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The coupling and coordination characteristics of agricultural green water resources and agricultural economic development in China

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Abstract
Water resources are the source of life for people to survive, especially in agriculture. Water resources provide necessary support for agricultural economic development and irrigation management. Using the panel data from 2013 to 2019, this paper uses the coupled coordination model to explore the degree of synergy between agricultural water resources efficiency (AWRE) and agricultural economic development level (AEDL), and analyzes the spatial correlation of coupling coordination degree (CCD) between the AWRE and AEDL, and further predicts the relationship between the two. The results are as follows: (1) There are superb variations in the CCD among provinces, and the diploma of coordination is greater in the south than in the north; (2) In the spatial correlation pattern, high–high agglomeration areas exhibit an growing trend, and the variety of low–low agglomeration areas is small; and (3) Through the prediction, it is found that in the further, the CCD will show a trend of slow increase in future. For purpose of the coordinated perfection of the two systems, we need to completely discover the connotation of coordinated improvement and promote regional cooperation.

Keywords Agricultural water resources efficiency (AWRE) · Agricultural economic development level (AEDL) · Coupled coordination · Spatial autocorrelation

1 Introduction

The ecological environment is very important. Protecting green waters and mountains and making people feel at ease have become the objective requirements of implementing the people-centered development concept. The vast countryside has become the main

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battlefield of green development. The goal of agricultural development has changed from increasing production and income to stabilizing production, increasing income and sustainable. Despite the remarkable achievements of modern agriculture, the water pollution caused by high-yield varieties and the large application of related chemical fertilizers and pesticides has attracted some criticism. Agricultural drainage have become an important source of pollution in China. China is the biggest a creating country in the world, which makes the international community place more expectations on China's contribution to pursuing the global sustainable development Goals. Therefore, China desires to enhance water use effectivity in accordance to its very own improvement state of affairs to meet worldwide expectations. Only by way of focusing on environmental safety while creating the financial system can China reap inexperienced and sustainable development.

Agriculture cannot develop without water support, but agricultural activities can cause pollution to the environment (Ismael et al., 2018). The irrational invest of land and water, the go beyond the limit invest of fertilizers, the invest of energy and many other aspects may cause the degradation of land quality and water pollution. Over-exploitation of arable land and increased resource constraints may affect agricultural development (Yao et al., 2021). In water-scarce areas, overuse of water for agriculture can damage ecological water resources and affect the function of the ecological sector (Zhang et al., 2016). The damaged ecology will readjust the water allocation. This may lead to water shortages for agriculture (Youzhi et al., 2021). The continued consumption of water for agricultural economic development leads to a reduction in water stocks, which in turn will further constrain the agricultural economy (Wu et al., 2022). Improving agricultural water efficiency is therefore essential for agricultural economic development.

This study, which aims to measure the coupled coordination of AWRE and the AEDL. We identify the areas with low coupling coordination and provide suggestions to improve the current situation. For this purpose, the SBM-DEA model and the combination of entropy method are employed for the purpose of calculating the AWRE and the AEDL.

As a result of to the special nation of herbal water assets in specific regions, the water consumption of every area is additionally different. Some scholars have used integrated analysis methods to analyze water resources efficiency (Guan et al., 2019; Sun et al., 2020). Compared with the comprehensive evaluation and analysis method, the efficiency measurement methods (SFA, DEA, SBM, etc.) based on the goal planning model have the advantages of not being affected by the input–output volume, so they have become the mainstream evaluation approach of AWRE (Deng et al., 2016; Geng et al., 2019; Laureti et al., 2021; Pan et al., 2020). With the deepening of research, scholars gradually pay attention to the unexpected output and consider the AWRE (Liu & Yuan, 2022; Song et al., 2022). In short, the learn about on water assets effectivity measures has been pretty mature. In this context, this research focuses the relationship between AWRE and AEDL the usage of the applicable strategies from preceding studies.

Cui et al. (2019) and Li & Li (2021) concluded that water quality is the key to agricultural economy and that a good water environment is what promotes economic progress. Hao et al. (2019) found that water resources and economic development are mutually influential. Wang et al. (2018) also argued that rapid growth of economy cannot be achieved without the use of water resources. Zhang et al. (2021) and Ngoran et al. (2016) studied the affect of water on the saving in arid regions of China and sub-Saharan African countries, respectively. They agree that water resources are important for economic growth, especially in countries with severe water shortages like those in Africa. Doungmanee (2016) found that water shortages run the risk of causing economic stagnation. Xing et al. (2020) regulated a study on the coupled correlation between AWRE and AEDL, and concluded that the essential deputy hindering the pullulate of a coupled degree of coordination between the two is regional differences.

From the related studies, most scholars have studied mainly the correlation between AWRE and AEDL. Most of the investigation outcomes are that the use of water resources takes an essential part in economic growth. They think that the agricultural sector is the sector that uses more water, and that water shortages and inadequate water use can lead to economic stagnation. In the studies of agricultural water use on the economy, it is mostly the overall economy, not the agricultural economy associated with agricultural water use. For countries where agriculture is crucial to economic development, it is important to increase agricultural productivity and use water resources efficiently. Therefore, based totally on preceding researches, this paper concentrate on the connection between AWRE and AEDL.

On the ground of the current lookup literature, through coupling the AEDL with the AWRE, we discover the diploma of coupling and coordinated improvement of 31 provinces in China, behavior aggregation evaluation and future prediction on the CCD, and similarly find out the troubles and future improvement route between the AWRE and the AEDL.

2 Data sources and methods

2.1 Index selection and data source

Referring to concerned papers (Cui et al., 2019; Xu et al., 2020; Yang et al., 2019), we, respectively, select the indicators that can largely reflect China AWRE and AEDL (Yang et al., 2022a). In the index system, the AWRE system includes two rule layers: AWRE input and output (Liu et al., 2020; Lu et al., 2021; Wang et al., 2019; Zhang et al., 2022). The AEDL system includes three rule layers: agricultural development foundation, agricultural development benefit, and residents' living standard (Abreu et al., 2019; Chen et al., 2022; Ma et al., 2019). The details are shown in Table 1. The data are mainly from official channels such as the *National Statistical Yearbook* and the *Statistical Bulletin of National Economic and Social Development from 2013 to 2019*.

