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Research on the Spatiotemporal Dynamic Evolution of the High-Quality Development of China's Agricultural Green Economy

Jialei Ge[1,#], Fan Tang[2,#] & Yihang Hu[2,3,*]

[1] *College of Landscape Architecture, Zhejiang A&F University, Hangzhou, Zhejiang, 311300, PR China*

[2] *College of Economics and Management, Zhejiang A&F University, Hangzhou, Zhejiang, 311300, PR China*

[3] *Research Academy for Rural Revitalization of Zhejiang Province, Zhejiang A&F University, Hangzhou, Zhejiang, 311300, PR China*

Abstract: Against the backdrop of China's national strategy for agricultural green development, systematically measuring its spatiotemporal pattern and driving mechanisms is crucial to agricultural modernization transformation. This study constructs a four-dimensional evaluation system covering resource utilization, environmental pressure, economic output and social benefits, and analyzes the panel data of China's 31 provinces from 2011 to 2023 via the entropy weight-TOPSIS method and Spatial Durbin Model (SDM). The findings are as follows: The national agricultural green economy level fluctuated in a "decline-rise-decline" trend, with its comprehensive index falling from 0.453 in 2011 to 0.337 in 2023 and mounting overall downward pressure; its spatial pattern shifted from "high in the east and low in the west" to a combination of "north-south differentiation" and a "plateau isolated island", the east-west gap widened from 0.122 to 0.143, and the "central collapse" was notable. Spatial correlation evolved from random distribution to significant "low-low agglomeration", with the local Moran's I rising from 0.085 to 0.214, trapping contiguous regions in low-value development. Economic development boosted local agricultural green economy but had negative spatial spillovers; urbanization and fiscal pressure exerted inhibitory effects, while industrial structure upgrading brought positive spatial spillovers and acted as the core driver for coordinated development. Based on these conclusions, this paper suggests advancing the coordinated high-quality development of agricultural green economy through contiguous comprehensive governance, gradient transmission, industrial chain linkage and horizontal compensation.

Keywords: agricultural green economy, spatiotemporal evolution, spatial durbin model

1. Introduction

The concept of agricultural green development originated from the international community's exploration of sustainable agriculture in the 1980s. The Food and Agriculture Organization of the United Nations defines it as a development model that "manages and protects the natural resource base, and implements technological and institutional changes to ensure that the food and agricultural product needs of the present and future generations are met" (Ji, 2026). Since then, academic circles have carried out continuous discussions on the coordination of resource conservation, environmental friendliness and economic benefits. In recent years, with the deepening of the concept of sustainable development, the high-quality development of agricultural green economy has gradually been regarded as a composite development paradigm constrained by resource

Corresponding Author: Yihang Hu
College of Economics and Management, Zhejiang A&F University; Research Academy for Rural Revitalization of Zhejiang Province, Zhejiang A&F University, PR China

carrying capacity and ecological environmental capacity, with the improvement of production efficiency and social welfare as the core.

As a fundamental industry, the development mode of agriculture exerts a profound impact on the food security pattern, resource utilization efficiency and ecosystem stability (Hu et al., 2025). Entering the 21st century, problems such as tightening resource constraints, worsening non-point source pollution and the degradation of ecological service functions have become increasingly prominent, and the unsustainability of the traditional growth model has forced all countries to explore transformation paths (Li et al., 2026). Against this background, agricultural green development has gradually become a global consensus, and relevant research has focused on the measurement of green total factor productivity, environmental efficiency evaluation and sustainable development models.

However, existing studies lack systematic measurement of the high-quality development of agricultural green economy and have limited depth in spatial analysis. Although some studies have initially revealed regional differences, the investigation of spatial agglomeration characteristics, spillover effects and their dynamic evolution laws is still unsystematic. The existing targeted policy suggestions are mostly based on static cross-sectional comparisons and fail to fully respond to the heterogeneous impact of the evolutionary stage of regions on policy transmission effects.

In response, this study conducts a systematic analysis from three aspects: the measurement of the development level of agricultural green economy, its spatiotemporal evolution characteristics and the identification of driving factors, aiming to reveal its spatiotemporal differentiation laws and spatial spillover mechanisms, and provide theoretical support and policy recommendations for promoting regional collaborative governance.

