

Article

Research on the Impact of China's Urbanization Process on the Green Efficiency of Agricultural Water Use

Zihuai Tang, Ruilin Sun, Juan Yang * and Wenxin Liu 

College of Economics and Management, Northwest A&F University, Xianyang 712100, China; tangzihuai@nwfau.edu.cn (Z.T.); sunruilin@nwfau.edu.cn (R.S.); liuwenxin@nwfau.edu.cn (W.L.)

* Correspondence: yangjuan@nwfau.edu.cn

Abstract

This study employs the Super-SBM model to evaluate the green efficiency of agricultural water use (GEAW) at the municipal level across China from 2013 to 2022. Urbanization levels are systematically assessed using the entropy weight method. Grounded in this theoretical framework, we employ a two-way fixed effects regression model to estimate the effect of urbanization on GEAW and to examine whether government water conservancy infrastructure investment intensity (GOVE) moderates this relationship. The findings of this study indicate that: (1) China's GEAW exhibited a fluctuating downward trend, with pronounced regional disparities. Geographically, the distribution exhibited a clear trend: elevated levels in the eastern and southern regions, contrasted with lower values in the western and northern areas. (2) The urbanization process is positively associated with GEAW. (3) The urbanization process exerts a heterogeneous promoting effect on GEAW contingent upon GOVE; a single-threshold effect is empirically identified. Specifically, when GOVE remains below the threshold level, the urbanization process exhibits no statistically significant positive impact on GEAW. However, once investment surpasses this critical threshold, the urbanization level (URBA) begins to exert a robust and positive influence on such efficiency. Therefore, within the broader context of ongoing urbanization, it is imperative to actively foster coordinated green development between urban and rural areas and optimize governmental investment strategies for water infrastructure—particularly through differentiated, targeted, and evidence-based governance approaches—thereby establishing favorable external conditions conducive to enhancing GEAW and advancing the modernization of agriculture.

Keywords: urbanization process; green efficiency of agricultural water use; government water conservancy infrastructure investment intensity; two-way fixed effects model; panel threshold model



Academic Editor: Jiandong Wang

Received: 7 August 2026

Revised: 12 September 2026

Accepted: 16 September 2026

Published: 18 September 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Water is the source of life and the foundation of production. As a core component of China's total water consumption, efficient and green utilization of agricultural water underpins national food security, high-quality agricultural development, and the construction of an ecological civilization [1]. China is currently in a critical phase of rapid urbanization: by the end of 2025, the urbanization rate of permanent residents reached 67.89%. While urbanization has driven the agglomeration of population, industry, and capital and fueled rapid economic growth, it has also triggered profound adjustments in urban–rural resource allocation, making problems such as the squeezing of agricultural water resources,

low utilization efficiency, and ecological pollution increasingly prominent [2]. Specifically, urbanization has (i) sharply increased non-agricultural water demand, producing an “agricultural-to-non-agricultural water transfer” that continuously squeezed agricultural water consumption down to 364.84 billion m³ in 2024 [3]; (ii) drawn a large number of rural laborers into cities, hindering the upgrading of agricultural production modes and perpetuating extensive irrigation and the overuse of fertilizers and pesticides [4]; and (iii) skewed capital and technology toward urban areas, leaving rural water conservancy infrastructure aged and underdeveloped [5]. Facing these challenges, market mechanisms alone are insufficient to achieve rational resource allocation; government investment intervention in water conservancy infrastructure, as a critical tool of macroeconomic regulation, can adjust the urban–rural water allocation pattern, optimize the agricultural water use structure, and drive the green transformation of agricultural water use [6]. Therefore, enhancing the green efficiency of agricultural water use through government water conservancy investment, so as to realize the coordinated advancement of urbanization and sustainable agricultural development, has become an urgent practical issue.

In recent years, the environmental problems derived from water resource utilization have received growing scholarly attention [7], giving rise to a substantial body of research on the green efficiency of agricultural water use, which can be broadly categorized into three strands. The first strand includes studies on its measurement. Scholars have progressively extended the evaluation from single economic efficiency to comprehensive efficiency by incorporating undesirable outputs [8]—for example, Chen Lei et al. (2015) evaluated the economic and environmental efficiency of water resources using a DEA model with undesirable outputs [9], and Liu Yu et al. (2019) incorporated agricultural ammonia nitrogen and COD into output indicators [10]. Nevertheless, most existing studies emphasize economic benefits, with few considering ecological and social benefits simultaneously, which may bias the scientific measurement of development efficiency [11,12]. The second strand includes studies on the nonlinear relationship between urbanization and agricultural green total factor productivity (AGTFP). While some scholars found that urbanization effectively allocates agricultural resources and enhances production efficiency [13,14], others reported an inhibitory or insignificant effect [15], and Guo Haihong and Zhang Zaixu (2019) identified a single threshold effect with rural per capita income as the threshold variable [16]. Overall, existing studies mostly operate at the macro level of AGTFP and devote insufficient attention to the nonlinear driving mechanism in the micro-subfield of agricultural water resources and the environment. The third strand includes studies on the impact of government water conservancy investment on agricultural development. Scholars have examined government interventions—such as agricultural insurance, technology extension, land transfer, fiscal support, and environmental regulation—on agricultural (low-carbon) production efficiency [17–19], for instance, by testing the effect of ecological civilization pilot zones via PSM-DID [20,21] or the nonlinear effect of environmental regulation via panel models [22]. However, urbanization, government water conservancy investment, and the green efficiency of agricultural water use are rarely incorporated into a unified analytical framework, with most studies focusing on only two of the three, yielding a relatively limited research perspective.

Based on the above analysis, this paper takes the impact of China’s urbanization process on the green efficiency of agricultural water use as the core research theme, using government investment in water conservancy infrastructure as a conditional influence factor. It systematically explores the evolutionary characteristics and influence mechanisms of GEAW in the context of urbanization. Although prior studies have described macro-level trends between urbanization and agricultural water use, accurate empirical identification requires complete and comparable prefecture-level panel data. Restricted by the release lag

of prefecture-level city statistical indicators, this paper adopts available unbalanced panel data on 280 prefecture-level cities from 2013 to 2022 to examine the interrelationships among urbanization, government water conservancy infrastructure investment, and GEAW. This study aims to provide theoretical support and practical references for optimizing urban–rural water resource allocation, improving government water conservancy investment policies, enhancing GEAW, and advancing the coordinated development of urbanization and sustainable agricultural water utilization.

The potential contributions of this study are as follows. First, by adopting the Super-SBM model considering undesirable outputs, this paper incorporates the agricultural grey water footprint into undesirable outputs to evaluate GEAW for 280 prefecture-level cities from 2013 to 2022. This improves evaluation accuracy by constructing a comparable quantitative framework that integrates economic output, social benefits and ecological constraints, thus filling the research gap in the existing literature, which mostly focuses on provincial-level samples while paying insufficient attention to prefecture-level units. Second, using a two-way fixed effects model, this paper estimates the direction and magnitude of urbanization’s effect on GEAW. A baseline regression, together with robustness and heterogeneity tests, verifies the reliability of empirical conclusions and reveals the dynamic influence pattern of urbanization on GEAW, offering empirical evidence for formulating differentiated urban–rural integration policies. Third, from the perspective of government water conservancy infrastructure investment intensity, this paper investigates transmission channels and potential threshold characteristics of urbanization’s effect on GEAW. It enriches research on the driving factors behind agricultural water use green efficiency and provides scientific evidence and practical guidance for optimizing government water conservancy investment strategies, advancing new-type urbanization and agricultural green transformation, and boosting agricultural water resource efficiency in the new-development stage.

2. Materials and Methods

2.1. Mechanism of the Urbanization Process on GEAW

2.1.1. The Impact of Urbanization on GEAW

Under the urban–rural integration paradigm, development driven by urban expansion serves as a critical lever for modernizing agriculture and rural areas. However, the impact of urbanization on GEAW is shaped—and frequently constrained—by a constellation of interrelated determinants, including local natural resource endowments, levels of socioeconomic development, and prevailing institutional and policy frameworks. Consequently, this relationship exhibits substantial ambiguity and multidimensional complexity.

The positive impacts of urbanization on GEAW are primarily manifested in the following dimensions: (1) Fiscal support. Urbanization drives the agglomeration of non-agricultural industries and economic growth [23], which effectively enhances local fiscal revenue. This provides financial guarantees for increasing government investment in water conservancy infrastructure and promoting water-saving irrigation technologies, thereby helping reduce agricultural water conveyance losses and improve agricultural output efficiency per unit of water resources—creating favorable conditions for improvements in GEAW [24]. (2) Scale effects and technological spillovers of population agglomeration. Urbanization promotes population concentration in urban areas. While the increased demand for urban domestic water may intensify water resource competition in the short term, the scale effects generated by population agglomeration facilitate the R&D, promotion, and application of water-saving irrigation technologies. This reduces water consumption per unit of output and drives the transformation of agricultural production toward efficient water use [25,26]. (3) Nonlinear driving effect of urbanization on agricultural water use efficiency. Urbanization does not exert a consistent unidirectional impact on agricultural

water use efficiency. After urbanization levels cross a certain developmental threshold, its positive driving effect on agricultural water use efficiency gradually emerges; in the early stages of urbanization, however, resource competition and unidirectional factor flows may lead to efficiency losses [27]. This nonlinear characteristic indicates that the promoting effect of urbanization on GEAW can only be fully unleashed at a moderate level of urbanization. (4) Natural endowment regulation. Regions with abundant PRE have sufficient water resource supply, so the crowding-out pressure of urbanization on agricultural water use is relatively small. TEM indirectly regulates the marginal output efficiency of agricultural water use by influencing crop evapotranspiration and irrigation water demand intensity. Favorable climatic conditions help improve water use efficiency and provide a natural foundation for improving GEAW during the urbanization process [28].

The negative effects of urbanization on GEAW are primarily manifested in the following dimensions: (1) Resource crowding-out. Urbanization drives industrialization and urban expansion, leading to a sustained rise in demand for production and domestic water. This may result in the excessive crowding-out of agricultural irrigation water. Especially during the rapid urbanization stage, the “crowding-out effect” of economic growth may outweigh its “support effect,” thereby exerting an inhibitory impact on GEAW [29]. (2) Imbalanced water use structure. Excessively rapid growth in urban population density may exacerbate regional water supply–demand conflicts, causing a continuous decline in the share of agricultural water use. When the technological spillover effect of population agglomeration is insufficient to offset the resource competition pressure it brings, the net effect of population urbanization on GEAW may turn negative [25]. (3) Aggravated supply–demand contradictions. In regions with water scarcity or harsh climatic conditions, the increase in water demand induced by urbanization may further intensify the strain on agricultural water resources, limiting the room for improvement in GEAW [28].

2.1.2. The Regulatory Impact of GOVE

Urbanization’s effect on GEAW differs by region and lacks consistency, making its overall impact uncertain. Among these influencing factors, GOVE plays a crucial and non-negligible role.

GOVE exerts a positive regulatory effect on GEAW. Government policies that regulate critical agricultural inputs and outputs at the macro level can substantially shape urbanization trends, improve the efficiency of water resource utilization, and accelerate agriculture’s transition toward sustainability [30,31]. On the one hand, agricultural operations—characterized by inherent vulnerability and exposure to both natural and market risks—are unable to independently resolve capital supply constraints. Consequently, their sustainable development necessitates government support and strategic guidance [32]. The government furnishes financial support—primarily through agricultural subsidies—to facilitate the construction of water-saving infrastructure in agriculture, advance the research and development of water-saving technologies, and promote their widespread adoption, thereby enhancing GEAW. On the other hand, government investment can facilitate the development and upgrading of agricultural infrastructure, mitigate the deficiencies in rural construction and public service provision precipitated by rapid urbanization, foster bidirectional flows of capital, labor, technology, and information between urban and rural areas, and thereby establish a conducive external environment for enhancing GEAW. At the same time, externalities associated with agricultural production should be effectively internalized through coordinated political and economic instruments. Policy mechanisms—including ecological compensation schemes and green subsidies—should be systematically designed and implemented to incentivize agricultural producers to adopt low-carbon practices, such as water-saving irrigation systems and environmentally sustainable farming

and livestock rearing. Additional supportive policies—especially those targeting environmental contamination—need to be enhanced to address agricultural non-point source pollution and promote more efficient water resource utilization. Advancing the transition of agricultural water use toward greener, more resource-efficient, and sustainable practices is essential. By establishing institutional safeguards for the agricultural socialization service system and promoting large-scale, intensive farming operations amid ongoing urbanization, this strategy fosters coordinated urban–rural development [33].

