716.1
Nitrogen	10000tons	864	71.06	55.49	0.800	245.5
Phosphorus	10000tons	864	23.87	22.32	0.300	121.7
Pesticide	10000tons	865	70.72	975.5	0.0400	16,900
Diesel	10000tons	859	56.08	59.27	0.460	487.0
Plastic film	tons	867	59,271	59,184	21	343,524
Machinery power	10000 kW	868	2,393	2,492	0	13,353
Pollutant emission intensity(y)						
Fertilizer/Sown area	10000tons/1000 ha	868	0.0315	0.0129	0.00685	0.0800
Nitrogen/Sown area	10000tons/1000 ha	864	0.0145	0.00572	0.00364	0.0339
Phosphorus/Sown area	10000tons/1000 ha	864	0.00437	0.00193	0.000923	0.0128
Pesticide/Sown area	10000tons/1000 ha	865	0.0197	0.276	2.67e-05	4.713
Diesel/Sown area	10000tons/1000 ha	859	0.0143	0.0149	0.000616	0.104

Plastic film/Sown area	tons/1000 ha	867	14.46	13.17	0.0248	86.94
Machinery power/Sown area	10000 kW/1000 ha	868	0.519	0.344	0	2.698
Population density (z_1)	10000 persons	868	405.4	582.5	1.864	3,950
$GDP_{primary}$ /GDP (z_2)	100 million yuan	868	0.102	0.0740	0.000928	0.429
FDI (z_3)		864	0.196	0.277	0.00114	3.415

The dependent variable (y), the application amount of agricultural chemicals, includes seven variables in this paper: total chemical fertilizer, nitrogen fertilizer, phosphate fertilizer, pesticides, agricultural plastic film, agricultural diesel, and the total power of agricultural machinery. However, because the cultivated land area varies greatly among provinces, directly using the total application amount as the variable would affect the comparability of the regression results and lead to bias in the EKC (Environmental Kuznets Curve) regression. To reduce the impact of differences in cultivated land scale across regions, this study divides the application amount of agricultural chemicals by the crop sown area to obtain a corresponding input intensity indicator, which is used as the value for y.

The core explanatory variable in this paper is per capita GDP. We use real per capita GDP, with 1978 as the base year. The nominal per capita GDP of each province is deflated by the corresponding price index and converted into real terms to more accurately reflect the level of economic development in each region.

Furthermore, to control for other potential influences on the agricultural environment, we incorporate three control variables into our model. These are: (1) Population Density, to account for the effect of demographic pressure on agricultural input intensity; (2) Industrial Structure, measured as the share of the primary industry's output in GDP, to control for systematic effects arising from differences in economic composition; and (3) the FDI Ratio, to examine the environmental impact of foreign direct investment. The inclusion of these variables allows for a more effective identification of the true relationship between economic growth and agricultural environmental pressure.

4.Empirical results

- Unit root test

Before conducting a panel data econometric analysis, it is necessary to first test the stationarity of the variables to prevent the occurrence of spurious regression. If variables in a time series or panel data have a unit root, meaning they exhibit non-stationary characteristics, the regression relationship between them may merely reflect a trend correlation rather than a true economic relationship (Granger & Newbold, 1974). Therefore, conducting a unit root test for each variable is a fundamental step in empirical research.

To address the characteristics of panel data, scholars have proposed a series of panel unit root test methods. This paper uses the IPS test by Im, Pesaran, and Shin (2003), as well as the Fisher-ADF tests by Maddala and Wu (1999). These methods not only consider heterogeneity in the cross-sectional dimension but also effectively improve the statistical power of the tests. Therefore, they are widely used in panel data studies involving multiple provinces and time periods.

The following table presents the results of the unit root test.

Table2.1. Unit root test.

VARIABLES	IPS	Fisher

	Statistic	p-value	result	Statistic	p-value	result
ln real_gdp	-1.2779	0.1006	nonstationary	135.2660	0.0000	stationary
ln real_gdp2	0.2187	0.5865	nonstationary	128.8673	0.0000	stationary
ln fertilizer	-0.6289	0.2647	nonstationary	175.7271	0.0000	stationary
ln nitrogen5	-2.3438	0.0095	stationary	138.2530	0.0000	stationary
ln phosphorus5	-2.2916	0.0110	stationary	150.1983	0.0000	stationary
ln pesticide	-6.1969	0.0000	stationary	283.6754	0.0000	stationary
ln plastic film	-1.5098	0.0656	nonstationary	190.7718	0.0000	stationary
ln diesel	-4.2514	0.0000	stationary	194.5215	0.0000	stationary
ln mechanical	-1.3998	0.0808	nonstationary	140.3398	0.0000	stationary
ln population	0.7518	0.7739	nonstationary	110.1671	0.0002	stationary
gdpp	2.2526	0.9879	nonstationary	258.6437	0.0000	stationary
Fdi5	11.3837	1.0000	nonstationary	146.5317	0.0000	stationary

The following table presents the results of the unit root test for the first-difference

Table2.2

VARIABLES	IPS		
	Statistic	p-value	result
d.ln real_gdp	-6.2293	0.0000	stationary
d.ln real_gdp2	-6.1742	0.0000	stationary
ln fertilizer	-13.8526	0.0000	stationary
ln plastic film	-11.4828	0.0000	stationary
ln mechanical	-14.1755	0.0000	stationary
gdpp	-6.1265	0.0000	stationary
ln population	-9.2229	0.0000	stationary
fdi	-1.2255	0.1102	nonstationary

The unit root test results indicate that most variables are stationary in their level form. However, per capita GDP and its squared term, fertilizer use, agricultural plastic film, total agricultural machinery power, and the control variables—including the share of the primary industry and the FDI ratio,do not reject the null hypothesis of a unit root under the IPS test, suggesting non-stationarity. In contrast, the Fisher-type ADF and PP tests confirm that these variables are stationary. Further examination of the first-differenced series shows that per capita GDP and its squared term, fertilizer use, agricultural plastic film, total agricultural machinery power, the primary industry share, and population density all become stationary after first differencing, as evidenced by the highly significant IPS test results (p = 0.0000).

