

Article

Dynamic Spatial Association Network and Formation Mechanisms of Environmentally Adjusted Water Use Efficiency in the Planting Industry of the Yangtze River Economic Belt, China: Implications for Sustainable Agricultural Water Management

Tao Liu ¹ , Ling Zhao ¹, Feilong Weng ¹ and Jixia Li ^{2,*}

¹ School of Finance and Economics, Henan Polytechnic University, Jiaozuo 454003, China; liutao2511001@126.com (T.L.); 212415020026@home.hpu.edu.cn (L.Z.); wengfl@hpu.edu.cn (F.W.)

² School of Public Administration, North China University of Water Resources and Electric Power, Zhengzhou 450046, China

* Correspondence: lijixia@ncwu.edu.cn

Abstract

Improving environmentally adjusted water use efficiency in the planting industry (EAWUE) is important for balancing agricultural production, water conservation, and water environmental protection. Using panel data for 101 prefecture-level cities in the Yangtze River Economic Belt during 2011–2023, this study integrates a Super-SBM model with undesirable outputs, a modified gravity model, social network analysis, and a temporal exponential random graph model (TERGM) to examine EAWUE dynamics, spatial association networks, and formation mechanisms. The results show that EAWUE improved overall, although spatial disparities remained evident. The spatial association network became denser and more connected, with inter-city linkages expanding from local associations to broader cross-regional and multi-node interactions. The Yangtze River Delta maintained a prominent core position, cities in the middle reaches played stronger bridging roles, and cities in the upper reaches showed increasing participation, forming four functional block types. Network tie formation was statistically associated with endogenous network structures, node attributes, spatial constraints, and temporal dependence. Reciprocity, transitive structures, and network persistence showed positive associations with tie formation, whereas geographic distance showed a negative association. Resource endowment, rural human capital, and industrial structure upgrading generally showed positive associations, while economic development and government support exhibited heterogeneous associations with sending and receiving roles. Sensitivity and robustness tests generally supported the main structural findings. These findings highlight the need for differentiated prefecture-level governance, stronger agricultural water conservation and non-point source pollution control, improved cross-regional coordination, and fuller use of core nodes and functional blocks to support sustainable agricultural water management.

Keywords: environmentally adjusted water use efficiency; sustainable agricultural water management; agricultural sustainability; spatial association network; TERGM; Yangtze River Economic Belt



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1. Introduction

Water resources are a fundamental input for agricultural production and provide essential support for food security, agricultural green transformation, and regional sustainable development. According to the 2024 China Water Resources Bulletin issued by the Ministry of Water Resources, total water use in China reached 592.80 billion m³ in 2024, of which agricultural water use amounted to 364.84 billion m³, accounting for 61.6% of the total. However, the effective utilization coefficient of farmland irrigation water was only 0.580, indicating that substantial potential remained for agricultural water conservation and efficiency improvement. With climate change, more frequent extreme hydrological events, and increasingly intensive agricultural production, the imbalance between agricultural water supply and demand, low water use efficiency, and pressure from non-point source pollution have become increasingly prominent [1–3]. The planting industry is not only a major sector for grain and agricultural product supply but also a key source of agricultural water consumption and non-point source pollution. Therefore, evaluating its water resource utilization performance only from a “water input–output” perspective is insufficient to reflect the associated ecological and environmental costs. Against the policy background of the Regulation on Water Conservation and the Yangtze River Protection Law of the People’s Republic of China, greater emphasis has been placed on the intensive and economical use of agricultural water resources and watershed ecological protection. The Yangtze River Economic Belt spans eastern, central, and western China and serves multiple functions in agricultural production, economic development, and ecological security. However, substantial differences exist within the region in terms of water resource endowment, planting industry foundation, and environmental carrying capacity. Therefore, water resource utilization in the planting industry requires coordinated improvements in water resource allocation, output growth, pollution control, and ecological constraints [4,5]. Meanwhile, resource flows, technology diffusion, and policy coordination among cities within the region indicate that efficiency improvement does not occur in isolation but may exhibit networked spatial associations. Accordingly, identifying the spatial association network and formation mechanism of EAWUE in the Yangtze River Economic Belt is necessary for promoting green and efficient agricultural water use and regional coordinated governance.

Existing studies have extensively examined the conceptual definition, measurement, spatiotemporal differentiation, and influencing factors of agricultural water use efficiency. Early studies mainly emphasized the transformation relationship between water resource inputs and agricultural outputs in agricultural production [6,7]. As resource and environmental constraints have intensified, this concept has gradually been extended to a comprehensive efficiency framework that incorporates water resource inputs, agricultural economic outputs, and ecological environmental constraints [8,9]. Agricultural water use efficiency has mainly been measured from two perspectives. The first is efficiency evaluation based on an input–output framework, in which agricultural water use, land, labour, machinery, and material inputs are usually treated as input variables, while agricultural output value and grain yield are used as desirable outputs to measure agricultural water use efficiency [10–12]. Some studies have further incorporated undesirable outputs, such as pollutant emissions, carbon emissions, and agricultural non-point source pollution, into the evaluation system to characterize agricultural water use efficiency under green development constraints [13,14]. The second is comprehensive evaluation based on the water footprint and resource–environment accounting framework, in which blue, green, and grey water footprints are used to measure water consumption and water environmental pressure in agricultural production, thereby revealing the coordination between agricultural water use and ecological environmental burden [15,16]. On this basis, some studies have further explored the spatiotemporal differentiation of agricultural water use efficiency at

different spatial scales, including national, provincial, watershed, and urban agglomeration scales. These studies have analyzed regional disparities, spatiotemporal dynamics, spatial dependence, and spatial spillover effects [17,18], and have further examined influencing factors such as resource endowment, economic development, technological progress, industrial structure, fiscal support, environmental regulation, and agricultural production conditions [19,20]. To overcome the limitations of traditional “attribute data” analysis, a small number of studies have also applied network analysis methods to investigate the spatial association network characteristics of agricultural water use efficiency and related resource–environment efficiency [21–23].

Although these studies provide a solid foundation, several issues remain to be further addressed. First, most existing studies on agricultural water use efficiency are based on traditional “attribute data” and mainly focus on measuring regional efficiency levels and explaining their influencing factors. Insufficient attention has been paid to spatial associations based on “relational data”, which limits the ability to characterize networked linkages of EAWUE among cities. Second, although a limited number of studies have applied network analysis methods to agricultural water use efficiency and agricultural ecological efficiency, most have focused on describing network density, centrality, and macro-level block characteristics. Systematic analysis of node functions, block division, and network structural features remains insufficient. Third, existing social network analysis frameworks often rely on methods such as the quadratic assignment procedure (QAP), which are mainly based on cross-sectional data or static networks. These methods are limited in their ability to reveal the dynamic formation mechanism and long-term evolution of spatial association networks, particularly the joint effects of endogenous network structures, node attributes, spatial constraints, and temporal dependence. To address these gaps, panel data for 101 prefecture-level cities in the Yangtze River Economic Belt from 2011 to 2023 are used in this study. A Super-SBM model with undesirable outputs is applied to measure EAWUE, and the grey water footprint is incorporated as an undesirable output to characterize water environmental pressure caused by non-point source pollution in the planting industry. A modified gravity model and social network analysis are then used to examine the overall characteristics, node positions, and block structure of the inter-city spatial association network of efficiency. On this basis, TERGM is introduced to identify the joint effects of endogenous network structures, node attributes, spatial constraints, and temporal dependence on the formation of the spatial association network from a dynamic evolutionary perspective. The results are expected to provide decision-making evidence for green and efficient agricultural water use and cross-regional coordinated governance in the Yangtze River Economic Belt. The marginal contributions of this study are as follows. First, spatial associations of EAWUE among cities are examined based on “relational data”, thereby extending beyond the limitations of traditional “attribute data” analysis. Second, the structural characteristics, node functions, and block division of the efficiency spatial association network are identified from a network perspective. Third, the effects of endogenous network structures, node attributes, spatial constraints, and temporal dependence on the dynamic formation mechanism of the network are further revealed, thereby extending the analysis from static network structure description to dynamic mechanism explanation.

2. Analytical Framework

The formation of the spatial association network of EAWUE is shaped by the joint effects of the input–output process of planting production, regional spatial interactions, and the dynamic evolution of network relationships. First, in the planting production process, water resources, land, labour, agricultural machinery, fertilizers, and other material inputs are jointly invested and transformed into economic output from the planting industry.

Meanwhile, nitrogen loss caused by fertilizer application can intensify agricultural non-point source pollution and water environmental pressure, which can be characterized by the grey water footprint as an undesirable output [24,25]. Therefore, EAWUE reflects not only the transformation relationship between water resource inputs and economic output in the planting industry, but also the degree of coordination among resource use, economic output, and water environmental constraints.

Second, cities are not isolated from one another when regional differences in efficiency levels exist. Cities with higher efficiency levels and larger economic and population scales usually have stronger capacities for resource agglomeration, technology diffusion, and the outward transfer of management experience. These cities may generate spillover effects on other cities through the diffusion of agricultural water-saving technologies, the sharing of production experience, factor mobility, and policy coordination. At the same time, geographic distance increases the cost of cross-regional linkages and weakens factor mobility, technology transmission, and governance cooperation among cities. As a result, the spatial linkages of EAWUE may extend beyond individual administrative boundaries and neighbouring areas, forming a cross-regional and multi-node networked association pattern [26].

Third, the formation and evolution of the spatial association network of EAWUE are influenced not only by city-level attributes but also by network structural relationships, spatial constraints, and historical ties. From the perspective of endogenous network structures, reciprocity and transitivity may be positively associated with the continuation, strengthening, and expansion of inter-city associations, whereas cyclic structures may reflect structural constraints within network relationships. From the perspective of node attributes, factors such as water resource endowment, economic development, rural human capital, fiscal support for agriculture, and industrial structure may affect the outward and inward association capacities of cities in the spatial association network. From the perspective of spatial constraints, geographic distance may be negatively associated with the formation of inter-city EAWUE associations. From the perspective of temporal dependence, existing network ties may be associated with subsequent network evolution through path dependence, while historical reciprocal relationships may also be associated with the direction of current inter-city association formation.

