COUPLING EFFECTS BETWEEN AGRICULTURAL INDUSTRIAL STRUCTURE ADJUSTMENT AND ENVIRONMENTAL PROTECTION IN CHINA: AN ECO-ECONOMIC PERSPECTIVE

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(Received 1st Sep 2025; accepted 25th Nov 2025)

Abstract. Under the background of ecological economy, the coordinated development of agricultural industrial structure adjustment and environmental protection is of vital importance for achieving regional sustainable development. To explore the coupling effect between the two, this study, from the perspective of ecological economy, conducts an analysis using the panel data of 31 provincial administrative regions in China from 2010 to 2023. This work first constructs a Comprehensive Evaluation Index (CEI) system for agricultural industrial structure adjustment and environmental protection, and uses the entropy weight method to calculate the CEI of the two systems. The coupling effect between two systems is analyzed through the coupling degree model and the Coupling Coordination Degree (CCD) model. The research found that from 2010 to 2023, the national coupling degree improved from 0.48 to 0.81, and the coordination level improved from "mild imbalance" to "good coordination". In 2023, the highest CCD in the eastern region was 0.76, while the overall lag in the western area was 0.51. The per capita GDP had the greatest impact on the eastern region at 0.42, while agricultural technological progress had a prominent impact on the central region at 0.41. The policy synergy degree was significant in all regions. The level of agricultural technology and policy synergy had the greatest impact on the coupling effect, with values of 0.31 and 0.25. The study offers a foundation for achieving a win-win situation between sustainable agricultural development and ecological environment protection, and formulates precise policies to promote regional coordinated development.
Keywords: *coordinated development, spatial heterogeneity, sustainable development, policy coordination, regional differences*

Abbreviations: AIS: Agricultural Industrial Structure, EP: Environmental Protection, CEI: Comprehensive Evaluation Index, CCD: Coupling Coordination Degree, CpD: Coupling Degree, SD: Sustainable Development, TI: Technological Innovation, ISU: Industrial Structure Upgrading, ADT: Agricultural Digital Transformation, DED: Digital Economy Development, EE: Ecological Environment, YRB: Yangtze River Basin, AED: Agricultural Economic Development, C&C: Coupling and Coordination, WMA: Weighted Moving Average, X-12-ARIMA: X-12 Autoregressive Integrated Moving Average, GWR: Geographically Weighted Regression, SDM: Spatial Durbin Model, EWM: Entropy Weight Method, EDL: Economic Development Level, ISL: Industrial Structure Level, AAV: Agricultural Added Value, ATL: Agricultural Technology Level, FEA: Farmers' Environmental Awareness, MII: Moran's I Index, OLS: Ordinary Least Squares, SMA: Simple Moving Average, GRM: Global Regression Model, RMSE: Root Mean Square Error, VIF: Variance Inflation Factor

Introduction

Against the backdrop of intensifying global climate change and environmental constraints, agriculture, as the fundamental industry of the national economy, is facing profound changes in its development model. The ecological economy concept emphasizes the coordination and unity of economic development and ecological

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_13671386

protection, providing important guidance for the coordinated promotion of Agricultural Industrial Structure (AIS) adjustment and Environmental Protection (EP) (Zhang, 2024). As a major agricultural country, China has long-term problems such as a single agricultural production structure, low added value of agricultural products, and inefficient resource utilization. Meanwhile, environmental challenges, including excessive utilization of fertilizers and pesticides, livestock and poultry breeding pollution, and wrong disposal of agricultural waste in the agricultural production process, have become increasingly prominent, seriously restricting sustainable agricultural development (Zhang et al., 2024). Nowadays, the importance of AIS adjustment and EP has become increasingly prominent (Parven et al., 2025). Currently, the academic community has carried out extensive research on AIS adjustment and EP, and has achieved a series of results (Shang et al., 2024). In terms of AIS adjustment, scholars have explored the modes, paths, and influencing factors of AIS adjustment in different regions. In terms of EP, this study focuses on areas such as agricultural pollution control and ecological compensation mechanisms. However, most existing studies have separated AIS adjustment from EP, lacking systematic research on the coupling effects of the two from an ecological and economic perspective (Bareille et al., 2024).

Industrial restructuring is vital for shifting economies toward higher value-added activities. Research shows that environmental regulations have a complex role: they have a negative impact on industrial rationalization but a positive impact on optimization, and these impacts exhibit nonlinear threshold characteristics (Tan et al., 2024). Furthermore, industrial upgrading significantly suppresses agricultural carbon emissions, especially above a certain threshold, a process mediated by energy efficiency and labor transfer (Shi et al., 2023). The relationship between environmental rules and industrial upgrading is U-shaped, with Technological Innovation (TI), acting as a partial mediator (Yan et al., 2025). Concurrently, agricultural digital transformation boosts farmers' income and production efficiency, thereby promoting industrial upgrading (Zhang et al., 2024). The digital economy also fosters low-carbon development, both directly and indirectly through industrial restructuring (Tan et al., 2024).

The Coupling and Coordination (C&C) of agriculture and the Ecological Environment (EE) is crucial for Sustainable Development (SD). Studies in the Yangtze River Basin show a trend of improving socioeconomic and ecological quality, albeit with regional disparities (Xia et al., 2024). The integration of agriculture and tourism has been found to enhance agricultural ecological efficiency, with a stronger effect at higher levels of integration (Wang et al., 2024). Pathways to achieve this coupling include transforming production methods, improving ecological compensation, and leveraging technology (Chen et al., 2025). Analyses of resilience reveal a trade-off, where rural settlements near cities have better social resilience, while remote areas possess stronger ecological resilience (Qu et al., 2025). In China, the synergy between agricultural resilience and ecological efficiency has evolved from low- to high-level coordination, with ecological efficiency acting as a key driver in this process (Qiao et al., 2024).

In summary, present studies focus on the impact of environmental standards, TI, digital transformation, and other factors on AIS adjustment, as well as the C&C between agriculture and EE, revealing nonlinear relationships, threshold characteristics, mediating effects, etc. However, most studies focus on the influence of a single factor or unilateral coupling. There is insufficient research on the bidirectional coupling effect of AIS adjustment and EP from an ecological and economic perspective. In addition, the exploration of the deep-seated mechanisms and dynamic evolution laws of regional

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_13671386

heterogeneity is not deep enough (Li et al., 2023). Based on this, this study will analyze the coupling effect of AIS adjustment and EP from the aspect of ecological economy, hoping to give theoretical support for achieving the coordinated development of the two. The innovation is mainly reflected in the measurement method of the coupling effect between AIS adjustment and EP, as well as the construction of the influencing factor analysis model. This study uses the Weighted Moving Average (WMA) method and the X12 Seasonal Adjustment Autoregressive Integrated Moving Average Model (X-12-ARIMA) to improve the processing accuracy of time series data. It also uses Geographically Weighted Regression (GWR) models and Spatial Durbin Model (SDM) to consider the influence of spatial factors on coupling effects, offering new analytical perspectives and methodologies for a deeper understanding and optimization of the coordinated development of agriculture and EP. The study aims to systematically analyze the coupling effect between the adjustment of China's AIS and EP from the perspective of ecological economy. The specific research goal is to establish a scientific Comprehensive Evaluation Index (CEI) system for AIS and EP adjustment, use the Entropy Weight Method (EWM) to objectively measure the development level of the two, reveal the coupling spatiotemporal laws, and identify key driving factors.