2.2 GWF calculation

Agricultural grey water footprint (GWF_{agr}) includes planting grey water footprint (GWF_{pla}) and aquaculture grey water footprint (GWF_{bre}). When calculating the GWF, the GWF generated by the same type of pollutants are aggregated, and the grey water footprints generated by different types of pollutants are taken as the maximum. The formula is as follows (Fu et al., 2022; Zhang et al., 2019, 2022):

$$\mathrm{GWF}_{\mathrm{agr}} = \max\left[\mathrm{GWF}_{\mathrm{bre(COD)}}, \left(\mathrm{GWF}_{\mathrm{pla(TN)}} + \mathrm{GWF}_{\mathrm{bre(TN)}}\right)\right] \quad (1)$$

$$\mathrm{GWF}_{\mathrm{pla}} = \frac{\alpha N_{\mathrm{Appl}}}{C_{\mathrm{TN,max}} - C_{\mathrm{TN,nat}}} \quad (2)$$

Table 1 Index system

Target layer	Rule layer	Index layer
AWRE	Agricultural water resources input	Agricultural water consumption
		Actual cultivated land area at the end of the year
		Agricultural labor population
		Agriculture, forestry and water expenditure
	Expected output of agricultural water resources	Gross Agricultural Product
	Unexpected output of agricultural water resources	Grey water footprint
AEDL	Development basis	Rural power consumption
		Total power of agricultural machinery
		Agricultural total factor productivity
		Fertilizer application amount
		Pesticide consumption
		Total investment in rural fixed assets
	Development benefits	Total output value of agriculture, forestry, animal husbandry and fishery
		Total meat output Grain output
	Residents' living standards	Engel coefficient of rural households
		Per capita disposable income of rural residents
		Health care consumption expenditure
		Retail sales of social consumer goods

$$\mathrm{GWF}_{\mathrm{bre}} = \max\left(\mathrm{GWF}_{\mathrm{bre(COD)}}, \mathrm{GWF}_{\mathrm{bre(TN)}}\right) \tag{3}$$

$$\mathrm{GWF}_{\mathrm{bre}(i)} = \frac{L_{bre(i)}}{C_{i,\max} - C_{i,\mathrm{nat}}} \tag{4}$$

Among, $L_{\mathrm{bre}(i)} = \sum_{h=1}^{4} N_h D_h \left(f_h p_{hf} \beta_{hf} + u_h p_{hu} \beta_{hu}\right)$

In the formula, α is the leaching rate of nitrogen fertilizer; N_{Appl} is the total amount of nitrogen fertilizer applied; $C_{\mathrm{TN,max}}$, $\mathrm{C}_{\mathrm{TN,nat}}$ is the water capability standard convergence of total nitrogen and the natural local convergence of total nitrogen; $\mathrm{GWF}_{\mathrm{bre}(i)}$, $L_{\mathrm{bre}(i)}$ is the GWF of the aquaculture industry of category *I* pollutants; *i* is total nitrogen or chemical oxygen demand; h means cattle, sheep, pigs and poultry; and N_h, D_h, f_h, u_h, P_{hf}, β_{hf}, and β_{hu} are the quantity of h feeding cycle, daily fecal output, daily urine output, contaminant directory in unit urine, pollutant content in unit feces, pollution logistics loss rate in unit feces, and pollution logistics loss rate in unit urine, respectively.

2.3 SBM-DEA model

TONE (2004) proposed a SBM model based mainly on slack variable to solve the input–output leisure issue (Yang et al., 2022b). The formula is as follows (Chen et al., 2021; Chu et al., 2016; Pishgar-Komleh et al., 2021; Ren et al., 2019):

$$\rho = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}}}{1 + \frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{ro}^g} + \sum_{r=1}^{s_2}\frac{s_r^b}{y_{ro}^b}\right)} \tag{5}$$

$$\text{s.t.}\begin{cases} \sum_{j=1}^{n}\lambda_j x_{ij} + s_i^- = tx_{io}, i = 1, 2, \dots, m \\ \sum_{j=1}^{n}\lambda_j y_{rj}^g - s^g = ty_{ro}^g, r = 1, 2, \dots, s \\ \sum_{j=1}^{n}\lambda_j y_{rj}^b - s^b = ty_{ro}^b, r = 1, 2, \dots, s \\ t + \frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{ro}^g} + \sum_{r=1}^{s_2}\frac{s_r^b}{y_{ro}^b}\right) = 1 \end{cases} \tag{6}$$

In the formula, $x = \left(x_1, x_2, \dots x_m\right)^{\mathrm{T}}$ is the input factor, $y = \left(y_1^g, y_2^g, \dots y_s^g\right)^{\mathrm{T}}$ and $y^b = \left(y_1^b, y_2^b, \dots y_s^b\right)^{\mathrm{T}}$ represent the expected and undesired outputs, respectively. ρ represents the calculated efficiency;λ represents the weight coefficient of input and output; s^g, s^b, respectively, represent the expected and non-expected output of the relaxation variable.

2.4 Model for measuring the AEDL

The entropy weight method is used to calculate the weight (Cui et al., 2019; Liu et al., 2021; Ma et al., 2022). Therefore, this paper first standardized each indicator. The details are as follows:

$$\mu_{ij} = \frac{X_{ij} - \min X_{.j}}{\max X_{.j} - \min X_{.j}} \tag{7}$$

$$\mu_{ij} = \frac{\max X_{.j} - X_{ij}}{\max X_{.j} - \min X_{.j}} \tag{8}$$

Equation (7) is positive index standardization treatment, and Eq. (8) is negative index standardization treatment. X_{ij} is the primitive value, μ_{ij} is the jth index of the ith subsystem. The calculation steps are outlined below.

