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Agricultural Water Use Efficiency: Is There Any Spatial Correlation between Different Regions?

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Abstract: Affected by global climate change and water shortages, food security continues to be challenged. Improving agricultural water use efficiency is essential to guarantee food security. China has been suffering from water scarcity for a long time, and insufficient water supply in the agricultural sector has seriously threatened regional food security and sustainable development. This study adopted the super-efficiency slack-based model (SBM) to measure the provincial agricultural water use efficiency (AWUE). Then, we applied the vector autoregression (VAR) Granger causality test and social network analysis (SNA) method to explore the spatial correlation of AWUE between different provinces and reveal the interprovincial transmission mechanism of spillover effects in AWUE. The results show the following: (1) In China, the provincial AWUE was significantly enhanced, and the gaps in provincial AWUE have widened in the past 20 years. (2) There were apparent spatial heterogeneity and correlations of provincial AWUE. The provinces with higher AWUE were mainly located in economically developed and coastal areas. (3) The correlation of AWUE between provinces showed significant network structure characteristics. Fujian, Hebei, Jiangsu, Shandong, and Hubei Qinghai were central to the network, with high centrality. (4) The AWUE spatial correlation network could be divided into four blocks. Each block played a different role in the cross-provincial transmission of spillover effects. Therefore, it is necessary to manage the agricultural water resources and improve water use efficiency from the perspective of the network.

Keywords: agricultural water use efficiency; undesirable super-efficiency SBM model; vector autoregression (VAR) Granger causality test; social network analysis (SNA); spatial correlation network

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1. Introduction

Water is indispensable and irreplaceable for human well-being and socio-economic sustainability. Among the 17 Sustainable Development Goals (SDGs) published by the United Nations General Assembly in 2015, at least 4 goals are related to the sustainable utilization and management of water resources, namely, SDG-6, SDG-7, SGD-12, and SDG-13 [1]. However, due to the rising water demands associated with population growth and economic development, coupled with diminishing water supplies caused by climate change and contamination, water is becoming scarce in most regions of the world [2,3]. The recent literature demonstrates that nearly half of the global population faces severe water scarcity, which directly conflicts with the above SDGs [4]. The agriculture sector is the largest water user globally, accounting for approximately 70% of global water withdrawal due to irrigation [5]. Insufficient water resources have posed a substantial threat to agricultural production and food security [6]. In addition, backward agricultural irrigation technology, extensive water use patterns, and low water use efficiency have further intensified water scarcity [7]. Thus, sustainable agricultural water resource management is related to regional food security and closely linked to economic development, ecological security, and quality of life [8,9]. When water supplies are limited, agricultural production should maximize net income per unit of water used rather than per land unit [10]. Evaluating and improving agricultural water use efficiency (AWUE) are also the basis for promoting regional water resource management [11,12].

Widening water demand and supply gaps have been a significant challenge for China. China has been suffering from water scarcity for a long time [13], whose per capita water supply is less than 2200 m^3, only one quarter of the world average [14]. Since 1998, agricultural water use in China has consumed over 60% of the total national water consumption [15], and this figure is as high as 80–90% in some arid regions, such as Ningxia and Xinjiang. Meanwhile, there has been severe conflict between water availability and food production in China, feeding 21% of the world's population needs with only 6% of the global freshwater resources [16]. As one of the largest agricultural countries, the improvement in AWUE in China could contribute to global sustainable water utilization and food security [17].

Generally, AWUE refers to the ratio of physical and economic output to water resource input during agricultural production, a broad concept of physiological, agronomic, and engineering processes, and management practice [18]. Many studies evaluated AWUE with a single-factor index. They focused on the ratio between crop biomass or grain production and the amount of water consumed by crops, including rainfall, the irrigation water applied, and crop transpiration [19–21]. Thus, AWUE also reflects the production ability of water resources, such as crop water productivity, irrigation water productivity, and generalized water productivity [22]. It was later recognized that water alone as the only input could not produce the necessary outputs in the production process. Other inputs are also essential in AWUE assessment [23]. Therefore, the total factor water use efficiency measured by multiple input models has entered the mainstream. The frequently used assessment methods are stochastic frontier analysis (SFA) and data envelopment analysis (DEA) [24,25]. Compared with SFA, DEA is a non-parametric evaluation model and does not require any distributional assumptions about efficiency [26], avoiding the influences of subjective factors on water resource efficiency assessment. In addition, improved DEA models can even deal with both desirable and undesirable outputs simultaneously, significantly improving the accuracy of resource use efficiency evaluation [27]. At present, DEA models have been widely used globally to assess the water use efficiency of a decision-making unit (e.g., farm, enterprise/company, irrigation district, industrial/agricultural sector) [25,28,29].

The spatial difference and correlation of water use efficiency have attracted significant attention in recent years. On the one hand, water use efficiency exhibits noticeable regional variation. The literature has shown that water use efficiency is sensitive to meteorological factors, such as temperature, precipitation, and moisture [30]. Water use efficiency increases with atmospheric CO_2 but declines with increasing atmospheric evaporative demand [31]. Water use efficiency is also influenced by socio-economic factors. The value of AWUE is higher in developed areas than in undeveloped areas in China [13]. On the other hand, water use efficiency has demonstrated a significant spatial correlation. The AWUE of one region is related to the geographical conditions and the economic development level, which is likely to be influenced by the neighboring regions [32]. The adjacent regions' agricultural production behaviors also affect the local region's AWUE, resulting in spatial spillover effects on the local region [13]. Awareness of spatial correlation among regional AWUE is essential for improving water utilization efficiency.

The temporal and spatial patterns of AWUE are related to various natural and socio-economic elements, which are types of agricultural ecosystems, agricultural production factors, and agricultural water resource management measures [3,25]. Agricultural production factors will flow spontaneously from the area with a low factor return rate to a high factor return rate [33]. In contrast, the management departments will actively guide the cross-region transfer of technology, information, talents, and goods to promote sustainable water use and regional synergy development [34,35]. Due to the cross-regional mobility of the agricultural production factors, various regions' agricultural water resource utilization may present close connections. As the scope of factors' mobility continues to expand, an increasing number of regions have shown relevance in AWUE, and the spatial correlation of AWUE shows a network characteristic [36,37]. Meanwhile, the spatial correlation network of AWUE could reflect the distribution pattern of spillover effects related to certain factors [38], which could guide the improvement in AWUE. However, this important feature is often ignored in AWUE studies. Utilizing this information on the spatial correlation of AWUE may help implement effective measures to improve AWUE.

In the spatial correlation of AWUE, different nodes (regions) have various resource (such as information, technology, knowledge, and talents related to water saving) control capabilities, resulting in diverse network structures [39]. Due to the spillover effects, the nodes with strong power may influence various other nodes and be in the central position of the network. Creating solid links among regions can enhance mutual learning and sharing of resources and advice [40]. Moreover, nodes similar to one another are better able to communicate information and apply the same governance [41]. For the whole network, centralization helps form groups and build support for collective action, such as the fast spread of particular water-saving technologies [42]. In contrast, over-centralization may not be conducive to long-term planning and problem solutions [43]. Thus, it is necessary to investigate the spatial network structure related to AWUE and propose appropriate strategies to improve AWUE.

This study aimed to explore the spatial correlation of AWUE between different provinces in China and provide support for the designation of agricultural water resource management strategies. In this study, AWUE is defined as a total factor water efficiency index. The super-efficiency slack-based model (SBM) with undesirable outputs and the social network analysis (SNA) method were used to: (1) evaluate AWUE at the province level within and beyond China, and (2) investigate the characteristics of the spatial correlation network of AWUE.

2. Materials and Methods

The analysis process for the spatial correlation of AWUE is illustrated in Figure 1.

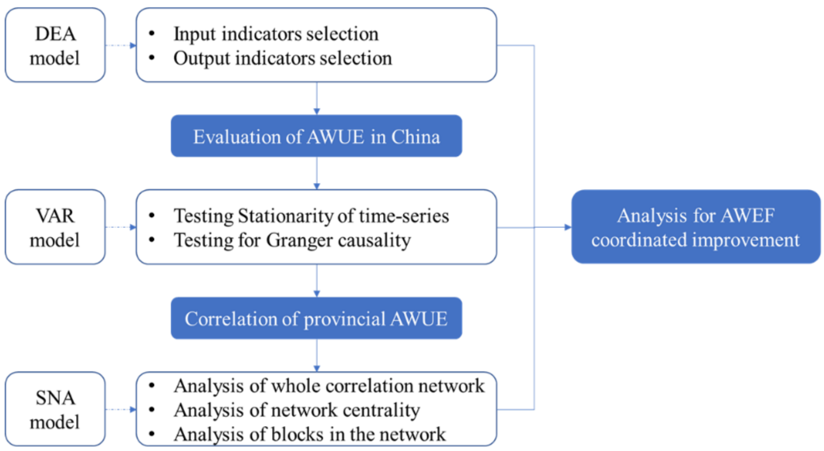

Figure 1. Technical route for analysis of spatial correlation network of agricultural water use efficiency (AWUE).

Firstly, to assess the AWUE of provinces in China, the super-efficiency SBM with undesirable outputs was used. This model is an improved DEA method and needs to select the appropriate input and output indicators for the production efficiency evaluation.

Secondly, the vector autoregression (VAR) Granger causality test model was used to analyze the dynamic connections between different provinces in China.

Thirdly, to investigate the characteristics of the spatial correlation network of AWUE, the SNA model was used. In particular, the centrality and block analysis can reveal the core provinces which influence the coordinated improvement in AWUE.