Methods and materials

Data source and processing

The main sources of research data include the "China Statistical Yearbook" and "China Rural Statistical Yearbook" released by the National Bureau of Statistics, agricultural and rural statistical data from the Ministry of Agriculture and Rural Affairs, environmental statistical data from the Ministry of Ecology and Environment, as well as statistical yearbooks and environmental quality reports from various provinces. The data cover a period of 14 years, from 2010 to 2023. The research area covers 31 province in China (excluding Hong Kong, Macao, and Taiwan) to comprehensively analyze the differences among various regions. To conduct a regional comparative analysis, this study adopts the standard economic regional division method of the National Bureau of Statistics, dividing the 31 provinces into four major regions:

Eastern region (10 provinces/municipalities): Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan.

Central region (8 provinces): Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan.

Western regions (12 provinces/autonomous regions): Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Xizang, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

Northeast China (3 provinces): Liaoning, Jilin, and Heilongjiang.

The paper will organize the collected raw data in a unified format and convert data from different sources and formats into a spreadsheet format that is easy to analyze. Missing data can be processed using the following method: if the missing value of a certain indicator in a certain year does not exceed 10% of the total sample size of that indicator, the mean of that indicator for that year can be used for interpolation (Gao et al., 2023). If the missing value exceeds 10%, reasonable estimation can be made by referring to data from adjacent years and similar regions. Secondly, the data are standardized to eliminate the influence of various indicator dimensions and magnitude orders. The calculation utilizing the range normalization method is given by *Equation 1* (Chang et al., 2024).

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$$x_{ij}^{*} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad \text{(Eq.1)}$$

In *Equation 1*, x_{ij} is the previous value of the *j*-th indicator in the *i*-th region. x_{ij}^{*} is the standardized value. $\min(x_j)$ and $\max(x_j)$ are the min and max of the *j*-th indicator. To credit the data reliability, outlier detection is performed on the data using the Z-score method. Outliers with an absolute value greater than 3 are considered extreme values and corrected or removed according to the actual situation.

Coupling effect measurement method

Coupling Degree (CpD) is originally a concept in physics, taken to measure the interaction degree and influence between systems. This study considers the AIS adjustment system (referred to as system A) and the EP system (referred to as system B) as two interrelated subsystems, and measures the coupling effect between the two by constructing a CpD model. Firstly, a CEI system for AIS adjustment and EP is built, as listed in *Table 1*.

Table 1. *Comprehensive evaluation index system for AIS adjustment and EP*

System	First-level indicator	Secondary indicators	Meaning of indicators
AIS adjustment system	Industrial rationalization	The output proportion of agriculture, forestry, animal husbandry and fishery	
		Conversion rate of Agricultural Product Processing (APP)	The output ratio of APP to the total output of agriculture reflects the industrial upgrading degree
EP system	Environmental quality	The proportion of days with good air quality	Reflect the status of atmospheric environmental quality
	Pollution emissions	Agricultural non-point source pollution load	Including the comprehensive emissions of pollutants including chemical fertilizers, pesticides, and livestock, and poultry breeding

The specific measurement methods and selection basis of the indicators are as follows:

The calculation of the output value structure of agriculture, forestry, animal husbandry, and fishery is achieved by calculating the proportion of various output values in the total output value and using the entropy method to calculate the structural rationalization index. This indicator directly reflects the degree of resource allocation and diversification in agricultural production. It is a core indicator for measuring the transformation of the AIS from traditional planting to diversification and efficiency.

Calculation of the conversion rate of agricultural product processing: the total output value of the agricultural product processing industry ÷ the total agricultural output value. This indicator is the key to achieving agricultural modernization by extending the agricultural industrial chain and increasing added value. It measures the extent to which agricultural production extends from raw material supply to processing and manufacturing fields and is an important sign of industrial upgrading.

The contribution rate of agricultural scientific and technological progress is measured through the Solow residual method. The method is calculated based on data on

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_13671386

agricultural output, material costs, labor force, cultivated land area, etc. This indicator directly measures the contribution share of technological investment to agricultural growth and reflects the level of transformation of the agricultural development mode towards a technology-intensive one.

The ratio of days with good air quality measures the percentage of days in a year whose air quality index is at the “excellent” and “good” levels among the total effective days. The data are sourced from the National Urban Air Quality Report of the Ministry of Ecology and Environment. This indicator adopts the “Air Quality Index” rating standard clearly defined by the Chinese authorities, avoiding the ambiguity of “good air quality”. Air quality is a direct reflection of the regional EE and is also closely related to agricultural production activities.

The measurement of agricultural non-point source pollution load intensity is carried out through the equal-scale pollution load method, standardizing and weighting the amount of chemical fertilizer application, pesticide application, and livestock and poultry manure production per unit area of cultivated land. This comprehensive indicator can effectively measure the environmental pressure that agricultural production activities exert on water bodies and soil. It is the core negative indicator of agricultural environmental performance.

The measurement of EP-TI capacity is based on the number of invention patents related to “agricultural pollution control” and “waste resource utilization” authorized by each province each year. This indicator measures the innovative vitality of society in EP and provides technical support for the continuous improvement of environmental quality.

Then, the CEIs U_A and U_B of the two systems are calculated utilizing the EWM, where U_A reflects the level of AIS adjustment and U_B reflects the level of EP. The formula for CpD C is given by *Equation 2* (Xu et al., 2025).

$$C = \frac{2\sqrt{U_A U_B}}{U_A + U_B} \tag{Eq.2}$$

In *Equation 2*, the value range for C is [0,1], and a larger C indicates a higher CpD between the two systems. To further analyze the coordinated development level between the 2 systems, the Coupling Coordination Degree (CCD) model D is introduced, as shown in *Equation 3*.

$$D = \sqrt{C \times T} \tag{Eq.3}$$

In *Equation 3*, T is the comprehensive coordination index, as shown in *Equation 4*.

$$T = \alpha U_A + \beta U_B \tag{Eq.4}$$

In *Equation 4*, both α and β are undetermined coefficients. Due to the equal importance of AIS adjustment and EP from an ecological and economic perspective, $\alpha = \beta = 0.5$ is chosen. To further qualitatively evaluate the coordination status, a general classification criterion is studied. Based on the numerical size of the CCD, the coordination levels are classified into the following 10 types. *Table 2* shows the classification criteria. This standard serves as the basis for determining descriptions such as “slight imbalance” and “good coordination” in subsequent analyses.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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Table 2. *CCD grade classification standards*

CCD interval	Coordination level	CCD interval	Coordination level
0.00-0.09	Extremely unbalanced	0.50-0.59	Barely coordinated
0.10-0.19	Serious imbalance	0.60-0.69	Primary coordination
0.20-0.29	Moderate imbalance	0.70-0.79	Good coordination
0.30-0.39	Slight imbalance	0.80-0.89	High-quality coordination
0.40-0.49	On the verge of imbalance	0.90-1.00	Extremely harmonious