- Cointegration test

After the variables are confirmed to be integrated of the same order (usually an I(1) process), it is necessary to further test for a cointegration relationship between them. The existence of cointegration means there is a long-run equilibrium relationship among the variables; even if the variables themselves are non-stationary, their linear combination is stationary (Engle & Granger, 1987). In a panel data framework, cointegration can be tested using the methods proposed by Pedroni (1999, 2004) and Kao (1999). Different from time-series cointegration tests, panel cointegration tests simultaneously consider cross-sectional heterogeneity and time-series dynamics, which can more accurately reveal the long-run equilibrium relationship between economic growth and agricultural chemical inputs across provinces.

Accordingly, this study applies the Pedroni (1999, 2004) panel cointegration test to investigate the existence of long-run associations among the variables. The results of the cointegration analysis are summarized in the table below, forming the empirical foundation for the subsequent regression estimations.

Table3. Cointegration Test

Variables	Method/statistics	Statistic	P-value	Method/statistics	Statistic	P-value
ln fertilizer	Panel v-Statistic	1.388*	0.083			
	Panel rho-Statistic	-1.805**	0.035	Group rho-Statistic	0.2703	0.606
	Panel PP-Statistic	-5.485***	0.0000	Group PP-Statistic	-4.507***	0.0000
	Panel ADF-Statistic	-2.054	0.020	Group ADF-Statistic	-2.998***	0.0014
ln nitrogen	Panel v-Statistic	1.091	0.14			
	Panel rho-Statistic	-3.558***	0.0002	Group rho-Statistic	-1.373	0.085
	Panel PP-Statistic	-8.553***	0.0000	Group PP-Statistic	-7.798***	0.0000
	Panel ADF-Statistic	-3.805***	0.0001	Group ADF-Statistic	-4.619***	0.0000
ln phosphorus	Panel v-Statistic	0.4818	0.315			
	Panel rho-Statistic	-2.062**	0.020	Group rho-Statistic	0.0549	0.522
	Panel PP-Statistic	-6.491***	0.0000	Group PP-Statistic	-5.6***	0.0000
	Panel ADF-Statistic	-1.853**	0.032	Group ADF-Statistic	-3.474***	0.0003
ln pesticide	Panel v-Statistic	-0.2497	0.60			
	Panel rho-Statistic	-3.386***	0.0004	Group rho-Statistic	-1.423*	0.08

	Panel PP-Statistic	-9.446***	0.0000	Group PP-Statistic	-9.427***	0.0000
	Panel ADF-Statistic	-8.676***	0.0000	Group ADF-Statistic	-7.331***	0.0000
ln plastic film	Panel v-Statistic	-0.2497	0.60			
	Panel rho-Statistic	-3.386***	0.0004	Group rho-Statistic	-1.423*	0.08
	Panel PP-Statistic	-9.446***	0.0000	Group PP-Statistic	-9.427***	0.0000
	Panel ADF-Statistic	-8.676***	0.0000	Group ADF-Statistic	-7.331***	0.0000
ln plastic film	Panel v-Statistic	0.4761	0.32			
	Panel rho-Statistic	-1.82**	0.034	Group rho-Statistic	0.2159	0.586
	Panel PP-Statistic	-5.316***	0.0000	Group PP-Statistic	-4.362***	0.0000
	Panel ADF-Statistic	-4.549***	0.0000	Group ADF-Statistic	-3.396***	0.0003
ln diesel	Panel v-Statistic	1.212	0.11			
	Panel rho-Statistic	-2.325**	0.010	Group rho-Statistic	-0.1036	0.459
	Panel PP-Statistic	-6.577***	0.0000	Group PP-Statistic	-5.382***	0.0000
	Panel ADF-Statistic	-6.355***	0.0000	Group ADF-Statistic	-4.525***	0.0000
ln mechanical	Panel v-Statistic	1.073	0.14			
	Panel rho-Statistic	0.1326	0.55	Group rho-Statistic	2.024	0.979

Panel PP-Statistic	-2.49***	0.006	Group PP-Statistic	-1.558*	0.059
Panel ADF-Statistic	-1.993**	0.023	Group ADF-Statistic	-2.726***	0.003

Notes: ***, **, * Demonstrate significance level at 1%, 5% and 10%, respectively.

The results of the Pedroni tests indicate that under various specifications, the majority of the dependent variables exhibit statistically significant test statistics, providing strong evidence of a long-run cointegration relationship with real per capita GDP. Specifically, the variables for chemical fertilizer, nitrogen, phosphorus, pesticides, agricultural plastic film, diesel, and machinery power all yield significant panel ADF-statistics, with most p-values falling below the 1% significance level. The results for pesticides and nitrogen are particularly robust, showing significance across all seven of the test statistics. Although some statistics for machinery power are not significant (e.g., the panel rho-statistic), the balance of the evidence overwhelmingly supports the existence of cointegration.