2.1. Undesirable Super-Efficiency SBM Model

DEA is a non-parametric evaluation method for measuring the relative efficiency of units where they have multiple inputs and outputs [44]. The primary analysis unit is defined as the decision-making unit (DMU). The efficiency value of a DMU is the distance from the DMU to the best-practice frontier. The frontier shows the maximum of diverse outputs with different input combinations or views the minimum combination of necessary inputs for diverse outputs. DMUs below the frontier are considered inefficient, while DMUs on the frontier are regarded as efficient. The traditional radial and angle DEA models calculate the efficiency according to a certain input–output proportion, ignoring the excess in inputs and shortfalls in outputs, which are likely to deviate from the efficiency measurement. The slack-based model (SBM) [45] was applied to avoid the slack problem of inputs and outputs, which belongs to a non-radial and non-angle DEA model. Moreover, when using conventional SBM-DEA models, the efficiency values of all DMUs are within the range of zero to one. This means that we fail to rank the DMUs with an efficiency value of one. Then, the super-efficiency model in DEA was proposed to exclude each observation from its own reference set, making it possible to obtain efficiency scores that exceed one [46]. Thus, the super-efficiency SBM model with undesirable outputs is suitable for the AUWE assessment in this study, which is defined as follows:

$$\rho = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \overline{x_i}/x_{i_o}}{1 + \frac{1}{S_1+S_2}\left[\sum_{p=1}^{S_1}\left(y_p^g/y_{p_o}^g\right) + \sum_{q=1}^{S_2}\left(y_q^b/y_{q_o}^b\right)\right]} \tag{1}$$

$$s.t. \begin{cases} \overline{x} \geq \sum\limits_{j=1,j\neq o}^{n} x_{ij}\lambda_j, \quad y_p^g \leq \sum\limits_{j=1,j\neq o}^{n} y_{pj}^g\lambda_j, \quad y_q^b \leq \sum\limits_{j=1,j\neq o}^{n} y_{qj}^b\lambda_j \\ \overline{x} \geq x_{io}, \quad y_p^g \leq y_{po}^g, \quad y_q^b \geq y_{qo}^b \\ \sum\limits_{j=1,j\neq o}^{n} \lambda_j = 1, \quad y^g \geq 0, \quad y^b \geq 0, \quad \lambda \geq 0 \\ i = 1,2,\cdots m; \ p = 1,2,\cdots S_1; \ q = 1,2,\cdots S_2; \ j = 1,2,\cdots n \end{cases} \tag{2}$$

where ρ represents the AWUE value, n is the number of evaluation units, m is the input elements, S_1 and S_2 are the number of desirable and undesirable outputs, $\overline{x}$, y^g, and y^b are slack variables for inputs, desirable outputs, and undesirable outputs, and λ is the envelope multiplier. If $\rho \geq 1$, the DMU is on the agricultural production frontier and DEA effective. If $0 < \rho < 1$, it means the DMU is not DEA effective, and there is still potential to improve the agricultural water use efficiency in the evaluation unit.

2.2. Social Network Analysis

SNA is a sociological research method used to investigate the relationships of actors, which consists of a set of nodes (actors) and ties (relationships between actors) [47]. SNA has also invented graph-theoretic properties to characterize structures, positions, links, and dyadic properties of the overall "shape" [39]. The AWUE of provinces is embedded in a social network by formal or informal relationships, and their changes are affected by the social network [48]. In the spatial correlation network of AWUE, the "nodes" are provinces, which present the AWUE of a particular region, and "ties" are the connection between these provinces, which show the spillover effects of factors related to AWUE. This section contains two parts: firstly, establishing the correlations in the AWUE in different provinces using the VAR Granger causality test; secondly, constructing the spatial correlation network of provincial AWUE with the method of SNA.

2.2.1. Vector Autoregression (VAR) Granger Causality Test

This step addresses the correlation among variables, which discusses a relationship between two nodes. In general, the influence of AWUE in different provinces has a lag, which means that the WUE information during a specific period in one area can predict the changing trend of WUE in the other regions [37]. Therefore, this paper used the VAR Granger causality test to build the dynamic correlation between provincial AWUE in China and construct a spatial correlation network matrix.

Firstly, the time series of AWUE in any given two provinces x, y were defined as $\{x_t\}$ and $\{y_t\}$, respectively. Secondly, two VAR models were constructed to test whether there is an interaction between the AWUE of the two regions.

$$x_t = \alpha_1 + \sum_{i=1}^{m} \rho_{1,i} x_{t-i} + \sum_{i=1}^{n} \sigma_{1,i} y_{t-i} + \varepsilon_{1,t} \tag{3}$$

$$y_t = \alpha_2 + \sum_{i=1}^{p} \rho_{2,i} x_{t-i} + \sum_{i=1}^{q} \sigma_{2,i} y_{t-i} + \varepsilon_{2,t} \tag{4}$$

where α_i, ρ_i, and σ_i $(i = 1, 2)$ are the parameters to be estimated, $\varepsilon_{i,t}$ $(i = 1, 2)$ represents the residual terms, which obeys the standard normal distribution, m, n, p, and q are the lag orders of the autoregressive terms. Through Equation (3), we can test whether the AWUE in region x is affected with a lag by its AWUE and the AWUE in region y. If the test result rejects the null hypothesis, the historical information of sequence $\{y_t\}$ is helpful to explain the variable change of sequence $\{x_t\}$, which means that $\{y_t\}$ is the Granger cause of $\{x_t\}$, and then create a directed link from region y to region x. According to this method, the links between all pairs of two regions in the study area are tested, and the spatial correlation network map of provincial AWUE is obtained. It should be noted that the stationarity test of time series was carried out by a unit root test model, the ultimate hysteresis order was set to an order of 2, and 1% was used as the significance test standard.

2.2.2. Spatial Correlation Network Characteristics

This step analyzes the spatial correlation network structure of provincial AWUE with two indicators: overall network characteristics and network centrality analysis [38,49,50]. This paper used the software UCINET (v 6.659) to obtain them.

(1) Overall network characteristic analysis

Four items were used to describe the overall network characteristics: network affinity, network density, network efficiency, and network hierarchy.

Network affinity describes the sum of all the actual connections in the network, which reflect the overall scale of the network. It is represented by M.

Network density measures the degree of cohesion in the network. The more connections there are in the provincial AWUE, the greater the network density. It is expressed as Equation (5). D represents the network density, N is the number of nodes in the network, and $N(N-1)$ is the maximum potential connection.

$$D = \frac{M}{N(N-1)} \tag{5}$$

Network efficiency refers to the connection efficiency between nodes in the network. The lower the network efficiency, the more redundant lines and overflow channels there are, and the more stable the whole network.

Network hierarchy reflects the asymmetric accessibility in the network. The higher the network hierarchy, the more rigid the network. The network hierarchy is calculated by Equation (6). H represents the network hierarchy, K is the group number of symmetric reachable points in the network, and $Max(K)$ is the number of groups of maximum possible reachable points.

$$H = 1 - \frac{K}{Max(K)} \tag{6}$$

(2) Network centrality analysis

Three parameters are used to describe the power of the nodes: point centrality, betweenness centrality, and closeness centrality. In a network, power means influence [47], and there is a positive relationship between centrality and power [51].

Point centrality measures the degree of association between a node and other nodes, indicating the degree to which a node is in the center of the network. The province with a higher point centrality has more connections with other provinces in the AWUE network and is likely to be the center node of the network. Point centrality (De) is calculated by Equation (7).

$$De = \frac{L}{N(N-1)-1} \tag{7}$$

where L stands for the number of provinces directly connected to the other; this centrality has two types in directed graphs: in-degree and out-degree. The former refers to the incoming spillover effects of factors related to AWUE from other provinces. In contrast, the latter is the outgoing spillover effects to other provinces.

Betweenness centrality indicates the mediation and bridge function, investigating how a node can control the communication between other nodes. It evaluates the number of times a node acts as a bridge along the shortest path between two other nodes, indicating the node's control ability of the overall network [52]. It is represented by C_b and is calculated by Equation (8).

$$C_b = \sum_{j}^{n}\sum_{k}^{n} b_{jk}(i);\ \ j \neq k \neq i,\ j < k \tag{8}$$

Closeness centrality refers to the closeness of a node to all other nodes in the network, which reflects the ability of a node to not be controlled by other nodes in the entire network.

2.2.3. Block Model Analysis

The block model is a primary social, spatial clustering analysis method [53]. It can explore the network's internal structure, investigate the position and role of each node in the block, evaluate the path of sending and receiving information between blocks, and conduct descriptive analysis. According to the block model, the social network is divided into four sections: bidirectional block, agent block, net beneficial block, and net spillover block. We used the CONCOR module in UCINET to finish the block model analysis. The maximum depth was set to 2. The focus on the standard was set to 0.2, dividing the 30 provinces into 4 blocks.

2.3. Data Source

In terms of the measurement of AWUE, five variables related to agricultural production were selected as input indicators, and the output indicators were from two aspects of desirable outputs and undesirable outputs, as shown in Table 1. For the availability and validity of the data, this research selected 30 provinces in China as the study area, excluding Hong Kong, Macao, Taiwan, and Tibet, and chose 2000 to 2019 as the research period.

Table 1. Input and output indicators in the assessment of agricultural water use efficiency.

Input and Output Elements	Variables	Unit
Input indicators	(I1) agricultural water use (I2) total sown area for crop (I3) total power of agricultural machinery (I4) labor force in agricultural production (I5) fertilizer content application	10^8 m^3 10^3 hm^2 10^4 kw 10^4 persons 10^4 t
Desirable output indicators	(O1) added value of agriculture	10^8 RMB
Undesirable output indicators	(O2) COD, TN, and TP emission from agriculture	10^4 ton

Since this paper evaluated agricultural water use efficiency, water withdrawal in the agricultural sector (irrigation, forestry, farming, and fishery) was the primary input indicator. As irrigation accounts for most of the agricultural water, this article prioritized the production factors related to the planting industry, such as crop sown area, agricultural machinery power, and fertilizer. In addition, the labor force was also included as an input element. Corresponding to the water use in the agricultural sector, we selected added value of agriculture as a desirable output indicator. To eliminate the influence of interannual price changes, we used the comparable price index to re-calculate the price based on the year 2000. Meanwhile, the undesirable output was mainly considered the non-point source pollution caused by agricultural production.

The data relating to the AWUE assessment were obtained from the *China Water Resources Bulletin*, *China Rural Statistical Yearbook*, and *China Statistical Yearbook*, covering 2000–2019. The discharges of agricultural non-point source pollution mainly come from crop fertilization, livestock breeding, and straw burning, which are estimated through the discharge of the pollution loads of chemical oxygen demand (COD), total nitrogen (TN), and total phosphorus (TP). The inventory analysis method was used to assess the above three indicators [54].

3. Results

3.1. Spatial and Temporal Differentiation of AWUE in China

3.1.1. Average AWUE of 30 Provinces

As shown in Table 2, all the average values of provincial AWUE were less than one, meaning that the agricultural water resource usage was inefficient at the province level. Thus, there is still room for improvement in agricultural water use in China.

Table 2. Average agricultural water use efficiency in China from 2000 to 2019.