Coupling effect spatiotemporal analysis method

The traditional moving average method assigns the same weight to all historical data. This study assigns higher weights to recent data based on developing the agriculture and the timeliness of EP policies, using the WMA method. Assuming the time series is $y_1, y_2, \ldots, y_t$, the WMA formula is shown in *Equation 5*.

$$WMA_t = \frac{\sum_{k=0}^{n-1} w_k y_{t-k}}{\sum_{k=0}^{n-1} w_k} \tag{Eq.5}$$

In *Equation 5*, WMA_t means the WMA value of period *t*, *n* denotes the amount of periods in the moving average, w_k is the weight of period *k*, and w_k decreases as *k* increases. To eliminate the influence of seasonal factors, seasonal adjustments are made to the data during the analysis process. X-12-ARIMA is used to decompose the trend cycle components, seasonal components, and irregular components in the time series, to more accurately analyze the long-term variation trend of coupling effects (Hamid et al., 2025). GWR is a spatial econometric analysis method that considers spatial non-stationarity and can reflect the differences in relationships between variables at different spatial positions (Lu et al., 2025). This study takes coupling coordination as the dependent variable and selects relevant factors that affect coupling effects as independent variables to construct a GWR model, as shown in *Equation 6*.

$$D_i = \beta_0(u_i, v_i) + \sum_{l=1}^{m} \beta_l(u_i, v_i) x_{il} + \varepsilon_i \tag{Eq.6}$$

In *Equation 6*, (u_i, v_i) and $\beta_0(u_i, v_i)$ are the geographic coordinates and intercept terms of the *i*-th region. $\beta_l(u_i, v_i)$ and x_{il} are the regression coefficients and values of the *l*-th independent variable in the i-th region. ε_i is a random error term that follows a normal distribution. To optimize the GWR model, an adaptive bandwidth selection approach is adopted to automatically decide the best bandwidth built on the spatial distribution characteristics of the data, to improve the estimation accuracy. Spatial correlation tests are conducted on the independent variables and Moran's I Index (MII) is utilized. If there is significant spatial autocorrelation, a spatial weight matrix is introduced in the model to better capture the impact of spatial factors on coupling effects (Agniyazov et al., 2025).

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Analysis model of influencing factors of coupling effect

The Economic Development Level (EDL), expressed as per capita GDP, is an important factor affecting the coupling effect. A higher EDL can give a financial foundation for AIS adjustment, promote agricultural development towards efficiency, quality, and green direction, and also allocate more resources to EP to improve environmental quality. The improvement of Industrial Structure Level (ISL) can drive the agricultural industry upgrading and reduce the pressure of agricultural production on the environment (Prioux et al., 2023). The increase in Agricultural Added Value (AAV) (represented by the value-added rate of APP) means the extension of the agricultural industry chain, which can improve resource utilization efficiency, reduce waste emissions, and enhance the coupling effect between AIS adjustment and EP (Tian et al., 2025). The Agricultural Technology Level (ATL) is expressed by the contribution rate of agricultural scientific and technological progress. Its improvement can promote the transformation of agricultural production methods, achieve efficient and environmentally friendly production modes, including precision and ecological agriculture, and reduce the utilization of fertilizers and pesticides. The EP-TI capability is expressed by the number of EP patent authorizations. Its enhancement can provide more effective technical means for EP, such as sewage treatment technology, air pollution control technology, etc., enhance the efficiency of environmental governance, and promote the coupling development of the two systems (Ma et al., 2025).

The synergy between agricultural policies (AIS adjustment policies, agricultural subsidy policies) and environmental policies (environmental emission standards, pollution control policies) occupies a vital regulatory position in the coupling effect. When agricultural policies and environmental policies complement and promote each other, they can guide agricultural production entities to pay attention to EP while adjusting industrial structure, achieving a win-win situation of economic and environmental benefits (Atanda et al., 2025; Tian et al., 2024). On the contrary, if there are conflicts or inconsistencies between policies, it will lead to inefficient resource allocation and inhibit the coupling effect. The improvement of Farmers' Environmental Awareness (FEA) can encourage them to actively adopt environmentally friendly production and lifestyle, reducing the damage of agricultural production to the environment. The improvement of rural labor quality helps farmers to accept novel agricultural technologies and EP concepts, improve the EP level of agricultural production, and thus have a positive impact on the coupling effect (Dehghani et al., 2024; Xiao et al., 2024). Therefore, this paper constructs a multiple linear regression model with CCD as the dependent variable, and selects EDL X_1, ISL X_2, AAV X_3, ATL X_4, ER-TI capability X_5, policy synergy X_6, FEA X_7, and rural labor quality X_8 as independent variables. The model form is shown in *Equation 7*.

$$\begin{aligned} D = &\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 \\ &+ \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \mu \end{aligned} \tag{Eq.7}$$

In *Equation 7*, β_0 is the intercept value. $\beta_1, \beta_2, \ldots, \beta_8$ are the regression coefficients of each variable, and μ is the random error term. The definition and explanation of variables in the multiple regression model are shown in *Table 3*.

To optimize the model, multi-collinearity tests are first carried out on the independent variables, and the Variance Inflation Factor (VIF) method is used. If the VIF > 10, it

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indicates severe multi-collinearity. Dimensionality can be reduced by removing variables with high correlation or using principal component analysis. Secondly, considering the influence of spatial factors on coupling effects, a spatial lag term is introduced in the model to construct SDM, to more comprehensively analyze the impact of various factors.

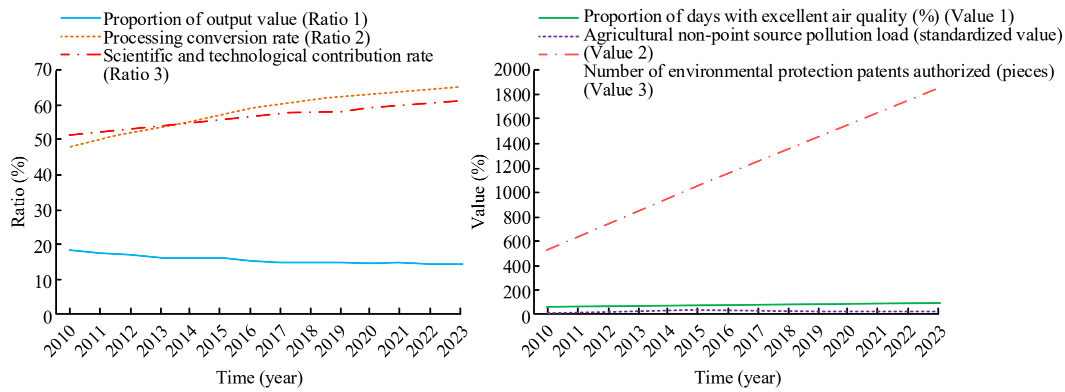
Table 3. *Definition and explanation of variables in multiple regression model*

