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How is agricultural water efficiency affected by the digital economy? Insights from China

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ABSTRACT

With the continued advancement of digital technology, the digital economy will gradually become the primary economic form in the future, having a profound impact on a variety of industries, including agriculture. Agriculture is a major source of global water use, and efficient water use in agriculture is critical to coping with water scarcity and ensuring food security. This study used publicly available data from 30 Chinese provinces from 2006 to 2017 to estimate the relationship between the digital economy and agricultural water use efficiency using the systematic generalized method of moments technique. According to the findings, a 1% increase in the digital economy indicator is associated with a 0.053% increase in agricultural water use efficiency. In addition, the digital economy improves agricultural water usage efficiency through three mediating channels: structural effect, scale effect, and spillover effect. For the digital economy and agricultural water use efficiency to develop in tandem, the Chinese government should strive to strengthen the development of the digital economy and work on the intermediate channels demonstrated in this study.

Key words: Agricultural water use efficiency, China, DEA, Digital economy, GMM, Mediating mechanism

HIGHLIGHTS

- Digital economy increases agricultural water efficiency.
- The digital economy improves agricultural water usage efficiency by encouraging agricultural industry structure upgrades.
- The digital economy improves agricultural water efficiency by increasing cultivation scale.
- The digital economy improves agricultural water efficiency by increasing the power of government support for agriculture.

1. INTRODUCTION

Agriculture is an important economic sector for developing countries, but it must contend with inefficient water use and dwindling water resources (WR). Concerns have been voiced regarding the global depletion and overexploitation of freshwater resources as a result of economic growth and rising demand for food, feed, and fuel. About 70% of the world's WR are used by irrigated agriculture (Li *et al.*, 2020). With rapid economic development, water use in the industrial and residential sectors has been increasing (Yan *et al.*, 2015). At the same time, the demand for food production has been increasing and is expected to increase by about 60% by 2050 (Li *et al.*, 2020). In addition, climate change is expected to exacerbate future water supply and demand imbalances, as well as increase variability in supply (Wang *et al.*, 2019a, 2019b). Climate change-induced droughts will require more irrigation and more water to ameliorate. All of these variables have a significant influence on the sustainable use of agricultural WR, and enhancing agricultural water use efficiency (AWE) is critical to resolving these difficulties. It is the only way to achieve food and ecological security (Bwambale *et al.*, 2022; Li *et al.*, 2022; Lu *et al.*, 2022).

Scholars have studied numerous influencing factors that affect AWE, including land fragmentation (Tang *et al.*, 2015), water rights system reform (Fei *et al.*, 2021), level of education of the farm households (Wang *et al.*, 2019a, 2019b), and urbanization (Wei *et al.*, 2021; Yang *et al.*, 2022), developing integrated plans (Nazari *et al.*, 2018), farm size (Wang, 2010), and number of years of experience in operating a Water Users Association (WUA) (Frija *et al.*, 2009). In addition, other factors such as climatic determinants (Fan *et al.*, 2018), water-saving technologies (Huang *et al.*, 2017), and perception of water scarcity (Tang *et al.*, 2015; Tang & Folmer, 2016; Hong & Yabe, 2017). However, research on the connection between the digital economy (DE) and the efficiency of agricultural water use is scarce. It is crucial to research how the DE and AWE are related because DE will likely play a significant role in the future of resource demand and distribution. Efficiency in agricultural water use is essential for both environmental and food security protection. Sustainable development will be ensured by knowing how the two interact to maximize resource allocation.

The DE refers to an economic structure in which individuals facilitate and achieve efficient allocation and regeneration of resources, as well as the high-quality advancement of the economy, by means of identifying, selecting, filtering, storing, and utilizing big data (i.e., digitized knowledge and information). The introduction of technologies like 5G, big data, artificial intelligence, cloud computing, and the Internet of things (IoT) are just a few examples of how quickly the DE has been growing in recent years. The study of the DE has become popular recently in academia. A new economic form known as the 'digital economy' uses information networks as its transport medium and is defined by the widespread use of digital technology and data as a production element, considerably promoting economic growth. As a result, governments in a wide variety of nations have enacted measures designed to foster the growth of digital infrastructure and the associated DE. While the United States announced its 'National Broadband Plan' and the European Union unveiled its 'European Digital Agenda' in 2010, both initiatives are examples of such plans. Singapore proposed the 'Smart Country' initiative in 2014 (Xu *et al.*, 2022). The People's Republic of China's 'Outline of the 14th Five-Year Plan (2021–2025) for National Economic and Social Development and Vision 2035' released in 2021 emphasized the need to 'accelerate the building of digital villages and promote the digital transformation of industries' in China. Studies have also looked at the relationship between the DE and total factor productivity, urban development, natural resources tax, energy transition, carbon emission, and sustainable economic growth (Hosan *et al.*, 2022; Ma *et al.*, 2022; Pan *et al.*, 2022; Shahbaz *et al.*, 2022; Wang *et al.*, 2022; Zhu & Chen, 2022). The link between the DE and AWE, for example, has not been fully explored or is understudied because the field surrounding the DE is still in its infancy. China, the largest developing country in the world, offers a more representative sample for research on how the DE affects agricultural water efficiency.

This study makes three primary contributions: First, it computes indicators for AWE and DE. Second, it addresses a vacuum in the literature on the study of the DE–AWE link by using an econometric model to quantify the influence of DE on AWE, and it also helps Chinese policymakers create both short- and long-term plans to enhance AWE from a DE-focused viewpoint. Third, the mediation model is used to examine the channel of DE's impact on AWE to gain illuminating insights into DE's impact on AWE.