Province	Efficiency	Rank	Province	Efficiency	Rank
Beijing	0.625	2	Henan	0.415	9
Tianjin	0.398	11	Hubei	0.258	20
Hebei	0.358	13	Hunan	0.222	22
Shanxi	0.216	23	Guangdong	0.368	12
Inner Mongolia	0.178	28	Guangxi	0.190	27
Liaoning	0.346	14	Hainan	0.494	3
Jilin	0.270	16	Chongqing	0.464	6
Heilongjiang	0.278	17	Sichuan	0.278	18
Shanghai	0.657	1	Guizhou	0.237	21
Jiangsu	0.469	5	Yunnan	0.212	25
Zhejiang	0.477	4	Shaanxi	0.460	7
Anhui	0.211	26	Gansu	0.264	19
Fujian	0.438	8	Qinghai	0.136	30
Jiangxi	0.215	24	Ningxia	0.159	29
Shandong	0.326	15	Xinjiang	0.410	10

There are distinct spatial disparities in AWUE among different provinces. In the past twenty years, the top five provinces with the highest average AWUE were Shanghai (0.657), Beijing (0.765), Hainan (0.494), Zhejiang (0.477), and Jiangsu (0.469). These five provinces are located in economically developed regions or coastal areas with abundant precipitation. In contrast, the bottom five districts with the lowest average AWUE were Qinghai (0.136), Ningxia (0.159), Inner Mongolia (0.178), Guangxi (0.190), and Anhui (0.211). These five provinces are mainly in arid and semi-arid areas with less precipitation, comparatively backward agricultural water technology, and large agricultural non-point pollution discharge [55]. The average AWUE in Shanghai was about five times that of Qinghai.

3.1.2. Temporal Evolution of the Provincial AWUE

The AWUE of most provinces has increased significantly over time, which means that the agricultural water use efficiency has considerably improved (Figure 2). In 2000, the AWUE of all 30 provinces was less than 0.4. In 2019, the AWUE in more than 50% of the provinces was more than 0.6. It is worth noting that the AWUE of 11 provinces gradually exceeded 1 since 2015, which indicates that agricultural water usage in these provinces had reached an utterly efficient state.

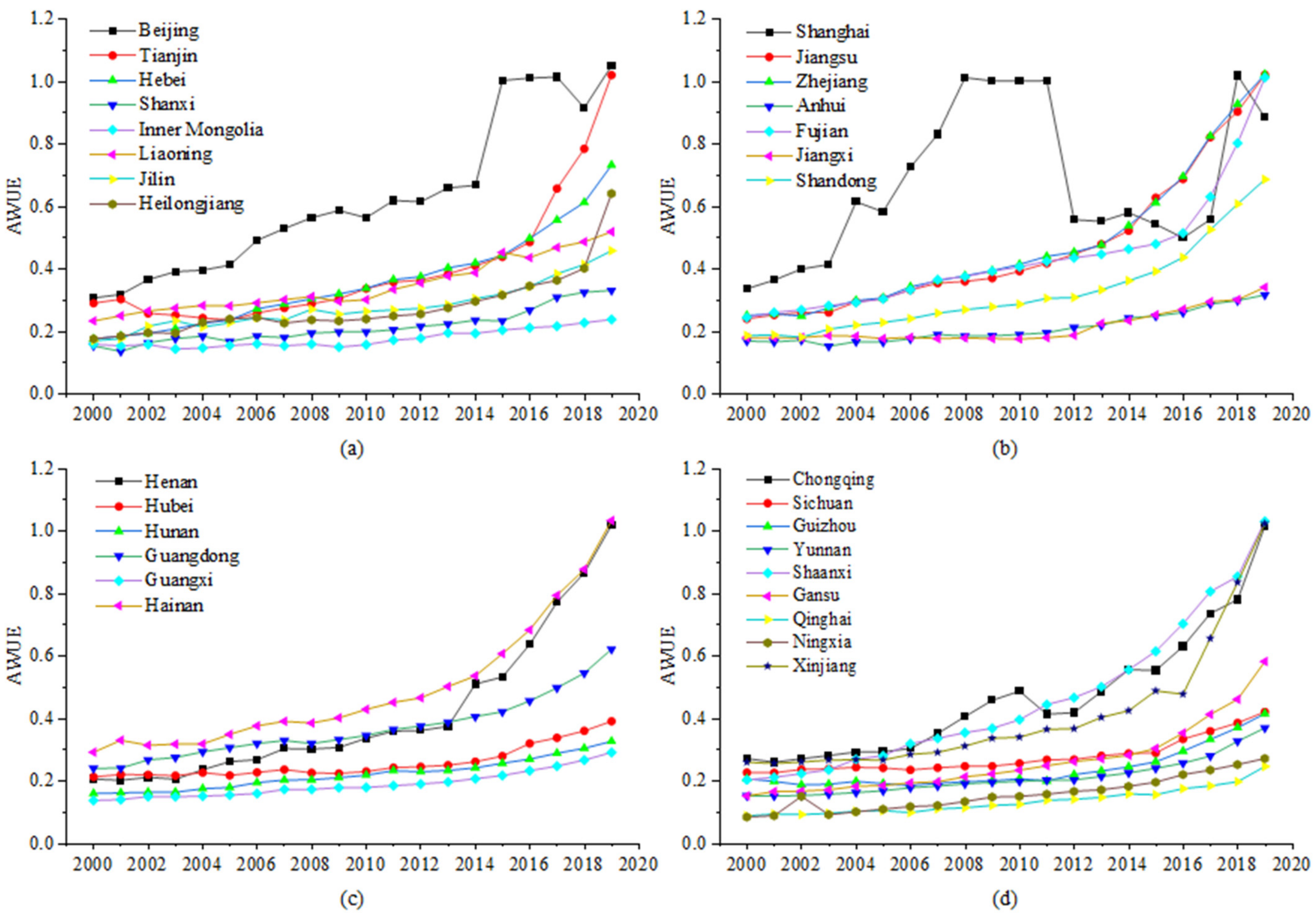

Figure 2. Temporal trends of provincial agricultural water use efficiency (AWUE) in China from 2000 to 2019. The above four charts are listed separately according to the geographical location of the province within (**a**) North China (8 provinces), (**b**) East China (7 provinces), (**c**) South China (6 provinces), and (**d**) West China (9 provinces).

In addition, the change trajectories of AWUE presented noticeable differences. The AWUE in most provinces experienced a process of first rising slightly and then rising drastically. The AWUE in Beijing and Shanghai started to increase around 2005, reaching 1 in 2015 and 2008. Meanwhile, the AWUE in most provinces such as Tianjin, Hebei, Jiangsu, Zhejiang, Fujian, Shandong, Henan, Hainan, Shaanxi, Gansu, and Xinjiang entered a stage of significant improvement since 2011 and exceeded 1 in 2019. Moreover, there are some provinces where AWUE has been low, with a minimal increment during the observation, including Inner Mongolia, Anhui, Guangxi, Qinghai, and Ningxia.

The average value of AWUE in China presented a significant increasing trend between 2000 and 2019. The variable coefficients of AWUE rose from 2000 to 2008 and reached a peak in 2008. Then, they decreased between 2009 and 2012 and increased again later (Figure 3). The fluctuations in variable coefficients revealed that the gaps in AWUE between the 30 provinces were the smallest in 2000 and the widest in 2008. Moreover, the gaps in the provincial AWUE are currently in the expanding stage. The spatial imbalance of China's agricultural water use efficiency is significant.

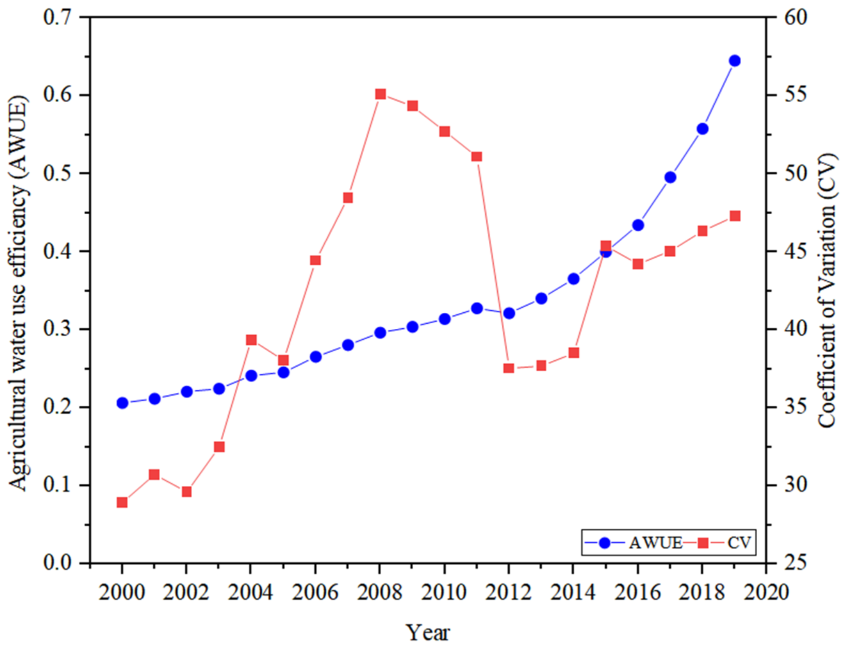

Figure 3. Average AWUE and the variable coefficients of AWUE in China.

3.1.3. Spatial Distribution of AWUE in 30 Provinces

To further analyze the spatial pattern of AWUE, the spatial distribution map of the AWUE of the 30 provinces in 2019 is plotted and shown in Figure 4. Overall, it is clearly illustrated that the AWUE in China presented apparent spatial aggregation and spatial variability at the provincial scale. According to the evaluation results of AWUE in 2019, we found that provinces with AWUE greater than one were mainly in southeastern and northwestern China. Provinces with AWUE lower than 0.4 were primarily in southwestern, south central, and northwestern China. The major grain-producing areas in northeast China, e.g., Heilongjiang, Jilin, and Liaoning, had AWUE between 0.4 and 0.7. Moreover, provinces whose AWUE was 0.6–0.8 were mainly concentrated on the Huang-Huai-Hai Plain [56], such as Hebei and Shandong in East China. The lowest AWUE was found in Inner Mongolia with 0.240 in 2019, followed by Qinghai (0.248) and Ningxia (0.273), all of which are arid provinces with water resource per unit area less than 20×10^4 m^3/km^2.

