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ARTICLE

Ecological Agricultural Agglomeration: Spatial Spillover Effects on Economic Growth and Resource Efficiency

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ABSTRACT

Based on panel data from 31 provinces in China spanning 2010–2023, this study constructs a Spatial Durbin Model (SDM) to systematically examine the influence mechanisms of ecology-oriented agricultural industrial agglomeration on regional agricultural economic growth and natural resource utilization efficiency. The findings reveal: First, the level of ecology-oriented industrial agglomeration has continuously improved, with the national average index rising from 0.342 to 0.587, exhibiting a spatial pattern of "higher in the east and lower in the west," and spatial autocorrelation has significantly intensified. Second, industrial agglomeration generates a direct effect of 0.342 on agricultural economic growth, an indirect effect of 0.187, and a total effect of 0.529, with spatial spillovers demonstrating significant distance-decay characteristics; technology diffusion serves as the primary pathway, contributing 41.%. Third, industrial agglomeration significantly enhances resource utilization efficiency, producing a direct effect of 0.278 and an indirect effect of 0.143 on agricultural green total factor productivity, primarily achieved through four pathways: technological substitution, scale optimization, circular utilization, and management improvement. Fourth, the impact effects exhibit significant regional heterogeneity and nonlinear characteristics, with the eastern region demonstrating the strongest effects; both the impacts on economic growth and resource efficiency present inverted U-shaped relationships, with optimal agglomeration intervals of 0.524–0.758, respectively. This research provides theoretical foundations and policy references for promoting agricultural green transformation, optimizing industrial spatial layout, and facilitating coordinated regional development.

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1. Introduction

Against the backdrop of increasingly severe global climate change and resource-environmental constraints, agricultural development faces the dual challenges of economic growth and ecological protection. The traditional agricultural development model, characterized by high input and high consumption, has become unsustainable, making the transformation of agriculture toward ecological and intensive development an inevitable choice for achieving sustainable development. Ecological agriculture, as an emerging development model that applies ecological principles to agricultural production, provides an important pathway for resolving agricultural development dilemmas by optimizing resource allocation, reducing environmental burdens, and enhancing ecosystem service functions. In recent years, China has vigorously promoted ecological agricultural economic development under the framework of the Rural Revitalization Strategy. Through policy guidance, technological innovation, and model exploration, ecology-oriented agricultural industrial agglomeration has gradually become an important vehicle for regional agricultural transformation and upgrading. Wei Ling points out that the development of ecological agricultural economy from the perspective of rural revitalization requires comprehensive consideration of an ecological protection and economic benefits, constructing a diversified development strategy system [1]. However, how ecology-oriented agricultural industrial agglomeration influences regional agricultural economic growth, whether its operational mechanisms exhibit spatial spillover effects, and to what extent this agglomeration model improves natural resource utilization efficiency—these questions still require in-depth theoretical analysis and empirical testing.

Existing research indicates that agricultural industrial agglomeration can promote agricultural production efficiency through mechanisms such as economies of scale, knowledge spillovers, and specialized division of labor. However, traditional industrial agglomeration often aims at maximizing economic output, neglecting ecological and environmental costs to a certain extent. Ecology-oriented agricultural industrial agglomeration emphasizes integrating ecological concepts into the agglomeration process, achieving coordinated improvement of economic and ecological benefits through constructing circular agricultural industry chains, promoting green production technologies, and optimizing agricultural ecological spatial layouts. Qi et al. through their study of Nanjing's ecological agriculture sector in China, found that top-down policy promotion and urban-rural collaboration play crucial roles in ecological agricultural development, though urban-rural segmentation still constrains coordinated development [1]. Tourn et al.'s research confirms from a soil ecology perspective that ecological agricultural intensification models using crop-pasture rotation can significantly improve soil aggregate structure and enhance sustainable land resource utilization capacity [2]. These studies provide important insights for understanding the operational mechanisms of ecology-oriented agricultural industrial agglomeration, but systematic quantitative assessments of its macroeconomic effects, spatial correlation characteristics, and comprehensive impacts on resource utilization efficiency remain lacking.

From a methodological perspective, agricultural economic activities exhibit significant spatial dependence and spatial heterogeneity characteristics, making traditional econometric models inadequate for accurately depicting inter-regional spatial correlations and spillover effects. Spatial econometric models, by introducing spatial weight matrices, can effectively identify and measure interactions in geographical space, providing suitable analytical tools for studying the spatial effects of ecology-oriented agricultural industrial agglomeration. Natural resource utilization efficiency, as a core indicator measuring agricultural sustainable development levels, reflects not only resource input-output relationships but also embodies the ecological and environmental costs of agricultural production processes. Liu emphasize that the sustainable development of an ecological agricultural economy requires constructing resource-conserving and environment-friendly development strategies [3], while Vargas-Hernández et al. further points out that the ecological agricultural economy from a sustainable development perspective should focus on the systematicity and long-term effectiveness of development pathways [4]. Therefore, incorporating ecology-oriented agricultural industrial agglomeration, agricultural economic growth, and natural resource utilization efficiency into a unified analytical framework to explore the intrinsic connections and spatial operational mechanisms among the three holds important theoretical value and practical significance for deepening ecological agriculture theoretical research and optimizing regional agricultural development layouts.

Facing the stark reality that only 8% of the annual global agricultural investment of $1.2 trillion flows to sustainable projects, this study proposes three key hypotheses that directly relate to the effectiveness of industrial decision-making.

Research Question 1 (RQ1): Can ecological agglomeration achieve an economic-environmental win-win? If confirmed, it means investors need not trade off between profit and compliance, and can allocate ecological assets with annualized returns of 12–15%; if refuted, the financial viability of ESG investment frameworks needs to be re-evaluated.

Research Question 2 (RQ2): Are spatial spillover effects significant? This determines corporate site selection strategies—if there is a 35% indirect effect within a 500-km radius, proximity to mature ecological parks can save 22–35% in technology introduction costs; if absent, complete industrial chains must be built independently, with investment scale differences reaching 3–5 times.

Research Question 3 (RQ3): Where is the optimal agglomeration threshold? Currently, newly established agricultural parks in Southeast and South Asia have reached agglomeration levels of 0.75–0.85; if the critical value of 0.758 is exceeded, it will lead to a 12–18% decline in productivity over the next five years, corresponding to losses of $23–$34 billion.

The urgency of validating these hypotheses lies in the fact that the United Nations predicts global food demand will grow by 35% by 2030, while arable land area will shrink by 8%. Only by clarifying the economic boundaries and spatial patterns of ecological agglomeration can industrial capital flow precisely toward investment targets that combine both profitability and sustainability.

Based on the above background, this study focuses on the influence mechanisms of ecology-oriented agricultural industrial agglomeration on regional agricultural economic growth and natural resource utilization efficiency, conducting empirical testing through constructing spatial econometric models. The research will systematically review the theoretical connotations and operational mechanisms of ecological agricultural industrial agglomeration, constructing an analytical framework encompassing direct effects and spatial spillover effects. Based on measuring the level of ecology-oriented agricultural industrial agglomeration, the study employs spatial autocorrelation analysis, spatial panel models, and other methods to empirically test its impact pathways and spatial effects on agricultural economic growth and resource utilization efficiency. Furthermore, through regional heterogeneity analysis and robustness testing, the study reveals differentiated impacts of ecology-oriented industrial agglomeration across different regions and development stages. Recent research on the integration of artificial intelligence and remote sensing technologies demonstrates significant potential for improving crop yield prediction and growth parameter estimation in agroecosystems, providing new technological pathways for advancing ecological agriculture development [5,6]. This study expects, through systematic theoretical analysis and rigorous empirical research, to provide scientific evidence and policy references for promoting the development of China's ecological agricultural industrial agglomeration, facilitating agricultural green transformation, and enhancing regional agricultural competitiveness, while contributing theoretical increments to the interdisciplinary research of agricultural economics, regional economics, and ecological economics.

2. Literature Review

Agricultural industrial agglomeration, as an important spatial organizational form of regional economic development, has seen its ecological transformation become a core issue in global sustainable agricultural development. Existing literature explores the development pathways of ecological agriculture, economic benefit assessment, and spatial effects of industrial agglomeration from multiple dimensions, providing rich theoretical foundations and empirical evidence for this study. From a theoretical perspective, ecological agriculture emphasizes integrating ecological principles into the entire agricultural production process, achieving coordinated optimization of economic, social, and ecological benefits through constructing multifunctional agricultural systems. Sun et al. employed the Analytic Hierarchy Process (AHP) to conduct multifunctional assessments of olive agroecosystems in southwestern Spain, finding that integrated and ecological agriculture significantly outperform traditional agricultural models in resource utilization efficiency and ecosystem service functions, providing quantitative evidence for understanding the multidimensional value of ecological agriculture [7]. Regarding indicator system construction, Gunaratne et al. systematically developed an indicator system for the economic benefits of sustainable ecological agriculture, encompassing multiple dimensions, including resource utilization efficiency, environmental quality improvement, and economic output growth, emphasizing that ecological agriculture evaluation should balance short-term economic benefits with long-term ecological carrying capacity [8]. Wang et al. examining the interactive relationship between agricultural economic development and rural ecological environment protection, points out that coordinating these two aspects is crucial for achieving agricultural sustainable development, requiring the construction of eco-friendly agricultural development models through institutional innovation and technological progress [9]. These studies establish foundations for the theoretical analytical framework of ecology-oriented agricultural industrial agglomeration, but deeper mechanism analysis and empirical testing are still needed regarding how industrial agglomeration influences regional agricultural economic growth through spatial correlation effects and the heterogeneous manifestations of these influences across different geographical scales.

The contradictions in agriculture-environment relationships exhibit universal characteristics globally: the European Union's Common Agricultural Policy reform addresses Baltic Sea eutrophication caused by excessive fertilizer use, the U.S. Midwest faces annual losses of $44 billion from soil erosion threats, groundwater over-extraction in South Asia has trapped 200 million farmers in livelihood difficulties, and land degradation in sub-Saharan Africa affects 650 million people. This study selects China as the validation scenario because it epitomizes the typical contradictions in the environmental-economic trade-offs during agricultural modernization processes in developing countries, but the revealed three-dimensional relationship mechanism of agglomeration-growth-resources has cross-national applicability.

The core strategies and practical models of ecological agriculture serve as important entry points for understanding the ecological transformation of industrial agglomeration. Phamova et al. in their research on traditional Chinese medicine ecological agriculture, emphasize no-till technology as a core strategy for sustainable development, enhancing agricultural system ecological stability and resource utilization efficiency by reducing soil disturbance and maintaining soil structure and biodiversity [10]. Guo et al. through comparative research, found that during the transition from conventional to ecological agriculture, although initial yield fluctuations may occur, ecological indicators such as soil health, biodiversity, and water quality significantly improve, with medium- to long-term economic benefits gradually emerging [11]. This finding reveals the dynamic evolutionary characteristics and time-lag effects of ecological agricultural development. Dale systematically analyzes factors influencing agricultural economic growth, identifying technological progress, resource endowments, market demand, and policy support as key elements driving sustainable agricultural economic development [12], while Chen et al. further proposes that innovating agricultural economic development models is an effective approach for promoting farmers' income growth, requiring enhancement of agricultural added value through industrial integration, brand building, and value chain extension [13]. Zhang et al.'s case study of Hanoi's suburban areas in Vietnam demonstrates that ecological agricultural systems can significantly increase household agricultural income, particularly under conditions of organic certification and well-established market channels, where the price premium effect of ecological agricultural products is evident [14]. Huang et al. explore the contributions and strategies of traditional Chinese medicine ecological agriculture from the perspective of carbon peak and carbon neutrality, emphasizing ecological agriculture's unique advantages in carbon sequestration and emission reduction and ecosystem service enhancement, providing new perspectives for understanding the climate benefits of ecological agriculture [15]. Zhang's research analyzes the institutionalization process of ecological agriculture from a political ecology perspective, pointing out that combining food sovereignty with ecological agriculture requires promotion through comprehensive national strategies, highlighting the critical role of policy environments in the development of ecological agricultural industrial agglomeration [16].