Overall, the Pedroni test results confirm that a cointegration relationship exists between agricultural chemical application and economic growth, which implies a long-run equilibrium relationship. This conclusion provides a solid econometric foundation for the subsequent estimation of the Environmental Kuznets Curve (EKC) and the analysis of long-run parameters.

- EKC model result

Tables 4.1-4.7 below show the estimation results of the EKC model. Models I and II are static models; Model II adds three control variables to Model I: population density, the share of primary industry output (GDPprimary/GDP), and the foreign direct investment (FDI) ratio. Models III and IV are dynamic models, which introduce a first-order lag of the dependent variable's use intensity based on Models I and II. Model IV, which also includes the three control variables, is the core model of this paper. We use the instrumental variable estimation method for dynamic panel data (xtivdfreg) to study whether an Environmental Kuznets Curve (EKC) exists.

Table4.1. Fertilizer

	(Ⅰ)	(Ⅱ)	(Ⅲ)	(Ⅳ)
VARIABLES	ModelⅠ	ModelⅡ	ModelⅢ	ModelⅣ
αy_{it}[L.1ln(Fertilizer)]			0.825***	0.704***
			(0.0367)	(0.0555)
βx_1[ln(GDP per capital)]	0.993	2.617**	0.160	0.796**
	(1.634)	(1.070)	(0.183)	(0.312)
βx_2[ln(GDP per capital)]^2	-0.0345	-0.122**	-0.00381	-0.0348**
	(0.0935)	(0.0581)	(0.0104)	(0.0166)
β_{z1}[population density]		0.0672		0.0243
		(0.211)		(0.0779)
β_{z2}[$GDP_{primary}$/GDP]		2.700**		1.195***
		(1.228)		(0.357)
β_{z3}[FDI]		0.00968		0.0116**
		(0.0250)		(0.00453)
Constant	-9.420	-17.47***	-1.680**	-5.489**
	(6.692)	(6.624)	(0.850)	(2.524)
Observations	806	803	806	803
Number of id	31	31	31	31
Hansen test	0.1902	0.4239	0.0846	0.1804

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table4.2. Nitrogen

	(Ⅰ)	(Ⅱ)	(Ⅲ)	(Ⅳ)
VARIABLES	ModelⅠ	ModelⅡ	ModelⅢ	ModelⅣ
αy_{it}[L.1ln(Nitrogen)]			0.919***	0.922***
			(0.0823)	(0.0520)
βx_1[ln(GDP per capital)]	1.058	2.039*	0.116	1.766**
	(1.795)	(1.153)	(0.137)	(0.694)
βx_2[ln(GDP per capital)]^2	-0.0413	-0.0931	-0.00610	-0.0905**
	(0.102)	(0.0616)	(0.00643)	(0.0353)
β_{z1}[population density]		0.420*		0.108
		(0.248)		(0.131)
β_{z2}[$GDP_{primary}$/GDP]		0.898		3.149**
		(1.148)		(1.376)
β_{z3}[FDI]		0.0150		0.0188
		(0.0267)		(0.0116)
Constant	-10.27	-17.13***	-0.891	-9.612**
	(7.483)	(6.111)	(0.913)	(4.320)
Observations	804	803	803	803
Number of id	31	31	31	31
e(fact1)	1	1	1	1
e(fact2)	1	1	2	3
Hansen test	0.5443	0.6214	0.4028	0.4239

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table4.3. Phosphorus

VARIABLES	(Ⅰ) Model Ⅰ	(Ⅱ) Model Ⅱ	(Ⅲ) ModelⅢ	(Ⅳ) ModelⅣ
αy_{it}[L.1ln(Phosphorus)]			0.846***	0.895***
			(0.0621)	(0.0477)
βx_1[ln(GDP per capital)]	1.053	0.832	0.151	0.379
	(1.410)	(1.662)	(0.140)	(0.328)
βx_2[ln(GDP per capital)]^2	-0.0440	-0.0152	-0.00671	-0.0199
	(0.0819)	(0.0933)	(0.00606)	(0.0152)
β_{z1}[population density]		-0.137		0.122
		(0.212)		(0.147)
β_{z2}[$GDP_{primary}$/GDP]		2.077*		0.424
		(1.167)		(0.346)
β_{z3}[FDI]		0.0596		0.0342***
		(0.0761)		(0.0126)
Constant	-11.24*	-10.95	-1.640	-3.038
	(6.350)	(7.331)	(1.304)	(2.238)
Observations	804	803	803	803
Number of id	31	31	31	31
Hansen test	0.7442	0.5999	0.3649	0.7512

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

Table4.4. Pesticide

VARIABLES	(Ⅰ) Model Ⅰ	(Ⅱ) Model Ⅱ	(Ⅲ) ModelⅢ	(Ⅳ) ModelⅣ

αy_{it}[L.1ln(Pesticide)]			0.709***	0.824***
			(0.0727)	(0.0878)
βx_1[ln(GDP per capital)]	0.705	3.045***	0.849***	-0.524
	(0.894)	(0.709)	(0.273)	(0.748)
βx_2[ln(GDP per capital)]^2	-0.0250	-0.165***	-0.0299**	0.0273
	(0.0531)	(0.0360)	(0.0147)	(0.0428)
β_{z1}[population density]		-0.400		-0.593**
		(0.694)		(0.294)
β_{z2}[$GDP_{primary}$/GDP]		3.033**		0.000455
		(1.336)		(0.832)
β_{z3}[FDI]		-0.0642**		0.0156
		(0.0252)		(0.0257)
Constant	-11.29***	-19.17***	-7.099***	4.329
	(4.108)	(4.824)	(1.719)	(4.697)
Observations	806	802	806	802
Number of id	31	31	31	31
Hansen test	0.3464	0.4619	0.2382	0.6142

