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ARTICLE

The Relationship between Water Resources Use Efficiency and Scientific and Technological Innovation Level: Case Study of Yangtze River Basin in China

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ABSTRACT

The Yangtze River Basin's water resource utilization efficiency (WUE) and scientific and technological innovation level (STI) are closely connected, and the comprehension of these relationships will help to improve WUE and promote local economic growth and conservation of water. This study uses 19 provinces and regions along the Yangtze River's mainstream from 2009 to 2019 as its research objects and uses a Vector Auto Regression (VAR) model to quantitatively evaluate the spatiotemporal evolution of the coupling coordination degree (CCD) between the two subsystems of WUE and STI. The findings show that: (1) Both the WUE and STI in the Yangtze River Basin showed an upward trend during the study period, but the STI effectively lagged behind the WUE; (2) The CCD of the two subsystems generally showed an upward trend, and the CCD of each province was improved to varying degrees, but the majority of regions did not develop a high-quality coordination stage; (3) The CCD of the two systems displayed apparent positive spatial autocorrelation in the spatial correlation pattern, and there were only two types: high-high (H-H) urbanization areas and low-low (L-L) urbanization areas; (4) The STI showed no obvious response to the impact of the WUE, while the WUE responded greatly to the STI, and both of them were highly dependent on themselves. Optimizing their interaction mechanisms should be the primary focus of high-quality development in the basin of the Yangtze River in the future. These results give the government an empirical basis to enhance the WUE and promote regional sustainable development.

Keywords: Water resource utilization efficiency (WUE); Scientific and technological innovation level (STI); Coupling coordination; Interactive response; Yangtze River Basin

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1. Introduction

Water, as established by UN-Water (2021), serves as the fundamental element for all developmental processes [1]. It holds significance as both a fundamental natural resource and a strategic economic asset, playing a vital function in human life, society development, and the sustainable advancement of the ecological environment [2]. However, the progression of social and economic development has resulted in a growing universal demand for water resources at an approximate rate of 1% per year [3]. Furthermore, alongside the vulnerable natural ecological environment and the utilization of unsound development approaches, the issue of water scarcity is becoming increasingly evident. Despite China's position as the sixth-largest global holder of water resources, its per capita allocation is merely 25% of the global average level. As a result, China is among the countries confronting severe water shortages [4]. It is expected that with further expansion of urbanization and economic growth, water scarcity will become even more severe. This may ultimately hinder the sustainable development of regional areas, but the total usable water resources cannot be expanded due to economic and technical constraints [5]. In this case, improving water resource utilization efficiency (WUE) and reducing pollutant discharge are considered two methods to alleviate the current water resource crisis [6]. Therefore, scientific evaluation of WUE based on consideration of water pollution is of considerable significance for improving WUE and optimizing water resource allocation [7].

Enhancing WUE stands as a reliable and assured approach for China to attain green and sustainable development. Therefore, the Chinese government has started several reform measures. For instance, in 2011, the Chinese government issued a document specifically aimed at expediting water conservation reforms within the country. This document unambiguously emphasized the imperative of strengthening water resource management and enhancing comprehensive WUE [8]. In the year 2012, the Chinese authorities declared their stance on enforcing a rigorous system for managing water resources. They also set up three primary goals known as "three red lines". These objectives are controlling water resource development and usage, managing water efficiency, and reducing pollution in water function areas [9]. China has also piloted innovative economic measures, including water rights and emissions trading. For the purpose of prompting sustainable development and alleviating the shortage of water resources, future development must adhere to these reforms, effectively utilize resources, and strictly protect the ecological environment. Technological innovation has changed the input–output proportion of productive factors and is the core power in improving the WUE [10]. Consequently, it becomes imperative to coordinate the Scientific and Technological Innovation (STI) and the water resource capacity. Such integration will ultimately lead to the harmonious convergence of STI and water resource management, culminating in the desired outcomes.

The Yangtze River Basin covers a large portion of China and is home to over 40% of the country's population, making its economic growth crucial. Despite abundant water resources, the basin's intensive production activities have led to water shortages and pollution. This paper focuses on the harmonious relationship between WUE and STI in the Yangtze River Basin through a coupling coordination model and panel VAR model, aimed at offering recommendations for resolving water resource problems and advancing economic development. The paper's structure consists of a literature review of current research, a case study introduction, the methodology of this paper, results, conclusions, and policy recommendations.

2. Literature review

WUE serves as a significant metric for assessing sustainable development at a regional level. At its essence, WUE aims to achieve maximum economic and social benefits while minimizing water loss and environmental pollution. This topic has garnered considerable attention among scholars in recent years. Scientific evaluation of WUE constitutes the initial step towards exploring strategies for balanced development and water resource utilization, and currently stands as a focal point of research.

Evaluation methods for WUE can generally be categorized into two approaches: single-factor evaluation and total-factor evaluation. Among them, single-factor evaluation methods primarily include the index system method [11] and the ratio analysis method [12]. For example, Gregg et al. take the ratio of agricultural water resources input to agricultural output as an index to measure the WUE [13]. The total-factor evaluation methods generally include Stochastic Frontier Analysis (SFA) [14,15] and Data Envelopment Analysis (DEA) [16,17]. In the research on the utilization of total-factor water resources, Carvalho and Marques explore the scale economy and scope economy of the Portuguese water industry by using Bayesian SFA [18]. Hong and Yabe applied SFA to determine irrigation water efficiency and its effect on small tea plantations in Vietnam and found that there is a large amount of water resource waste under the condition of diminishing rebound to scale [19]. Zhang et al. use DEA based on the relaxation model to calculate the utilization ratio of interprovincial agricultural water resources capacity in China [20]. Gautam et al. use the smooth heterogeneous bootstrap program in the DEA method to evaluate irrigation water usage efficiency in crop productive efficiency in Louisiana, USA [21].

The majority of studies concerning WUE have focused on agriculture and industry, focusing on the evaluation of WUE as their primary research object. This scholarly attention has spurred research investigating the driving factors and mechanisms that influence WUE. For instance, Segovia-Cardozo et al. employed satellite images to estimate crop coefficients and evaluated the WUE of major crops in four irrigated areas in Spain [22]. Geng et al. utilized DEA to assess the water usage efficiency in agriculture across 31 provinces in China from 2003 to 2013, revealing a noteworthy improvement post-2008 [23]. Chen et al. assessed the industrial WUE in China from 2005 to 2015, exploring provincial variations and spatial spill-over effects through bootstrap DEA analysis [24]. Oulmane et al. calculated the WUE of a small horticultural farm in Algeria and employed a Tobit model to identify determinants of WUE, encompassing factors such as total crop and water source count, greenhouse gas emissions percentage, level of educational and technical support, and credit opportunities for farmers [25]. Wang argued that factors such as age, gender, education level, and farmers' awareness of water scarcity impact the irrigation efficiency of water resources [26].

The STI serves as a crucial metric for assessing a country's high-quality development. Advancements in STI facilitate the development of environmental protection technologies, which profoundly influence the utilization efficiency of biological resources [27]. In recent years, scholars have made notable strides in researching the relationship between WUE and STI. Kang et al. posit that enhancing water-saving irrigation technology contributes to improved WUE [28]. Through empirical research, Miao et al. employ the random frontier analysis method and demonstrate that technological innovation exhibits a vital positive effect on the energy usage efficiency of industries between 2000 and 2015, exhibiting a consistent upward trend [29]. Wang and Wang, utilizing the generalized method of moments system regression analysis, discover that technological development had a substantial and positive influence on national-level total-factor energy efficiency from 2001 to 2013 [30]. However, they also found that technological innovation in central China impeded the advancement of total-factor energy efficiency.

Recently, the coupling coordination model has gained widespread recognition as an effective tool for evaluating the overall development of research areas [31]. Prior studies by Xu et al. and Zhang et al. have used this method to study the relationship between WUE and economic development, as well as economic development and the water environment [32,33]. However, there is little research that has utilized this method to study the mutual relationship between WUE and STI. Most existing research primarily focuses on the one-way impact of STI on WUE, with less attention given to the factors that impede the coordinated development of these two systems. To facilitate their harmonized development, it is crucial to conduct a systematic evaluation of their spatial and temporal characteristics and identify the factors influencing their development.

This paper aims to utilize the coupling coordination model to assess the relationship between WUE and STI in the Yangtze River Basin. By establishing an overall evaluation index system and measuring both WUE and STI, we will analyze the temporal and spatial characteristics of their coordinated development using a panel VAR model. This empirical analysis will provide valuable insights into the positive interaction between the two systems, ultimately supporting the promotion of their coordinated development.