GOVE may likewise exert a detrimental effect on GEAW in the context of urbanization. Some local governments—seeking to accelerate regional urbanization—have relaxed environmental regulations and actively attracted water-intensive, highly polluting enterprises. In doing so, they have effectively prioritized short-term urban economic growth over the sustainability of water resources, leading to excessive water consumption, severe degradation of aquatic ecosystems, diminished internal impetus for green agricultural development, and substantial adverse impacts on regional sustainable development and GEAW [34]. Furthermore, intergovernmental competition among regional governments over urbanization development undermines regional communication and collaboration, exacerbates spatial disparities in urbanization progress, impedes the optimal allocation of critical resources—particularly water—and adversely affects enhancements in green efficiency in agricultural water use. Excessive administrative intervention may distort market price signals, impede the innovation and adoption of agricultural water-saving technologies, lock agricultural production into a “high-water-consumption, low-efficiency” path dependence, and ultimately hinder the green transformation of agricultural water use. Such intervention further attenuates the positive effect of urbanization on GEAW, thereby exerting long-term adverse impacts on regional agricultural sustainability [35]. The logical relationship among the three entities is illustrated in Figure 1.

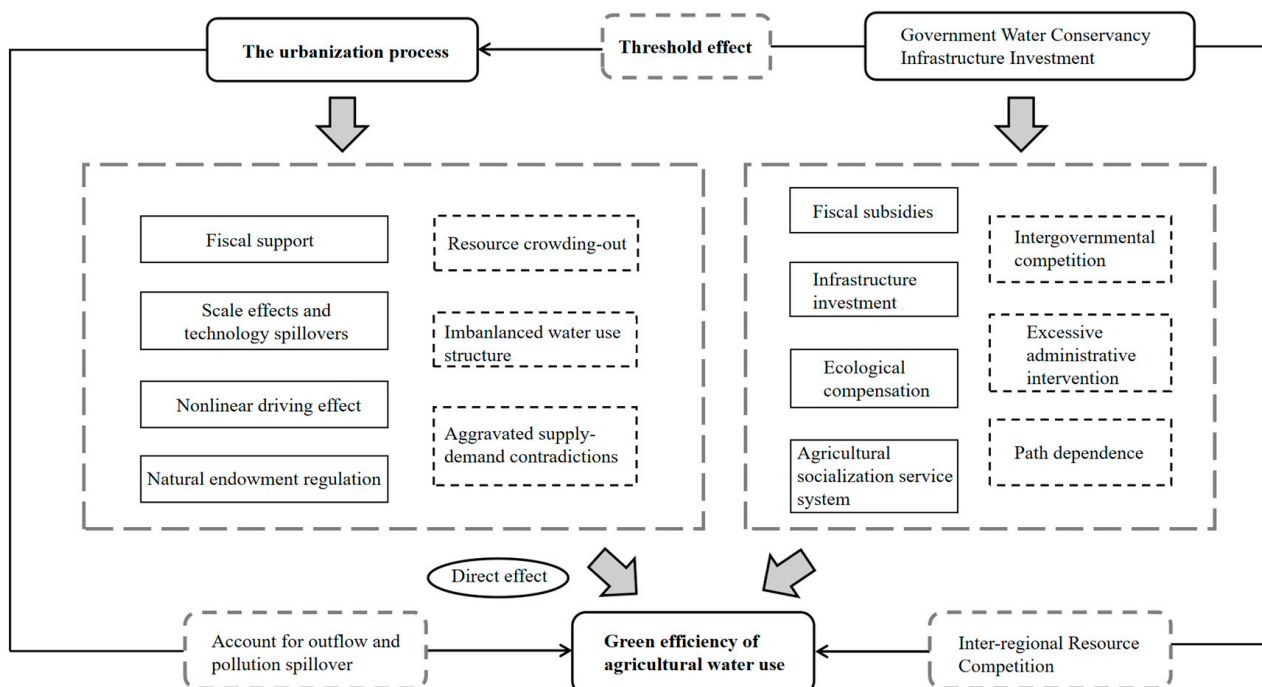


Figure 1. Mechanism of urbanization on agricultural water use green efficiency.

2.2. Indicator Selection

2.2.1. The Dependent Variable

Green Efficiency of Agricultural Water Use (GEAW). Broadly defined, agriculture encompasses crop farming, forestry, animal husbandry, fisheries, and their associated

service sectors. Narrowly defined, agriculture refers specifically to crop farming [36]. In this study, GEAW is measured based on this narrow definition. GEAW represents an extension and advancement of the environmental efficiency of agricultural water use. It reflects a strategic endeavor to synergistically achieve economic, ecological, and social benefits within the context of high-quality development. This study comprehensively incorporates both input and output indicators, explicitly accounting for undesirable outputs within the output dimension to construct a green efficiency evaluation index system for agricultural water use, as presented in Table 1. Among these, economic benefits are quantified by the total output value of crops, reflecting the economic value generated through enhanced agricultural productivity; social benefits are measured by the total crop output, underscoring agriculture’s foundational role in ensuring food security and sustaining the supply of agricultural products. Ecological benefits are assessed from both positive and negative dimensions—positively via farmland carbon sequestration capacity, which reflects the carbon sink function of the agricultural ecosystem, and negatively via the agricultural grey water footprint, which captures the environmental dilution cost imposed on aquatic systems by agricultural non-point source pollution. Furthermore, investment in environmental carrying capacity—representing an environmental cost at the input stage—can, when excessive, exacerbate non-point source pollution, thereby increasing the grey water footprint and ultimately diminishing ecological benefits.

Table 1. Input–output indicators for assessing GEAW.

Indicator Type	Primary Indicator	Secondary Indicator	Unit
Input Indicators	Water Resource Investment	Agricultural Water Consumption	100 million cubic meters
		Effective Irrigation Area	10 thousand hectares
	Input of Production Factors	Cropland Sown Area	hectare
		Labor Input	10 thousand people
Output Indicators	Desirable Output	Total Power Output of Agricultural Machinery	10 thousand kilowatt-hours
		Investment in Environmental	ton
		Fertilizer Dosage	ton
	Undesirable Output	Pesticide Dosage	ton
		Total Output Value of Crops	100 million yuan
		Farmland Carbon Sequestration	ton
		Total Crop Yield	ton
		Agricultural Grey Water Footprint	100 million cubic meters

The undesired output is quantified by the agricultural grey water footprint. The agricultural grey water footprint (AWF_{grey}) represents the volume of freshwater required to assimilate pollutants generated during agricultural production—specifically, to dilute associated wastewater to levels compliant with applicable water quality standards. This metric follows the methodological framework established by Xu et al. (2023) and, in the present study, is defined as the aggregate grey water footprint across three subsectors: crop production, livestock farming, and aquaculture [37–39]. The specific calculation formula is:

$$AWF_{grey} = WF_{grey,plant} + WF_{grey,live} + WF_{grey,fishery} \tag{1}$$

In Equation (1), AWF_{grey} denotes the agricultural grey water footprint (in m^3), where $WF_{grey,plant}$ represents the grey water footprint of crop production, $WF_{grey,live}$ denotes the grey water footprint of livestock and poultry farming, and $WF_{grey,fishery}$ refers to the grey water footprint of aquaculture.

Among these components, the grey water footprint of crop production $WF_{grey,plant}$ is derived from three major non-point pollution sources—nitrogen fertilizer application, phosphorus fertilizer application, and pesticide application—and is defined as the maximum value across the three corresponding pollutant-specific footprints. The grey water footprint of livestock and poultry farming $WF_{grey,live}$ is calculated by aggregating the total nitrogen (TN) and total phosphorus (TP) emissions from feces and urine, differentiated by livestock and poultry category. The grey water footprint of aquaculture $WF_{grey,fishery}$ is estimated for representative species—including grass carp, white shrimp, and freshwater mussels—and is determined as the maximum value among the three pollutant-specific footprints: TN, TP, and chemical oxygen demand (COD).

2.2.2. Core Explanatory Variable

The core explanatory variable is urbanization level (URBA). Urbanization is not merely the spatial concentration of population in cities; rather, it is a multidimensional process encompassing economic, ecological, social, demographic, and spatial dimensions. This study builds upon the methodology proposed by Zhao and Fang (2019) [40], adhering rigorously to the core principles of scientific validity, cross-regional comparability, and practical operability. Building upon these theoretical and practical foundations, we construct an integrated evaluation framework for URBA, comprising a set of carefully selected metrics spanning five core dimensions: economy, ecology, society, population, and spatial structure. Further details regarding the indicator selection and system construction are presented in Table 2. To reduce subjectivity-induced bias, this study standardizes the raw data and employs the entropy weight method to determine objective, data-driven weights for each urbanization indicator—ultimately generating composite urbanization scores across all prefecture-level cities.

Table 2. Evaluation index system for URBA.

Target Layer	Indicator Layer	Variable	Attribute	References
Economic Urbanization	Industrial Structure	Tertiary Industry's Gross Value Added/	+	[41]
		Secondary Industry's Gross Value Added		
	Economic Vitality	Per Capita Fiscal Revenue	+	[42]
		Scientific and Patent Grant Rate	+	[43]
	Technological Capacity	R&D Output Value per R&D Personnel	+	[44]
Ecological Urbanization	Market Development Level	Per Capita Actual Utilization of Foreign Investment	+	[45]
	Natural Livability	Urban Sewage Treatment Rate	+	[46]
		Domestic Waste Treatment Rate	+	[47]
		Urban Green Coverage Rate	+	[48]
	Social Livability	Population Density	-	[49]
		Number of Public Toilets per 10,000 Residents	+	[50]

Table 2. Cont.

Target Layer	Indicator Layer	Variable	Attribute	References
Social Urbanization	Educational Attainment	Per Capita Expenditure on Education	+	[51]
	Public Culture	Number of Health Technicians per 1000 Population	+	[52]
	Infrastructure	Proportion of Population with Access to Improved Water Supply	+	[50]
		Per Capita Electricity Consumption	+	[53]
	Information Infrastructure Development	Communication Coverage	+	[54]
Population Urbanization	Consumption Level	Urban Residents' Average per Capita Consumption Expenditure	+	[55]
	Employment Quality	Proportion of Individuals Employed in Non-farm Sectors Relative to the Total Working-age Population	+	[56]
	Income Level	Average Disposable Income of Urban Residents	+	[57]
	Quality of Life	Urbanization Rate	+	[58]
Spatial Urbanization	Economic scale	Engel's Coefficient	-	[59]
		Per Capita Fixed Asset Investment	+	[60]
	Urban Construction	Economic Density	+	[61]
		Per Capita Housing Floor Area	+	[62]
		Transportation Network Density	+	[63]
		Proportion of Urban Built-Up Area	+	[64]

(+) means that the indicator is a positive value; (-) means that the indicator is a negative value.

2.2.3. Control Variables

Drawing on existing research [65], this study selects seven control variables for the regression analysis, defined as follows: precipitation (PRE), measured by annual average precipitation; temperature (TEM), measured by annual average temperature; rural human capital (RHC), measured by the average years of education of rural employees; Agricultural Technology Extension Intensity (GTI), measured by the ratio of total agricultural machinery power to total crop sown area; Agricultural Planting Structure (APS), measured by the ratio of grain crop sown area to total crop sown area; agricultural water use structure (AWC), measured by the ratio of water-saving irrigation area to total crop sown area; and Rural Per Capita Disposable Income (RUR), measured by the per capita disposable income of rural residents.

2.2.4. Moderating Variables

This study analyzes the transmission mechanism underlying the impact of urbanization on GEAW from the perspective of government water conservancy infrastructure investment intensity (GOVE). Drawing on existing research and considering data availability, this paper operationalizes GOVE as the ratio of water conservancy infrastructure investment expenditure to regional gross domestic product [66].

2.3. Research Methodology

2.3.1. Super-SBM Model

Developed by Tone (2001), the Slack-Based Measure (SBM) model represents a non-radial, non-angular extension of Data Envelopment Analysis (DEA) and has become a prevalent method for evaluating operational efficiency [66]. To enhance both the discriminatory power and interpretability of efficiency estimates, Tone (2002) extended this framework

by developing the Super-SBM model—a modified formulation that enables differentiation and ranking among decision-making units that are already identified as technically efficient under the standard DEA frontier [67]. The formal mathematical specification of this enhanced model is presented below:

$$\rho = \text{Min} \frac{\frac{1}{m} \sum_{i=1}^m \left(\frac{\bar{X}_i}{X_{ik}} \right)}{\frac{1}{r_1 + r_2} \left(\sum_{s=1}^{r_1} \frac{\bar{y}^d}{y_{sk}^d} + \sum_{q=1}^{r_2} \frac{\bar{y}^u}{y_{sk}^u} \right)} \quad (2)$$

$$\text{s.t.} \begin{cases} \bar{x} \geq \sum_{j=1, \neq k}^n X_{ij} \theta_j; \bar{y}^d \leq \sum_{j=1, \neq k}^n y_{sj}^d \theta_j; \bar{y}^d \geq \sum_{j=1, \neq k}^n y_{qj}^d \theta_j; \\ \bar{x} \geq x_k; \bar{y}^d \leq y_k^d; \bar{y}^u \geq y_k^u; \bar{y}^d \geq 0; \theta \geq 0; j \neq 0; \\ i = 1, 2, \dots, m; j = 1, 2, \dots, n; s = 1, 2, \dots, r_1; q = 1, 2, \dots, r_2 \end{cases} \quad (3)$$

In Equations (1) and (2), ρ denotes the measured GEAW. A higher value of ρ indicates greater efficiency of the decision-making unit; x denotes the vector of input factors; y^d and y^u denote the vectors of expected and non-expected output factors, respectively; m , r_1 , and r_2 represent the numbers of indicators associated with x , y^d , and y^u , respectively; and θ_j is the weight vector.