The rest of this article is organized as follows: Section 2 provides an overview of the material, variables, and empirical method. The empirical findings and their importance are examined in Section 3. The mechanism analysis is covered in greater detail in Section 4. The study's findings are outlined in Section 5 along with some policy suggestions.

2. METHODS AND DATA

2.1. Agricultural water use efficiency

A well-known technique for assessing effectiveness is data envelopment analysis. Charnes Cooper Rhodes (CCR) and Banker Charnes Cooper (BCC) are the two basic types of data envelopment analysis (DEA) models. While the BCC model contends that activities have variable returns to scale, the CCR model suggests that activities have constant returns to scale. The DEA distinguishes between three types of technical efficiency: scale efficiency, overall technical efficiency (as assessed by the CCR model), and pure technical efficiency (as found by the BCC model). This study aims to establish AWE, which evaluates the ability to create a certain output with the fewest feasible water inputs. As a result, the input-oriented CCR model is put into practice.

$$\mathrm{AWE}_{i,t} = \frac{\mathrm{OAWI}_{i,t}}{\mathrm{AAWI}_{i,t}} \tag{1}$$

where $\mathrm{AWE}_{i,t}$ represents agricultural water efficiency, $\mathrm{AAWI}_{i,t}$ is the actual agricultural water use, $\mathrm{OAWI}_{i,t}$ is the optimal agricultural water use, i denotes the province, and t denotes the time.

Individual provinces in this study serve as the decision-making units (DMUs), which are used in the efficiency calculations. The relationship between the most efficient DMUs cannot be further compared because DEA gives the most effective DMU a score of 1, making further comparisons impossible. This issue is addressed by the super efficiency DEA approach, a classification method for DMUs that keeps the original noneffective value assessment and permits comparison if the original effective value assessment is higher than 1 (Andersen & Petersen, 1993). Using superefficiency DEA models to measure AWE is a better approach. Think about a scenario where there are n DMUs, m input metrics, and q output metrics.

$$\min\left(\theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{j=1}^{q} s_j^+\right)\right) \tag{2}$$

$$\text{s.t}\begin{cases} \sum\limits_{\substack{k=1 \\ k\neq j}}^{n} \lambda_k x_{ik} + s_i^- = \theta x_i & i = 1, 2, \cdots, m \\ \sum\limits_{\substack{k=1 \\ k\neq j}}^{n} \lambda_k y_{jk} - s_j^+ = y_j & j = 1, 2, \cdots, q \\ \lambda_k \geq 0, & k = 1, \ldots, n \\ s_i^- \geq 0, & s_j^+ \geq 0 \end{cases}$$

For the kth DMU, x_{ik} denotes the ith input indicator, y_{jk} represents the jth output indicator, and s_i^- and s_j^+ are input and output slack variables, respectively. λ_k denotes the weight coefficient. θ is the result of calculating the AWE. θ represents the overall production efficiency.

In addition, the DEA model includes the following variables: To determine pesticide input, the quantity of pesticide sprayed on agricultural product is used. The quantity of fertilizer input is determined by the amount of nitrogen and phosphate fertilizer applied to agricultural products. Energy input is substituted by fuel use in agricultural output. Agricultural film refers to the entire amount of plastic film used in agricultural production. The total area of plants planted represents the land input. Total agricultural water utilization is a proxy for water input. As a measure of production value, the agricultural planting business's yield value is employed. Table 1 provides a summary of the variables used by the DEA model. The geographical distribution of AWE in China is shown in Figure 1 for the years 2006, 2009, 2013, and 2017. AWE has been increasing over time and overall does not show significant differences in spatial terms. Further convergence analysis revealed that AWE showed statistically significant absolute β convergence (coefficient of -0.091 and t-statistic of -2.61). This suggests that the differences between regions in AWE are decreasing.

2.2. Measuring digital economy

This research develops a comprehensive index of the DE by dividing it into four subindicators: innovation, economic and employment, infrastructure, and social influence, using the OECD's classification criteria for the DE (OECD, 2018; Wang *et al.*, 2022).

Innovation is at the heart of the DE, and employing digital technology to create novel goods and services is known as digital innovation (Shaikh *et al.*, 2020). The sectors that create the most items connected to the DE, provide other industries digital technology services, and serve as the main drivers of the DE include electronic information manufacturing, software development, and information technology services.

Digitization provides a platform for technological development, encourages corporate innovation, and improves economic development. It also creates a large number of new jobs, such as delivery workers who deliver online food orders and video bloggers who showcase rural life. Driving economic development and employment is thus central to the DE (Jurayevich & Bulturbayevich, 2020). The core content of a high DE is infrastructure construction.

The creation of the new infrastructure is crucial to the development of the DE (Jiang *et al.*, 2020). The DE has, in some ways, changed how people live their lives and had a big impact on how much is produced and how people live their lives. For instance, the Internet has started to make its way into millions of households and has grown to be a crucial tool and method for people to work and learn (Luo *et al.*, 2021). For example, online e-commerce has allowed many agricultural products from remote and impoverished areas to reach modern markets. It is clear that the social effect is the central meaning of the DE.

Table 1 | Descriptive statistics of variables in the DEA model.