3. Methodology and data

3.1 Study area

This study focuses on the research conducted in the Yangtze River Basin, which includes its tributaries. The basin boasts a well-developed water system, encompassing a water supply and drainage area of 1.8 million square kilometers, approximately one-fifth of the total area [34]. Geographically, it spans the eastern, central, and western economic zones of China, covering 19 provinces, autonomous regions, and centrally-administered municipalities. However, the region grapples with significant resource imbalances, environmental challenges, economic disparities, and unbalanced distribution of water resources, which hinder the development of the Yangtze River Basin. The Yangtze River is categorized into three parts: the upper, middle, and lower reaches, with 19 provinces allocated to each section accordingly (**Figure 1**). Hubei and Jiangxi provinces are designated as part of the middle reaches, based on both geographical and economic regional divisions.

3.2 Methodology

Calculation of ash water footprint

According to the literature [35-37], the gray water footprint (TWF_{grey}) includes agricultural grey water footprint (AWF_{grey}), industrial grey water footprint (IWF_{grey}), and domestic grey water footprint (DWF_{grey}). As there are many kinds of water pollutants and the concentration difference is large, only the most important pollutants are considered when calculating the grey water footprint. The specific calculation formula can be represented as follows:

$$TWF_{grey} = AWF_{grey} + IWF_{grey} + DWF_{grey} \tag{1}$$

Agricultural grey water footprint (AWF_{grey}) includes planting grey water footprint (AWF_{pla}) and aquaculture grey water footprint (AWF_{bre}). Nitrogen in the fertilization is the largest origin of aquatic pollution in the farming industry. The chemical oxygen de-

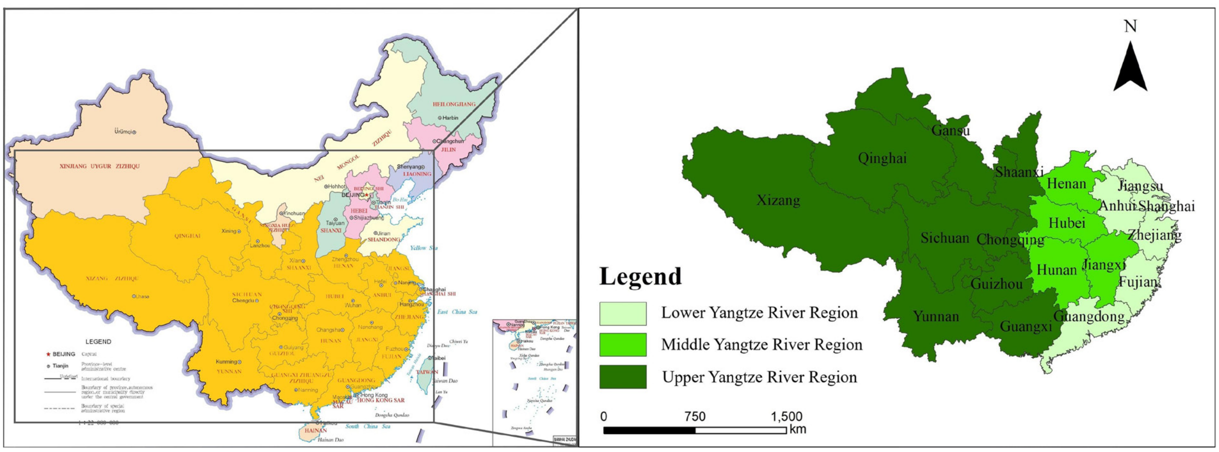

Figure 1. Study area.

mand (COD) and total nitrogen in the feces of cattle, sheep, pigs, and poultry are the main source factors of water deterioration in the breeding industry [37,38]. For calculating grey water footprint, the grey water footprints originating from the same categories of pollutants are summed up, and the grey water footprints originating from different categories of pollutants take the maximum value. The calculation formula is as follows:

$$AWF_{grey} = max\left[AWF_{bre(COD)},\ \left(AWF_{pla(TN)} + AWF_{bre(TN)}\right)\right] \tag{2}$$

$$AWF_{pla} = \frac{\alpha N_{Appl}}{C_{TN,\ max} - C_{TN,\ nat}} \tag{3}$$

$$AWF_{bre} = max\left(AWF_{bre(COD)}, AWF_{bre(TN)}\right) \tag{4}$$

$$AWF_{bre(i)} = \frac{L_{bre(i)}}{C_{i,\ max} - C_{i,\ nat}},\ L_{bre(i)} = \sum_{h=1}^{4} N_h D_h\left(f_h p_{hf}\beta_{hf} + u_h p_{hu}\beta_{hu}\right) \tag{5}$$

In the above formula: α is the leaching rate of nitrogen fertilizer; N_{appl} is the total amount of nitrogen application; $C_{TN, max}$ is the standard concentration of total nitrogen concerning water quality; $C_{TN, nax}$ is the natural local concentration of total nitrogen; $AWF_{bre(i)}$ is the grey water footprint of the aquaculture industry of category i pollutants; $L_{bre(i)}$ is the emission of class i pollutants; i is total nitrogen or COD; h refers to cattle, sheep, pigs, and poultry; N_h, D_h, f_h, u_h, P_{hf}, β_{hf}, β_{hu}, are the quantity of h, feeding cycle, daily urine output, pollutant content per unit of urine, pollutant content per unit of faeces, pollutant flow loss rate per unit of faeces, and pollutant flow loss rate per unit of urine, respectively.

COD and ammonia nitrogen emissions ($NH_3 - N$) are the main pollutants in industrial wastewater [39,40], and the calculation formula of IWF_{grey} is as follows:

$$IWF_{grey} = max\left(IWF_{grey(COD)},\ IWF_{grey(NH_3-N)}\right) \tag{6}$$

$$IWF_{grey(k)} = \frac{L_{ind(k)}}{C_{k,\ max} - C_{k,\ nat}} \tag{7}$$

In the formula: $IWF_{grey(k)}$ is the industrial grey water footprint of class k pollutants; $L_{ind(k)}$ is the discharge amount of class k pollutants in industrial wastewater; k is the pollutant COD or $NH_3 - N$.

Domestic and industrial sewage belong to point source pollution, and the main pollutants are COD and $NH_3 - N$ [20,41]. The calculation formula of $NH_3 - N$ is as follows:

$$DWF_{grey} = max\left(DWF_{grey(COD)},\ DWF_{grey(NH_3-N)}\right) \tag{8}$$

$$DWF_{grey(k)} = \frac{L_{dom(k)}}{C_{k,\ max} - C_{k,\ nat}} \tag{9}$$

Method for estimating WUE

In order to ensure objectivity and minimize deviation in efficiency measurement, this paper employs DEA, a nonparametric frontier approach. DEA is used as the evaluation method for assessing WUE in this study. Unlike traditional DEA models that do not account for input or output relaxation, the calculation model [42], addresses this limitation and offers a solution to overcome this issue.

$$\min_{\rho,\lambda,s^-,s^g,s^b} \rho = \frac{1-(1/m)\sum_{j=1}^{m}\left(s_j^- / x_{j0}\right)}{1+\left(1/\left(n_1+n_2\right)\right)\left(\sum_{j=1}^{n_1}\left(s_j^g / y_{j0}^g\right)+\sum_{j=1}^{n_2}\left(s_j^b / y_{j0}^b\right)\right)}$$

$$\text{s.t. } x_{j0} = \sum_{j=1}^{m}\lambda_j x_j + s_j^-, y_{j0}^g = \sum_{j=1}^{n_1}\lambda_j y_j^g - s_j^g, y_{j0}^b = \sum_{j=1}^{n_2}\lambda_j y_j^b + s_j^b, \lambda_j \ge 0, s_j^- \ge 0, s_j^g \ge 0, s_j^b \ge 0 \tag{10}$$

where $\rho, s_j^-, s_j^b, s_j^g$ represent efficiency value, input redundancy, undesirable output redundancy, and desirable output deficiency, respectively. When $\rho = 1$ (equivalently, $s_j^- = s_j^b = s_j^g = 0$), DMU_0 is efficient.