2.3.2. Entropy Weight Method

According to existing research, the extreme value standardization method is first applied to normalize the data for each indicator when assessing the level of urbanization. This preprocessing step eliminates dimensional inconsistencies and mitigates heteroscedasticity across indicators, thereby enhancing inter-indicator comparability [68]. Subsequently, the entropy weight method is employed to compute the entropy value E_j for the j -th indicator of the system:

$$E_j = -k \sum_{i=1}^n (p_{ij} \times \ln p_{ij}) \quad (4)$$

In the above formula, $k = \frac{1}{\ln m}$; $p_{ij} = \frac{Y'_{ij}}{\sum_{i=1}^n Y'_{ij}}$; $i = 1, 2, \dots, n$; and $j = 1, 2, \dots, m$. The entropy weight can then be computed using Equation (4).

$$w_j = \frac{1 - E_j}{m - \sum_{j=1}^m E_j} \quad (5)$$

2.3.3. Two-Way Fixed Effects Model

Given that data indicators may evolve over time, our baseline specification adopts a two-way fixed effects model to jointly control for time-invariant individual heterogeneity and common temporal shocks. Moreover, to mitigate potential heteroscedasticity and reduce scale disparities across variables, we apply natural logarithmic transformations to key continuous variables prior to estimation. The resulting baseline regression equation is specified as follows:

$$GEAW_{it} = \alpha_0 + \alpha_1 URBA_{it} + \alpha_2 \gamma_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (6)$$

where i and t represent the i -th prefecture-level city and the t -th year, respectively. $GEAW_{it}$ denotes GEAW. $URBA_{it}$ denotes the degree of URBA. γ_{it} denotes the outcome variable, μ_i represents the regional fixed effect, λ_t denotes the year fixed effect, ε_{it} denotes the stochastic error term, and the remaining parameters represent the estimated regression coefficients.

2.3.4. Panel Threshold Model

Building on Hansen's (1997) threshold estimation framework, this study employs GOVE as the threshold variable and constructs the following model to examine whether the effect of urbanization on GEAW is nonlinear and contingent on specific threshold values [69,70].

$$GEAW_{it} = \beta_0 + \beta_1 URBA_{it} I(GOVE_{it} \leq \eta_1) + \beta_2 URBA_{it} I(\eta_1 < GOVE_{it} \leq \eta_2) + \dots + \beta_n URBA_{it} I(\eta_{n-1} < GOVE_{it} \leq \eta_n) + \beta_{n+1} URBA_{it} I(\eta_n < GOVE_{it}) + \delta \sum_{i=1}^n X_{it} + \tau_{it} \quad (7)$$

where η denotes the threshold value. β denotes the coefficient capturing the effect of URBA on GEAW, conditional on the threshold variable falling within distinct interval ranges. If one or more of the coefficients— $\beta_1, \beta_2, \dots, \beta_n$ and β_{n+1} —exhibit statistically significant and substantively distinct estimates, this provides evidence that the chosen threshold variable is appropriate and effectively captures regime-dependent heterogeneity. δ denotes the coefficient quantifying the effect of the control variable on GEAW. The notation $I(\cdot)$ denotes the indicator function, which takes the value 1 if the condition(s) enclosed in parentheses hold true and 0 otherwise. τ_{it} represents a stochastic error term.

2.4. Data Sources and Methodological Explanations

This study selects 280 prefecture-level cities in China as the research sample. Regarding the time scope of the sample: On the one hand, official statistical data on agricultural water use, water resources, and socioeconomic indicators at the prefecture level exhibit systematic release lags, with complete data for some prefecture-level cities in 2023 and subsequent years yet to be fully disclosed. On the other hand, since 2023, the implementation and advancement of policies such as the Outline for National Water Network Construction have introduced new changes to the policy environment in the field of agricultural water resource management; therefore, incorporating this period into the analysis may cause structural interference with the identification of historical trends. Thus, this study sets the time interval as 2013–2022. Research data are sourced from the China Statistical Yearbook, China Rural Statistical Yearbook, and China Environmental Statistical Yearbook, as well as statistical yearbooks and bulletins of individual prefecture-level cities. Missing data for some years are supplemented using linear interpolation. Furthermore, to enhance the reliability of the results and mitigate the interference of outliers, logarithmic transformation is applied to some variables, leading to the exclusion of 150 observations due to missing values generated by the transformation. All continuous variables are winsorized at the 1st and 99th percentiles. The descriptive statistics of the main variables are presented in Table 3.

Table 3. Descriptive statistics of key variables.

Variable	Sample Size	Mean	Std. Deviation	Minimum	Maximum
lnGEAW	2650	−0.588	0.217	−0.693	0.918
lnURBA	2650	−1.226	0.272	−1.778	−0.514
lnPRE	2650	6.792	0.547	5.152	7.682
TEM	2650	14.307	5.315	1.883	23.400
lnRHC	2650	−1.769	0.244	−2.454	−0.847
GTI	2650	0.315	0.490	0.000	2.734
lnAPS	2650	−2.935	2.712	−10.483	0.634
lnAWC	2650	−2.713	1.913	−7.801	−0.142
lnRUR	2650	0.379	0.388	−0.560	1.377

Based on the distributional patterns of missing observations, sample gaps arise from two primary sources: (i) insufficient disclosure of original statistical data by local authorities and (ii) the application of logarithmic transformations to variables. Specifically, certain indicators contain zero-valued observations in their original form; taking logarithms of such values yields undefined entries, necessitating their exclusion. Consequently, 150 observations were dropped from the analytical sample.

Along the temporal dimension, missing data are concentrated in the early years of the study period—namely, 2014 and 2015—during which the number of available observations is markedly lower than in subsequent years. In contrast, the sample size is relatively ample and stable for the period 2016–2022.

At the city level, 80.22% of the prefecture-level cities exhibit complete longitudinal coverage across all ten years (2013–2022). The remaining 19.78% display partial observation gaps: the majority of these cities miss only one or two periods, whereas a small number—including, for example, Haidong City—exhibit multiple consecutive missing periods. Such gaps are closely tied to regional disparities in statistical transparency and reporting practices. Notably, the observations excluded due to logarithmic transformation correspond precisely to zero-valued entries in the raw data. As these zero values often reflect distinctive local development conditions, their systematic exclusion introduces potential sample selection bias.

To mitigate this concern and enhance identification rigor, our empirical strategy employs a two-way fixed effects model that jointly controls for city-specific and year-specific unobservables. Furthermore, we conduct a battery of robustness checks—including alternative sample specifications, alternative variable constructions, and sensitivity analyses—to assess and alleviate the potential influence of missing data on our core estimation results.

3. Results

3.1. Analysis of the Measurement Results on GEAW

Using the natural breaks classification method, GEAW across 280 prefecture-level cities in China was categorized into five hierarchical levels: low, relatively low, medium, relatively high, and high efficiency. As illustrated in Figure 2, across China's prefecture-level cities, the spatiotemporal dynamics of GEAW display clear phase-dependent features, highlighting significant regional disparities.

Overall, the spatial distribution of agricultural water use green efficiency in China exhibited a distinct gradient pattern throughout the observation period. Highly efficient prefectures are predominantly concentrated in the eastern coastal regions and the middle–lower reaches of the Yangtze River, forming a spatially contiguous belt on the map. Prefectures exhibiting low or suboptimal efficiency display significant spatial agglomeration, predominantly concentrated across extensive regions of the northwestern, northeastern, and southwestern territories.

In terms of average GEAW, the eastern coastal regions and the middle–lower Yangtze River basin—underpinned by abundant water and land resources, a well-developed agricultural–industrial system, extensive water conservation infrastructure, and stringent environmental governance—have consistently demonstrated high performance, thereby forming a resilient and high-performing regional cluster. Most prefecture-level cities within these regions continue to maintain high or above-average GEAW levels. In certain regions of the northwest, northeast, and southwest, GEAW has remained persistently low over an extended period. This stagnation stems from multiple interrelated factors—including constraints imposed by local water resource endowments, the continued prevalence of extensive agricultural production practices, and inadequate adoption and dissemination of water-saving technologies—resulting in a spatially contiguous pattern of low efficiency.

Notably, efficiency deficits are especially pronounced in resource-based cities and traditional agricultural provinces. The central region functions as a pivotal nexus—bridging the eastern and western regions while simultaneously connecting the northern and southern parts of the country. GEAW in this region is generally moderate. It benefits from industrial relocation and technological spillovers emanating from the more developed eastern region, yet it remains constrained by resource scarcity and extensive input-intensive agricultural production practices inherited from the western region. As a result, its green efficiency exhibits a pronounced transitional character, rendering it a pivotal determinant in balancing the geographical distribution of GEAW nationwide.

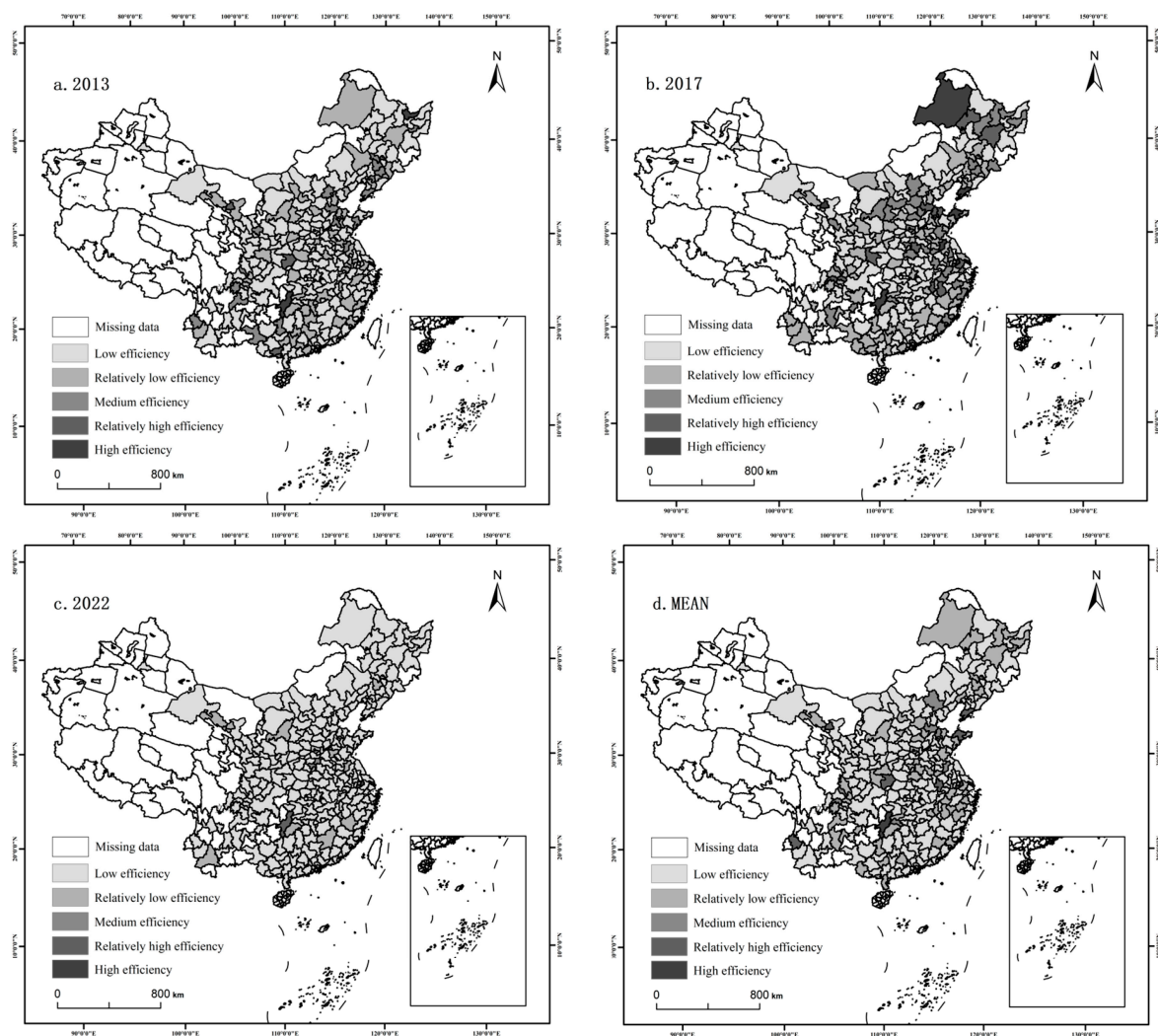


Figure 2. (a) Spatial distribution pattern of GEAW across Chinese municipal administrative areas in 2013. (b) Spatial distribution pattern of GEAW across Chinese municipal administrative areas in 2017. (c) Spatial distribution pattern of GEAW across Chinese municipal administrative areas in 2022. (d) Multi-year average spatial distribution pattern of GEAW across Chinese municipal administrative areas during 2013–2022.