Index information entropy calculation:

$$e_j = \frac{1}{\ln m}\left(\sum_{i=1}^{m} f_{ij} \times \ln f_{ij}\right) \tag{9}$$

In the formula, $f_{ij} = \left(1 + \mu_{ij}\right) / \sum_{i=1}^{m}\left(1 + \mu_{ij}\right) \quad 0 \le e_j \le 1$

Redundancy calculation: $\theta_j = 1 - e_j$

Index weight calculation:

$$w_j = \frac{\theta_j}{\sum_{j=1}^{n}\theta_j} \tag{10}$$

System comprehensive score calculation:

$$\mu_j = \sum_{j=1}^{n} w_j \times \left(1 + \mu_{ij}\right) \quad (i = 1, 2, \ldots, m) \tag{11}$$

2.5 CCD model

The coupled coordination model is a good way to measure the development status between AWRE and AEDL. The model is built as follows (Cui et al., 2019; Liu et al., 2021; Yang et al., 2019):

$$C = 2\left[\frac{\mu_1 \times \mu_2}{\left(\mu_1 + \mu_2\right)^2}\right]^{\frac{1}{2}} \tag{12}$$

$$T = \alpha\mu_1 + \beta\mu_2 \tag{13}$$

$$D = \sqrt{C \times T} \tag{14}$$

In formula (12), μ_1 and μ_2 are the entirety evaluation indexes of AEDL and AWRE, respectively. The value of $D \in [0, 1]$, when $D = 1$, it represents that the two systems are in the best coordination state. When $D = 0$, represents that the two systems are unrelated. In this paper, both are considered equally important, so $\alpha = \beta = 0.5$. The coupling coordination levels are shown in Table 2 (Xu et al., 2020).

2.6 Spatial autocorrelation analysis

Spatial autocorrelation analysis can explore the spatial correlation degree of data and reflect its spatial clustering characteristics (Cen et al., 2020). Global Moran's I(MI) can reflect the spatial agglomeration state of data (Ma et al., 2021). The unique components of the global MI is as follows (Yang et al., 2021):

$$I = \frac{n \times \sum_{i=1}^{n} \sum_{j\neq 1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\left(\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}\right) \times \sum_{i=1}^{n} (x_i - \overline{x})^2} \tag{15}$$

In the above equation, I is MI, n is the quantity of provinces, $x_i$andx_j are the CCD of the location of the province and city, respectively, and $\overline{x}$ is the average of the CCD. W_{ij}

Table 2 The level of coupling coordination

Coupling coordination degree (CCD)	Level
0–0.20	Low coordination
0.20–0.40	Basic coordination
0.40–0.50	Moderate coordination
0.50–0.80	High coordination
0.80–1.00	Quality coordination

Indicates the neighbor relationship between provinces. W_{ij}=1 when i and j are adjacent, otherwise 0.

In order to replicate the unique spatial place of data, local MI is additionally used to discover the imbalance of CCD in neighborhood space (Sarrión-Gavilán et al., 2015). The formula is described as follows:

$$I_i = \frac{(x_i - \overline{x})}{m_0} \sum_j W_{ij}(x_j - \overline{x}) \tag{16}$$

In the above formula, x_i is the value of CCD of provinces; $\overline{x}$ is the average value of CCD of provinces (Anselin, 1995).

2.7 GM (1,1) grey prediction model

Grey system theory can carry out specific description, prediction, decision-making and control for this system with incomplete information (Zeng et al., 2022). The model established by the grey system theory and method is called the grey model, which is a differential equation of n order and h variables. The model is constructed as follows (Song and Mei, 2021; Yao et al., 2020):

1. The original system sequence is $X_0 = \{X_0(i)\}(i = 1, 2, \ldots, n)$. Through the formula $X_1(k) = \sum_{i=1}^{k} x_0(i)$, the original system sequence is accumulated to generate the sequence $X_1 = \{X_1(i)\}(i = 1, 2, \ldots, n)$.
2. To improve the accuracy of model generation, the generated X_1 is averaged to generate $Z_1 = \{z_1(1), z_1(2), \ldots, z_1(n)\}$, where $z_1(1) = x_1(1), z_1(k) = \left(x_1(k) + x_1(k-1)\right)/2$.
3. Construction $\frac{dx_1(k)}{dk} ax_1(k) = u$, where $k = 1, 2, \ldots, n-1$, a and u are parameters to be estimated. It is rewritten as a matrix form $\overline{Y} = B\overline{V}$, where $\overline{Y} = \begin{bmatrix} x_0(2) \\ x_0(3) \\ \vdots \\ x_0(n) \end{bmatrix}$,B$= \begin{bmatrix} -z_1(1) & 1 \\ -z_1(2) & 1 \\ \vdots & \vdots \\ -z_1(n) & 1 \end{bmatrix}$, $\overline{\overline{V}} = \begin{pmatrix} \hat{a} \\ \hat{u} \end{pmatrix}$.
4. The approximately value obtained by the least square method is $\overline{\overline{V}} = \begin{pmatrix} \hat{a} \\ \hat{u} \end{pmatrix} = \left(B^T B\right)^{-1} B^T \overline{Y}$. The GM (1,1) algorithm equation can be obtained by incorporating the approximately value $\hat{a}$ and $\hat{u}$ into the equation:$\hat{x_1}(k+1) = \left(x_0(1) - \frac{\hat{u}}{\hat{a}}\right)e^{-\hat{a}k} + \frac{\hat{u}}{\hat{a}}$.

3 Result analysis

3.1 Analysis of AWRE

This research calculate the AWRE in China by the SBM-DEA model. The starting and ending years and selected four time nodes during the learning circle as delegates to evaluate the AWRE outcome, as shown in Table 3. We found that from 2013 to 2019, the AWRE in coastal provinces is generally higher, as well as higher than that in inland provinces. Cities with high efficiency, such as Jiangsu and Zhejiang, can be maintained at 1 all year round, but cities with low efficiency, such as Inner Mongolia and Qinghai, can be maintained