Model (2) is generally converted to the following linear programming model:

$$\min_{\tau,t,\gamma,S^-,S^g,S^b} \quad \tau = t - \frac{1}{m}\sum_{j=1}^{m}\frac{S_j^-}{x_{j0}}$$

$$\text{s.t. } 1 = t + \frac{1}{n_1+n_2}\left(\sum_{j=1}^{n_1}\frac{S_j^g}{y_{j0}^g} + \sum_{j=1}^{n_2}\frac{S_j^b}{y_{j0}^b}\right)$$

$$\text{s.t. } x_{j0} = \sum_{j=1}^{m}\gamma_j x_j + S_j^-, ty_{j0}^g = \sum_{j=1}^{n_1}\gamma_j y_j^g - S_j^g, ty_{j0}^b = \sum_{j=1}^{n_2}\gamma_j y_j^b + S_j^b, \gamma_j \ge 0, S_j^- \ge 0, S_j^g \ge 0, S_j^b \ge 0 \tag{11}$$

where τ is the efficiency value (equal to ρ), $\gamma_j = t\lambda_j$, $S_j^- = ts_j^-$, $S_j^- = ts_j^-$, $S_j^g = ts_j^g$, $S_j^b = ts_j^b$.

Evaluation model for the comprehensive development level

First, the indicators are dimensionless to eliminate the dimensional difference of the indicator system, specifically:

$$X'_{ij} = (X_{ij} - minX_{.j})/(maxX_{.j} - minX_{.j}) \tag{12}$$

$$X'_{ij} = (maxX_{.j} - X_{ij})/(maxX_{.j} - minX_{.j}) \tag{13}$$

where Equation (12) is a positive indicator normalization process, and Equation (13) is a negative indicator normalization process.

To mitigate potential measurement biases stemming from subjective weighting, this paper utilizes the entropy weight method. This method is selected due to its strong objectivity, practicality, and widespread applicability in determining the weights of different indicators. By employing this method, the study aims to enhance the objectivity and reliability of the weight allocation process for various indicators [43]:

$$\begin{cases} w_j = d_j / \sum_{j}^{m} d_j \text{, } d_j = 1 - e_j \\ e_j = -k \sum_{i=1}^{n} P_i \times ln(P_i) \text{, } k = 1/ln(n) \\ P_i = X'_i / \sum_{i=1}^{n} X'_i \end{cases} \tag{14}$$

w_j represents the weight of the j-th index; P_j represents the weight of sample indicators; e_j represents the information entropy of the j-th index; d_j indicates the utility value of the j-th index; n represents the number of samples.

Finally, according to the weights of the different indicators, the comprehensive evaluation indexes of the *STI* are further calculated:

$$STI = \sum_{j=1}^{m} w_j \times x'_{ij} \tag{15}$$

CCD model

The CCD model comprises two distinct components, namely the coupling degree model and the coordination degree model. While the former is responsible for delineating the extent of system interaction, it falls short of capturing the comprehensive potency and collaborative impact thereof [44]. Thus, the coordination degree model has been introduced to encompass both the level of inter-system interaction and the degree of coordinated development. The formula for calculating the coupling degree is:

$$C = 2\left[\frac{WUE \times STI}{(WUE + STI)}\right]^{\frac{1}{2}} \tag{16}$$

C is the coupling degree, in which the value is [0, 1]. When C gets smaller, the correlation and coupling relationship between the two subsystems gets smaller. Otherwise correlation and coupling relationship between the two subsystems gets larger. The calculation formula for the degree of coordination is as follows:

$$\begin{cases} D = \sqrt{C \times T} \\ T = \alpha WUE + \beta STI \end{cases} \tag{17}$$

where D is the CCD, and the value is (0, 1); T is the overall coordination index of WUE and the STI, and the value is (0, 1); α and β are undetermined parameters, indicating the weight of the two subsystems to the overall system. In this paper, both α and β are considered equally important, so $\alpha = \beta = 0.5$.

There is no unified standard for the division of coupled cooperative scheduling in the academic community. According to the existing research and the actual coupling coordination value calculated in this paper, the CCD of the two systems is divided into five levels [45], as shown in **Table 1**.

Table 1. Coupling coordination level.

D	Level
0.0-0.20	Low coordination
0.20-0.40	Basic coordination
0.40-0.50	Moderate coordination
0.50-0.80	Highly coordinated
0.80-1.00	Excellent coordination

Spatial autocorrelation

Spatial autocorrelation is a valuable approach capable of examining the spatial relationships within data. It helps elucidate the interrelationship patterns and spatial clustering characteristics of spatial attribute data [44]. Moran's I is a commonly utilized measure for such analysis, and it encompasses both global Moran's I and local Moran's I. Global spatial autocorrelation is employed to describe the overall degree of spatial correlation among attribute values within the study area. The specific formula is as follows:

$$I = \frac{n\times\sum_{i=1}^{n}\sum_{j\neq1}^{n}W_{ij}(x_i-\bar{x})(x_j-\bar{x})}{(\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij})\times\sum_{i=1}^{n}(x_i-\bar{x})^2} \tag{18}$$

The above formula$I$ represents Moran's I, n represents the number of provinces and cities, x_i and x_j represent the CCD at the i and j locations of provinces and cities, respectively, and $\bar{x}$ represents the average value of the CCD; W_{ij} represents the neighborhood relationship between i and j. When i and j are adjacent, $W_{ij} = 1$; otherwise, it is 0. The value of global Moran's I is in the interval of [–1, 1]. If it is greater than 0, it indicates a positive spatial correlation. The larger value means an evident spatial correlation. Less than 0 indicates a negative spatial correlation, and a smaller value means greater spatial difference. The space equal to 0 presents randomness.

Local spatial autocorrelation can be a useful method to further measure the specific location of the coupling coordination between WUE and STI in local space and then analyze the imbalance in local space and find the spatial heterogeneity of the coupling coordination. The calculation formula of local Moran's I is as follows:

$$I_i = \frac{(x_i-\bar{x})}{m_0}\sum_j W_{ij}(x_j-\bar{x}) \tag{19}$$

The above formula x_i represents the CCD value of province and city i, $\bar{x}$ represents the average value of CCD of all provinces and cities, $I_i > 0$ represents the spatial clustering (high-high [H-H] or low-low [L-L]) of observation values similar to the CCD value of a province and city, and $I_i < 0$ represents the spatial clustering (L-H or H-L) of observation values not similar to the CCD value of a province.

VAR model

The intricate mechanisms of interaction and causality between WUE and STI call for the adoption of a panel VAR (Vector Autoregression) model. By combining panel data and modeling techniques, the panel VAR model leverages the strengths of both approaches, enabling the prediction of the influence of random disturbances on the variables of interest. Thus, the panel VAR model proves to be a suitable analytical tool for examining the interactive responses between WUE and STI within the context of the Yangtze River Basin.

3.3 Indicator selection and data sources

Indicator selection

Based on the connotation and characteristics of WUE and STI, with reference to existing research results, and following the fundamentals of scientificity, comparability, and representativeness of index selection, select indicators can reflect WUE and STI to a large extent and build an overall evaluation index system. This is shown in **Table 2**. When constructing the evaluation index model of WUE, this paper builds the input and output required by WUE based on the neoclassical growth theory and previous studies [5,36]. As for the input indicators, the number of employees, fixed assets, and total regional water consumption are selected to reflect this indicator. In terms of output indicators, regional GDP (based on 2009) and gray water footprint are selected to represent both the expected and unexpected output, respectively.

The STI evaluation index system comprises two standard levels, namely STI input and STI output, each consisting of seven indexes. This study has opted for three input indicators, namely the full-time equivalent of research and development (R & D) personnel, the internal expenditure of R & D funds, and the number of R & D institutions. As for output indicators, four have been chosen, comprising the number of patent authorizations, the number of R & D projects, the sales profit of new commodities in high-tech industries, and the number of advanced development projects in high-tech industries.

Based on the above indicators and methods, the framework of this research is established in **Figure 2**.