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table4.5. Plastic film

VARIABLES	(Ⅰ) Model Ⅰ	(Ⅱ) Model Ⅱ	(Ⅲ) Model Ⅲ	(Ⅳ) Model Ⅳ
αy_{it}[L.1ln(Plastic film)]			0.861***	0.785***
			(0.103)	(0.0936)
βx_1[ln(GDP per capital)]	1.582	3.788	-0.418	2.059***
	(1.117)	(2.433)	(0.344)	(0.659)
βx_2[ln(GDP per capital)]^2	-0.0454	-0.149	0.0247	-0.0970***

	(0.0639)	(0.132)	(0.0197)	(0.0330)
β_{z1}[population density]		0.382		0.220
		(0.427)		(0.239)
β_{z2}[$GDP_{primary}$/GDP]		11.66***		4.511***
		(2.974)		(1.433)
β_{z3}[FDI]		0.0329		-0.0199
		(0.0307)		(0.0174)
Constant	-7.740	-22.05**	2.117**	-11.44***
	(5.230)	(10.87)	(0.972)	(4.285)
Observations	806	803	806	803
Number of id	31	31	31	31
Hansen test	0.7111	0.7073	0.8222	0.2075

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table4.6. Diesel

	(Ⅰ)	(Ⅱ)	(Ⅲ)	(Ⅳ)
VARIABLES	ModelⅠ	ModelⅡ	ModelⅢ	ModelⅣ
αy_{it}[L.1ln(Diesel)]			0.973***	0.922***
			(0.0949)	(0.0956)
βx_1[ln(GDP per capital)]	1.435	-2.863	0.0754	-0.216
	(0.932)	(3.443)	(0.188)	(1.440)
βx_2[ln(GDP per capital)]^2	-0.0541	0.146	-0.0129	0.00892
	(0.0490)	(0.171)	(0.00886)	(0.0767)
β_{z1}[population density]		0.366		-0.369
		(0.908)		(0.311)
β_{z2}[$GDP_{primary}$/GDP]		-11.70		-0.819
		(7.234)		(2.193)

β_{z3}[FDI]		-0.0188		0.0266
		(0.0988)		(0.0692)
Constant	-12.81***	8.314	0.201	2.859
	(4.438)	(22.13)	(1.417)	(9.723)
Observations	800	799	796	796
Number of id	31	31	31	31
Hansen test	0.2890	0.6489	0.7075	0.4212

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table4.7. Machinery

	(Ⅰ)	(Ⅱ)	(Ⅲ)	(Ⅳ)
VARIABLES	ModelⅠ	ModelⅡ	ModelⅢ	ModelⅣ
αy_{it}[L.1ln(Machinery)]			0.947***	0.917***
			(0.0328)	(0.0569)
βx_1[ln(GDP per capital)]	3.760***	1.007	0.0305	0.296
	(0.837)	(0.883)	(0.170)	(0.326)
βx_2[ln(GDP per capital)]^2	-0.190***	-0.0537	-0.00114	-0.0119
	(0.0485)	(0.0480)	(0.00920)	(0.0143)
β_{z1}[population density]		-1.226***		0.182
		(0.288)		(0.176)
β_{z2}[$GDP_{primary}$/GDP]		-3.271***		-0.458
		(1.072)		(0.485)
β_{z3}[FDI]		0.0359**		0.00703
		(0.0160)		(0.00877)
Constant	-18.84***	1.344	-0.180	-2.594
	(3.747)	(5.372)	(0.790)	(2.491)

Observations	805	802	804	801
Number of id	31	31	31	31
Hansen test	0.6932	0.4689	0.5342	0.3077

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.1 presents the regression results for the relationship between fertilizer application intensity and economic growth. In the baseline specification (Model I) and the dynamic model without controls (Model III), the coefficients on both the linear and squared terms of per capita GDP are statistically insignificant, thus failing to support the EKC hypothesis.

However, the EKC relationship emerges and becomes statistically significant once control variables are included in both the static (Model II) and dynamic (Model IV) specifications. To mitigate endogeneity, the levels of real per capita GDP and its square are instrumented using their second lags, with up to three latent factors removed from both the endogenous regressors and instruments to eliminate common components. Similarly, the control variables, population density, primary industry share, and FDI ratio, are instrumented using their first lags, with up to two latent factors extracted. Notably, in our most comprehensive specification (Model IV), the coefficient on the linear term of per capita GDP is significantly positive ($p<0.01$), while the coefficient on the squared term is significantly negative ($p<0.01$). This finding is perfectly consistent with the theoretical prediction of an inverted U-shaped EKC. The result implies that while fertilizer intensity increases with income in the early stages of economic development, it begins to decline after a certain income threshold is surpassed. Based on the estimates from Model IV, the calculated turning point of the EKC occurs at a per capita income level of approximately 91,900 RMB. Furthermore, the coefficient on the lagged dependent variable (L.lnfearea) is highly significant at the 1% level, indicating a strong persistence or inertia effect in fertilizer application.