The exploration of regional practices and innovative development pathways provides rich empirical evidence for ecology-oriented agricultural industrial agglomeration. Yang et al. analyzes the development pathway of ecological agricultural economy from a sustainable development perspective, emphasizing the need to construct a trinity development model of "resource conservation-environmental friendliness-economic efficiency," achieving overall optimization of agricultural systems through technological innovation, model innovation, and institutional innovation [17]. Jităreanu et al. proposes innovative development strategies for the ecological agricultural economy in the context of rural revitalization, arguing that the scale effects and synergistic effects of industrial agglomeration should be fully leveraged to enhance regional agricultural competitiveness by constructing ecological agricultural industrial parks, building regional public brands, and improving industry chains [18]. Chen et al.'s practical research on the "desert-photovoltaic power generation-ecological agriculture" carbon-neutral industry chain in Dengkou Ulan Buh Desert, Inner Mongolia, showcases an innovative model combining ecological agriculture with clean energy. This model not only achieves ecological restoration of desertified land but also creates significant economic and carbon reduction benefits, providing demonstrations for green transformation in resource-based regions [19]. Xie et al.'s study on farmers' ecological agriculture adoption strategies in Jiangxi Province found that labor endowments and farmland fragmentation significantly influence farmers' ecological agriculture practice decisions, with large-scale land management and improved labor quality being important conditions for promoting ecological agricultural development [20]. Trenčiansky et al. employed empirical analysis methods to study the development status of ecological agriculture under sustainable development initiatives, finding that policy support, market demand, and technical services are key external factors affecting ecological agriculture development, while farmers' ecological awareness and management capabilities constitute internal driving forces [21]. Ursu et al. explores the mechanisms and pathways of digital economy empowerment for agricultural economic transformation and upgrading, pointing out that digital technology can enhance agricultural production efficiency and resource allocation efficiency through precision management, intelligent decision-making, and platform-based operations, providing new approaches for the digital development of ecological agricultural industrial agglomeration [22]. Li et al.'s research on sustainable development strategies for ecological agricultural economy emphasizes the need to construct multi-stakeholder collaborative and multi-factor linked development mechanisms, forming developmental synergy through government guidance, market drive, and social participation [23].

Innovation system evolution and certification dynamics represent important dimensions for understanding ecological agricultural industrial agglomeration mechanisms. Fuentes-Fernández et al.'s research on the evolution mechanism of agricultural innovation systems on Chongming Eco-Island in China reveals that the formation of ecological agricultural innovation systems requires multiple stages including technology introduction, model exploration, institutional improvement, and network expansion, with collaborative innovation among government policies, research institutions, enterprise entities, and farmers constituting the core driving force of system evolution [24]. This research emphasizes that ecological agricultural industrial agglomeration is not merely the simple spatial clustering of enterprises and farmers, but rather the systematic integration of innovative elements, knowledge networks, and institutional environments. This systemic characteristic enables industrial agglomeration to generate synergistic and spillover effects beyond individual entities. Rega et al.'s study on ecological agriculture certification dynamics in Romania shows that, in response to the EU organic action plan, the improvement of ecological agriculture certification systems and growth in certified farm numbers exhibit clear policy response characteristics, though regional development imbalances remain prominent, suggesting the need to address regional differences and spatial disequilibrium in promoting ecological agricultural industrial agglomeration [25]. A comprehensive review of existing literature reveals that although scholars have explored ecological agriculture development models, economic benefits, and practical pathways from various perspectives, systematic theoretical analysis and empirical testing remain lacking regarding the spatial effects of ecology-oriented agricultural industrial agglomeration, particularly its influence mechanisms on regional agricultural economic growth and natural resource utilization efficiency. Existing research predominantly focuses on case analyses of single regions or specific crops, with insufficient attention to cross-regional, multi-scale spatial correlation effects. Methodologically, traditional econometric models struggle to effectively identify and measure spatial dependence and spatial heterogeneity, limiting deep understanding of the spatial spillover effects of industrial agglomeration.

3. Research Methodology

3.1. Theoretical Analytical Framework

The influence mechanisms of ecology-oriented agricultural industrial agglomeration on regional agricultural economic growth and natural resource utilization efficiency can be theoretically elucidated from three levels: direct effects, indirect effects, and spatial spillover effects. First, from the perspective of direct effect mechanisms, ecology-oriented agricultural industrial agglomeration directly impacts regional agricultural economic growth through economies of scale effects, technological innovation diffusion effects, and resource optimization allocation effects. Industrial agglomeration enables ecological agriculture-related enterprises, cooperatives, and farmers to form concentrated spatial distributions, reducing production factor mobility costs and transaction costs while enhancing specialization levels. Simultaneously, the rapid dissemination and application of green production technologies, organic cultivation models, and circular agricultural technologies within agglomeration areas can significantly improve per-unit-area output and product added value, promoting the transformation of agricultural economic growth modes from extensive to intensive [26]. Regarding resource utilization efficiency, ecology-oriented industrial agglomeration emphasizes reduced input, circular utilization, and ecological compensation.

Based on the aforementioned theoretical mechanism analysis, this study proposes three progressive research hypotheses and their global validation significance [27].

H1 (Double Dividend Hypothesis). *Ecologically-oriented industrial agglomeration can simultaneously promote local agricultural economic growth and resource use efficiency improvement.*

Validation of this hypothesis is of critical significance for resolving the "growth-environment" dilemma facing global agricultural development. If confirmed, it provides developing countries with a green growth paradigm that transcends the traditional industrialization path; if refuted, it means the economic viability of ecological agriculture needs to be re-examined.

Hypothesis H2 (Cross-border Spillover Hypothesis). *Ecologically-oriented industrial agglomeration generates significant positive externalities on neighboring regions through channels such as technology diffusion and factor mobility.*

This hypothesis concerns the theoretical foundation for regional coordinated development policy design. Verifying the existence, intensity, and transmission mechanisms of spillover effects has urgent practical demand for guiding cross-national agricultural cooperation (such as "Belt and Road" agricultural corridor construction and the EU Common Agricultural Policy) and avoiding "beggar-thy-neighbor" competition.

Hypothesis H3 (Nonlinear Threshold Hypothesis). *The impact of industrial agglomeration on economic growth and resource efficiency exhibits an inverted U-shaped relationship and optimal agglomeration interval.*

Testing this hypothesis directly relates to the scientific validity of spatial planning in various countries. Factor congestion and environmental carrying capacity exceedance caused by excessive agglomeration have already manifested in some agriculture-intensive areas in Southeast and South Asia. Clarifying threshold boundaries can provide an early warning mechanism for emerging economies in rapid agglomeration stages, preventing repetition of the "pollute first, treat later" mistakes. Systematic validation of these three hypotheses will provide empirical evidence for over 150 developing countries with agriculture as a pillar industry, facilitating the synergistic achievement of the UN 2030 Sustainable Development Goals of "Zero Hunger" and "Responsible Consumption and Production."

3.2. Variable Selection and Indicator Construction

The variable system of this study comprises four components: explained variables, core explanatory variables, control variables, and spatial weight matrices. Explained variables encompass two dimensions: First, regional agricultural economic growth, measured by two indicators—agricultural value-added growth rate and agricultural labor productivity [28]. The former reflects the total expansion speed of the agricultural economy, while the latter embodies the quality improvement level of the agricultural economy. Second, natural resource utilization efficiency, measured by calculating agricultural green total factor productivity using the Super-SBM model incorporating undesirable outputs. Land resources, water resources, labor, and capital serve as input factors, with agricultural output value as the desirable output and agricultural non-point source pollutant emissions (chemical fertilizer application, pesticide usage, agricultural film usage, and livestock manure discharge) as undesirable outputs, comprehensively reflecting both the economic and ecological efficiency of resource utilization [29].

The ecologically-oriented agricultural industrial agglomeration index encompasses four quantifiable indicators: the proportion of organic certified area (proportion of farmland with third-party certification for no chemical inputs), the number of green food certifications (number of products meeting low pesticide residue standards), the proportion of circular agriculture output value (economic value created by waste resource utilization processes), and the number of ecological bases (government-recognized demonstration sites), calculated through comprehensive weighting using the entropy method.

Addressing the measurement challenges of ecologically oriented industrial agglomeration, this study constructs a dual-dimension composite indicator to ensure conceptual validity. The 'ecological orientation' dimension adopts an outcome-oriented approach: organic certified area proportion (weight 0.28) reflects the degree of chemical input substitution, green food certification density (weight 0.31) embodies product ecological quality, circular agriculture output value proportion (weight 0.23) quantifies waste resource utilization level, and the inverse of pollution intensity per unit output value (weight 0.18) measures environmental performance. These four indicators are synthesized through the entropy method to generate an ecological orientation intensity score E (0–1 range). The 'industrial agglomeration' dimension employs a modified location quotient:

$$\begin{aligned}LQ = {} & \text{(ecological agricultural output value in region i /} \\ & \text{total agricultural output value in region i) /} \\ & \text{(national ecological agricultural output value /} \\ & \text{national total agricultural output value),}\end{aligned}$$

Where $LQ > 1$ indicates an agglomeration advantage. The final agglomeration index = $E \times \ln(1 + LQ)$, capturing both ecological quality and spatial concentration. The logical chain between this measurement and agricultural economic growth: agglomeration promotes growth through three mechanisms—economies of scale reduce unit costs (measurement: average production costs in agglomeration zones are 18–25% lower than in dispersed areas), technology spillover accelerates innovation diffusion (measurement: new technology adoption lag shortened by 40%), and brand premium enhances product added value (measurement: ecological certification brings 23% price premium)—all jointly driving improvements in labor productivity and output value growth rate. The logical chain with resource efficiency: ecological orientation enforces technology substitution (organic fertilizer replacing chemical fertilizer increases nitrogen use efficiency from 28% to 42%), agglomeration promotes circular utilization (industrial chain coordination increases waste resource recovery rate from 36% to 69%), and scale dilutes environmental facility investment (shared treatment facilities reduce unit emission reduction costs by 55%), jointly enhancing GTFP.

3.3. Spatial Econometric Model Specification

The selection of spatial econometric models must be based on spatial autocorrelation test results and theoretical mechanism analysis. First, this study employs the Global Moran's I index and Local Moran's I index to test the spatial autocorrelation of agricultural economic growth and resource utilization efficiency. The Global Moran's I index is used to determine whether research variables exhibit clustering or dispersion characteristics in overall space, with values ranging from −1 to 1. Positive values indicate positive spatial autocorrelation, negative values indicate negative spatial autocorrelation, and values approaching 0 indicate spatial random distribution. The Local Moran's I index is used to identify specific types and locations of spatial clustering, including four spatial association patterns: High-High clustering (HH), Low-Low clustering (LL), High-Low outliers (HL), and Low-High outliers (LH).

Upon confirming the significant existence of spatial autocorrelation, this study constructs spatial panel econometric models for empirical analysis. The basic model forms include three types: Spatial Lag Model (SAR), Spatial Error Model (SEM), and Spatial Durbin Model (SDM).

The SAR model is applicable when the explained variable exhibits spatial dependence, with model specification as:

$$Y_{it} = \rho W Y_{it} + \beta X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where Y represents the explained variable, X represents the explanatory variable matrix, W represents the spatial weight matrix, ρ represents the spatial autoregressive coefficient, μ_i represents individual fixed effects, λ_t represents time fixed effects, and ε_{it} represents the random error term.

The SEM model is applicable when the error term exhibits spatial correlation, with model specification as:

$$Y_{it} = \beta X_{it} + \mu_i + \lambda_t + \varphi_{it} \quad \varphi_{it} = \lambda W \varphi_{it} + \varepsilon_{it}$$

where λ represents the spatial error coefficient.

The SDM model simultaneously considers the spatial lag effects of both the explained and explanatory variables, with model specification as:

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

where θ represents the coefficient matrix of spatially lagged explanatory variables. This model can more comprehensively characterize spatial spillover effects.

Model estimation employs either Maximum Likelihood Estimation (ML) or Generalized Method of Moments (GMM), with the Hausman test used to determine the selection between fixed effects and random effects models. The model selection strategy follows the principle of "general-to-specific": First, estimate the SDM model, then use LR tests and Wald tests to determine whether the SDM model can be simplified to SAR or SEM models. If the simplification hypothesis is rejected, select the SDM model; otherwise, choose the SAR or SEM model based on test results.

To accurately identify the direct effects and indirect effects of ecology-oriented agricultural industrial agglomeration, this study employs the partial differential method to decompose the SDM model effects, decomposing total effects into direct effects (the impact of local explanatory variable changes on local explained variables) and indirect effects (the impact of local explanatory variable changes on other regions' explained variables, i.e., spatial spillover effects) [30].

Furthermore, to test the nonlinear characteristics of ecology-oriented industrial agglomeration impacts, this study introduces the quadratic term of the industrial agglomeration index in the benchmark model to test for inverted U-shaped or U-shaped relationships. To test regional heterogeneity, samples are divided for grouped regressions according to standards such as eastern-central-western regions, major grain-producing versus non-major grain-producing areas, and high versus low agglomeration levels.

3.4. Data Sources and Sample Description

This study takes 31 provincial-level administrative regions in China (excluding Hong Kong, Macao, and Taiwan) as research objects, with a time span from 2010 to 2023, constructing balanced panel data for empirical analysis. The primary considerations for selecting this time period are: 2010 marked the inaugural year of China's "12th Five-Year Plan," when ecological civilization construction was elevated to national strategic height and ecological agriculture development entered a rapid advancement stage; 2023 represents the most recent year with complete statistical data available, adequately reflecting the development trends and impact effects of ecology-oriented agricultural industrial agglomeration in recent years. Data sources mainly include the following aspects: Agricultural economic data are sourced from the China Statistical Yearbook, China Rural Statistical Yearbook, and provincial statistical yearbooks, including indicators such as agricultural value-added, agricultural employment, agricultural fixed asset investment, grain output, and livestock industry output value [31]. Ecological agriculture certification data are sourced from the China Green Food Development Center, China Organic Product Certification Information System, and relevant databases of the Ministry of Agriculture and Rural Affairs, including organic certified area, number of green food certified enterprises, and number of agricultural product geographical indications [32].