2. Data Sources and Indicator Construction

2.1 Data sources

This study utilizes panel data from 31 provinces (municipalities and autonomous regions, excluding Hong Kong, Macau, and Taiwan) in China, covering the period from 2011 to 2023. The primary data sources include the "China Statistical Yearbook," "China Rural Statistical Yearbook," "China Agricultural Yearbook," and the statistical yearbooks of various provinces and municipalities. To enhance the transparency and reproducibility of our research, we processed the raw data as follows: (1) Linear interpolation was employed to impute missing values; (2)Outliers were identified and removed using the boxplot method; (3) Indicators were subjected to directional consistency processing to ensure uniformity in direction for all indicators within the entropy weight method. This resulted in a balanced panel dataset comprising 31 provinces, 13 years, and 12 indicators.

2.2 Principles for constructing the evaluation indicator system

To comprehensively, objectively, and scientifically measure the level of agricultural green economic development in various provinces of China, this study adheres to the following fundamental principles in constructing the evaluation indicator system: Systemic Principle: The indicator system should comprehensively reflect the multi-dimensional characteristics of agricultural green economic development, including resources, environment, economy, and society, encompassing key elements throughout the entire agricultural production process.Scientific Principle: The selection of indicators is based on the theory of agricultural green development and relevant research findings, ensuring the theoretical basis and statistical connotations of the indicators are accurate.Operability Principle :Priority is given to indicators that are obtainable and quantifiable from statistical data, ensuring the objectivity and comparability of the evaluation results. Guidance Principle: The setting of indicators reflects the policy orientation of agricultural green development, guiding regions to transform their agricultural development models and promote sustainable agricultural development.

2.3 Indicator selection and construction

Based on the intrinsic characteristics of agricultural green development and referencing relevant research findings (Hu et al., 2024), this study constructs an evaluation indicator system for high-quality agricultural green economic development from four dimensions: resource utilization, environmental pressure, economic output, and social benefits. The specific indicators are presented in Table 1.

Table 1. Evaluation Indicators for High-Quality Agricultural Green Economic Development

Target Layer	Primary Indicator	Secondary Indicator	Basic Indicator
High-Quality Development of Agricultural Green Economy	Resource Utilization	Agricultural Water Use Efficiency (+)	Agricultural Added Value / Agricultural Water Consumption
		Agricultural Mechanization Level (+)	Total Agricultural Machinery Power / Sown Area
		Proportion of Agricultural Water Use (-)	Agricultural Water Consumption / Total Water Consumption
	Environmental Pressure	Fertilizer Application Intensity (-)	Fertilizer Application Amount / Sown Area
		Pesticide Application Intensity (-)	Pesticide Application Amount / Sown Area
		Plastic Film Application Intensity (-)	Plastic Film Application Amount / Sown Area
		Proportion of Affected Area (-)	Crop Affected Area / Sown Area
	Economic Output	Land Productivity (+)	Agricultural Added Value / Sown Area
		Capital Productivity (+)	Agricultural Added Value / Total Agricultural Machinery Power
	Social Benefits	Proportion of Agricultural Employees (-)	Agricultural Employees / Total Employment
		Per Capita Disposable Income of Urban Residents (+)	(Directly obtained)
		Income Ratio of Urban to Rural Residents (-)	Urban Resident Income / Rural Resident Income

3. Research Methodology

This study employs the Entropy Weight-TOPSIS method to calculate the comprehensive index of high-quality green economic development in agriculture for each province. This approach synergistically combines the objective weighting advantages of the entropy weight method with the comprehensive ranking capabilities of the TOPSIS method, effectively mitigating the arbitrariness associated with subjective weighting (Cao et al., 2026).

The calculation steps are as follows:

Step one: data standardization

$$X'_{ij} = \frac{X_{ij} - X_{\min}}{X_{\max} - X_{\min}} \quad (Positive\ indicator)$$

$$X'_{ij} = \frac{X_{\max} - X_{ij}}{X_{\max} - X_{\min}} \quad (Negative\ indicator)$$

Here, i represents the province and j represents the measurement indicator.