Based on the above analysis, this study first measures EAWUE in the planting industry and then constructs an inter-city spatial association network using a modified gravity model. Social network analysis is applied to identify network structure, node positions, and block division. Furthermore, TERGM is introduced to reveal the formation mechanism of the EAWUE spatial association network in the Yangtze River Economic Belt from four dimensions: endogenous network structures, node attributes, spatial constraints, and temporal dependence. The analytical framework is shown in Figure 1.

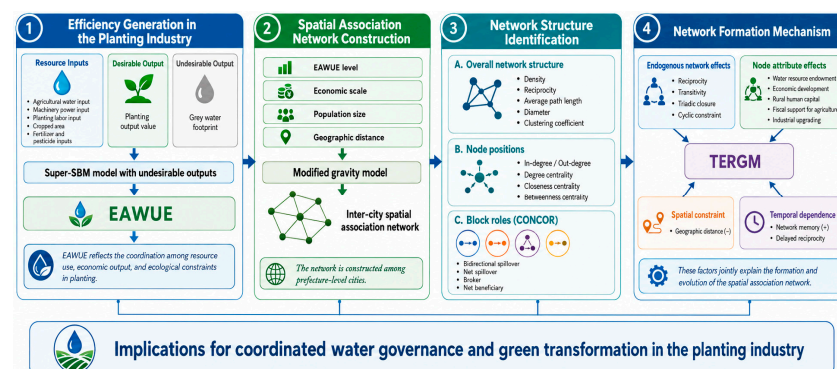


Figure 1. The analytical framework for the formation mechanism of the spatial association network of environmentally adjusted water use efficiency in the planting industry of the Yangtze River Economic Belt.

3. Materials and Methods

3.1. Study Area and Data

The Yangtze River Economic Belt covers 11 provincial-level administrative regions, including Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Chongqing, Sichuan, Guizhou, and Yunnan. It spans approximately 2.05 million km², accounting for about 21% of China's total land area, and represents an important region for economic development, agricultural production, and ecological protection. The region is characterized by complex geomorphological conditions, including plains, basins, plateaus, mountains, and hills. Significant differences exist across regions in water resource endowment, cultivated land conditions, irrigation infrastructure, and agricultural production patterns. Against the strategic background of “ecological priority and green development”, the spatial association network and formation mechanism of EAWUE in the Yangtze River Economic Belt are of practical significance. Considering the research scope and data availability, 101 prefecture-level cities were selected as the research objects. The spatial distribution of the sample cities is shown in Figure 2.

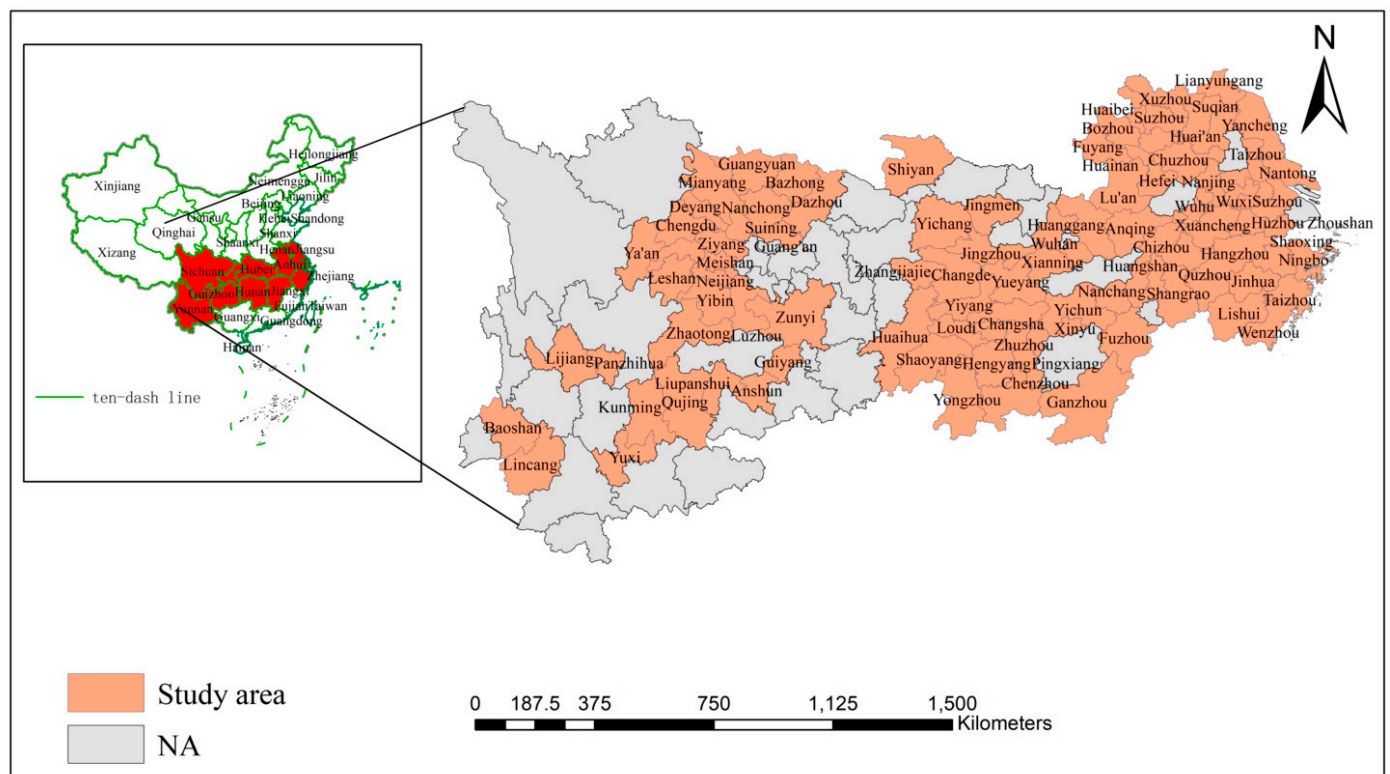


Figure 2. The study area and distribution of the sample cities in the Yangtze River Economic Belt, China.

Panel data for 101 prefecture-level cities in the Yangtze River Economic Belt from 2011 to 2023 were used in this study. The data were mainly obtained from the China City Statistical Yearbook, prefecture-level city statistical yearbooks, provincial statistical yearbooks, and provincial water resources bulletins. Some data related to water resources and agricultural production were collected through government information disclosure. Missing data for individual years were supplemented using linear interpolation. Specifically, agricultural water use data were missing for Yuxi in 2015 and 2021, while total crop planting area data were missing for Yancheng in 2013 and 2017, Fuzhou in 2020 and 2021, and Bijie in 2021. In total, 7 city-year observations involving 4 cities and 2 indicators were interpolated, accounting for 0.53% of the total 1313 observations. These missing observations were

limited in number and did not show a clear concentration in specific cities or years. The output value of the planting industry was deflated using 2011 as the base year to ensure data completeness, continuity, and comparability.

3.2. Indicator System and Variable Construction

Based on existing studies on agricultural water use efficiency, water environmental constraints were incorporated into the evaluation framework. An evaluation indicator system for EAWUE was constructed from the perspective of “inputs–desirable output–undesirable output” (Table 1) [14,27].

Table 1. The evaluation indicator system for environmentally adjusted water use efficiency in the planting industry of the Yangtze River Economic Belt.

First-Level Indicator	Second-Level Indicator	Third-Level Indicator	Unit
Input indicators	Water input	Prefecture-level agricultural water use × (provincial planting industry water use/provincial agricultural water use)	10 ⁸ m ³
Input indicators	Machinery input	Total power of agricultural machinery	10 ⁴ kW
Input indicators	Labour input in the planting industry	Employees in the primary industry × (gross output value of the planting industry / gross output value of agriculture, forestry, animal husbandry, and fishery)	10 ⁴ persons
Input indicators	Material input	Pesticide and fertilizer application	10 ⁴ t
Input indicators	Land input	Total sown area of crops	10 ³ km ²
Desirable output indicator	Planting industry output	Gross output value of the planting industry, calculated at constant 2011 prices	10 ⁸ yuan
Undesirable output indicator	Water pollution	Grey water footprint, measured as the freshwater required to dilute nitrogen fertilizer pollution to the prescribed standard	10 ⁸ m ³

Note: The gross output value of the planting industry was converted to constant 2011 prices using the prefecture-level gross output value index of agriculture, forestry, animal husbandry, and fishery (previous year = 100). The index was chain-linked year by year to express the planting industry output values for all years in comparable 2011 prices.

In terms of input indicators, various resource inputs in the agricultural production process were used to characterize input levels, including machinery input, water input, labour input, material input, and land input. Machinery input was measured by the total power of agricultural machinery. Water input was measured by prefecture-level agricultural water use multiplied by the proportion of planting industry water use in provincial agricultural water use. Labour input was calculated based on the number of employees in the primary industry, adjusted by the proportion of planting output value in the total output value of agriculture, forestry, animal husbandry, and fishery. Material input was measured by the sum of pesticide application and fertilizer application. Land input was measured by the total sown area of crops. In terms of output indicators, both desirable and undesirable outputs were considered. The desirable output was measured by the total output value of the planting industry at constant 2011 prices, which was used to reflect economic output. The undesirable output was measured by the grey water footprint (GWF). Following the grey water footprint accounting method proposed by Hoekstra et al. [28,29] and related studies [30,31], nitrogen loss from nitrogen fertilizer application

was treated as the main pollution source. The *GWF* was calculated as the amount of freshwater required to dilute pollutants generated during agricultural production to meet environmental standards. The calculation formula is expressed as follows:

$$GWF = \frac{N \times \alpha}{C_{max} - C_{nat}} \quad (1)$$

where *GWF* denotes the grey water footprint (m³); *N* denotes the total amount of nitrogen fertilizer application (kg); α denotes the nitrogen loss coefficient, which was set at 14.3% according to related studies; *C_{max}* denotes the maximum allowable nitrogen concentration, set at 0.0001 kg/m³; and *C_{nat}* denotes the natural background nitrogen concentration, set at 0. It should be noted that fertilizer application in material input reflects production material input in the planting industry, whereas the *GWF* reflects water environmental pressure caused by fertilizer application; the two therefore correspond to production input and undesirable environmental output, respectively. Considering the potential mechanical association between the *GWF* and nitrogen fertilizer application, fertilizer application was further excluded from material input, with pesticide application alone used to measure material input, and EAWUE was re-estimated to test the sensitivity of the efficiency results to the indicator specification.