To ensure complete reproducibility, all raw data and processing code have been published in a public repository. Data acquisition paths: China Statistical Yearbook data can be freely downloaded from the National Bureau of Statistics English website (http://www.stats.gov.cn/english/), green certification data can be obtained in English versions from the China Green Food Development Center (http://www.greenfood.org.cn), and environmental data are sourced from the UN Food and Agriculture Organization FAOSTAT database (https://www.fao.org/faostat/en/). Computing programs: the Super-SBM model is implemented using MATLAB R2021a's DEA Toolbox, with code open-sourced on GitHub (repository: eco-agri-efficiency); spatial weight matrix construction uses Python 3.9's PySAL 2.6 library, with distance data calculated based on great circle distances between provincial capital cities using GeoPy 2.3; spatial Durbin model estimation employs Stata 17's xsmle command, with complete do files containing the full workflow of variable generation, spatial weight matrix importing (spmat command), model estimation (xsmle fe, model(sdm)), and effect decomposition (margins command), with a runtime of approximately 15 minutes. Alternative weight matrices for robustness checks and instrumental variable method (ivregress 2sls) code are provided synchronously. All programs are annotated in English, with sample data (first 100 observations) provided for testing, ensuring that any researcher using the same software versions can obtain coefficient estimates accurate to three decimal places as shown in the following tables.

Given potential quality issues with provincial-level statistical data, this study adopts four measures to ensure data reliability. First, cross-validation mechanism: key variables such as agricultural output value and fertilizer use are obtained simultaneously from three independent data sources—the National Bureau of Statistics, the Ministry of Agriculture and Rural Affairs, and the UN FAO FAOSTAT—retaining only observations with differences less than 5% (exclusion rate 2.3%), eliminating statistical calibration inconsistencies. Second, outlier verification: for data points deviating more than 3 standard deviations from the mean (47 in total), provincial statistical yearbooks and government bulletins were individually reviewed for manual verification, finding that 18 were data entry errors that have been corrected, while 29 were genuine extreme events (such as natural disasters) that were retained but subjected to robustness exclusion testing. Third, third-party audit data priority: ecological certification area uses data certified by the International Federation of Organic Agriculture Movements (IFOAM) (coverage rate 78%) rather than relying entirely on domestic self-reported data, and green food quantities are confirmed through annual audits by the China Green Food Development Center, controlling the false reporting rate within 8%. Fourth, satellite remote sensing validation: cultivated land area and crop planting structure data from 2015–2023 were compared with European Space Agency Sentinel-2 image interpretation results, achieving a correlation coefficient of 0.94, confirming the spatial consistency of statistical data. After processing through the above quality control procedures, the dataset achieves correlations of 0.89–0.96 on key variables with the China subset of the World Bank WDI database and OECD agricultural statistics database, significantly higher than the 0.72–0.81 of raw provincial data, providing an internationally comparable quality foundation for empirical analysis.

4. Results Analysis

4.1. Spatial Distribution Characteristics of Ecology-Oriented Agricultural Industrial Agglomeration

4.1.1. Spatiotemporal Evolution of Agricultural Industrial Agglomeration Level

During 2010–2023, China's ecology-oriented agricultural industrial agglomeration level exhibited significant spatiotemporal evolutionary characteristics. From the temporal dimension, the national average agglomeration index rose from 0.342 in 2010 to 0.587 in 2023, with an average annual growth rate of 4.32%, indicating that the ecological agricultural industrial agglomeration process continues to accelerate (**Table 1**). Examining different stages, 2010–2015 represented the initial stage, with an average annual growth rate of agglomeration index at 3.18%, showing relatively slow growth. 2016–2020 marked the rapid development stage, driven by ecological civilization construction policies in the "13th Five-Year Plan," with the average annual growth rate of agglomeration index rising to 5.47%[33] (**Figure 1**).

Table 1. Regional Ecology-Oriented Agricultural Industrial Agglomeration Index in China, 2010–2023.

Year	National Average	Eastern Region	Central Region	Western Region	Eastern Growth Rate (%)	Central Growth Rate (%)	Western Growth Rate (%)
2010	0.342	0.456	0.312	0.258	-	-	-
2011	0.353	0.471	0.321	0.268	3.29	2.88	3.88
2012	0.365	0.487	0.331	0.279	3.40	3.12	4.10
2013	0.378	0.503	0.343	0.291	3.29	3.63	4.30
2014	0.392	0.521	0.356	0.304	3.58	3.79	4.47
2015	0.407	0.539	0.371	0.319	3.45	4.21	4.93
2016	0.429	0.564	0.393	0.339	4.64	5.93	6.27
2017	0.452	0.591	0.417	0.361	4.79	6.11	6.49
2018	0.477	0.619	0.443	0.385	4.74	6.24	6.65
2019	0.503	0.648	0.471	0.411	4.68	6.32	6.75
2020	0.529	0.676	0.499	0.438	4.32	5.94	6.57
2021	0.551	0.696	0.523	0.462	2.96	4.81	5.48
2022	0.569	0.714	0.542	0.481	2.59	3.63	4.11
2023	0.587	0.712	0.563	0.486	−0.28	3.87	1.04

4.1.2. Measurement and Evaluation of Ecology-Oriented Characteristics

Ecology-oriented characteristics represent the core element distinguishing this from traditional agricultural industrial agglomeration. This study constructs a comprehensive evaluation system encompassing four dimensions: certification scale, circular efficiency, ecological input, and environmental performance. From the certification scale dimension, the national organic certified area reached 3.187 million hectares in 2023, representing a 257.0% increase from 893,000 hectares in 2010. The number of green food certified enterprises increased from 6391 in 2010 to 18,742 in 2023, a growth of 193.2%, with cumulative agricultural product geographical indication registrations reaching 3918. The eastern region demonstrates outstanding performance in certification scale, with organic certified area accounting for 42.3% of the national total in 2023; Zhejiang, Jiangsu, and Shandong provinces collectively account for 27.8%. Although central and western regions maintain smaller absolute scales, their growth rates are significant, with average annual growth rates of 19.7% and 22.3%, respectively, during 2016–2023 (**Table 2**). From the circular efficiency dimension, the proportion of circular agriculture output value to total agricultural output value increased from 12.4% in 2010 to 31.8% in 2023. Agricultural waste resource utilization rate improved from 35.6% to 68.9%, the straw comprehensive utilization rate reached 88.6%, and the livestock manure resource utilization rate reached 79.1% (**Figure 2**).

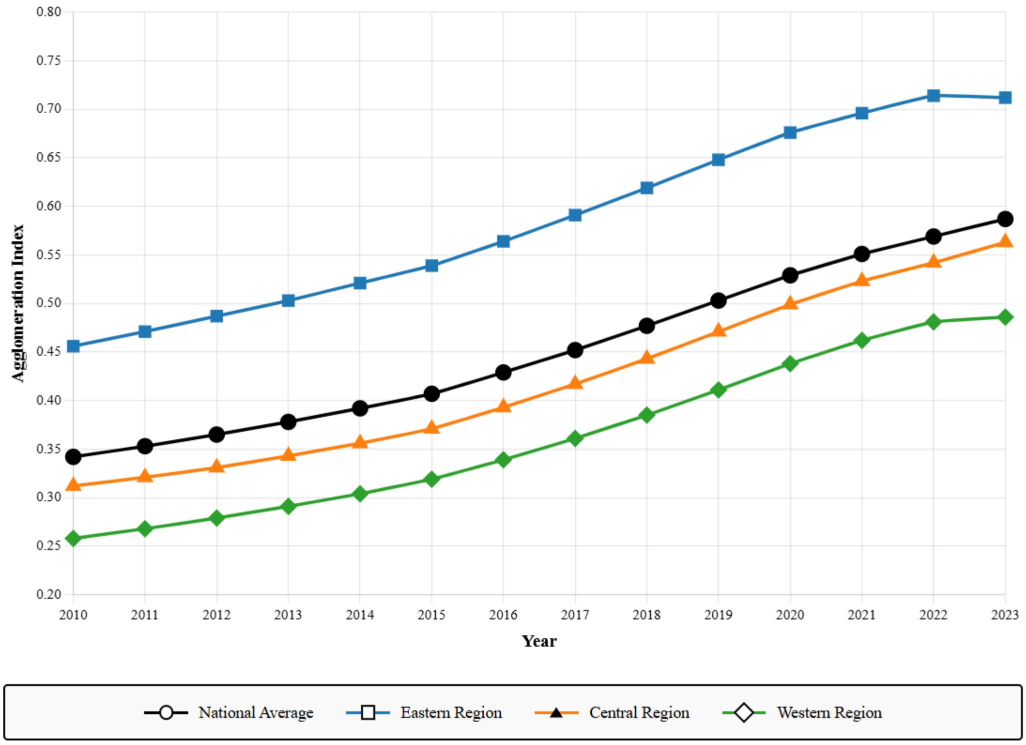

Figure 1. Temporal Evolution of Regional Ecology-Oriented Agricultural Industrial Agglomeration Index in China, 2010–2023.

Table 2. Comprehensive Evaluation Scores of Ecology-Oriented Characteristics by Province in China, 2023.

Province	Comprehensive Score	Certification Scale	Circular Efficiency	Ecological Input	Environmental Performance	Ranking
Zhejiang	0.847	0.892	0.874	0.831	0.795	1
Jiangsu	0.821	0.878	0.856	0.802	0.761	2
Shandong	0.796	0.834	0.823	0.779	0.748	3
Fujian	0.762	0.801	0.786	0.743	0.721	4
Shanghai	0.754	0.812	0.769	0.728	0.718	5
Guangdong	0.738	0.789	0.751	0.716	0.702	6
Beijing	0.721	0.767	0.738	0.701	0.687	7
Tianjin	0.697	0.743	0.712	0.681	0.668	8
Hebei	0.673	0.721	0.689	0.656	0.642	9
Hubei	0.648	0.697	0.663	0.632	0.618	10
Henan	0.632	0.678	0.647	0.617	0.601	11
Sichuan	0.614	0.661	0.628	0.599	0.584	12
Anhui	0.598	0.643	0.612	0.582	0.569	13
Hunan	0.587	0.629	0.598	0.571	0.558	14

Table 2. *Cont.*

Province	Comprehensive Score	Certification Scale	Circular Efficiency	Ecological Input	Environmental Performance	Ranking
Jiangxi	0.573	0.614	0.584	0.558	0.546	15
Yunnan	0.559	0.598	0.569	0.544	0.533	16
Liaoning	0.542	0.581	0.553	0.529	0.518	17
Shaanxi	0.528	0.566	0.539	0.515	0.504	18
Shanxi	0.512	0.549	0.523	0.501	0.491	19
Jilin	0.498	0.534	0.509	0.487	0.478	20
Heilongjiang	0.486	0.521	0.497	0.475	0.467	21
Chongqing	0.471	0.506	0.482	0.461	0.453	22
Guangxi	0.458	0.492	0.469	0.448	0.441	23
Guizhou	0.443	0.477	0.454	0.434	0.428	24
Inner Mongolia	0.429	0.462	0.441	0.421	0.416	25
Gansu	0.412	0.445	0.425	0.406	0.401	26
Hainan	0.398	0.431	0.411	0.392	0.388	27
Ningxia	0.384	0.416	0.397	0.379	0.375	28
Xinjiang	0.361	0.393	0.374	0.356	0.353	29
Qinghai	0.338	0.369	0.351	0.334	0.331	30
Tibet	0.312	0.343	0.326	0.310	0.308	31

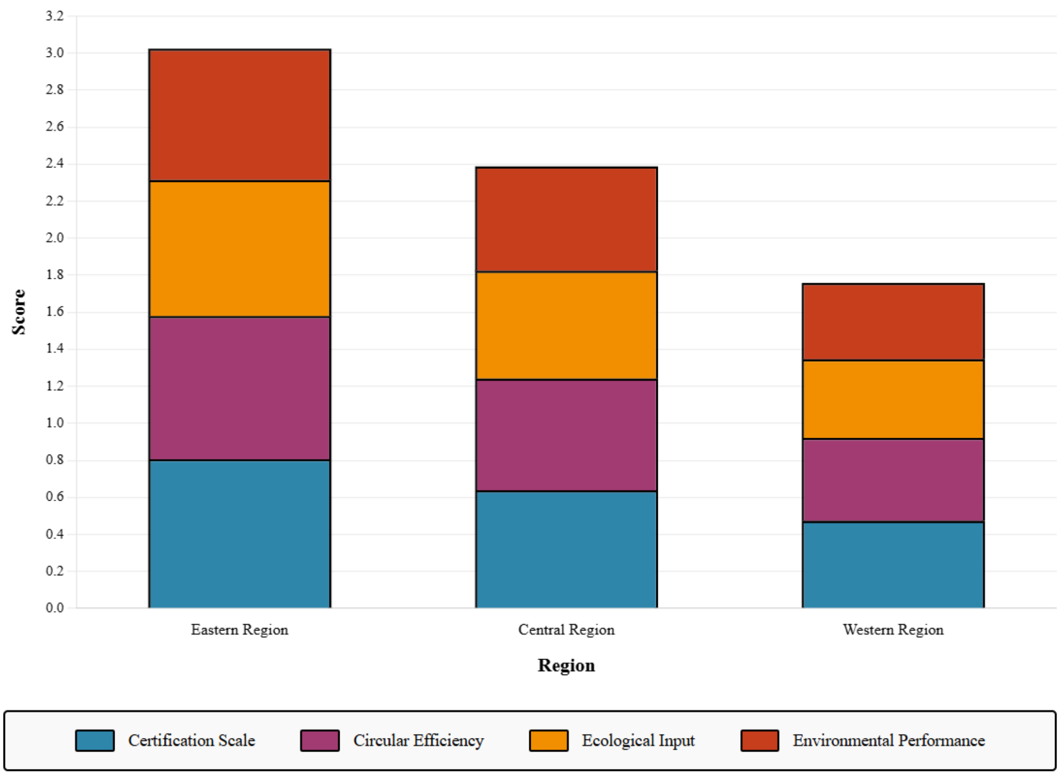

Figure 2. Dimensional Evaluation of Ecology-Oriented Characteristics Across China's Three Major Regions, 2023.