Step two: Calculate the information entropy E_j

$$P_{ij} = \frac{X'_{ij}}{\sum_{i=1}^{n} X'_{ij}}$$

$$E_j = -k\sum_{i=1}^{n} P_{ij}\ln(P_{ij}), k = \frac{1}{\ln(n)}$$

Step 3: Calculate the weights Wj

$$W_j = \frac{1 - E_j}{\sum_{j=1}^{m}(1 - E_j)}$$

Step 4: Construct the weighted matrix r_{ij}

$$r_{ij} = W_j \times X'_{ij}$$

Step 5: Determine the optimal solution Q_j^+ and the worst-case solution Q_j^-

$$Q_j^+ = (\max r_{i1}, \max r_{i2}, \ldots, \max r_{im})$$

$$Q_j^- = (\min r_{i1}, \min r_{i2}, \ldots, \min r_{im})$$

Step 6: Calculate the Euclidean distances di+ and di−

$$d_i^+ = \sqrt{\sum_{j=1}^{m}(Q_j^+ - r_{ij})^2}$$

$$d_i^- = \sqrt{\sum_{j=1}^{m}(Q_j^- - r_{ij})^2}$$

Step 7: Calculate Relative Closeness Ci

$$C_i = \frac{d_i^-}{d_i^+ + d_i^-}$$

In this context, the range of Ci is (0,1), where a higher value indicates a superior level of high-quality development in the region's green agricultural economy.

4. Spatiotemporal Evolution Characteristics of the High-Quality Development of China's Agricultural Green Economy

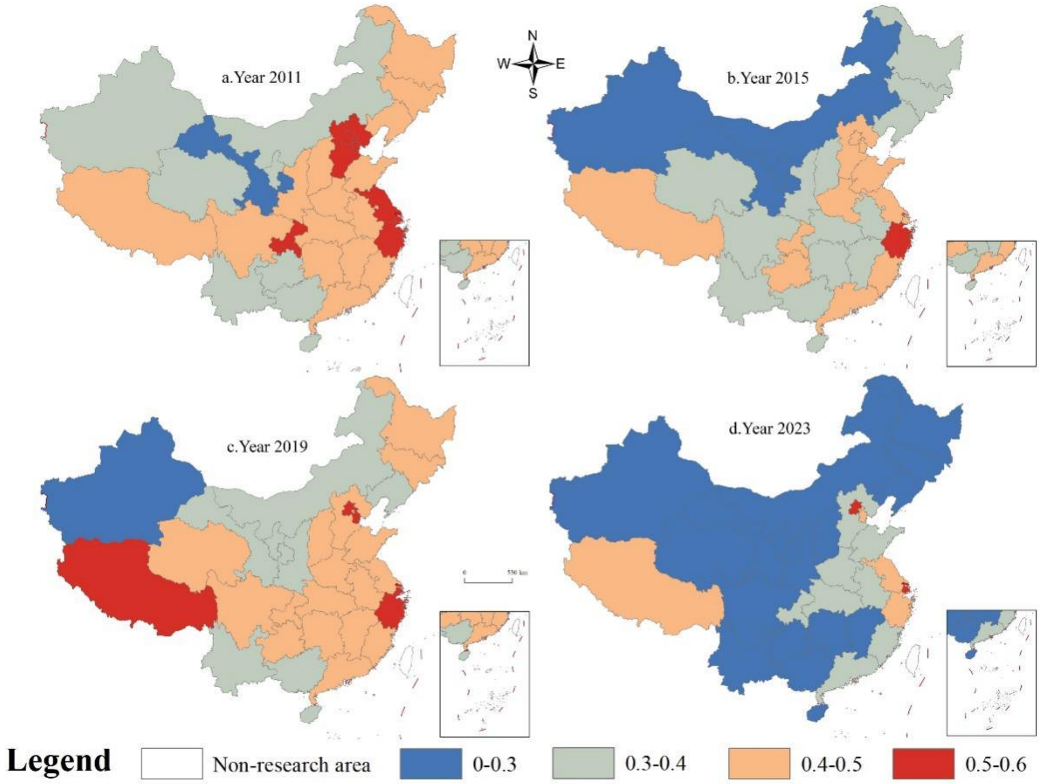
4.1 Temporal evolution characteristics: coexistence of overall decline and phased fluctuation

