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Agricultural Eco-Efficiency and the Urban-Rural Income Gap in China: Mechanisms, Thresholds, and Spatial Spillovers

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Abstract

In the context of global advocacy of sustainable agriculture and urban-rural coordinated development, it is important to explore the socio-economic effects of agricultural eco-efficiency. In this study, we aim to empirically examine the impact of agricultural eco-efficiency (AEE) on the urban-rural income gap (URIG) and its mechanisms in China in order to provide policy recommendations for promoting the coordinated development of environmental sustainability and social equity. Based on Chinese provincial panel data from 2011 to 2024, a two-way fixed-effects model was employed. Robustness was tested through winsorization and variable replacement, and the lag of AEE was used as a variable to address endogenous problems. Furthermore, the adjustment effect model, the panel threshold model, and group regression were used to analyse the regulatory effect of financial support, threshold effect of urbanization levels, and heterogeneity across regions, technologies, and infrastructure. The research results show the following: (1) Improvement in AEE is significantly associated with a narrowing of the URIG, and this conclusion remains true under multiple tests. (2) Financial support plays a significant positive moderating role. (3) The impact of AEE has a double threshold effect based on the urbanization level, which is only significant in the range of medium urbanization level. (4) The effect is more obvious in the main grain-producing areas, areas with a high agricultural mechanization level, and areas with a high transportation infrastructure level. (5) AEE helps narrow the URIG in the target and neighbouring areas. Improving the ecological efficiency of agriculture has both environmental and income distribution benefits. Policy formulation should focus on strengthening the precise orientation of financial support and implementing differentiated strategies according to the urbanization stage, regional functional positioning, and technical foundation, so as to maximise its effectiveness in reducing poverty, increasing income, and promoting urban and rural equity.

Keywords: AEE; urban-rural income gap; moderating effect; threshold effect; heterogeneity analysis; sustainable agriculture



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1. Introduction

In the context of the global response to climate change and the pursuit of sustainable development, the promotion of green agricultural transformation has become a core strategy for countries aiming to achieve environmental goals through economic and social development [1]. As the world's largest developing country and agricultural country,

China is also facing the challenge of narrowing the urban-rural income gap (URIG) and promoting the sustainable development of agriculture. Since the initiation of the reform and opening-up policy, China's agriculture sector has achieved remarkable progress in ensuring food security and boosting economic output [2]. However, this growth is accompanied by profound environmental costs, such as through resource overexploitation, chemical use, excessive investment [3], and the degradation of groundwater and land ecosystem functions [4,5]. More seriously, the imbalance of the agro-ecological environment not only restricts the long-term healthy development of the rural economy but may also aggravate the urban-rural development gap, making it difficult for rural residents to fully share the dividends of modernization development while bearing the environmental costs, thus further solidifying the URIG [5]. In this context, it is theoretically and practically significant to explore how agricultural green transformation can contribute to urban and rural incomes, Chinese modernization, and the achievement of the global Sustainable Development Goals (SDGs).

Agricultural ecological efficiency (agricultural eco-efficiency, AEE) is a core indicator used to evaluate the development of a green agricultural system under a set level of production inputs, with minimal resource consumption and environmental pollution, to achieve maximum agricultural economic output [6]. It goes beyond the traditional single economic efficiency or environmental performance index by providing an integrated framework for evaluating the comprehensive performance of sustainable agricultural development [7]. With the transformation of global agriculture from the traditional "high-input and high-pollution" model to a sustainable development model [8], the agricultural green total factor productivity (AGTFP), or eco-efficiency, has become a key indicator for evaluating the quality of agricultural modernisation [9,10]. Especially in China, agricultural greenhouse gas emissions account for approximately 17% of the national total [11]. Moreover, China has long faced dual pressures of resource constraints and environmental degradation [12]. It is particularly urgent to systematically investigate the socio-economic effects of improving agricultural ecological efficiency, especially its impact on urban-rural income distribution.

In terms of AEE research, the concept of ecological efficiency was first proposed by Schaltegger and Sturm in 1990 [13]. Early international research focused on the input-output efficiency assessment of the farm scale. In recent years, it has gradually improved the measurement system and expanded to the spatial dimension. A significant progress is to systematically argue that crop carbon sinks are included in AEE measurement, challenging the traditional framework that only considers carbon emissions and believing that the traditional framework underestimates the net contribution of farmland ecosystems to ecosystems [14,15]. Domestic AEE research in China gained momentum after 2010, with the super-efficiency SBM model, an extension of the standard Slack-Based Measure (SBM) model that allows for ranking efficient Decision-Making Units (DMUs), becoming the mainstream measurement method [16]. Studies generally confirm an overall upward trend in China's AEE since 2010, with a spatial clustering pattern characterised by "high values at the periphery and low values in the centre" [17]. However, two significant unresolved debates persist. First, there is substantial disagreement on measurement indicators: approximately 70% of domestic studies treat agricultural surface pollution as the sole undesirable output, neglecting the bidirectional impact of agricultural carbon emissions and carbon sinks, thus diverging from the international frontier framework [18]. Second, the impact of agricultural mechanization remains contested. Some scholars find its effect on AEE to be insignificant based on national panel data [19], while others, focusing on the Huanghuaihai Plain, confirm that mechanization significantly promotes AEE improvement by enhancing resource utilisation efficiency [20]. This discrepancy likely stems from heterogeneity in regional planting structures and mechanization types. Critically, existing research lacks a

unified explanation for this divergence and offers limited linkage analysis on micro-level farmer behavioural responses, making it difficult to explain the distributional effects of efficiency improvements.

Turning to the urban-rural income gap (URIG) literature, Lewis's dual economy theory and Kuznets's inverted-U hypothesis constitute the core theoretical framework. International empirical research has expanded the discussion to various influencing factors. For instance, research on Sub-Saharan Africa verifies the inverted-U characteristics of the income gap during urbanization while emphasising the moderating role of institutional factors [21]; other scholars find that e-commerce development can narrow the URIG by expanding market access, albeit with regional heterogeneity [22]. Early domestic research focused on the dual urban-rural structure and the household registration system, while recent studies have gradually expanded to dimensions such as the digital economy and industrial agglomeration. Yet, the conclusions diverge sharply. Some scholars confirm that urbanization's convergence effect on the income gap exhibits threshold characteristics [23]; others find that the digital economy's impact on the URIG follows an inverted-U shape [24]; still others obtain opposite linear convergence conclusions based on provincial panel data [25]. These contradictions are largely attributable to heterogeneity in sample periods and stages of digital economic development. A common and critical shortcoming across existing studies is the neglect of agricultural ecological transformation as an emerging explanatory factor. Furthermore, most studies treat the agricultural sector as a homogeneous entity and fail to disaggregate the heterogeneous changes in rural residents' income structure—specifically, the distinct impacts on operational versus wage income. Research from the International Labour Organisation has long shown that wage income growth driven by labor transfer—released by agricultural technological progress—is a core channel for rural income increase, yet this pathway has been largely overlooked in domestic URIG studies. Our study explicitly addresses this oversight by examining how AEE improvement differentially affects income components through labor reallocation and industrial integration.

Regarding the direct relationship between AEE and the URIG, the existing literature features extensive discussions but has not reached consensus. Two competing views can be identified. One stream of research supports a positive convergence effect. Empirical studies based on China's provincial panel data generally find that improvements in agricultural green total factor productivity (AGTFP) can significantly inhibit the expansion of the URIG by optimising resource allocation [26]. Case studies further reveal channel roles, such as enabling premium-quality pricing and promoting rural labour transfer to non-agricultural sectors [7]. Additionally, positive spatial spillover effects have been documented [17]. Conversely, another stream of research reveals complexity and uncertainty. Some scholars find a non-linear "U-shaped" relationship, where the income gap first decreases and then expands [27]. More alarmingly, specific green transformation policies may increase the URIG in the short term due to sharp rises in production costs and urban-biased industrial structure adjustments during early implementation [28]. Cross-national evidence suggests that environmental regulation intensity exhibits significant "U-type" threshold characteristics with respect to AGTFP [29], and the expansion of the URIG may, in turn, inhibit green agricultural technological progress [30], implying a complex dynamic feedback mechanism among environmental policy, income distribution, and green productivity.

These divergent findings strongly suggest that the AEE-URIG relationship is not a simple linear causality but rather a complex process moderated by multiple contextual factors. Our study is designed to reconcile these contradictions by systematically testing four underexplored dimensions. First, the underlying mechanism needs to be explored in greater depth. Most studies focus on verifying the direct effect but lack empirical

tests on how key external policy environments, such as financial support for agriculture, regulate this process. Moreover, financial support, as the core means of government intervention in resource allocation, can deeply influence the ecological efficiency of the income distribution pattern [31,32]. Second, there should be more focus on nonlinear characteristics. The role of AEE tends to depend on the development stage of the region, and the urbanization level may be a key threshold variable [33], but existing research has not tested the multiple possible threshold effects. Thirdly, heterogeneity analyses should be expanded to consider more dimensions. China has a large geographical area, with huge differences in functional positioning (such as major and non-major grain-producing areas), production technology conditions (such as mechanization level), and market connection basis (such as transportation infrastructure). These structural conditions may systematically change the impact of AEE. However, systematic heterogeneity tests considering these multi-dimensional perspectives are lacking. Fourth, the spatial correlation effect has been neglected. According to the first law of geography, there is always spatial correlation between economic and environmental variables between regions [34]. Both the URIG and AEE may show spatial agglomeration characteristics. Ignoring this spatial dependence and potential spillover effect may lead to errors in model estimation and failure to reveal the inter-regional diffusion mechanism of agricultural green transformation benefits.