Table 3 Values of AWRE and AEDL level

Province	Year							
	AWRE				AEDL			
	2013	2015	2017	2019	2013	2015	2017	2019
Beijing	0.451	0.384	0.402	0.221	0.450	0.472	0.612	0.516
Tianjin	0.361	0.356	0.291	0.243	0.446	0.477	0.588	0.506
Hebei	1.000	0.544	0.482	0.433	0.610	0.617	0.687	0.653
Shanxi	0.472	0.388	0.306	0.309	0.506	0.469	0.611	0.602
Inner Mongolia	0.197	0.170	0.174	0.197	0.547	0.483	0.652	0.567
Liaoning	0.388	0.418	0.357	0.448	0.546	0.499	0.623	0.554
Jilin	0.246	0.233	0.149	0.202	0.540	0.538	0.643	0.582
Heilongjiang	1.000	0.386	0.485	0.421	0.599	0.549	0.655	0.603
Shanghai	1.000	1.000	0.353	0.232	0.312	0.353	0.452	0.424
Jiangsu	1.000	1.000	1.000	1.000	0.448	0.388	0.592	0.518
Zhejiang	1.000	1.000	1.000	1.000	0.502	0.450	0.607	0.567
Anhui	0.429	0.397	0.401	0.373	0.515	0.563	0.679	0.642
Fujian	1.000	1.000	1.000	0.547	0.450	0.432	0.605	0.584
Jiangxi	0.296	0.345	0.393	0.481	0.520	0.525	0.658	0.607
Shandong	1.000	1.000	1.000	1.000	0.740	0.688	0.824	0.820
Henan	1.000	1.000	1.000	1.000	0.716	0.650	0.785	0.787
Hubei	0.573	0.500	0.557	0.733	0.570	0.525	0.697	0.647
Hunan	1.000	1.000	1.000	0.791	0.555	0.530	0.670	0.634
Guangdong	1.000	1.000	1.000	1.000	0.440	0.427	0.549	0.515
Guangxi	0.421	0.444	0.537	1.000	0.497	0.506	0.633	0.593
Hainan	0.584	1.000	1.000	1.000	0.384	0.428	0.532	0.479
Chongqing	1.000	1.000	1.000	1.000	0.463	0.449	0.578	0.561
Sichuan	1.000	1.000	1.000	1.000	0.653	0.581	0.730	0.734
Guizhou	0.405	1.000	1.000	1.000	0.509	0.524	0.670	0.601
Yunnan	0.449	0.553	0.459	0.699	0.516	0.547	0.670	0.648
Tibet	0.084	0.171	0.102	0.116	0.428	0.394	0.552	0.576
Shaanxi	1.000	1.000	1.000	1.000	0.500	0.466	0.593	0.559
Gansu	0.299	0.325	0.258	0.297	0.412	0.462	0.553	0.518
Qinghai	0.163	0.154	0.184	0.151	0.427	0.440	0.554	0.494
Ningxia	0.127	0.128	0.136	0.134	0.453	0.441	0.601	0.492
Xinjiang	0.282	0.265	0.377	0.296	0.514	0.492	0.632	0.593

Since it is difficult to obtain data from Hong Kong, Macao, and Taiwan, 31 provinces in Mainland China are taken as the research scope

below 0.2 all year round. In 2013, there were 15 provinces with efficiency of 0.5 or above; in 2015, there were 16 provinces with efficiency of 0.5 or above; in 2017, there were only 14 provinces with efficiency of 0.5 or above; and in 2019, there were 15 provinces with efficiency of 0.5 or above. According to the statistics, 14 provinces in 2017 had AWRE of 0.5 or above from 2013 to 2019. In a word, due to variations in financial improvement level, insurance policies and regional geographic location, water sources use effectivity in distinct areas of China is extensively specific. High efficiency and low efficiency provinces can each be regarded as accounting for around half.

3.2 Analysis of AEDL

By dividing the research period into four equal parts and taking them as representative years and then processing and analyzing the research data by using the stiffness free quantification method, the AEDL of each province in China is obtained, as shown in Table 3. The estimated indicators of the AEDL of each province are not very different. We found that the AEDL of most provinces remains between 0.4 and 0.7, with a relatively small difference. On the whole, Shanghai and Hainan have the lowest AEDL while Shandong and Henan have the highest level.

3.3 Average level of CCD

Table 4 shows the outcome of the coupling coordination model. From the results, there are differences between the provinces, but most of the provinces in a high level of coordination. There are 19 high-level provinces, with the highest number of provinces in all levels. Quality level provinces are few, only 4. High-level provinces are potential stocks to grow into high-quality provinces, there is a greater room for progress. The four provinces of Shanghai, Qinghai, Tibet and Ningxia are at the basic level. On the whole, the CCD in all provinces in China is at a lower stage. There are not only no provinces with low coordination but also a few provinces with basic coordination and a few provinces with quality coordination.

A visual analysis of the coupling coordination levels is shown in Fig. 1. The CCD in China has shown descensive tendency as a whole. The CCD has varied from quality coordination to low coordination, which indicates that the relationship between AWRE and AEDL is deteriorating. Moreover, on the whole, the CCD in southeast provinces is always better than that in northwest provinces, and the gap between north and south is obvious.

In 2013, the CCD is basic in Tibet, Ningxia and Shanghai, moderate in Qinghai and Gansu, high in some provinces, and quality in others, and there is no low-level coordination nationwide. In 2015, Inner Mongolia decreased from a high CCD to a basic one, Gansu increased from a moderate to a high CCD, and the number of provinces with quality coordination decreased. In 2017, Gansu, Jilin, Beijing, and Tianjin decreased from high coordination to medium coordination, Inner Mongolia increased from basic to medium coordination, Shanghai increased from basic to low coordination, and Hunan decreased from quality coordination to high coordination, Guangxi increased from high coordination to quality coordination, and there was no significant change in the coordination level of other provinces. In 2019, Beijing and Tianjin increased to high coordination, Shanghai decreased to basic coordination, Qinghai increased to medium coordination, and the number of quality coordination provinces increased. On the whole, there are many provinces with high coordination, and most of them are in the southeast. There are few provinces with quality coordination, and the range of change is large.