From a temporal perspective, the comprehensive score of the high-quality development of China's agricultural green economy from 2011 to 2023 showed a "decline-rise-decline" fluctuation, with an overall downward trend (Pan et al., 2024). The national average score dropped from 0.453 in 2011 to 0.337 in 2023, with a cumulative decline of 25.6%. Specifically, the evolution during the research period can be divided into three stages: a continuous decline stage from 2011 to 2015, with a score drop of 13.5%; a fluctuating recovery stage from 2015 to 2019, with an increase of 11.2%; and an accelerated decline stage from 2019 to 2023, with a drop of 22.7%, reflecting the great pressure faced by agricultural green transformation in recent years. From the perspective of the evolution types of each province, most provinces showed a continuous or fluctuating decline, and only the Xizang Autonomous Region achieved counter-trend growth, with its score in 2023 increasing by 10.1% compared with 2011, becoming the only region with sustained improvement, which may be related to its ecological compensation policies and the construction of green agricultural demonstration zones.

4.2 Spatial pattern evolution: from "High in the East and Low in the West" to coexistence of "North-South Differentiation" and "Plateau Isolated Island"

The spatial distribution pattern of high-quality agricultural green development is shown in Figure 1.

In terms of the spatial distribution pattern, the regional distribution of high-quality agricultural green development has undergone significant changes (Li et al., 2023). In 2011, high-value areas were concentrated in the eastern coastal regions such as Beijing, Tianjin, Shanghai and Zhejiang, with scores all above 0.57; low-value areas were mainly distributed in the western regions such as Gansu, Yunnan, Ningxia and Xinjiang, presenting a typical pattern of "high in the east and low in the west". By 2023, the spatial pattern has been reconstructed: high-value areas shrank to three isolated high points including Beijing, Shanghai and Xizang; the three northeastern provinces experienced an overall collapse with scores all below 0.3; the northwest region remained in a downturn; in the southwest region, except for Xizang, Yunnan and Guizhou were also in the low-value range. The evolution of this pattern indicates that the spatial distribution of China's high-quality agricultural green development is shifting from the early "strong in the east and weak in the west" to "north-south differentiation", and at the same time, Xizang has formed a "green plateau isolated island".



(Figure 1.Spatial Distribution of the High-Quality Development of Agricultural Green Economy in 2011 and 2023)

4.3 Spatial correlation evolution: from random distribution to significant "Low-Low Agglomeration"

The results of spatial correlation analysis show that the spatial correlation characteristics of China's high-quality agricultural green development have undergone a transformation from "random distribution" to "significant agglomeration" (Liu et al., 2023). The specific indicators are presented in Table 2.

The global spatial autocorrelation analysis (Table 2) shows that the tests were not significant in 2011 (p=0.143>0.05), 2015 (p=0.314>0.05) and 2019 (p=0.242>0.05), indicating that the development levels of various provinces were randomly distributed in space during this period. However, the p-value dropped to 0.024 (<0.05) in 2023, passing the significance test at the 5% level, which means that the spatial autocorrelation has increased significantly in recent years . Combined with the spatial distribution characteristics of the comprehensive scores, this significant global spatial autocorrelation is mainly manifested as "low-low agglomeration", that is, contiguous low-value agglomeration areas have formed in parts of the northeast, north China, northwest and southwest China, while high-value provinces such as Beijing, Shanghai and Xizang show an isolated distribution pattern.