In view of this, the aim of this study was to develop an integrated analytical framework to systematically and empirically test the impact, mechanisms, and boundary conditions of AEE on the URIG in China. Specifically, we attempt to answer the following core questions: (1) Can improvement in AEE significantly reduce the URIG? (2) What is the role of local financial support? Does it play a moderating or mediating role? (3) Does this impact show nonlinear threshold characteristics with the change in urbanization level? (4) Is there a spatial spillover effect on the impact of AEE?

The possible contributions of this study are as follows: Theoretically, by combining the concept of eco-efficiency in environmental economics with the income distribution in development economics, this study provides a more detailed and context-based analytical framework for understanding the comprehensive socio-economic benefits of agricultural green transformation, enriching the interdisciplinary research in the field of sustainable agriculture and inclusive development. Empirically, in this study, we not only use China's provincial panel data to verify the core causal relationship but also reveal the enabling mechanism of financial support, the stage constraints of the urbanization level, the multi-dimensional heterogeneity pattern, and the potential spatial spillover effect through the moderating effect model, panel threshold model, group regression, and spatial Durbin model (SDM). Thus, we present a more realistic complexity than a simple linear relationship, supported by robust empirical evidence. In terms of policy, the research conclusions provide a direct and specific basis for government departments when designing differentiated, precise, and regionally coordinated policy combinations to promote agricultural green development and shared urban and rural prosperity.

The remainder of this paper is structured as follows: Section 2 presents the theoretical analysis and proposes research hypotheses, and Section 3 introduces the research method, model setting, and data sources. Section 4 presents the empirical results and an in-depth analysis, Section 5 comprehensively discusses the research findings, and summarises the research conclusions and proposes corresponding policy recommendations.

2. Theoretical Analysis and Research Hypotheses

2.1. Direct Impact of AEE on URIG

The main idea of the AEE is to maintain or improve agricultural economic output while reducing resource consumption and environmental pollution [35]. Improving the AEE may affect the URIG through the following paths:

The first pathway operates through productivity improvement and income growth. The improvement of the AEE is usually accompanied by the adoption of green technologies, such as water-saving irrigation and precise fertilisation [36], and the innovation of agricultural production methods, which can directly improve the productivity of land, labour, and other factors [37], reduce production costs, and thus increase the net income of agricultural operators [38]. The direct growth of farmers' income is the most fundamental route toward narrowing the URIG. The second path is through the effect of industrial integration and value chain extension. Ecological agriculture is often closely combined with leisure tourism, rural tourism, brand agriculture, and other high-value-added industries. Improving the AEE is conducive to creating a distinctive ecological agricultural product brand [39], promoting the integration of rural primary, secondary, and tertiary industries, and expanding the multiple functions of agriculture, thus creating more non-agricultural employment opportunities and value-added income and attracting some non-agricultural values to remain in rural areas. The third pathway operates through factor reallocation. The pursuit of ecological efficiency will force production factors, such as labour, capital, and land, to be shifted from the traditional agricultural production mode characterised by high pollution and low efficiency and be reallocated to more efficient and greener agricultural links or non-agricultural sectors [27]. In the long run, this process will help improve the marginal output and remuneration of rural labour and optimise the factor return structure between urban and rural areas.

Based on the above analysis, improving the AEE is expected to create a converging effect on the URIG by increasing farmers' incomes and optimising the rural economic structure. Therefore, H1 is proposed.

H1: *AEE has a significantly negative impact on the URIG.*

2.2. Moderating Effect of Financial Support

However, the improvement of the AEE and the realisation of its income-increasing effect are not automatic. It is highly dependent on the external policy environment, especially on government financial support. Financial support may play a key role in improving the AEE, thereby affecting the URIG.

First, financial support reduces upfront costs and adoption risks. Adopting eco-friendly technologies or models usually requires high upfront investment and technical learning costs, which pose obstacles for individual farmers [40]. The government's financial subsidies, green credit, ecological compensation, and other policies [41] can directly share farmers' transformation costs and reduce the risk of adoption, thereby accelerating the popularisation of the AEE improvement technologies.

Second, the supply of public goods and the strengthening of positive externalities need to be considered. Improvements in the AEE often have positive environmental externalities that can only be partially compensated for by the market. Financial support can internalise these external benefits through the purchase of environmental services and investment in ecological infrastructure so that farmers engaged in ecological agriculture can obtain higher returns and enhance their ability to increase income [42].

Third, market connection and brand building support are important. Funds can be used to support the marketing promotion of ecological agricultural products, the quality cer-

tification system, and cold chain logistics construction, helping farmers better connect with high-end markets and achieve high quality and preferential prices, thereby transforming the improvement of ecological efficiency into real income growth [7].

Therefore, strong financial support can effectively ease constraints and amplify the income-increasing and distribution effects of the AEE. Based on this, H2 is proposed.

H2: *Financial support plays a positive moderating role in the effect of AEE on narrowing the URIG. That is, stronger financial support will enhance the efficiency of the negative agricultural–ecological impact on the URIG.*

2.3. Threshold Effect of Urbanization Level

The impact of the AEE on the URIGs may not be a simple linear relationship as it may be constrained by the regional development stage, especially the urbanization level, which is a key variable that determines the urban-rural relations, factor mobility, and economic structure [43] and may constitute a threshold condition.

In low-urbanization areas, the dual structure of urban and rural areas is evident. The factor market, especially the labour, capital, and land markets, is clearly divided, and the connection between urban and rural areas is weak. At this time, even if the AEE has been improved, the effect of increasing income may be blocked by the difficulty of smoothly transferring surplus rural labour to the non-agricultural sector [44], the insufficient accumulation of agricultural capital, and use of poor channels for the value realisation of ecological products [45]. The benefits of agricultural efficiency cannot be effectively split or locked into the narrow rural economy so that the overall urban-rural income gap is not significantly reduced.

As urbanization progresses to a medium level, the flow of factors between urban and rural areas accelerates, infrastructure interconnection improves, and non-agricultural employment opportunities increase [46]. At this time, the labour and capital released by improvements in the AEE can be transferred more smoothly to the more efficient non-agricultural sector. At the same time, the urban demand for high-quality ecological agricultural products has also created new market opportunities for rural areas [47]. At this stage, improving AEE can more effectively promote farmers' income growth through measures such as productivity improvement, industrial integration, and factor reallocation, thereby significantly narrowing the URIG [48].

When urbanization reaches a high level, the share of agriculture in the economy becomes very low [49], and the dominant factors in the URIG are more likely to be the skill premium, property income gap, and education gap within the non-agricultural sector [50]. Although improvements in agricultural efficiency are beneficial to the income of minority groups engaged in agriculture, the marginal impact on the overall URIG will become very limited or even no longer significant [33].

In summary, the impact of the AEE on the URIG may exhibit nonlinear characteristics as urbanization levels change, with one or more thresholds. Therefore, the third research hypothesis is put forward:

H3: *The influence of AEE on the URIG is based on the threshold of the urbanization level effect. It is obvious only in a specific urbanization level range.*

2.4. Consideration of Spatial Correlation

Improvement in AEE does not occur in isolation within a closed administrative area but is embedded in a network of regional linkages and geographical dependencies [51]. Based on the theory of new economic geography and technology diffusion, both the URIG

and AEE may show spatial cluster characteristics [26]; that is, improvement in AEE in the region can narrow not only the URIG but also neighbouring urban and rural areas through demonstration effects, factor flow, and environmental coordination. The income pattern has a positive impact.

First, the diffusion effect of technological progress and the green management model is an important channel for spatial spillover. Compared with long-distance provinces, geographically neighbouring provinces usually exhibit greater homogeneity in topography, climate, soil types, and crop-planting structures. Recent studies have found that, when measuring the green efficiency of China's provincial agriculture, the green development of agriculture across provinces exhibits a significant spatially related network structure and a forward overflow path. Together, geographical proximity, government support, and progress in green technology strengthen this spatial linkage [52,53]. This means that when a region achieves a win-win situation for ecology and economy by improving the AEE, the surrounding areas will have a strong benchmarking effect, prompting agricultural producers in neighbouring provinces to abandon the traditional loose management model and adopt a green life production mode, which in turn drives the increase in the income of rural residents in the surrounding area and the convergence of the URIG.