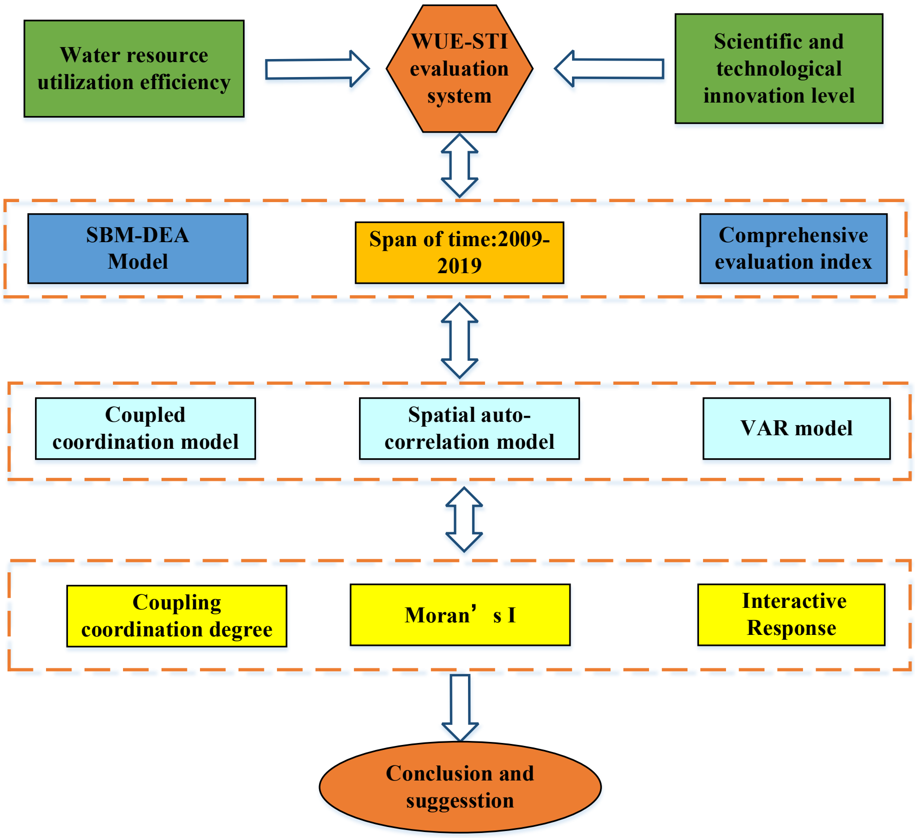

Figure 2. Research framework.

Table 2. Evaluation index system of WUE and STI.

Target level	Criterion level	Indicator level	Unit
WUE	Input indicators	Number of employees	Ten thousand people
		Fixed assets	RMB100 mil
		Total regional water consumption	100 million m^3
	Desirable output indicators	GDP	RMB100 mil
	Undesirable output indicators	Gray water footprint	10,000 t
STI	Investment in scientific and technological innovation	Number of R & D institutions	Individual
		R & D personnel full-time equivalent	Man year
		Internal expenditure of R & D funds	CNY10 thousand
	Scientific and technological innovation output	Number of patent authorizations	Piece
		Number of R & D projects (subjects)	Term
		Sales revenue of new products of high-tech industry	CNY10 thousand
		Number of new product development projects in high-tech industry	Term

Data source

All the information and data utilized in this academic article have been sourced exclusively from reliable and authoritative references. These include the China Statistical Yearbook, various provincial and city Statistical Yearbooks, China Science and

Technology Statistical Yearbook (covering the period from 2009 to 2019), Science and Technology Statistical Yearbook, Education Statistical Yearbook, Water Conservancy Statistical Yearbook, Water Resources Bulletin, and National Economic and Social Development Statistical Bulletin.

In cases where specific data points were unavailable, they have been estimated employing the average growth rate over the successive three-year period. This approach ensures a consistent and reliable analysis throughout the study. It is important to note that the scope of this analysis encompasses the 19 provinces located within the Yangtze River Basin, providing a comprehensive understanding of the region's dynamics and trends.

4. Result analysis

4.1 Spatial and temporal evolution characteristics of WUE and STI

Using the aforementioned methodologies, we have calculated the WUE index and STI index for the nineteen provinces located within the Yangtze River Basin from 2009 to 2019. Additionally, we have summarized the average values of each year for both indices and examined the CCD of the two systems. Upon careful analysis of **Figure 3**, it becomes evident that there is a consistent upward trend in the average values of WUE and STI within the Yangtze River Basin from 2009 to 2019. Furthermore, the time characteristics of the two indices exhibit a clear positive correlation. This correlation suggests a mutually reinforcing relationship between WUE and STI within the region.

Spatial and temporal distribution of WUE

(1) Temporal characteristics. In terms of temporal analysis, the average rate of the WUE index for the 19 provinces (autonomous regions) within the Yangtze River Basin exhibited a positive trend from 2009 to 2019. The average WUE index rose from 0.3041 in 2009 to 0.3800 in 2019, indicating a stable overall development and a favorable growth trajectory (**Figure 3**). These findings highlight the achievements made in water pollution prevention, energy conservation, emission cutback, and ecological control within the Yangtze River Basin in recent decades. The positive trend in WUE demonstrates the region's progress in the sustainable utilization of water resources.

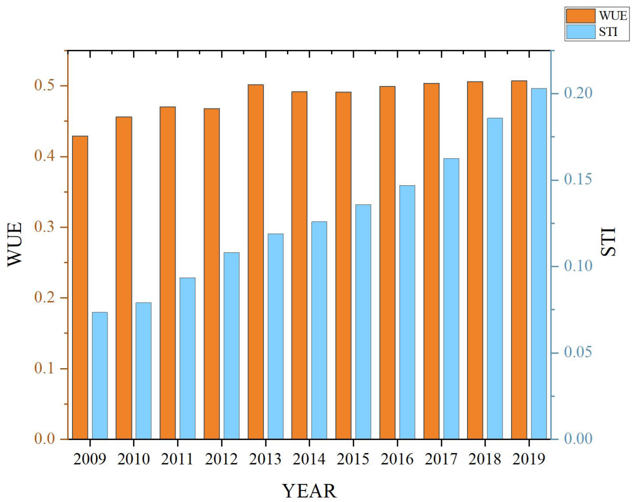

Figure 3. Time series change of WUE and STI in the Yangtze River Basin.

(2) This study employs the DEA model to compute the WUE of 19 provinces and regions located in the Yangtze River Basin from 2009 to 2019, and utilizes the initial, final, and middle years of the research period to investigate the findings within the study area. To better illustrate the dissimilarities in the spatial distribution of WUE in the Yangtze River Basin, ArcGIS10.2 software is employed to visualize the same in 2009, 2013, 2016, and 2019 (**Figure 4**), and subsequently assess the disparity in WUE among different regions. Based on the obtained results, the efficiency index is classified into five ranges using the natural breakpoint method (Jenks), whereby the higher the efficiency value, the darker the shade.

On the whole, the WUE of the Yangtze River Basin changes significantly from 2009 to 2019, and the efficiency value shows an upward trend. From a regional perspective, from 2009 to 2019, the WUE showed an overall development trend higher in the lower reaches and lower in the middle and upper reaches. The efficiency value of the upstream region changes obviously. Excluding that the efficiency value of Tibet remains at the low level of 0.2235, the efficiency value of other upstream provinces and regions fluctuates to varying degrees, and the spatial pattern changes obviously. In the middle reaches, the efficiency values of Jiangxi and Hubei increased to varying degrees in the four periods, while the efficiency values of Hebei and Hunan both decreased in 2016 after experiencing increases in 2009 and 2013; they increased again in 2019. There is no obvious fluctuation in the WUE in the downstream areas, showing a stable trend. Excluding that the WUE of Anhui remains at the low efficiency level of 0.2 to 0.3, the WUE of Guangdong, Fujian, Zhejiang, Shanghai, and Jiangsu is generally at a high efficiency level of 0.5 to 1.

Spatial and temporal distribution of STI

(1) Temporal characteristics. The temporal analysis reveals that the average value of the STI index for the 19 provinces and regions demonstrates a consistent upward trend, as depicted in **Figure 3**. This trend signifies that the STI of each province and region within the Yangtze River Basin is in a positive state and is progressing in a favorable direction. Over the period from 2009 to 2019, the overall evaluation index of STI in the Yangtze River Basin experienced a gradual increase, rising from 0.0735 in 2009 to 0.2030 in 2019. Notably, between 2013 and 2019, the comprehensive evaluation index of STI ranged between 0.1 and 0.2, indicating a moderate level of overall technological advancement within the region.