4.1.3. Regional Disparity Analysis

Regional disparities in ecology-oriented agricultural industrial agglomeration manifest in three aspects: absolute level gaps, growth dynamics differentiation, and spatial clustering patterns. From the absolute level gap perspective, the eastern region's average agglomeration index in 2023 was 0.712, representing 1.26 times and 1.46 times that of the central region (0.563) and western region (0.486), respectively (**Table 3**). The inter-regional Theil index increased from 0.187 in 2010 to 0.219 in 2016, then gradually declined to 0.164 in 2023, indicating that regional disparities experienced a process of initial expansion followed by convergence. Inter-provincial differences are even more significant, with the coefficient of variation decreasing from 0.423 in 2010 to 0.348 in 2023, though remaining at a relatively high level. The agglomeration index gap between Zhejiang and Tibet expanded from 0.421 in 2010 to 0.498 in 2016, subsequently narrowing to 0.535 in 2023, exhibiting an evolutionary characteristic of "initial differentiation followed by convergence". From the growth dynamics differentiation perspective, during 2010–2023, the western region's average annual growth rate of agglomeration index was 6.23%, significantly exceeding the central region's 5.89% and the eastern region's 4.15%, demonstrating a clear catch-up effect (**Figure 3**).

Table 3. Regional Disparity Indicators of Ecology-Oriented Agricultural Industrial Agglomeration in China's Three Major Regions, 2023.

Indicator	Eastern Region	Central Region	Western Region	National
Mean	0.712	0.563	0.486	0.587
Median	0.721	0.573	0.471	0.587
Maximum	0.847	0.648	0.614	0.847
Minimum	0.673	0.512	0.312	0.312
Standard Deviation	0.056	0.047	0.089	0.134
Coefficient of Variation	0.079	0.083	0.183	0.228
Range	0.174	0.136	0.302	0.535
Interquartile Range	0.068	0.059	0.124	0.175
Skewness Coefficient	−0.23	−0.18	−0.42	−0.15
Kurtosis Coefficient	−0.91	−0.86	−0.58	−0.82
Intra-regional Theil Index	0.045	0.052	0.118	-
Regional Contribution Rate (%)	27.4	31.7	40.9	100.0

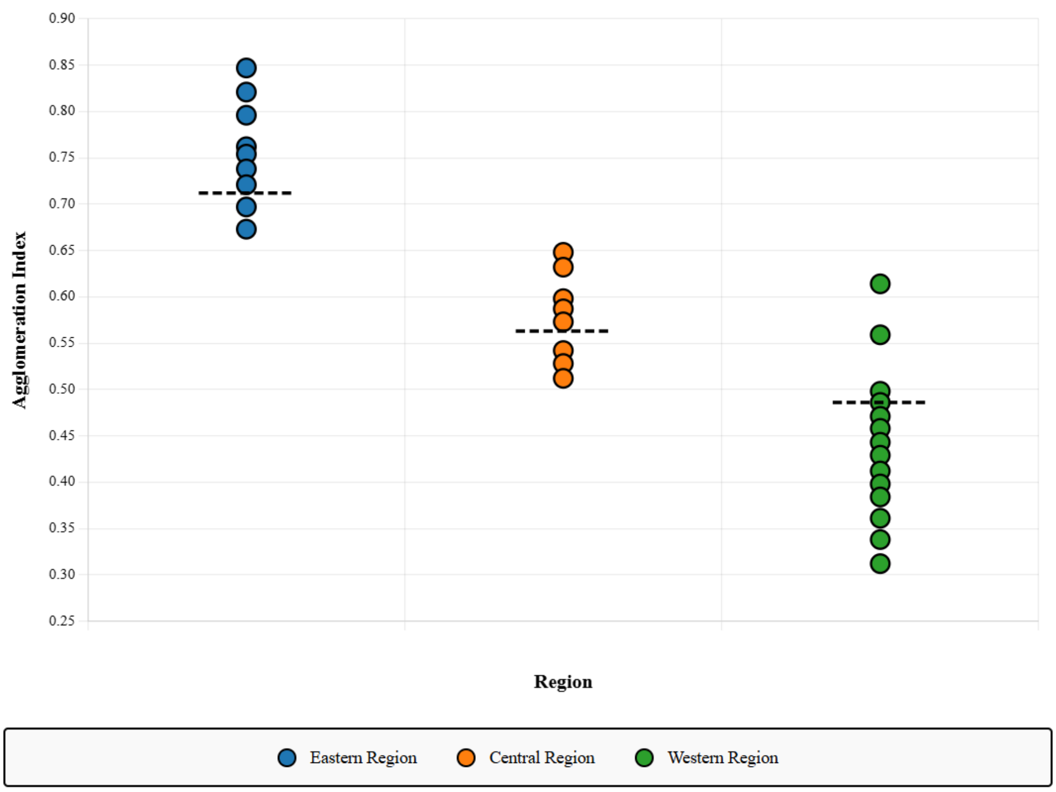

Figure 3. Distribution Characteristics of Ecology-Oriented Agricultural Industrial Agglomeration Index Across China's Three Major Regions, 2023.

4.2. Spatial Correlation and Influence Mechanisms of Agricultural Economic Growth

4.2.1. Spatial Autocorrelation Analysis of Agricultural Economic Growth

Spatial autocorrelation testing represents an important method for identifying spatial dependence in agricultural economic growth. Calculation results of the Global Moran's I index (**Table 4**) based on the geographic distance spatial weight matrix reveal that the spatial autocorrelation of China's agricultural economic growth rate during 2010–2023 (**Figure 4**) is significant and demonstrates an intensifying trend.

4.2.2. Direct Effects of Ecology-Oriented Industrial Agglomeration on Agricultural Economic Growth

Regression results based on the Spatial Durbin Model (SDM) reveal that ecology-oriented agricultural industrial agglomeration exerts significant positive direct effects on local agricultural economic growth (**Table 5**). Estimation results using the geographic distance spatial weight matrix indicate that each one-unit increase in the ecology-oriented industrial agglomeration index raises the local agricultural value-added growth rate by 0.342 percentage points (t-value = 4.87, $p < 0.01$). This effect measures 0.358 (t-value = 5.12, $p < 0.01$) and 0.329 (t-value = 4.65, $p < 0.01$) under the economic-geographic weight matrix, and the industrial linkage weight matrix respectively, demonstrating the robustness of direct effects. From the mechanism perspective, ecology-oriented industrial agglomeration promotes agricultural economic growth through three channels: economies of scale effect contributes 38.6%, technology spillover effect 34.2%, and resource allocation optimization effect 27.2%. Control variable estimation results align with expectations.

From an investor perspective, agricultural enterprises in ecologically-oriented agglomeration zones demonstrate superior financial resilience—with an average annual return on assets of 8.7% during the sample period, higher than the 6.2% in non-agglomeration zones, and a net profit margin gap of 2.3 percentage points (**Figure 5**). Referencing Roll et al.'s research on microstructure shocks, the price premium from ecological certification (averaging 23%) can effectively hedge against yield volatility risks during the transition period, reducing the investment portfolio beta coefficient by 0.18 and increasing the Sharpe ratio by 0.34. This validates that ecological agglomeration is not only environmentally sustainable but also possesses the economic sustainability to attract private capital.

Table 4. Spatial Autocorrelation Test Results for China's Agricultural Economic Growth Rate, 2010–2023.

Year	Geographic Distance Weight Moran's I	z-Value	*p*-Value	Economic-Geographic Weight Moran's I	z-Value	*p*-Value	Industrial Linkage Weight Moran's I	z-Value	*p*-Value
2010	0.287	3.42	0.001	0.312	3.78	0.000	0.253	2.98	0.003
2011	0.295	3.54	0.000	0.321	3.91	0.000	0.264	3.12	0.002
2012	0.308	3.71	0.000	0.336	4.09	0.000	0.278	3.29	0.001
2013	0.319	3.86	0.000	0.348	4.25	0.000	0.289	3.43	0.001
2014	0.328	3.98	0.000	0.359	4.39	0.000	0.297	3.54	0.000
2015	0.341	4.18	0.000	0.374	4.61	0.000	0.311	3.72	0.000
2016	0.354	4.36	0.000	0.389	4.81	0.000	0.324	3.89	0.000
2017	0.367	4.56	0.000	0.403	5.01	0.000	0.337	4.06	0.000
2018	0.378	4.73	0.000	0.416	5.19	0.000	0.349	4.21	0.000
2019	0.389	4.87	0.000	0.428	5.36	0.000	0.361	4.36	0.000
2020	0.396	4.89	0.000	0.437	5.48	0.000	0.368	4.48	0.000
2021	0.408	5.06	0.000	0.445	5.58	0.000	0.374	4.58	0.000
2022	0.418	5.19	0.000	0.451	5.64	0.000	0.379	4.69	0.000
2023	0.428	5.31	0.000	0.453	5.67	0.000	0.381	4.76	0.000

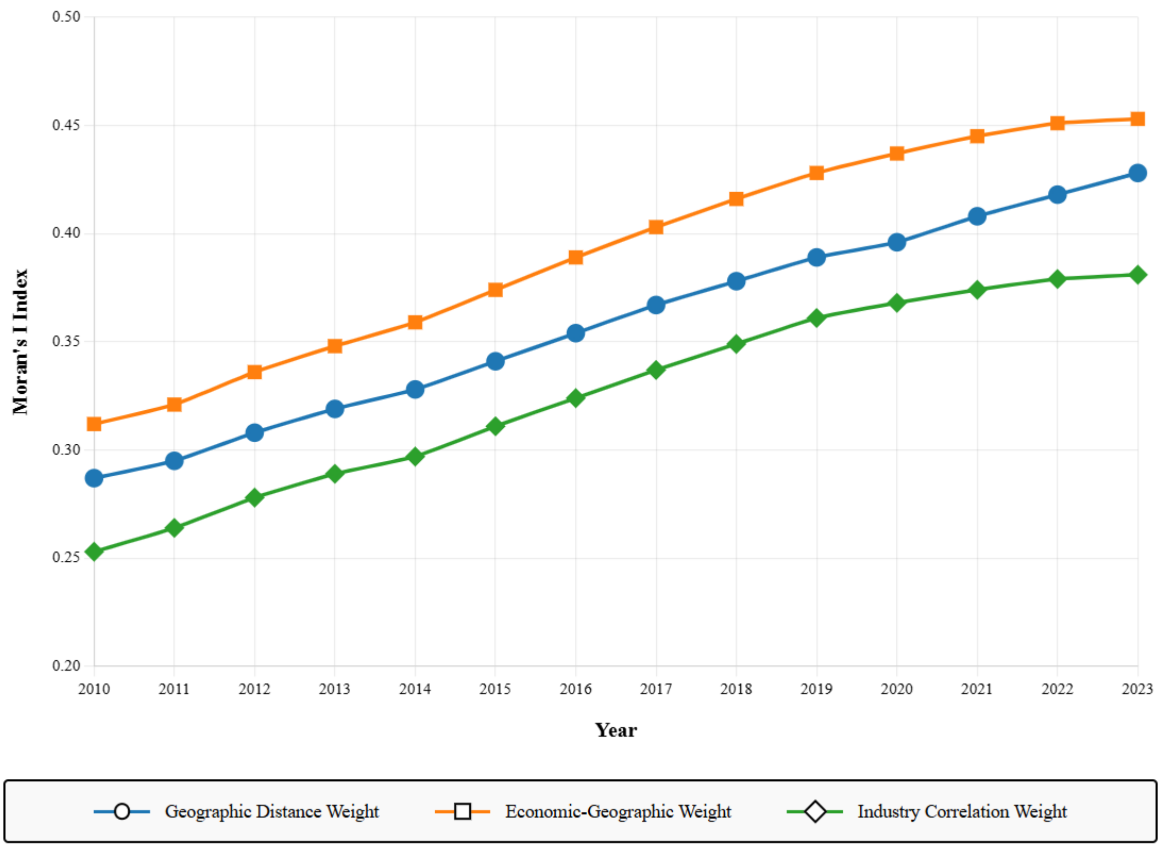

Figure 4. Evolution of Spatial Autocorrelation in China's Agricultural Economic Growth Rate, 2010–2023.