Secondly, the public goods of the ecological environment imply that agricultural ecological benefits have positive cross-regional externalities. Agricultural production is highly dependent on natural elements, and environmental factors such as air and water flow are highly fluid and interconnected across space. Agricultural surface pollution control, soil and water conservation, and biodiversity protection in a region can often produce ecological dividends across administrative boundaries. For example, in upstream areas, reducing fertiliser and pesticide losses by improving the AEE can not only improve local water quality but also reduce the natural risks of agricultural production in downstream areas and ensure the ecological safety of downstream farmland [54]. In the opposite direction, if a high-pollution, advanced agricultural model is adopted, negative environmental effects such as heavy metal accumulation in soil and water eutrophication will also spread to surrounding areas. Improving the level of natural circulation and agricultural ecological efficiency essentially means increasing the supply of regional public ecological products. This improvement in environmental welfare benefits the surrounding environment; it creates a strong foundation for sustainable agricultural development in neighbouring areas and increases farmers' incomes, thus indirectly helping narrow the URIG.

Based on the above analysis, the impact of the AEE on the URIG should not be limited to local effects but should also include significant cross-regional linkages. Based on this, the fourth research hypothesis is put forward:

H4: *The impact of AEE on the URIG has a positive spatial spillover effect.*

The overall mechanism framework derived from the above hypothesis is visualized in Figure 1.

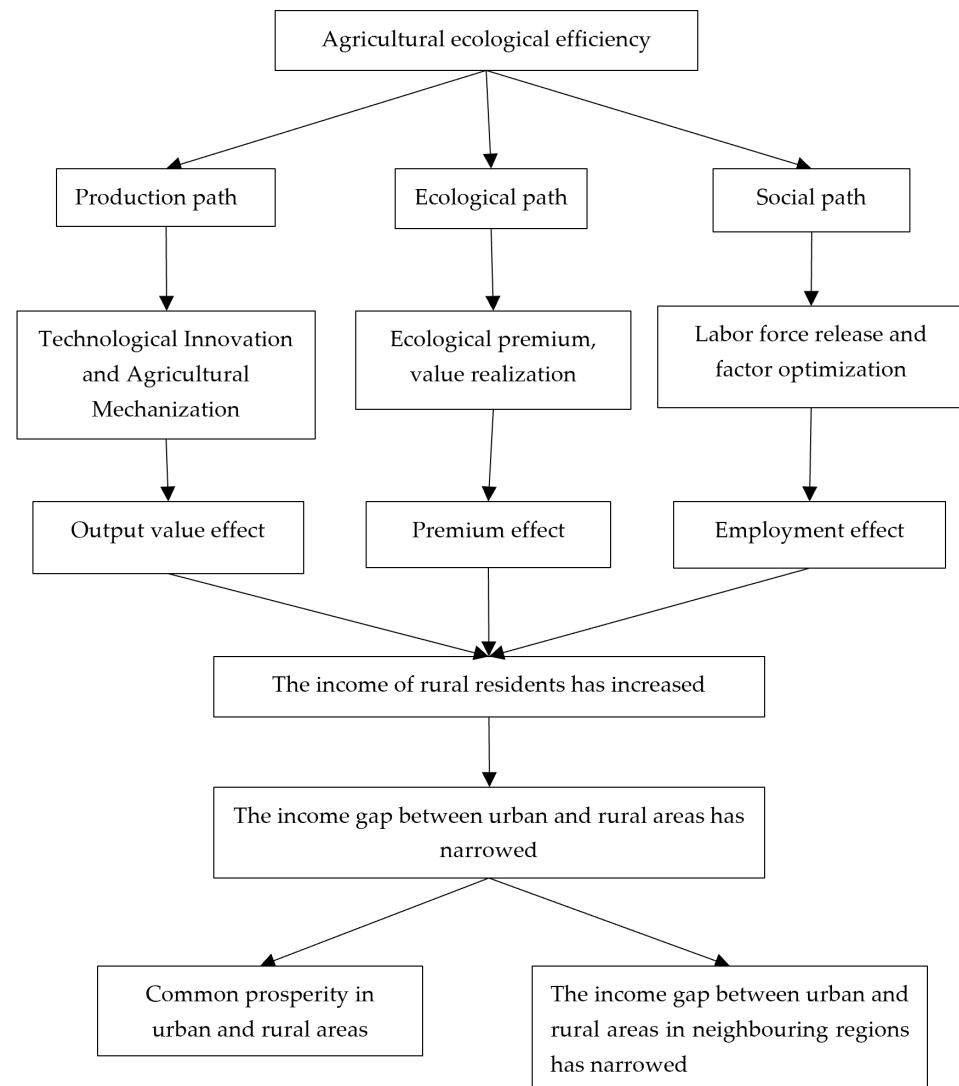


Figure 1. Map of the mechanism of agricultural ecological efficiency affecting the urban-rural income gap (Compiled by the author).

3. Materials and Methods

To systematically test the research hypotheses, we adopted a rigorous econometric method to build an empirical analysis framework based on China's provincial panel data. This section discusses the data source and their processing, the measurement method of the core variables, the settings of the measurement model, and the robustness and endogenous processing strategies.

3.1. Data Source

This study is based on the panel data of 31 provinces, autonomous regions, and municipalities directly under the Central Government in China (excluding Hong Kong, Macao, and Taiwan) from 2011 to 2024. All raw data came from authoritative official statistical publications, including the China Statistical Yearbook, the China Rural Statistical Yearbook, the China Population and Employment Statistics Yearbook of each year, and the statistical yearbook of each province, ensuring the reliability and consistency of the data. For a small number of missing data in individual years or provinces, linear interpolation was used to reasonably estimate and supplement the data points to maintain the balance and continuity of the panel data. Finally, we obtained a balanced panel data set containing 434 observations.

3.2. Variable Definitions and Measures

3.2.1. Explained Variable: Urban-Rural Income Gap (URIG)

With the current method of calculating the URIG, the ratio of urban-rural income struggles to reflect the actual impact of urban and rural population flow. Not only is the Gini coefficient more sensitive to the structural changes in middle-income groups, but it is also unable to distinguish between urban and rural groups for differential analysis [55]. In view of this, we used the Theil Index, which is constructed via population weighting, to measure the URIG. The lower the index value, the smaller the URIG.

$$URIG_{it} = \sum_{i=1}^2 \left(\frac{I_{it}}{I_t} \right) \ln \left(\frac{I_{it}/P_{it}}{I_t/P_t} \right)$$

where $i = 1$ and 2 represent urban and rural areas, respectively; I_{it} , the total income of urban or rural areas in region i in the year; and P_{it} , the corresponding population of urban or rural areas. I_t represents the total income of region i , while P_t denotes the total population of region i .

3.2.2. Core Explanatory Variable: Agricultural Ecological Efficiency (AEE)

The super-efficiency SBM model accounts for undesired output and slack variables. It is suitable for measuring efficiency when inputs and outputs may change disproportionately. It can evaluate the effectiveness of multiple decision-making units of the same type under multi-input and multi-output indicators. The efficiency measurement is more accurate and reasonable [56]; therefore, we use the super-efficient SBM model with a non-expected output to measure the AEE.

Assuming that there are n decision-making units, each decision-making unit contains m inputs, s expected outputs, and q unexpected outputs. For the evaluated unit k , its input, expected output, and non-expected output vectors are denoted as x_{ik} , y_{rk}^g , and y_{tk}^b , respectively. The specific form of the super-efficiency SBM model is as follows:

$$\rho^* = \min \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{ik}}}{1 + \frac{1}{s+q} \left(\sum_{r=1}^s \frac{s_r^g}{y_{rk}^g} + \sum_{t=1}^q \frac{s_t^b}{y_{tk}^b} \right)}$$

$$\text{s.t.} \begin{cases} x_{ik} - s_i^- = \sum_{j=1, j \neq k}^n x_{ij} \lambda_j, \forall i = 1, 2, \dots, m; s_i^- \geq 0 \\ y_{rk}^g + s_r^g = \sum_{j=1, j \neq k}^n y_{rj}^g \lambda_j, \forall r = 1, 2, \dots, s; s_r^g \geq 0 \\ y_{tk}^b - s_t^b = \sum_{j=1, j \neq k}^n y_{tj}^b \lambda_j, \forall t = 1, 2, \dots, q; s_t^b \geq 0 \\ \sum_{j=1, j \neq k}^n \lambda_j = 1, \lambda_j \geq 0 \end{cases}$$

where ρ^* is the efficiency value, λ_j is the weight coefficient, and variables s_i^- , s_r^g , and s_t^b are the input slack, desired output slack, and undesired output slack, respectively.