3.2. Spatial Correlation Network of AWUE in China

With the VAR Granger causality test (1% significance level), the spatial correlation matrix of AWUE in China was established. Then, the network map was drawn to show the structure and pattern of the spatial correlation network of AWUE, as shown in Figure 5. The spatial correlation of China's interprovincial AWUE presents a typical network structure. There are no isolated nodes in the whole spatial correlation network, which indicates that correlations of the agricultural water utilization of provinces in China have transcended geographically adjacent areas and evolved to form a massive spatial network. In other words, due to the frequent mobility of production factors related to AWUE, there has been a close correlation of AWUE between geographically non-adjacent regions. Therefore, the improvement in AWUE in any province will affect other provinces through the network.

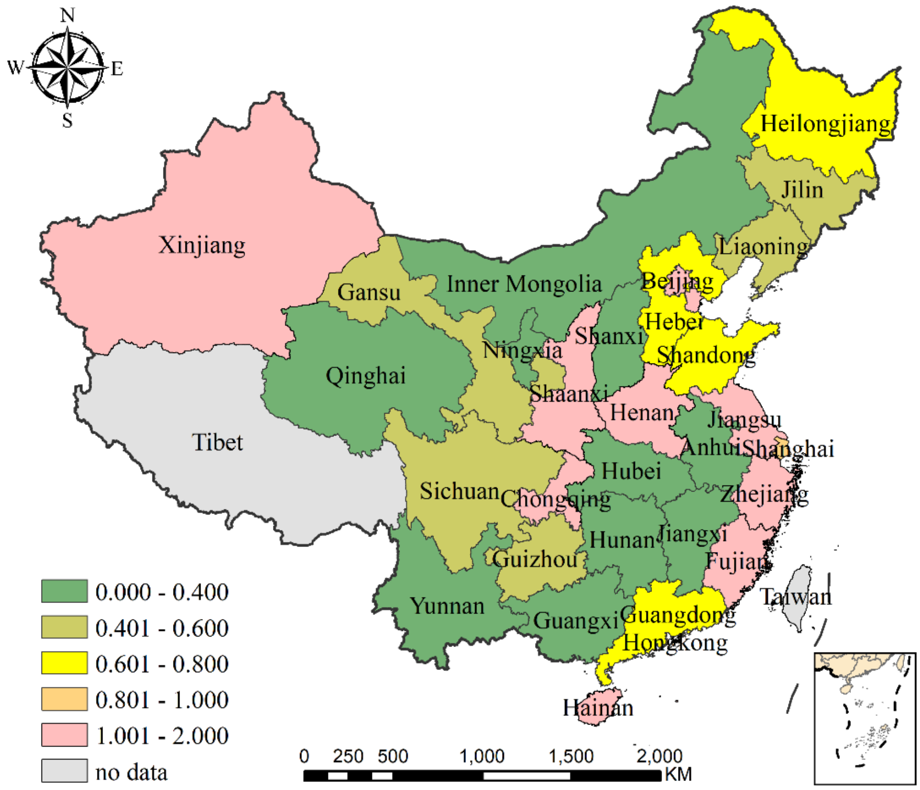

Figure 4. Agricultural water use efficiency of 30 provinces in China in 2019.

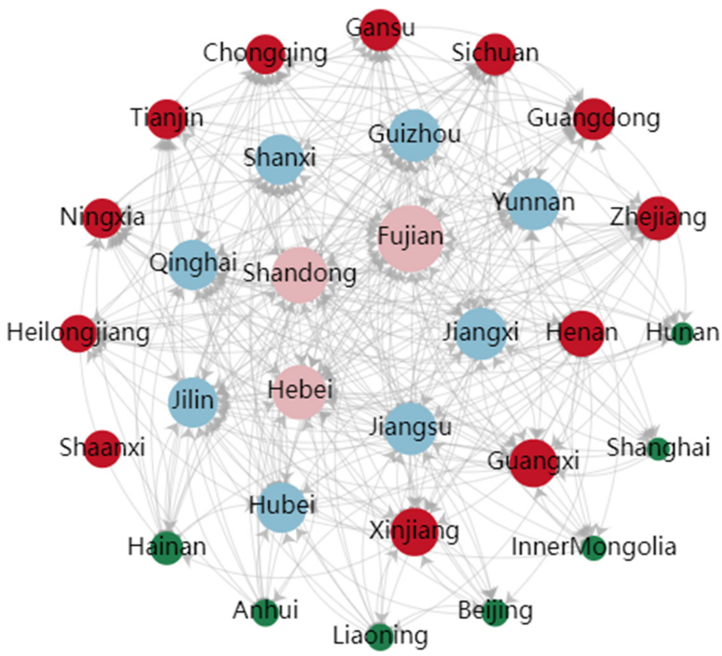

Figure 5. Spatial correlation network of agricultural water use efficiency in China.

3.2.1. Overall Network Characteristics and Evolution Trend

Table 3 shows the overall features of the spatial correlation network of AWUE. Meanwhile, to study the evolution trend of the interprovincial AWUE spatial correlation network, this paper divided the whole sample investigation period into two stages, with 2000–2009 and 2010–2019.

Table 3. Overall characteristics of interprovincial agricultural water use efficiency spatial network.

Item	2000–2009	2010–2019	2000–2019
Network affinity	136	200	301
Network density	0.156	0.230	0.346
Network efficiency	0.746	0.616	0.404
Network hierarchy	0.537	0.242	0
Average distance	2.302	2.045	1.789
Clustering coefficient	0.210	0.305	0.371

The potential maximum spatial correlation of the spatial correlation network of AWUE in the 30 provinces is 870 (30 × 29). From 2000 to 2019:

(1) The total actual spatial correlation (network affinity) was 307, and the network density was 0.346, indicating that the level of spatial correlation in the provincial AWUE in China was not high. There is still enormous scope to improve the interprovincial correlation of AWUE in the network.

(2) The network correlation was 1, meaning all 30 provinces were in the spatial correlation network of AWUE, and the accessibility and connectivity of the whole network were good. The AWUE of each province always had direct or indirect links with that of other provinces, presenting significant spillover effects of production factors related to AWUE.

(3) The network hierarchy was 0, indicating that there was no rigid network structure, and there was a close interrelation between these provinces.

(4) The network efficiency was 0.397, reflecting that there were many redundant links in the network, and the spatial spillover effects of AWUE had a multiple superposition phenomenon. The more redundant and invalid connections there are, the stabler and more robust the network is, and the slower the transmission speed among the nodes.

(5) The average distance and clustering coefficient of the network were 1.775 and 0.378, implying that the spatial correlation network of AWUE in China had prominent small-world characteristics. The short average distance revealed that we could establish a connection between any two nodes in the network through 1–2 intermediary provinces. The high clustering coefficient indicated a frequent connection and interaction in the provincial AWUE.

From the perspective of evolution, the features of the spatial correlation network of AWUE in China show a noticeable variation (Table 3). The network affinity and density in 2010–2019 were higher than in 2000–2009. The network efficiency and hierarchy in 2010–2019 were lower than in 2000–2009. With the growth of AWUE in China, the spatial correlations of AWUE in different provinces have risen significantly, indicating that the spillover effects of interprovincial agricultural water use efficiency have been enhanced.

3.2.2. Centrality Analysis

The point centrality, betweenness centrality, and closeness centrality of the spatial correlation network of AWUE in China were calculated to reveal the status and role of each province (Table 4).

Table 4. Central analysis of spatial correlation network of agricultural water use efficiency in China.

Province	Point Centrality				Betweenness Centrality		Closeness Centrality	
	Out-Degree	In-Degree	Centrality	Rank	Centrality	Rank	Centrality	Rank
Beijing	7	5	37.931	27	1.029	23	61.702	27
Tianjin	11	8	55.172	20	1.969	16	69.048	20
Hebei	8	18	79.310	2	6.927	4	82.857	2
Shanxi	8	16	72.414	10	2.505	12	78.378	10
Inner Mongolia	7	5	34.483	28	1.474	17	60.417	28
Liaoning	11	2	44.828	25	0.442	29	64.444	25
Jilin	5	19	75.862	4	2.145	14	80.556	4
Heilongjiang	8	10	55.172	21	4.201	9	69.048	21
Shanghai	7	4	34.483	29	2.672	10	60.417	29
Jiangsu	17	8	79.310	3	4.319	8	82.857	3
Zhejiang	14	7	62.069	17	1.233	21	72.500	17
Anhui	11	2	44.828	26	0.66	28	64.444	26
Fujian	9	23	82.759	1	8.909	1	85.294	1
Jiangxi	12	13	68.966	13	8.797	2	76.316	13
Shandong	14	13	75.862	5	4.798	5	80.556	5
Henan	20	1	72.414	11	1.052	22	78.378	11
Hubei	15	8	75.862	6	2.601	11	80.556	6
Hunan	2	8	34.483	30	0.886	25	60.417	30
Guangdong	3	16	65.517	15	0.385	30	74.359	15
Guangxi	9	13	72.414	12	1.333	19	78.378	12
Hainan	14	2	55.172	22	0.917	24	69.048	22
Chongqing	3	16	65.517	16	1.465	18	74.359	16
Sichuan	13	6	62.069	18	0.707	27	72.500	18
Guizhou	11	13	75.862	7	4.407	7	80.556	7
Yunnan	11	14	75.862	8	2.220	13	80.556	8
Shaanxi	14	3	55.172	23	0.770	26	69.048	23
Gansu	11	8	51.724	24	1.299	20	67.442	24
Qinghai	8	16	75.862	9	7.640	3	80.556	9
Ningxia	4	15	58.621	19	2.140	15	70.732	19
Xinjiang	14	9	68.966	14	4.579	6	76.316	14
Mean	10.033	10.033	62.989	–	2.816	–	73.401	–

The average out-degree, in-degree, and point-degree of each province in China were 10.033, 10.033, and 62.989, respectively. The top nine provinces with the highest point centrality were Fujian, Hebei, Jiangsu, Jilin, Shandong, Hubei, Guizhou, Yunnan, and Qinghai. Their degree centrality value exceeded 80, which indicates that these provinces had many more connections with other regions and played the role of central actors in the network. As shown in Figure 6, the nodes representing these provinces had more links and were in the center of the network. Meanwhile, Beijing, Inner Mongolia, Liaoning, Shanghai, Anhui, Hunan, and Hainan had low ranks of point centrality and acted as marginal actors in the whole network.