3.3. Methods

3.3.1. Super-SBM Model

The Super-SBM model with undesirable outputs was used to measure EAWUE. To ensure the intertemporal comparability of the efficiency estimates, all 1313 city-year observations for the 101 prefecture-level cities from 2011 to 2023 were incorporated into a unified production technology set to construct a common production frontier, so that EAWUE in different years was evaluated based on the same reference technology set. A non-oriented specification under variable returns to scale (VRS) was adopted, allowing inputs, desirable outputs, and undesirable outputs to be adjusted simultaneously. Compared with traditional radial DEA models, the SBM model can account for input redundancy and output shortfalls, while the Super-SBM model further enables the ranking of efficient decision-making units [32–34]. Considering water environmental pollution in planting production, the grey water footprint was directly incorporated into the model as an undesirable output without positive transformation and was treated through the undesirable output term and corresponding constraints, thereby comprehensively evaluating efficiency under water resource input, economic output, and ecological environmental constraints.

The model is expressed as follows:

$$\rho^* = \min \frac{\frac{1}{m} \sum_{i=1}^m \frac{\bar{x}_i}{x_{ik}}}{\frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{\bar{y}_r^g}{y_{rk}^g} + \sum_{r=1}^{s_2} \frac{y_{tk}^g}{\bar{y}_t^b} \right)} \quad (2)$$

subject to:

$$\bar{x}_i \geq \sum_{j=1, j \neq k}^n \lambda_j x_{ij}, \quad i = 1, 2, \dots, m, \quad (3)$$

$$\bar{y}_r^g \leq \sum_{j=1, j \neq k}^n \lambda_j y_{rj}^g, \quad r = 1, 2, \dots, s_1, \quad (4)$$

$$\bar{y}_t^b \geq \sum_{j=1, j \neq k}^n \lambda_j y_{tj}^b, \quad t = 1, 2, \dots, s_2, \quad (5)$$

$$\bar{x}_i \geq x_{ik}, \quad \bar{y}_r^g \leq y_{rk}^g, \quad \bar{y}_t^b \geq y_{tk}^b, \quad \sum_{j=1, j \neq k}^n \lambda_j = 1 \quad (6)$$

$$\lambda_j \geq 0, j = 1, 2, \dots, n, j \neq k \quad (7)$$

where x denotes input factors, y^s denotes desirable outputs, and y^b denotes undesirable outputs. $\bar{x}$, $\bar{y}^s$ and $\bar{y}^b$ represent input, desirable output, and undesirable output slack variables, respectively. λ is the weight vector. m , s_1 and s_2 denote the numbers of input indicators, desirable output indicators, and undesirable output indicators, respectively. n denotes the number of decision-making units, and ρ^* denotes the super-efficiency value. The constraint $\sum_{j=1, j \neq k}^n \lambda_j = 1$ indicates that the model is estimated under the VRS assumption.

3.3.2. Modified Gravity Model

The construction of the spatial association network of EAWUE requires the measurement of edges based on inter-node relationships. Existing studies commonly use vector autoregression (VAR) models and gravity models to measure spatial associations. Compared with VAR models, which depend heavily on time-series data, gravity models can systematically quantify spatial interaction intensity between geographic units by incorporating regional economic potential and geographic distance decay. Therefore, following existing studies [35–37], efficiency-related variables were embedded into a modified gravity model to construct a gravity matrix. The gravity matrix was binarized using the mean value of each row as the threshold: a value higher than the corresponding row mean was assigned 1, and otherwise 0. The row-mean threshold uses each city's own average association intensity as the reference and allows the number of network ties and network density to vary over time, making it more suitable for capturing the dynamic evolution of the network. To test the sensitivity of the network to threshold selection, the row median and the 75th percentile of each row were further used as alternative thresholds to reconstruct the network and compare the main network structural characteristics. The modified gravity model is specified as follows:

$$X_{ij} = K_{ij} \frac{\sqrt[3]{G_i H_i M_i} \sqrt[3]{G_j H_j M_j}}{\left[\frac{D_{ij}}{|a_i - a_j| + 0.001} \right]^2} \quad (8)$$

$$K_{ij} = \frac{M_i}{M_i + M_j} \quad (9)$$

where i and j denote different cities. X_{ij} denotes the gravitational force between city i and city j . K_{ij} is the correction coefficient, which reflects the contribution rate of the efficiency linkage between the two cities. M_i and M_j denote the EAWUE values of cities i and j , respectively. G_i and G_j denote the real gross regional products of cities i and j , respectively. H_i and H_j denote the year-end populations of cities i and j , respectively. D_{ij} denotes the geographic distance between the two cities. a_i and a_j denote the per capita gross regional products of cities i and j , respectively. The main specification of Equation (8) follows the modified gravity model in Ref. [35], in which the cube root of the product of economic scale, population size, and the core indicator is used to characterize the comprehensive “mass” of a city, while geographic distance and the difference in per capita gross regional product are jointly incorporated to reflect the economic–geographical difference between cities. The directional correction coefficient K_{ij} also follows the basic specification adopted in previous studies [35,36]. In the present study, the core indicator was specified as EAWUE in the planting industry to match the research objective. To avoid division by zero when two cities have identical per capita gross regional products, $|a_i - a_j| + 0.001$ was used in the calculation. Pairwise comparisons across cities in each year showed that the minimum non-zero difference in per capita gross regional product was 2 CNY

per capita, which is far greater than 0.001. Therefore, the constant was introduced only to ensure numerical stability and does not materially affect the calculated gravitational force. Based on the modified gravity model, the constructed network reflects potential spatial associations among cities derived from EAWUE-related characteristics, economic scale, population size, and geographic proximity. These associations represent the potential linkages embedded in regional development processes rather than directly observed flows of technology, resources, or policy cooperation. Accordingly, the subsequent network analysis and TERGM estimation examine the structural characteristics and influencing factors of the EAWUE spatial association network.

3.3.3. Social Network Analysis

Social network analysis is a comprehensive methodological framework for examining “relational data” and has been widely applied in sociology, economics, and management [38]. In this study, social network analysis was used to examine the spatial association network characteristics of EAWUE from three dimensions: overall network characteristics, individual network characteristics, and block model analysis. Overall network characteristics were measured using five indicators: network density, reciprocity, average path length, network diameter, and clustering coefficient. Individual network characteristics were measured using in-degree, out-degree, degree centrality, closeness centrality, and betweenness centrality. Block model analysis was used to identify differences in the roles and positions of different individuals or groups within the network. Following the classification criteria proposed by Wasserman et al. [39], the spatial association network of EAWUE was divided into four types of functional blocks, as shown in Table 2.

Table 2. The block types and relational characteristics of the EAWUE spatial association network in the Yangtze River Economic Belt.

Proportion of Internal Relationships Within the Block	Proportion of Relationships Received by the Block	
	≈ 0	> 0
$\geq \frac{g_k - 1}{g - 1}$	Bidirectional spillover block	Net beneficiary block
$< \frac{g_k - 1}{g - 1}$	Net spillover block	Broker block

Note: g_k denotes the number of members in a given block, and g denotes the number of members in the whole network.

3.3.4. TERGM

Traditional exponential random graph models (ERGMs) are mainly used to analyze static network structures and do not adequately capture temporal changes in network relationships. To address this limitation, Hanneke et al. [40] proposed the temporal exponential random graph model (TERGM), which incorporates time-series features into the ERGM framework and can characterize the mechanisms through which network relationships evolve over time.

The TERGM assumes that network relationships follow a Markov process in discrete time. In other words, the current network state is affected not only by endogenous network structures and exogenous factors, but also by the network structure in the previous period. Let Y_t denote the network structure at time t . The basic form of the TERGM is expressed as follows:

$$P(Y_t = y_t | Y_{t-1} = y_{t-1}, \theta) = \frac{\exp(\sum_H \theta_H g_H(y_t, y_{t-1}))}{c(\theta, y_{t-1})} \quad (10)$$

where $g_H(y_t, y_{t-1})$ denotes the statistic function associated with network characteristics, θ_H denotes the corresponding parameter vector, and $c(\theta, y_{t-1})$ denotes the normalizing constant.

The TERGM estimation was conducted in R version 4.6.1 using the *statnet*, *ergm*, *xergm.common*, *btergm*, and *texreg* packages. To ensure reproducibility of the simulation-based estimation, the random-number seed was fixed at 10. Model parameters were estimated using the Markov Chain Monte Carlo Maximum Likelihood Estimation (MCMC-MLE) approach. During the MCMC simulation process, 1000 sampling draws and a thinning interval of 1000 iterations were adopted to reduce autocorrelation and improve estimation stability. Unless otherwise specified, the remaining estimation-control parameters were retained at their default settings. Model convergence was assessed using standard MCMC diagnostics, including trace plots, autocorrelation diagnostics, and convergence statistics. The diagnostic results showed stable chain mixing without systematic trends, with autocorrelation generally decreasing as the lag increased, indicating satisfactory convergence. Model fit was evaluated using log likelihood, AIC, and BIC, while model adequacy was further assessed using goodness-of-fit (GOF) diagnostics by comparing structural characteristics of networks simulated from the fitted model with those of the observed networks.

The explanatory variables in the TERGM were divided into three categories.

The first category refers to endogenous network effects, which were used to characterize the basic topological features of the EAWUE spatial association network. The *edges* term denotes the number of network ties and reflects the overall connectivity of the network. The *mutual* term denotes reciprocity and measures the tendency toward bidirectional associations between cities. The *ttriple* term denotes transitive triples and captures triadic closure in the network. The *transitivities* term denotes the density of transitive ties and reflects local clustering and transitive structures. The *ctriple* term denotes cyclic triples and is used to describe cyclic association structures and potential structural constraints in the network.