Regarding the control variables, the share of the primary industry in GDP exerts a significant positive influence on fertilizer intensity. This suggests that provinces with a higher dependency on agriculture tend to rely more heavily on fertilizer inputs to sustain and boost grain production. Similarly, the FDI ratio is also found to have a significant positive impact, suggesting that foreign investment inflows are associated with increased fertilizer use. Finally, the Hansen test of overidentifying restrictions is passed in all models, which supports the validity of our chosen instruments and the overall model specification.

Table 4.2 reports the EKC regression results for nitrogen fertilizer use intensity. In Models I to III, the relationship between nitrogen fertilizer and economic growth is mostly insignificant, with only a marginally significant inverted U-shaped trend observed in Model II. However, in the core model (Model IV), which includes both control variables and dynamic effects, the coefficients of the linear and squared terms of per capita GDP are significantly positive and negative at the 5% level, respectively. This clearly supports the validity of the EKC hypothesis. This result indicates that as the economy grows, nitrogen fertilizer use intensity follows a path of first rising and then falling. We calculated that its turning point corresponds to a per capita GDP of approximately 17,400 yuan. In Model II and Model IV, real per capita GDP and its square are instrumented using their second lags, with up to three latent factors removed to account for unobserved common components. Meanwhile, population density and FDI ratio are instrumented using their first lags, with up to two latent factors extracted.

This result is consistent with several domestic and international empirical studies. The study by Li et al. (2016) also shows that fertilizer use and economic growth in China had a significant inverted U-shaped relationship in provincial panel data from 1989–2009. The findings of Yu et al. (2022) also indicate that the application of nitrogen fertilizer in China has been decreasing since 2014. However, differences remain among studies regarding the level of the turning point and regional variations. Liu et al. (2021) found in their county-level study that fertilizer use intensity in some parts of China showed an "N-shaped" relationship, suggesting that regional differences in environmental regulations and green technologies may lead to inconsistencies in the timing of the EKC turning point.

Turning to the control variables, neither population density nor the FDI ratio has a statistically significant impact on nitrogen fertilizer intensity. In contrast, the coefficient for industrial structure (share of the primary industry) is significantly positive. This implies that regions with a higher proportion of agriculture in their economy tend to have greater nitrogen fertilizer input intensity, likely reflecting a dependency on fertilizers to ensure food security. Finally, all models pass the Hansen test of overidentifying restrictions, supporting the validity and appropriateness of our chosen instrumental variables.

Table 4.3 reports the EKC regression results for phosphate fertilizer use intensity. To mitigate endogeneity, in the Model II and Model IV , real per capita GDP and its square are instrumented using their second lags, with up to three latent factors removed to eliminate common components. Meanwhile, population density, FDI ratio, and the primary industry share are instrumented using their first lags, with up to two latent factors extracted through defactoring. Unlike the findings for total chemical and nitrogen fertilizers, the results do not support an EKC relationship between phosphate fertilizer application intensity and economic growth. Under all four model specifications, regardless of whether control variables or dynamic effects are introduced, the coefficients of per capita GDP and its squared term do not reach a statistically significant level. This result stands in contrast to some previous research, such as Li et al. (2014), who found an inverted U-shaped relationship.

Although the EKC hypothesis is rejected, the model results reveal a strong path dependency in phosphate fertilizer application. In the dynamic specifications (Models III and IV), the coefficient on the lagged dependent variable is highly significant at the 1% level, indicating that application levels are strongly determined by their historical values. Among the other covariates, the significant positive effect of Foreign Direct investment (FDI) is particularly noteworthy. This may imply that FDI inflows have promoted the adoption of modern agricultural technologies or intensive production models that are more phosphorus-dependent, thereby increasing its consumption. In contrast, neither population density nor industrial structure exerts a significant influence in this model.

In summary, while our analysis does not identify a significant inverted U-shaped relationship between phosphate fertilizer use and economic growth, it does uncover a significant path dependency and a foreign investment-driven effect in its application. This finding suggests that, at the current stage of development, achieving phosphate reduction targets cannot be expected to occur through an "automatic adjustment" mechanism of economic growth alone. Instead, it necessitates targeted policy interventions and precisely aimed technological advancements.

Table 4.4 presents the regression results for pesticide input intensity, where the findings vary substantially across specifications, revealing a high degree of sensitivity of the EKC relationship to the chosen model configuration. All potentially endogenous variables, including real per capita GDP, its square, population density, FDI ratio, and primary industry share are instrumented by their second lags, with up to three latent factors extracted to remove unobserved common components.

Specifically, in the static specification with control variables (Model II), the coefficients on the linear and squared terms of per capita GDP are significantly positive and negative, respectively. This provides initial evidence for an inverted U-shaped EKC, with a calculated turning point of approximately 10,200 RMB. However, this relationship proves not to be robust. In the dynamic model without controls (Model III), while the coefficients remain significant, the estimated turning point (approximately 1.47 million RMB) lies far outside the sample range, rendering it economically meaningless. These initial findings are consistent with some existing literature. Wang et al. (2022)

noted a general decline in pesticide intensity in China after 2012, which aligns with the inverted U-shape found in Model II, and Li et al. (2014) also identified a significant inverted U-shaped relationship. More importantly, in the final model (Model IV), which considers both dynamic effects and control variables, the aforementioned EKC relationship completely disappears. The coefficients of per capita GDP and its squared term are no longer statistically significant.

Nevertheless, the effects of certain control variables merit attention. For example, the results from Model II show that industrial structure has a significant positive effect on pesticide use, while foreign direct investment (FDI) shows a significant negative effect. This might suggest that FDI promotes greater efficiency in pesticide use through technology spillovers.