Temporally, the geographical distribution of GEAW in China has undergone a stage-wise and evolving transformation. Specifically, in 2013, the number of prefecture-level cities exhibiting green and highly efficient agricultural water use remained relatively low, with such cities predominantly distributed across select regions of East and Central China—areas characterized by comparatively advanced levels of agricultural modernization. Medium-efficiency and low-efficiency prefectures constitute the majority, with most regions across the country falling within the medium–low efficiency range. Most prefecture-level cities in

the northwest and northeast regions face water scarcity and rely on inefficient agricultural production practices, resulting in generally low operational efficiency and pronounced spatial imbalances. In 2017, the continuous implementation of agricultural water-saving policies, advances in agricultural modernization, and stricter environmental regulations collectively contributed to an expansion in the geographic coverage of cities exhibiting high and relatively high levels of GEAW. In the northern and northeast regions of China, several prefecture-level cities shifted from low to medium efficiency, resulting in a steady improvement in the overall regional efficiency level. Meanwhile, parts of Inner Mongolia have leveraged water-saving agricultural pilot initiatives and ecological governance policies, creating localized high-efficiency, high-concentration zones. In 2022, the number of highly efficient prefecture-level cities declined, driven by multiple interrelated factors—including extreme weather events, an intensifying imbalance between water resource supply and demand, and the regional resurgence of traditional (less water-efficient) agricultural production practices. Concurrently, medium-efficiency prefecture-level cities emerged as the predominant urban type nationwide. The eastern coastal regions—characterized by advanced water-saving technologies and well-established policy frameworks—continue to exhibit a pronounced efficiency advantage. Conversely, certain regions in the northwest and northeast have recently exhibited a decline in performance efficiency, yielding a spatial efficiency pattern characterized by “higher efficiency in the eastern and southern regions and lower efficiency in the western and northern regions.”

3.2. Baseline Regression Analysis

Before estimating the panel data model, the first methodological consideration is the choice between fixed effects and random effects specifications. Using Stata 18, we performed a Hausman test, which yielded a statistically significant result ($p < 0.01$), leading us to reject the null hypothesis that the random effects estimator is both consistent and efficient. Consequently, a fixed effects model was adopted. Subsequently, annual dummy variables were included to assess the presence of a time-specific (i.e., year-level) effect. Table 4 reports the joint significance test for the full set of year-specific dummy variables, which are included to account for potential temporal variation. The test yields a p -value < 0.01 , allowing us to reject the null hypothesis—that time exerts no effect—decisively. This result confirms the presence of a statistically significant time effect in the model. Consequently, our analysis employed a two-way fixed effects specification and used cluster-robust standard errors to accommodate heteroscedasticity and serial correlation within clusters, thereby ensuring valid statistical inference.

Table 4. Joint significance of annual dummy variables.

Joint Test of Year Dumies	
(1) 2014.year = 0	(6) 2019.year = 0
(2) 2015.year = 0	(7) 2020.year = 0
(3) 2016.year = 0	(8) 2021.year = 0
(4) 2017.year = 0	(9) 2022.year = 0
(5) 2018.year = 0	F(9, 279) = 60.26
Prob > F = 0.0000	

Table 5 presents the estimated regression outcomes across four distinct model specifications: (1) a pooled ordinary least squares (OLS) model; (2) an individual fixed effects model (FE_robust); (3) a time fixed effects model (FE_time); and (4) a two-way fixed effects model (FE_TW_DED).

Table 5. Regression results of the panel model.

Variable	(1) OLS	(2) FE_robust	(3) FE_time	(4) FE_TW_DED
lnURBA	0.140 *** 0.020	0.182 *** 0.048	0.084 *** 0.029	0.104 ** 0.042
lnPRE	−0.001 0.014	0.025 0.039	0.004 0.017	0.021 0.036
TEM	−0.000 0.001	0.096 *** 0.018	−0.001 0.001	0.007 0.016
lnRHC	−0.005 0.017	−0.070 ** 0.029	−0.018 0.020	−0.041 * 0.025
GTI	−0.002 0.009	−0.021 0.015	−0.003 0.010	−0.017 0.014
lnAPS	0.004 * 0.002	−0.002 0.008	−0.000 0.003	−0.001 0.007
lnAWC	0.007 *** 0.003	0.020 ** 0.009	0.004 0.003	0.005 0.008
lnRUR	−0.102 *** 0.014	−0.322 *** 0.029	0.008 0.022	−0.115 ** 0.058
_cons	−0.350 *** 0.104	−1.865 *** 0.371	−0.602 *** 0.125	−0.855 ** 0.342
N	2650	2650	2650	2650
R-sq	0.029	0.102		0.401

Note: ① Statistical significance is indicated by *** (1%), ** (5%), and * (10%). ② Clustered robust standard errors at the individual level.

Analysis of the estimation results from Model (4) in Table 5 reveals that the coefficient of lnURBA on GEAW is 0.104, which is significantly positive at the 5% significance level. This result indicates a statistically significant positive association between URBA and GEAW, suggesting that an increase in URBA is accompanied by an improvement in GEAW. Urbanization may exert a positive impact on GEAW through two potential channels: First, it facilitates the flow of production factors between urban and rural areas, creating favorable conditions for the adoption of moderate-scale agricultural operations and the promotion of water-saving technologies. Second, the economic growth and enhanced fiscal capacity associated with urbanization may drive increased government investment in rural water conservancy infrastructure construction and the dissemination of water-saving technologies, thereby further optimizing the external environment for agricultural water use [71].

Regarding control variables, the impacts of various factors on GEAW exhibit heterogeneous characteristics. The coefficient of lnRHC is −0.041, which is significantly negative at the 10% significance level. A plausible explanation is that during the urbanization process, high-quality rural labor migrates to non-agricultural sectors in urban areas, leading to a relative decline in the human capital level of the agricultural labor force. This, in turn, constrains the improvement in GEAW to a certain extent. The coefficients of lnAWC and lnAPS are 0.005 and −0.001, respectively, neither of which passes the significance test. This indicates that after controlling for other factors, the direct effects of water use structure and planting structure on GEAW remain inconclusive. The coefficient of lnRUR is −0.115, significantly negative at the 5% significance level. This may reflect that as rural residents' income levels rise, the share of water costs in agricultural production decreases, which weakens the incentives for water conservation to some degree. The coefficients of lnPRE, TEM, and GTI also fail to pass the significance test. This could be because their impacts on GEAW are partially indirectly reflected through core variables such as URBA, or their effects exhibit a certain degree of lag.

Overall, the estimation results of the two-way fixed effects model reveal a statistically significant positive association between URBA and GEAW, indicating that regions with higher URBA values typically exhibit higher GEAW. After controlling for individual fixed effects and time fixed effects, the model's goodness-of-fit shows a substantial improvement compared to the pooled ordinary least squares model. This suggests that the inclusion of two-way fixed effects significantly enhances the model's ability to explain variations in GEAW. Both the Hausman test and the joint significance test of annual dummy variables support the adoption of the two-way fixed effects model over alternative specifications. These findings provide a robust empirical basis for subsequent investigations into the transmission mechanisms and threshold effects underlying the impact of urbanization on GEAW.

3.3. Robustness Checks

3.3.1. Replacing the Core Explanatory Variable

To mitigate potential bias arising from the measurement of the core explanatory variable, this study conducts a robustness check by substituting the URBA indicator. Specifically, we replace the composite URBA index with the share of urban population (PROP) as the primary measure of URBA and re-estimate the baseline model. As shown in Column (1) of Table 6, the estimated coefficient on PROP is 0.135 and statistically significant at the 1% level—consistent with the baseline results. This finding confirms that the main conclusions are not sensitive to the particular operationalization of URBA and thus demonstrates the robustness of our empirical findings.

Table 6. Results of the robustness test conducted by replacing the core explanatory variable.

Variable	Replacing the Core Explanatory Variable
PROP	0.135 *** (0.042)
lnPRE	0.017 (0.031)
TEM	−0.078 (0.101)
lnRHC	−0.193 (0.152)
GTI	−0.014 (0.019)
lnAPS	−0.002 (0.008)
lnAWC	0.091 (0.066)
lnRUR	−0.128 ** (0.054)
_cons	0.555 (0.362)
N	2650
R-sq	0.454
Year fixed effects	YES
Individual fixed effects	YES

Statistical significance is indicated by *** (1%), ** (5%).

3.3.2. Incorporating Fixed Effects

Building on the methodological framework proposed by Zhao et al. (2020) [71], we conducted a robustness check to evaluate the stability and validity of our core findings. In particular, we enhanced the baseline two-way fixed effects framework by adding both

provincial fixed effects and province-by-year interaction terms. This specification helps mitigate potential biases arising from macro-level systemic environmental shifts associated with rapid urbanization [72]. As shown in Columns (1) and (2) of Table 7, the estimated coefficients on lnURBA—the primary explanatory variable—are 0.393 and 0.533, respectively, both statistically significant at the 1% level after controlling for the specified fixed effects. This robustness across specifications confirms that the core positive association between urbanization and the outcome variable persists even after accounting for broad macroeconomic heterogeneity.

Table 7. Results of the robustness test with fixed effects added and municipalities excluded.

Variable	(1) Province Fixed Effects	(2) Province–Year Interaction Fixed Effects	(3) Exclusion of Municipalities Directly Under the Central Government
lnURBA	0.091 ** (0.036)	0.083 * (0.046)	0.099 ** (0.043)
lnPRE	0.017 (0.029)	0.033 (0.055)	0.024 (0.036)
TEM	0.005 (0.013)	0.027 (0.028)	0.005 (0.016)
lnRHC	−0.034 (0.022)	−0.036 (0.029)	−0.043 * (0.025)
GTI	−0.017 (0.013)	−0.008 (0.017)	−0.015 (0.014)
lnAPS	−0.001 (0.006)	0.002 (0.007)	−0.000 (0.007)
lnAWC	0.005 (0.008)	0.010 (0.009)	0.005 (0.008)
lnRUR	−0.065 * (0.033)	−0.071 (0.045)	−0.119 ** (0.058)
_cons	−0.796 *** (0.283)	−0.796 *** (0.283)	−0.851 ** (0.346)
N	2650	2650	2610
R-sq	0.464	0.470	0.394
Provincial fixed effects	YES	YES	NO
Province × year interactions	NO	YES	NO
Year fixed effects	YES	YES	YES
Individual fixed effects	YES	YES	YES

Statistical significance is indicated by *** (1%), ** (5%), and * (10%).

3.3.3. Excluding Municipalities Under the Direct Jurisdiction of the Central Government

The urbanization initiatives in Beijing, Shanghai, Tianjin, and Chongqing are underpinned by a robust institutional foundation and have attained a comparatively high developmental level. Furthermore, these municipalities—directly administered by the State Council—have benefited from targeted national policy support and substantial fiscal investment, conferring them a distinct comparative advantage in regional economic growth and in advancing residents' living standards. Therefore, after excluding municipalities from the sample, this study conducts a new regression analysis. The findings presented in Column (3) of Table 7 are consistent with the baseline regression results, thereby reinforcing the conclusion that urbanization-driven infrastructure expansion significantly enhances GEAW.

3.4. Endogeneity Test

To ensure the robustness of the research findings, this paper performs endogeneity tests from the following three dimensions.

(1) Dynamic Analysis Using the System GMM Estimator.