The second category refers to node attribute effects, which were used to examine how city-level characteristics affect the formation of spatial associations. Specifically, *nodecov(X1)* and *nodeicov(X1)* denote the outward and inward effects of average years of rural education, respectively, and were used to measure rural human capital. *nodecov(X2)* and *nodeicov(X2)* denote the outward and inward effects of fiscal support for agriculture, respectively, and were used to reflect government support. *nodecov(X3)* and *nodeicov(X3)* denote the outward and inward effects of mean nighttime light intensity, respectively, and were used to represent regional economic development. *nodecov(X4)* and *nodeicov(X4)* denote the outward and inward effects of per capita water resources, respectively, and were used to capture the influence of resource endowment on network tie formation. *nodecov(X5)* and *nodeicov(X5)* denote the outward and inward effects of the share of the tertiary industry, respectively, and were used to measure industrial structure upgrading. Regarding variable scaling, the original measure of average years of rural education was transformed using $\ln(1 + x)$ before being entered into the TERGM as X1, in order to reduce potential skewness and the influence of extreme values. The remaining node-level covariates—fiscal support for agriculture (X2), mean nighttime light intensity (X3), per capita water resources (X4), and the share of the tertiary industry (X5)—were entered into the model in their original measurement scales. The same variable-processing procedure was applied consistently across all years and model specifications.

The third category refers to external constraint effects, which were used to characterize the influence of spatial conditions and historical network relationships on association formation and evolution. The *distance* term denotes the inter-city geographic distance matrix and was used to measure the effect of spatial distance on network tie formation. The *memory* term denotes the persistence of previous network ties over time, capturing whether existing relationships in the previous period are more likely to continue in the

current network. The delayed reciprocity term (delrecip) denotes the influence of historical reciprocal relationships on current network tie formation, capturing whether previous bidirectional associations affect the formation of current network relationships.

Since the memory and delayed reciprocity terms require lagged network information from the previous period, the models incorporating temporal dependence effects (Models 6 and 7) contain fewer effective observations than other models.

4. Empirical Results and Analysis

4.1. Spatiotemporal Evolution of Environmentally Adjusted Water Use Efficiency in the Planting Industry

The Super-SBM model with undesirable outputs was used to measure EAWUE in the Yangtze River Economic Belt from 2011 to 2023, with MATLAB R2023b employed for model estimation. The results for 2011 and 2023 were spatially visualized using ArcGIS 10.8. As shown in Figure 3, compared with 2011, the number of high-efficiency cities increased in 2023, while the area covered by low-efficiency cities decreased. However, spatial imbalance within the region remained evident.

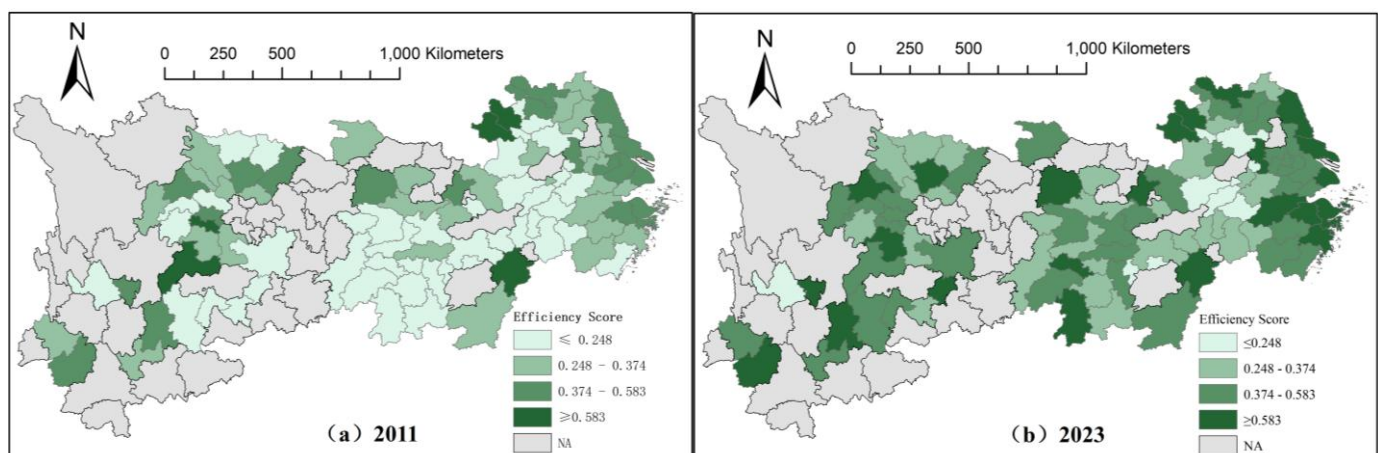


Figure 3. The spatial distribution of EAWUE of the Yangtze River Economic Belt in 2011 and 2023.

From the perspective of temporal evolution, EAWUE in the Yangtze River Economic Belt showed an overall upward trend, although inter-city differentiation persisted. Specifically, the mean efficiency value increased from 0.310 in 2011 to 0.498 in 2023. The number of cities with efficiency values above 1.000 increased from one to 13, while the number of cities with efficiency values below 0.200 decreased from 20 to two. These results indicate that high-efficiency cities increased and low-efficiency areas contracted during the study period. However, the efficiency range expanded from 0.972 in 2011 to 1.065 in 2023, suggesting that inter-city efficiency gaps did not narrow simultaneously with the overall improvement in efficiency.

From the perspective of spatial evolution, EAWUE in the Yangtze River Economic Belt shifted from a pattern dominated by a small number of high-value cities to a multi-point expansion pattern. In 2011, high-value cities were mainly distributed in a scattered pattern, with relatively high efficiency levels observed in Zhaotong, Fuzhou, Bozhou, and Zigong, whereas Liupanshui, Anshun, Pu'er, and Zhangjiajie showed relatively low efficiency levels. By 2023, the number of high-efficiency cities had increased markedly, with Yongzhou, Loudi, Bijie, and Bozhou recording efficiency values above 1.000. Nevertheless, efficiency levels in Chizhou, Huainan, Ma'anshan, and Xinyu remained relatively low, indicating that the spatially uneven pattern had not been fundamentally changed.

4.2. Sensitivity Analysis of the EAWUE Indicator Specification

The sensitivity test results show that, after fertilizer application was excluded from material input, the absolute level of EAWUE decreased to some extent (Table 3). However, the Pearson correlation coefficient and Spearman rank correlation coefficient between the efficiency values under the two indicator specifications reached 0.835 and 0.876, respectively. In addition, the annual mean efficiency series from 2011 to 2023 remained highly consistent (Pearson $r = 0.992$). These results indicate that the potential mechanical association between fertilizer application and the grey water footprint affected the absolute level of EAWUE to some extent, but did not change its overall evolutionary trend or the relative spatial pattern among cities. Therefore, the main findings regarding the spatiotemporal evolution of EAWUE were relatively robust to the alternative specification of material input.

Table 3. The sensitivity test results for the EAWUE indicator specification.

Core Indicator	Result
Number of observations	1313
Mean efficiency in the baseline model	0.384
Mean efficiency after excluding fertilizer input	0.325
Relative change in the mean	−15.50%
Pearson correlation coefficient	0.835
Spearman rank correlation coefficient	0.876
Pearson correlation coefficient of annual mean efficiency	0.992

4.3. Evolutionary Characteristics of the Spatial Association Network

ArcGIS 10.8 was used to visualize the spatial association network of EAWUE in the Yangtze River Economic Belt in 2011 and 2023. Linkage intensity was measured by the gravitational-force values derived from the modified gravity model and classified into four levels—low, medium, high, and very high—using the Natural Breaks (Jenks) classification method in ArcGIS 10.8. To facilitate temporal comparison, the same class thresholds were applied to both 2011 and 2023. As shown in Figure 4, compared with 2011, the spatial association network of EAWUE in 2023 exhibited an increase in linkages, an expansion of the association range, and stronger multi-node interactions.

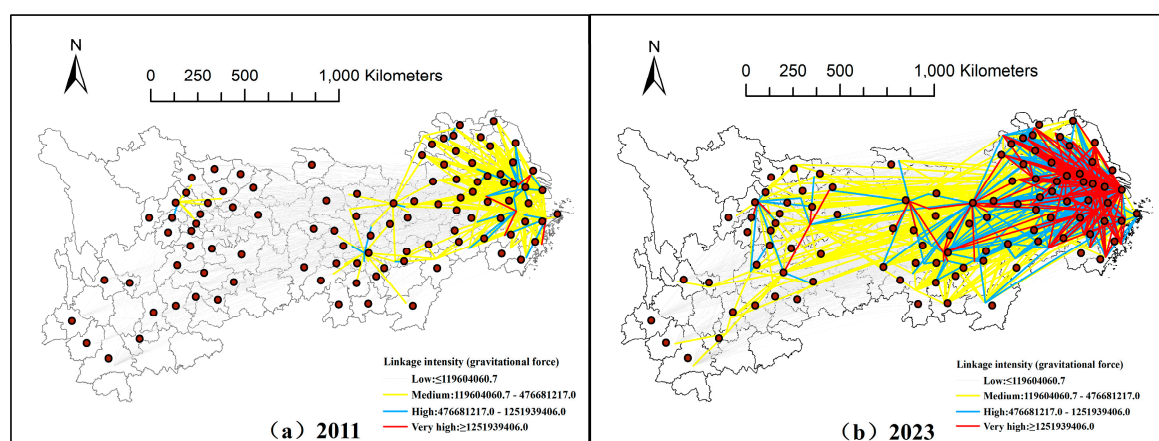


Figure 4. The evolutionary characteristics of the environmentally adjusted water use efficiency spatial association network in the planting industry of the Yangtze River Economic Belt in 2011 and 2023.

From the perspective of network evolution, the EAWUE spatial association network in the Yangtze River Economic Belt shifted from local concentration to multi-node interaction. In 2011, relatively few gravity-based linkages were observed among cities, and spatial

associations were mainly concentrated among geographically proximate cities and a limited number of economically prominent nodes. By 2023, inter-city linkages had increased markedly, and the overall connectivity of the network had improved. This indicates that the spatial association of EAWUE gradually extended beyond local areas and evolved toward broader cross-regional and multi-node interactions. It should be noted that these linkages represent potential spatial associations constructed using the modified gravity model rather than directly observed flows of technology, resources, or policy cooperation.