Referring to relevant research [57,58], the AEE index system built is shown in Table 1. Here, the expected agricultural output is expressed in terms of total agricultural output. To eliminate the influence of price factors, 2005 is used as the reference year for price flattening. Agricultural carbon emissions can be estimated by multiplying the six indicators of fertiliser, pesticides, agricultural film, diesel, agricultural irrigation, and agricultural sowing by their corresponding carbon emission coefficients. Agricultural carbon emissions are estimated as follows: $E = \sum E_i = \sum T_i \cdot \delta_i$. In the formula, E is the total carbon emissions of agriculture,

E_i is the carbon emissions of various carbon sources, T_i is the amount of each carbon emission source, and δ_i is the carbon emission coefficient of each carbon emission source. The emission coefficient of 6 types of carbon sources is shown in Table 2, according to which agricultural carbon emissions are calculated. The main sources of agricultural surface source pollution include residues of pesticides, fertilisers and agricultural films. Following the fixed-proportion weighting method [59], agricultural surface source pollution emissions is equal to fertiliser input $\times$ fertiliser loss + pesticide input $\times$ pesticide pollution rate + agricultural film input $\times$ agricultural film residue rate, among which, refer to Ji & Shang (2021), the fertiliser loss rate, pesticide pollution rate and agricultural film residue rate are set to 65%, 50% and 10% [60], respectively.

Table 1. AEE index system.

Attribute	Type	Measure
Input Indicator	Agricultural natural resource	Total sown area of crops
		Water consumption for agriculture
	Agricultural machinery	Total power of agricultural machinery
		Volume of agricultural diesel used
	Agricultural Labour Force	Number of people employed in agriculture
	Geochemistry	Volume of agricultural chemical fertilisers used
		Volume of agricultural plastic film used
		Pesticide usage amount
Expected Output Indicator	Total value of farm output	Total value of farm output
Unexpected Output Indicator	Agricultural carbon emissions	Total carbon emissions resulting from the use of fertilisers, pesticides, agricultural films, diesel, irrigation systems, and crop-planting practices.
	Agricultural non-point source pollution	Comprehensive index of pollution from fertiliser loss, pesticide residues, and agricultural film residues

Table 2. The Agricultural Carbon Source Emission Coefficient and Its References.

Carbon Source	Emission Factor	Unit	Reference Source
Fertilizer	0.8956	kg/kg	Oak Ridge National Laboratory (ORNL)
Pesticide	4.9341	kg/kg	
Plastic film	5.1800	kg/kg	The Institute of Agricultural Resources and Ecological Environment at Nanjing Agricultural University
Diesel fuel	0.5927	kg/kg	
Agricultural irrigation	20.4760	kg/hm ²	Intergovernmental Panel on Climate Change [61]
Agricultural sowing	3.1260	kg/hm ²	Li et al. (2011) [62]
			Duan et al. (2011) [63]

3.2.3. Moderating Variable: Financial Support (FSA)

To measure the intensity of government financial support for agriculture, the proportion of local expenditure on agriculture, forestry, and water affairs to that on the general public budget is adopted as the proxy variable, according to existing research [64]. This index can better reflect the degree of actual resource inclination of local governments toward agricultural and rural development.

3.2.4. Threshold Variable: Urbanization Level (URB)

The proportion of urban resident population to the total population is used to measure the level of urbanization in each province, which is the indicator most commonly used to measure the stage of regional development and the urban-rural structure.

3.2.5. Control Variables

To control other factors that may affect the URIG, we referred to the relevant literature [65,66] and selected the levels of economic development, industrial structure, natural disaster rate, opening-up level, and human capital level as control variables. Specifically, the level of economic development (LnPGDP) is expressed by the per capita regional gross domestic product (10,000 yuan/person, taken in logarithm); the industrial structure (IS) is expressed by the ratio of the added value of the tertiary industry to that of the secondary industry, which is used to reflect the degree of economic structure upgrading; the natural disaster rate (DIS) is expressed by the ratio of the affected area of crops to the total area of sown crops to control the impact of natural risks on agricultural output and farmers' income; the opening-up level (OPEN) is expressed by the ratio of total import and export to the gross regional product; and the level of human capital (EDU) is defined as the average education of the rural labour force. The number of years is indicated, calculated as follows: illiterate and semi-illiterate ratio $\times 1$ + primary school ratio $\times 6$ + junior high school ratio $\times 9$ + high school ratio $\times 12$ + junior college and above ratio $\times 16$ (Table 3). The results of this descriptive statistical analysis of all variables are shown in Table 4.

Table 3. Summary of Variable Definitions.

Variable	Symbol	Definition	Measurement	Unit
Urban-rural income gap	URIG	Disparity in income between urban and rural products	Theil index	-
Agricultural eco-efficiency	AEE	Ratio of desirable outputs to inputs plus undesirable outputs	The super-efficient SBM model includes non-desired outputs such as carbon emissions.	-
Economic development	LnPGDP	Level of regional economic development	Natural log of GDP per capita	-
Industrial structure	IS	Share of non-agricultural sectors in the economy	Ratio of secondary + tertiary industry value-added to GDP	%
Urbanization level	URB	Proportion of population residing in urban areas	Urban population/total population	%
Financial support for agriculture	FSA	Government fiscal expenditure on agricultural support	Per capita agricultural fiscal expenditure (CNY)	CNY/person
Openness	OPEN	Degree of international trade engagement	Ratio of total import + export value to GDP	%
Education level	EDU	Human capital endowment of rural labor force	Average years of schooling of rural population	Years
Disaster intensity	DIS	Severity of natural disasters affecting agriculture	Ratio of affected crop area to total sown area	%

Table 4. Descriptive statistics of main variables.

Variable Name	Notation	Mean	Standard Deviation	Minimum	Maximum	Number of Observations
URIG (Theil Index)	URIG	0.0832	0.0402	0.0105	0.2017	434
Argo-eco-efficiency	AEE	0.4637	0.2531	0.1599	1.1904	434
Strength of financial support	FSA	0.0763	0.0537	0.0088	0.2038	434
Level of urbanization	URB	0.5991	0.1294	0.2271	0.8985	434
GDP per capita (log)	LnPGDP	10.1744	1.1321	6.4159	12.3378	434
Industrial structure	IS	1.4085	0.7700	0.5271	5.8809	434
Natural disaster rate	DIS	0.1460	0.1285	0.0014	0.6955	434
Outward openness	OPEN	0.2623	0.2707	0.0076	1.4638	434
Level of human capital (years)	EDU	8.7143	1.2737	4.5587	12.6975	434

3.3. Measurement Model Setting

3.3.1. Benchmark Regression Model

To test H1 (AEE directly impacts the URIG) and control for the provincial characteristics that do not change over time and the common trends that change with time, we constructed the following two-way fixed-effects model:

$$\text{URIG}_{it} = \alpha_0 + \alpha_1 \text{AEE}_{it} + \alpha_2 \text{Control}_{it} + \mu_i + \text{year}_t + \varepsilon_{it} \quad (1)$$

where URIG_{it} is the URIG of the i -th province in the t -th year; AEE_{it} is the core explanatory variable of AEE; Control_{it} is the vector of the aforementioned series of control variables; μ_i and year_t are the province and year fixed effects, respectively; ε_{it} is the random error term. The coefficient α_1 is the main concern. If it is significantly negative, H1 is supported.

3.3.2. Moderating Effect Model

To test H2 (the moderating effect of financial support), the moderating variable (financial support FSA_{it}) and its interaction term with the core explanatory variable were added to the benchmark model, and the following moderating effect model was constructed:

$$\text{URIG}_{it} = \beta_0 + \beta_1 \text{AEE}_{it} + \beta_2 \text{FSA}_{it} + \beta_3 \text{AEE}_{it} \times \text{FSA}_{it} + \beta_4 \text{Control}_{it} + \mu_i + \text{year}_t + \varepsilon_{it} \quad (2)$$

Here, FSA_{it} denotes fiscal support intensity, with its coefficient denoted as β_2 , and the interaction term between the AEE and the moderating variable is defined as $\text{AEE}_{it} \times \text{FSA}_{it}$, with coefficient β_3 . If $\beta_3 < 0$ and is statistically significant, then fiscal support enhances the negative impact of AEE on the URIG, suggesting a positive moderating effect and support for H2.