Input/output	Measurement units	Mean	SD
Pesticide	10 thousand ton	5.495	4.400
Fertilizer	10 thousand ton	181.648	145.361
Energy	10 thousand ton	66.476	66.174
Agricultural plastic film	10 thousand ton	7.400	6.618
Land	thousand hectares	4,271.434	3,152.180
Water	100 million m^3	121.341	103.571
Output value	100 million CNY	940.415	757.964

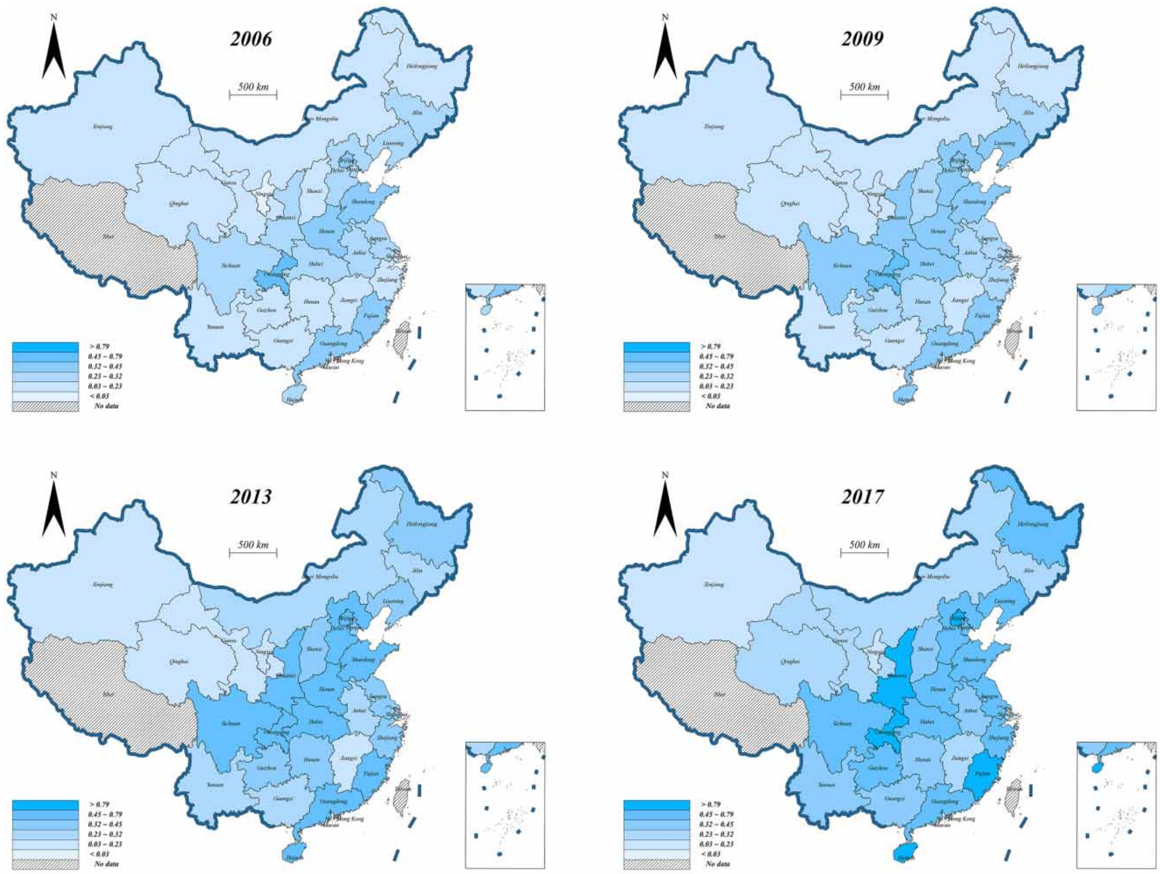

Fig. 1 | The spatial distribution of China's province-level agricultural water use efficiency for selected years.

Table 2 lists the indicators chosen based on the four dimensions mentioned earlier. Referring to the study by Wang *et al*. (2022), these DE indicators are calculated utilizing the improved entropy method (IEM). The progression of the DE is depicted in Figure 2. These indicators are calculated using the IEM to obtain the DE indicators. Figure 2 depicts the DE development trend. The DE as a whole is showing an upward trend. The increasing amount of gray areas indicates the increasing imbalance of DE development among regions. Figure 3 depicts the spatial differences in the level of development of China's DE. It is imperative for policymakers to exercise caution to mitigate the emergence of novel forms of inequality and actively strive toward diminishing regional disparities while fostering the growth of the DE.

2.3. Econometric model

The influence of DE on AWE is investigated in this study. Therefore, AWE is the dependent variable and DE is the independent variable. The following econometric model is used to accurately study the effect of DE on AWE:

$$\ln\mathrm{AWE}_{it} = \alpha + \beta_0 \ln\mathrm{AWE}_{i,t-1} + \beta_1 \mathrm{DE}_{it} + \beta_2 X_{it} + \varepsilon_{it} \tag{3}$$

Table 2 | Digital economy indicators.