From the perspective of linkage intensity, as measured by gravitational force, the spatial associations of EAWUE in the Yangtze River Economic Belt showed clear gradient differentiation. Low-intensity associations remained the dominant form of network linkage, while medium-intensity associations were mainly distributed among neighbouring cities and within major urban agglomerations. High- and very-high-intensity associations were mainly concentrated in the Yangtze River Delta, the middle reaches of the Yangtze River, and some interprovincial border areas. Compared with 2011, stronger associations became more widely distributed in 2023, indicating that the spatial association network gradually extended from relatively localized linkages toward broader cross-regional interactions.

From the perspective of spatial pattern, the EAWUE spatial association network in the Yangtze River Economic Belt showed a pattern characterized by a prominent downstream core, an enhanced bridging role in the middle reaches, and increased participation in the upper reaches. Dense linkages continued to be observed around major cities in the Yangtze River Delta, including Shanghai, Hangzhou, Nanjing, and Ningbo. Meanwhile, the network participation of middle-reach cities, including Wuhan, Yichang, Nanchang, and Huanggang, became more pronounced, strengthening their intermediary position in cross-regional associations. In the upper reaches, cities such as Chengdu, Chongqing, Guiyang, and Bijie also exhibited increased network participation, indicating a gradual expansion of the spatial association network toward the upper reaches.

4.4. Overall Structural Characteristics of the Spatial Association Network

UCINET 6 was used to calculate the network density, reciprocity, average path length, network diameter, and clustering coefficient of the spatial association network of EAWUE in the Yangtze River Economic Belt from 2011 to 2023. As shown in Table 4, during the study period, the EAWUE spatial association network exhibited improved connectivity, stronger bidirectional interactions, enhanced network accessibility, and increased local clustering.

Table 4. The overall structural characteristics of the environmentally adjusted water use efficiency spatial association network in the Yangtze River Economic Belt from 2011 to 2023.

Year	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Network density	0.191	0.226	0.268	0.301	0.324	0.335	0.369	0.399	0.420	0.412	0.465	0.494	0.503
Reciprocity	0.385	0.423	0.458	0.458	0.490	0.489	0.513	0.529	0.563	0.537	0.576	0.590	0.582
Average path length	1.749	1.697	1.632	1.587	1.566	1.550	1.512	1.478	1.462	1.464	1.410	1.378	1.364
Network diameter	3.000	3.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000	2.000
Clustering coefficient	0.275	0.328	0.388	0.425	0.458	0.470	0.508	0.539	0.556	0.558	0.613	0.638	0.652

In terms of network connectivity, network density increased overall from 0.191 in 2011 to 0.503 in 2023, with an average value of 0.362, despite some year-to-year fluctuations. This indicates that the number of EAWUE associations among cities increased substantially during the study period and that the overall connectivity of the network was enhanced. In terms of relational interaction, reciprocity increased from 0.385 in 2011 to 0.582 in 2023, with an average value of 0.507. Although slight fluctuations occurred in individual years, the overall upward trend suggests that bidirectional associations among cities became increasingly pronounced. In terms of network accessibility, the average path length decreased from 1.749 in 2011 to 1.364 in 2023. The network diameter remained at 3.000 in 2011 and 2012, declined to 2.000 in 2013, and remained stable thereafter. These results indicate that fewer intermediate nodes were required to connect cities within the network, the network structure became more compact, and overall network accessibility improved. In terms of local clustering, the clustering coefficient increased from 0.275 in 2011 to 0.652 in 2023, with an average value of 0.493, indicating that local associations among cities became increasingly concentrated and that the clustering tendency of the network became more pronounced.

4.5. Individual Characteristics of the Spatial Association Network

UCINET 6 was used to calculate individual network indicators of EAWUE in the Yangtze River Economic Belt. ArcGIS 10.8 was then used to visualize the spatial distribution of node centrality in 2011 and 2023. As shown in Figure 5, compared with 2011, the node centrality of the EAWUE spatial association network in 2023 exhibited clear spatial differentiation, characterized by the prominent position of core cities in the downstream region, the continued intermediary importance of several cities in the middle reaches, and increased participation of cities in the upper reaches.

In terms of in-degree and out-degree, the mean values of both indicators increased markedly in the EAWUE spatial association network, indicating that inter-city efficiency associations became more extensive and that the participation of individual nodes in the network increased. In 2023, Wuxi, Shanghai, Suzhou, Nanjing, and Hangzhou showed relatively high in-degree values, while Zhoushan, Yichang, Shanghai, Wuhan, and Bijie exhibited relatively high out-degree values, indicating clear differences in the receiving and outward-linkage positions of cities within the network. In terms of degree centrality, central cities remained mainly concentrated in the Yangtze River Delta, with Wuxi, Shanghai, Suzhou, Nanjing, and Hangzhou maintaining relatively high positions. This indicates that the Yangtze River Delta continued to occupy a prominent structural position and maintain broad connections within the EAWUE spatial association network. In terms of betweenness centrality, both the mean and maximum values declined substantially between 2011 and 2023, suggesting that, as network connections became denser, inter-city efficiency associations became less dependent on a small number of intermediary nodes. The network structure gradually shifted from relatively strong dependence on a few key nodes toward broader multi-node interaction. Nevertheless, Yichang and Wuhan remained among the cities with relatively high betweenness centrality in 2023, while Nanchang also retained a comparatively important intermediary position, indicating that several cities in the middle reaches continued to play important bridging roles in the network. In terms of closeness centrality, the mean value increased markedly, indicating that inter-city linkage paths were shortened and overall network accessibility was enhanced. Wuxi, Shanghai, Suzhou, Hangzhou, and Ningbo maintained relatively high closeness centrality, suggesting that these cities occupied structurally accessible positions and could connect with other cities through relatively short network paths.

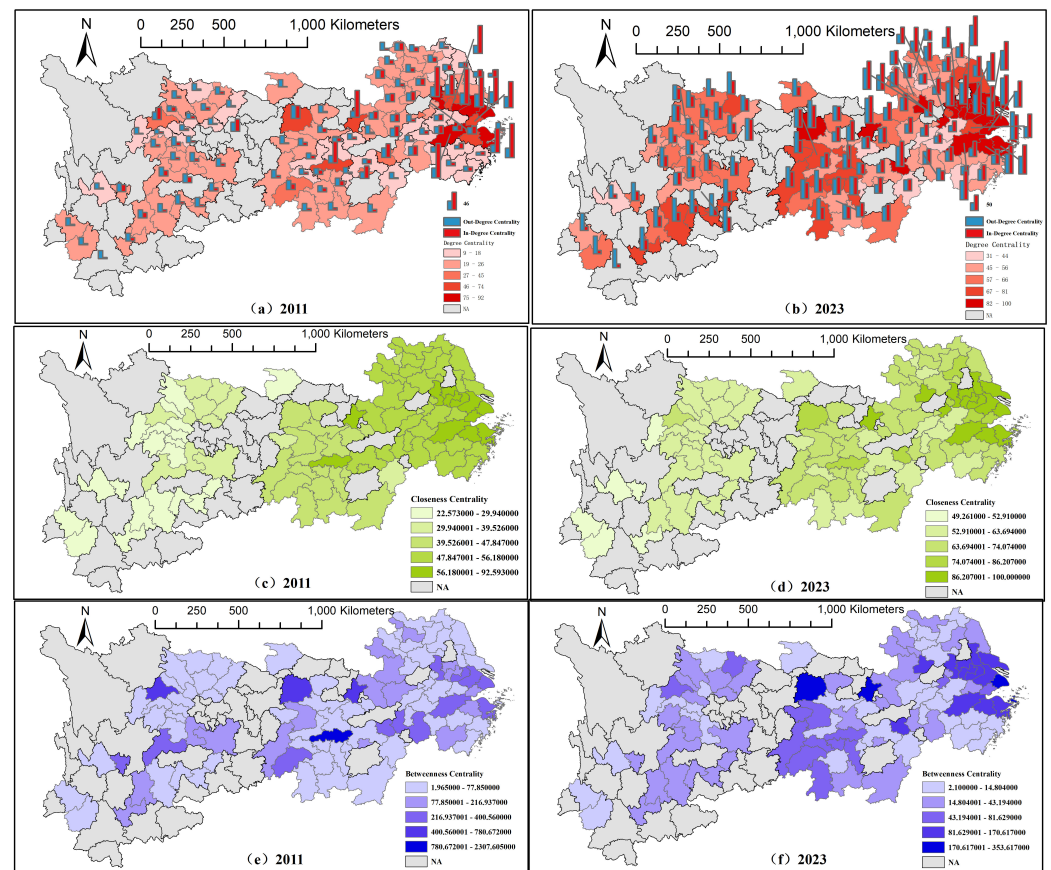


Figure 5. The spatial distribution of node centrality in the EAWUE spatial association network of the Yangtze River Economic Belt in 2011 and 2023. Note: Panels (a) and (b) show the spatial distributions of degree centrality in 2011 and 2023, respectively, with the overlaid bars representing out-degree and in-degree; panels (c) and (d) show the spatial distributions of closeness centrality in 2011 and 2023, respectively; and panels (e) and (f) show the spatial distributions of betweenness centrality in 2011 and 2023, respectively.

4.6. Block Structure Characteristics of the Spatial Association Network

UCINET 6 and the CONCOR algorithm were used to divide the 2023 spatial association network of EAWUE in the Yangtze River Economic Belt into blocks. As shown in Table 5, a clear pattern of block division was formed in the EAWUE spatial association network in 2023. Different blocks performed differentiated functions in the spillover, transmission, and reception of efficiency associations.

Table 5. The block relationship characteristics of the EAWUE spatial association network in the Yangtze River Economic Belt in 2023.