The dependent variable—GEAW—may exhibit temporal persistence, implying that the current efficiency level is partly determined by its prior value. Neglecting such dynamic dependence risks biased and inconsistent parameter estimates. To account for this feature and mitigate potential endogeneity concerns, we adopt the System Generalized Method of Moments (System GMM) estimator for robustness checks. As reported in Table 8, the Arellano–Bond autocorrelation test yields a statistically significant first-order autocorrelation (AR(1): $p < 0.05$), while the second-order autocorrelation is insignificantly different from zero (AR(2): $p > 0.10$). This pattern confirms that the first-differenced residuals satisfy the required orthogonality conditions for valid GMM estimation. Furthermore, the Hansen J-test ($p > 0.10$) fails to reject the null hypothesis of instrument validity, supporting the overall appropriateness and exogeneity of the chosen instrumental variables.

Table 8. The endogeneity test results within the GMM framework.

Model Selection	(1) SYS-GMM
L.InGEAW	0.360 *** (2.91)
lnURBA	0.053 * (1.89)
lnPRE	0.029 (1.32)
TEM	−0.028 * (−1.75)
lnRHC	0.048 (0.55)
GTI	−0.005 (−0.99)
lnAPS	−0.021 (−0.58)
lnAWC	0.024 (0.62)
lnRUR	0.004 (0.26)
_cons	−0.299 * (−1.75)
AR(1)	0.001
AR(2)	0.970
Hansen test	0.300
Year fixed effects	YES
Individual fixed effects	YES

Statistical significance is indicated by *** (1%), * (10%).

The estimation results reveal that the coefficient on the one-period lagged dependent variable (L.InGEAW) is 0.360 and statistically significant at the 1% level, providing strong evidence of dynamic persistence in green agricultural water use efficiency. Meanwhile, the coefficient on the key explanatory variable—lnURBA—is 0.053 and significant at the 10% level, aligning with the baseline regression findings. These results confirm that the positive effect of URBA on green agricultural water use efficiency remains robust after jointly addressing serial correlation in the dependent variable and potential endogeneity through the System GMM framework.

(2) Lagged Control Variables.

Drawing on the approach of Wang et al. (2025) [73], this paper addresses omitted variable bias by incorporating one-period-lagged values of all control variables into the regression. The results, presented in Column (1) of Table 9, show that the coefficient of URBA remains at 0.1409 and is statistically significant at the 5% level after introducing lagged control variables.

Table 9. Endogeneity test results.

Model Selection	(1) Lagged Control Variables	(2) Exclusion of Outlier Samples
lnURBA	0.1409 ** (0.0572)	0.1177 ** (0.0512)
lnPRE	−0.0191 (0.0358)	0.0088 (0.0405)
TEM	−0.0105 (0.0223)	0.0102 (0.0160)
lnRHC	−0.0430 (0.0441)	−0.0491 * (0.0251)
GTI	−0.0027 (0.0214)	−0.0293 * (0.0173)
lnAPS	−0.0135 * (0.0081)	−0.0049 (0.0103)
lnAWC	−0.0042 (0.0085)	0.0045 (0.0088)
lnRUR	−0.2293 (0.2038)	−0.0996 * (0.0568)
N	2291	2375
R-sq	0.5619	0.5539
Year fixed effects	YES	YES
Individual fixed effects	YES	YES

Statistical significance is indicated by ** (5%), and * (10%).

(3) Exclusion of Outlier Samples.

Given the potential disruptive impact of the 2020 COVID-19 pandemic—an exogenous public health shock—on agricultural production systems, this study re-estimates the baseline model after excluding the 2020 sample observations. The results, presented in Column (2) of Table 9, show that the coefficient of URBA is 0.1177, which remains statistically significant at the 5% level and consistent with the baseline regression results. This finding confirms that the core conclusions of this study are robust to the exogenous shock of the 2020 pandemic.

3.5. Moderating Role of GOVE

Both the baseline regression and robustness test results confirm that urbanization significantly enhances GEAW. To further unpack the mechanisms through which URBA and GOVE influence GEAW, this study empirically investigates the moderating effect of GOVE on the URBA-GEAW relationship.

The extent of regional water infrastructure is measured by lnGOVE. Following Gu and Cao (2025), this study employs a grouped regression approach to examine heterogeneity effects [74]. Specifically, the sample is dichotomized into a high-investment-intensity group and a low-investment-intensity group based on the median value of lnGOVE. The corresponding grouped regression results are presented in Table 10.

Table 10. Test results of GOVE's regulatory effect.

Variable	(1) High-Investment-Intensity Group	(2) Low-Investment-Intensity Group
lnURBA	0.1170 ** (0.0575)	0.0730 (0.0464)
_cons	−0.7224 ** (0.3124)	−0.6008 (0.4349)
N	1311	1339
R-sq	0.4948	0.4539
Year fixed effects	YES	YES
Individual fixed effects	YES	YES
Controls	YES	YES
Chow test	F = 2.28 (Prob > F = 0.0016)	

Statistical significance is indicated by ** (5%).

In the high-investment-intensity group for water infrastructure, the coefficient of lnURBA is 0.1170, which is statistically significant at the 5% level; in contrast, in the low-investment-intensity group, the coefficient of lnURBA is 0.0730 and is not statistically significant. Furthermore, a Chow test was conducted to assess structural differences between the regression models estimated for the two groups. The test yields an F-statistic of 2.28 ($p = 0.0016$), indicating that the full sets of regression coefficients differ significantly across the two subsamples. These findings suggest heterogeneity in the effect of URBA on GEAW—conditional on GOVE. Specifically, higher GOVE strengthens the positive and statistically discernible impact of URBA on GEAW.

The likely explanation for this phenomenon is that regions with higher GOVE typically possess more comprehensive supporting conditions for farmland water management. Such conditions facilitate the effective reallocation of capital, technology, and skilled labor—resources released during URBA—to the water-saving agricultural sector. This, in turn, accelerates the structural transformation of agricultural production toward water-efficient and environmentally sustainable pathways, thereby amplifying URBA's positive impact on GEAW. Conversely, regions with inadequate water conservancy investment often lack the institutional and infrastructural capacity to absorb and harness the positive spillovers generated by URBA. As a result, the potential benefits of URBA for enhancing GEAW remain underrealized. The existing literature indicates that, during urbanization, local government public investment—and the associated enabling conditions—exerts a significant influence by improving rural resource allocation efficiency and strengthening the provision of public services [75]. Effective government investment thus constitutes a critical prerequisite for translating urbanization into tangible developmental gains. The subgroup regression results presented in this study align closely with these prior findings: URBA exerts a significantly stronger positive effect on GEAW in regions characterized by higher levels of GOVE. This suggests that robust water conservancy infrastructure enhances the efficient allocation of heterogeneous resources and enables fuller realization of policy dividends arising from URBA. Therefore, as China advances its new urbanization strategy, priority should be given to upgrading the supporting facilities and institutional frameworks underpinning GOVE—thereby maximizing URBA's contribution to the green transformation of agricultural water use.

3.6. Threshold Effect Test

Before estimating the regression model, we employed bootstrap resampling with 300 iterations to identify the optimal functional form for the panel threshold model. The results are summarized in Table 11. As shown, the p -value for the single-threshold effect of

GOVE is 0.0667, indicating statistical significance at the 10% level. In contrast, the double-threshold specification yields a p -value of 0.7100, which is not statistically significant at conventional levels. Consequently, the single-threshold specification was adopted for subsequent analysis. After confirming the appropriateness of the single-threshold model for our analysis, we identified the optimal threshold value for GOVE—the key threshold variable—by selecting the value that minimizes the residual sum of squares. The estimated threshold is 3.8453, which lies well within its 95% confidence interval, thereby providing robust empirical support for the selected single-threshold specification.

Table 11. Threshold-Effect Estimation Results.

Threshold Behavior	F-Statistic	p -Value	10% Significance Threshold	5% Significance Threshold	1% Significance Threshold	Estimated Threshold	95% Confidence Interval
Single Threshold	14.47	0.0667	12.9878	16.7665	27.4558	$\eta_1 = 3.8453$	(3.4943, 3.9730)
Double Threshold	4.26	0.7100	17.9434	25.3176	35.9621		

Based on the above tests, threshold regression estimates are conducted with $\ln\text{GOVE}$ as the threshold variable; detailed results are presented in Table 12. When $\ln\text{GOVE}$ is below the threshold value of 3.8453, the coefficient of $\ln\text{URBA}$ on GEAW is -0.079 and statistically insignificant, indicating that the impact of URBA on GEAW is not pronounced under low GOVE . When GOVE exceeds the threshold value of 3.8453, the impact coefficient of URBA on GEAW becomes 0.091—statistically significant at the 10% level. These findings suggest that the positive effect of URBA on GEAW is conditional. Specifically, this promoting effect only emerges when GOVE surpasses a critical threshold. This result further implies that GOVE may function as a necessary enabling condition for unlocking the latent benefits of urbanization. A well-developed water infrastructure system facilitates the reallocation of resource elements during urbanization toward agricultural green development.

Table 12. Estimation results of the threshold model parameters.

Variable	Coefficient	t-Value
$\ln\text{URBA}$ ($\text{GOVE} \leq 3.8453$)	-0.079	-0.56
$\ln\text{URBA}$ ($\text{GOVE} > 3.8453$)	0.091^*	1.89
$\ln\text{PRE}$	0.0343	0.82
TEM	0.0009	0.05
$\ln\text{RHC}$	-0.0750^{**}	-2.44
GTI	-0.0212	-1.38
$\ln\text{APS}$	-0.00388	-0.47
$\ln\text{AWC}$	0.00185	0.22
$\ln\text{RUR}$	-0.122^*	-1.81
_cons	-0.949^{**}	-2.35
N		2650
R-sq		0.386

Statistical significance is indicated by ** (5%), and * (10%).

In terms of controlling variables, the coefficient for $\ln\text{RHC}$ is -0.0750 , statistically significant at the 5% level. This suggests that, under current conditions, rural education development exerts a statistically significant inhibitory effect on GOVE . Such a finding may reflect a structural mismatch between the existing composition of rural human capital and the requirements of green, resource-efficient agriculture—indicating that the adoption and diffusion of green technologies remain in a transitional phase. The coefficient for $\ln\text{RUR}$ is

−0.122, statistically significant at the 10% level, implying a significant negative association between $\ln RUR$ and $GEAW$. This result may indicate that, at the present stage of agricultural development, income growth among farmers is largely driven by traditional, extensive production practices—characterized by high input intensity, high water consumption, and high output—which temporarily constrain improvements in green efficiency. All other control variables fail to attain conventional levels of statistical significance; thus, their influence on $GEAW$ remains inconclusive in this analysis.

URBA may exhibit a single-threshold effect on $GEAW$ with distinct phase-specific patterns emerging across different ranges of the threshold variable. At low levels of the threshold variable, the integration of urban development initiatives with “agriculture, rural areas, and farmers” remains insufficient. Consequently, the flow of factors—such as labor, capital, technology, and information—between urban and rural areas, as well as the allocation of resources, fails to adequately support agricultural green transformation. As the threshold variable increases, the institutional and infrastructural environment facilitating inter-regional factor circulation and resource allocation gradually improves. This enhancement, in turn, promotes the transmission of urbanization-driven development dividends—such as technological spillovers, institutional innovations, and improved public services—to the domain of agricultural green development. In summary, URBA’s driving effect on $GEAW$ appears to be contingent on specific developmental phases or contextual conditions. Its long-term implications and underlying mechanisms warrant further empirical investigation and theoretical refinement in future research.

3.7. Heterogeneity Analysis

3.7.1. Analysis of Spatial Heterogeneity in Location

Given the pronounced disparities in regional development levels across China, significant spatial variation exists in $GEAW$, the pace of URBA and GOVE. To more clearly capture such regional heterogeneity, this study follows the regional classification approach adopted by Shen et al. (2021) and Yang et al. (2023) [76,77], dividing China’s economic regions into three major zones: the eastern, central, and western regions. Subsequently, separate regression analyses are conducted for each sub-regional sample. However, simply comparing the magnitudes and statistical significance of estimated coefficients across subsamples may yield misleading inferences regarding interregional differences. To rigorously test for structural heterogeneity across regions, this paper further constructs an interaction term model and formally conducts a Chow test for coefficient equality across groups. The estimation results are presented in Table 13.

The empirical results indicate that the regression coefficient of $\ln URBA$ in the western region is 0.1443, statistically significant at the 1% level; in the central region, the coefficient is 0.0475, significant at the 5% level. These findings suggest that higher URBA values exert a statistically significant positive effect on $GEAW$ in both the central and western regions. In contrast, the estimated coefficient for the eastern region is 0.0659, yet it is not statistically significant at conventional levels. Collectively, these regional heterogeneities imply that the urbanization–green efficiency nexus holds only for the central and western subsamples. Comparing these estimates with the baseline regression results for the full sample reveals that the overall significant positive effect of URBA on $GEAW$ is primarily attributable to the central and western regions, whereas URBA exerts no statistically discernible impact on such efficiency in the eastern region.