In terms of spillover and reception among the provinces (Figure 7), Henan, Jiangsu, Hubei, Shandong, Zhejiang, Hainan, Shaanxi, and Xinjiang were overflowing with higher out-degree, indicating these areas had more impacts on AWUE in the rest of the provinces than the rest of the provinces on themselves. Meanwhile, Fujian, Jilin, Hebei, Shanxi, Guangdong, Chongqing, and Qinghai were mainly beneficial with high in-degree, meaning that the AWUE levels of these provinces were primarily affected by other regions. The spillover and reception of Shandong, Jiangxi, and Guizhou were nearly equal.

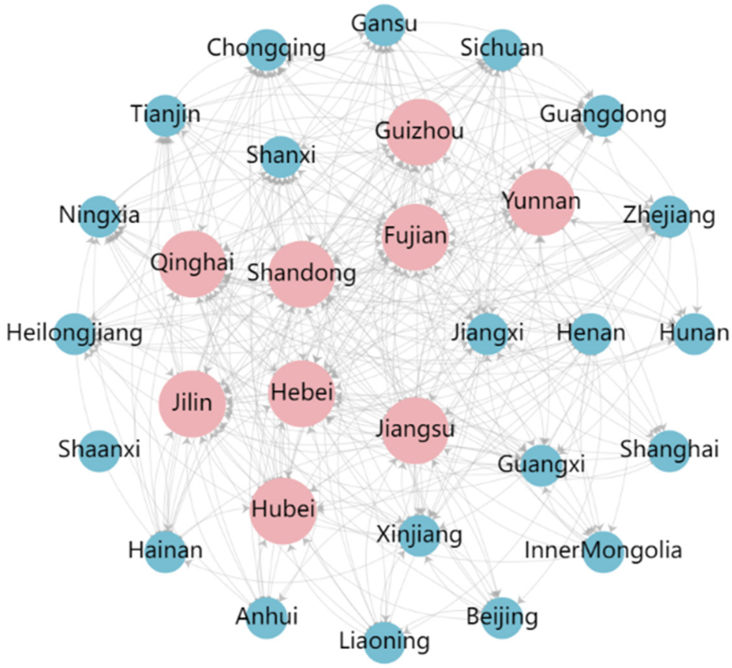

Figure 6. Network diagram corresponding to point centrality.

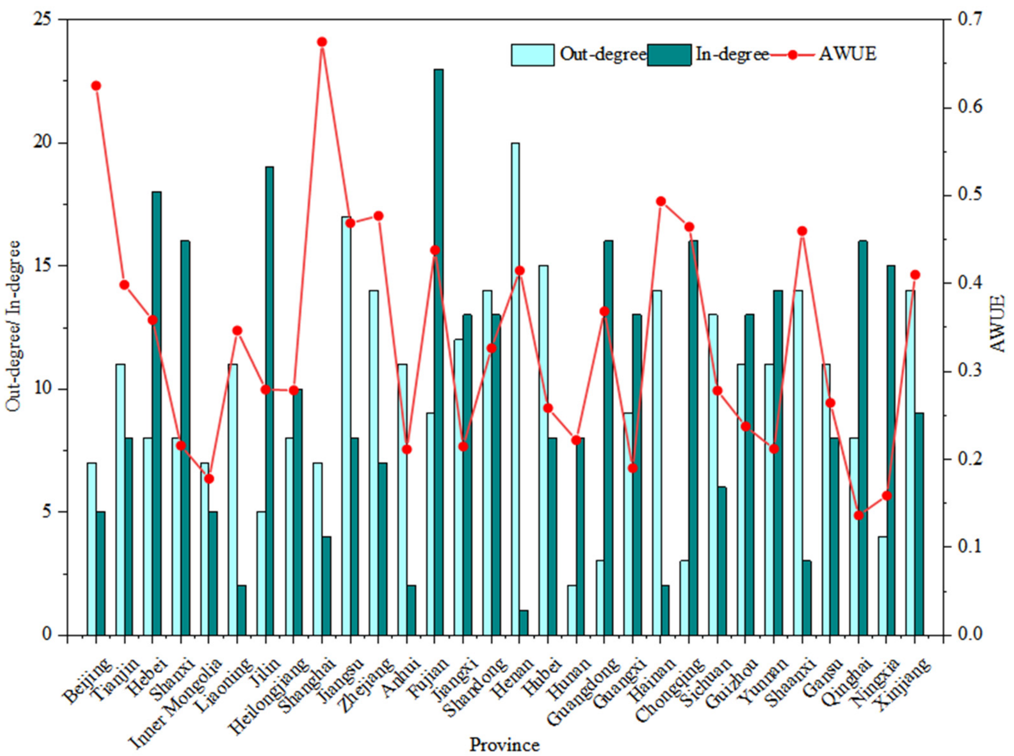

Figure 7. Spillover and reception correlation network of agricultural water use efficiency (AWUE) in China.

In general, provinces with high average AWUE were likely to have higher out-degree than in-degree, suggesting that regions with higher AWUE would have more significant spillover effects of factors related to AWUE, which would benefit the improvement in AWEU in other areas. On the contrary, provinces with low AWUE would have higher in-degree and lower out-degree, and other districts may affect their AWUE.

However, provinces with high AWUE, such as Fujian and Chongqing, did not have apparent spillover effects as expected and had absorbed advanced experience from others through high in-degree. Meanwhile, provinces with low AWUE, such as Liaoning, Anhui, and Hubei, had more spillover effects than receiving effects. Considering these three regions are main grain-producing areas in China, we must promote them to receive spillover effects of factors related to effectively using water.

The average betweenness centrality in the network was 2.816, and nine provinces had a higher value than that (Figure 8). The betweenness centrality in Fujian, Jiangxi, Qinghai, and Hebei was about 7, indicating that these four provinces had controlled more than seven transmission channels in the spatial correlation network of AWUE in China. The betweenness centrality in Shandong, Xinjiang, Guizhou, Jiangsu, and Heilongjiang was more than 4. Provinces with high betweenness centrality play a role as a "bridge" in the network, meaning they are critical nodes for disseminating and exchanging information technology related to agricultural water utilization.

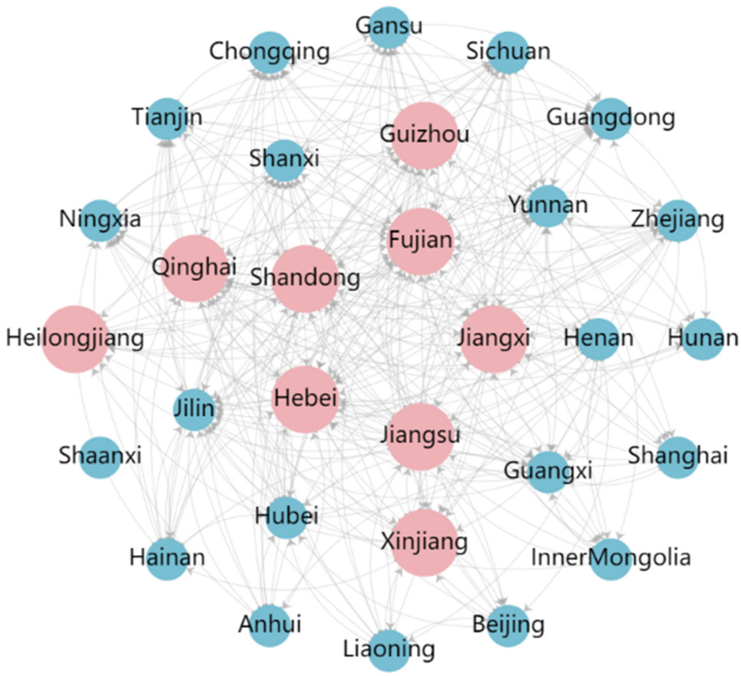

Figure 8. Network diagram corresponding to betweenness centrality.

There are slight differences between the rankings of the centrality degree and betweenness centrality of the 30 provinces in the network.

The average closeness centrality of the nodes in the network was 73.401, and more than 50% of the provinces had a higher value than that, which indicates the whole network was relatively balanced. As shown in Figure 9, Fujian, Hebei, Jiangsu, Jilin, Shandong, Hubei, Guizhou, Yunnan, and Qinghai ranked higher in closeness centrality, meaning they had a short distance to other nodes and could communicate with other provinces quickly in the network.

By comparing the point centrality, betweenness centrality, and closeness centrality of the spatial correlation network of AWUE in China, we found that Fujian, Hebei, Jiangsu, Shandong, Guizhou, and Qinghai had high point centrality, centrality, and closeness centrality at the same time. These provinces were essential nodes in the network and could play a vital role in improving AWUE.

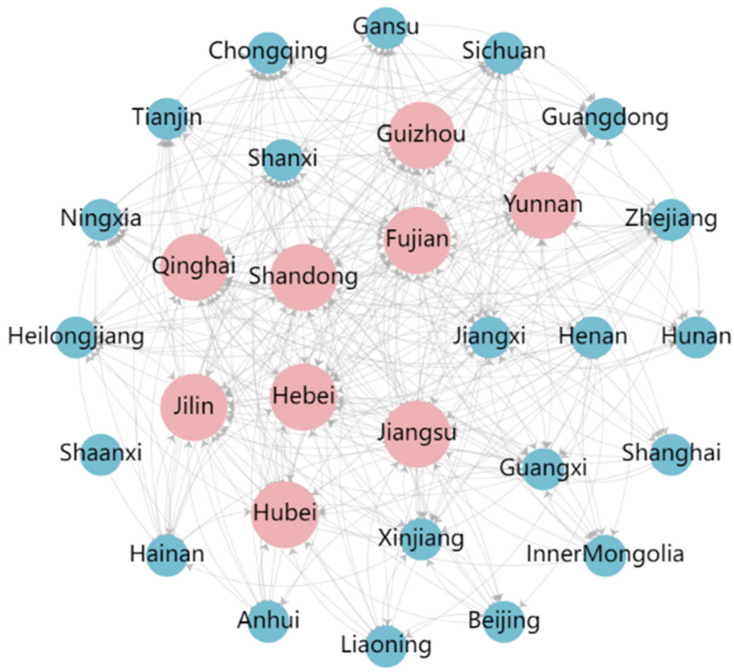

Figure 9. Network diagram corresponding to closeness centrality.

3.2.3. Block Model Analysis

The total correlation in the network was 301. The number of correlations within blocks was 63, with a ratio of 20.93%. Meanwhile, the correlation out of blocks was 238, with a ratio of 79.07%, meaning that the spillover effects between blocks were more significant (Table 5). Moreover, the net spillover block, bidirectional spillover block, and agent block contained most of the nodes and links in the spatial correlation network of AWUE.