According to the general principles of geographical division, China's provinces are divided into seven administrative geographical divisions. On this basis, the above coordination levels are analyzed by sub-region. It is seen from Fig. 1a that there are certain differences in the CCD of different divisions. There are also some differences in the CCD between different provinces in each division. As observed in Fig. 1a, a large gap exists

Table 4 Average level of CCD of China in 2013–2019

Level	Low coordination	Basic coordination	Moderate coordination	High coordination	Quality coordination
Province	None	Shanghai, Qinghai, Tibet, Ningxia	Gansu, Jilin, Inner Mongolia, Tianjin	Beijing, Hebei, Shanxi, Liaoning, Heilongjiang, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Hubei, Guangdong, Guangxi, Hainan, Chongqing, Guizhou, Yunnan, Shaanxi, Xinjiang	Hunan, Shandong, Henan, Sichuan

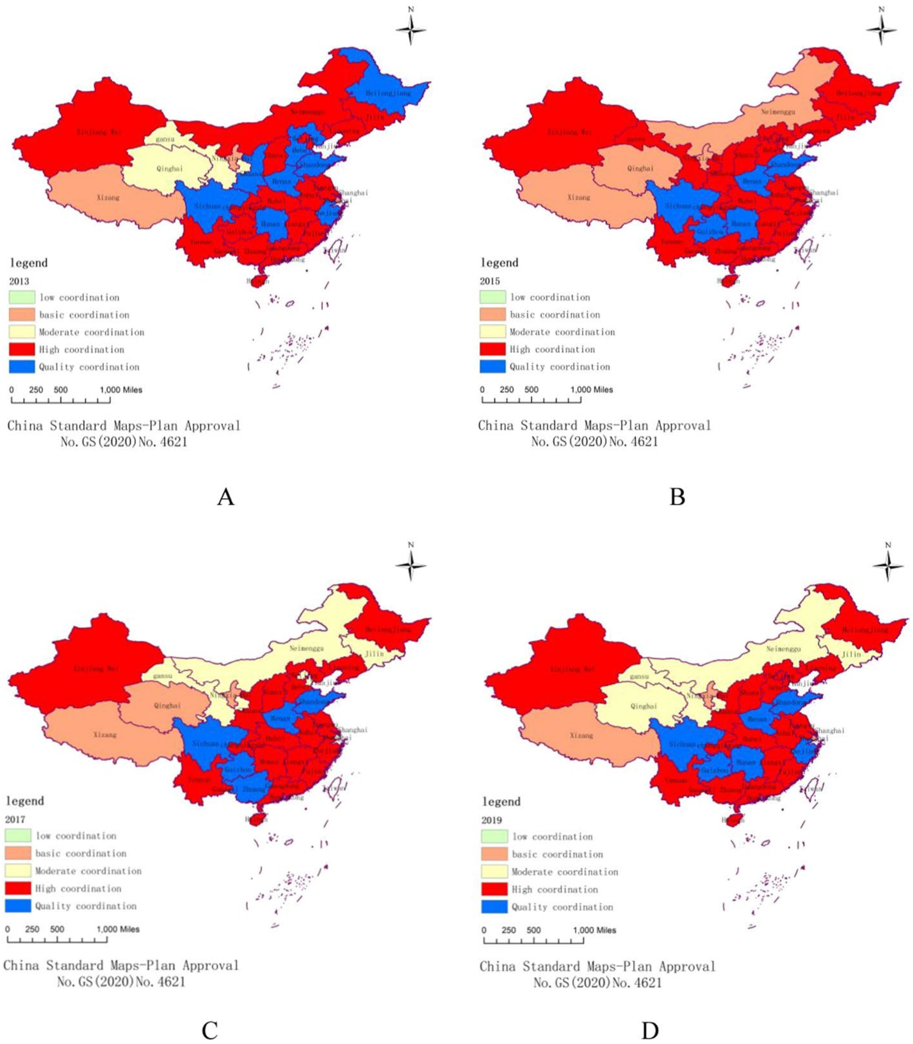

Fig. 1 Spatial distribution of CCD

in the CCD between provinces in East China, Southwest China, and Northwest China. In some regions, the CCD is below 0.3, and in some regions, the CCD is above 0.7 and 0.8. This shows that the CCD between different provinces can be divided into strong and weak. Compared with East China, Southwest China, and Northwest China, the CCD of provinces in the other four regions is closer, and the CCD in Central China is around 0.8, with a strong coupling degree.

Figure 1b shows the changes in CCD in seven regions from 2013 to 2019. We found that Central China has the best CCD, which is above 0.8, belonging to the quality coordination level. The CCD of Northwest China is the weakest, ranking the last among the seven regions. However, after 2016, its coupling coordination shows a slow growth trend. The CCD of East China and Southwest China is similar. The development of the CCD in East China is relatively gentle, showing a gentle U-shape. The development of the CCD in

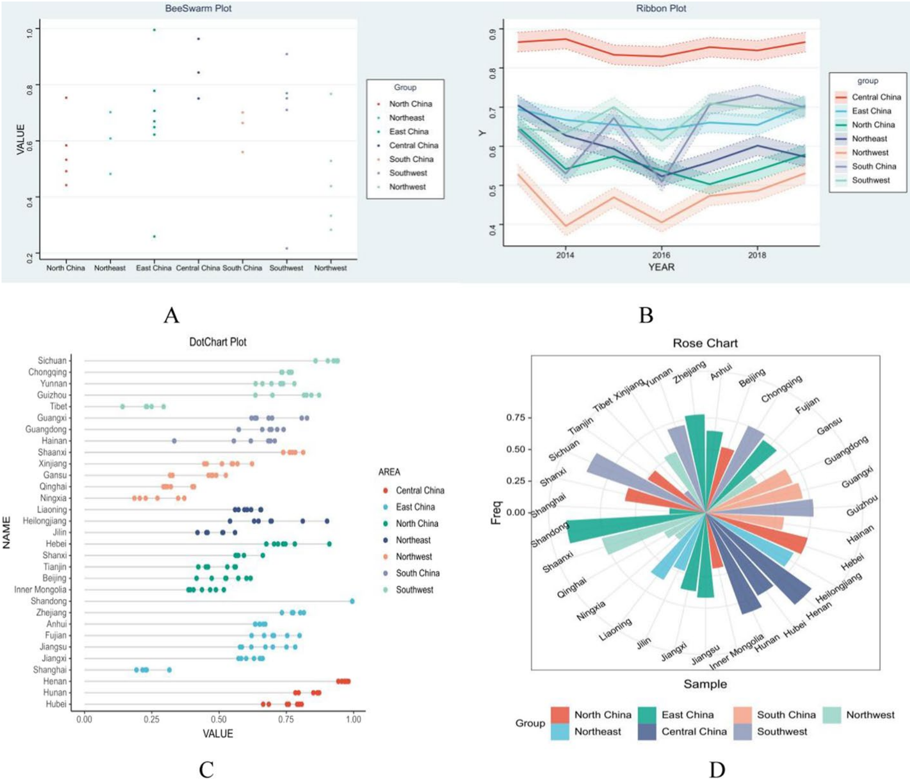

Fig. 2 Zoning map of CCD

Southwest China fluctuates, both rising and falling. The CCD in North China is slightly better than that in Northwest China, fluctuating at around 0.55. The CCD in South China is unstable and fluctuates greatly. The CCD in Northeast China shows a downward trend before 2016 and partially recovers after 2016.