3.3.3. Threshold Effect Model

To further explore the AEE of the urban and rural income gap, its nonlinear and threshold effects, and to test the hypotheses, we adopted a threshold regression model [67]. The single-threshold model is shown in Equation (3):

$$\text{URIG}_{it} = \eta_0 + \eta_1 \text{AEE}_{it} I(\text{URB}_{it} \leq q) + \eta_2 \text{AEE}_{it} I(\text{URB}_{it} > q) + \eta_3 \text{Control}_{it} + \mu_i + \text{year}_t + \varepsilon_{it} \quad (3)$$

Here, Z_{it} denotes the threshold variable, and q represents the threshold value. η_1 is the coefficient measuring the impact of AEE on the URIG when $Z_{it} \leq q$, while η_2 measures its impact when $Z_{it} > q$. If $\eta_1 \neq \eta_2$ and the difference is statistically significant, it indicates

the presence of a threshold effect. If a double threshold exists, we use the following type of model:

$$URIG_{it} = \eta_0 + \eta_1 AEE_{it} I(URB_{it} \leq q_1) + \eta_2 AEE_{it} I(q_1 < URB_{it} \leq q_2) + \eta_3 AEE_{it} I(URB_{it} > q_2) + \eta_4 Control_{it} + \mu_i + year_t + \varepsilon_{it} \quad (4)$$

3.3.4. Spatial Econometric Model

(1) Construction of spatial measurement model

To control for spatial dependence and explore possible spatial spillover effects, our robustness analysis incorporated AEE into the Spatial Durbin Model (SDM). The SDM can simultaneously capture the spatial interaction between explained and explanatory variables [68]. The model is set as follows:

$$URIG_{it} = \gamma_0 + \rho \sum_{j=1}^n W_{ij} URIG_{jt} + \delta_1 AEE_{it} + \delta_2 C_{it} + \sum_{j=1}^n W_{ij} (\theta_1 AEE_{jt} + \theta_2 C_{jt}) + \mu_i + year_t + \varepsilon_{it} \quad (5)$$

Here, $URIG_{it}$ denotes the URIG; AEE_{it} , the core explanation variable; C_{it} , the control variables set; and W_{ij} , the row-standardised spatial weight matrix, which is used to capture the characteristics of geographical proximity. Coefficient ρ reflects the URIG of the spatial effect, revealing the neighbourhood gap's impact on local demonstration or linkage; δ_1 and θ , respectively, measure AEE's influence on the URIG of direct and indirect spillover effects. In addition, the fixed-effects model is introduced into the individual μ_i and $year_t$ with the time fixed effects, to strictly control the regional heterogeneity and time trend shocks and ensure the unbiasedness and robustness of the estimation results.

(2) Construction of spatial weight matrix

Spatial weight matrices are typically constructed based on geographical distance. To ensure robust results, we constructed a spatial adjacency matrix to test the spatial effect of the impact of AEE on the urban-rural income gap. And utilizes a nested spatial economic geography matrix for robustness analysis. The spatial adjacency matrix is represented by a 31×31 matrix of 0 s and 1 s. If two provinces are adjacent, their value is 1, and if they are not adjacent, the value is 0. The formula is as follows:

$$W1_{ij} = \begin{cases} 1, & \text{If adjacent} \\ 0, & \text{If it is not adjacent} \end{cases} \quad (6)$$

In order to comprehensively consider the impact of geographical proximity and similarity of economic development level on spatial correlation, this paper constructs an economic geographical nesting weight matrix. The specific form is the product of the corresponding elements of the geographical distance weight matrix W^d and the economic distance weight matrix W^e :

$$W2_{ij}^{de} = \begin{cases} W_{ij}^d \times W_{ij}^e, & i \neq j \\ 0, & i = j \end{cases} \quad (7)$$

The geographical distance weight is defined as $W_{ij}^d = \frac{1}{d_{ij}}$, where d_{ij} represents the spherical distance between region i and the capital city of region j ; the economic distance weight is given by $W_{ij}^e = \frac{1}{|Y_i - Y_j|}$, with Y_i and Y_j denoting the per capita GDP of regions i and j , respectively.

4. Results

This section systematically reports the empirical results. Firstly, a benchmark regression analysis was conducted, and the adjustment mechanism of the financial support and the threshold effect of the urbanization level are discussed in depth here. Then, heterogeneity is analysed from the three dimensions: regional function, technical conditions, and infrastructure. Finally, a series of robustness tests were conducted to verify the reliability of the core conclusions, including dealing with endogeneity and incorporating spatial econometric models.

4.1. Benchmark Regression Results

Table 5 shows the results of the benchmark regression analysis of AEE on the URIG. Column (1) reports that there is a significant negative correlation between the core variables at the 1% significance level. Column (2) includes the relevant control variables based on the results of column (1). Here, the coefficient of AEE is -0.012 , which is significantly negative at the 5% level. Column (3) further controls the individual and time effects. The coefficient of AEE is stable at -0.012 , and it is significant at the 1% level. Under all settings, AEE improvement is significantly associated with a narrowing of the URIG. Based on the two-way fixed-effect model results in column (3), the URIG decreases by 0.012 for each unit increase in AEE. This effect is significant at the statistical level of 1%, indicating that improving AEE is not only statistically significant but can also bring about a substantial redistribution effect of urban and rural income. Compared with columns (1) and (2), the R-squared value (0.978) of column (3) is much higher (0.136 and 0.615), indicating that the introduction of the two-way fixed individual and time effects has significantly improved the fit of the model, and more accurately revealed the relationship between AEE and the URIG.

Table 5. Benchmark return results.

Variables	(1)	(2)	(3)
AEE	-0.059^{***} (-7.74)	-0.012^{**} (-2.02)	-0.012^{***} (-2.84)
LnPGDP		-0.017^{***} (-14.25)	-0.004^{***} (-4.15)
IS		-0.002 (-0.97)	0.015^{***} (8.18)
DIS		0.022^{**} (2.08)	0.006 (1.59)
OPEN		-0.036^{***} (-6.17)	-0.048^{***} (-9.27)
EDU		-0.008^{***} (-7.34)	0.000 (0.14)
Constant	0.110^{***} (29.24)	0.339^{***} (24.85)	0.123^{***} (8.67)
Observations	434	434	434
R-squared	0.136	0.615	0.978
Province fixed effects	NO	NO	YES
Year fixed effects	NO	NO	YES

Robust t-statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2. Robustness and Endogeneity

4.2.1. Robustness Test

First, the variables were winsorized at the 1% level to ensure the accuracy and reliability of the analysis results. Secondly, the disposable income ratio of urban and rural families

was used to replace the Tyre index as the explained variable. The results of columns (1) and (2) in Table 5 show that the AEE is significant at the level of 1% regardless of treatment choice, indicating that AEE improvement can significantly reduce the URIG and verify the robustness of the model.

4.2.2. Endogeneity Concerns

Although the two-way fixed-effects model can control for provincial characteristics that do not change over time and common year-shock factors, endogeneity may remain between the AEE and URIG, thereby affecting the unbiasedness of the estimated results. Specifically, reverse causality and omitted variables are the main sources of endogeneity. On the one hand, narrowing the URIG may improve the ecological efficiency of agriculture by encouraging the adoption of agricultural technologies or optimising resource allocation; on the other hand, unobservable factors that vary over time, such as the intensity of regional environmental regulation and changes in rural institutions, may simultaneously confound the trends of both variables. To alleviate these problems and obtain more robust causal inference, we used lagged AEE as an instrumental variable and performed an instrumental variable estimation. The theoretical basis is that the AEE of the first phase is closely related to the current efficiency level.

Table 6 reports the results of the two-stage regression of instrumental variables and relevant statistical tests. First, the results of the under-identification test show that the lag variable is highly related to the current AEE, and the weak identification test value (64.05) is higher than the conventional critical value (16.38), which rejects the hypothesis of weak instrumental variables, indicating that the instrumental variables are valid. Secondly, after considering the endogeneity problem, the estimated coefficient of AEE remains significantly negative at the 5% statistical significance level. This result not only confirms the reliability of the benchmark regression finding—that is, AEE improvement can significantly narrow the URIG—but also excludes the interference caused by reverse cause and effect to a certain extent.

Table 6. Robustness test and endogeneity treatment.

Variables	(1)	(2)	(3)	
	Tail Reduction 1%	Replacing Variable	2SLS	
			First Stage	Second Stage
Lagged AEE			1.076 *** (27.01)	
AEE	−0.012 *** (−3.064)	−0.122 ** (−2.20)		−0.015 ** (−2.19)
Constant	0.123 *** (8.127)	3.235 *** (13.11)	−0.242 *** (−2.90)	0.329 *** (23.26)
Under-identification Test				15.289 ***
Weak Identification Test				64.05 [16.38]
Observations	434	434	403	403
R-squared	0.978	0.921	0.929	0.604
Control variables	YES	YES	YES	YES
Province fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES

Note: Values in [] represent the Stock–Yogo critical value at the 10% significance level. The instrumental variable results are reported as supplementary evidence of robustness. Robust t-statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

It is worth noting that although the correlation of instrumental variable is fully supported statistically, the over-identification constraints on whether the AEE of the lag phase is strictly exogenous do not fully satisfy the statistical test; that is, the possibility that lagged

AEE affects the current income gap through other historical paths cannot be completely ruled out. Therefore, compared with the fully confirmed causal relationship, the 2SLS instrumental variable regression results in this section should be regarded as robust evidence, which further supports the core assertion that AEE improvement helps narrow the URIG. As a result of comprehensive shrinkage processing and variable replacement, the conclusion of this paper shows strong robustness.

4.3. Moderating Effect Analysis

To test the regulatory role of financial support (FSA) (H2), FSA and its interaction with AEE were added to the benchmark model. The results are shown in Table 7. Column (1) lists the benchmark results without interaction items for comparison, and column (2) shows that after adding the interaction item, the interaction item ($AEE \times FSA$) coefficient of AEE and FSA is -0.241 , which is highly negative at the 1% level. This shows that financial support has significantly enhanced the negative impact of AEE on the URIG; that is, the greater the financial support, the stronger its effect in improving AEE and narrowing the URIG. This supports H2 and confirms the key empowering role of government financial support in the green transformation of agriculture. FSA effectively amplifies the effect of increasing income and benefiting lower-income farmers by improving ecological efficiency through cost reductions in technology adoption, thereby compensating for the positive externality of the environment and improving market access.