Variable type	Variable symbol	Variable name	Measurement method	Data source
Independent variable	D	CCD	Calculated by CCD model	Research calculation
Dependent variable	X_1	EDL	Per capita GDP (yuan)	China Statistical Yearbook
	X_2	ISL	Proportion of output of secondary and tertiary industries in GDP (%)	China Statistical Yearbook
	X_3	AAV	Value added rate of agricultural products processing (%)	China Rural Statistical Yearbook
	X_4	ATL	Contribution rate of agricultural science and technology progress (%)	Bulletin on the Contribution Rate of Agricultural Science and Technology Progress in China, Ministry of Agriculture and Rural Affairs
	X_5	ER-TI capacity	Number of EP patents authorized (PCs)	Patent Database of the National Intellectual Property Administration of China
	X_6	Policy synergy degree	Determined by policy text analysis and expert scoring method	Government work reports of various provinces in China and policy documents of agricultural, rural and environmental departments
	X_7	FEA	Questionnaire survey score (1-10 points)	The questionnaire survey of the research organization and the “Annual Statistical Report on Rural Management and Operation in China”
	X_8	The quality of rural labor force	Average length of schooling of rural labor force (years)	China Population and Employment Statistical Yearbook

Results

Descriptive statistical analysis

This study conducts descriptive statistics on AIS adjustment and EP related indicators in 31 provinces across the country from 2010 to 2023. *Figure 1* shows the descriptive statistics of indicators for AIS adjustment system and EP system. In *Figure 1a*, the Ratio 1 is generally lower in the eastern area (Shanghai and Beijing), and higher in the central and western areas, reflecting differences in industrial structure. The average Ratio 2 reaches 62.45%, but the regional gap is significant. Shandong, Jiangsu, and other major agricultural provinces have outstanding processing levels, while Qinghai, Xizang, and other provinces still need to improve. The Ratio 3 is showing an increasing trend, and Beijing, Tianjin, and other municipalities have obvious advantages in scientific and technological investment. In *Figure1b*, the Value 1 shows a characteristic of “better in the south and worse in the north”. The air quality in southern provinces such as Hainan and Fujian is relatively good, while in heavy industrial concentration areas such as Hebei and Shanxi, due to extensive regional pollution caused by the industrial and energy structure, the air quality is poor. It should be emphasized that this indicator reflects the overall air environmental quality of the region, and its pollution sources are comprehensive, including industry, transportation, coal burning and agricultural activities, etc. The Value 2 specifically addresses the pollution generated by agriculture itself. This indicator is closely related to the scale of agricultural production. In major grain-producing areas such as Henan and Shandong, due to the high intensity of fertilizer and pesticide input and the large scale of livestock and poultry breeding, the pollution load from agricultural sources is relatively high. However, in provinces like Zhejiang, due to the better promotion of ecological agriculture, the pollution load from agricultural sources is relatively low. The construction of this indicator enables the pollution emissions of the agricultural sector to be separated from the complex total regional pollution for independent evaluation, thereby more accurately revealing the relationship between AIS and the environmental pressure caused by itself. The Value 3 is positively correlated with EDL, and provinces such as Guangdong and Jiangsu have strong TI capabilities.



(a) Related indicators of AIS adjustment

(b) Related indicators of EP

***Figure 1.** The distribution of indicators of the AIS adjustment system and EP system in various provinces of China from 2010 to 2023*

Table 4 presents descriptive statistics of comprehensive indicators related to coupling effects. The AIS adjustment is close to the mean of the EP comprehensive index, but there are significant regional differences. Jiangsu, Zhejiang, and other provinces have balanced development of the two systems, while Xizang, Gansu, and other regions have low comprehensive indexes due to natural conditions or economic base constraints. The overall CCD is at a moderate level (0.57), indicating that the two systems have not yet formed efficient collaboration nationwide.

AIS adjustment and EP coupling degree calculation

By using the EWM and CpD model, the CpD and CCD results of the national and regional levels from 2010 to 2023 are obtained. *Figure 2* shows the time series of national CpD and CCD. To objectively verify the statistical significance of its upward trend, this

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_13671386

study adopts the non-parametric Mann-Kendall trend test method for analysis. The test results show that the Z-statistics of the CpD and CCD time series at the national level are 4.32 and 4.15, respectively, with both $p < 0.001$. This statistically confirms that there is an extremely significant upward trend in CpD and CCD from 2010 to 2023. Specifically, the CpD has increased from 0.48 to 0.81, and the CCD has upgraded from "slightly unbalanced" to "well-coordinated", indicating that the interaction between the adjustment of AIS and EP is gradually strengthening. The coordinated accelerated growth after 2015 may be related to the promotion of ecological civilization construction policies since the 13th Five-Year Plan.

Table 4. *Descriptive statistics of the CEI and CCD of agricultural and environmental systems in various provinces of China from 2010 to 2023*

Index	Area	Mean	Standard deviation	Min	Max
Comprehensive index of AIS adjustment	National	0.53	0.18	0.21	0.89
	East	0.68	0.12	0.52 (Hebei)	0.89 (Jiangsu)
	Central	0.55	0.1	0.41 (Jiangxi)	0.72 (Hubei)
	West	0.42	0.15	0.21 (Xizang)	0.65 (Sichuan)
	Northeast	0.51	0.08	0.45 (Heilongjiang)	0.60 (Liaoning)
Comprehensive index of EP	National	0.49	0.22	0.15	0.92
	East	0.65	0.14	0.48 (Tianjin)	0.90 (Zhejiang)
	Central	0.48	0.11	0.32 (Henan)	0.63 (Hunan)
	West	0.39	0.18	0.15 (Shanxi)	0.92 (Hainan)
	Northeast	0.46	0.09	0.38 (Jilin)	0.55 (Liaoning)
CCD	National	0.57	0.16	0.23	0.88
	East	0.76	0.07	0.65 (Hebei)	0.88 (Jiangsu)
	Central	0.62	0.06	0.54 (Jiangxi)	0.71 (Hubei)
	West	0.51	0.11	0.23 (Gansu)	0.68 (Sichuan)
	Northeast	0.58	0.05	0.53 (Heilongjiang)	0.63 (Liaoning)

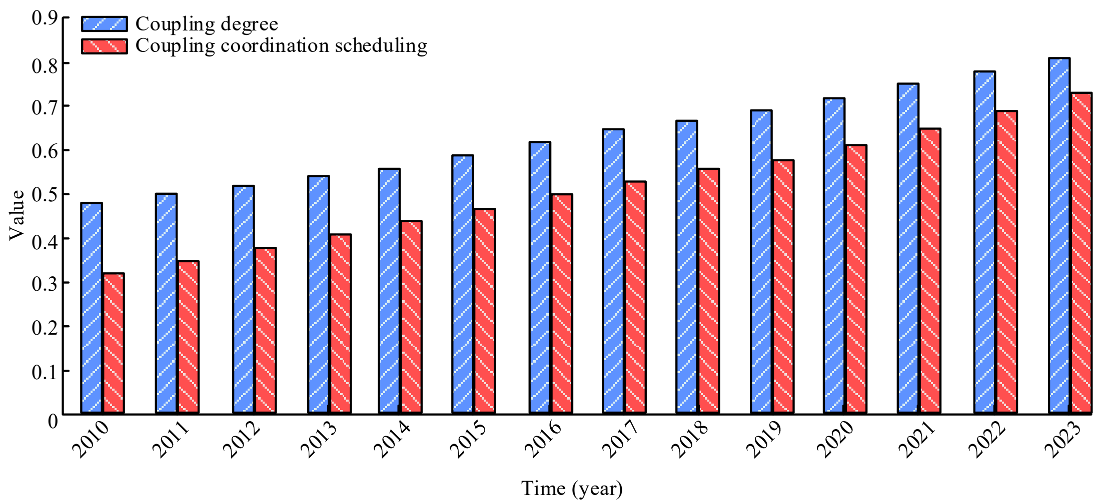


Figure 2. *The evolution of time series of CpD and CCD at the national level in China from 2010 to 2023*