Table 5. Spillover effect of agricultural water use efficiency spatial correlation block in China.

Block	Reception		Spillover		Expected Internal Relationship Ratio %	Actual Internal Relationship Ratio %	Block Properties
	Intra Block	Out of Block	Intra Block	Out of Block			
I	8	32	8	75	24	10	Net Spillover Block
II	34	43	34	106	31	24	Bidirectional Spillover Block
III	19	119	19	44	28	30	Agent Block
IV	2	44	2	13	7	13	Net Beneficial Block

Block I had eight nodes: Beijing, Inner Mongolia, Liaoning, Shanghai, Zhejiang, Anhui, Jiangxi, and Hainan. There were 83 spillover relations in block I, and 75 issuing spillover relations to other blocks. The expected internal relationship was 24%, while the actual internal proportion was 10%. Therefore, block I was named the net spillover block, whose members are more likely to send spillover effects on AWUE to other blocks. Among the members, Inner Mongolia, Liaoning, Jiangxi, and Anhui are major grain-producing areas in China, contributing about 20% of the grain production. Beijing, Shanghai, Zhejiang, and Hainan have high agricultural water use efficiency levels.

Block II had ten nodes: Tianjin, Jiangsu, Shandong, Henan, Hubei, Sichuan, Guizhou, Shaanxi, Gansu, and Xinjiang. There were 140 spillover relations in block II, 34 spillover connections within the block, and 106 spillover relations to other blocks. The expected internal relationship proportion was 31%, more than the actual relationship proportion of 24%. Therefore, we called block II the bidirectional spillover block. Members in this block likely have bidirectional spillover effects on nodes inside and outside. Jiangsu, Henan, and Hubei are also major grain-producing provinces.

Block III had nine nodes: Hebei, Shanxi, Jilin, Heilongjiang, Guangdong, Guangxi, Chongqing, Yunnan, and Qinghai. There were 63 spillover relations in block III, 19 within this block, and 44 issuing spillovers to other blocks. The expected internal relationship was 28%, while the actual internal proportion was 30%. According to the above characteristics, block III was classified as the agent block, which plays the role of an "intermediary" and "bridge" in the correlation network. Provinces in this block are evenly distributed in the northeast, northwest, southwest, southeast, and north central subregions of China, which is conducive to the spread of the spillover effects of AWUE across provinces.

Block IV had three nodes: Fujian, Hunan, and Ningxia. There were only 15 spillover relations in this block, 2 within the block, 44 receiving spillover relations in other blocks, and 13 sending spillover relations to other blocks. The expected internal relationship proportion was 7%, and the actual relationship proportion was 13%, meaning block IV was classified as the net beneficial block. Provinces in the net beneficial block mainly receive the spillover effects of other blocks. Fujian's food demand is great, but the local grain output is small, whose external food dependence is high.

Then, the density matrix was calculated to further analyze the spillover effects of AWUE between the four blocks in the network. According to the results in Table 3, the density of the whole spatial correlation network of AWUE was 0.346. If the density of each block in the density matrix is higher than 0.346, the corresponding value in the image matrix is 1; otherwise, the value is 0. The results are shown in Table 6.

Table 6. Density matrix and image matrix of agricultural water use efficiency in China.

Block	Density Matrix				Image Matrix			
	I	II	III	IV	I	II	III	IV
I	0.143	0.375	0.486	0.417	0	1	1	1
II	0.188	0.378	0.867	0.433	0	1	1	1
III	0.194	0.100	0.264	0.778	0	0	0	1
IV	0.125	0.133	0.222	0.333	0	0	0	0

Block I and block II mainly overflowed to block III and block IV, which meant that the former two blocks had substantial spillover effects of AWUE on the latter two blocks. Meanwhile, block III mainly overflowed to block IV. Moreover, only block II overflowed to itself, which suggests that the AWUE of nodes in this block had a significant correlation.

Figure 10 shows the transmission mechanism of spillover effects of factors related to agricultural water utilization between the four blocks. The net spillover block (block I) was the "engine" of the AWUE spatial correlation network, driving changes in agricultural water use efficiency in other members of the network. The net spillover block mainly sent spillover effects of factors related to agricultural water utilization to block II and block III. The bidirectional spillover block (block II) was the "steering wheel" of the network, leading to improving agricultural water resource management. The agent block (block III) was the "bridge" of the network, coordinating the exchange and dissemination of information and technology concerning water resources among the provinces. The net beneficial block (block IV) was the weak link of the whole network due to the low level of AWUE or the great import of agricultural products from other blocks.

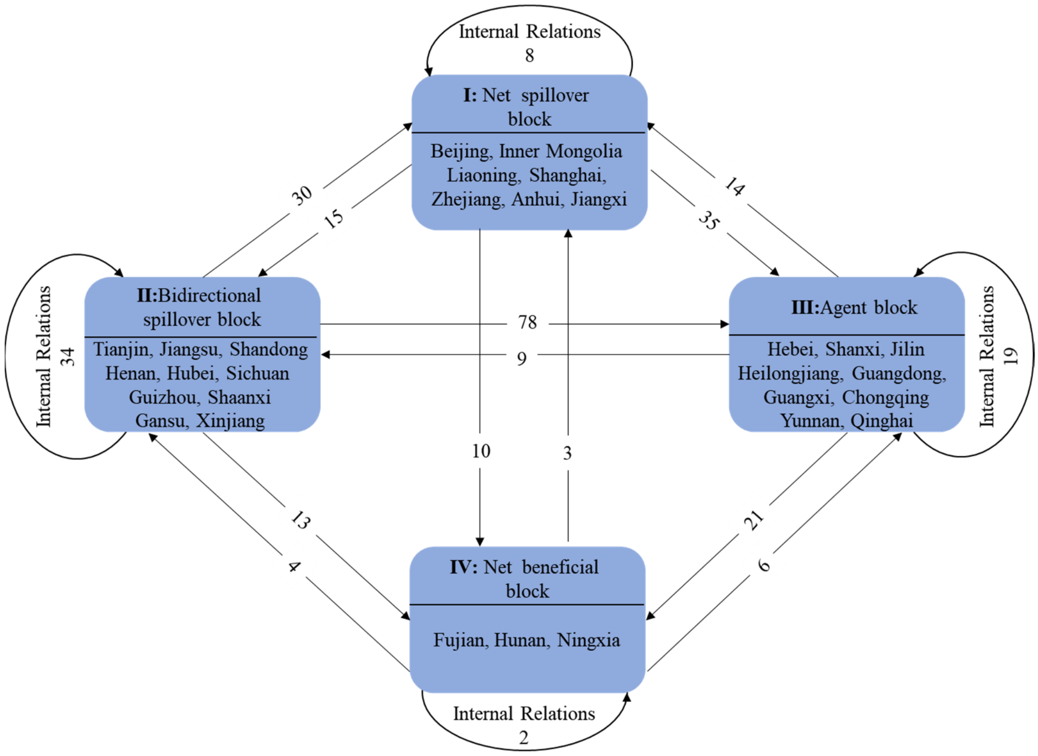

Figure 10. Spatial correlation between the four blocks.

4. Discussion

4.1. Discussion of Overall Level of Provincial AWUE

The overall agricultural water use efficiency of China was at a low level. This result is consistent with the research conclusion of Wang et al. [13]. The main reasons for this were the backward irrigation technology, extensive water use pattern, and inefficient agricultural water management. Only 1.1% of rural residents in major irrigation districts have adopted modern water-saving technology [57], meaning there is great potential for AWUE improvement. In addition, using chemical fertilizers will increase the grain yield, but excessive use of them will affect the soil and water environment through non-point source pollution [32]. Therefore, water-saving management and reducing non-point source pollution should be involved when implementing measures to improve agricultural water use efficiency.

4.2. Discussion of the Temporal Trend of AWUE

On the one hand, the evaluation value of AWUE is determined by the ratio of inputs and outputs. Due to the rapid increase in the economic outputs of the agricultural sector, and the reduction in non-point source pollution, AWUE in certain provinces showed a significant upward trend, such as Beijing, Shanghai, Jiangsu, and Zhejiang. On the other hand, AWUE reflects the condition of water conservancy facilities, the application of water-saving measures, farmers' awareness of water saving, etc. [13]. Economically developed or major grain-producing provinces always have advanced agricultural water use technology and information, causing their AWUE to have apparent temporal trends. In addition, policies related to agricultural production also introduce significant drives for AWUE improvement. In 2011, the Decision on Accelerating the Reform and Development of Water Conservancy, released by the CPC Central Committee and State Council, required the government to pay great attention to water conservancy construction and establish the rational allocation and efficient utilization system of water resources. In 2015, the Planning of National Agriculture Sustainable Development (2015–2030) was issued by the China Ministry of Agriculture, which aims to increase the effective utilization coefficient of farmland irrigation water. Therefore, provincial AWUE showed growth after 2011 and 2015. Due to regional differences in policy implementation measures and standards, there would be regional differences in the effects of the above policies on AWUE.

4.3. Discussion of Spatial Pattern of AWUE

The spatial performance of AWUE is primarily determined by the regional climate and agricultural system characteristics [56]. In general, the southern subregions are rich in precipitation and have well water resource endowment, which would benefit crop growth. Moreover, developed provinces always have advanced agricultural production technology and higher value-added agricultural products, which results in increased economic outputs per unit of water use. Thus, provinces with high AWUE values were located in southeastern China, while provinces with low values were mainly located in southwestern, south central, and north central China. Meanwhile, neighboring provinces always have similar geographical conditions and close communication, conducive to spreading spatial spillover effects between the adjacent areas [13,22,32].

However, the AWUE in several major grain-producing areas was low, including Hubei, Hunan, Jiangxi, and Anhui. Since it is often necessary to input a lot of irrigation water to ensure grain outputs, redundancy and shortage of irrigation water are the main reasons for low AWUE [58]. Moreover, the economic value per unit area for growing wheat and rice is lower than that for planting vegetables, fruits, and other cash crops.

4.4. Discussion of Spatial Correlation of Provincial AWUE

In the context of regional coordinated development, mobility of agricultural production factors has become more frequent [59], resulting in closer connections of resource utilization efficiency between different regions [38]. Each province could receive and send spillover effects of factors concerning agricultural water utilization, resulting in a significant correlation of AWUE between provinces. Meanwhile, with the increase in connections of AWUE between different provinces, the whole network became more robust.