Table 2. Test Results of Global Moran's I

Year	Moran's I	Z-score	P-value
2011	0.085	1.466	0.143
2015	0.062	1.006	0.314
2019	0.071	1.118	0.242
2023	0.214	2.261	0.024

4.4 Evolution of regional differences: the gap narrowed first and then widened, with a prominent "Central Collapse"

From the perspective of the differences among the eastern, central and western regions, the regional gap showed an evolutionary trend of "narrowing first and then widening". In 2011, the average scores of the eastern, central and western regions were 0.507, 0.447 and 0.385 respectively; by 2019, the gap among the three narrowed to 0.479, 0.428 and 0.411; however, from 2019 to 2023, the gap widened again, with the average scores of the eastern, central and western regions being 0.398, 0.285 and 0.255 in 2023 respectively. Notably, the central region experienced the sharpest score decline: the central region led the western region by 0.062 in 2011, and by 2023 its score was basically close to that of the western region (0.285 vs 0.255), showing a significant "central collapse" phenomenon.

To further reveal the structural sources of regional differences, this study adopts the Dagum Gini coefficient and its subgroup decomposition method for analysis. The results show that the overall Gini coefficient presented a U-shaped trend of "decline-rise" during the research period. From the decomposition results, the contribution rate of inter-regional differences has always been above 60%, which is the main source of the overall differences; the contribution rate of intra-regional differences is stable at 20%–25%; the contribution rate of transvariation density shows a downward trend, indicating that the characteristics of regional differentiation are becoming increasingly obvious.

5. Analysis of Influencing Factors

5.1 Theoretical basis and research hypotheses

This paper constructs a theoretical framework from five dimensions: economic development, industrial structure, urbanization, government intervention, and opening up to the outside world.

First, the level of economic development. According to the Environmental Kuznets Curve theory, there is an inverted U-shaped relationship between economic development and environmental pollution. We propose hypothesis H1: The level of economic development has a promoting effect on the green economic development of agriculture.

Second, industrial structure upgrading. The structural transformation from traditional high-energy-consuming industries to low-pollution service industries affects environmental quality. We propose hypothesis H2: Industrial structure upgrading has a positive promoting effect on the green economic development of agriculture, and there is a spatial spillover effect.

Third, urbanization. Urbanization can improve resource allocation efficiency through agglomeration, but it may also cause environmental problems. We propose hypothesis H3: The impact of urbanization on the green economic development of agriculture is uncertain.

Fourth, government intervention. Governments can support environmental protection through fiscal expenditure, but there may also be "race to the bottom" competition. We propose hypothesis H4: The impact of government intervention on the green economic development of agriculture is uncertain.

Fifth, opening up to the outside world. Opening up can introduce green technologies, but it may also introduce polluting industries. We propose hypothesis H5: The impact of opening up to the outside world on the green economic development of agriculture is uncertain.

5.2 Benchmark Regression Analysis

To examine the fundamental impact of various factors on the level of green development, this paper first employs a mixed OLS model (Han & Choi, 2025) and a two-way fixed effects model (Wang et al., 2023) for benchmark regression, serving as the foundational conclusions for the empirical analysis throughout the paper. The regression results are presented in Table 3.

Table 3. Benchmark Regression Results

Variable	Mixed OLS	Fixed Effects (FE)
ln_gdp	0.030*	0.110
	(0.058)	(0.113)
industry_ratio	0.048	-0.135
	(0.490)	(0.429)
urban_rate	-0.228***	-0.871**
	(0.001)	(0.007)
fiscal_ratio	0.015	-0.186
	(0.591)	(0.119)
trade_ratio	0.022***	0.009*
	(0.000)	(0.058)
Individual Fixed Effects	No	Yes
Time Fixed Effects	No	Yes
R^2	0.328	0.218

Table Note: P-values corresponding to robust standard errors are presented in parentheses; ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. After controlling for provincial fixed effects and year fixed effects, the direction and significance of the core variables remain robust, indicating the reliability of the baseline regression results.

5.3 Spatial autocorrelation test and model selection

To ascertain whether there is a spatial correlation in regional green development levels, this study initiated a global spatial autocorrelation test on the explained variable, green_score, using a 500 km threshold inverse distance spatial weight matrix. The results from 2011–2023 consistently showed that the global Moran's I index for each year was significantly positive at the 1% level, ranging from 0.185 to 0.680. This indicates a pronounced spatial positive autocorrelation in the green development levels across Chinese provinces, suggesting that regions are not independent but rather exhibit a spatial linkage pattern of "high-high clusters" or "low-low clusters." This finding underscores the inherent bias in estimation results from traditional panel regression models that disregard spatial correlation, necessitating the use of spatial econometric models for analysis.