The results of the intergroup coefficient difference test indicate that the p -values for the differences between the eastern and central regions and between the eastern and western regions are 0.651 and 0.149, respectively—neither reaching conventional levels of statistical significance. In contrast, the p -value for the difference between the central and western regions

is 0.068, which is marginally significant at the 10% level. These findings suggest no statistically significant difference in the URBA regression coefficients between the eastern and central regions, nor between the eastern and western regions; only the coefficient difference between the central and western regions approaches statistical significance. Consistent with this, the estimated coefficient for URBA is numerically larger—thus reflecting a stronger positive effect—in the western region than in the central region.

Table 13. Regression results accounting for location-based heterogeneity.

Variable	(1) Eastern Region	(2) Central Region	(3) Western Region
lnURBA	0.0659 (0.0407)	0.0475 ** (0.0239)	0.1443 *** (0.0321)
lnPRE	−0.0151 (0.0328)	0.0297 * (0.0166)	0.0702 *** (0.0259)
TEM	−0.0040 (0.0032)	−0.0017 (0.0014)	−0.0143 *** (0.0039)
RHC	0.0076 (0.0372)	0.0002 (0.0192)	−0.0636 (0.0440)
lnGTI	−0.0048 (0.0136)	−0.0137 (0.0099)	−0.0035 (0.0292)
lnAPS	−0.0033 (0.0042)	−0.0012 (0.0020)	0.0081 ** (0.0037)
AWC	0.0035 (0.0061)	0.0029 (0.0036)	−0.0023 (0.0064)
lnRUR	0.0382 (0.0451)	0.0276 (0.0237)	0.0687 ** (0.0307)
_cons	−0.4363 ** (0.2216)	−0.7911 *** (0.1154)	−0.8185 *** (0.1597)
N	937	1181	532
R-sq	0.3021	0.3721	0.3484
Year fixed effects	YES	YES	YES
Individual fixed effects	YES	YES	YES
The <i>p</i> -value for the intergroup difference coefficient	0.651	0.068 *	0.149

Note: For the significance test of coefficient differences across the three regression models, ① the *p*-value in column (1) corresponds to the test of whether the coefficient in column (1) differs significantly from that in column (2); ② the *p*-value in column (2) corresponds to the test of whether the coefficient in column (2) differs significantly from that in column (3); and ③ the *p*-value in column (3) corresponds to the test of whether the coefficient in column (3) differs significantly from that in column (1). Statistical significance is indicated by *** (1%), ** (5%), and * (10%).

At the control variable level, the regression results for each variable across the three regions exhibit pronounced regional heterogeneity. Specifically, the coefficient of lnPRE is 0.0702 in the western region—statistically significant at the 1% level; 0.0297 in the central region—significant at the 10% level; and statistically insignificant in the eastern region. This pattern indicates that precipitation exerts a significantly positive effect on GEAW only in the central and western regions. The coefficient of TEM is −0.0143 in the western region, significant at the 1% level, whereas it is statistically insignificant in both the central and eastern regions—suggesting that the adverse impact of TEM on GEAW is predominantly observed in the western region. For lnAPS, the coefficient is 0.0081 in the western region, significant at the 5% level, while remaining statistically insignificant in both the eastern and central regions—implying that this variable exhibits a statistically robust positive association with green efficiency solely in the western subsample. The remaining control

variables—RHC, lnGTI, lnAWC, and lnRUR—generally lack statistical significance across all three regional subsample regressions.

From the regional empirical results presented above, it is evident that the effects of URBA—as well as various other control variables—on GEAW exhibit pronounced regional heterogeneity. A plausible explanation lies in the objective disparities across regions in terms of economic foundations, natural resource endowments, and prevailing agricultural development models, which collectively shape the differential impacts of these variables. Consequently, when leveraging URBA to advance green agricultural water use, policymakers must explicitly account for regional heterogeneity and design context-specific differentiated strategies—thereby fully harnessing the green development potential enabled by URBA.

3.7.2. Heterogeneity Analysis of Urban Administrative Levels

The sample is stratified into provincial capital cities and non-provincial capital cities based on urban administrative hierarchy. Column (1) in Table 14 reports results for provincial capitals: the coefficient of the core explanatory variable (URBA) is 0.041, which is statistically insignificant. Column (2) presents results for non-provincial capital cities. The urbanization coefficient is 0.107, significant at the 5% level and consistent with the baseline regression findings. The Chow test results revealed a statistically significant difference between the groups. These results indicate significant heterogeneity in the promoting effect of urbanization on GEAW across urban administrative hierarchies. The underlying mechanism for this heterogeneity may be as follows: As core regional growth poles, provincial capitals already exhibit relatively advanced economic development, technological innovation capacity, and infrastructure support, resulting in an inherently high baseline level of lnAWC. Thus, marginal increases in urbanization alone are insufficient to further enhance GEAW. In contrast, non-provincial capital cities lag in economic development and technological innovation, leaving greater room for marginal gains from urbanization. Elevating URBA in these cities facilitates urban–rural factor mobility and optimizes agricultural resource allocation, thereby exerting a more pronounced positive impact on GEAW. These findings imply that when advancing the new urbanization strategy, the heterogeneity across cities in different administrative hierarchies should be fully considered. For provincial capitals, priority should be given to improving urbanization quality rather than scale expansion. For non-provincial capital cities, the driving role of urbanization in agricultural green development should be fully leveraged—for example, by improving urban–rural factor mobility mechanisms and strengthening agricultural technology extension services—to amplify the promoting effect of urbanization on GEAW.

Table 14. Regression results on heterogeneity across urban administrative levels.

Variable	(1) Provincial Capital Region	(2) Non-Provincial Capital Region
lnURBA	0.041 (0.119)	0.107 ** (0.045)
lnPRE	−0.152 (0.103)	0.040 (0.038)
TEM	−0.036 (0.055)	0.014 (0.016)
lnRHC	−0.104 (0.179)	−0.039 * (0.024)
GTI	−0.041 (0.042)	−0.016 (0.015)

Table 14. Cont.

Variable	(1) Provincial Capital Region	(2) Non-Provincial Capital Region
lnAPS	0.010 (0.020)	−0.002 (0.008)
lnAWC	0.018 (0.024)	0.002 (0.009)
lnRUR	−0.187 (0.155)	−0.092 * (0.048)
_cons	0.778 (0.766)	−1.071 *** (0.368)
N	274	2376
R-sq	0.344	0.401
Year fixed effects	YES	YES
Individual fixed effects	YES	YES
Chow test	F = 1.79 (Prob > F = 0.0000)	

Statistical significance is indicated by *** (1%), ** (5%), and * (10%).

3.7.3. Temporal Heterogeneity Analysis

To test for temporal heterogeneity, this study follows the methodology of Cui and Zhou (2020) [78] and divides the sample into two subperiods—2013–2017 and 2018–2022—for grouped regression analysis. This approach enables us to examine whether the effect of the core explanatory variable on GEAW exhibits temporal heterogeneity. Table 15, Column (1), reports the estimation results for the 2013–2017 subsample: the coefficient on URBA is 0.057 but is statistically insignificant. Column (2) presents the corresponding estimates for the 2018–2022 subsample, where the coefficient on URBA rises to 0.062 and is statistically significant at the 5% level—consistent with the baseline regression findings. These results suggest that the positive effect of URBA on GEAW emerges only during the 2018–2022 period. A formal Chow test for structural breaks across the two periods yields an F-statistic of 42.01 ($p < 0.001$), which is significant at the 1% level. This confirms a statistically significant difference in the magnitude and significance of URBA's effect on GEAW between the two subperiods.

Table 15. Regression results of temporal heterogeneity.

Variable	(1) Initial Impact	(2) Subsequent Impact
lnURBA	0.057 (0.058)	0.062 ** (0.025)
lnPRE	0.065 (0.051)	0.006 (0.017)
TEM	0.038 * (0.021)	−0.003 (0.002)
lnRHC	−0.051 (0.045)	0.005 (0.024)
GTI	−0.023 (0.024)	0.000 (0.009)
lnAPS	0.017 (0.021)	−0.000 (0.002)
lnAWC	−0.008 (0.012)	0.005 (0.004)

Table 15. *Cont.*

Variable	(1) Initial Impact	(2) Subsequent Impact
lnRUR	−0.108 (0.100)	0.047 ** (0.021)
_cons	−1.648 *** (0.495)	−0.347 *** (0.114)
N	1276	1349
R-sq	0.491	0.196
Time horizon	2013–2017	2018–2022
Year fixed effects	YES	YES
Individual fixed effects	YES	YES
Chow test	F = 42.01 (Prob > F = 0.0000)	

Statistical significance is indicated by *** (1%), ** (5%), and * (10%).

The impact of URBA on GEAW exhibits marked temporal heterogeneity across the two sample periods. This divergence likely stems from distinct developmental dynamics: During the initial phase of rapid urbanization, large-scale reallocation of land and agricultural resources occurred, delaying the immediate manifestation of water-saving and efficiency-enhancing effects. In contrast, in the later stage, deepening factor mobility between urban and rural areas—coupled with the sustained implementation of evolving policies—shifted policy priorities from mere expansion in scale to integrated urban–rural development. Consequently, greater emphasis was placed on the spillover and catalytic effects of urban growth on rural regions. As a result, the “green empowerment” effect of URBA gradually materialized, yielding a statistically significant positive association with GEAW. From a policy perspective, greater attention should therefore be devoted to establishing robust long-term institutional mechanisms while explicitly recognizing and leveraging the endogenous, positive role of URBA in enhancing GEAW, rather than prioritizing short-term policy outcomes.

4. Summary and Discussion

4.1. Research Conclusions

This study employs an unbalanced panel dataset covering 280 prefecture-level cities in China from 2013 to 2022 to comprehensively investigate the impact of urban expansion on GEAW, including its underlying mechanisms, heterogeneous patterns across regions and city types, and potential nonlinear relationships. The principal conclusions are as follows:

- (1) The spatiotemporal distribution of China’s GEAW presents obvious non-equilibrium. Spatially, high- and relatively high-GEAW cities are mainly concentrated in eastern coastal areas and the middle-lower Yangtze River reaches, whereas low- and relatively low-GEAW units are widespread in northwest, northeast and southwest China, forming a gradient pattern of “higher in the east and south, lower in the west and north”. In terms of temporal evolution across four major economic regions: benefiting from industrial and technological strengths, the eastern region becomes a core growth pole with improved GEAW; restricted by backward water-saving technologies and management systems, the central region suffers drastic efficiency fluctuations with limited sustained growth; the western region’s GEAW keeps declining and stays persistently low, lacking green-transformation momentum; and the northeast loses its traditional efficiency advantages and hits an improvement bottleneck, accompanied by widening inter-regional efficiency gaps.
- (2) The urbanization process is significantly positively correlated with GEAW. Base-line regression yields an lnURBA coefficient of 0.104, significant at the 5% level, meaning higher URBA corresponds to improved GEAW. This conclusion holds after

multiple robustness checks, including core variable replacement, adding provincial and provincial-year fixed effects, and excluding municipalities directly under the Central Government. It also survives endogeneity mitigation via System GMM, lagged control variables and outlier sample removal, confirming the reliability of this positive relationship.

- (3) The correlation between URBA and GEAW presents group-level heterogeneity conditional on GOVE. Grouped regression returns a URBA coefficient of 0.117 ($p < 0.05$) for the above-median high-GOVE group and an insignificant coefficient of 0.073 for the low-GOVE group. The Chow test indicates significant overall structural differences between the two subsamples, yet this does not constitute direct statistical evidence that the URBA coefficients themselves differ. We only identify a descriptive subgroup pattern: the positive URBA-GEAW association is statistically observable exclusively in the high-GOVE subsample. Higher GOVE optimizes urban-rural water resource allocation and improves agricultural water-saving infrastructure, which creates favorable conditions for GEAW enhancement.
- (4) The results yield suggestive evidence for a potential single-threshold effect of GOVE on the URBA-GEAW relationship, with only marginal statistical support at the 10% level. When GOVE falls below the sample-estimated threshold of 3.8453, the URBA-GEAW association is insignificant. Once this threshold is exceeded, URBA shows a positive correlation with GEAW at the 10% marginal significance level. Note that this threshold value is sample-specific and cannot be treated as a universal critical cutoff.
- (5) URBA exerts multidimensional heterogeneous impacts on GEAW. Regionally, URBA produces a significant positive effect in central and western China but shows no significance in the eastern region. The Chow test shows only a 10%-level marginal difference between central and western coefficients, with no significant gaps between other regional pairs. The full-sample significance mainly originates from central-western observations, especially the western subsample. Administratively, the promoting effect of URBA is significant only in non-capital cities, which enjoy greater potential to optimize resource allocation efficiency. Temporally, the URBA-GEAW correlation is significant for 2018–2022 yet insignificant for 2013–2017; the Chow test confirms overall structural differences across the two periods. This temporal feature suggests that policy-making should prioritize durable long-term institutional mechanisms instead of short-term performance targets.