Indicator	Measurement
Innovation	Percentage of R&D personnel working in the software and IT services sectors Quantity of firms in the electronic information manufacturing sector Number of companies providing software and information technology services The amount spent on R&D by the software and information technology services industry Electronic information manufacturing industry assets
Economic and employment	Employee salaries in software and information technology services Staff members working in the software and information technology service sectors The average number of workers in the electronic information manufacturing business Electronic information product import Electronic information goods exported
Infrastructure	Long-distance optical fiber core length The switch capacity for mobile communications The quantity of Internet access ports The average amount of bytes used per webpage The percentage of IPv4 addresses Amount of webpages CN domain names
Social Impact	The percentage of workers in the software and information technology services business having undergraduate degrees or higher Internet use percentage The total number of people using broadband Internet Total amount of mobile phone owners

Note: Digital economy indicators were constructed according to OECD (2018) and Wang *et al*. (2022).

where i and t indicate province and year. With an independent and identical distribution, ε_{it} stands for the random disturbance term and α stands for the intercept term. The estimated coefficients are denoted by β_i ($i \geq 1$). AWE stands for agricultural water efficiency. DE stands for DE. Cropping structure (CS), natural disasters (ND), the availability of WR, and the degree of traffic development (TD) are the primary components of the vector represented by the X. X represents the control variable, determined from the study by Shi *et al*. (2022b).

Furthermore, the percentage of vegetable planted area to all crops seeded is used to calculate CS. The ratio of the affected area to the cultivated area is used to calculate ND. By dividing available regional WR by crop area, WR is calculated (100 million cubic meters per thousand hectares). Road miles divided by arable land (km/thousand hectares) is used to calculate TD.

To further explore the mediating effects, the following econometric model is developed based on the study by Baron & Kenny (1986).

$$\mathrm{LnM}_{it} = \gamma_0 \mathrm{LnM}_{i,t-1} + \gamma_1 \mathrm{LnDE}_{it} + \gamma_2 X_{it} + \varepsilon_{it} \tag{4}$$

$$\mathrm{LnAWE}_{it} = \delta_0 \mathrm{LnAWE}_{i,t-1} + \delta_1 \mathrm{LnDE}_{it} + \delta_2 \mathrm{LnM}_{it} + \delta_3 X_{it} + \varepsilon_{it} \tag{5}$$

LnM_{it} denotes the mediating variable. In this study, LnM_{it} includes agricultural industry structure upgrading, grain size per capital, and financial support for agriculture. The goal of setting these mediating variables is to explore whether structural effects, scale effects, and spillover effects are intermediate channels of the

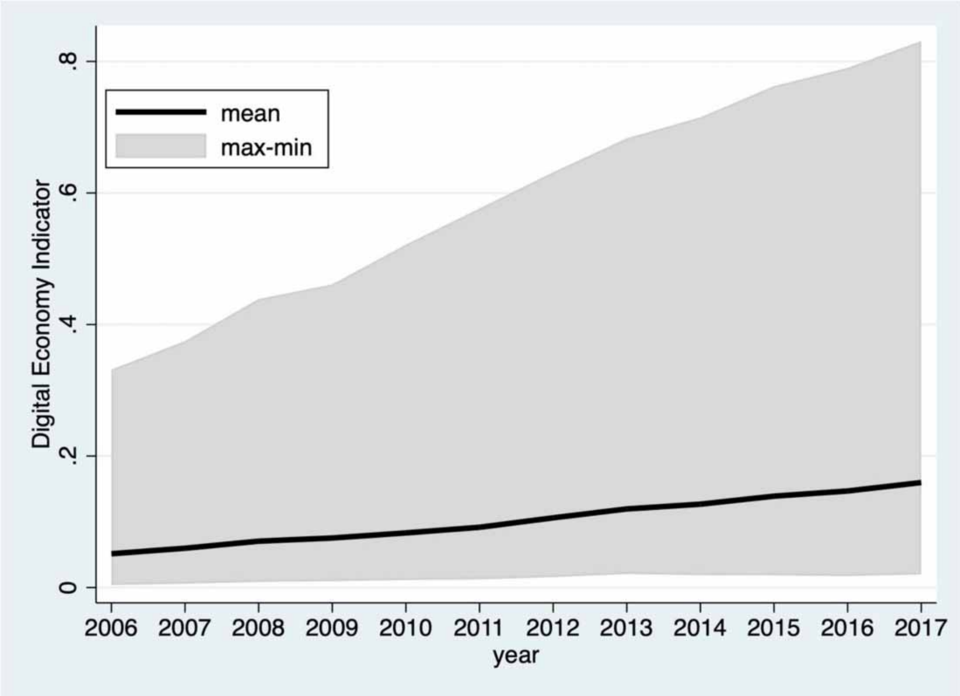

Fig. 2 | China's digital economy's trend.

DE–AWE relationship. A more detailed analysis is presented later in Section 4. In the presence of mediating effects, both γ_1 and δ_2 are statistically significant. Table 3 displays the summary statistics for the variables included in the econometric model (Equations (3)–(5)).

2.4. Data

The present study's analysis is grounded in data obtained from a sample of 30 provinces within the geographical boundaries of China, spanning the time period from 2011 to 2017. The data for this study were gathered entirely from public databases, including the China Statistical Yearbook, China Rural Statistical Yearbook, China Agriculture Yearbook, China Population and Employment Statistics Yearbook, China Agricultural Machinery Industry Yearbook, China Industry Statistical Yearbook, the China Internet Development Status Report, the Yearbook of the China Information Industry, and the China Information Almanac.

3. RESULTS

This section estimates the relationship between DE and AWE using econometric methods and summarizes the estimation results thoroughly. Section 3.1 describes a few of the tests that must be performed before regression to ensure that the estimated results based on the data are reliable. Section 3.2 estimates the DE–AWE relationship based on the econometric model developed earlier, with system generalized method of moments (SYS-GMM) estimates serving as benchmark regression. The DE–AWE relationship is then estimated using multiple additional econometric techniques to ensure the results' robustness.