Table 7. Analysis of the moderating effect of financial support.

Variables	(1) URIG	(2) URIG
AEE	−0.012 *** (−2.84)	−0.008 * (−1.93)
FSA		−0.099 ** (−2.49)
$AEE \times FSA$		−0.241 *** (−4.88)
LnPGDP	−0.004 *** (−4.15)	−0.001 (−0.55)
IS	0.015 *** (8.18)	0.013 *** (6.95)
DIS	0.006 (1.59)	0.004 (1.31)
OPEN	−0.048 *** (−9.27)	−0.046 *** (−9.81)
EDU	0.000 (0.14)	0.000 (0.25)
Constant	0.123 *** (8.67)	0.095 *** (4.94)
Observations	434	434
R-squared	0.978	0.981
Province fixed effects	YES	YES
Year fixed effects	YES	YES

Robust t-statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.4. Threshold Effect Analysis

Theoretical analysis [15] suggests that the convergence effect of AEE on the URIG is not a simple linear relationship and may be constrained by the urbanization stage. There are nonlinear threshold characteristics, but the specific number of thresholds and threshold intervals as well as the intensity of different intervals of this effect still need to be empirically

tested. To test H3, we adopted the Hansen panel threshold model, took the urbanization level (URB) as the threshold variable, carried out the threshold effect significance test through repeated sampling 300 times using the bootstrap method, determined the existence of a single, double threshold, or triple threshold in turn, and then estimated the impact coefficient of the AEE on the URIG in different urbanization intervals. The test results are shown in Table 8. The single- and double-threshold tests for urbanization level passed the 5% significance level test, indicating a double-threshold effect at the 5% confidence level. The two threshold values are 0.3114 and 0.8201, respectively. The maximum likelihood ratio function was used to verify whether the threshold value is true. Further details can be seen in Figure 2.

Table 8. Test results based on the threshold effects of the urbanization level.

Threshold Variables	Threshold Count	F-Statistic	<i>p</i> -Value	10% Critical Value	5% Critical Value	1% Critical Value	Threshold	Confidence Interval
URB	Single	59.76	0.0033	31.0316	39.9363	53.1503	0.8201	[0.7553, 0.8293]
	Double	38.63	0.0500	30.2378	36.6030	52.0060	0.3114	[0.2575, 0.3641]
	Triple	47.39	0.7000	120.3638	144.6823	174.7202	0.4781	[0.4705, 0.4812]

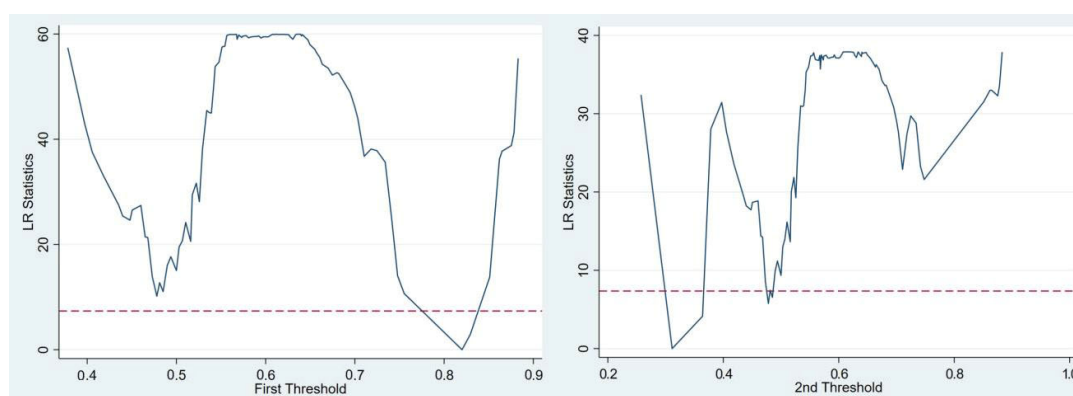


Figure 2. Double-threshold estimates and likelihood ratio test plots.

Figure 2 shows that in the estimation process of the first and second threshold, the LR curve shows the characteristics of a “V-type valley”, the LR statistics at the lowest point of the curve are close to 0, and the corresponding horizontal coordinates are 0.8201 and 0.3114, respectively. The intersection intervals of the two curves and the critical value of the 95% confidence level of the horizontal dotted line are [0.7553, 0.8293] and [0.2575, 0.3641], respectively. The widths of these intervals are relatively narrow, indicating good convergence and that the estimated threshold value is robust and accurate, providing a reliable basis for parameter estimation through subsequent segmented regression analyses based on the threshold effect.

Table 9 shows that the role of AEE on the URIG is affected by the urbanization level, as well as a nonlinear relationship. When the urbanization level is lower than 0.3114, the coefficient of AEE is -0.005 , which fails to pass the significance test. At this stage, the dual structure of urban and rural areas is prominent. The flow of labour, capital, and other factors of production between urban and rural areas faces strong institutional and market barriers. It is difficult to smoothly transfer the surplus labour force in rural areas to the non-agricultural sector. At the same time, the circulation system for ecological agricultural products is imperfect, and the market incentive mechanism of “high quality and preferential price” is difficult to implement. The income growth effect brought about

by AEE improvement is locked into the relatively closed rural economy and cannot be effectively transmitted to the convergence of the overall URIG, so it has not shown a significant inhibitory effect.

Table 9. Regression results of threshold effect based on urbanization level.

Variables	URIG
($URB \leq 0.3114$)	−0.005 (−0.7753)
($0.3114 < URB \leq 0.8201$)	−0.0489 *** (−7.8087)
($URB \geq 0.8201$)	0.0030 (0.3416)
Control variables	YES
Observations	434
R-squared	0.7584

Robust t-statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

When the urbanization level is between 0.3114 and 0.8201, the coefficient of AEE is −0.0489, which is significantly negative at the statistical level of 1%. This means that for every 1-unit improvement in AEE at this stage, the URIG will decrease significantly by 0.0489, representing a ‘golden window’ during which agricultural green transformation of agriculture can contribute to poverty reduction and income growth. During the middle stage of urbanization, demand for high-quality ecological agricultural products in cities is increased, and the rural labour force has gradually shifted to the non-agricultural sector. Improving AEE has not only increased the operating income of agricultural business entities but also raised farmers’ wage income through labour reallocation. Therefore, the convergence effect on the URIG is the most prominent.

When the urbanization rate exceeds 0.8201, the coefficient of AEE becomes 0.0030 and fails to pass the significance test. At this time, the proportion of agriculture in the national economy is relatively low. The gap between urban and rural areas is mainly dominated by factors such as skill premium and property income in the non-agricultural sector. The marginal contribution of the improvement of AEE to the urban and rural income gap is very limited, so its convergence effect is no longer significant.

4.5. Heterogeneity Analysis

Considering regional functional heterogeneity, we divided the sample into main grain-producing areas and non-grain-producing areas. As shown in Table 10, the coefficient of AEE is −0.018, which is highly significant at the 1% level in the main grain-producing areas, whereas in non-grain-producing areas, the coefficient is −0.009 and not significant. This shows that the income-associated effect of AEE is more pronounced in areas that assume the core function of national food security. This may be because the main grain-producing areas are more likely to receive centralised policy support, operate under large-scale production conditions, and experience a more stable market demand, such that improvement in ecological efficiency can be more effectively transformed into economic benefits.

Based on the heterogeneity of technical conditions, we grouped areas by their median level of agricultural mechanization. In high-mechanization areas, the AEE coefficient is −0.022, which is highly significant at the 1% level; in areas with low mechanization, the coefficient is positive and not significant. This confirms that the foundation of advanced production technology is an “empowerment” that contributes to ecological efficiency. High mechanization implies a stronger capacity for technology absorption and application, enabling ecological agricultural technology to be deeply integrated with modern equipment to achieve significant cost savings and efficiency.

Table 10. Results of heterogeneity analysis.

Variables	(1) Main Grain-Producing Areas	(2) Non-Main Grain-Producing Areas	(3) High Mechanization Level	(4) Low Mechanization Level	(5) High Level of Transportation Infrastructure	(6) Low Level of Transportation Infrastructure
AEE	−0.018 *** (−3.938)	−0.009 (−1.598)	−0.022 *** (−5.21)	0.001 (0.10)	−0.019 *** (−3.548)	−0.013 ** (−2.099)
Control variables	YES	YES	YES	YES	YES	YES
Province/year FE	YES	YES	YES	YES	YES	YES
Observations	182	252	216	217	216	216
R ²	0.967	0.981	0.976	0.984	0.977	0.982

Robust t-statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Considering infrastructure heterogeneity, we tested groups based on their median level of transportation infrastructure (highway density). The results show that the coefficient of AEE is negative in areas with either high or low levels of transportation facilities, indicating that the positive spillover of improvements in ecological efficiency on farmers' income is universal. However, the size and significance of the contrast coefficient indicate that the empowerment effect is stronger in areas with high levels of transportation facilities. This highlights the key role of market accessibility: a perfect transportation network effectively reduces the logistics costs and market barriers for ecological agricultural products, so that ecological dividends can benefit farmers more fully.