Block	Received Relationships				Number of Cities	Relationships Received from Outside the Block	Relationships Spilled over to Outside the Block	Block Type
	I	II	III	IV				
I	259	435	429	71	20	1477	935	Net beneficiary
II	479	116	328	53	27	1163	860	Broker
III	639	569	121	304	32	1160	1512	Net spillover
IV	359	159	403	339	22	428	921	Bidirectional spillover

In terms of block functions, Block I included 20 cities. The numbers of relationships received from outside the block and spilled over to other blocks were 1477 and 935, respectively. The number of externally received relationships was substantially higher than that of outward spillover relationships, indicating a stronger role in association reception;

therefore, it was identified as a net beneficiary block. Block II included 27 cities. It both received associations from other blocks and transmitted associations outward, playing a bridging and intermediary role in inter-block linkages. It was therefore identified as a broker block. Block III included 32 cities, making it the largest block. The numbers of relationships received from outside the block and spilled over to other blocks were 1160 and 1512, respectively. Its outward spillover relationships exceeded its externally received relationships, indicating a prominent role in efficiency association output; therefore, it was identified as a net spillover block. Block IV included 22 cities. It maintained relatively strong internal associations while also forming substantial linkages with other blocks and was therefore identified as a bidirectional spillover block.

On this basis, cohesive subgroup analysis was further applied to calculate the block density matrix and image matrix of the 2023 EAWUE spatial association network in the Yangtze River Economic Belt. As shown in Table 6, Block I had relatively high association densities with Blocks II and III and played an important role in inter-block linkages. Block II was mainly connected with Block I, indicating a high degree of directional concentration. Block III maintained close connections with external blocks and showed clear outward interaction characteristics. Block IV maintained strong internal associations and also formed stable linkages with external blocks. Overall, the 2023 EAWUE spatial association network in the Yangtze River Economic Belt was characterized by Block I as an important association-receiving block, Block II as an intermediary block, Block III as a block with prominent outward interactions, and Block IV as a block with both internal and external connections.

Table 6. The block density matrix and image matrix of the EAWUE spatial association network in the Yangtze River Economic Belt in 2023.

Block	Density Matrix				Image Matrix			
	I	II	III	IV	I	II	III	IV
I	0.695	0.826	0.689	0.175	1	1	1	1
II	0.894	0.168	0.392	0.093	2	1	0	1
III	0.998	0.669	0.125	0.435	3	1	1	0
IV	0.857	0.274	0.58	0.745	4	1	1	1

4.7. Formation Mechanism of the Spatial Association Network

The TERGM was used to examine the statistical factors associated with the formation of the spatial association network from four dimensions: endogenous network structures, node attributes, spatial constraints, and temporal dependence. The TERGM was estimated using R version 4.6.1, and goodness-of-fit (GOF) diagnostics were further applied to evaluate the capability of the final model to reproduce the observed network characteristics. As shown in Table 7, the formation of the EAWUE spatial association network in the Yangtze River Economic Belt was statistically associated with endogenous network structures, city-level attributes, spatial conditions, and temporal dependence during the study period. Among these factors, reciprocity, transitive structures, and network persistence exhibited significant associations with network tie formation.

In terms of model specification and performance, the statistical performance of the TERGM improved as endogenous network effects, node attribute effects, spatial constraint effects, and temporal dependence effects were gradually introduced. Because Models 6 and 7 incorporate lagged temporal dependence terms, their effective observation counts differ from those of Models 1–5. Therefore, AIC and BIC were used primarily for comparisons among models estimated on the same effective sample rather than as the sole criterion for selecting the final specification. Model 7 was preferred because it incorporates endogenous network structures, node attributes, spatial constraints, and temporal dependence simultaneously, providing a more comprehensive representation of the EAWUE spatial as-

sociation network. Furthermore, as shown in Figure 6, the GOF diagnostics based on Model 7 showed that the simulated networks could adequately reproduce the major structural characteristics of the observed network, supporting the adequacy of the final specification.

Table 7. The TERGM estimation results for the formation mechanism of the EAWUE spatial association network in the Yangtze River Economic Belt from 2011 to 2023.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
edges	−0.57 *** (0.01)	−1.52 *** (0.01)	−0.55 *** (0.02)	−2.75 *** (0.04)	−2.93 *** (0.11)	−2.74 *** (0.21)	−2.77 *** (0.21)
mutual		2.30 *** (0.02)	2.14 *** (0.02)	2.93 *** (0.03)	3.28 *** (0.03)	2.52 *** (0.04)	2.98 *** (0.06)
distance			−1.08 *** (0.01)	−1.16 *** (0.02)	−1.20 *** (0.02)	−0.60 *** (0.04)	−0.57 *** (0.04)
ttriple					0.02 *** (0.003)	0.02 *** (0.003)	0.02 *** (0.003)
transitivities					−0.17 * (0.10)	1.31 *** (0.18)	1.32 *** (0.18)
ctriple					−0.11 *** (0.004)	−0.09 *** (0.004)	−0.09 *** (0.004)
nodecov(X1)				−0.18 *** (0.01)	−0.05 *** (0.01)	0.09 *** (0.02)	0.08 *** (0.02)
nodecov(X2)				0.83 *** (0.10)	0.05 (0.10)	1.22 *** (0.21)	1.16 *** (0.21)
nodecov(X3)				−0.04 *** (0.004)	0.01 *** (0.003)	0.004 * (0.003)	0.004 ** (0.002)
nodecov(X4)				0.13 *** (0.03)	0.01 (0.02)	0.12 ** (0.05)	0.12 ** (0.05)
nodecov(X5)				1.25 *** (0.11)	1.23 *** (0.10)	0.40 ** (0.19)	0.50 *** (0.19)
nodeicov(X1)				0.33 *** (0.01)	0.28 *** (0.01)	0.23 *** (0.02)	0.23 *** (0.02)
nodeicov(X2)				−2.23 *** (0.10)	−2.09 *** (0.10)	−1.08 *** (0.19)	−1.09 *** (0.19)
nodeicov(X3)				0.10 *** (0.004)	0.07 *** (0.003)	0.03 *** (0.003)	0.03 *** (0.003)
nodeicov(X4)				−0.33 *** (0.03)	−0.33 *** (0.03)	−0.38 *** (0.05)	−0.38 *** (0.05)
nodeicov(X5)				1.61 *** (0.11)	2.72 *** (0.11)	0.47 ** (0.20)	0.47 ** (0.20)
memory						2.58 *** (0.02)	2.64 *** (0.02)
delrecip							−0.51 *** (0.06)
Num.obs.	131,300	131,300	131,300	131,300	131,300	121,200	121,200
AIC	171,912.63	154,895.37	147,967.17	118,965.84	112,359.30	40,100.87	40,010.93
BIC	171,922.41	154,914.95	147,996.54	119,093.05	112,515.86	40,265.87	40,185.63
Log Likelihood	−85,955.31	−77,445.69	−73,980.59	−59,469.92	−56,163.65	−20,033.44	−19,987.47

Note: Standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; the same applies below.

The sequential specifications further indicate that the main conclusions remained generally consistent when additional network effects were introduced. For example, the mutual coefficient remained positive and statistically significant across models after the introduction of endogenous network terms, while the distance coefficient consistently maintained a negative association after controlling for additional structural effects. Similarly, the major node attribute effects, such as rural human capital and industrial structure upgrading, generally maintained their primary directions across alternative specifications. Although some coefficients changed in magnitude after additional network structures were incorporated, these changes mainly reflected the interdependence among different network processes rather than substantial changes in the underlying relationships.

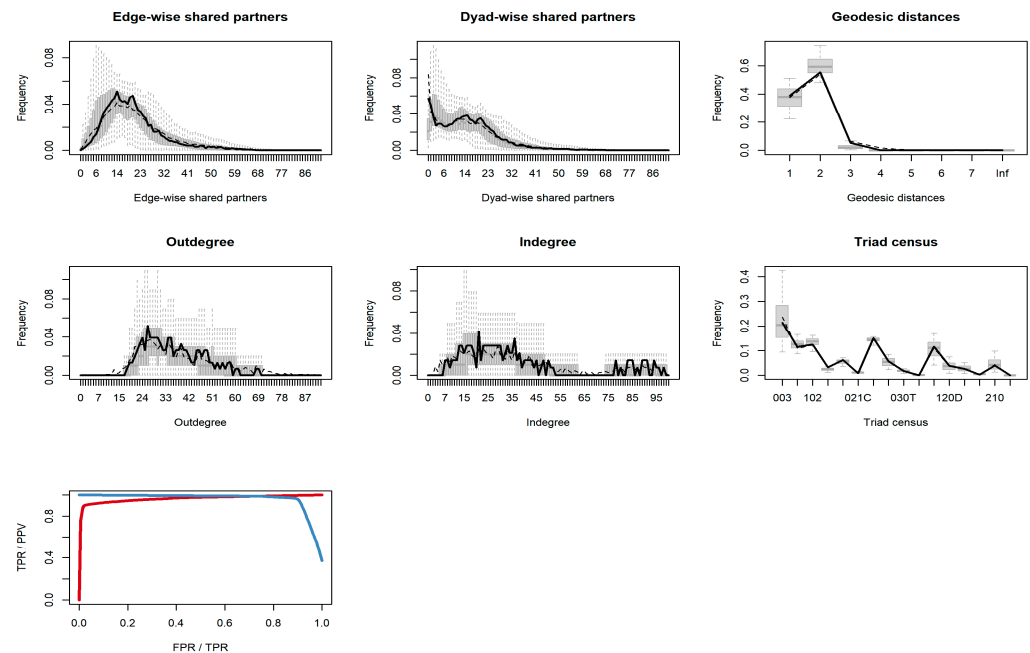


Figure 6. Goodness-of-fit diagnostics for Model 7. Note: In the first six panels (edge-wise shared partners, dyad-wise shared partners, geodesic distances, outdegree, indegree, and triad census), the black solid line represents the statistic of the observed network, and the gray shaded area (dashed lines) indicates the distribution of the corresponding statistics generated from networks simulated based on Model 7. In the bottom-left panel, the red and blue lines represent the true positive rate (TPR) and false positive rate (FPR), respectively.

Regarding endogenous network effects, the edges coefficient was significantly negative, indicating that the EAWUE spatial association network remained relatively sparse after controlling for other factors. This suggests that the probability of tie formation among cities was relatively limited. The mutual coefficient was significantly positive, indicating the existence of reciprocal structures within the network. Specifically, cities with existing unilateral associations were more likely to establish bidirectional associations.