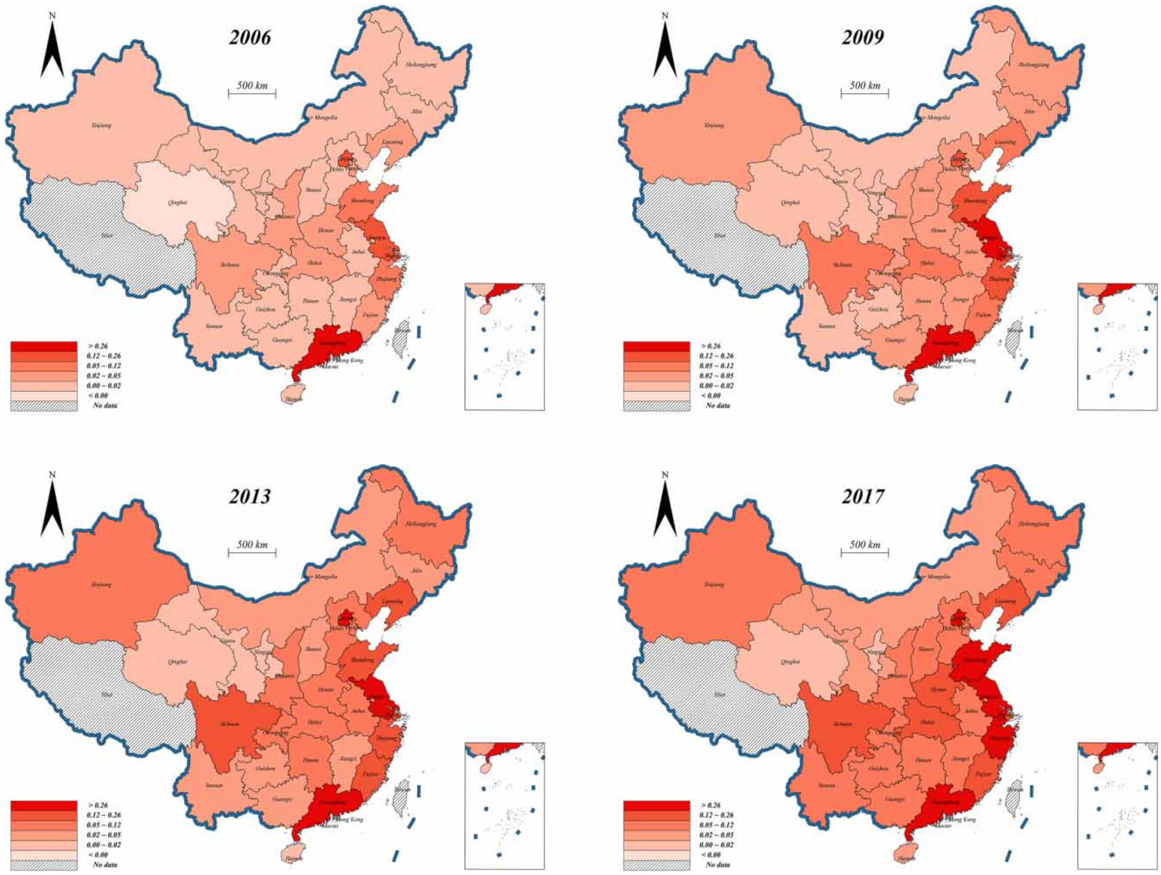

Fig. 3 | The spatial distribution of China's province-level digital economy for selected years.

3.1. Prebenchmark regression

Before conducting an appropriate econometric study, it is necessary to determine whether cross-sectional dependency exists in panel data. Failure to take into account cross-sectional independence is often blamed for unreliability, inconsistencies, and inconsistent outcomes in empirical data analysis (Grossman & Krueger, 1995). As a result, Breusch-Pagan LM test (Breusch & Pagan, 1980), the Pesaran CD test (Pesaran, 2004), and the Frees test (Frees, 2004) are used in this research to examine cross-sectional dependence.

The results of the four tests of cross-sectional dependence are shown in Table 4. All cross-sectional tests of dependence had p-values larger than 1%. Therefore, this study strongly disproves the null hypothesis, which states that there is no cross-sectional dependence. This indicates that the cross-sectional units were not independent in this research. Consequently, the cross-sectional dependence present in the data must be considered while performing the subsequent empirical investigation.

3.2. Benchmark regression

Reasonable econometric approaches are required to evaluate the impact of the DE on agricultural water consumption efficiency, which is the main focus of this study, due to the potential for endogeneity issues during

Table 3 | Variable summary statistics in the econometric model (logarithm).

Variable	Indicator	Measure	Mean	SD
Agricultural water use efficiency	lnAWE	Calculated from the DEA	−1.137	0.612
Digital economy	lnDE	According to the Section 2.2	−2.806	0.997
Cropping structure	lnCS	The proportion of vegetable planting area	−2.080	0.713
Natural disasters	lnND	Calculation of the affected area as a percentage of the cultivated area	−1.795	0.822
Water resource	lnWR	Calculated by dividing the amount of water available in the region by the area planted with crops (100 million cubic meter per thousand hectares)	−2.011	1.263
Traffic development	lnTD	Divided by the number of kilometers per thousand hectares of fertile land	1.040	0.907
Agricultural industry structure upgrading	lnAIS	The proportion of agricultural processing sector output to agricultural output	−0.260	0.914
Grain size per capital	lnGS	Cultivated land area (thousands of hectares) divided by rural population (10,000)	0.618	0.605
Agriculture's financial support	lnAF	Fiscal agriculture spending as a share of overall fiscal spending	−2.283	0.371

Table 4 | Cross-sectional dependence test results.