Regarding the selection of spatial econometric models, the LM test(Ou et al., 2019) is primarily designed for screening between spatial lag models (SAR) and spatial error models (SEM) within a cross-sectional data framework. For panel data structures, spatial LM tests in current econometric practice face significant data constraints and model limitations, making them difficult to reconcile with the spatial Durbin model (SDM) employed in this study. Furthermore, the SDM, as a more general and inclusive spatial econometric model, can simultaneously incorporate both the spatial lag of the explained variable and the spatial lags of the explanatory variables. This allows for the identification of both direct and spatial spillover effects, aligning more closely with my research objectives and theoretical mechanisms.

To further validate the appropriateness of the model specification, the research conducted a Wald test (Muhammad et al., 2023) to examine whether the SDM model could be simplified to the more constrained SAR model. The test yielded a Wald statistic of 68.02, with a corresponding p-value of 0.000. At the 1% significance level, this strongly rejects the null hypothesis that "all spatial lag coefficients of the independent variables are simultaneously zero." This evidence suggests that the SDM model captures the spatial interactions between variables more comprehensively and is therefore a more suitable choice for this research. Consequently, the paper ultimately adopted the spatial Durbin model (SDM) for empirical analysis and subsequently decomposed the direct, indirect, and total effects to precisely identify the mechanisms and spatial transmission pathways of various influencing factors.

5.4 Spatial econometric model specification

Given the spatial interdependencies inherent in regional green development, I employed the Spatial Durbin Model (SDM) to simultaneously capture the spatial spillover effects of both the dependent and independent variables (Chen & Zhang, 2025). The model is specified as follows:

$$Y_{it} = \rho WY_{it} + \beta X_{it} + \theta WX_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

In this model, Y_{it} represents the dependent variable, W is the spatial weight matrix, X_{it} denotes the explanatory variables, ρ signifies the spatial autoregressive coefficient, β and θ are the coefficients for the explanatory variables and their spatial lags, respectively, μ_i and λ_t denote the individual and time fixed effects, and ε_{it} is the random error term.

5.5 Spatial Durbin Model (SDM) Benchmark Regression

From the Spatial Durbin Model (SDM) regression results presented in Table 4, several key insights emerge:

Economic Development:The coefficient for the level of economic development (ln_gdp) is significantly positive (0.1168) at the 1% significance level. This finding validates Hypothesis 1 (H1), indicating that economic development serves as a crucial driving force for green development.

Urbanization and Fiscal Pressure: Both the urbanization rate (urban_rate) and fiscal pressure (fiscal_ratio) exhibit significantly negative coefficients (-0.4571 and -0.2144, respectively) at the 1% significance level. These results provide empirical support for the hypothesized directions of Hypotheses 3 (H3) and 4 (H4), suggesting that rapid urbanization and substantial fiscal pressure exerted an inhibitory effect on green development during the sample period.

Industrial Structure: The local coefficient for industrial structure upgrading (industry_ratio) is negative but not statistically significant. However, its spatial lag term is significantly positive, hinting at the potential presence of spillover effects.

Spatial Autocorrelation: The spatial autocorrelation coefficient, rho, is notably high at 0.8942 and is significant at the 1% level. This strongly indicates substantial positive spatial autocorrelation in the levels of green development.

Table 4. Spatial Durbin Model (SDM) Benchmark Regression Results

Variable	Coefficient	Std. err.	t value	P>|t|
ln_gdp	0.1168***	0.0379	2.95	0.003
industry_ratio	-0.1234	0.0793	-1.56	0.120
urban_rate	-0.4571***	0.1292	-3.54	0.000
fiscal_ratio	-0.2144***	0.0611	-3.51	0.001
trade_ratio	0.0129	0.0261	0.49	0.621
W_green_score	0.8942***	0.0453	19.80	0.000
W_ln_gdp	-0.1247**	0.0491	-2.54	0.011
W_industry_ratio	0.3208**	0.1232	2.60	0.010
W_urban_rate	0.3502	0.2455	1.43	0.155
W_fiscal_ratio	0.1662	0.1143	1.46	0.146
W_trade_ratio	0.0047	0.0037	1.25	0.213
_cons	-0.1570	0.3179	-0.49	0.622
sigma_u	0.0796	—	—	—
sigma_e	0.0274	—	—	—
rho	0.8942***	—	—	—
F-test (u_i=0)	22.92	—	—	0.000