Figure 2c, d reflects the presentation of the CCD between provinces in various regions. In the same region, the coordinated progress of provinces is different. In the southwest region, the CCD of Tibet is far lower than that of other area in the southwest region. The development of the CCD of the three provinces in South China is similar, and only Hainan has a low CCD. In Northeast China, Heilongjiang has a large CCD range. The CCD in Northwest China is gradually decreasing in a ladder shape. The CCD of Shaanxi is the best in Northwest China and the worst in Ningxia. In East China, Shanghai has the worst CCD. Shandong has the best CCD, which has been stable at around 0.9 for seven years. The development of coupling and coordination in other provinces in East China is similar. The development of the CCD in Central China is in a ladder shape, whereas the CCD in Henan is high and aggregated.

Figure 2d reflects the development of the mean value of the seven-year CCD in all provinces and regions. The overall CCD of provinces in Central China is high, and the distinction between provinces is small. In Northwest China, the CCD of other provinces is low except Shaanxi. Tibet coordinated degree in Southwest China is the lowest, and there is an obvious distinction with other provinces. In East China, Shanghai has a low CCD and Shandong has a high CCD. There is a small gap in the CCD between provinces in other regions.

To sum up, the CCD in Central China is high, and the gap between provinces is small. The CCD between Shanghai and Tibet is poor, and they are at the bottom of all regions. Shandong, Henan and Sichuan have a high CCD and are in the forefront among all provinces. There is a large gap in the CCD between provinces in other regions. In each region, there is a certain gap in the CCD between provinces.

3.4 Analysis of spatial correlation pattern of CCD

The spatial characteristics of the 31 provinces were studied using the MI index correlation tool and visualized using GeoDa software. As shown in Table 5, the global MI indices were all positive greater than 0, and all passed the 10% significance test. On top of, the change of MI index shows an overturned "U" shape, reflecting that the spatial agglomeration effect first strengthens and then weakens. There is a phase characteristic of spatial differences. From 2013 to 2017, the global MI index increases from 0.1466 to 0.2427, which is in a continuous increasing phase. 2017 to 2019, the global MI index decreases from 0.2427 to 0.1992, which is in the decreasing stage.

Through local spatial autocorrelation, the spatial agglomeration degree of the CCD at the four time nodes in 2013, 2015, 2017, and 2019 is analyzed. The agglomeration results are spatially processed with the help of ArcGIS software to obtain a LISA clustering map of the CCD to show the spatial heterogeneity of CCD more intuitively.

As shown in Fig. 3, within the four nodes, the H–H agglomeration provinces are gradually increasing. In 2013 and 2015, there was only one province in Hubei. Yunnan joined the high-concentration cluster in 2017, and Anhui joined the high-concentration cluster in 2019. This shows that the CCD between provinces in Hubei agglomeration area and the surrounding adjacent areas is high, and the spatial internal differences are small. There is an increase in the number of provinces in H–H areas increases, indicating that the radiation driving effect of H–H agglomeration areas is strengthening. L–L areas have been reduced from two provinces in Xinjiang and Tibet in 2013 to one province in Xinjiang. This shows that the CCD of provinces of this type is lower than that of their surrounding areas, which is a deficiency that hinders the coordinated development of the region. Areas with low and high convergence are gradually decreasing. In 2013, Shanxi and Anhui were in low- and high-concentration areas. In 2015, only Shanxi was in low- and high-concentration areas. In 2017, there were no low- and high-concentration provinces. Conversely, Anhui joined the H–H agglomeration area in 2019, which indicates that Hubei has a certain radiating effect on Anhui and affects the agglomeration status of Anhui.

Table 5 Global MI index of CCD

Year	Moran's I	$E(I)$	Z score	P value
2013	0.1466	−0.0333	1.3681	0.0870
2015	0.2015	−0.0333	1.7990	0.0450
2017	0.2427	−0.0333	1.9897	0.0280
2019	0.1992	−0.0333	1.7847	0.0450