Test	Statistics	*p*
Pesaran CD test	5.289*	0.0000
Breusch-Pagan LM test	1361.95*	0.0000
Frees test	3.537*	0.0000

Note: $^*p < 0.01$.

the estimate process. First, it is conceivable that endogeneity results from inaccurate measurements. The social sciences are particularly prone to this problem since variable measurement is seldom error-free (Ullah *et al.*, 2018, 2021). Omitted variable bias, which occurs when important variables are overlooked in the model, may also lead to endogeneity. It has been shown that the SYS-GMM is an effective statistical tool for addressing estimate bias, endogeneity, and heterogeneity (Ullah *et al.*, 2018, 2021). Lagging values of the dependent variables are used in the SYS-GMM estimating technique to create internal instruments that address endogeneity problems. The best method to comprehend the current state of a phenomenon is to look at the values of lagged variables. The 'problem of too many instruments' is resolved by the inclusion of delays (Ullah *et al.*, 2018, 2021).

The results of this study's estimation of Equation (2) using SYS-GMM as the benchmark method are displayed in the last column of Table 5. The results of fixed effects (FE), random effects (RE), and pooled ordinary least squares (OLS) are also presented in Table 5. The empirical results in this research are robust and trustworthy because the sign and statistical significance of the variables are substantially consistent across the four estimating approaches.

For doing dynamic panel data analysis, the Sargan and Arellano-Bond (A-B) tests are crucial (Che *et al.*, 2013). The former is mainly concerned with the validity of the instrumental variables, while the latter is primarily

Table 5 | Estimation of DE-AWE nexus.

	OLS	FE	RE	SYS-GMM
L.lnAWE				0.909* (0.0261)
LnDE	0.292* (0.0320)	0.555* (0.0226)	0.543* (0.0224)	0.0525* (0.0189)
LnCS	0.230* (0.0450)	0.103** (0.0427)	0.0990** (0.0413)	0.0487* (0.0151)
LnND	−0.0952* (0.0350)	−0.00487 (0.0142)	−0.00879 (0.0143)	0.00509 (0.00448)
LnWR	−0.00531 (0.0216)	0.0190 (0.0325)	0.0143 (0.0299)	0.0188** (0.00855)
LnTD	−0.0964* (0.0340)	0.0377** (0.0160)	0.0339** (0.0161)	0.00408* (0.000758)
Constant	0.0808 (0.168)	0.624* (0.123)	0.571* (0.146)	0.255* (0.0515)
AR(1)				0.0070
AR(2)				0.8406
Sargan test				0.9999
Observations	360	360	360	330
R^2	0.4155	0.7599	0.7598	

Note: $*p < 0.01$.; $**p < 0.05$; standard errors are in parentheses.

concerned with the autocorrelation qualities of the difference term in the random disturbance term. The Sargan test results are displayed in Table 2. The Sargan test of the two-step GMM estimates, according to Roodman (2009), produces nonsignificant *p*-values, demonstrating the validity of all instrumental variables utilized in this work. In addition, in Table 3, *p*-values for first-order differences (AR (1)) and second-order differences (AR (2)) are both larger than 0.1, indicating that the SYS-GMM approach is suitable.

With all four estimating methodologies, the influence of DE on AWE is positive and statistically significant, as shown in Table 2. Based on SYS-GMM estimated results, for every 1% increase in the development level of DE, AWE increases by around 0.0525%. The DE has the potential to significantly improve the water use efficiency of agriculture. Field irrigation management is simplified by digital technology. Installing electronic metering facilities, for example, can provide a clear guide to which household has used how much irrigation water, giving farmers a better sense of actual water use and water use records. These data, aggregated and analyzed regionally, serve as the foundation for the government's policy on overuse markups and water rights trading. This will improve both the micro and macro levels of field irrigation management. The collection and analysis of agricultural production data help to improve field irrigation. More advanced, sophisticated, and intelligent irrigation techniques decrease water waste and increase AWE. The DE will have a catalytic effect on agricultural water efficiency, as is intuitively expected.

CS has a statistically significant positive effect on AWE, indicating that CS influences AWE and that the cultivation of more cash crops necessitates more refined management, which drives water use efficiency. There is an impact effect of ND on AWE, but it is not statistically significant, and this study anticipates that increased exposure to disaster will decrease AWE because increased exposure reduces crop yields and raises agricultural production costs, thereby reducing AWE. WR has a statistically significant positive effect on AWE, as water abundance promotes AWE by facilitating access to WR and reducing the difficulty and expense of water collection, thereby contributing to efficiency gains. TD significantly and positively affects AWE. A high level of TD indicates a high level of regional economic development, as well as improved access to modern markets and circulation of production factors, which in turn increases the AWE.