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DOI: http://dx.doi.org/10.15666/aeer/2401_13671386

Table 5 shows the comparison of CCD among different regions in 2023. There are obvious regional discrepancies, with the highest C&C in the eastern region (0.76). Due to the optimization of industrial structure and high investment in EP, provinces such as Jiangsu and Zhejiang have entered a state of “good coordination”. The overall lag in the west, with provinces including Gansu and Qinghai having a CCD of less than 0.5 due to high agricultural dependence and fragile ecology. The three provinces in Northeast China are influenced by traditional agricultural models and have moderate coordination.

Table 5. *The level and distribution of C&C among the four major regions in China in 2023*

Region	The number of provinces	Mean value of CCD	The number of highly coordinated zones (≥0.7)	The number of central coordination zones (0.5-0.7)	Number of low coordination zones (<0.5)
East	10	0.76	8	2	0
Central	8	0.62	3	5	0
West	12	0.51	1	7	4
Northeast	3	0.58	1	2	0

Figure 3 shows the trend of coupling coordination changes in typical provinces. To ensure the representativeness and persuasiveness of the selected provinces, the nomination of “typical provinces” in this study is based on the following principles: (1) Geographical coverage: covering the four major regions of eastern, central, western, and northeastern China; (2) Type representativeness: selecting exemplary models from different types such as “high-quality collaborative type”, “industry-led type”, “environment-priority type”, and “low-level collaborative type”; (3) Significance of change: The changing trend or current situation of its CCD can clearly reflect a certain typical development model or problem. From 2010 to 2023, the CCD in Jiangsu, Hainan and other provinces shows an increasing trend, reaching 0.36 and 0.37, respectively. Jiangsu achieves synergy through the development of efficient agriculture and ecological governance, while Hainan relies on its ecological advantages to achieve significant results in agricultural green transformation. Although Gansu continues to make progress, it has not yet broken through the “moderate coordination” due to weak foundations.

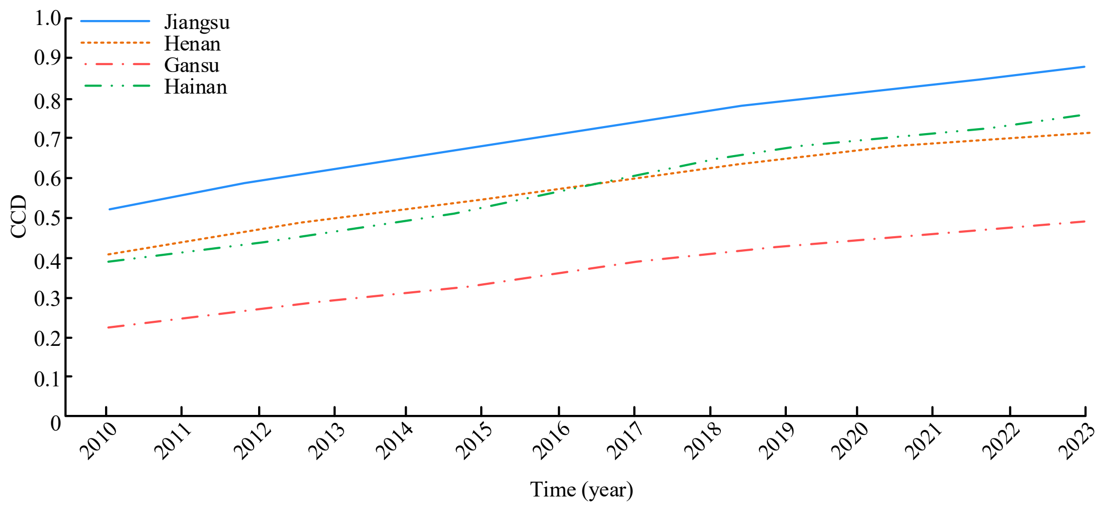

Figure 3. *The changing trend of CCD of typical provinces in China from 2010 to 2023*

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Analysis of the spatiotemporal evolution of coupling effects

This study analyzes the spatiotemporal characteristics of coupling effects based on WMA and GWR models. *Figure 4* shows the CCD time series WMA. The period from 2015 to 2020 is a period of rapid increase in coupling effects, and the growth rate slows down after 2020, possibly due to the diminishing marginal benefits of industrial restructuring. The recent data have a higher weight, proving that the timeliness of policies has an obvious impact on the coupling effect.

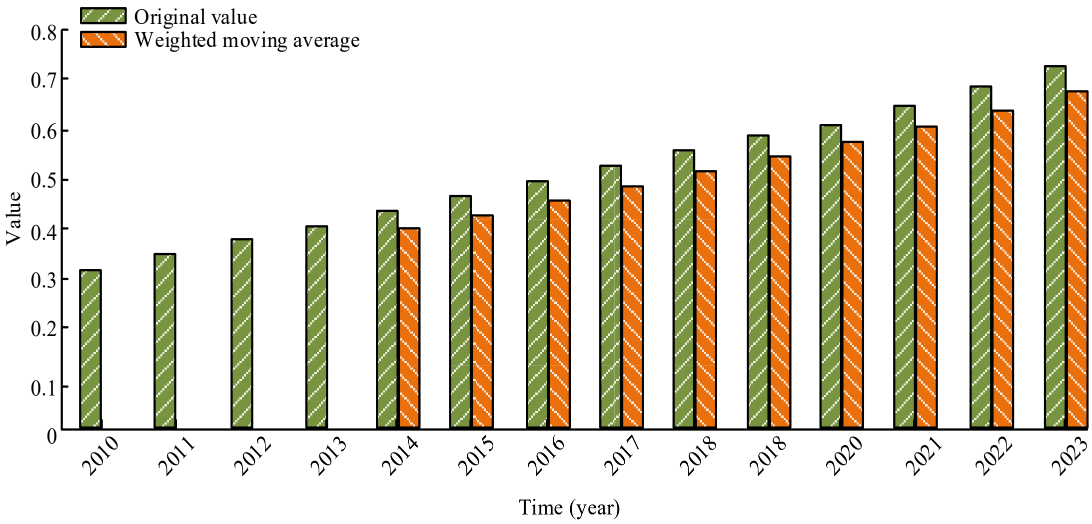

Figure 4. *The WMA trend of China's CCD time series from 2010 to 2023*

Figure 5 shows the spatial correlation test results of CCD for typical years. The study selects 2012 and 2023 as typical years for comparative analysis based on the following: 2010 is the starting point of the research period, and the data are still in the benchmark period, while in 2012, the effects of various policies have already begun to emerge, and the data are more stable. Selecting two time sections spaced approximately ten years apart (2012 and 2023) can reveal to the greatest extent the spatio-temporal evolution characteristics and spatial pattern stability of the CCD over a long period. From 2012 to 2023, the MII of C&C in 31 provinces across the country increases from 0.213 to 0.521, and all pass the 1% or 5% significance tests. This indicates that the spatial positive correlation continues to strengthen, showing the characteristics of "high value area clustering and low value area contraction". This is coincided with the trend of the national CCD upgrading from "mild imbalance" to "good coordination", reflecting the spatial spillover effect of the coordinated development of AIS adjustment and EP.