Table Note: p<0.01, p<0.05, p<0.10; W_ denotes the spatial lag of the corresponding variable; the model controls for year fixed effects.

5.6 Decomposition of spatial effects

Table 5 presents the decomposition of direct, indirect, and total effects in the Spatial Durbin model. Given that the regression coefficients of the spatial Durbin model do not directly represent marginal effects, this paper further decomposes the model results into direct, indirect, and total effects to more clearly identify the spatial spillover mechanisms.

Table 5. Decomposition of Effects in the Spatial Durbin Model [Note: Please verify the data here against the original calculation results.]

Variable	Direct Effect	Indirect Effect	Total Effect
ln_gdp	1.068	-0.237	-0.125
industry_ratio	-1.181	2.012	1.888
urban_rate	-4.373	-0.566	-1.023
fiscal_ratio	-2.051	-0.246	-0.461
trade_ratio	0.012	0.056	0.057

Table Note: p < 0.01, p < 0.05, p < 0.10.

In order to more clearly identify the spatial spillover mechanism of each variable, Table 5 further reports the direct effect, indirect effect and total effect decomposition results of the SDM model.

The direct effect reflects the impact of variables on the green development of the region, and its direction and significance are basically consistent with the baseline regression, indicating that the core conclusions of this paper are robust. The direct effect of economic development (ln _ gdp) is positive, indicating that it has a direct role in promoting local green development; The direct effects of urbanization (urban _ rate) and fiscal pressure (fiscal _ ratio) are negative, which once again confirms their inhibitory effect on local green development.

Indirect effects reflect the spatial spillover of variables to green development in other regions, and are the core of spatial analysis. The indirect effect of industrial structure upgrading (industry _ ratio) is positive (2.012) and is relatively large in an economic sense, indicating that a province's industrial structure upgrading can not only improve its own green development level, but also significantly promote it through technology spillover and standard output. The green transformation of neighboring provinces reflects the regional linkage of green development. The indirect effect of economic development (ln _ gdp) is negative (-0.237), indicating that the "siphon effect" brought about by economic development may inhibit the green development investment of neighboring provinces to a certain extent.

The total effect is the sum of direct effects and indirect effects, which represents the comprehensive impact of variables on global green development. The total effect of industrial structure upgrading (industry _ ratio) is positive (1.888), indicating that from an overall perspective, promoting industrial structure upgrading is an effective path to achieve regional coordinated green development.

5.7 Robustness test

In order to ensure the reliability of the core conclusions of this paper, this paper carries out robustness tests from the following three dimensions:

First, replace the spatial weight matrix: replace the 500km distance threshold inverse distance matrix used in the benchmark analysis with an adjacency spatial weight matrix (Rook adjacency) for re-estimation. The regression results show that the core conclusions of the coefficient direction, significance level and spatial spillover effect of the core variables are highly consistent with the benchmark regression.

Second, replace the core explanatory variable: replace the logarithmic form of per capita GDP (ln _ GDP) with the horizontal value of per capita GDP, and re-perform the regression analysis. The results show that the positive role of economic development in promoting green development is still significant, and the inhibitory effect of urbanization rate and fiscal pressure remains stable.

Third, adjust the sample interval: subsample regression is performed by shortening the sample interval (excluding early year data). The results show that the influence direction, significance and spatial spillover mechanism of each variable are consistent with the results of full-sample regression.

Based on the above robustness test results, the core conclusions of this paper, such as "economic development promotes green development, urbanization and fiscal pressure inhibit green development, and there is a significant positive spatial spillover in industrial structure upgrading", show a high degree of consistency and reliability in different model settings, variable measures and sample intervals, indicating that the research conclusions are robust and credible.