Table 4.5 shows the estimation results for the input intensity of agricultural plastic film. In Models I and II, the signs of the coefficients for per capita GDP and its squared term are consistent with the Environmental Kuznets Curve (EKC) hypothesis, but they do not reach statistical significance. However, after considering dynamic inertia in Models III and IV, plastic film use shows a strong path dependency; the coefficient of the first-order lag is significantly positive at the 1% level, indicating that past inputs have a significant impact on current inputs. Particularly in Model IV, the linear term of per capita GDP is positive and the squared term is negative, both significant at the 1% level. This is consistent with the inverted U-shaped EKC hypothesis, with a turning point corresponding to a per capita GDP level of approximately 40,500 yuan per person. In addition, all models passed the Hansen test, indicating that the instrumental variable setup is reasonable.

The results for the control variables in Model IV show that industrial structure has a significant positive effect on plastic film input intensity, while population density and foreign direct investment do not show a significant impact. Overall, a significant EKC relationship exists between the use intensity of plastic film and economic growth, but this relationship is conditioned by strong path dependency and industrial structure factors.

To mitigate endogeneity, in Models II and IV real per capita GDP and its square are instrumented using their second lags, with up to three latent factors extracted to remove common components. In addition, population density, primary industry share, and FDI ratio are instrumented using their first lags, with up to two latent factors defactored.

Table 4.6 reports the EKC regression results for agricultural diesel consumption intensity. The conclusion is that no EKC relationship exists between agricultural diesel consumption and economic growth. Under all static and dynamic model specifications, per capita GDP and its squared term did not pass the significance test. Furthermore, the signs of the coefficients for these two core variables show instability across different models, further confirming the lack of a recognizable and stable quadratic relationship.

Although the EKC hypothesis does not hold, the model results reveal that agricultural diesel consumption has a very strong path dependency. In the dynamic models (Models III and IV), the coefficient of the first-order lag is not only highly significant at the 1% level, but its value is also very close to 1. This indicates that the current period's consumption is largely determined by the previous period's consumption level. This strong inertia may be closely related to the stock of agricultural machinery, technological lock-in effects, and long-standing farming practices.

To mitigate endogeneity, in Models II and IV real per capita GDP and its square are instrumented using their second lags, with up to three latent factors removed from both the regressors and instruments to eliminate unobserved common components. Meanwhile, population density and FDI ratio are instrumented using their first lags, with up to two latent factors extracted through defactoring.

Finally, the Hansen test of overidentifying restrictions did not reject the null hypothesis in all four models, indicating that the instrumental variables used in this study are valid and reasonable.

Table 4.7 reports the regression results for the intensity of total agricultural machinery power, and its conclusion reveals the sensitivity of the EKC relationship to the model specification. In the basic model without control variables (Model I), the results show a typical inverted U-shaped relationship: the linear term of per capita GDP is significantly positive, and the squared term is significantly negative, with a calculated turning point of approximately 19,800 yuan per person.

In Models II and IV real per capita GDP and its square are instrumented using their second lags, with up to three latent factors extracted to eliminate common unobserved components. Meanwhile, population density, FDI ratio, and primary industry share are instrumented using their first lags, with up to two latent factors removed through defactoring.

However, when we introduce control variables in Models II and IV, this EKC relationship no longer holds, and the coefficients of per capita GDP and its squared term lose their statistical significance. This shift suggests that the key factors affecting agricultural machinery power may not be general economic growth, but rather other specific factors related to it. For example, in Model II, population density and industrial structure have a significant negative impact on machinery power, while foreign direct investment (FDI) shows a significant positive promotional effect, which could be related to technological upgrading or capital deepening brought by foreign investment.

This finding has important policy implications: simply relying on economic growth to automatically achieve the "turning point" for sustainable agricultural transformation may not be reliable. Policy efforts should focus more on directly promoting technological progress and efficiency improvements, for example, by increasing the operational efficiency per unit of horsepower through subsidies or R&D support, thereby accelerating the process of green agricultural modernization.

5.Conclusion

This study systematically examined the relationship between economic growth and the intensity of agricultural chemical inputs in Chinese provinces from 1993–2020 and tested the Environmental Kuznets Curve (EKC) hypothesis. The results both validated the EKC hypothesis for some agricultural chemicals and found cases that do not follow the EKC pattern, highlighting the complexity of China's agricultural environmental problems.

First, the input intensities of chemical fertilizer, nitrogen fertilizer, and agricultural plastic film all conform to the EKC hypothesis, showing a typical inverted U-shape and having already passed their turning points. The turning point for chemical fertilizer is at a per capita GDP of approximately 91,900 yuan, for plastic film, it is around 40,500 yuan, and for nitrogen fertilizer, it is around 17,400 yuan. This indicates that China has entered a stage where the intensity of these inputs is declining, and economic growth is now promoting their gradual decrease rather than causing a continued increase. This finding is consistent with the promotion of green agricultural policies and efficient input technologies in China in recent years.

Second, the results for pesticide intensity show an inverted U-shape in the model with control variables (Model II), with a turning point of about 10,200 yuan, meaning many provinces have reached or surpassed their peak pesticide use. However, its significance depends on the model specification. Total agricultural machinery power only shows an inverted U-shaped EKC curve in the static baseline model (Model I), with a turning point of about 19,800 yuan, but this relationship is not robust and no longer holds after introducing dynamic effects and control variables. The use of agricultural machinery power may be constrained by technical support, pest control systems, and local government supervision, so relying only on economic development is not enough to bring about its turning point.