4.2. Research Implications

Based on the insights derived from the above research, the following policy recommendations can be proposed:

- (1) Given the positive effect of urbanization on GEAW, priority should be given to enhancing the quality of urbanization. We should remove barriers to the free flow of factors between urban and rural areas, introducing urban talent, water-saving technologies, and social capital into rural areas; adhere to the 1.8 billion mu arable land red line and strengthen the construction of high-standard farmland; and intensify the control of agricultural non-point source pollution so as to achieve coordinated urban-rural development.
- (2) In response to the positive moderating effect and threshold characteristics of GOVE, local governments should promptly optimize their investment strategies. On the one hand, they should increase fiscal support for agricultural and rural water conservation and strengthen the supervision of fiscal funds to ensure their effective implementation. On the other hand, given the threshold effect, regions with relatively low investment

should continue to redress deficiencies so as to activate key enabling factors and reallocate urban–rural capital, technology, and human capital into green agriculture. Meanwhile, governments should strengthen institutional construction, provide water-saving and green production technology training for agricultural producers, and actively promote advanced production technologies and environment-friendly agricultural chemicals.

- (3) In response to the heterogeneous effects of urbanization on GEAW, differentiated and precision governance should be implemented. Regionally, the water-saving and efficiency-enhancing effects of URBA are pronounced in the central and western regions but muted in the eastern region; hence, the central and western regions should continuously strengthen their foundational infrastructure, while the eastern region should shift from sheer urban-scale expansion to improving urbanization quality through industrial transformation and upgrading. At the city level, non-capital cities require enhanced institutional support to unlock their factor mobility potential, whereas capital cities should expedite industrial restructuring and pursue connotative, high-quality development. From a temporal perspective, establishing a robust, long-term governance mechanism is essential to ensure policy continuity and stability.

4.3. Deficiencies and Prospects

The conclusions of this study hold certain practical significance, yet they are subject to several limitations.

First, the characterization of government water conservancy infrastructure investment intensity tools is overly simplistic. Governments employ a diverse array of interventions to influence GEAW, but due to the difficulty of quantifying some tools and the unavailability of relevant data, this study only uses government water conservancy infrastructure investment as a proxy, which is one-sided and may introduce bias into the estimation results. Therefore, future research should scientifically construct an evaluation indicator system to comprehensively measure the intensity of government water conservancy infrastructure investment and explore its complex impacts on GEAW in depth.

Second, the mechanism analysis and spatial perspective are insufficiently expanded. Regarding GOVE, this study employs group-wise regression to conduct a heterogeneity analysis, thereby examining variations in the URBA coefficient across subgroups. Notably, the analysis does not incorporate an interaction term between URBA and GOVE; as such, the observed heterogeneity should be interpreted as descriptive evidence—specifically, heterogeneity along the dimension of GOVE—rather than as causal evidence of moderation effects. Simultaneously, the spatial distribution of GEAW is visualized solely via the natural break classification method. The study does not perform formal spatial autocorrelation tests; consequently, the resulting maps offer only a qualitative depiction of spatial patterns and cannot rigorously detect statistically significant spatial clustering or quantify potential spatial spillover effects. Moreover, the analysis focuses exclusively on GOVE as a single transmission channel. It does not investigate alternative or complementary mechanisms—such as technological diffusion, cross-regional factor mobility, or the multifaceted effects arising from interregional collaborative governance—that may also mediate the relationship between policy intervention and outcomes. Future research should therefore broaden its scope to encompass these additional pathways and their interactions.

Third, the causal explanatory power of the threshold effect is limited. The threshold effect test results in this study reflect the nonlinear characteristics of the impact of urbanization on GEAW at different levels of GOVE. However, this threshold effect itself reveals the limitations of causal interpretation imposed by potential inter-regional hetero-

geneity. Specifically, the estimation of the threshold value 3.8453 depends on the sample interval and variable selection in this study. Differences in economic development stages, resource endowments, and policy environments across regions can lead to variation in their threshold values. Therefore, the threshold effect conclusions of this study should be understood as correlational evidence that “when the intensity of government water conservancy infrastructure investment reaches a certain level, urbanization has a significant positive impact on GEAW,” rather than universal causal inference. Future research can further expand the sample scope and integrate empirical data from more regions to enhance the external validity of the conclusions. Meanwhile, regarding endogeneity treatment, the threshold variable (GOVE) itself may be endogenous. Due to the limited availability of instrumental variables, this study does not fully control for this, so the threshold effect should be interpreted as a statistical association.

Fourth, there are constraints on data time limits and variable measurement precision. Restricted by the availability of prefecture-level city data, the analysis of some heterogeneity issues remains insufficiently detailed, and the underlying mechanisms and operating conditions behind them also require further research expansion.

Author Contributions: Conceptualization, W.L. and J.Y.; methodology, R.S.; software, Z.T.; validation, Z.T. and R.S.; formal analysis, Z.T.; investigation, Z.T.; resources, J.Y.; data curation, R.S.; writing—original draft preparation, Z.T. and R.S.; visualization, J.Y.; supervision, W.L.; funding acquisition, W.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Social Science Foundation Project (25FJYB045) and the Social Science Foundation of the Ministry of Education (24YJC630143).

Data Availability Statement: All the data used in this manuscript are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Zheng, S.; Suo, Y.; Kou, Z. Study on the Optimization Strategy of Cultivated Land and Water Resources Allocation in Beijing from the Perspective of Food Security. *Beijing Plan. Constr.* **2025**, *2*, 129–132.
2. Zhao, X. Ways of Sustainable Utilization of Agricultural Resources in China. *Jiangxi Agric.* **2018**, *10*, 73+83. [[CrossRef](#)]
3. Wang, H.; Jiang, S.; Zhu, Y. Research on the Collaborative Safety Development Strategy of Water-Energy-Food Nexus in China. *China Water Resour.* **2024**, *17*, 5–12.
4. Xue, X.; Song, P. Spatiotemporal Heterogeneity and Driving Factors of Green Efficiency of Agricultural Water Resources Under Environmental Regulation: A Case Study of Nine Provinces in China’s Yellow River Basin. *Chin. J. Agric. Resour. Reg. Plan.* **2025**, *in press*.
5. He, Y. Experience and Enlightenment of Foreign Rural Water Conservancy Construction Project Financing. *Water Resour. Plan. Des.* **2017**, *8*, 27–28+57.
6. Ma, H.; Xu, J.; Wang, P. Water Resource Utilization and China’s Urbanization. *Resour. Sci.* **2014**, *36*, 1121–1129.
7. Bhagabati, S.; Kawasaki, A.; Babel, M. A Cooperative Game Analysis of Transboundary Hydropower Development in the Lower Mekong: Case of the 3S Sub-basins. *Water Resour. Manag.* **2014**, *28*, 3417–3437. [[CrossRef](#)]
8. Morillas, L.; Hund, S.V.; Johnson, M.S. Water Use Dynamics in Double Cropping of Rainfed Upland Rice and Irrigated Melons Produced Under Drought-Prone Tropical Conditions. *Water Resour. Res.* **2019**, *55*, 4110–4127. [[CrossRef](#)]
9. Chen, L.; Wu, J.G.; Wang, Y.M. Efficiency Evaluation of Water Resource-Economic-Environment System Based on Spatial Perspective. *Sci. Geogr. Sin.* **2015**, *20*, 227–233. [[CrossRef](#)]
10. Liu, Y.; Song, Y. Evaluation and Influencing Factor Analysis of Agricultural Water Resource Efficiency in China Based on Super-efficiency SBM Model. *China Rural Water Hydropower* **2019**, *1*, 102–107.
11. Liu, S.; Cao, J. Spatiotemporal Differentiation and Driving Factors of Green Efficiency of Agricultural Water Use in China. *Bull. Soil Water Conserv.* **2023**, *43*, 346–357.
12. Li, Q.S.; Zhang, F.T.; Su, W.C. Measurement of Green Efficiency of Agricultural Water in the Yangtze River Economic Belt and Analysis of Influencing Factors—Based on the Super-efficiency EBM-Geodetector Model. *Chin. J. Agric. Resour. Reg. Plan.* **2022**, *43*, 40–52.

13. Guo, J.H.; Ni, M.; Li, B.Y. Research on Agricultural Production Efficiency Based on Three-stage DEA Model. *J. Quant. Tech. Econ.* **2010**, *12*, 27–38.
14. Zhou, P.; Shen, Y.; Zheng, J. Research on Measurement and Influencing Factors of Agricultural Green Total Factor Productivity in Chongqing Section of the Three Gorges Reservoir Area: Based on the Data from 2009 to 2018. *J. Chongqing Norm. Univ. (Nat. Sci. Ed.)* **2020**, *3*, 107.
15. Liang, J.; Long, S. China's Agricultural Green Total Factor Productivity Growth and Its Affecting Factors. *J. South China Agric. Univ. (Soc. Sci. Ed.)* **2015**, *14*, 1–10.
16. Guo, H.; Zhang, Z. The Threshold Effect of New Urbanization on Agricultural Green Total Factor Productivity. *J. Soc. Sci. Hunan Norm. Univ.* **2019**, *48*, 56–65. [\[CrossRef\]](#)
17. Chen, S. Analysis on the Operating Situation and Development Countermeasure of China's Policy-driven Agricultural Insurance. *Issues Agric. Econ.* **2010**, *3*, 35–42. [\[CrossRef\]](#)
18. Zhang, J.; Zhu, P.; Wang, M. Farmland Transfer Under Government Intervention: Household Income and Resources Allocative Efficiencies. *China Popul. Resour. Environ.* **2016**, *26*, 130–139.
19. Chu, D. Innovation Mechanism of Agricultural Green Technology Based on Public Goods Attributes. *J. Huanan Agric. Univ. (Soc. Sci. Ed.)* **2022**, *21*, 23–32.
20. Wang, X.Q.; Cao, T.Y.; Zou, W. Impact of Local Governments' Intervention in Farmland Circulation on Agricultural Production Efficiency: Based on the Analysis of Rice Growers. *China Popul. Resour. Environ.* **2018**, *28*, 112–120.
21. Lu, S.; Xiong, J. Can the Establishment of the First Demonstration Area of Ecological Civilization Improve the Green Efficiency of Agriculture?—Based on the Empirical Data of Hunan Province. *J. Cent. South Univ. (Soc. Sci. Ed.)* **2020**, *26*, 90–101.
22. Ma, G.; Tan, Y. Impact of Environmental Regulation on Agricultural Green Total Factor Productivity—Analysis Based on the Panel Threshold Model. *Agric. Technol. Econ.* **2021**, *5*, 77–92. [\[CrossRef\]](#)
23. Lu, W.; Sarkar, A.; Hou, M.; Liu, W.; Guo, X.; Zhao, K.; Zhao, M. The Impacts of Urbanization to Improve Agriculture Water Use Efficiency—An Empirical Analysis Based on Spatial Perspective of Panel Data of 30 Provinces of China. *Land* **2022**, *11*, 80. [\[CrossRef\]](#)
24. Ding, X.; Zhao, L.; Imran, M.; Chen, M.; Zhu, S. Does urban scale borrowing accelerate the diffusion of agricultural green water use efficiency? A case study of the Central Plains urban agglomeration. *Water Policy* **2025**, *27*, 684–714. [\[CrossRef\]](#)
25. Li, G.; Ma, H.; Zhao, C. Dynamic Evolution and Driving Factors of Agricultural Water Use Efficiency in the Yellow River Irrigation Districts of the Lower Reaches (Henan Section). *China Agric. Resour. Reg. Plan.* **2024**, *45*, 64–74.
26. Jia, R.; Fang, S.; Tu, W.; Sun, Z. Driven Factors Analysis of China's Irrigation Water Use Efficiency by Stepwise Regression and Principal Component Analysis. *J. Chem.* **2016**, *2016*, 8957530. [\[CrossRef\]](#)
27. Zhao, J.; Wang, Y.; Zhang, X.; Liu, Q. Industrial and Agricultural Water Use Efficiency and Influencing Factors in the Process of Urbanization in the Middle and Lower Reaches of the Yellow River Basin, China. *Land* **2022**, *11*, 1248. [\[CrossRef\]](#)
28. Wang, S.; Xue, J.; D'Odorico, P.; Qin, Y.; Zhu, Y.; Li, F.; Duan, W.; Gong, L.; Zeng, F.; Chang, J.; et al. Agricultural crop trade alleviates China's water shortage but redistributes water value unevenly. *npj Sustain. Agric.* **2026**, *4*, 44. [\[CrossRef\]](#)
29. Xu, R.; Gao, J. Evolutionary Trends, Regional Differences and Influencing Factors of the Green Efficiency of Agricultural Water Use in China Based on WF-GTWR Model. *Int. J. Environ. Res. Public Health* **2023**, *20*, 1946. [\[CrossRef\]](#)
30. Huang, Y.; Huang, X.; Xie, M.; Cheng, W.; Shu, Q. A study on the effects of regional differences on agricultural water resource utilization efficiency using super-efficiency SBM model. *Sci. Rep.* **2021**, *11*, 9953. [\[CrossRef\]](#) [\[PubMed\]](#)
31. Layani, G.; Mehrjou, S.; Farajzadeh, Z. Effects of Government Policies Reform on Environmental Sustainability: An Integrated Approach of PMP and System Dynamics Simulation Model. *J. Clean. Prod.* **2023**, *426*, 138985. [\[CrossRef\]](#)
32. Iqbal, J.; Amin, G.; Su, C. Assessment of Landcover Impacts on the Groundwater Quality Using Hydrogeochemical and Geospatial Techniques. *Environ. Sci. Pollut. Res.* **2024**, *31*, 38927–38942. [\[CrossRef\]](#) [\[PubMed\]](#)
33. Basharat, F.U.; Ashraf, E.; Luqman, M. Adoption of Environment-Friendly Climate Smart Agricultural Practices and Prevailing Constraints: Policy Implications for Cotton Growers of Southern Punjab, Pakistan. *Pol. J. Environ. Stud.* **2024**, *33*, 1235–1246. [\[CrossRef\]](#)
34. Yang, X.H.; Du, D. Regional Differentiation and Influencing Factors of Green Efficiency of Agricultural Water Resources in Major Grain Producing Areas. *Water Sav. Irrig.* **2023**, *6*, 19–26. [\[CrossRef\]](#)
35. Wu, S.; Wang, X.; Li, J. Logical Reflection on the Policy of Grain Production Increase Under the Concept of Big Food Security. *Agric. Econ.* **2024**, *1*, 35–37.
36. Chang, X.; Zhang, Y. Mechanism and Effect of Agriculture-Tourism Integration on Agricultural Eco-Efficiency in China. *J. Agro For. Econ. Manag.* **2022**, *21*, 310–319.
37. Xu, R.F.; Zhao, M.J.; Gao, J.Z. Measurement and Spatiotemporal Differentiation of Agricultural Grey Water Footprint in China. *Chin. J. Agric. Resour. Reg. Plan.* **2023**, *44*, 52–66.
38. Han, Q.; Sun, C.Z.; Zou, W. Measurement and Driving Pattern Analysis of Provincial-Level Grey Water Footprint Efficiency in China from 1998 to 2012. *Resour. Sci.* **2016**, *38*, 1179–1191.