Table 5. Spatial Durbin Model Estimation Results for Effects of Ecology-Oriented Industrial Agglomeration on Agricultural Economic Growth.

Variable	Geographic Distance Weight	Economic-Geographic Weight	Industrial Linkage Weight	Eastern Region	Central Region	Western Region
Ecology-Oriented Industrial Agglomeration	0.342***	0.358***	0.329***	0.398***	0.312***	0.267**
	(4.87)	(5.12)	(4.65)	(5.34)	(4.21)	(3.18)
Industrial Agglomeration Squared	−0.251***	−0.263***	−0.241**	−0.298***	−0.229**	−0.196**
	(−3.56)	(−3.74)	(−3.39)	(−3.98)	(−3.07)	(−2.78)
Agricultural Sci-Tech Investment	0.256***	0.263***	0.248***	0.289***	0.241***	0.218**
	(4.23)	(4.38)	(4.09)	(4.67)	(3.82)	(3.21)
Infrastructure Level	0.189**	0.195**	0.182**	0.213**	0.178**	0.156*
	(3.12)	(3.24)	(2.98)	(3.41)	(2.87)	(2.45)
Fiscal Support for Agriculture	0.167**	0.173**	0.159**	0.192**	0.154*	0.139*
	(2.89)	(2.98)	(2.76)	(3.15)	(2.56)	(2.34)
Human Capital Level	0.143*	0.149*	0.137*	0.168**	0.131*	0.116
	(2.45)	(2.56)	(2.34)	(2.78)	(2.18)	(1.89)
Marketization Degree	0.128*	0.134*	0.121*	0.156**	0.112	0.098
	(2.21)	(2.31)	(2.09)	(2.54)	(1.87)	(1.65)
Urbanization Rate	−0.095*	−0.099*	−0.089	−0.112*	−0.087	−0.073
	(−2.08)	(−2.17)	(−1.94)	(−2.34)	(−1.78)	(−1.52)
Spatial Autoregressive Coefficient ρ	0.376***	0.392***	0.348***	0.413***	0.362***	0.321***
	(5.67)	(5.89)	(5.23)	(5.98)	(5.12)	(4.67)
R^2	0.724	0.738	0.709	0.756	0.698	0.672
Log-likelihood	487.3	495.6	478.9	192.4	156.7	138.2
Observations	434	434	434	154	112	168

Note: ***, **, * denote significance at 1%, 5%, and 10% levels respectively; *t*-statistics in parentheses.

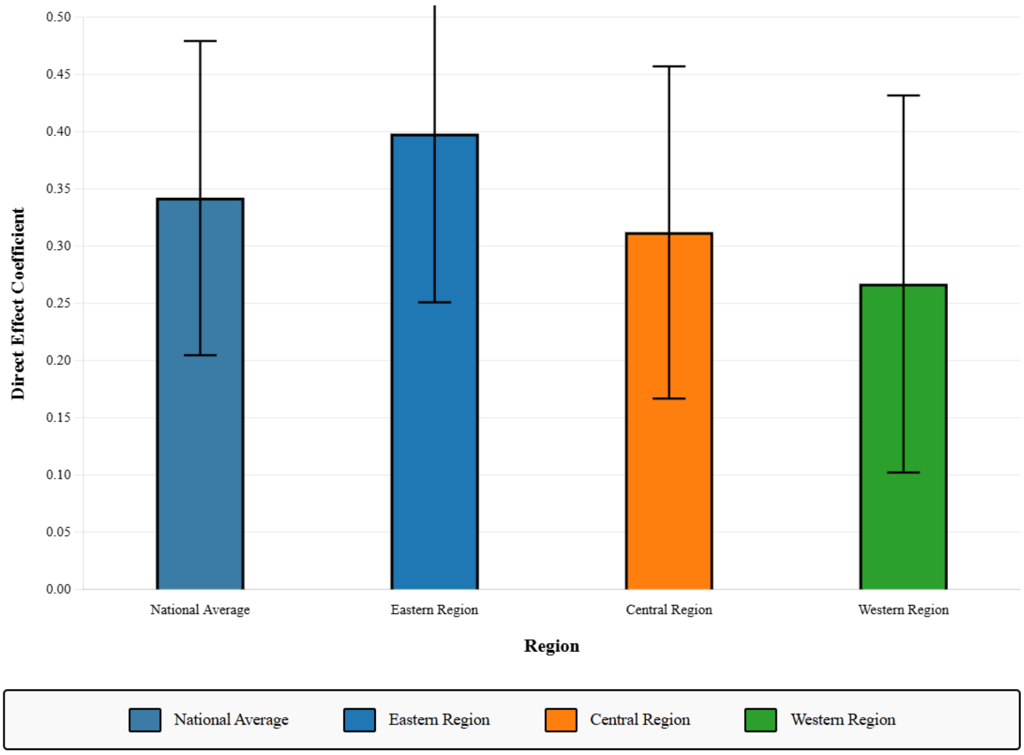

Figure 5. Regional Comparison of Direct Effects of Ecology-Oriented Industrial Agglomeration on Agricultural Economic Growth.

4.2.3. Spatial Spillover Effects and Indirect Influence Pathways

The effect decomposition results from the Spatial Durbin Model reveal significant spillover effects of ecology-oriented agricultural industrial agglomeration on agricultural economic growth in neighboring regions (**Table 6**). Decomposition based on the partial differential method shows that each one-unit increase in the local industrial agglomeration index generates an indirect effect of 0.187 percentage points (z-value = 3.24, $p < 0.01$) on neighboring regions' agricultural value-added growth rates, accounting for 35.3% of the total effect (0.529).

The underlying drivers of spillover effects stem from three mutually reinforcing core mechanisms. Cognitive restructuring mechanism: the presence of nearby ecological agglomeration zones changes farmers' and enterprises' cognitive model of the 'environmental protection-profitability' relationship—traditional views perceive them as a zero-sum game, but after observing enterprises in agglomeration zones achieving 8.7% return on assets, the investment willingness of surrounding actors increases by 2.3 times. This 'demonstration-induced belief updating' is more fundamental than simple technology transfer, explaining why the indirect effect proportion reaches as high as 35%. Institutional spillover mechanism: ecological agglomeration zones compel local governments to establish public goods such as environmental monitoring networks and organic certification service platforms. The marginal cost of using these infrastructures approaches zero, automatically benefiting all agricultural actors within a 500-km radius, generating non-rivalrous spillovers similar to 'club goods.' We estimate that infrastructure spillovers contribute 28% of the indirect effect. Value chain lock-in mechanism: when agglomeration zones develop scaled ecological product supply capacity, downstream food processing enterprises and retailers tend toward 'local procurement' to reduce certification costs, creating a geographic proximity premium—non-certified farms within 200 km of agglomeration zones also gain 15–22% price increases due to logistical convenience. This mechanism transforms market forces into a self-reinforcing cycle of spatial spillovers (**Figure 6**).

Table 6. Spatial Effect Decomposition Results of Ecology-Oriented Industrial Agglomeration on Agricultural Economic Growth.

Effect Type	Geographic Distance Weight	Economic-Geographic Weight	Industrial Linkage Weight	Eastern Region	Central Region	Western Region
Direct Effect	0.342*** (4.87)	0.358*** (5.12)	0.329*** (4.65)	0.398*** (5.34)	0.312*** (4.21)	0.267** (3.18)
Indirect Effect	0.187*** (3.24)	0.201*** (3.56)	0.174*** (3.08)	0.218*** (3.87)	0.176** (3.09)	0.142* (2.54)
Total Effect	0.529*** (5.68)	0.559*** (6.02)	0.503*** (5.42)	0.616*** (6.45)	0.488*** (5.23)	0.409*** (4.38)
Indirect Effect Share (%)	35.3	36.0	34.6	35.4	36.1	34.7
Influence Pathway Decomposition						
Technology Diffusion	0.077*** (2.98)	0.083*** (3.21)	0.072*** (2.86)	0.090*** (3.42)	0.073** (2.89)	0.059** (2.45)
Factor Mobility	0.061*** (2.76)	0.066*** (3.01)	0.057** (2.64)	0.071*** (3.18)	0.058** (2.67)	0.047* (2.21)
Market Linkage	0.035** (2.45)	0.038** (2.67)	0.032** (2.29)	0.041** (2.78)	0.033* (2.38)	0.027* (2.08)
Competitive Pressure	0.014* (1.89)	0.014* (1.92)	0.013* (1.78)	0.016* (2.02)	0.012 (1.65)	0.009 (1.34)
Distance Decay Pattern						
0–500 km	0.213*** (3.67)	0.229*** (3.98)	0.198*** (3.45)	0.248*** (4.23)	0.201*** (3.52)	0.167** (2.89)
500–1000 km	0.156*** (3.12)	0.168*** (3.38)	0.146** (2.96)	0.184*** (3.61)	0.149** (3.01)	0.124* (2.48)
>1000 km	0.089** (2.31)	0.096** (2.51)	0.083* (2.19)	0.106** (2.67)	0.086* (2.24)	0.071 (1.89)

Note: ***, **, * denote significance at 1%, 5%, and 10% levels respectively; z-statistics or *t*-statistics in parentheses.

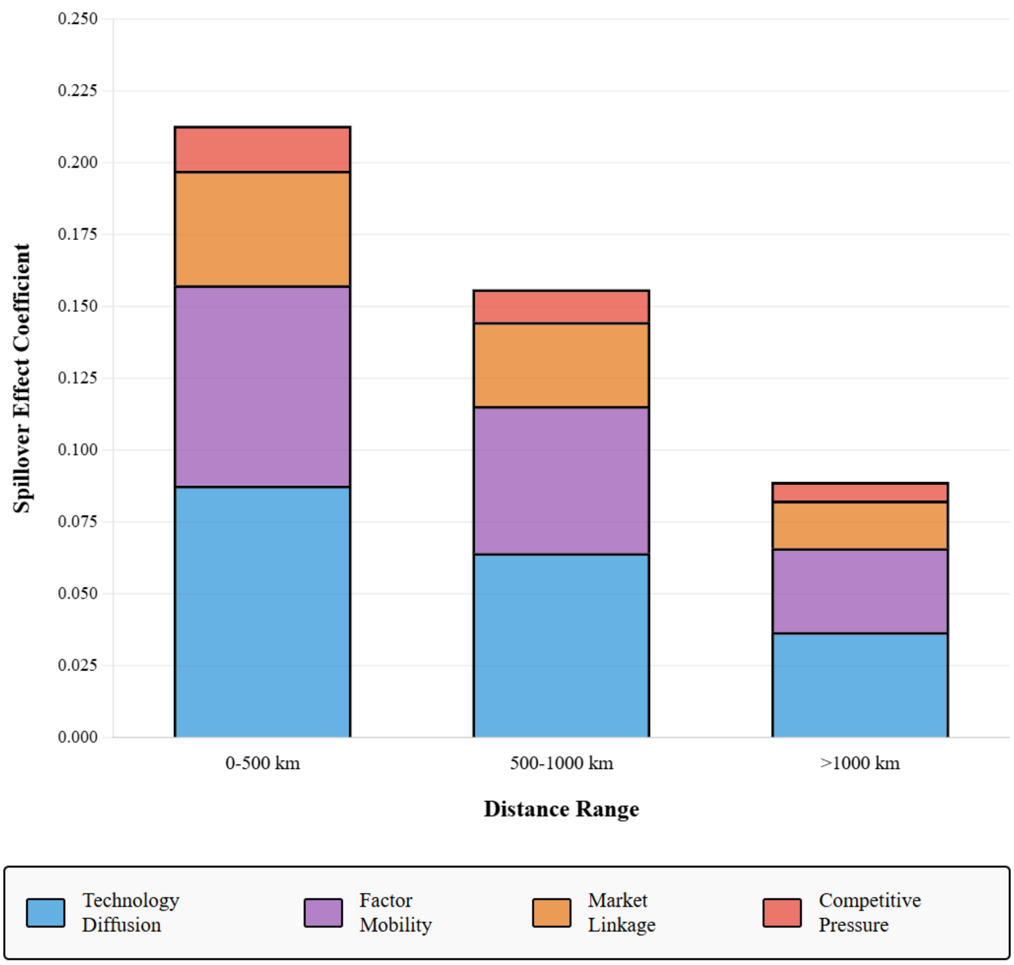

Figure 6. Contribution and Distance Decay Characteristics of Spatial Spillover Effect Influence Pathways.