Third, the EKC hypothesis does not hold for the use intensity of phosphate fertilizer and diesel fuel. They are not significant under any model, which means their use intensity does not naturally decline as income rises. Diesel input, in particular, shows strong path dependency and is driven more by historical stock than by economic growth.

From a policy perspective, the research suggests that differentiated governance strategies should be adopted. For chemicals like fertilizer and plastic film, where the EKC is established, the policy focus should shift to consolidating efficiency gains and ensuring the sustainability of the reduction. For pesticides and machinery power, targeted supervision and regional monitoring are needed. Finally, for phosphate fertilizer and diesel fuel, where the EKC hypothesis does not hold, the government should intervene promptly. It should invest in technological innovation, strengthen regulation, and popularize agricultural education and technical assistance to guide the sector towards sustainable development.

Overall, this study shows that the EKC hypothesis is only partially applicable in China's agricultural sector and should not be seen as an automatic process. Especially for phosphate fertilizer and agricultural diesel, effective policy intervention remains the key to achieving the dual goals of agricultural modernization and environmental sustainability.

References

Engle, R. F., & Granger, C. W. J.,1987. "Co-Integration and Error Correction: Representation, Estimation, and Testing. " *Econometrica*, *55*(2), 251–276. doi:10.2307/1913236

Gene Grossman, Alan Krueger, 1991, "Environmental Impacts of a North American Free Trade Agreement", *National Bureau of Economic Research*, paper 3914. doi:10.3386/w3914

Gene Grossman, Alan Krueger, 1995, "conomic Growth and the Environment.", *The Quarterly Journal of Economics*, vol.110(2), pages 353–377. doi:10.2307/2118443

PANAYOTOU, THEODORE,1997, "Demystifying the Environmental Kuznets Curve: Turning a Black Box into a Policy Tool.", *Environment and Development Economics*, vol.2(4), pages 465–84. doi:10.1017/S1355770X97000259

Dinda, Soumyananda, 2004. "Environmental Kuznets Curve Hypothesis: A Survey." *Ecological Economics, Elsevier*, vol. 49(4), pages 431-455, August. doi:10.1016/j.ecolecon.2004.02.011

C.W.J. Granger, P. Newbold, 1974. "Spurious regressions in econometrics. "*Journal of Econometrics,* vol.2(2), pages 111-120. doi:10.1016/0304-4076(74)90034-7

Huang, Jikun, and Scott Rozelle, 2018. “China’s 40 Years of Agricultural Development and Reform.” China’s 40 Years of Reform and Development: 1978–2018, edited by Ross Garnaut et al., ANU Press, pages 487–506. doi:10.22459/CYRD.07.2018.24

Kyung So Im, M.Hashem Pesaran, Yongcheol Shin, 2003, "Testing for unit roots in heterogeneous panels. "*Journal of Econometrics*, vol. 115(1), pages 53-74. doi:10.1016/S0304-4076(03)00092-7

Maddala, G. S., Wu, Shaowen ,1999, "A Comparative Study of Unit Root Tests with Panel Data and a New Simple Test. " *Oxford Bulletin of Economics and Statistics*, vol.61(S1), pages 631-652. doi:10.1111/1468-0084.0610s1631

Peter Pedroni, 1999, "Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple Regressors," *Oxford Bulletin of Economics and Statistics*, vol. 61(S1), pages 653-670. doi:10.1111/1468-0084.0610s1653

Pedroni, P.,2004, "Panel Cointegration: Asymptotic and Finite Sample Properties of Pooled Time Series Tests with an Application to the PPP Hypothesis. " *Econometric Theory*, vol.20(3), pages 597–625. doi:10.1017/S0266466604203073

David I Stern, 2004, "The Rise and Fall of the Environmental Kuznets Curve. "*World Development*, vol.32(8), pages 1419-1439. doi:10.1016/j.worlddev.2004.03.004

Wang X, Chi Y, Li F,2022, "Exploring China stepping into the dawn of chemical pesticide-free agriculture in 2050. " *Front Plant Sci*, vol.13, pages 942117. doi:10.3389/fpls.2022.942117

YAN Taihua,ZHU Mengcheng,2023, "The impact of technological innovation and industrial structure upgrading on environmental pollution.", *Journal of Chongqing University (Social Science Edition)*,vol.29(5), pages 70-84. doi:10.11835/j.issn.1008-5831.jg.2021.12.002

Yu, Zhen, Jing Liu and Giri Raj Kattel,2022, "Historical nitrogen fertilizer use in China from 1952 to 2018. " *Earth System Science Data*, vol.14(11), pages 5179–5194. doi:10.5194/essd-14-5179-2022

X. Zhang, E. A. Davidson, D. L. Mauzerall, T. D. Searchinger,2015, Managing nitrogen for sustainable development. ", *Nature*, vol.528(7580). doi:10.1038/nature15743

Patrícia Hipólito Leal, António Cardoso Marques,2022, "The evolution of the environmental Kuznets curve hypothesis assessment: A literature review under a critical analysis perspective.", *Heliyon*, vol.8(11), e11521. doi:10.1016/j.heliyon.2022.e11521

Massimiliano Caporin, Arusha Cooray, Bekhzod Kuziboev and Inomjon Yusubov,2024, "New insights on the environmental Kuznets curve (EKC) for Central Asia", *Empirical Economics*, vol.66(5), pages, 2335-2354. Doi:10.1007/s00181-023-02520-9