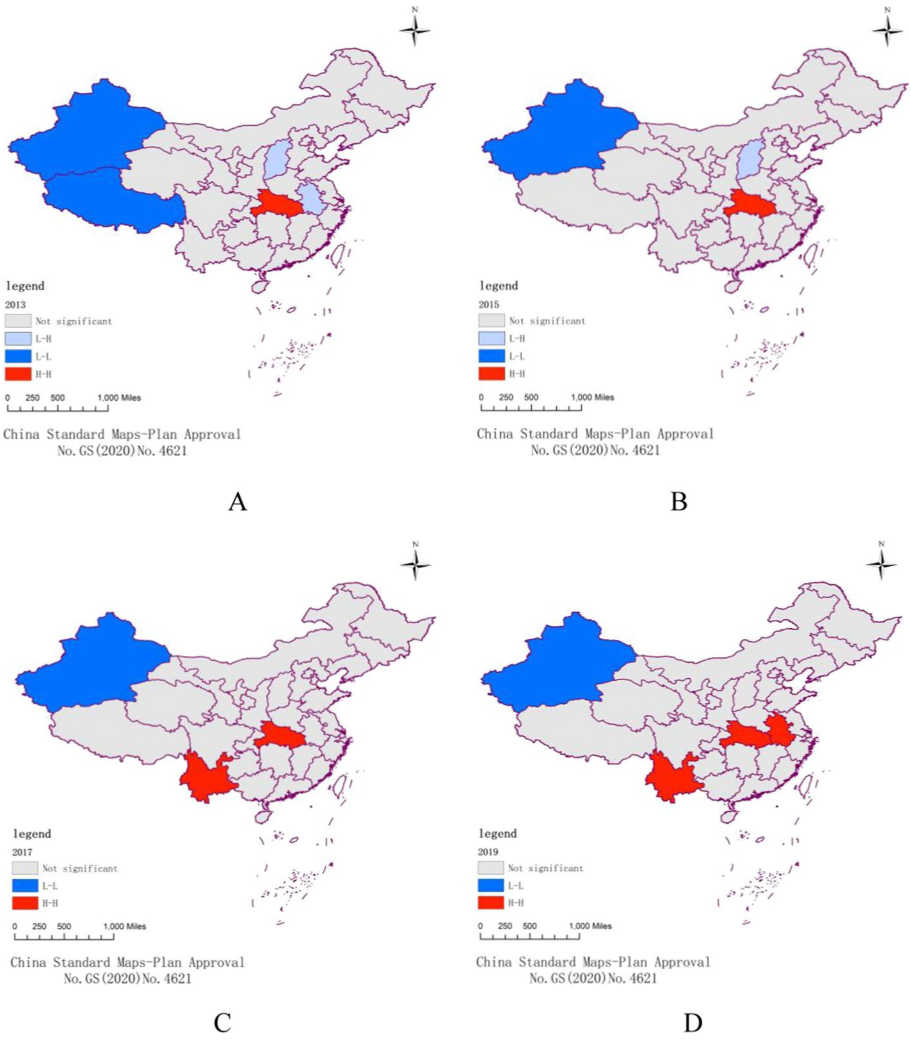

Fig. 3 LISA concentration diagram

In general, the number of provinces with H–L agglomeration is adding, and the number of provinces with L–L agglomeration is diminishing. This shows that although the coupling state between AEDL and AWRE is gradually improving, on the whole, the CCD of the two is not concentrated, and there are many insignificant provinces. We should attach importance to strengthening the internal connection entre AEDL and AWRE in various provinces and improve the coupling coordination between the two. Areas with low and high concentration are easily affected by the radiation of surrounding provinces and have great development potential. We should focus on low-level agglomeration areas as the primary development object to improve the combination.

Table 6 Error test based on GM (1,1) grey prediction model

Particular year	Original value	Estimate value	Residual	Relative error (%)
2014	0.601	0.625	−0.024	3.914
2015	0.632	0.626	0.006	0.99
2016	0.576	0.628	−0.051	8.935
2017	0.626	0.629	−0.003	0.519
2018	0.636	0.631	0.005	0.858
2019	0.657	0.633	0.025	3.776

3.5 Prediction and analysis of CCD

To better understand the future development trend of CCD, the average of CCD in all provinces from 2013 to 2019 was selected as the original data. And the GM (1,1) grey prediction model is used to simulate and anticipate the standard of combination in the next six years. The results are shown in Table 6. According to the model error test results, the average simulation relative error is 0.035114, which is less than 0.1, indicating that the model meets high requirements.

The prediction results are shown in Fig. 4. The average of the CCD in all provinces will still show a slow rising tendency. The CCD is 0.632 in 2020, 0.634 in 2021, and 0.636 in 2022. This suggests that the average value of the CCD will rise slowly in future, and although the coupling level will gradually move closer to the highly coordinated stage, the range of change is small. After 2022, the CCD slows down, and the growth impact is not obvious.

According to the prediction results, the CCD will be stage by stage advanced in future. However, the level of CCD has not achieved a phased breakthrough, making the two

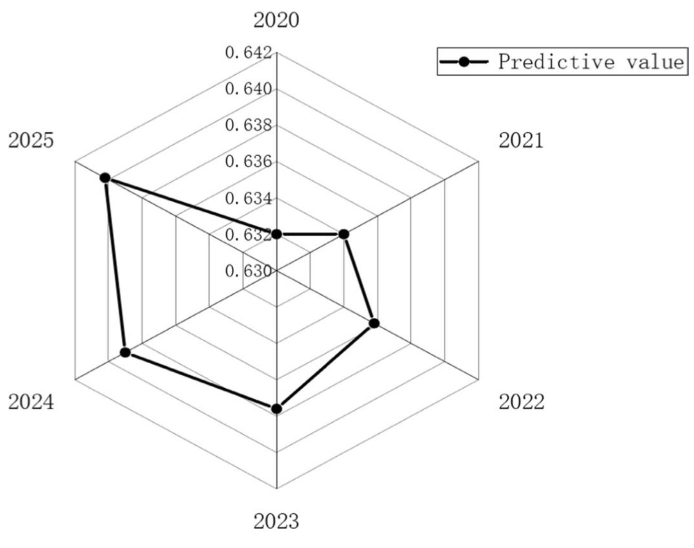

Fig. 4 Prediction trend diagram of CCD

systems of AWRE and AEDL promote each other and develop together. In future, with the progress of science and technology and the deepening of reform, the AWRE will encounter new chances and dare. To improve the innovation ability of agricultural water resources, we should continue to strengthen independent innovation, increase investment in innovation elements, and effectively improve the comprehensive innovation ability of agricultural green water resources. Furthermore, accelerate the green production capacity, green economy, and other fields; and improve the level of coordination between the two systems of AWRE and AEDL.

4 Discussion

The above study discusses the level of CCD, as well as the state of agglomeration. First, the SBM-DEA model and the combined use of entropy value method were employed to, respectively, calculate the AWRE and the AEDL in 31 provinces on the mainland. The study shows that there is a gigantic distinction in AWRE between diverse provinces. Among the 31 provinces, Jiangsu, Zhejiang, Shandong and other 8 provinces have high AWRE in agriculture, which is maintained as 1 year-round. Four provinces, including Tibet and Qinghai, have a low level of AWRE, remaining below 0.2 year-round. This has a relationship with the geographical location of the provinces. Provinces with high AWRE are mostly located in eastern and southern China, which are under the influence of monsoon, have abundant precipitation, and have many rivers and lakes, and have more water resources per capita, which exert a greater infection on the AWRE. Tibet, Qinghai and other provinces in the northwest inland areas, dry climate, low precipitation, shortage of water resources, per capita possession of water resources is low, AWRE is low. This is alike to the consequences of Ma's et al. (2019) study.