The role of a particular province in the network may be related to its position in the national agricultural system. Figure 11 shows the ranking of provinces in agricultural economic outputs, grain outputs, and AWUE. Hebei, Jiangsu, Jilin, Shandong, and Hubei are major grain-producing areas from functional zoning. Provinces with a high added value of agriculture and large grain outputs may export many agricultural products to other provinces. Along with the frequent agricultural products trade, information and technology related to agricultural water utilization would be widespread. The AWUE in these provinces is more likely to correlate with other regions. From water use efficiency, agricultural sectors in Jilin, Shandong, Hubei, Guizhou, Yunnan, and Qinghai consumed water with low-level efficiency. To alleviate their water shortage, they had urgent needs to absorb information, technology, and the experience of water management from other regions [37]. Accordingly, the low-AWUE provinces would receive more spillover effects of water use efficiency from high-AWUE regions, resulting in the value of in-degree mostly in low-AWUE areas being higher than the value of out-degree.

Beijing and Shanghai are highly developed cities and have a high average value of AWUE. However, their agricultural outputs are significantly smaller than in other areas. Hebei has replaced Beijing's network functionality and has provided many resources for developing the Beijing-Tianjin-Hebei region [60]. Shanghai's network functionality was also replaced by Jiangsu [38]. For Inner Mongolia and Liaoning, their crop yield and economic output are high, and their agricultural water use efficiency is at the middle level. However, they are located in northern China and face severe water shortages. Correspondingly, it is more challenging to improve their water use efficiency, resulting in fewer connections between these provinces and others in AWUE.

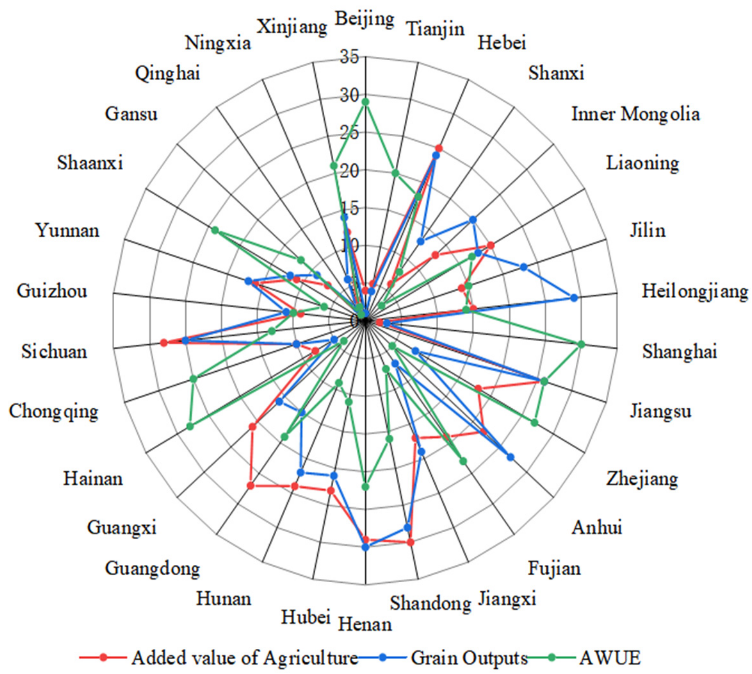

Figure 11. Ranking of average value of added value of agriculture, grain outputs, and AWUE (agricultural water use efficiency) in China from 2000 to 2019. (For comparison and display purposes, the highest value rank is 30, and the lowest value rank is 1.).

Fujian, Jiangxi, Qinghai, Hebei, Shandong, Guizhou, Jiangsu, Xinjiang, and Heilongjiang had high betweenness centrality, playing the role of a "bridge" to promote the dissemination of information, experience, knowledge, and technology concerning water use efficiency in the network. Most of the above provinces are major agricultural production regions. Generally, major grain-producing provinces are more sensitive to water shortages and are willing to adopt new management strategies and technology to improve agricultural water use efficiency [61]. For example, Jiangxi and Xinjiang are the primary agricultural production areas in China, and there is great demand for agricultural water. Xinjiang is even located in arid northwestern China. The two provinces are pilot regions for water rights trading. They have accumulated rich experience in water saving and constructed an advanced platform for the exchange and communication of water resource information [62]. They could assume the role of a bridge to promote the interactions of AWUE in other provinces.

Provinces in the net spillover block were mainly major grain-producing areas or had high levels of AUWE. They always possessed an advanced agricultural water management capacity and could drive the whole spatial correlation network, such as Inner Mongolia and Shanghai. Provinces within the middle level of AWUE mainly belonged to the bidirectional spillover block, which could receive spillover effects from other areas to improve AWUE and send helpful knowledge and information to others. Members in the agent block were more complex, including nodes with a high value, median value, and low value of AWUE. Therefore, this block can serve as a transfer station for agricultural water use efficiency information.

5. Conclusions

Affected by global climate change and water shortages, food security continues to be challenged. Improving agricultural water use efficiency and increasing the outputs of per unit water usage are essential to guarantee global food security. This article used the undesirable super-efficiency SBM model to measure the AWUE of 30 provinces in China from 2000 to 2019. Then, we investigated the spatial correlation of provincial AWUE with the social network analysis (SNA) method. The results found that:

(1) The overall agricultural water use efficiency in China was inefficient, and there is still great potential to improve it. The focus of sustainable agricultural water resource management included the broad application of water-saving technology and strict control of water pollution.

(2) All the provinces had experienced increasing AWUE in the past 20 years, but with apparent gaps. The growth rate of AWUE experienced a slight increase first and then a substantial increase. Provinces with higher AWUE were primarily located in the east, while the lower-AWUE areas were located in central and western China.

(3) There was a strong spatial correlation in provincial AWUE in China, presenting a typical network structure. It was necessary to manage water resources from a system and network perspective and improve coordinated agricultural water use efficiency.

(4) Fujian, Hebei, Jiangsu, Jilin, Shandong, Hubei, Guizhou, Yunnan, and Qinghai had high centrality in the network. Improvement in AWUE should pay more attention to the province with high centrality in the network and promote the spillover effects of agricultural water utilization between different regions.

(5) The nodes and links in the network were highly concentrated in the net spillover block, bidirectional spillover block, and agent block. We should focus on the driving role of the net spillover block, which is the power source of the improvement in AWUE in the whole network. Moreover, it is needed to strengthen the transmission of the bidirectional spillover block and agent block to promote the coordinated development of AWUE.

Therefore, when formulating relevant measures and policies to improve agricultural water use efficiency, they must pay attention to the spatial correlation of water resource utilization in different provinces to promote the common improvement in water use efficiency in all provinces.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The methods for the collection and preprocessing of the data are presented in Section 2. Data used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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

References

1. Pradhan, P.; Costa, L.; Rybski, D.; Lucht, W.; Kropp, J.P. A systematic study of sustainable development goal (SDG) interactions. *Earth's Future* **2017**, *5*, 1169–1179. [CrossRef]
2. Jones, E.; Qadir, M.; Van Vliet, M.T.; Smakhtin, V.; Kang, S.-M. The state of desalination and brine production: A global outlook. *Sci. Total Environ.* **2019**, *657*, 1343–1356. [CrossRef] [PubMed]
3. Pereira, L.S.; Oweis, T.; Zairi, A. Irrigation management under water scarcity. *Agric. Water Manag.* **2002**, *57*, 175–206. [CrossRef]
4. Schewe, J.; Heinke, J.; Gerten, D.; Haddeland, I.; Arnell, N.W.; Clark, D.B.; Dankers, R.; Eisner, S.; Fekete, B.M.; Colón-González, F.J. Multimodel assessment of water scarcity under climate change. *Proc. Natl. Acad. Sci. USA* **2014**, *111*, 3245–3250. [CrossRef] [PubMed]
5. Haddeland, I.; Heinke, J.; Biemans, H.; Eisner, S.; Flörke, M.; Hanasaki, N.; Konzmann, M.; Ludwig, F.; Masaki, Y.; Schewe, J. Global water resources affected by human interventions and climate change. *Proc. Natl. Acad. Sci. USA* **2014**, *111*, 3251–3256. [CrossRef] [PubMed]
6. Shaozhong, K.; Xinmei, H.; Taisheng, D.; Tong, L.; Su, X.; Lu, H.; Li, X.; Huo, Z.; Li, S.; Ding, R. Improving agricultural water productivity to ensure food security in China under changing environment: From research to practice. *Agric. Water Manag.* **2017**, *179*, 5–17.