Gokmenoglu KK, Taspinar N, Kaakeh M,2019, "Agriculture-induced environmental Kuznets curve: the case of China.", *Environmental Science and Pollution Research*, vol.26(36), pages 37137-37151. doi:10.1007/s11356-019-06685-8

Fei Li, Suocheng Dong, Fujia Li, Libiao Yang,2014, "Is there an inverted U-shaped curve? Empirical analysis of the Environmental Kuznets Curve in agrochemicals.", *Frontiers of Environmental Science & Engineering*, vol.10, pages 276–287. doi:10.1007/s11783-014-0700-y

Li, Shixiang, Jianru Shi, and Qiaosheng Wu,2020, "Environmental Kuznets Curve: Empirical Relationship between Energy Consumption and Economic Growth in Upper-Middle-Income Regions of China", *International Journal of Environmental Research and Public Health*, vol.17(19), pages 6971. https://doi.org/10.3390/ijerph17196971

Ye Li, Yiyan Chen,2024, "Robotics, environmental regulation, and agricultural carbon emissions: an examination of the environmental Kuznets curve theory and moderating effects", F*rontiers in Sustainable Food Systems*, vol.8. doi:10.3389/fsufs.2024.1336877

Tingting Li, Yong Wang, Dingtao Zhao, 2016, "Environmental Kuznets Curve in China: New evidence from dynamic panel analysis.", *Energy Policy*, vol.91, pages 138-147. doi:10.1016/j.enpol.2016.01.002

Yue Liu, Xin Cheng, Wenjing Li,2021, "Agricultural chemicals and sustainable development: the agricultural environment Kuznets curve based on spatial panel model. ", *Environmental Science and Pollution Research*, vol.28(37), pages 51453-51470. doi:10.1007/s11356-021-14294-7

Liu, Hongbo, Hanho Kim, Shuanglu Liang, Oh-Sang Kwon, 2018, "Export Diversification and Ecological Footprint: A Comparative Study on EKC Theory among Korea, Japan, and China" *Sustainability*, vol,10(10), 3657. doi:10.3390/su10103657

Mahmood, Haider, Maham Furqan, Muhammad Shahid Hassan, Soumen Rej, 2023, "The Environmental Kuznets Curve (EKC) Hypothesis in China: A Review" *Sustainability*, vol.15(7),6110. doi:10.3390/su15076110

Joshua Sunday Riti, Deyong Song, Yang Shu, Miriam Kamah,2017, "Decoupling CO2 emission and economic growth in China: Is there consistency in estimation results in analyzing environmental Kuznets curve?", *Journal of Cleaner Production*, vol.166, pages 1448-1461. doi:10.1016/j.jclepro.2017.08.117

Shota Moriwaki, Masayuki Shimizu,2021, "A simultaneous investigation of the environmental Kuznets curve for the agricultural and industrial sectors in China.", *Journal of the Asia Pacific Economy*, vol.28(1), pages 133-155. doi:10.1080/13547860.2020.1870068

Wang, Yan, and Neng Shen,2016, "Agricultural Environmental Efficiency and Agricultural Environmental Kuznets Curve Based on Technological Gap: the Case of China.", *Polish Journal of Environmental Studies*, vol.25(3), pages 1293–1303. doi:10.15244/pjoes/61701

Wang, Zhenjie, and Donghui Lv. 2022, "Analysis of Agricultural CO2 Emissions in Henan Province, China, Based on EKC and Decoupling.", *Sustainability*, vol,14(3), 1931. doi:10.3390/su14031931

Wu, Haoyue, Bangwen Ding, Lu Liu, Lei Zhou, Yue Meng, Xiangjiang Zheng, 2024, "Have Agricultural Land-Use Carbon Emissions in China Peaked? An Analysis Based on Decoupling Theory and Spatial EKC Model," *Land*, vol,13(5), 585. doi:10.3390/land13050585

Yan, Jun, Wenting Lu, Xiaoyan Xu,, Jiamin Lian, 2023, "Empirical Study of the Environmental Kuznets Curve in China Based on Provincial Panel Data.", *Sustainability*, vol.15(6), 5225. doi:10.3390/su15065225

Xiaomin Yu, Karsten Schweikert, Reiner Doluschitz, 2022, "Investigating the environmental Kuznets curve between economic growth and chemical fertilizer surpluses in China: a provincial panel cointegration approach.", *Environmental Science and Pollution Research*, vol.29(13), pages 18472–18494. doi:10.1007/s11356-021-17122-0

Gui Zeng, Hana Wang, 2025, "Deterioration and improvement: The U-shaped impact of industrialization on agricultural carbon productivity in China.", *Science Progress*, vol.108(1). doi:10.1177/00368504241302960

Li He, Xiaoling Zhang, Yaxue Yan,2021, "Heterogeneity of the Environmental Kuznets Curve across Chinese cities: How to dance with 'shackles'?", *Ecological Indicators*, vol.130, p. 108128. doi:10.1016/j.ecolind.2021.108128

Yun Liu, Warren Mabee, Huiwen Zhang, 2021, "Conserving fertilizer in China's rural-agricultural development: The reversal shifts and the county-specific EKC evidence from Hubei.", *Cleaner Environmental Systems*, vol.3, p.100050. doi:10.1016/j.cesys.2021.100050

Sebastian Kripfganz, Vasilis Sarafidis, 2021, "Instrumental-variable estimation of large-T panel-data models with common factors", *The Stata Journal Promoting communications on statistics and Stata*, vol.21(3), pages659-686. doi:10.1177/1536867X211045558