6. Conclusions and Policy Recommendations

6.1 Conclusions

Based on the panel data of 31 provinces in China from 2011 to 2023, this paper comprehensively uses the entropy weight-TOPSIS method and the Spatial Durbin Model to systematically examine the spatiotemporal evolution characteristics and influencing factors of the high-quality development of China's agricultural green economy. The main conclusions are as follows:

First, in terms of spatiotemporal evolution characteristics, the national level of high-quality development of agricultural green economy showed a "decline-rise-decline" fluctuation with increasing overall downward pressure; the spatial pattern evolved from "high in the east and low in the west" to a coexistence of "north-south differentiation" and "plateau isolated island"; spatial correlation changed from random distribution in the early stage to significant "low-low agglomeration", indicating that agricultural green transformation is facing a structural predicament of locked-in contiguous low values; regional differences showed a U-shaped evolution with a prominent "central collapse" phenomenon.

Second, in terms of influencing factors, the level of economic development can significantly improve the local green development level but shows a negative spatial spillover effect in space; industrial structure upgrading not only has a positive effect on local green development, but also can generate a significant positive spatial spillover through technology spillover, which is the key driving force for realizing regional coordinated green development (H2 is verified); the urbanization process and local fiscal pressure have formed significant constraints on regional green development during the sample period (the specific directions of H3 and H4 are clear); opening up has a positive but not significant impact on green development (H5 fails to pass the significance test).

Third, in terms of the spatial transmission mechanism, regional green development as a whole presents significant positive spatial correlation characteristics, and there are obvious linkage and diffusion effects among the green development levels of various regions, indicating that the spatial transmission of green development exists objectively and plays an important role in regional coordinated development (Xu et al., 2022).

6.2 Policy recommendations

Based on the above conclusions, the following recommendations are put forward:

First, attach importance to the collaborative governance mechanism of low-value locked-in areas. Contiguous low-value agglomeration areas have formed in parts of the northeast, north China and northwest China, indicating that a single-point breakthrough is difficult to effectively promote the overall transformation. In the future, attention can be paid to the construction of cross-regional collaborative governance mechanisms, explore regional cooperation models based on ecological functional zones and major agricultural producing areas, promote the adaptation and popularization of green technologies in a wider range, and form a regional joint force for green transformation.

Second, focus on the experience transformation and transmission path of green high-value areas. The practices of green high-value areas such as Xizang provide an important case for understanding the green development path of ecologically fragile areas. However, the spillover of its experience is limited by geographical and institutional factors. Follow-up research can focus on the transferability of the experience in high-value areas, and discuss the institutional conditions and realization paths for the promotion of ecological compensation mechanisms and green industrial models among regions.

Third, strengthen the spatial linkage effect of industrial structure upgrading.

Industrial structure upgrading is the only factor with a significant positive spatial spillover effect, indicating that it plays an "engine" role in regional green transformation. In the future, further research can be conducted on the spatial organization mode of the green agricultural industrial chain, explore the regional division of labor and coordination mechanisms in R&D, production, processing, sales and other links, and promote the transformation of green agriculture from "point-like development" to "network linkage".

Fourth, improve the inter-regional interest coordination and compensation mechanism. Economic development shows a certain negative spillover effect on neighboring areas, suggesting that attention should be paid to the balance of inter-regional interest distribution in the process of green transformation. In the future, research on the realization mechanism of the value of ecological products can be deepened, explore the horizontal compensation path based on the ecosystem service function, and enhance the institutional linkage between ecological protection areas and beneficiary areas.

Fifth, optimize the structural arrangement of local development incentives.

The inhibitory effect of urbanization and fiscal pressure on green development indicates that the current local development incentive structure is still incompatible with the goal of green transformation to a certain extent. Follow-up research can proceed from the perspective of institutional economics to discuss the inherent tension between the behavioral logic of local governments, fiscal system arrangements and green development performance, and provide theoretical support for building a more coordinated incentive system.

Conflict of Interest

The authors declare that they have no conflicts of interest to this work.

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