In summary, the effect of AEE on narrowing the URIG is particularly prominent in the main grain-producing areas, areas with a high agricultural mechanization level, and areas with a high transportation infrastructure level. This provides a basis for designing differentiated regional agricultural environmental policies.

4.6. Spatial Effect Analysis

4.6.1. Spatial Correlation Test

The global Moran index of urban-rural income gap under the adjacency matrix (W1) and the spatial economic and geographical nesting matrix (W2) is shown in Table 11. It can be seen that the Moran index of urban and rural income gap under the two spatial weighting matrices is both positive and significant at the level of 1%, indicating that the urban and rural income gap is significantly positive in space and has the spatial clustering characteristics. The Moran index under the adjacency matrix is larger than the Moran index under the spatial economic and geographical nesting matrix, and its spatial correlation is higher. Therefore, the spatial adjacency matrix is chosen to analyse the spatial self-correlation between agricultural ecological efficiency and urban-rural income gap. Taking the adjacency matrix (W1) as an example, the global Moran's I of the URIG consistently remained between 0.543 and 0.484 from 2011 to 2024, both of which are significant at the 1% level ($p < 0.001$). This shows that the URIG in China's provinces is not independent of each other but shows extremely significant characteristics of "high-high aggregation" and "low-low aggregation"—that is, high-income areas tend to be adjacent to high-income areas, and low-income areas tend to be adjacent to low-income areas, with obvious spatial dependence attributes. Given the significant spatial dependence of the URIG, the traditional panel model may introduce estimation bias by ignoring spatial disturbance terms. Therefore, the spatial measurement model introduced below was used to further analyse the spatial effect.

To further reveal the spatial characteristics of differences in AEE, we present Moran scatter plots of the AEE for 2011, 2015, 2018, and 2024. As shown in Figure 3, the slope of the scatter plot fit line is positive, and the vast majority of sample points are concentrated in the first and third quadrants, indicating that the AEE is not randomly distributed in space as it shows a significant "club convergence" phenomenon. Additionally, the sample points in the second and fourth quadrants are relatively small, indicating that barriers to cross-

Table 11. Global Moran's I of URIG in China from 2011 to 2024.

Year	W1		W2	
	Moran's I	p-Value	Moran's I	p-Value
2011	0.543	0.000	0.182	0.000
2012	0.534	0.000	0.178	0.000
2013	0.531	0.000	0.176	0.000
2014	0.537	0.000	0.178	0.000
2015	0.554	0.000	0.180	0.000
2016	0.541	0.000	0.175	0.000
2017	0.536	0.000	0.173	0.000
2018	0.528	0.000	0.171	0.000
2019	0.507	0.000	0.168	0.000
2020	0.501	0.000	0.163	0.000
2021	0.512	0.000	0.170	0.000
2022	0.502	0.000	0.167	0.000
2023	0.494	0.000	0.161	0.000
2024	0.484	0.000	0.162	0.000

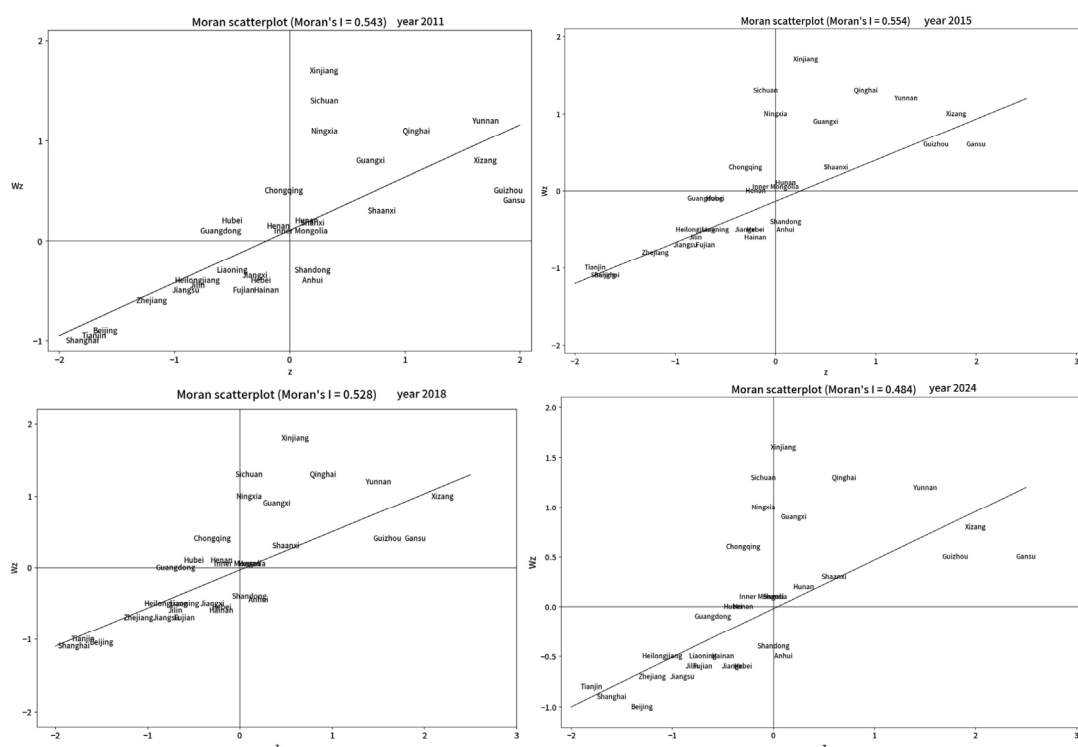


Figure 3. Moran scatter plots of the URIG index in China for the years 2011, 2015, 2018, and 2024.

4.6.2. Model Testing and Spatial Spillover Effect Analysis

An adaptability test was performed on the spatial model, revealing the LM-error (26.236), Robust LM-error (7.488), LM-Lag (101.144), Robust LM-lag (82.396), LR (SDM vs. SAR) (62.64), and LR (SDM vs. SEM) (97.11), and the p -value of the Wald (50.52) test is less than 0.01. It was also found that the SDM cannot be degraded. The results of the Hausman test show that the fixed-effects model is better than the random-effects model, and those of the likelihood comparison test show that the model has individual and time fixed effects. Therefore, the two-way fixed-effects spatial Durbin model was selected.

Table 12 shows the regression results based on the spatial Dubin model, in which the spatial autoregressive coefficient (ρ) represents the spatial coefficient of the URIG and is significant within the 1% confidence range. This shows that the URIG has spatial effects and may be influenced by surrounding areas.

Table 12. Spatial Dubin effect decomposition.

Variables	(1) Main	(2) Wx	(3) Spatial	(4) Direct Effect	(5) Indirect Effect	(6) Total Effect
AEE	−0.014 *** (−4.94)	−0.023 *** (−3.93)		−0.017 *** (−5.76)	−0.045 *** (−4.57)	−0.062 *** (−5.69)
LnPGDP	−0.002 ** (−2.03)	0.004 ** (2.49)		−0.002 * (−1.77)	0.005 ** (2.19)	0.003 (1.36)
IS	0.012 *** (7.44)	0.026 *** (7.31)		0.015 *** (9.91)	0.049 *** (8.92)	0.065 *** (10.19)
DIS	0.005 * (1.78)	−0.003 (−0.54)		0.005 * (1.76)	−0.001 (−0.17)	0.003 (0.35)
OPEN	−0.034 *** (−9.19)	−0.002 (−0.30)		−0.036 *** (−9.37)	−0.025 ** (−2.44)	−0.061 *** (−5.04)
EDU	0.000 (0.03)	−0.002 * (−1.87)		−0.000 (−0.26)	−0.003 (−1.61)	−0.003 (−1.42)
rho (ρ)			0.411 *** (7.31)			
Observations	434	434	434	434	434	434
R-squared	0.006	0.006	0.006	0.006	0.006	0.006
Number of id	31	31	31	31	31	31

Robust t-statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Since the estimated coefficients in the spatial model cannot fully capture the impact of independent variables on the dependent variable and can only indicate directionality and significance, it is necessary to use the partial differential method to decompose the total effect into direct and indirect effects [69]. Among them, the direct effect includes the direct and feedback effects [70] of AEE improvement on the urban-rural income gap, and the indirect effect reflects the impact of AEE improvement on the urban-rural income gap in surrounding areas.