Table 6 shows the spatial distribution characteristics of CCD in 2023. The GWR model shows that there is spatial heterogeneity in the impact of various factors on coupling effects. The per capita GDP has the greatest impact on the eastern region (0.42), as the eastern region has a strong economic foundation and capital investment has a stronger driving force for coordinated development. The impact of agricultural technological progress on the central region is prominent (0.41), reflecting the role of technology in the ecological agricultural transformation of major grain producing areas. The degree of policy synergy is significant in all regions, indicating that institutional factors are a key driving force at the national level.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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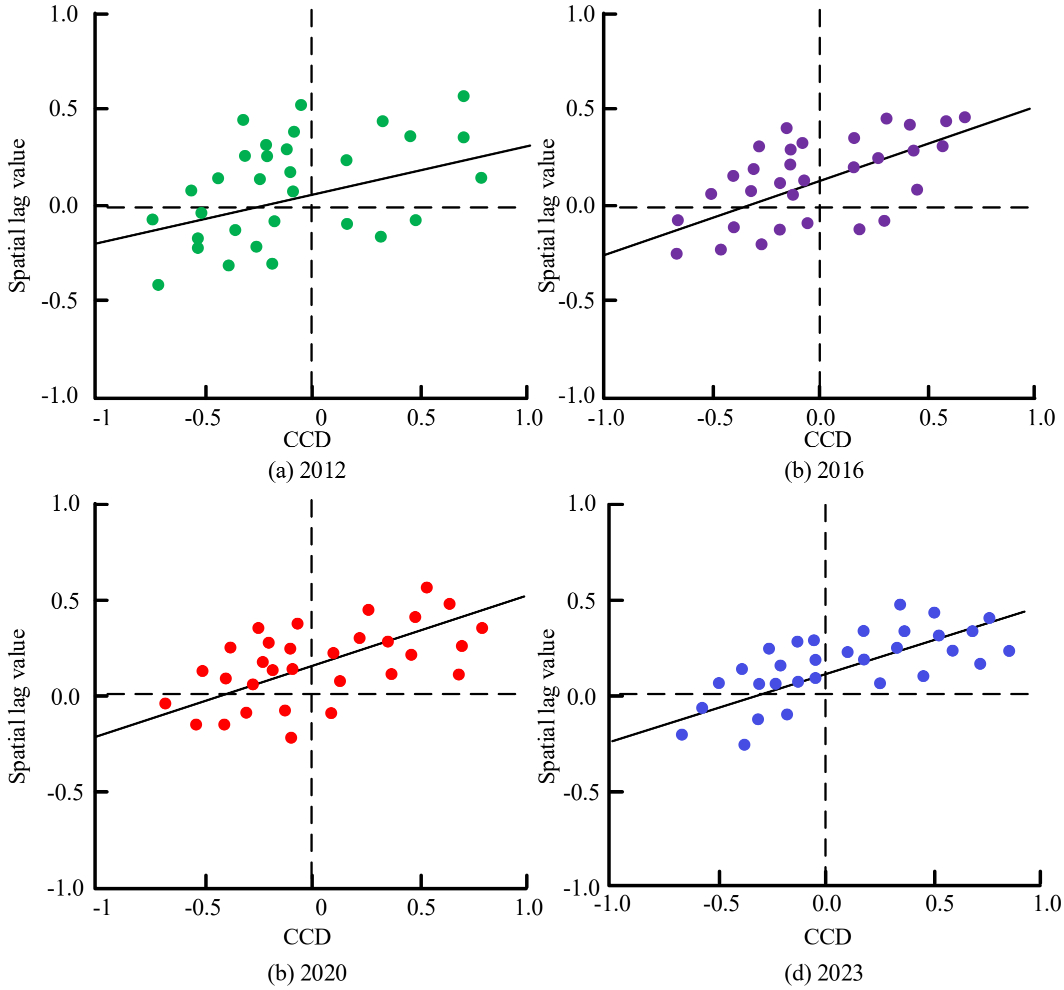

Figure 5. *Spatial auto-correlation analysis results of CCD of various provinces in China in 2012 and 2023*

Table 6. *Main results of the GWR model affecting the CCD of various provinces in China in 2023*

Variable	Region coefficients			p
	Eastern	Central	Western	
X_1	0.42***	0.35***	0.28**	< 0.01
X_4	0.38***	0.41***	0.33***	< 0.01
X_5	0.29***	0.25**	0.18*	< 0.05
X_6	0.36***	0.32***	0.27**	< 0.01
X_3	0.30***	0.26***	0.22**	< 0.01
X_7	0.16**	0.14**	0.10*	< 0.01

*, **, and *** indicate significant levels at 1%, 5%, and 10%

Table 7 shows the seasonal adjustment results of CCD in 2023. After seasonal adjustment, the quarterly fluctuation of CCD in 2023 decreases. The seasonal factor for Q1

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is 1.03, indicating that the coordination level of this quarter is usually higher than the annual average. This is mainly related to the agricultural production cycle in most parts of China during this period: the period from the end of the first quarter to the beginning of the second quarter is a crucial time for spring ploughing and preparation. The input of agricultural production materials such as fertilizers and pesticides increases intensively, exerting short-term pressure on the EE and may lead to seasonal tension in the coordination between the agricultural and environmental systems. Due to the increased EP efforts in summer, the seasonal factor fell back to 0.97 in Q2, indicating that the seasonal synergy between agricultural production and EP measures is gradually optimizing.

Table 7. *Seasonal adjustment results of quarterly data on CCD in China in 2023*

Quarterly	Original value	Seasonally adjusted value	Seasonal factor	Typical province original values
Q1	0.70	0.72	1.03	Beijing (0.68), Hebei (0.62), Jiangsu (0.81)
Q2	0.75	0.73	0.97	Zhejiang (0.83), Anhui (0.69), Hunan (0.67)
Q3	0.74	0.74	1.00	Shandong (0.80), Hubei (0.71), Sichuan (0.65)
Q4	0.73	0.72	0.99	Guangdong (0.82), Shaanxi (0.63), Gansu (0.45)

Types and characteristics of coupling effects

This study divides 31 provinces into four types based on CCD and system comprehensive index. *Table 8* shows the classification of coupling effect types. High quality collaborative provinces have achieved a two-way promotion of industrial upgrading and EP. Industry led provinces have better AIS, but insufficient investment in EP (such as Hebei, where heavy industry pollution has dragged down the environmental index). Environmental priority provinces have a good ecological foundation, but their level of agricultural modernization is relatively low (such as insufficient investment in agricultural science and technology in Yunnan). Low level collaborative provinces are mostly underdeveloped areas in the west, and the development of the two systems lags behind.