4. DISCUSSION

The previous section evaluated the connection between the DE and AWE and concluded that the DE has a positive effect on AWE. However, the precise channels by which the DE affects AWE need to be discussed in greater detail. This is due to the fact that clarifying the specific channels is the most practical way to translate the development results of the DE into an increase in the AWE. For the realization of the DE for AWE, discussing the possible channels of action has a practical role and provides important policy recommendations. This is crucial for water conservation, ensuring food security, economic development, and environmental sustainability. In this section, the effect of DE pathways on AWE will be examined in detail. The discussion and empirical testing of three possible action channels are presented. The structural effect is discussed in Section 4.1. Scale effect is covered in Section 4.2. The spillover effect is discussed in Section 4.3. The results of the discussion are reported in Section 4.4.

4.1. Structural effect

Numerous research studies have looked at how the DE and industrial structure are related, and they have come to the conclusion that the DE may considerably help with the improvement of industrial structure (Liu *et al.*, 2022; Zhao *et al.*, 2022b). The effects of the DE on modernizing the agricultural industrial system have not been extensively studied. The ratio of the output value of the agricultural processing industry to the output value of agricultural production is how this study defines the agricultural industrial structure upgrading in accordance with the literature that is currently available (Hong & Zhang, 2021; Chen *et al.*, 2022a, 2022b; Zhao *et al.*, 2022a). Agricultural industrial structure upgrading can improve the overall efficiency of agriculture, increase farmers' income, and facilitate farmers' investment in irrigation facilities. Simultaneously, the modernization of the agricultural industry structure will result in more advanced management and an increase in the production efficiency of agriculture, which will lead to a rise in the water use efficiency. The phenomenon that DE promotes the upgrading of agricultural industrial structure is the structural effect, which may be a crucial intermediate step for DE to enhance AWE.

4.2. Scale effect

The work landscape could be changed by the DE (Wu & Yang, 2022; Zhang *et al.*, 2022). Farmers now have more power and opportunities to work outside the farm because of the rise of the DE. Some farmers now rely less on agricultural production as their main source of income. Many new jobs have emerged as a result of the DE, including take-away food dispensers and rural e-commerce. China's fundamental situation is 'large country and smallholder farmers,' and the scale of agricultural production is hampered by the dispersed small farmers (Shi, 2021; Shi *et al.*, 2022b, 2022a). The DE's nonagricultural workers have shifted surplus labor in rural areas and, to some extent, have accelerated the rural land transfer. Fewer farmers and more land are an important basis for large-scale production. Grain size per capital (GS) is a good indicator to describe the scale effect. To calculate GS, the area under cultivation is divided by the number of farmers (i.e., 10,000 farmers per 1,000 ha). Scaled agricultural production improves AWE. For example, large-scale agricultural production can directly lay large areas of water-saving facilities (Shi, 2021). As a result, the scale effect could be a significant avenue for the DE to influence AWE.

4.3. Spillover effect

The DE, as the main economic form of the future, has a spillover effect and can bring the development of other industries (Chen *et al.*, 2022a, 2022b; Ding *et al.*, 2021; Pang *et al.*, 2022). Against the backdrop of slowing macroeconomic growth, the DE is actually growing at a very impressive CAGR of 14% annualized. The DE has created a major increment in the economy. This gives the state the ability to provide more support for agricultural development, such as building more advanced irrigation water-saving facilities. The spillover effect of the DE on agriculture is expressed in terms of financial support for agriculture (AF). Fiscal agricultural spending divided by total fiscal expenditure is used to calculate the financial support for agriculture (abbreviated as AF). Spillover effects are likely to be important mediating variables for the DE to increase water use efficiency in agriculture.

4.4. Results

The baseline regression is displayed in the first column of Table 6, the results of the mediation analysis of the structural effect are displayed in the second and third columns, the results of the mediation analysis of the scale effect are displayed in the fourth and fifth columns, and the results of the mediation analysis of the spillover effect are displayed in the sixth and seventh columns.

The findings of the analysis are all statistically significant, suggesting that the aforementioned channels of the DE can assist in increasing the efficiency of agricultural water use. By supporting changes to the structure of the agricultural business, the DE increases the efficiency of agricultural water use. By expanding the volume of

Table 6 | DE-AWE mechanism analysis results.

Variables	(1) lnAWE	(2) lnAIS	(3) lnAWE	(4) lnGS	(5) lnAWE	(6) lnAF	(7) lnAWE
L.lnAWE	0.909* (0.0261)		0.877* (0.0374)		0.885* (0.0429)		0.873* (0.0319)
lnDE	0.0525* (0.0189)	0.185* (0.0183)	0.0542** (0.0283)	0.0680* (0.00359)	0.0525*** (0.0263)	0.0198*** (0.00861)	0.0667* (0.0238)
L.lnAIS		0.723* (0.0176)					
lnAIS			0.0209* (0.00733)				
L.lnGS				0.953* (0.00357)			
lnGS					0.0502*** (0.0247)		
L.lnAF						0.557* (0.0224)	
lnAF							0.0521*** (0.0221)
lnCS	0.0487* (0.0151)	−0.00338 (0.00818)	0.0459* (0.0144)	−0.0585* (0.00142)	0.0624* (0.0149)	−0.0571* (0.0196)	0.0537* (0.0171)
lnND	0.00509 (0.00448)	0.0221* (0.00779)	0.000262 (0.00432)	0.0165* (0.00161)	0.00453 (0.00411)	−0.00381 (0.00442)	0.00292 (0.00436)
lnWR	0.0188*** (0.00855)	−0.0627* (0.0121)	0.0296* (0.00857)	0.0251* (0.00190)	0.0253*** (0.0121)	0.00462 (0.00597)	0.0167*** (0.00811)
lnTD	0.00408* (0.000758)	0.0148* (0.00182)	0.00411* (0.000887)	−0.0237* (0.00451)	0.00546* (0.000966)	−0.0115* (0.00344)	0.00575* (0.000729)
Constant	0.255* (0.0515)	0.422* (0.0558)	0.232* (0.0537)	0.211* (0.0100)	0.234* (0.0423)	−1.043* (0.0556)	0.370* (0.0585)

Note: $*p < 0.01.$; $**p < 0.05$; $***p < 0.1$; standard errors are in parentheses.

cultivation, the DE increases the efficiency of agricultural water use. The power of government assistance for agriculture is increased by the DE, increasing the effectiveness of agricultural water use.