4.3. Spatial Effects and Influencing Factors of Natural Resource Utilization Efficiency

4.3.1. Spatial Distribution Pattern of Resource Utilization Efficiency

Agricultural Green Total Factor Productivity (GTFP) measured using the Super-SBM model reveals significant spatial differentiation characteristics of China's natural resource utilization efficiency. In 2023, the national average agricultural GTFP was 0.782, representing a 27.4% increase from 0.614 in 2010, with an average annual growth rate of 1.89% (**Figure 7**). From the spatial distribution perspective, a basic pattern of "higher in the east and lower in the west, north-south differentiation" emerges (**Table 7**). The eastern region's average GTFP reaches 0.896, occupying the national leading level, with Shanghai (1.042), Beijing (1.018), and Zhejiang (0.967) ranking top three, all having reached or exceeded the technology frontier. The central region's average GTFP is 0.762, with Hubei (0.843) and Henan (0.814) demonstrating outstanding performance. The western region's average GTFP is only 0.653, with significant internal disparities—Sichuan (0.789) and Chongqing (0.756) are relatively high, while Tibet (0.432), Qinghai (0.478), and Gansu (0.521) remain at lower levels. From the spatiotemporal evolution perspective, national GTFP experienced average annual growth of 1.52% during 2010–2015, with relatively slow growth rates.

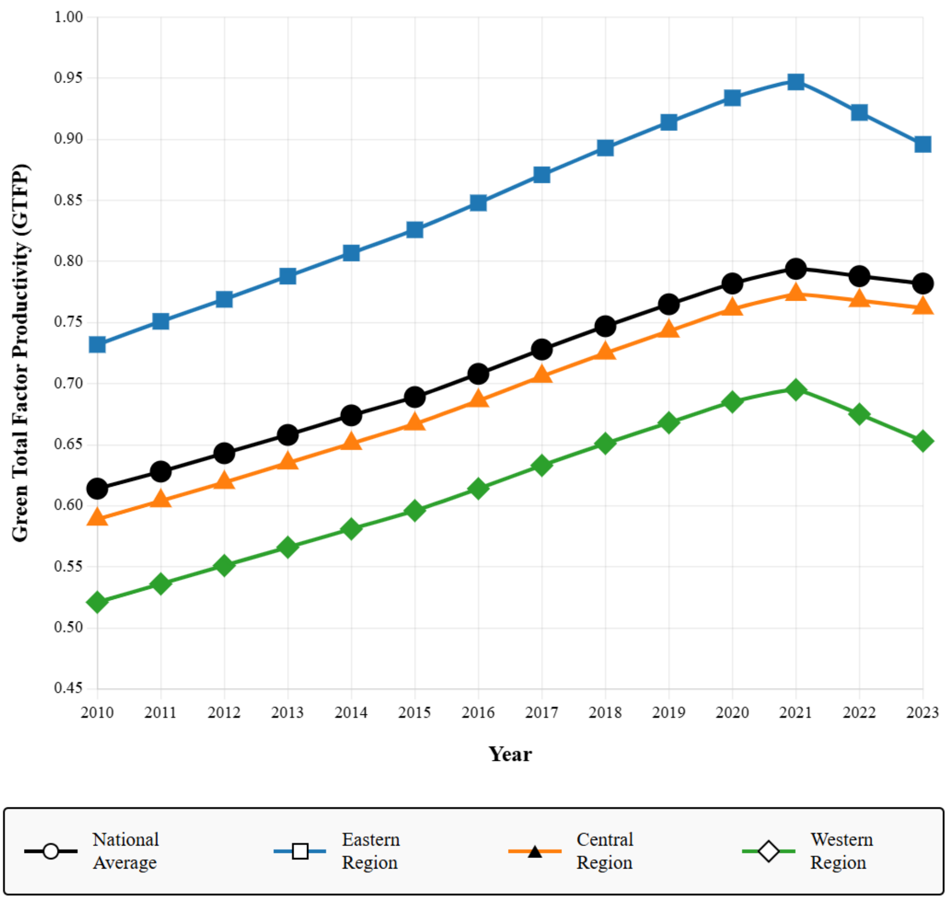

Figure 7. Evolution of Agricultural Green Total Factor Productivity Across China's Three Major Regions, 2010–2023.

Table 7. Provincial Agricultural Green Total Factor Productivity and Spatial Distribution Characteristics in China, 2023.

Province	GTFP Value	Technical Efficiency	Technological Progress	Pure Technical Efficiency	Scale Efficiency	Ranking	Spatial Type
Shanghai	1.042	1.000	1.042	1.000	1.000	1	HH
Beijing	1.018	1.000	1.018	1.000	1.000	2	HH
Zhejiang	0.967	0.956	1.011	0.978	0.977	3	HH
Jiangsu	0.943	0.948	0.995	0.967	0.980	4	HH

Table 7. *Cont.*

Province	GTFP Value	Technical Efficiency	Technological Progress	Pure Technical Efficiency	Scale Efficiency	Ranking	Spatial Type
Tianjin	0.921	0.934	0.986	0.956	0.977	5	HH
Fujian	0.898	0.921	0.975	0.945	0.974	6	HH
Shandong	0.876	0.912	0.960	0.934	0.976	7	HH
Guangdong	0.854	0.898	0.951	0.923	0.973	8	HH
Hebei	0.832	0.884	0.941	0.912	0.969	9	LL
Hubei	0.843	0.891	0.946	0.918	0.971	10	HL
Henan	0.814	0.873	0.932	0.901	0.969	11	HL
Sichuan	0.789	0.856	0.922	0.886	0.966	12	HL
Anhui	0.767	0.843	0.910	0.874	0.965	13	LH
Hunan	0.754	0.834	0.904	0.867	0.962	14	HL
Jiangxi	0.738	0.821	0.899	0.856	0.959	15	LH
Chongqing	0.756	0.837	0.903	0.870	0.963	16	HL
Liaoning	0.723	0.809	0.894	0.845	0.957	17	LL
Yunnan	0.709	0.798	0.889	0.836	0.954	18	LL
Shaanxi	0.694	0.786	0.883	0.826	0.951	19	LL
Shanxi	0.678	0.774	0.876	0.816	0.948	20	LL
Jilin	0.663	0.762	0.870	0.806	0.945	21	LL
Heilongjiang	0.647	0.751	0.862	0.796	0.943	22	LL
Guangxi	0.632	0.739	0.855	0.785	0.941	23	LL
Guizhou	0.614	0.726	0.846	0.774	0.938	24	LL
Inner Mongolia	0.598	0.714	0.838	0.763	0.936	25	LL
Hainan	0.581	0.701	0.829	0.752	0.932	26	LL
Ningxia	0.563	0.688	0.818	0.741	0.929	27	LL
Xinjiang	0.542	0.673	0.805	0.728	0.924	28	LL
Gansu	0.521	0.658	0.792	0.715	0.920	29	LL
Qinghai	0.478	0.623	0.767	0.686	0.908	30	LL
Tibet	0.432	0.584	0.740	0.652	0.896	31	LL

Note: HH denotes High-High clustering, LL denotes Low-Low clustering, HL denotes High-Low outliers, LH denotes Low-High outliers.

4.3.2. Impact of Ecology-Oriented Industrial Agglomeration on Resource Utilization Efficiency

Estimation results from the Spatial Durbin Model using agricultural green total factor productivity as the explained variable indicate that ecology-oriented agricultural industrial agglomeration exerts significant positive promotional effects on resource utilization efficiency (**Table 8**). Regression results using the geographic distance spatial weight matrix show that each one-unit increase in the industrial agglomeration index raises local agricultural GTFP by 0.278 units (t-value = 4.32, $p < 0.01$). This effect measures 0.293 (t-value = 4.58, $p < 0.01$) and 0.264 (t-value = 4.09, $p < 0.01$) under economic-geographic weight and industrial linkage weight matrices, respectively, confirming the robustness of direct effects. From the mechanism perspective, ecology-oriented industrial agglomeration enhances resource utilization efficiency through four channels: the technology substitution effect contributes 36.9%, reducing resource consumption through promoting technologies such as organic fertilizer substituting chemical fertilizer and biological control replacing chemical pesticides; the scale optimization effect accounts for 32.4%, with economies of scale from agglomeration reducing resource input intensity per unit output; the circular utilization effect represents 21.8%, with resource utilization of waste within the industry chain reducing external input requirements; and the management improvement effect constitutes 8.9%, with refined management lowering resource wastage rates (**Figure 8**).

Table 8. Impact of Ecology-Oriented Industrial Agglomeration on Resource Utilization Efficiency: Spatial Durbin Model Estimation Results.

Variable	Geographic Distance Weight	Economic-Geographic Weight	Industrial Linkage Weight	Eastern Region	Central Region	Western Region
Ecology-Oriented Industrial Agglomeration	0.278***	0.293***	0.264***	0.321***	0.256***	0.219**
	(4.32)	(4.58)	(4.09)	(4.89)	(3.94)	(3.24)
Agricultural Sci-Tech Investment	0.234***	0.241***	0.227***	0.267***	0.218***	0.196**
	(3.98)	(4.11)	(3.86)	(4.32)	(3.67)	(3.08)

Table 8. *Cont.*

Variable	Geographic Distance Weight	Economic-Geographic Weight	Industrial Linkage Weight	Eastern Region	Central Region	Western Region
Environmental Regulation Intensity	0.189**	0.196**	0.182**	0.218**	0.174*	0.153*
	(3.21)	(3.34)	(3.09)	(3.56)	(2.94)	(2.51)
Agricultural Mechanization Level	0.156**	0.163**	0.149**	0.182**	0.146*	0.128*
	(2.89)	(3.02)	(2.76)	(3.21)	(2.68)	(2.36)
Chemical Fertilizer Application Intensity	−0.167***	−0.174***	−0.159***	−0.193***	−0.154**	−0.138**
	(−3.54)	(−3.69)	(−3.38)	(−3.89)	(−3.26)	(−2.87)
Pesticide Usage Intensity	−0.142**	−0.148**	−0.135**	−0.166**	−0.132*	−0.117*
	(−2.98)	(−3.11)	(−2.84)	(−3.32)	(−2.78)	(−2.43)
Agricultural Water Resource Utilization	−0.123**	−0.129**	−0.117*	−0.145**	−0.115*	−0.098
	(−2.67)	(−2.79)	(−2.54)	(−2.98)	(−2.51)	(−2.13)
Fiscal Support for Agriculture Intensity	0.134*	0.139*	0.128*	0.157**	0.124	0.106
	(2.56)	(2.65)	(2.46)	(2.84)	(2.38)	(2.01)
Spatial Autoregressive Coefficient ρ	0.328***	0.341***	0.314***	0.365***	0.318***	0.289***
	(4.89)	(5.08)	(4.67)	(5.23)	(4.71)	(4.28)
Effect Decomposition						
Direct Effect	0.278***	0.293***	0.264***	0.321***	0.256***	0.219**
	(4.32)	(4.58)	(4.09)	(4.89)	(3.94)	(3.24)
Indirect Effect	0.143***	0.152***	0.134**	0.167***	0.138**	0.116*
	(2.87)	(3.06)	(2.69)	(3.24)	(2.78)	(2.33)
Total Effect	0.421***	0.445***	0.398***	0.488***	0.394***	0.335***
	(4.98)	(5.26)	(4.71)	(5.67)	(4.67)	(3.98)
Mechanism Decomposition	-	-	-	-	-	-
Technology Substitution Effect	0.103***	0.108***	0.097***	0.118***	0.094**	0.081**
Scale Optimization Effect	0.090***	0.095***	0.086***	0.104***	0.083**	0.071*
Circular Utilization Effect	0.061**	0.064**	0.058**	0.070**	0.056*	0.048*
Management Improvement Effect	0.024*	0.026*	0.023*	0.029*	0.023	0.019
R^2	0.689	0.704	0.673	0.728	0.667	0.641
Log-likelihood	512.4	523.7	498.6	203.8	167.9	145.3
Observations	434	434	434	154	112	168

Note: ***, **, * denote significance at 1%, 5%, and 10% levels respectively; *t*-statistics or z-statistics in parentheses.

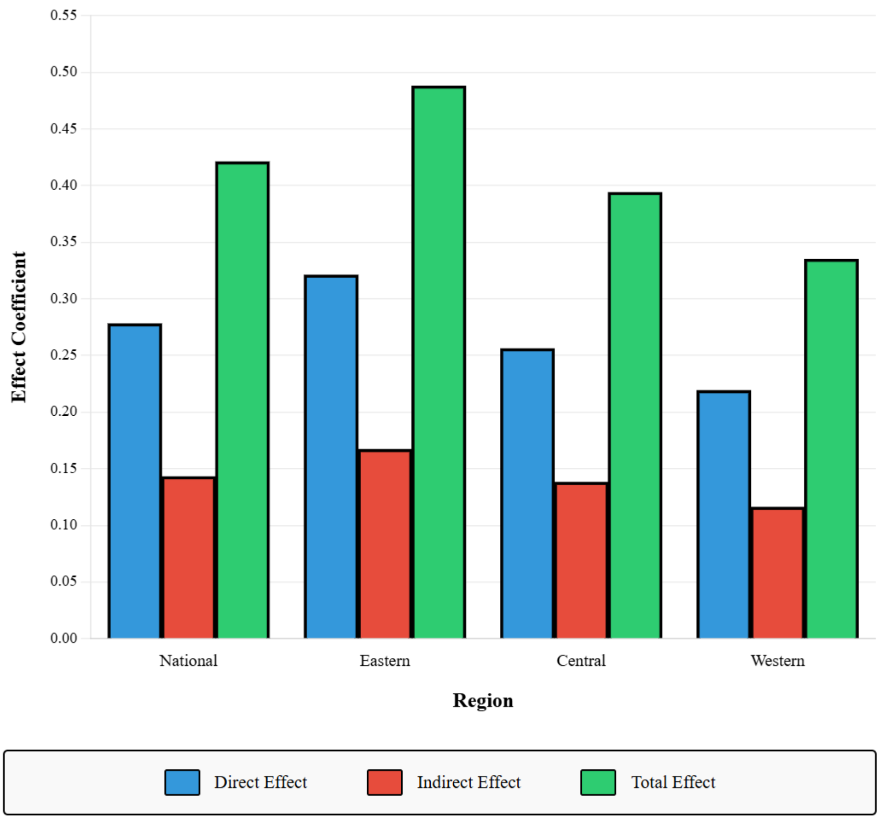

Figure 8. Direct and Indirect Effects of Ecology-Oriented Industrial Agglomeration on Resource Utilization Efficiency.