Table 8. *Classification of Chinese provinces in 2023 based on the C&C level*

Type	The number of provinces	CCD	Agricultural system index	EP system index	Typical province
High-quality collaborative type	7	≥0.75	≥0.7	≥0.7	Jiangsu, Zhejiang, Hainan
Industry-led type	10	0.6-0.75	≥0.65	<0.65	Shandong, Henan, Hebei
EP priority type	6	0.6-0.75	<0.65	≥0.65	Fujian, Yunnan, Guangxi
Low-degree collaborative type	8	<0.6	<0.6	<0.6	Gansu, Qinghai, Ningxia

Figure 6 shows a comparison of indicators for different types of provinces in 2023. High quality collaborative provinces are significantly leading in indicators such as processing conversion rate and EP patents. Industry-oriented provinces have higher processing conversion rates, but their air quality and patent numbers lag behind those of environmentally

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friendly priority provinces. The indicators of provinces with low degree of synergy are all at a low level, and insufficient policy synergy is an important constraint factor.

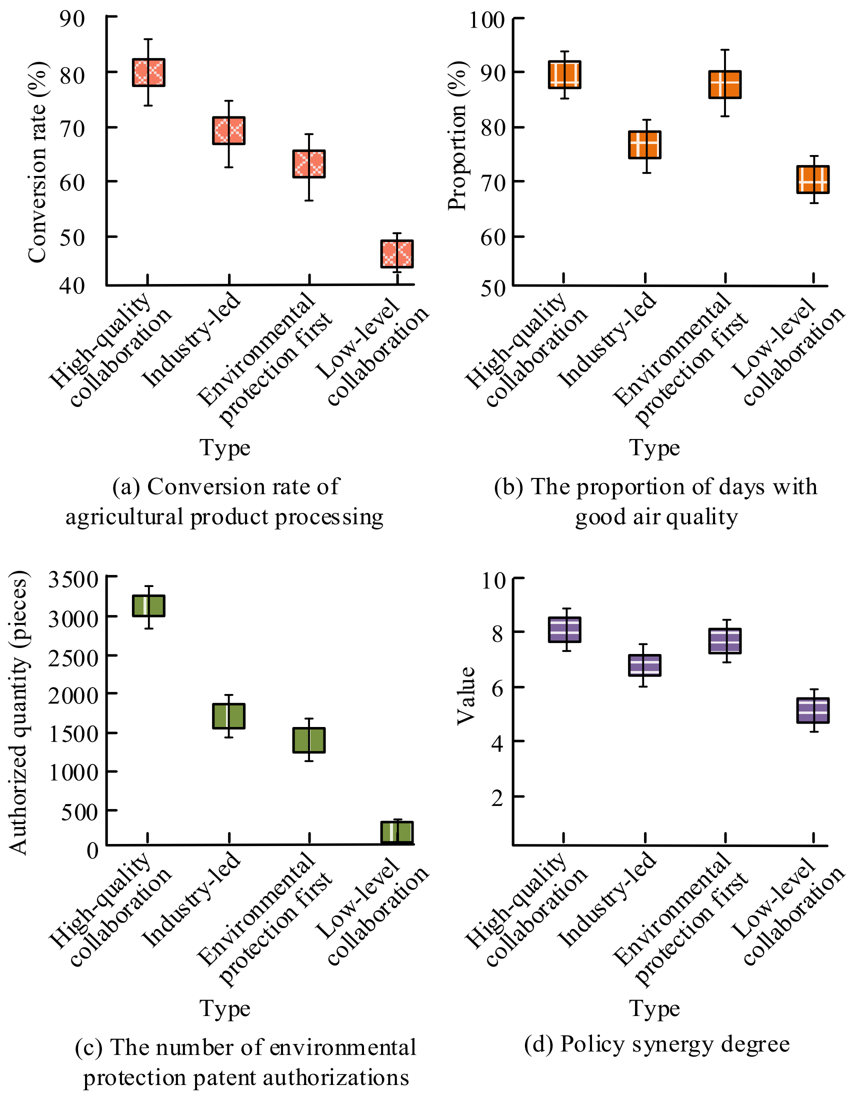

***Figure 6.** Comparison of core indicators of agricultural and environmental systems in different types of provinces in China in 2023*

Figure 7 shows the trend of type evolution from 2010 to 2023. In the past 14 years, the number of provinces with low collaboration has decreased by 14, while the number of provinces with high-quality collaboration has increased by 6, indicating an overall improvement in the coupling effect nationwide. Policy guidance and EDL have promoted more provinces to shift towards a collaborative approach, but some western provinces still need key support.

Analysis results of influencing factors of coupling effect

This study is based on multiple linear regression and SDM to obtain the analysis results of influencing factors. *Table 9* shows the results of multiple linear regression. All independent variables are significant ($p < 0.05$), VIF is less than 3, and there is no severe multi-collinearity. The level of agricultural technology (0.31) and policy synergy (0.25) have the greatest impact on the coupling effect, indicating that technological support and institutional design are key factors. The impact of FEA is relatively small (0.12), indicating that public participation still needs to be improved.

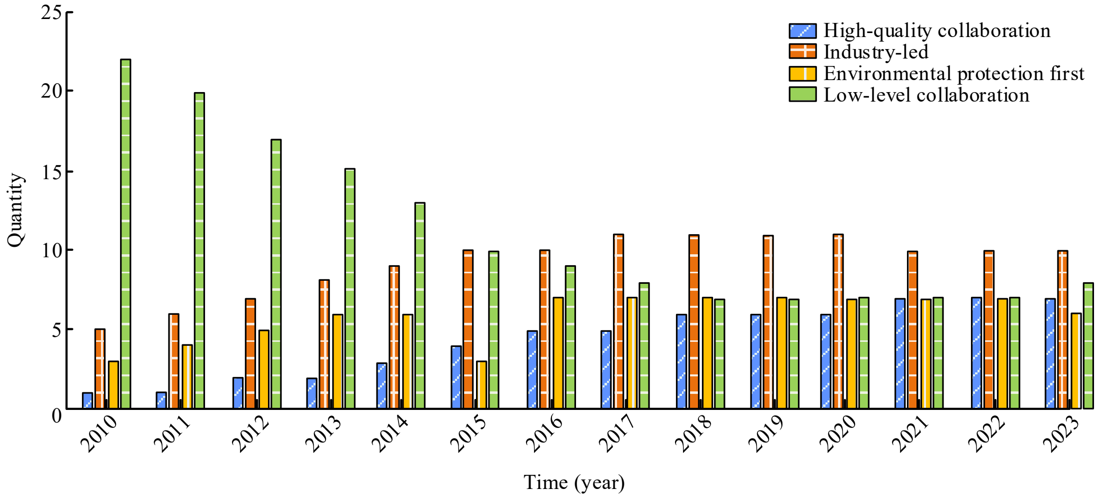

Figure 7. *The evolution trend of C&C types in various provinces of China from 2010 to 2023*

Table 9. *Results of multiple linear regression model for influencing factors of CCD*