(2) Spatial features. To analyze the spatial distribution of STI, the comprehensive evaluation index value of STI is calculated by employing the overall entropy weight method. Additionally, ArcGIS 10.2 software is employed to visualize the STI in the years 2009, 2013, 2016, and 2019 (**Figure 5**). At the regional level, a consistent pattern of "downstream > midstream > upstream" is observed in the STI of the Yangtze River Basin across the four periods. The spatial pattern of the STI system remains relatively stable. At the provincial level, the STI of the provinces and regions within the Yangtze River Basin

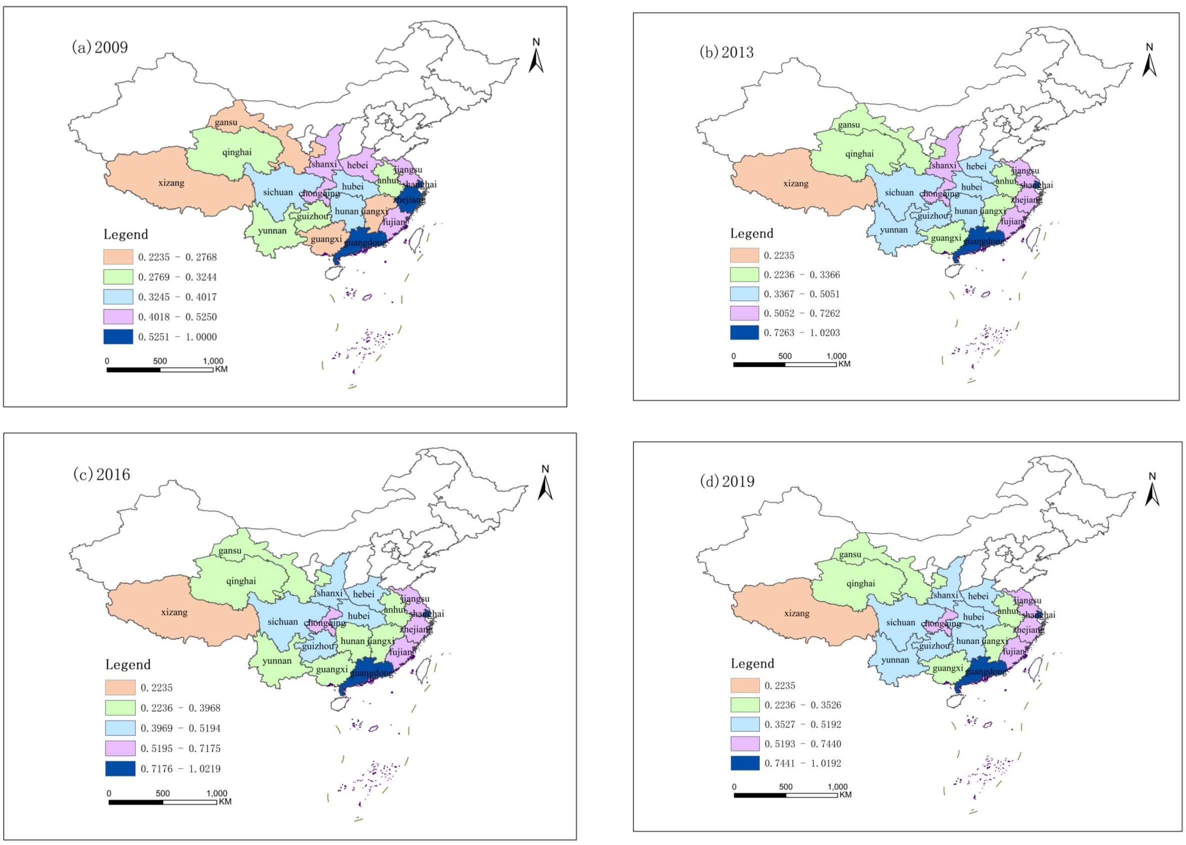

Figure 4. Spatial distribution of WUE of each province in the Yangtze River Basin.

exhibits varying degrees of improvement. There is a notable gap between the upper and middle reaches. On the contrary, the gap between the lower reaches is relatively small. Guangdong and Jiangsu consistently exhibit high STI indices across the four periods, consistently ranking in the top three and representing regions with a high level of STI. Conversely, Tibet and Qinghai consistently demonstrate lower STI indices, consistently ranking in the last three, indicating lower STI levels compared to other provinces and regions during the same period. These findings highlight the close relationship between STI and regional economic development. Provinces and regions with high economic development exhibit stronger human resource capabilities and other factors that contribute to the enhancement of regional STI.

4.2 Spatial and temporal distribution characteristics of CCD

Time characteristics

From the time series changes, the mean value of CCD of the two subsystems showed an increasing trend from 2009 to 2019 (**Figure 6a**). This trend suggests that there was an enhancement in the interaction between WUE and STI. Specifically, the coupling coordination level between WUE and STI during the study duration was within the basic coordination stage from 2009 to 2011, and progressed to the moderate coordination stage from 2012 to 2019. It is noteworthy that the stable improvement of the coupling coordination level throughout the research period was due to the common progress of both subsystems. Improvement in STI provided impetus for WUE, while the progress in WUE in turn facilitated STI improvement, leading to a joint promotion of the coupling coordination level from the basic coordination stage to the intermediate coordination stage. Overall, the coupling coordination level between WUE and STI in the Yangtze River Basin exhibited a positive trend; however, there is still room for further advancement in the overall coordination level.

From the perspective of basin division (**Figure 6b**), the mean CCD of the lower reaches of the Yangtze River Basin is higher than that of the upper reaches. There are significant differences among different river basins. The average value of the upper reaches of the Yangtze River Basin is between 0.2-0.4, which belongs to the basic coordination stage; the average value of the middle reaches is between 0.4-0.5, which belongs to the moderate coordination stage; while the average value of the lower reaches is between 0.4-0.7, which is mostly in the highly coordinated stage. Mainly due to the influence of geographical factors and regional economic conditions among regions, the eastern coastal areas are relatively developed economically and have higher investment in scientific and technological innovation, so the CCD of STI and WUE is better.

Spatial distribution characteristics

To evaluate the spatial distribution characteristics of the CCD of the two subsystems, the provinces and regions are taken as the basic units, and 2009, 2013, 2016, and 2019 are selected as the representative years. The CCD is visualized using ArcGIS10.2 software, and the spatial distribution map of the CCD is drawn. The results are shown in **Figure 7**.

During the study period, the CCD of all provinces is generally not high, and most provinces and regions are in the basic coordination stage in the early stage. Thanks to the continuous progress of WUE and STI, the CCD of all provinces and regions shows an upward trend. From the regional aspect, the CCD of the two systems in the lower reaches is significantly higher than that in the upper and middle reaches of the Yangtze River Basin. Specifically, in 2009, the two regions of Guangdong and Jiangsu were highly coordinated, the two regions of Tibet and Qinghai were loosely coordinated, and the other regions were in moderate coordination. In 2016, highly coordinated provinces and cities began to appear in Guangdong, and then in 2019, highly coordinated provinces and cities were added in Jiangsu. The CCD of the two subsystems in Anhui, Fujian, and Hebei provinces, in the lower reaches of the Yangtze River, changed from basic coordination in 2009 to high coordination in 2019 after experiencing moderate coordination in 2013 and 2016. The CCD of Shanghai, Hubei, and Sichuan subsystems experienced three periods of moderate coordination, after that is then rose to high coordination in 2019. In the three periods of 2009, 2013, and 2016, the CCD of the two subsystems in Jiangxi, Chongqing, and Shaanxi had been in the basic coordination stage, but in 2019, they entered the medium coordination stage. Between 2009 and 2019, there was a decrease in the number of provinces and regions that of basic coordination, while the number of highly coordinated provinces and regions showed an increase. This trend indicates an enhanced coordination between WUE and STI during the coupling process. Notably, the CCD of the two subsystems remains the most stable in Guangxi, Guizhou, Yunnan, Tibet, Gansu, and Qinghai, which are adjacent to the lower reaches of the Yangtze River Basin. However, these regions have predominantly remained in the basic coordination or low-level coordination stage, and the rate of improvement has been relatively slow.