39. Kong, Y.; He, W.; Zhang, Z. Spatial Temporal Variation and Driving Factors Decomposition of Agricultural Grey Water Footprint in China. *J. Environ. Manag.* **2022**, *318*, 115601. [[CrossRef](#)] [[PubMed](#)]
40. Zhao, L.; Fang, C. Distribution Dynamics and Driving Mechanism of China's Provincial New Urbanization Development Level. *J. Quant. Tech. Econ.* **2019**, *5*, 36–52. [[CrossRef](#)]
41. He, C.; Li, L.; Zhou, H.; Huang, P.; Yang, Z. Urbanization Space Evolution in Dadu River and Analysis of Driving Factors. *J. Southwest China Norm. Univ. (Nat. Sci. Ed.)* **2016**, *41*, 123–130. [[CrossRef](#)]
42. Liu, Z. Does New Urbanization Improve China's Agricultural Green Total Factor Productivity?—Based on Spatial Spillover Effect and Threshold Characteristics. *Sci. Technol. Manag. Res.* **2021**, *41*, 201–208.
43. Hu, M.; Mei, Y. Research on New Urbanization and Cultivated Land Change Based on Pearson Correlation Coefficient and Linear Regression—A Case of Suqian City. *Land Resour. Her.* **2018**, *15*, 40–44.
44. Zhang, P.D.; Yuan, S.; Xia, X. Influence Factor Analysis for Collaborative Development of “5-tasks” and Agricultural Modernization. *Econ. Geogr.* **2017**, *27*, 152–157.
45. Liu, S.; Sun, F. Research on the Interaction Between New Urbanization and Industrial Structure Upgrading in the Yangtze River Economic Belt. *West Forum Econ. Manag.* **2023**, *34*, 49–59.
46. Ding, C.; Yang, F.; Guo, Q. Research on Coupling Coordinated Development of New Industrialization, New Urbanization and Rural Revitalization. *Stat. Decis.* **2020**, *2*, 71–75. [[CrossRef](#)]
47. Gao, Z.; Ren, Y.; Han, Y. Research on the Coupling and Coordinated Development of New Industrialization, New Urbanization and Rural Revitalization Level. *Reg. Econ. Rev.* **2022**, *5*, 58–69. [[CrossRef](#)]
48. Zhang, P. Research on the Coupling Development of Village Tourism and New Urbanization. Master's Thesis, Liaoning University, Shenyang, China, 2021. [[CrossRef](#)]
49. Guo, F.; Li, C.; Chen, C.; Gan, J. Spatial-Temporal Coupling Characteristics of Population Urbanization and Land Urbanization in Northeast China. *Econ. Geogr.* **2015**, *35*, 62–69. [[CrossRef](#)]
50. Lu, C.; Li, S.; Liu, J. Coupling Coordination and Dynamic Response Analysis of New-type Urbanization, Urban Infrastructure and Urban Environment—A Case Study of the Jiadong Economic Circle. *Int. J. Environ. Res. Public Health* **2022**, *19*, 14909. [[CrossRef](#)] [[PubMed](#)]
51. Feng, Y.; Wang, X. Impact of Co-agglomeration of Manufacturing and Producer Services on New-type Urbanization in China. *Econ. Probl. Explor.* **2018**, *11*, 66–76.
52. Shao, H.; Wu, W.; Wang, Z. Temporal and Spatial Coupling Coordination of Green Utilization Efficiency of Tourism Resources and New Urbanization in the Yangtze River Economic Belt. *Econ. Geogr.* **2021**, *41*, 204–213.
53. Gao, H.; Luo, Y. The Coupling Measurement of Urbanization and Ecological Environment Quality in the Yangtze River Economic Belt. *Stat. Decis.* **2021**, *1*, 111–115. [[CrossRef](#)]
54. Alvarado, R.; Ortiz, C.; Bravo, D. Urban Concentration, Non-renewable Energy Consumption, and Output: Do Levels of Economic Development Matter? *Environ. Sci. Pollut. Res.* **2020**, *27*, 2760–2772. [[CrossRef](#)] [[PubMed](#)]
55. Chen, Y.; Jiang, B.; Chu, N. Urban Land Use Efficiency and New Urbanization Index Selection and System Reconstruction. *Chin. J. Agric. Resour. Reg. Plan.* **2021**, *42*, 67–75.
56. Masini, E.; Tomao, A.; Barbati, A. Urban Growth, Land-use Efficiency and Local Socioeconomic Context: A Comparative Analysis of 417 Metropolitan Regions in Europe. *Environ. Manag.* **2019**, *63*, 312–324. [[CrossRef](#)] [[PubMed](#)]
57. Nguyen, H.T.T.; Nguyen, C.V.; Nguyen, C.V. The Effect of Economic Growth and Urbanization on Poverty Reduction in Vietnam. *J. Asian Finance Econ. Bus.* **2020**, *7*, 229–239. [[CrossRef](#)]
58. Yang, H.; Ni, P. Study on the Financial Support to New-type Urbanization—From the Perspective of Coordinated Development. *J. Shanxi Univ. Finance Econ.* **2015**, *37*, 45–53. [[CrossRef](#)]
59. Wang, F.; Qin, Y.; Liu, J.; Wu, C. A Study on the Influencing Factors of Carbon Emissions from the Perspective of Multi-dimensional Urbanization: Based on the Spatial Dubin Panel Model of China Provinces. *China Popul. Resour. Environ.* **2017**, *27*, 89–98.
60. Rahman, M.M.; Alam, K. Clean Energy, Population Density, Urbanization and Environmental Pollution Nexus: Evidence from Bangladesh. *TERI Inf. Dig. Energy Environ.* **2021**, *20*, 357–363. [[CrossRef](#)]
61. Zhang, Z.; Zhou, M.; Jin, G.; Liu, Y.Z.; Luo, X. Coordination Analysis of New Urbanization and Intensive Land-use Under the Spatial Pattern of “Two Circles Two Belts” in Hubei Province. *World Reg. Stud.* **2026**, *27*, 65–75.
62. Li, G. Study on the Influence of Urbanization on the Susceptibility and Prevention Efficiency of Landslide Flow in China. Master's Thesis, China University of Geosciences (Beijing), Beijing, China, 2018.
63. Wei, L. Study on the Impact of New Urbanization on the Multi-functionality of Cultivated Land in Guizhou Province. Master's Thesis, Guizhou University of Finance and Economics, Guiyang, China, 2022. [[CrossRef](#)]
64. Liu, W.; Wang, R.; Xu, R. Analysis of Spatial and Temporal Differentiation and Influencing Factors of Coordinated Development of Urban and Rural Water Poverty. *Stat. Decis.* **2023**, *39*, 85–89. [[CrossRef](#)]
65. Han, F.; Wang, Y. Market Potential, Government Intervention and Population Urbanization. *China Popul. Sci.* **2017**, *1*, 59–70+127.
66. Tone, K. A Slacks-based Measure of Efficiency in Data Envelopment Analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [[CrossRef](#)]

67. Tone, K. A Slacks-based Measure of Super-efficiency in Data Envelopment Analysis. *Eur. J. Oper. Res.* **2002**, *143*, 32–41. [[CrossRef](#)]
68. Cheng, Q.Y. Structure Entropy Weight Method to Confirm the Weight of Evaluating Index. *Syst. Eng. Theory Pract.* **2010**, *30*, 1225–1228.
69. Hansen, B.E. Threshold Effects in Non-Dynamic Panels: Estimation, Testing, and Inference. *J. Econom.* **1999**, *93*, 345–368. [[CrossRef](#)]
70. Lamadridcontreras, A. Panel Data Models with Two Threshold Variables. *Stud. Nonlinear Dyn. Econom.* **2022**, *27*, 315–333. [[CrossRef](#)]
71. Zhao, T.; Zhang, Z.; Liang, S. Digital Economy, Entrepreneurship, and High Quality Economic Development: Empirical Evidence from Urban China. *Front. Econ. China* **2022**, *17*, 393–426. [[CrossRef](#)]
72. Hayakawa, K.; Qi, M.; Adam, C. Further Results on the Weak Instruments Problem of the System GMM Estimator in Dynamic Panel Data Models. *Oxf. Bull. Econ. Stat.* **2020**, *82*, 1123–1140. [[CrossRef](#)]
73. Wang, W.; Zou, Y.; Xie, Y. The Impact of ESG Disclosure on Firm Total Factor Productivity from the Perspective of New Quality Productive Forces: Mediating Effect through Investment Structure Optimization. *Econ. Manag. Rev.* **2025**, *41*, 83–96. [[CrossRef](#)]
74. Gu, H.; Cao, Y. Financial Flexibility, Cross-border Capital Flows, and Bank Risk-taking. *World Econ. Res.* **2025**, 73–88+135. [[CrossRef](#)]
75. Avazdahandeh, S.; Khalilian, S. The Effect of Urbanization on Agricultural Water Consumption and Production: The Extended Positive Mathematical Programming Approach. *Environ. Geochem. Health* **2020**, *42*, 1234–1248. [[CrossRef](#)] [[PubMed](#)]
76. Shen, X.B.; Chen, Y.; Lin, B.Q. Impacts of Technological Progress and Industrial Structure Distortion on China's Energy Intensity. *Econ. Res. J.* **2021**, *56*, 157–173.
77. Yang, L.X.; Li, W.; Wang, Q.S. Tax Preference, Supply-Chain Transmission and Trade Credit: A Quasi-Natural Experiment Based on the VAT Refund Policy for Uncredited Input Tax. *Econ. Res. J.* **2023**, *58*, 41–58.
78. Cui, Z.; Zhou, X. A Study on the Heterogeneous Effects of Internet Penetration on Regional Employment. *Soft Sci.* **2020**, *34*, 7–12. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.