Variable	Coefficient	Standard error	t	p	R^2	F
X_1	0.28***	0.05	5.60	<0.01	0.87	127.53***
X_2	0.19***	0.04	4.75	<0.01		
X_3	0.22***	0.03	7.33	<0.01		
X_4	0.31***	0.04	7.75	<0.01		
X_5	0.17***	0.03	5.67	<0.01		
X_6	0.25***	0.04	6.25	<0.01		
X_7	0.12**	0.05	2.40	<0.05		
X_8	0.15***	0.04	3.75	<0.01		

Table 10 shows the SDM results for 2023. All factors have a significant impact on both the local and surrounding areas. The indirect effect of per capita GDP (0.18) indicates that economically developed regions have a radiating driving effect on their surrounding areas. The overall effect of X_4 (0.43) is the highest, indicating that technological progress not only enhances local coupling effects, but also promotes peripheral collaboration through technology diffusion. The indirect effect of policy synergy (0.19) is significant, reflecting the enhancing effect of regional synergy of environmental policies (such as cross regional pollution control) on the overall coupling effect.

Table 11 shows the differences in influencing factors among different regions in 2023. The impact on per capita GDP in the east is more prominent (0.32). The role of X_4 is

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strongest in the central (0.33). The policy synergy in the western has the greatest impact (0.31), reflecting the need for differentiated strategies in different regions. The eastern region relies on its economic advantages to deepen the application of science and technology, the central region strengthens the promotion of agricultural technology, and the western region compensates for resource gaps through policy coordination.

Table 10. *Effect decomposition of influencing factors of CCD based on SDM (2023)*

Variable	Effect		
	Direct	**Indirect**	**Total**
X_1	0.25***	0.18***	0.43***
X_4	0.28***	0.15***	0.43***
X_6	0.23***	0.19***	0.42***
X_5	0.16***	0.12***	0.28***

Table 11. *Comparison of regression coefficients of core influencing factors in different regions of China in 2023*

Variable	Coefficient		
	East	**Central**	**West**
X_1	0.32***	0.27***	0.21***
X_4	0.25***	0.33***	0.28***
X_6	0.28***	0.26***	0.31***
X_7	0.18***	0.15**	0.12*
X_8	0.17***	0.16***	0.14**
X_3	0.22***	0.20***	0.19**

To evaluate the effectiveness of the research methods, a comparative analysis with the commonly used methods in related work is supplemented in the result analysis. Three typical research methods are selected as the comparison benchmarks: Ordinary Least Squares Regression (OLS), Simple Moving Average (SMA), and Global Regression Model (GRM). These methods are widely used in existing literature. For instance, Tan et al. (2024) used OLS to analyze the impact of environmental regulations on AIS adjustment, Shi et al. (2023) used SMA for time series analysis, and Yan et al. (2025) used GRM to study regional heterogeneity. The evaluation indicators for comparison include goodness of fit (R^2), Root Mean Squares Error (RMSE), and computational efficiency (calculation time in seconds), which can reasonably reflect the accuracy and practicality of the method. The results are shown in *Table 12*.

In *Table 12,* the EWM adopted in this study outperforms the methods used in related studies in terms of goodness-of-fit (R^2 =0.92) and RMSE (0.08) (typically R^2 is approximately 0.85). The improved CpD model has higher accuracy than the simple CpD model (R^2 = 0.89 vs. 0.82). The GWR model performs exceptionally well in spatial analysis, with R^2 reaching 0.91, which confirms the significance of considering spatial non-stationarity. Overall, the research method is superior to the comparative methods in accuracy and efficiency, providing a more reliable tool for analyzing the coupling effect between AIS adjustment and EP.

Table 12. *Comparative analysis of research methods*

Research methods	R^2	RMSE	Calculation time (s)
EWM	0.92	0.08	5.2
OLS	0.89	0.10	3.8
SMA	0.85	0.12	4.5
GRM	0.91	0.09	6.1

Discussion

This study systematically analyzed the coupling effect of AIS adjustment and EP in 31 provinces across China from 2010 to 2023 by constructing a CpD model and a CCD model. The national CpD and CCD showed a significant upward trend, indicating that the interaction between AIS adjustment and EP was gradually strengthening. This was closely related to China's vigorous promotion of ecological civilization construction in recent years. Especially since the 13th Five Year Plan, the implementation of relevant policies has accelerated this process, reflecting the positive role of policies in guiding system C&C. The research results were similar to the conclusion of reference (Wang et al., 2024), that the integration of agricultural industries had a significant impact on agricultural ecological efficiency, indicating that the optimization of AIS could promote ecological protection. Meanwhile, this study also echoed the research on the coordinated development of the agricultural economy and ecology in reference, further expanding the understanding of the interaction between agricultural systems and EE. However, this study was innovative in the construction of indicator systems, data processing methods, and spatiotemporal analysis, providing a new perspective for a more comprehensive analysis of coupling effects.

Although multiple methods are used for data analysis in this study, there are still certain limitations. Firstly, the accuracy and completeness of data may be affected by statistical caliber and local data quality. Secondly, the selection of variables in the model may have limitations and may not cover all factors that may affect coupling effects. For example, social and cultural factors, as well as policy implementation efforts, are not fully considered in this study. Finally, due to data limitations, the analysis of some micro-level mechanisms is not yet in-depth enough, and future research can further explore these aspects. This study expands the application of coupling theory in agriculture and the environment, revealing the complex interaction between AIS regulation and EP. By introducing the WMA method and GWR model, this study provides new methodological support for analyzing the spatiotemporal characteristics of coupling effects, enriches the relevant theoretical system, and provides a more comprehensive decision-making basis for policy makers.

Conclusion

This study performed in-depth research on the coupling effect of AIS adjustment and EP in 31 provinces across China from 2010 to 2023. The C&C between AIS adjustment and EP showed a significant upward trend, proving that the interaction between the two was gradually strengthening. The national average CCD reached 0.57 in 2023, but there were significant regional differences. The eastern region had the highest C&C, and some provinces have entered a state of good coordination, while the western region lagged behind overall, and some provinces had lower coordination. Through the analysis of WMA and GWR models, it was found that the timeliness of policies had a significant impact on the coupling effect, and there was spatial heterogeneity in the influence of various factors on the coupling effect. Per capita GDP had the greatest impact on the eastern region, while agricultural technological progress had a prominent impact on the central region. Policy synergy was significant in all regions and was a key driving force nationwide. The level of agricultural technology and policy synergy had the greatest impact on the coupling effect and was a key factor in promoting coordinated development of coupling. The influencing factors vary in different regions. The eastern region should rely on its economic advantages to deepen the application of science and technology. The central region should strengthen the promotion of agricultural technology. The western region should make up for the shortage of resources through policy coordination. This study provides theoretical support and decision-making reference for achieving coordinated SD agriculture and ecological EP. Future work should further strengthen policy guidance, optimize resource allocation, and enhance the technological level to promote efficient collaboration between AIS adjustment and EP.

Conflict of interests. The authors declare that there is no conflict of interest.

Data availability statement. The datasets generated during and/or analyzed during this study will be available from the corresponding author upon request.

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