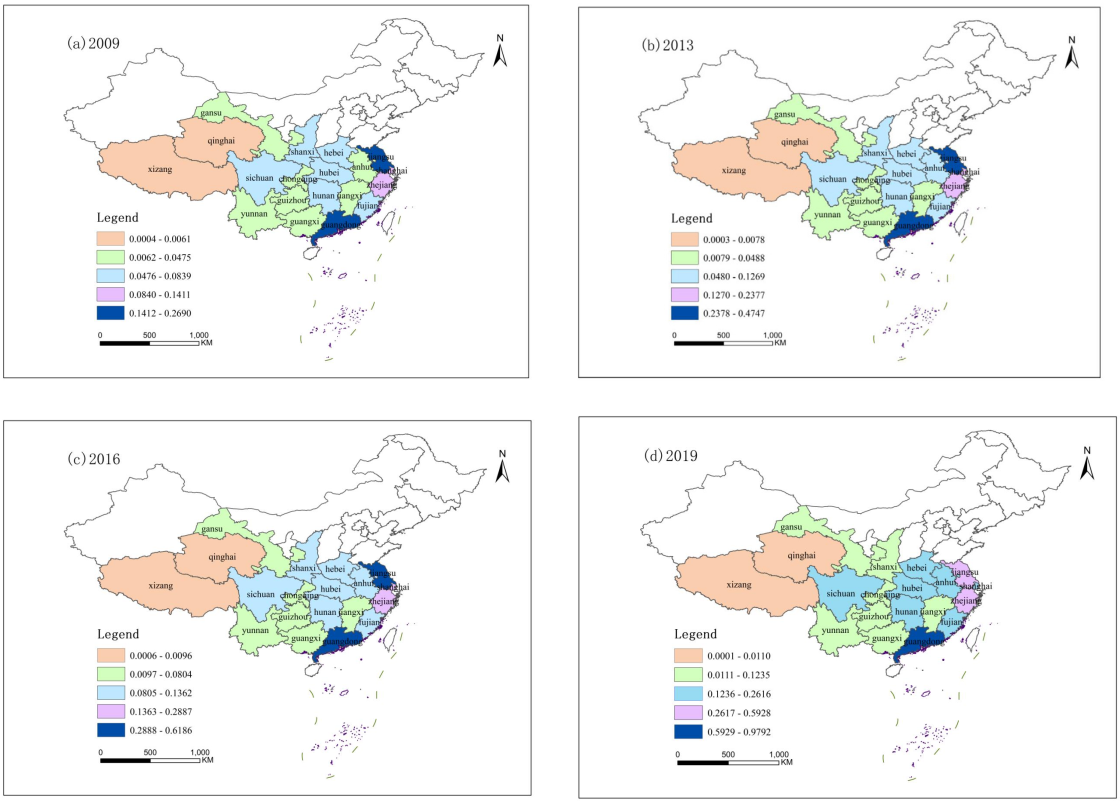

Figure 5. Spatial distribution of STI of each province in the Yangtze River Basin.

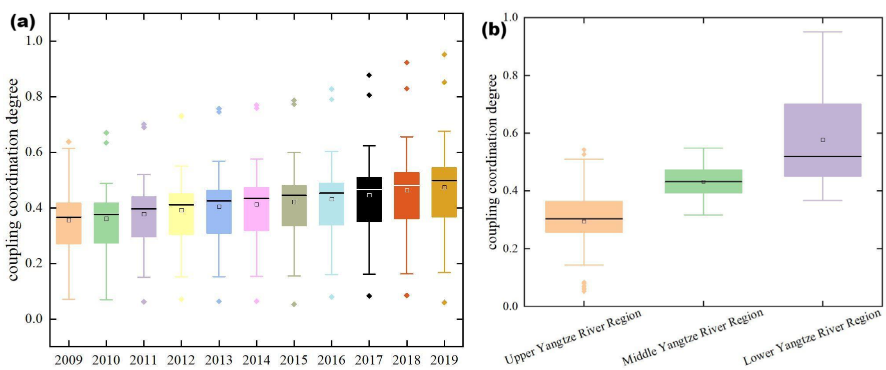

Figure 6. CCD mean time series change.

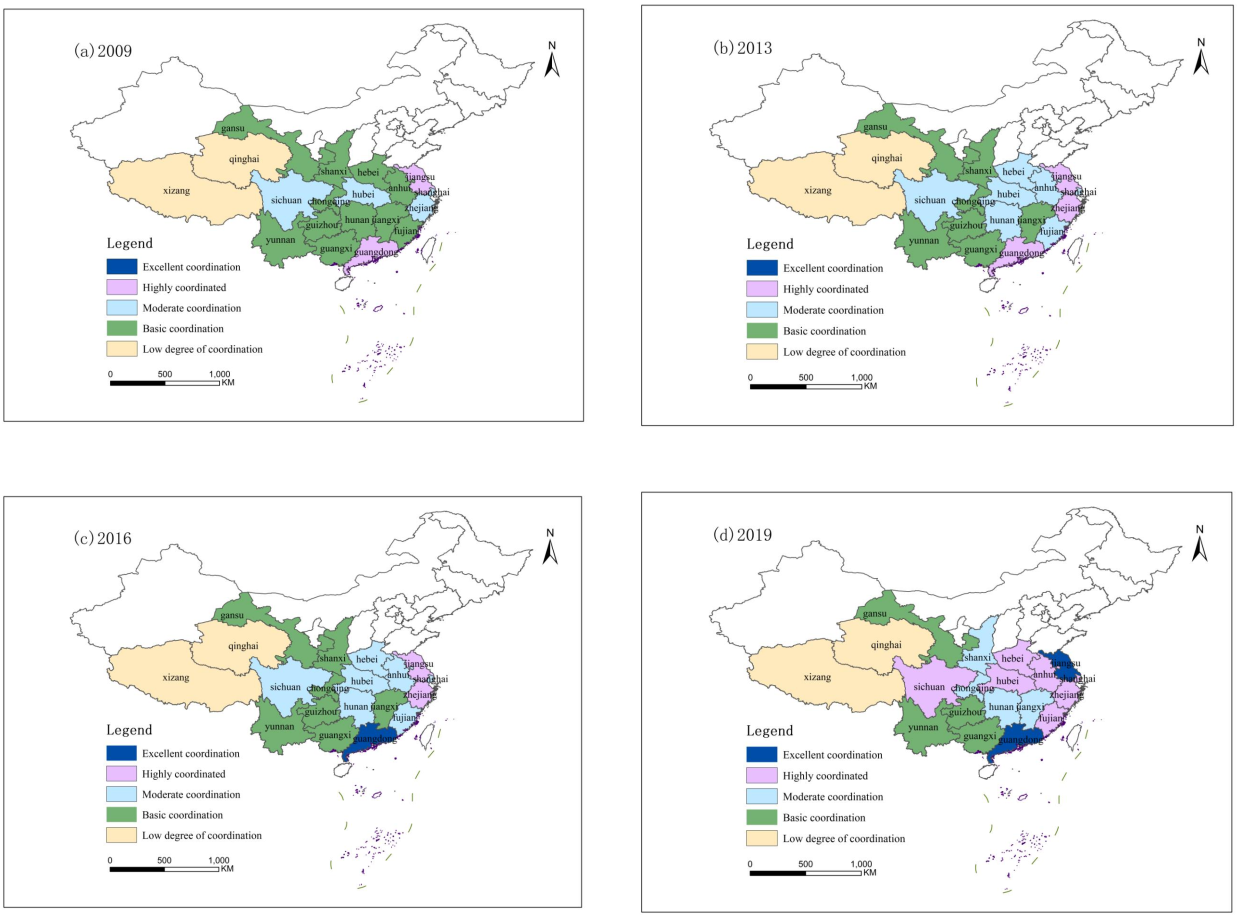

Figure 7. Spatial distribution of CCD between WUE and STI in the Yangtze River Basin.

4.3 Spatial correlation pattern analysis of CCD

The geographical spatial relationship among the 19 provinces in the Yangtze River Basin was taken into account by using distance spatial weight. GeoDa software was utilized to calculate the global Moran's I value. The results of this analysis are summarized in **Table 3**. The findings reveal a significant positive spatial correlation between the coupling coordination level of WUE and STI during the investigation period. This conclusion is supported by statistical indicators such as Moran's I, Z, and P values, which indicate a clear positive spatial autocorrelation.

Table 3. Global Moran's I of CCD.

Year	Moran's I	Z value	P value
2009-2013	0.2873	2.7935	0.0052
2013-2016	0.2915	2.8605	0.0042
2016-2019	0.3080	2.9154	0.0036

The precise location of the provincial spatial cluster and the intensity of regional correlation were determined using the local spatial autocorrelation index. This analysis also characterized the local spatial agglomeration features of the CCD in WUE and STI for the years 2009, 2013, 2016, and 2019. ArcGIS 10.2 software was employed to perform analytical processing on the spatial clustering results, resulting in the generation of a LISA clustering map for the CCD (**Figure 8)**. This map provides a visually striking representation of the spatial heterogeneity of the CCD in the Yangtze River Basin. The local spatial correlation characteristics can be classified into two categories: High-High (H-H) concentration and Low-Low (L-L) concentration, observed in both subsystems of the Yangtze River Basin.