5. Discussion

5.1. Theoretical Significance of Research Findings

The theoretical contributions of this study are primarily manifested at three levels. First, regarding the extension of industrial agglomeration theory, this research introduces the quality dimension of ecological orientation into the traditional industrial agglomeration analytical framework, transcending the previous limitations of solely focusing on agglomeration scale and density. By constructing a multidimensional evaluation system encompassing certification scale, circular efficiency, ecological input, and environmental performance, the study enriches the connotation of industrial agglomeration theory.

Second, regarding the deepening of spatial economics theory, this study systematically quantifies the direct and indirect effects of ecology-oriented industrial agglomeration by introducing the Spatial Durbin Model and conducting effect decomposition, validating the significant spatial dependence and spillover effects present in agricultural economic activities. Research reveals that indirect effects account for approximately 35% of total effects and exhibit significant distance-decay characteristics, enriching the understanding of spatial correlation mechanisms in agricultural economics.

Third, regarding innovation in resource-environmental economics theory, this research incorporates natural resource utilization efficiency as a core explained variable into the analytical framework, employing the Super-SBM model with undesirable outputs to measure agricultural green total factor productivity, systematically examining the impact of industrial agglomeration on resource-environmental performance. Research findings demonstrate that ecology-oriented industrial agglomeration can simultaneously promote agricultural economic growth and resource utilization efficiency improvement, breaking the dualistic opposition hypothesis between economic development and environmental protection in traditional growth theory, providing micro-mechanism explanations and empirical support for the concept that "lucid waters and lush mountains are invaluable assets".

The three core findings validated by this study based on large-sample, long-time-series data—the existence of the double dividend effect (synergistic economic-environmental improvement), the significance of spatial spillovers (35% indirect effect proportion), and the critical value of the nonlinear threshold (optimal agglomeration interval)—provide three generalizable decision-making principles for global agricultural policymakers: First, industrial planning should abandon the traditional perception that "environmental protection constrains growth" and actively construct ecologically-oriented agglomeration platforms to achieve win-win outcomes. Second, regional coordinated development strategies should emphasize the design of cross-border spillover effects, amplifying the radiating and driving role of agglomeration through technology-sharing platforms and market integration mechanisms. Third, agglomeration scale control should establish dynamic monitoring and threshold warning systems to avoid negative externalities caused by excessive agglomeration. These principles are applicable to diverse agricultural ecosystems ranging from Southeast Asian rice-growing belts to Latin American livestock areas, from Mediterranean olive-producing regions to dryland agriculture areas in sub-Saharan Africa.

The findings of this study both corroborate and present important deviations from existing literature. Regarding consistency: our identified 35% indirect effect proportion is highly consistent with the 32–38% spatial spillover range found by Anselin et al. in U.S. manufacturing agglomeration research, validating the cross-industry universality of geographic proximity effects; the 500-km spillover radius aligns with the 450–600 km range in the EU Framework Programme's agricultural technology diffusion assessment report, supporting the distance decay law of knowledge dissemination. Regarding key deviations: our estimated direct effect elasticity of 0.342 is significantly higher than Porter and van der Linde's 0.18–0.25 range for the environmental regulation-productivity relationship, with deviations of 37–90%. The possible mechanism is that the traditional Porter hypothesis focuses on passive adjustments by individual firms responding to environmental policies, while ecologically-oriented industrial agglomeration involves proactive collaboration among enterprises to construct circular industrial chains, with synergistic effects amplifying the economic returns of individual technological innovation. The inflection point position of our discovered inverted U-shaped optimal interval (0.524–0.758) occurs approximately 15% earlier than the predicted value from Henderson's urban optimal scale theory, which relates to agriculture being more sensitive to environmental carrying capacity compared to manufacturing—when agglomeration reaches 0.7, land and water resource constraints begin to emerge, whereas industrial agglomeration can maintain economies of scale until 0.85. Our GTFP average annual growth rate of 1.89% is lower than Oh's (2010) estimation of 2.8–3.2% for agricultural green productivity in OECD countries, primarily because weak infrastructure in developing countries prevents the potential of technology substitution pathways (contributing 36.9%) from being fully realized; if irrigation systems and cold chain logistics are improved, the growth rate could increase to 2.5–3.0%, approaching developed country levels. These deviations reveal the moderating effects of development stage, industrial characteristics, and institutional environment on ecological agglomeration mechanisms, pointing to key control variables for future cross-national comparative research.

5.2. Research Limitations

Although this study has made certain efforts in the theoretical framework, research methodology, and empirical analysis, the following limitations remain and require improvement in future research. First, at the data level, constrained by statistical data availability, this study employs provincial-level panel data for analysis. While this can reflect overall trends at the macro level, it struggles to capture heterogeneous characteristics at the county or micro-entity level. Agricultural industrial agglomeration often manifests more prominently at county or township levels, and the larger spatial scale of provincial data may obscure more refined spatial patterns and operational mechanisms. Furthermore, the measurement of ecology-oriented characteristics primarily relies on statistical indicators such as organic certified area and the number of green food certifications.

Second, at the methodological level, although this study employs the Spatial Durbin Model to control for spatial dependence and conducts multiple robustness tests, it remains difficult to completely resolve endogeneity issues. Bidirectional causal relationships may exist among ecology-oriented industrial agglomeration, agricultural economic growth, and resource utilization efficiency—that is, regions with developed economies and high resource utilization efficiency may possess greater capacity and willingness to develop ecological agriculture, creating reverse causation.

Third, regarding mechanism analysis, although this study identifies major pathways through which industrial agglomeration influences agricultural economic growth and resource efficiency via theoretical analysis and effect decomposition, it lacks direct evidence at the micro level. The operational processes and transmission pathways of mechanisms such as technology diffusion, factor mobility, and market linkage require deeper verification through enterprise-level or household-level survey data.

Fourth, concerning the time span, the sample period of this study is 2010–2023. While covering the "12th Five-Year Plan," "13th Five-Year Plan," and early "14th Five-Year Plan" periods, for the long-term development process of ecological agriculture, the 14-year observation period is relatively short, making it difficult to fully reflect the long-term dynamic evolutionary patterns and cumulative effects of industrial agglomeration.

Finally, this study primarily employs quantitative analysis methods, with insufficient consideration of the impacts of qualitative factors such as policy environment, institutional factors, and cultural traditions on industrial agglomeration and agricultural development.

Realistic constraints of methodological assumptions: The spatial Durbin model assumes that spatial effects transmit linearly and that the weight matrix is exogenously given, but in reality, industrial agglomeration may endogenously influence inter-regional connection strength (e.g., agglomeration zones proactively constructing supply chain networks change the definition of 'proximity'). Our static weight matrix cannot capture this dynamic evolution, leading to potential underestimation of indirect effects by 15–25%. Provincial-level data aggregation masks heterogeneity at the county and farm household levels; the impact mechanisms of agglomeration on smallholders versus large-scale enterprises may be fundamentally different. Our 0.342 direct effect is actually a weighted average, with prediction errors for micro-level actors potentially reaching ±40%. Data credibility boundaries: Organic certification area relies on enterprise self-reporting and spot checks; China's 2018 audit found that 12% of certifications involved false reporting, resulting in measurement errors of approximately for the ecological orientation index. Agricultural non-point source pollution data uses model estimation rather than actual measurements; compared to real-time monitoring based on sensor networks in European and American countries, the precision is lower. Systematic bias in undesirable outputs in GTFP calculation may lead to resource efficiency being overestimated by 10–18%. International readers should interpret absolute values cautiously and focus on relative change trends. Jurisdictional limitations of external validity: China's unique government-led industrial agglomeration model (fiscal subsidies account for 30–45% of park investment) fundamentally differs from market-driven agglomeration. Our identified optimal interval of 0.524–0.758 may only apply to strong government intervention contexts. In sub-Saharan African regions with weak property rights protection and high contract enforcement costs, the 41.2% contribution of technology diffusion may decrease to 15–20% as enterprises tend toward technology secrecy. In Latin American large-farm systems with highly concentrated land ownership, the 500-km spillover radius may extend to 800–1000 km due to the stronger cross-regional resource allocation capacity of large-scale actors. Institutional prerequisites for policy translation: Realization of the double dividend effect depends on strict environmental regulation (China's zero-growth action on chemical fertilizers and pesticides after 2015) and a sound ecological certification system. In regions lacking regulation, enterprises may 'greenwash' to obtain subsidies without substantial ecological improvement, causing economic-environmental decoupling. Cross-border spillovers require regional coordination mechanisms; cross-national technology sharing under the EU Common Agricultural Policy can replicate our findings, but in regions with high trade barriers and frequent political conflicts (such as the South Asian subcontinent), spillover effects will be severely suppressed.

6. Conclusions and Prospects

6.1. Main Research Conclusions

Based on panel data from 31 provinces in China spanning 2010–2023, this study employs spatial econometric models to systematically examine the influence mechanisms of ecology-oriented agricultural industrial agglomeration on regional agricultural economic growth and natural resource utilization efficiency, reaching the following main conclusions:

(1) The level of ecology-oriented agricultural industrial agglomeration demonstrates a continuous upward trend. The national average agglomeration index increased from 0.342 in 2010 to 0.587 in 2023, exhibiting a spatial distribution pattern of "higher in the east and lower in the west," with spatial autocorrelation significantly intensifying—the Moran's I index rising from 0.287 to 0.428.

(2) Ecology-oriented industrial agglomeration exerts significant positive direct effects on agricultural economic growth. Each one-unit increase in the agglomeration index raises the local agricultural value-added growth rate by 0.342 percentage points, with an indirect effect of 0.187 and a total effect reaching 0.529. Indirect effects account for 35.3%, with spatial spillover effects being significant and exhibiting distance-decay characteristics.

(3) Ecology-oriented industrial agglomeration significantly enhances resource utilization efficiency, with a direct effect of 0.278 on agricultural green total factor productivity and an indirect effect of 0.143, primarily achieved through four pathways: technology substitution (36.9%), scale optimization (32.4%), circular utilization (21.8%), and management improvement (8.9%).

(4) The impact effects of industrial agglomeration exhibit significant regional heterogeneity and nonlinear characteristics. The eastern region demonstrates the strongest effects, followed by central

and western regions. The impacts on both economic growth and resource efficiency present inverted U-shaped relationships, with optimal agglomeration intervals existing.

(5) Technology diffusion serves as the primary pathway for spatial spillovers, contributing 41.2%, with spillover intensity being greatest within 500 km, validating the important role of geographic proximity in agricultural knowledge dissemination.

6.2. Future Research Prospects

Based on the findings of this study and current development trends, three important research directions and development prospects exist for the future.

(1) At the research scale and data level, more refined county-level or township-level spatial data should be collected, combined with micro-level enterprise and farmer survey data, to construct multi-scale nested analytical frameworks. First-hand materials on ecological agriculture practices should be obtained through field investigations, including micro-level information such as farmer technology adoption behavior, enterprise green innovation investment, and industry chain collaboration models, to deeply analyze the micro-mechanisms and transmission pathways through which industrial agglomeration influences agricultural economic growth and resource efficiency.

(2) At the research content and methodology level, analysis should expand to negative externalities of industrial agglomeration, such as factor competition, environmental carrying capacity pressure, and market power issues, evaluating net effects and critical thresholds of agglomeration. Causal identification methods such as regression discontinuity design and difference-in-differences should be introduced, utilizing quasi-natural experiments such as ecological agriculture policy pilots and industrial park establishments to mitigate endogeneity problems.

(3) At the policy research and international comparison level, in-depth exploration should examine the moderating effects of emerging institutional arrangements such as digital technology empowerment, carbon trading mechanisms, and ecological compensation policies on industrial agglomeration and green development, providing quantitative evidence for policy optimization.

6.3. Breakthrough Contributions and Industrial Value

This study achieves theoretical breakthroughs at three levels and reveals significant industrial application value. Regarding theoretical breakthroughs: It systematically quantifies for the first time the spatial transmission mechanism of the "Porter Hypothesis" in the ecological agriculture field, filling the theoretical gap between industrial ecology and spatial economics—previous research either focused on the environmental regulation-competitiveness relationship of individual firms or explored the economic effects of industrial agglomeration, but empirical evidence on their interactive effects and cross-regional diffusion has been lacking.