The coefficients of *ttiple* and *transitivities* were both significantly positive in the final model, suggesting the existence of triadic closure and transitive structures in the EAWUE spatial association network. It should be noted that the coefficient of *transitivities* changed from negative in Model 5 to positive in Models 6 and 7. This variation may be related to the interdependence among endogenous network terms in TERGM estimation. When fewer structural effects are included, the *transitivities* term may partially capture other unobserved network dependencies. After reciprocity, triadic closure, cyclic structures, and other network effects were simultaneously controlled for, the coefficient in Model 7 reflects the independent association between transitive structures and tie formation probability. Therefore, the positive coefficient of *transitivities* in the final model indicates that, after controlling for other endogenous network effects, transitive structures were positively associated with the probability of establishing network ties.

The *ctriple* coefficient was significantly negative, indicating that cyclic network structures were less likely to emerge and that certain structural constraints existed during network evolution. This suggests that different endogenous structures may play distinct roles in shaping the evolution of the EAWUE spatial association network.

Regarding node attribute effects, rural human capital, regional economic development, and industrial structure upgrading generally showed positive statistical associations with the formation of the EAWUE spatial association network. The coefficients of *nodecov(X1)* and *nodecov(X1)* were both significantly positive, indicating that cities with higher levels

of rural education were more likely to establish outward associations and receive associations from other cities. The coefficients of $\text{nodecov}(X3)$ and $\text{nodecov}(X3)$ were also positive, suggesting that higher nighttime light intensity, as a proxy for regional economic development, was positively associated with cities' participation in the network, although the outward effect was relatively small in magnitude. The coefficients of $\text{nodecov}(X5)$ and $\text{nodecov}(X5)$ were positive, indicating that a higher share of the tertiary industry was positively associated with both outward and inward EAWUE associations.

It should be noted that economic indicators incorporated in the gravity model and nighttime light intensity included in the TERGM may contain partially overlapping information. However, they serve different analytical purposes in this study. Economic scale indicators in the gravity model are used to estimate potential association intensity among cities, whereas nighttime light intensity is introduced as a city-level attribute to examine whether regional economic characteristics are statistically associated with network participation after the network has been constructed. Moreover, the robustness test excluding nighttime light intensity confirms that the main network formation conclusions remain generally consistent.

In contrast, fiscal support for agriculture ($X2$) and per capita water resources ($X4$) exhibited heterogeneous outward and inward effects. Their outward coefficients were positive, whereas their inward coefficients were negative. These results suggest that government support and resource endowment may be associated with different network roles. For example, cities with stronger fiscal support or resource advantages may have greater capacity to generate outward associations, while their roles as receivers may depend on existing network structures and regional interactions. These interpretations represent possible explanations of the observed statistical associations rather than directly verified causal mechanisms.

Regarding spatial constraint effects, the distance coefficient was significantly negative, indicating a negative association between geographic distance and the probability of EAWUE spatial association formation. Holding other conditions constant, cities with greater spatial separation were less likely to establish network ties. This result suggests that spatial proximity remained an important constraint affecting the formation of the regional EAWUE spatial association network.

Regarding temporal dependence effects, the memory coefficient was significantly positive, indicating that the EAWUE spatial association network exhibited clear temporal persistence. Existing network ties showed continuity in subsequent network evolution, reflecting the cumulative characteristics of network development. In contrast, the delrecip coefficient was significantly negative, indicating that previous reciprocal ties did not necessarily continue to strengthen over time. Instead, reciprocal relationships may experience adjustment and restructuring during the dynamic evolution of the network.

4.8. Robustness Tests

To further examine the reliability of the TERGM estimation results, robustness tests were conducted using Bootstrap TERGM, a static ERGM based on the 2023 network, TERGMs with two-year and three-year intervals, an alternative model excluding nighttime light intensity, and alternative network threshold specifications. The corresponding results are presented in Table 8.

Overall, the robustness tests showed that the core network structural effects and temporal persistence remained relatively stable across different model specifications, whereas several node attribute effects and delayed reciprocity were sensitive to alternative specifications. Therefore, the robustness evidence supports the relative stability of the principal

structural and temporal persistence findings, while indicating that some city-level attribute effects and delayed reciprocity depend on model specification.

Table 8. The robustness test results for the formation mechanism of the EAWUE spatial association network in the Yangtze River Economic Belt from 2011 to 2023.

	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
edges	−2.53 *	−17.13 ***	−2.57 ***	−2.89 ***	−2.84 ***	−2.50 ***	−1.15 ***
	[−4.50; −1.42]	(0.34)	(0.25)	(0.37)	(0.21)	(0.40)	(0.16)
mutual	3.17 *	3.90 ***	2.93 ***	2.94 ***	2.99 ***	3.61 ***	3.56 ***
	[2.59; 3.52]	(0.24)	(0.05)	(0.05)	(0.06)	(0.07)	(0.09)
distance	−0.47 *	−0.07	−0.57 ***	−0.56 ***	−0.57 ***	−0.58 ***	−0.87 ***
	[−0.69; −0.26]	(0.13)	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)
ttriple	0.02 *	0.02 ***	0.02 ***	0.02 ***	0.02 ***	0.02 ***	0.01 ***
	[0.01; 0.02]	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
transitivities	1.00 *	14.11 ***	1.07 ***	1.18 ***	1.33 ***	1.52 ***	0.32 ***
	[0.79; 1.86]	(0.34)	(0.23)	(0.35)	(0.18)	(0.38)	(0.06)
ctriple	−0.08 *	−0.08 ***	−0.10 ***	−0.11 ***	−0.09 ***	−0.06 ***	−0.10 ***
	[−0.10; −0.08]	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
nodecov(X1)	0.09	0.26 **	0.10 ***	0.11 **	0.10 **	0.003	0.01
	[−0.02; 0.19]	(0.07)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
nodecov(X2)	1.36 *	−0.91	1.67 ***	2.13 ***	0.93 **	0.51 **	0.93 ***
	[0.71; 2.92]	(1.63)	(0.22)	(0.24)	(0.21)	(0.22)	(0.29)
nodecov(X3)	0.001	0.003	0.01 ***	0.01 ***		0.01 ***	0.01 ***
	[−0.01; 0.01]	(0.01)	(0.002)	(0.002)		(0.002)	(0.002)
nodecov(X4)	0.20 *	−0.02	0.07 *	0.03	0.03	0.21 ***	0.14 **
	[0.00; 0.35]	(0.34)	(0.04)	(0.03)	(0.05)	(0.06)	(0.07)
nodecov(X5)	0.73	0.99	0.46 ***	0.72 ***	0.36 **	0.93 ***	1.65 ***
	[−0.42; 2.11]	(0.75)	(0.16)	(0.15)	(0.18)	(0.20)	(0.26)
nodecov(X1)	0.20 *	0.06	0.26 ***	0.27 ***	0.31 ***	0.25 ***	0.02
	[0.09; 0.29]	(0.08)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
nodecov(X2)	−1.05 *	1.70	−1.30 ***	−1.80 ***	−1.50 ***	−0.78 ***	−0.98 ***
	[−2.13; −0.65]	(1.58)	(0.19)	(0.23)	(0.17)	(0.21)	(0.29)
nodecov(X3)	0.04 *	0.03 ***	0.03 ***	0.03 ***		0.03 ***	0.05 ***
	[0.03; 0.05]	(0.01)	(0.003)	(0.003)		(0.003)	(0.004)
nodecov(X4)	−0.36 *	0.30	−0.46 ***	−0.46 ***	−0.65 ***	−0.18 ***	−0.52 ***
	[−0.79; −0.10]	(0.37)	(0.05)	(0.04)	(0.05)	(0.05)	(0.09)
nodecov(X5)	0.13	0.66	0.36 **	0.45 ***	1.03 ***	0.54 **	1.64 ***
	[−0.54; 0.88]	(0.84)	(0.17)	(0.16)	(0.19)	(0.21)	(0.27)
memory	2.64 *	2.88 ***	2.12 ***	1.80 **	2.66 **	2.89 ***	3.20 ***
	[2.43; 3.02]	(0.06)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
delrecip	−0.58	−1.73 ***	−0.19 ***	0.03	−0.52 ***	−1.44 ***	−1.49 ***
	[−0.97; 0.12]	(0.18)	(0.04)	(0.04)	(0.06)	(0.06)	(0.08)
Num.obs.	121,200	10,100	111,100	101,000	121,200	121,200	121,200
AIC	—	3091.59	51,409.11	55,856.35	40,303.62	35,907.22	23,605.76
BIC	—	3221.57	51,582.23	56,027.75	40,458.90	36,081.91	23,780.45
Log Likelihood	—	−1527.80	−25,686.55	−27,910.17	−20,135.81	−17,935.61	−11,784.88

Note: Model 8 is the Bootstrap TERGM estimation based on 1000 bootstrap replications; Model 9 is the static ERGM estimation using 2023 data; Models 10 and 11 are TERGM estimations using two-year and three-year intervals, respectively; Model 12 excludes nighttime light intensity from the node attributes; Model 13 reconstructs the spatial association network using the row-median threshold; Model 14 reconstructs the spatial association network using the 75th percentile threshold. For Model 8, confidence intervals were obtained from the bootstrap distribution. Standard errors are reported in parentheses for Models 9–14. In Model 8, the values in square brackets are 95% bootstrap confidence intervals, and significance is assessed based on whether these intervals contain zero; * indicates that the corresponding bootstrap confidence interval does not contain zero. In Models 9–14, the values in parentheses are standard errors, and *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

In terms of endogenous network effects, the variables of mutual, ttriple, transitivities, and ctriiple generally maintained consistent directions across different robustness tests. Specifically, the mutual coefficient remained positive and statistically significant in all specifications, indicating that reciprocal relationships among cities showed a stable posi-

tive association with the formation of EAWUE spatial associations. The triple coefficient consistently remained positive and significant, suggesting that triadic closure structures remained positively associated with network tie formation. The cyclic coefficient remained negative across all models, indicating that cyclic network structures were negatively associated with the formation of spatial associations. Although the coefficient of transitivity varied in magnitude across different models, it generally remained positive and significant, suggesting that transitive structures showed a relatively stable positive association with network connectivity.