The H-H concentration area refers to provinces or cities with a high CCD between WUE and STI. In 2013 and 2016, Jiangsu was the only province in this category, and its spatial pattern remained unchanged. However, in 2019, influenced by the surrounding provinces and cities, Jiangsu withdrew from the H-H cluster, resulting in zero provinces in this category. Provinces and cities in the H-H concentration area play a crucial role in regional coordinated development and are considered the weak points in provincial development. It is challenging for these regions to improve WUE and STI solely based on their own resources. Therefore, it is crucial for them to enhance connections with surrounding provinces and formulate targeted development strategies to make breakthroughs and promote WUE and STI.

L-L concentration area. In the four periods of 2009, 2013, 2016, and 2019, Tibet and Qinghai remained in the L-L concentration area, with no evident difference in their spatial distribution. The CCD of WUE and STI in this region is consistently low, indicating a need for improvement in regional coordinated development. The L-L agglomeration areas should be prioritized as the main focus for enhancing the level of coupling and coordination. To improve the coupling and coordination development in these provinces, it is important to strengthen exchanges and cooperation with surrounding provinces and cities, and formulate a development path that aligns with the specific circumstances of the region.

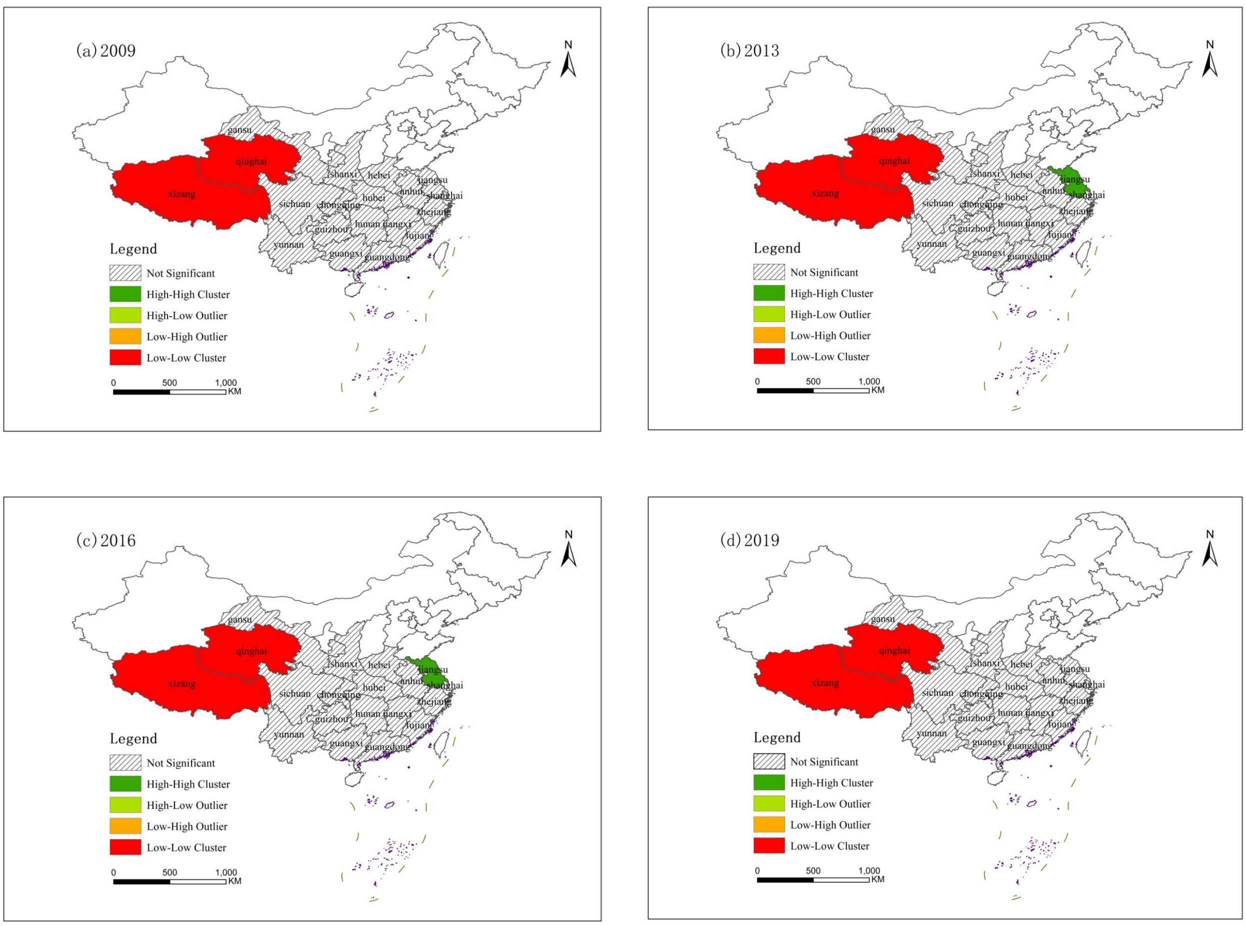

Figure 8. LISA concentration diagram of CCD.

4.4 Interactive response relationship between WUE and STI

Unit root inspection

The premise of the proposed VAR model is that the variables follow a single-order unit process. In this paper, ADF unit root test is performed on the level of each variable by using Eviews10.0 software (**Table 4**). There are three auxiliary equations for ADF test and three auxiliary equations for DF test:

(1) No intercept term and no trend term:

$$\Delta y_t = \rho y_{t-1} + \sum_{i=1}^{k} \gamma_i \Delta y_{t-i} + u_t \tag{20}$$

(2) Contains only intercept term:

$$\Delta y_t = c + \rho y_{t-1} + \sum_{i=1}^{k} \gamma_i \Delta y_{t-i} + u_t \tag{21}$$

(3) Contains intercept term and time trend term:

$$\Delta y_t = c + \alpha t + \rho y_{t-1} + \sum_{i=1}^{k} \gamma_i \Delta y_{t-i} + u_t \tag{22}$$

where the symbol Δ represents the first-order difference operator, c is the intercept term, αt is the trend term, $\sum_{i=1}^{k} \gamma_i \Delta y_{t-i}$ is n-distributed lag terms, u_t is the stationary random error term, and k is the maximum lag for determining u_t to satisfy the white noise. According to the calculation results of the three equations and the comparison of Akaike, the variables of WUE and STI are stable, with intercept term and time trend term.

According to the lag order information criterion, the optimal lag order is 8. Based on the criterion, the Granger causality test is performed on the above data. The results show that the P value of STI on WUE is 0.0000 (< 0.05), and the P value of WUE on STI is 0.0000 (< 0.05), which indicates that there is a two-way causal relationship between WUE and STI in each district and county, that is, WUE and STI are mutually endogenous variables.

Impulse response analysis based on panel VAR

In the Yangtze River Basin, it has been observed that the WUE and STI exhibit a notable positive response to the self-generated impulse in the first period, which gradually weakens until it is no longer significant. The study findings indicate that the self-enhancement mechanism of WUE persisted up to the fifth stage (**Figure 9a**), while that of STI continued up to the second stage (**Figure 9d**). These outcomes suggest that the different provinces and regions have varying degrees of self-enhancement and path dependence for STI and WUE. Therefore, in addition to harnessing the self-enhancement mechanism, proactive measures must be implemented to avert any possible weakening of this mechanism.

Table 4. Inspection results of unit root.

	Level	T statistic	P value
WUE		–12.0080	0.0000
	1%	–4.0061	
	5%	–3.4332	
	10%	–3.1404	
STI		–10.5488	0.0000
	1%	–4.0060	
	5%	–3.4332	
	10%	–3.1404	

With regard to the driving effect of STI on WUE (**Figure 9c**), it is evident that while the former has an effect on the latter, the impacts are not very strong. A crucial factor responsible for this limited effect is the presence of a technical support system that impedes technological innovation in WUE, given the high level of uncertainty involved. Furthermore, the spatial accumulation effect of each district and county is not readily discernible, making it challengingly to pinpoint an overall effect. In response to WUE, the STI does not show an obvious impact, that is, the WUE has no significant encouraging effect on the STI (**Figure 9b**).

Prediction variance decomposition

The variance decomposition analysis provides insights into the cumulative contribution of one variable to another variable over time. **Table 5** presents the results of the variance decomposition, revealing important trends. The impact of WUE on itself shows a declining trend, decreasing from 100% in the first phase to 85.62% in the tenth phase. Conversely, the contribution of WUE to STI shows an increasing trend, starting from 0% in the first phase and reaching 14.38% in the twentieth phase. These findings indicate that WUE has a practical significance in promoting STI, as it plays a role in positively influencing STI over time.