In contrast, the results of the AEDL are less variable, mainly around 0.4–0.7. AEDL is influenced by various factors of production, geographic climate, economic conditions, agricultural science and technology, and government actions (Cetin, 2019). Henan and Shandong are the largest agricultural provinces in China, with the total arable land area accounting for nearly 50% of the total land area. The two places are influenced by monsoon climate and have abundant precipitation, which can fulfills the needs of irrigation for agricultural production perfectly (Cui et al., 2022). Together with the good economic development, the economic benefits obtained from agricultural cultivation are high. Therefore, the AEDL of the two places is around 0.7. Although Shanghai is a modern city with good economic development, the arable land is limited and fragmented, and the conflict between human and land is prominent, so the level of agricultural development is weaker, at around 0.4.

Secondly, the coupled synergy model is used to measure the synergy relationship between AWRE and AEDL. Overall, there are no cities with low levels of coordination among the 31 provinces. Several cities are at a high level of coordination. Only four provinces, Hunan, Shandong, Henan and Sichuan, are at the high-quality coordination level. In terms of regional distribution, Central China has the highest level, with East China and Southwest China second only to Central China. Northwest China has the lowest CCD, while North China, South China, and Northeast China are better than Northwest China. One is because the economic development of the interior of the Northwest lags behind other regions. Economic development is the foundation. Economically developed regions have more financial investment in agricultural technology research and development, quality crop breeding, and expansion of agricultural production. Financial support can promote the better development of agricultural cultivation, high-quality crops can obtain economic income, and then act on agricultural cultivation, forming a cycle of development. Second, the geographical location. The Northwest is located inland, far from the sea, arid climate, arable land area is small and poor quality, and the lack of water, is not conducive to agricultural development. Third, the deterioration of the ecological environment has led to serious soil erosion and a decline in the quality of arable land (Dutta, 2017).

Finally, according to the spatial agglomeration effect of the CCD was evaluated by using the MI index related tools. It was found that although the H–H agglomeration areas showed a slow increasing trend, the overall coupling coordination was not strong agglomeration. This indicates that the country's coordinated development is unbalanced and inadequate. There are gaps in the development of the agricultural industry, which has failed to form a clustering effect. The study found that the coupling coordination will be further developed in the next six years, but at a slow pace. This indicates that the link between AWRE and the ADEL is not yet strong enough, and the dependence between the two is weak.

The article makes the following guidelines to similarly enhance the stage of coordination. First, the problem of difficult crop cultivation in the northwest should be solved. In the northwest, where the land is barren and the climate is arid, drought-resistant crops should be cultivated, and the planting area should be decided according to the degree of drought tolerance of the crops (Sevik et al., 2020). Crop planting should match the local water resources distribution pattern, reduce the waste of water caused by small-scale scattered operations, and form a scale effect to pull agricultural output. Strengthen the promotion of water-saving irrigation machines, for instance channel impermeability technology, drip irrigation technology under the membrane and other water-saving technologies, improve the renewal of old dams, ditches and other water conservancy facilities, and improve the AWRE (Li et al., 2019).

Secondly, the problem of poor coupling between the AWRE and the AEDL should be solved. AWRE and AEDL are not an opposite development process. The Northwest is the least coupled of all regions and should strengthen its agro-industrial development even more. The first is to focus on farmers' issues. We are inclined to the farmers' group from multiple perspectives, such as basic medical care and pension, to guide more working people to continue to take part in agricultural progress and to guarantee the fundamental agricultural development inheritance problem. Secondly, we should further promote the progress of technology agriculture. We should work on planting techniques, planting methods and good seed breeding to improve crop yields and effectively promote the agricultural economic development from a technical perspective. Thirdly, agricultural resources should be integrated. With the acceleration of urbanization, land resources in rural areas are deserted and wasted. Agricultural resources should be integrated from the perspective of development. For example, land utilization can be improved by means of land transfer. Fourth to strengthen the training of agricultural personnel. We should precisely train agricultural talents, from the basic perspective of breeding and planting, to cultivate high-quality professional agricultural talents and enhance the adaptability of talents to agricultural development. To introduce new composite talents for agricultural development, strengthen the introduction of technology through the introduction of talents, and promote the transformation of ideas through the introduction of technology, so as to accelerate the standard of agricultural development (Ma et al., 2019).

5 Conclusions

By exploring the CCD between AWRE and AEDL in 31 provinces of China, we draw the following conclusions.

1. It is found that AWRE in agriculture in Eastern and Southern China provinces is generally higher, as well as higher than that in Northwest inland provinces. Moreover, a big gap exists in the AWRE. Cities with high efficiency, such as Jiangsu and Zhejiang, can be maintained at 1 all year round, but cities with low efficiency, such as Inner Mongolia and Qinghai, can be maintained below 0.2 all year round. The AEDL remained between 0.4 and 0.7, with a small range of change.
2. The CCD of provinces in China shows a falling tendency. In particular, Tibet, Ningxia, Shanghai, and Qinghai have been in basic coordination for many years, and their CCD is at the bottom of the country in all time nodes. In the spatial layout, the coordination level in southeast is high and the coordination level in northwest is low. Especially, the CCD of northwest inland region lags behind other regions for ages. On the ground of geographical location, climate deviation, local resources, and other reasons, the AEDL in Central China is better than that in Northwest China. From the perspective of the seven regions, Central China has a high CCD, and the gap between provinces in the region is small, realizing the overall quality development of the region. In Northwest China, Shaanxi has a high CCD while other areas have a low degree. There is a large disparity between provinces, and the overall coupling coordination level of the region is weak. There is a disparity in the CCD of provinces in most regions, indicating that the development of provinces in the same region is unbalanced and insufficient.
3. In terms of the degree of agglomeration, H–H agglomeration areas show a slow increasing trend, the quantity of L–L areas is small, the low and high agglomeration areas show a decreasing trend, and there are no high and low agglomeration areas. On the whole, the CCD is not concentrated, and there are many provinces that are not significant. This indicates that the CCD is unbalanced and insufficient.
4. The GM (1,1) grey prediction model serve as prospect the CCD. It is found that the CCD will further develop in the next six years, but the development speed is slow.

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Data availability The authors do not have permission to share data.

Declarations

Conflict of interests 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.

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