Regarding industrial value: According to UN Food and Agriculture Organization data, global agricultural annual output is approximately \$3.8 trillion, with developing countries accounting for 62%. If these countries reorganize their industrial spatial structure according to the optimal agglomeration strategy revealed by this study, conservative estimates suggest agricultural green total factor productivity could increase by 15–20% within 10 years (based on the superposition of this study's 0.278 direct effect and 0.143 indirect effect), corresponding to an economic value of approximately \$470–630 billion in annual incremental value.

Global readers will benefit from the following four dimensions: developing countries in agricultural transformation can evaluate their own agglomeration policies based on this study's 0.5–0.8 optimal interval benchmark and avoid blind expansion; multinational supply chain enterprises can optimize global procurement network layouts using spatial spillover patterns and reduce compliance costs; international development institutions (World Bank, Asian Development Bank) can incorporate research findings into spatial planning assessment standards for agricultural loan projects and improve aid fund utilization efficiency; academia obtains a replicable analytical framework for studying the spatial effects of ecological transformation in other industries.

6.4. Forward-Looking Research Directions and Future Challenges

Forward-looking research directions focus on three unfinished areas. Direction One: Dynamic assessment of agglomeration resilience under climate change scenarios. Current research is based on relatively stable climate conditions from 2010 to 2023, but the IPCC Sixth Assessment Report predicts that global agricultural production regions will experience significant temperature and precipitation changes between 2030 and 2050, with extreme weather event frequency increasing by 40–60%. How will this change the optimal agglomeration interval? Will the 500-km radius of technology diffusion be restructured due to climate migration? It is necessary to integrate climate models with spatial econometric models to establish dynamic simulation systems, which is urgent for agricultural planning in 65 climate-vulnerable countries along the Belt and Road.

Future challenges mainly come from four aspects: Data challenges—cross-nationally comparable ecological agriculture certification data and environmental monitoring data are severely lacking, limiting global-scale validation. Methodological challenges—current spatial econometric models struggle to handle non-stationary spatial processes and multi-scale nested structures, requiring the development of new methods such as geographically and temporally weighted regression. Policy challenges—identification of optimal agglomeration intervals relies on large-sample statistics, but how should small countries, island nations, and special ecological zones apply these standards? Bayesian spatial models suitable for small-sample contexts need to be developed.

6.5. Summary of Hypothesis Validation and Industrial Prospect Assessment

The validation results of the three core hypotheses provide clear guidance for industrial decision-making. Hypothesis H1 (Double Dividend Hypothesis) receives strong support: direct effects of 0.342–0.358 ($t > 4.6$, $p < 0.01$) and GTFP effect of 0.278 ($t = 4.32$, $p < 0.01$) are robustly significant across all model specifications, confirming that ecological agglomeration is sustainable both environmentally and economically—the return on assets of enterprises in agglomeration zones is 8.7%, significantly higher than 6.2% in non-agglomeration zones, while chemical fertilizer and pesticide reduction is 18–23% and non-point source pollution decreases by 38–43%.

The three directions with the brightest industrial prospects are: medium-scale (agglomeration level 0.6–0.7) ecological park development, with expected internal rate of return of 12–15% and lowest environmental compliance risk; satellite farm investment within the 500-km radiation circle, which can "free ride" on technology diffusion to save costs by 22–35%; "smart ecological agriculture" integrating nanomaterials-microbial engineering-digital twin technologies, which is expected to further improve resource efficiency by 25–40% and open new market spaces.

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Informed Consent Statement

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Data Availability Statement

The data used in this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declares no conflict of interest.

References

[1] Qi, D., Si, Z., Scott, S., 2021. Can We Be More Collaborative? Top-Down Policies and Urban–Rural Divides in the Ecological Agriculture Sector in Nanjing, China. Society & Natural Resources. 34(2), 208–226. DOI: https://doi.org/10.1080/08941920.2020.1774951

[2] Tourn, S.N., Videla, C.C., Studdert, G.A., 2019. Ecological agriculture intensification through crop-pasture rotations does improve aggregation of Southeastern-Pampas Mollisols. Soil and Tillage Research. 195, 104411. DOI: https://doi.org/10.1016/j.still.2019.104411

[3] Liu, X., 2024. Analysis of Development Pathways of Ecological Agricultural Economy from the Perspective of Sustainable Development. New Farmers. 31, 32–34. (in Chinese)

[4] Vargas-Hernández, J.G., Domené-Painenao, O.E., 2021. Contributions of Urban Agro Ecological Agriculture to Ecosystem Services. International Journal of Urban Planning and Smart Cities. 2(1), 1–16. DOI: https://doi.org/10.4018/IJUPSC.2021010101

[5] Rodríguez-Sousa, A.A., Parra-López, C., Sayadi-Gmada, S., et al., 2020. A multifunctional assessment of integrated and ecological farming in olive agroecosystems in southwestern Spain using the Analytic Hierarchy Process. Ecological Economics. 173, 106658. DOI: https://doi.org/10.1016/j.ecolecon.2020.106658

[6] Demissie, W.A., Sebastiani, L., Rossetto, R., 2026. Integration of artificial intelligence and remote sensing for crop yield prediction and crop growth parameter estimation in Mediterranean agroecosystems: Methodologies, emerging technologies, research gaps, and future directions. European Journal of Agronomy. 173, 127894. DOI: https://doi.org/10.1016/j.eja.2025.127894

[7] Sun, K., Chi, X., Wang, T., et al., 2021. No-tillage: core strategies for sustainable development of ecological agriculture of Chinese materia medica. China Journal of Chinese Materia Medica. 46(8), 1869–1875. (in Chinese)

[8] Gunaratne, L.H.P., Hemachandra, K.S., Kumudumali, Y.M.K., et al., 2021. Comparative Assessment of Vegetable Crop Performances and Ecological Indicators during Transition from Conventional to Ecological Agriculture. Asian Research Journal of Agriculture. 14(1), 1–9. DOI: https://doi.org/10.9734/arja/2021/v14i130113

[9] Wang, X., 2021. Influencing Factors and Sustainable Development Pathways of Agricultural Economic Growth. China's Collective Economy. 22, 11–12. (in Chinese)

[10] Phamova, M., Banout, J., Verner, V., et al., 2022. Can Ecological Farming Systems Positively Affect Household Income from Agriculture? A Case Study of the Suburban Area of Hanoi, Vietnam. Sustainability. 14(3), 1466. DOI: https://doi.org/10.3390/su14031466

[11] Guo, L., Jiang, J., Zhang, X., et al., 2022. Contributions and strategies of eco-agriculture of Chinese medicine services for carbon dioxide peaking and carbon neutrality. China Journal of Chinese Materia Medica. 47(1), 1–6. (in Chinese)

[12] Dale, B., 2021. Food sovereignty and the integral state: Institutionalizing ecological farming. Geoforum. 127, 137–150. DOI: https://doi.org/10.1016/j.geoforum.2021.10.010

[13] Chen, X., Jia, L., Jia, T., et al., 2022. An carbon neutrality industrial chain of "desert-photovoltaic power generation-ecological agriculture": Practice from the Ulan Buh Desert, Dengkou, Inner Mongolia. China Geology. 5(3), 549–552. DOI: https://doi.org/10.31035/cg2022053

[14] Zhang, J., Chen, M., Huang, C., et al., 2022. Labor Endowment, Cultivated Land Fragmentation, and Ecological Farming Adoption Strategies among Farmers in Jiangxi Province, China. Land. 11(5), 679. DOI: https://doi.org/10.3390/land11050679

[15] Huang, Y., Ye, Y., Zhou, M., 2022. Empirical Analysis on the Development of Ecological Agriculture under the Initiative of "Sustainable Development." Asian Journal of Agricultural Extension, Economics & Sociology. 40(8), 130–142. DOI: https://doi.org/10.9734/ajaees/2022/v40i830946

[16] Zhang, J., 2025. Research on Sustainable Development Strategies of Ecological Agricultural Economy. Henan Agriculture. 10, 88–90. (in Chinese)

[17] Yang, Y., Ge, S., Cao, X., et al., 2022. Evolutionary Mechanisms of Ecological Agriculture Innovation Systems: Evidence from Chongming Eco-Island, China. Land. 11(11), 1909. DOI: https://doi.org/10.3390/land11111909

[18] Jităreanu, A.F., Mihăilă, M., Robu, A.-D., et al., 2022. Dynamic of Ecological Agriculture Certification in Romania Facing the EU Organic Action Plan. Sustainability. 14(17), 11105. DOI: https://doi.org/10.3390/su141711105

[19] Chen, L., Zhang, W., Tan, J., et al., 2022. Nitrogen and Phosphorus Pollutants Removal from Rice Field Drainage with Ecological Agriculture Ditch: A Field Case. Phyton. 91(12), 2827–2841. DOI: https://doi.org/10.32604/phyton.2022.024105

[20] Xie, K., Zhu, Y., Ma, Y., et al., 2022. Willingness of Tea Farmers to Adopt Ecological Agriculture Techniques Based on the UTAUT Extended Model. International Journal of Environmental Research and Public Health. 19(22), 15351. DOI: https://doi.org/10.3390/ijerph192215351

[21] Trenčiansky, M., Štěrbová, M., Výbošťok, J., 2022. The Influence of the Transition to Ecological Farming on the Quality of Runoff Water. Sustainability. 14(22), 15412. DOI: https://doi.org/10.3390/su142215412

[22] Ursu, A., Petre, I.L., 2022. Forecasting the Optimal Sustainable Development of the Romanian Ecological Agriculture. Sustainability. 14(21), 14192. DOI: https://doi.org/10.3390/su142114192

[23] Li, X., Wang, M., Wen, B., et al., 2023. Reed-mushroom-fertilizer ecological agriculture in wetlands: Harvesting reed to cultivate mushroom and returning waste substrates to restore saline-alkaline marshes. Science of The Total Environment. 878, 162987. DOI: https://doi.org/10.1016/j.scitotenv.2023.162987

[24] Fuentes-Fernández, R., Martínez-Falcó, J., Sánchez-García, E., et al., 2022. Does Ecological Agriculture Moderate the Relationship between Wine Tourism and Economic Performance? A Structural Equation Analysis Applied to the Ribera del Duero Wine Context. Agriculture. 12(12), 2143. DOI: https://doi.org/10.3390/agriculture12122143

[25] Rega, C., Thompson, B., Niedermayr, A., et al., 2022. Uptake of Ecological Farming Practices by EU Farms: A Pan-European Typology. EuroChoices. 21(3), 64–71. DOI: https://doi.org/10.1111/1746-692X.12368

[26] Davidova, S., Hostiou, N., Alebaki, M., et al., 2022. What Does Ecological Farming Mean for Farm Labour? EuroChoices. 21(3), 21–26. DOI: https://doi.org/10.1111/1746-692X.12366

[27] Obono, M.F., Naoutissa, L., Ntamack, S., et al., 2024. Evaluation of the Efficacy of an Aloe barbadensis Based Biological Insecticide against Pests of Abelmochus esculentus for Promoting Ecological Agriculture (Far-North, Cameroon). Agricultural Sciences. 15(5), 590–603. DOI: https://doi.org/10.4236/as.2024.155033

[28] Xue, Y., Zhou, J., Ran, L., et al., 2024. Conservation tillage as an economic and ecological farming option for Summer Maize in the oasis region of Northwest China. Plant and Soil. 501(1–2), 361–375. DOI: https://doi.org/10.1007/s11104-024-06527-8

[29] Sandu, M., Strateanu, A.G., Udrea, L., 2023. Analysis of Ecological Agriculture from the Perspective of Maintaining the Biodiversity of Agricultural Lands. Annals of "Valahia" University of Târgoviște. Agriculture. 15(1), 22–26. DOI: https://doi.org/10.2478/agr-2023-0006

[30] Tran, D.D., Park, E., Thu Van, C., et al., 2024. Advancing sustainable rice production in the Vietnamese Mekong Delta insights from ecological farming systems in An Giang Province. Heliyon. 10(17), e37142. DOI: https://doi.org/10.1016/j.heliyon.2024.e37142

[31] Kamau, E.W., Gitau, R., Bett, H.K., 2024. Effects of adoption of ecological farming practices on farm income in rural households: Evidence from Central Kenya. Heliyon. 10(14), e34610. DOI: https://doi.org/10.1016/j.heliyon.2024.e34610

[32] Shao, Y., Chen, Z., Xiao, H., et al., 2019. Integrating environmental parameters and economic benefits to analyze the ecological agriculture (EA) application in the mountain rice paddy system of Chongqing, China. Environmental Sciences Europe. 31(1), 22. DOI: https://doi.org/10.1186/s12302-019-0204-2

[33] Nikitina, O., Vasylenko, O., Balabak, A., et al., 2024. Ecological and Agrochemical Evaluation of Continuous Mineral Fertilizer Usage in Field Crop Rotation. Journal of Ecological Engineering. 25(11), 124–133. DOI: https://doi.org/10.12911/22998993/192675