Through the decomposition of the spillover effect, it can be obtained that the direct effect of AEE on the urban and rural income gap in the region (−0.0174) and its spatial spillover effect on neighbouring areas (indirect effect, −0.0451) are both significantly negative at the 1% level. This shows that AEE improvement is not only beneficial to the local area but can also benefit the surrounding areas through technological diffusion, factor flow, and other channels, resulting in a positive effect on regional coordinated development. The spatial autoregression coefficient is significantly positive, confirming that the URIG exhibits spatial aggregation. The test not only strengthens the robustness of the benchmark conclusion but also reveals the spatial spillover dimension of the impact.

4.6.3. Robustness Test for Spatial Regression Results

To further verify the robustness of the spatial regression results, this paper conducts a robustness test by replacing the spatial weight matrix (Table 13). Specifically, the model is re-estimated after replacing the adjacency matrix with the economic and geographical nested matrix. The results show that, although the coefficient estimates differ somewhat from the baseline model, there is no substantial change in the coefficient symbol and significance level of the core explanatory variable. This shows that considering the weight of economic and geographical nesting, agricultural ecological efficiency still has a significant effect on the income gap between urban and rural areas, which is consistent with the previous

benchmark regression conclusion, indicating that the research results of spatial effects are stable.

Table 13. A robust test based on the replacement of the space-weight matrix.

Variables	(1) Main	(2) Wx	(3) Spatial	(4) Direct Effect	(5) Indirect Effect	(6) Total Effect
AEE	−0.014 *** (−5.49)	−0.051 *** (−2.91)		−0.018 *** (−5.40)	−0.130 ** (−2.41)	−0.147 *** (−2.64)
LnPGDP	−0.001 (−1.37)	−0.011 * (−1.81)		−0.002 ** (−2.26)	−0.027 * (−1.82)	−0.029 * (−1.94)
IS	0.018 *** (11.60)	0.087 *** (8.05)		0.024 *** (9.23)	0.218 *** (3.63)	0.242 *** (3.89)
DIS	0.002 (0.89)	0.012 (0.74)		0.003 (1.11)	0.031 (0.79)	0.034 (0.85)
OPEN	−0.035 *** (−8.95)	−0.005 (−0.22)		−0.036 *** (−8.53)	−0.051 (−0.95)	−0.086 (−1.57)
EDU	0.000 (0.41)	−0.011 *** (−2.68)		−0.000 (−0.43)	−0.024 ** (−2.17)	−0.024 ** (−2.13)
rho (ρ)			0.547 *** (5.39)			
Observations	434	434	434	434	434	434
Number of id	31	31	31	31	31	31

Robust t-statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. Discussion and Conclusions

A narrower URIG represents the consolidation and benefits of poverty alleviation. Improving AEE plays an important role as a key driving force in narrowing the URIG. In this study, 31 provinces in China were used as research subjects for theoretical and empirical analyses. The results show the following:

- (1) AEE exhibits a steady negative association with the URIG. The two-way fixed-effects model shows that, after controlling for individual characteristics, time trends, and a series of provincial economic and social interference factors, for every one-unit increase in AEE, the URIG, measured by the Theil Index, is significantly reduced by 0.012. This finding remains robust after incorporating control variables. The lag instrumental variable method remains valid after correcting for endogeneity, confirming that China's agricultural green transformation has the dual dividends of environmental improvement and social equity, providing long-term empirical evidence from developing countries for the theoretical hypothesis of "green fairness" coordination.
- (2) Financial support for farmers is a key policy lever that can be used to strengthen the convergence effect. The results show that financial support plays a significant positive regulatory role in the process of AEE, thereby affecting the URIG. This shows that strong, green-oriented financial support can effectively reduce the cost and risk of adopting ecological technologies, improve the market docking mechanism for ecological agricultural products, and amplify the income-increasing and poverty-alleviating effects of improving AEE.
- (3) The impact of AEE has the characteristics of a nonlinear dual threshold based on the urbanization level. Its effect on the narrowing of the URIG is only significant at the moderate urbanization level. This indicates that the income dividend of agricultural green transformation is contingent on the development stage from the green transformation of agriculture, which fully reveals the degree of integration that depends on the urban and rural factor markets. At the same time, agriculture still accounts for a certain proportion of the economy at a specific development stage.

- (4) There is significant multi-dimensional heterogeneity in the impact of AEE. Its positive effect is more prominent and significant in staple grain-producing areas, areas with a high level of agricultural mechanization, and areas with a high level of transportation infrastructure. This shows that the income distribution effect of AEE is highly dependent on the region's large-scale production conditions, modern technical equipment base, and efficient market connectivity.
- (5) The improvement of AEE has a significant spatial spillover effect. Spatial measurement analysis shows that improving the AEE in a region can not only narrow the URIG but also have a positive radiating and driving effect on neighbouring areas. This shows that the benefits of agricultural green transformation have "regional public goods" characteristics and offer a new perspective on cross-regional collaborative governance. Existing studies also support this perspective. For example, some research using national panel data found that improving AEE can significantly reduce the URIG and have a positive spatial spillover effect [14].

The following recommendations are proposed:

First, enhance strategic coordination while avoiding unwarranted causal claims. At both national and regional levels, rural revitalization strategies could more explicitly recognize the potential complementarity between agricultural green development and farmers' income growth, rather than treating them as a zero-sum trade-off. Policymakers might consider incorporating AEE-related indicators into agricultural support and performance evaluation systems, thereby incentivizing practices that simultaneously improve ecological efficiency and rural livelihoods. However, it must be emphasized that the observed negative statistical association does not warrant a direct inference that any specific green technology promotion policy causally reduces the URIG. The net impact of particular policy interventions requires rigorous policy evaluation designs, such as randomized controlled trials or well-identified quasi-experiments.

Additionally, optimise the agricultural financial support system. First, refine green subsidy and ecological compensation mechanisms. Expanding subsidy standards and coverage for water-saving irrigation, organic fertiliser substitution, green pest control and other emission-reduction and efficiency-enhancing technologies may help incentivise green production. Accelerating the establishment of vertical and horizontal ecological compensation mechanisms based on ecosystem service value can help ensure that farmers and regions engaged in ecological protection receive adequate and stable economic returns. Second, innovate green financial tools: vigorously develop "green credit", provide interest-discounted loans, and guarantee support for ecological farms, green food certified enterprises, and cooperatives; actively explore the market-oriented mechanism for the value realisation of ecological products such as agricultural carbon sink transactions and water rights transactions and open up new property income channels for farmers. Third, invest in the market connection infrastructure: financial funds should focus on supporting the cold chain logistics of agricultural products, warehousing and preservation facilities, digital trading platforms, and regional public brand construction of green agricultural products; and make every effort to break the bottlenecks of ecological agricultural products logistics and information to ensure that ecological premiums can be fully obtained by producers.

At the same time, strengthen the mechanism for the diffusion and coordination of green technology at the regional level. The decomposition results of the spatial Dubin model show that the green transformation of a single region not only benefits the local area but also radiates to the surrounding area through technology diffusion, market linkage, and other channels. Therefore, it is recommended to break the administrative division restrictions and establish a cross-regional agricultural green technology-sharing platform for ecological product production and marketing alliance. However, note that this study only statistically

identifies spatial correlation; it is not possible to accurately quantify the contribution of specific channels, such as technology diffusion and factor flows. Policymakers should remain wary of overestimating the spillover effect.

Finally, adopt differentiated and phased implementation strategies to improve policy targeting. First, priority may be given to moderately urbanised areas to advance the coordination between AEE improvement and urban-rural integrated development. In these areas, deepening market-orientated reforms of household registration and land systems may help strengthen the income-enhancing potential of the agricultural green transition. Second, provide targeted guidance tailored to local conditions: in major grain-producing areas, with national food security as the bottom line, promoting green, high-yield and efficient technology models and building a “green granary” can help coordinate food security, ecological conservation and farmer income growth; in highly urbanised areas, intelligent agricultural machinery, remote sensing monitoring and big data applications may be prioritised to enhance production efficiency; in areas with high transportation accessibility, urban agriculture, leisure agriculture and rural tourism can be further developed to promote the deep integration of ecological agriculture with secondary and tertiary industries. For less developed areas with low urbanization, low mechanization or poor transportation access, policies should first address foundational bottlenecks. Specifically, strengthening transportation, digital and water conservancy infrastructure and improving basic public services can create enabling conditions for future green technology adoption and industrial spillover effects.

This research is based on provincial panel data. Although such data can reveal the overall trends in AEE and the URIG at the macro-level, this study is limited by the data’s macro-aggregated characteristics. Moreover, we did not fully incorporate micro-heterogeneous factors at the farmer level, such as farmers’ health endowments, business scale differences, risk preferences, and technology adoption. Future research should use nationwide, multi-time, micro-level research data to deeply analyse the behavioural response mechanism of micro-subjects, thereby further enhancing the practical interpretation of our conclusions. Nevertheless, the reliability of our core conclusions is assured through the multi-dimensional empirical strategy and series of robustness checks employed. In the future, with the in-depth promotion of China’s agricultural green transformation strategy, how to specifically translate improvements in AEE into increases in farmers’ income and common prosperity, especially regarding the differentiated impacts of farmers’ endowments across different resource levels, will become one of the most valuable research directions.

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