According to the estimation results in Table 6, specifically, the mediating effect values of structure effect, scale effect, and spillover effect are 0.00387, 0.00341, and 0.00103, respectively. This means that in the process of realizing the development of the DE to drive the efficiency of agricultural water use, the upgrading of the structure of the agricultural industry and the scale of agricultural production are the more important paths to achieve.

5. CONCLUSIONS

The following are the study's primary conclusions: China's AWE has improved annually but remains low overall, showing that there is still a lot of room for water conservation. The overall degree of development of the DE has been rising steadily, though unevenly across space. According to the findings of the baseline regression, the DE greatly improves China's AWE. A rise of 1% in the index of the DE would result in a 0.0525% increase in the effectiveness of agricultural water use. The aforementioned conclusions are considered accurate when computed using the other three estimating methods (OLS, FE, and RE). The mechanism analysis shows how the structural, scale, and spillover effects of the DE indirectly boost AWE. The DE specifically encourages the modernization of the agricultural industry's organizational structure, increases the area under cultivation, and provides financial support for agriculture, all of which enhance the effectiveness of agricultural water use.

Here are the most important policy suggestions based on the findings: The enhancement of the DE has the potential to enhance the efficiency of water utilization in the agricultural sector. This highlights the significance of digital technology advancement and the facilitation of information technology in achieving mutually beneficial outcomes for both the economy and the environment. The utilization of digital technologies and information and communication technologies has the potential to enhance the magnitude and productivity of agricultural production. An illustration of the application of the IoT in the agricultural sector involves the utilization of precision agriculture techniques and agricultural automation systems. These technologies enable farmers to effectively monitor crucial factors such as crop growth, soil moisture levels, and meteorological conditions. Consequently, farmers are empowered to make informed decisions and efficiently manage their farmland.

The utilization of digital technology in the context of extensive agricultural production has the potential to enhance the efficiency of water resource allocation. Farmers could enhance their professionalism by utilizing accurate information to make informed decisions regarding the timing and quantity of irrigation. This approach would effectively mitigate irrigation waste and curtail excessive water consumption, advocate for the implementation of the DE to facilitate the enhancement of the agricultural industry's structural framework, and enhance the agricultural value chain through the implementation of novel technologies and value-added services, aiming to optimize the utilization of agricultural input factors, with a particular focus on irrigation WR. An illustration of the potential benefits of incorporating the IoT in agriculture and employing big data analytics is the ability of farmers to achieve enhanced value-added products. It is recommended that governments employ digital technologies to enhance the monitoring and administration of agricultural initiatives, allocate agricultural subsidies and assistance, and facilitate the development of associated infrastructure, such as improvements to irrigation systems. The implementation of these financial support measures has the potential to enhance water use efficiency within the agricultural sector, thereby enabling more effective mitigation of water scarcity and environmental sustainability concerns. It is imperative for the government to extend financial assistance toward the advancement of digital agricultural technologies, encompassing research and development efforts as well as enhancements in areas such as the IoT in agriculture, big data analytics tools, and agricultural robots. Furthermore, it is imperative for governments to implement training programs aimed at equipping farmers and agricultural practitioners with the necessary skills to effectively utilize these technologies. It is imperative for governments to allocate resources toward the development of digital infrastructure, encompassing high-speed Internet and communication networks, to facilitate equitable access to these technologies for rural regions as well. This will facilitate the proliferation of digital agricultural technologies, even in geographically isolated regions. Governments should use the development of the DE to facilitate the implementation of water rights and agricultural water pricing reforms to improve water use efficiency. Pay attention to the new jobs that the DE has created and encourage farmers to get DE-related jobs outside of farming. The DE needs to keep growing, and the structure of the agricultural industry needs to be updated all the time. China should promote the equitable development of the DE to prevent new forms of inequality due to the digital economy from hindering water conservation in agriculture.

The impact of the DE on irrigation management practices and CS was not discussed in depth in this study. All of these are closely related to water use efficiency in agriculture. Future research may focus on the effects of the DE on irrigation management practices, crop planting structure, and other relevant topics. The findings of this study hold practical implications for other countries aspiring to foster digital economies and enhance AWE. However, it is important to note that the conclusions drawn from this research are not readily applicable to other regions, as they were specifically derived from the examination of this particular region in China.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Ming Chang: writing – original draft, data curation, formal analysis, investigation, methodology, project administration, and software. Fei Li: investigation and data curation. Songwei Lin: investigation and data curation. Jinhao Zhang: investigation. Hongxu Shi: conceptualization and writing – review and editing.

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We certify that the submission is original work and is not published at any other publications.

CONSENT TO PARTICIPATE

All authors gave explicit consent to participate in this work.

CONSENT TO PUBLISH

All authors gave explicit consent to publish this manuscript.

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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