In terms of node attribute effects, variables related to rural education level, per capita water resources, and the share of the tertiary industry generally maintained relatively stable directions, whereas fiscal support and nighttime light intensity exhibited greater sensitivity across alternative specifications. Specifically, rural education level generally showed positive outward and inward effects, indicating that higher levels of rural human capital were generally positively associated with both the generation and reception of EAWUE spatial associations, although its significance varied under some alternative model settings. The effects of per capita water resources remained generally positive in outward link formation but showed some differences in inward effects, suggesting that resource endowment was heterogeneously associated with different network roles. The share of the tertiary industry generally maintained positive effects, indicating that industrial structure upgrading was positively associated with the formation of spatial associations. In contrast, the effects of nighttime light intensity varied across some specifications, implying that the relationship between economic development and city roles within the network may depend on model settings. Similarly, the coefficients of fiscal support variables showed differences in significance and direction, suggesting that the statistical association between government support and network tie formation may vary across model specifications.

In terms of spatial constraint and temporal dependence effects, the distance variable generally remained negative across different robustness tests, indicating that geographic distance remained negatively associated with the probability of EAWUE network tie formation, although its statistical significance weakened in some alternative specifications. The memory coefficient remained positive and statistically significant across all robustness models, providing further evidence of the temporal persistence of the EAWUE spatial association network. In contrast, the significance and coefficient direction of the delrecip coefficient varied across some models, suggesting that the association between historical reciprocal relationships and current network formation may depend on temporal structures and alternative model specifications.

Furthermore, alternative spatial association networks were reconstructed using the row-median threshold and the 75th percentile threshold. The corresponding overall network characteristics and individual node-level indicators are reported in Tables S1–S4 of the Supplementary Materials, while the TERGM results under alternative threshold specifications are presented in Table 8 (Models 13 and 14). Although different threshold criteria resulted in variations in network density and some structural indicators, the overall evolutionary patterns, node differentiation characteristics, and the main endogenous network effects, spatial constraint effect, and temporal persistence effect remained generally consistent. These findings suggest that the identified formation characteristics of the EAWUE spatial association network are not driven by a specific threshold selection strategy and remain robust under alternative network construction approaches.

5. Conclusions and Discussion

5.1. Main Conclusions

Based on panel data for 101 prefecture-level cities in the Yangtze River Economic Belt from 2011 to 2023, this study examined the spatiotemporal evolution, spatial association network structure, and statistical mechanisms underlying the formation of EAWUE by integrating a Super-SBM model with undesirable outputs, a modified gravity model, social network analysis, and a TERGM. The main conclusions are as follows.

First, EAWUE in the Yangtze River Economic Belt exhibited an overall upward trend, although spatial imbalance within the region remained evident. During the study period, the number of high-efficiency cities increased, while low-efficiency areas gradually declined. The spatial pattern evolved from one dominated by a limited number of high-efficiency cities toward a multi-point expansion pattern. However, improvements in overall efficiency were not accompanied by a simultaneous reduction in inter-city efficiency disparities.

Second, the potential spatial association network of EAWUE became increasingly connected during the study period. Inter-city associations increased continuously, and network connectivity, reciprocal interactions, accessibility, and local clustering were enhanced. The spatial association pattern gradually evolved from relatively localized linkages toward broader cross-regional and multi-node interactions.

Third, the EAWUE spatial association network exhibited clear node differentiation and functional block characteristics. The Yangtze River Delta maintained a prominent core position, cities in the middle reaches strengthened their intermediary roles, and cities in the upper reaches increased their participation in the network. Four functional block types were identified, including bidirectional spillover blocks, net spillover blocks, broker blocks, and net beneficiary blocks, reflecting differentiated positions in association output, reception, and intermediary functions.

Fourth, the formation of the EAWUE spatial association network was statistically associated with endogenous network structures, node attributes, spatial constraints, and temporal dependence. Reciprocity, transitive structures, and network persistence showed positive associations with network tie formation, whereas geographic distance was negatively associated with the probability of establishing network ties. Resource endowment, rural human capital, and industrial structure upgrading generally showed positive statistical associations with network participation, while economic development and government support exhibited heterogeneous effects on cities' outward and inward network roles. These findings should be interpreted as statistical associations within the constructed spatial association network rather than direct evidence of technology transfer, resource flows, or policy coordination.

5.2. Discussion

During the study period, EAWUE in the Yangtze River Economic Belt showed an overall upward trend, with the mean efficiency value increasing from 0.310 in 2011 to 0.498 in 2023. This indicates an improvement in the coordination between water resource inputs, economic output, and environmental pressure in the regional planting industry. The finding is generally consistent with previous studies on agricultural water use efficiency, water footprint assessment, and efficiency-related driving mechanisms [4,5,9,12,17,41]. However, the efficiency range expanded from 0.972 in 2011 to 1.065 in 2023, indicating that the overall improvement in efficiency was not accompanied by a simultaneous reduction in inter-city disparities. Previous studies have shown that agricultural infrastructure affects crop water footprints and virtual water flows [42], planting management practices can improve crop water use and related environmental effects [43], and watershed-scale agricultural water use efficiency exhibits clear spatiotemporal differences and multiple

driving factors [44]. Therefore, inter-city differences in EAWUE were not determined solely by water resource inputs but were likely associated with resource endowment, irrigation conditions, production management, and non-point source pollution control capacity.

The EAWUE spatial association network gradually expanded from local city linkages to cross-regional and multi-node interactions. The increases in network density, reciprocity, and clustering coefficient, together with the decline in average path length, indicate that inter-city associations became closer and that network connectivity and bidirectional interactions were enhanced. These findings suggest that EAWUE is not only an efficiency attribute of individual cities but also exhibits spatial association characteristics among cities. Previous studies have mainly used spatial autocorrelation and spatial econometric approaches to analyze the spatial dependence and spatial spillover effects of agricultural water use efficiency [9,12,17]. In contrast, this study further identifies potential spatial associations among cities from a network perspective, extending the understanding of how EAWUE is organized across space. Related studies have also shown that water resource utilization efficiency can exhibit spatial association characteristics [36]. Research on agricultural water footprints and virtual water flows further indicates that agricultural production conditions, trade linkages, and consumption demand may generate cross-regional water resource associations [45,46]. In addition, the spatial heterogeneity and hotspot clustering characteristics of agricultural water use at the prefecture-level city scale [47] provide further support for examining EAWUE from a spatial relational perspective. It should be noted that the spatial association network constructed in this study is based on the modified gravity model and reflects potential spatial associations among cities rather than directly observed flows of resources, technology, or policy cooperation. Therefore, changes in network structures mainly represent the evolution of EAWUE-related spatial associations rather than specific transmission channels.

The node and block analyses indicate that different regions performed differentiated functions within the EAWUE spatial association network. The persistent core position of the Yangtze River Delta may be associated with its stronger economic foundation, resource agglomeration capacity, and network connectivity. The enhanced bridging role of the middle reaches reflects their intermediary function in connecting cities across different regions. Increased participation of the upper reaches suggests that the network structure gradually shifted from dependence on a limited number of core nodes toward broader multi-node interaction. The CONCOR analysis further identified four types of functional blocks: bidirectional spillover blocks, net spillover blocks, broker blocks, and net beneficiary blocks. This result indicates that city efficiency levels do not necessarily correspond directly to their network positions. Different blocks exhibited differentiated roles in network tie formation, relational connection, and association reception. This finding extends existing analytical perspectives that have primarily focused on the direction and intensity of spatial spillover effects by emphasizing the importance of network positions and structural roles in understanding EAWUE spatial associations.

The TERGM results further reveal the structural characteristics associated with the formation of the EAWUE spatial association network. Reciprocity, transitive structures, and network persistence showed significant positive associations with network tie formation, indicating that inter-city associations exhibited characteristics of bidirectional interaction, structural continuity, and temporal persistence. The significantly negative coefficient of geographic distance indicates that spatial separation was negatively associated with the probability of EAWUE network tie formation, suggesting that spatial constraints remained important in network evolution. It should be noted that this result reflects a statistical association between geographic distance and network tie formation rather than directly demonstrating that distance increases the costs of technology diffusion, factor mobility, or

information exchange. The node attribute results show that per capita water resources, rural human capital, and the share of the tertiary industry generally exhibited positive statistical associations with network formation. This finding is consistent with previous studies showing that agricultural water use efficiency is jointly associated with resource conditions, production management, and spatial allocation [41,43]. Research on agricultural water footprints and virtual water flows also indicates that regional production conditions, consumption demand, and water resource constraints are closely related to water resource associations [46,48], suggesting that city-level characteristics are associated with network embeddedness. Moreover, the outward and inward effects of mean nighttime light intensity and fiscal support for agriculture differed, indicating that economic development and government support exhibited heterogeneous associations with cities' roles as senders and receivers within the network.

5.3. Research Limitations and Future Directions

Several issues remain to be addressed in future research. First, at the research-scale level, finer-scale data, including county-level, irrigation district, crop-specific, and remote sensing grid data, could be incorporated to further identify local differences and spatial heterogeneity in EAWUE and improve the explanatory power of the findings for micro-level governance units. Second, in terms of network construction, inter-city spatial associations were identified primarily using a modified gravity model. Future studies could combine spatial econometric models, causal identification methods, multilayer networks, and weighted networks to cross-validate the identified spatial associations and further improve the robustness of the results. Third, in terms of mechanism identification, future research could incorporate directly observed data on water-saving policy implementation, agricultural green technology exchange, cross-regional ecological compensation, and coordinated watershed governance to further examine the evolutionary processes and governance implications of the EAWUE spatial association network.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/su18199881/s1>, Table S1. Overall structural characteristics of the EAWUE spatial association network under the row-median threshold from 2011 to 2023. Table S2. Individual network characteristics of the EAWUE spatial association network under the row-median threshold in 2011 and 2023. Table S3. Overall structural characteristics of the EAWUE spatial association network under the row-75th-percentile threshold from 2011 to 2023. Table S4. Individual network characteristics of the EAWUE spatial association network under the row-75th-percentile threshold in 2011 and 2023.

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