7. Fuentes, E.; Arce, L.; Salom, J. A review of domestic hot water consumption profiles for application in systems and buildings energy performance analysis. *Renew. Sustain. Energy Rev.* **2018**, *81*, 1530–1547. [CrossRef]
8. Munir, A.H.; MEjaz, Q. Global water crisis and future food security in an era of climate change. *Food Policy* **2010**, *35*, 365–377.
9. Brown, L.R.; Halweil, B. China's water shortage could shake world food security. *World Watch* **1998**, *11*, 10–21.
10. Fereres, E.; Soriano, M.A. Deficit irrigation for reducing agricultural water use. *J. Exp. Bot.* **2007**, *58*, 147–159. [CrossRef]
11. Mehrazar, A.; Bavani, A.R.M.; Gohari, A.; Mashal, M.; Rahimikhoob, H. Adaptation of water resources system to water scarcity and climate change in the suburb area of megacities. *Water Resour. Manag.* **2020**, *34*, 3855–3877. [CrossRef]
12. Wallace, J. Increasing agricultural water use efficiency to meet future food production. *Agric. Ecosyst. Environ.* **2000**, *82*, 105–119. [CrossRef]
13. Fengting, W.; Chang, Y.; Lichun, X.; Chang, Y. How can agricultural water use efficiency be promoted in China? A spatial-temporal analysis. *Resour. Conserv. Recycl.* **2019**, *145*, 411–418.
14. De Fraiture, C.; Giordano, M.; Liao, Y. Biofuels and implications for agricultural water use: Blue impacts of green energy. *Water Policy* **2008**, *10*, 67–81. [CrossRef]
15. Liangxin, F.; Guobin, L.; Fei, W.; Ritsema, C.J.; Geissen, V. Domestic water consumption under intermittent and continuous modes of water supply. *Water Resour. Manag.* **2014**, *28*, 853–865.
16. Qingling, G.; Qingfu, R.; Rachael, H.N.; Wu, P.; Yu, Q. Assessing China's agricultural water use efficiency in a green-blue water perspective: A study based on data envelopment analysis. *Ecol. Indic.* **2019**, *96*, 329–335.
17. Gao, H.; Wei, T.; Lou, I.; Yang, Z.; Shen, Z.; Li, Y. Water saving effect on integrated water resource management. *Resour. Conserv. Recycl.* **2014**, *93*, 50–58. [CrossRef]
18. Jian, K.; Xinmei, H.; Huiping, Z.; Ding, R. An integrated strategy for improving water use efficiency by understanding physiological mechanisms of crops responding to water deficit: Present and prospect. *Agric. Water Manag.* **2021**, *255*, 107008.
19. Brent, C.; Nebo, J.; Xiying, Z. Reporting on water productivity and economic performance at the water-food nexus. *Agric. Water Manag.* **2020**, *237*, 106123.
20. Condon, A.G. Drying times: Plant traits to improve crop water use efficiency and yield. *J. Exp. Bot.* **2020**, *71*, 2239–2252. [CrossRef] [PubMed]
21. Blum, A. Effective use of water (EUW) and not water-use efficiency (WUE) is the target of crop yield improvement under drought stress. *Field Crops Res.* **2009**, *112*, 119–123. [CrossRef]
22. Xinchun, C.; Wen, Z.; Mengyang, W.; Li, T.; Chen, S.; Wang, W. Water resources efficiency assessment in crop production from the perspective of water footprint. *J. Clean. Prod.* **2021**, *309*, 127371.
23. Jin-Li, H.; Shih-Chuan, W.; Fang-Yu, Y. Total-factor water efficiency of regions in China. *Resour. Policy* **2006**, *31*, 217–230.
24. Zewdie, M.C.; Moretti, M.; Tenessa, D.B.; Ayele, Z.; Nyssen, J.; Tsegaye, E.; Minale, A.; Van Passel, S. Agricultural Technical Efficiency of Smallholder Farmers in Ethiopia: A Stochastic Frontier Approach. *Land* **2021**, *10*, 246. [CrossRef]
25. Ali, M.K.; Klein, K. Water use efficiency and productivity of the irrigation districts in Southern Alberta. *Water Resour. Manag.* **2014**, *28*, 2751–2766. [CrossRef]
26. Mardani, A.; Zavadskas, E.K.; Streimikiene, D.; Jusoh, A.; Khoshnoudi, M. A comprehensive review of data envelopment analysis (DEA) approach in energy efficiency. *Renew. Sustain. Energy Rev.* **2017**, *70*, 1298–1322. [CrossRef]
27. D'inverno, G.; Carosi, L.; Romano, G.; Guerrini, A. Water pollution in wastewater treatment plants: An efficiency analysis with undesirable output. *Eur. J. Oper. Res.* **2018**, *269*, 24–34. [CrossRef]
28. Gadanakis, Y.; Bennett, R.; Park, J.; Areal, F.J. Improving productivity and water use efficiency: A case study of farms in England. *Agric. Water Manag.* **2015**, *160*, 22–32. [CrossRef]
29. Azad, M.A.; Ancev, T.; Hernández-Sancho, F. Efficient water use for sustainable irrigation industry. *Water Resour. Manag.* **2015**, *29*, 1683–1696. [CrossRef]
30. Tian, Z.; Jian, P.; Wei, L.; Yang, Y.; Liu, Y. Spatial–temporal patterns of water use efficiency and climate controls in China's Loess Plateau during 2000–2010. *Sci. Total Environ.* **2016**, *565*, 105–122.
31. Dekker, S.C.; Groenendijk, M.; Booth, B.B.; Huntingford, C.; Cox, P.M. Spatial and temporal variations in plant water-use efficiency inferred from tree-ring, eddy covariance and atmospheric observations. *Earth Syst. Dyn.* **2016**, *7*, 525–533. [CrossRef]
32. Jingxue, W.; Yalin, L.; Huajun, Y.; Ge, J.; Wu, S.; Liu, L. Estimation and influencing factors of agricultural water efficiency in the Yellow River basin, China. *J. Clean. Prod.* **2021**, *308*, 127249.
33. Easterly, W.; Levine, R. What have we learned from a decade of empirical research on growth? It's Not Factor Accumulation: Stylized Facts and Growth Models. *World Bank Econ. Rev.* **2001**, *15*, 177–219. [CrossRef]
34. Leydesdorff, L. Synergy in knowledge-based innovation systems at national and regional levels: The Triple-Helix model and the Fourth industrial revolution. *J. Open Innov. Technol. Mark. Complex.* **2018**, *4*, 16. [CrossRef]
35. Ostrom, E. A general framework for analyzing sustainability of social-ecological systems. *Science* **2009**, *325*, 419–422. [CrossRef]
36. Caizhi, S.; Qifei, M. Spatial correlation network of water resources green efficiency between provinces of China. *Geogr. Res.* **2020**, *39*, 53–63.
37. Teng, Q.; Jinping, T.; Hengquan, Z. Construction and evolutionary factors of spatial correlation network of China's provincial water resource efficiency under environmental constraints. *China Popul. Resour. Env.* **2020**, *30*, 84–94.
38. Yan, B.; Erda, W.; Jinhong, B.; Shi, Q. Spatial pattern and driving factors for interprovincial natural gas consumption in China: Based on SNA and LMDI. *J. Clean. Prod.* **2020**, *263*, 121392.

39. Borgatti, S.P.; Mehra, A.; Brass, D.J.; Labianca, G. Network analysis in the social sciences. *Science* **2009**, *323*, 892–895. [CrossRef]
40. Newman, L.; Dale, A. Network structure, diversity, and proactive resilience building: A response to Tompkins and Adger. *Ecol. Soc. Nat. Resour.* **2005**, *10*, r2. [CrossRef]
41. Prell, C.; Hubacek, K.; Reed, M. Stakeholder analysis and social network analysis in natural resource management. *Soc. Nat. Resour.* **2009**, *22*, 501–518. [CrossRef]
42. Olsson, P.; Folke, C.; Hahn, T. Social-ecological transformation for ecosystem management: The development of adaptive co-management of a wetland landscape in southern Sweden. *Ecol. Soc. Nat. Resour.* **2004**, *9*, 2. [CrossRef]
43. Crona, B.; Bodin, Ö. What you know is who you know? Communication patterns among resource users as a prerequisite for co-management. *Ecol. Soc. Nat. Resour.* **2006**, *11*, 7. [CrossRef]
44. Cook, W.D.; Tone, K.; Zhu, J. Data envelopment analysis: Prior to choosing a model. *Omega* **2014**, *44*, 1–4. [CrossRef]
45. Cook, W.D.; Seiford, L.M. Data envelopment analysis (DEA)–Thirty years on. *Eur. J. Oper. Res.* **2009**, *192*, 1–17. [CrossRef]
46. Cooper, W.W.; Seiford, L.M.; Tone, K. *Introduction to Data Envelopment Analysis and Its Uses: With DEA-Solver Software and References*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2006.
47. Kharanagh, S.G.; Banihabib, M.E.; Javadi, S. An MCDM-based social network analysis of water governance to determine actors' power in water-food-energy nexus. *J. Hydrol.* **2020**, *581*, 124382. [CrossRef]
48. Carlson, E.J.; Poole, M.S.; Lambert, N.J.; Lammers, J.C. A study of organizational reponses to dilemmas in interorganizational emergency management. *Commun. Res.* **2017**, *44*, 287–315. [CrossRef]
49. Liu, G.; Yang, Z.; Fath, B.D.; Shi, L.; Ulgiati, S. Time and space model of urban pollution migration: Economy-energy-environment nexus network. *Appl. Energy* **2017**, *186*, 96–114. [CrossRef]
50. Furht, B. *Handbook of Social Network Technologies and Applications*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2010.
51. Krackhardt, D. Assessing the political landscape: Structure, cognition, and power in organizations. *Adm. Sci. Q.* **1990**, *35*, 342–369. [CrossRef]
52. Cui, P.; Li, D. A SNA-based methodology for measuring the community resilience from the perspective of social capitals: Take Nanjing, China as an example. *Sustain. Cities Soc. Nat. Resour.* **2020**, *53*, 101880. [CrossRef]
53. White, H.C.; Boorman, S.A.; Breiger, R.L. Social structure from multiple networks. I. Blockmodels of roles and positions. *Am. J. Sociol.* **1976**, *81*, 730–780. [CrossRef]
54. Lilin, Z.; Yansui, L.; Yongsheng, W.; Hu, X. Assessment and analysis of agricultural non-point source pollution loads in China: 1978–2017. *J. Environ. Manag.* **2020**, *263*, 110400.
55. Yujie, H.; Xianke, H.; Munan, X.; 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.
56. Xinchun, C.; Jianfeng, X.; Mengyang, W.; Zeng, W.; Huang, X. Agricultural Water Use Efficiency and Driving Force Assessment to Improve Regional Productivity and Effectiveness. *Water Resour. Manag.* **2021**, *2021*, 2519–2535.
57. Qiuqiong, H.; Jinxia, W.; Yumin, L. Do water saving technologies save water? Empirical evidence from North China. *J. Environ. Econ. Manag.* **2017**, *82*, 1–16.
58. Ricart, S.; Rico, A.M. Assessing technical and social driving factors of water reuse in agriculture: A review on risks, regulation and the yuck factor. *Agric. Water Manag.* **2019**, *217*, 426–439. [CrossRef]
59. Hongjun, C.; Fuji, X. How technological proximity affect collaborative innovation? An empirical study of China's Beijing–Tianjin–Hebei region. *J. Manag. Anal.* **2018**, *5*, 287–308.
60. Hongmei, Z.; Xinjing, W.; Mingjing, L.; Zhang, Y.; Fan, Y. Interregional trade among regions of urban energy metabolism: A case study between Beijing-Tianjin-Hebei and others in China. *Resour. Conserv. Recycl.* **2017**, *132*, 339–351.
61. Xi-Ping, D.; Lun, S.; Heping, Z.; Turner, N.C. Improving agricultural water use efficiency in arid and semiarid areas of China. *Agric. Water Manag.* **2006**, *80*, 23–40.
62. Lin, F.; Lin, Z. Does the trading of water rights encourage technology improvement and agricultural water conservation? *Agric. Water Manag.* **2020**, *233*, 106097.