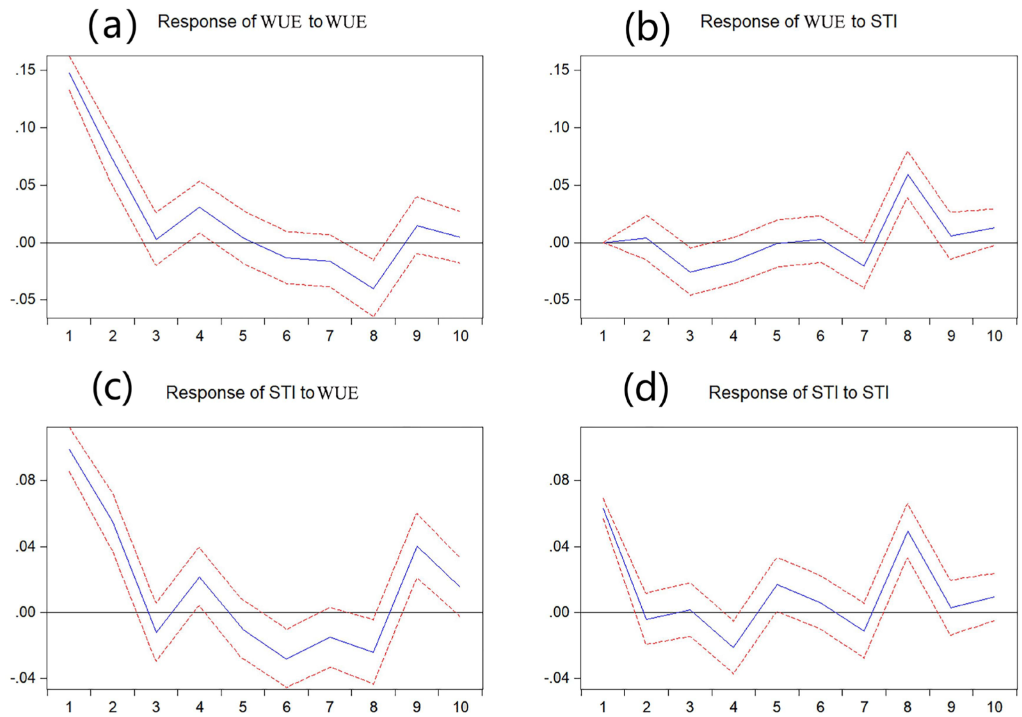

Figure 9. Impulse response of WUE and STI.

The impact of STI on its own decreased first and then increased, but the overall increase, from 28.85% in the first stage to 30.40%, reflects the self-improvement of STI. This suggests that STI has been experiencing self-improvement and growth. However, the impact of STI on WUE exhibits a declining trend, decreasing from 71.15% in the first phase to 69.60% in the tenth phase, albeit at a slow rate. This indicates that STI has a strong and sustainable role in promoting WUE.

Table 5. Variance decomposition results estimated based on panel VAR model.

Number of periods/period	WUE		STI	
	WUE	STI	WUE	STI
1	100.00	0.00	71.15	28.85
2	99.94	0.06	76.33	23.67
3	97.56	2.44	76.52	23.48
4	96.75	3.25	75.19	24.81
5	96.75	3.25	74.16	25.84
6	96.75	3.25	75.10	24.90
7	95.43	4.56	74.90	25.10
8	86.03	13.97	67.37	32.63
9	86.03	13.97	69.55	30.44
10	85.62	14.38	69.60	30.40

5. Conclusions and suggestions

5.1 Conclusions

The Yangtze River Basin plays a significant function in the economic development of China in the present era. Efficient utilization of water resources is vital for promoting sustainable development of the economy and society in this area, given its crucial ecological value. Enhancing WUE is essential for achieving ecological protection and fostering sustainable development in this region. STI is recognized as a key driver to overcome the challenges associated with low water resource efficiency. To delve deeper into this matter, the present study utilizes relevant data from 19 provinces and regions within the Yangtze River Basin spanning the years 2009 to 2019. Through the application of a coupling and coordination model, an indicator system is established to assess the coupling and coordination relationship between WUE and STI. Furthermore, a VAR model is employed to examine the relationship between WUE and STI, shedding light on their interdependence and mutual influence.

(1) A comprehensive analysis of the two systems reveals their overall growth, but also highlights the disparity in their development. The progress of WUE outpaces that of STI. For the spatial distribution, WUE shows a pattern of higher values in the lower reaches, followed by the higher middle reaches and lower upper reaches of the Yangtze River Basin. Similarly, the distribution of STI across different provinces and regions also exhibits a division into lower, middle, and upper reaches, with the lower reaches displaying higher values compared to the middle and upper reaches.

(2) Over time, the CCD values of both the WUE and STI subsystems in the Yangtze River Basin regions have shown varying degrees of improvement. Notably, provinces such as Guangdong, Zhejiang, Shanghai, and Jiangsu have demonstrated significant advancements, with their CCD values consistently leading across all stages. In particular, Guangdong and Jiangsu have achieved high-quality coordination between WUE and STI. However, it is essential to note that the other areas in the region have yet to reach this stage of high-quality coordination and further progress is required in these regions.

(3) The spatial distribution of the CCD in the Yangtze River Basin reveals two distinct patterns: H-H agglomeration areas and L-L agglomeration areas. There are no regions exhibiting L-H or H-L agglomeration. Furthermore, the degree of CCD agglomeration in most provinces is not pronounced. The L-L concentration areas are primarily observed in Tibet and Qinghai, situated in the upper reaches of the Yangtze River. On the other hand, the H-H concentration area is solely located in Guangdong in the lower reaches. The polarization of agglomeration in the basin indicates an imbalance and inadequacy in the coupling coordination of WUE and STI. Consequently, it is crucial for all regions within the basin to prioritize enhancing the mutual development of both subsystems to achieve better coordination and balance.

(4) Moreover, it is observed that the STI does not exhibit a substantial response to the influence of WUE, while WUE demonstrates a noticeable response to STI. Both systems display diverse levels of self-enhancement and path dependence. Hence, the optimization of the interaction between these subsystems should be prioritized in order to achieve sustainable development in the Yangtze River Basin.

5.2 Suggestions

To facilitate the coordinated development of WUE and STI in the Yangtze River Basin, the current study offers several recommendations derived from the aforementioned research findings and the prevailing conditions within the basin.

(1) Efforts should be made to enhance WUE in the Yangtze River Basin region. It is imperative to ensure the strict implementation and continuous improvement of regulations pertaining to water resources management, taking into account the current developmental context. Stringent control measures should be imposed on total water consumption, with the refinement of consumption indicators at various levels and effective monitoring of compliance by provincial entities. Rational allocation of water resources is crucial, necessitating the implementation of robust planning and allocation strategies. The intensity of water resource development within the basin should be carefully controlled to maintain a sustainable balance. Coordinated management of water demand for different purposes is essential, while ensuring that ecological water replenishment is not compromised.

(2) Efforts should be directed towards enhancing the STI and achieving sustainable and environmentally friendly development in this regard. Provinces and autonomous regions within the Yangtze River Basin should prioritize optimizing their industrial structures by promoting the growth of low-energy consumption, eco-friendly, and high-tech industries, as well as emphasizing environmental protection and ecological industries. This approach will facilitate the realization of green development within the STI domain. Moreover, it is essential to allocate increased investments towards research and development (R & D) funds and advanced equipment to support scientific research and foster innovation activities.

Furthermore, there should be a focus on nurturing a pool of skilled scientific researchers, expanding the team of innovative talents, and facilitating the successful transformation of STI achievements.

(3) The coordinated development of WUE and STI should be attended to. The achievements of STI will be applied to the management and protection of water resources in the Yangtze River Basin. Through STI, the WUE will be promoted, and the pressure on water environments will be reduced. All provinces and regions should take into account the strengthening of the capacity of STI and the improvement of WUE, establish and improve the linkage between the two, achieve the two-pronged approach, and ensure coordinated development.

Author Contributions

Guangming Yang: Supervision, Funding acquisition. **Fengtai Zhang:** Conceptualization, Supervision. **Junyue Liu:** Formal analysis. **Qingqing Gui:** Data curation, Writing–original draft. **Siyi Cheng:** Visualization, Methodology.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The authors do not have permission to share data.

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