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Research on the impact and mechanism of digital economy on China's food production capacity

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Enhancing and strengthening food production capacity has always been a top priority in agricultural research, serving as a cornerstone for ensuring national food security and stable economic development. This study, based on panel data spanning from 2011 to 2021 across 30 provinces in China, delves into the mechanism through which the digital economy impacts food production capacity. Employing a double fixed effect model, a mediation effect model, and a panel threshold model, we uncover several key findings: The digital economy significantly boosts food production capacity, with robustness tests affirming the reliability of our results. Mechanism analysis reveals that the digital economy enhances food production capacity by elevating total factor productivity and bolstering agricultural resilience. The threshold effect underscores that urbanization levels exhibit a single-threshold impact, wherein the influence of the digital economy on food production capacity intensifies upon crossing this threshold. Heterogeneity analysis reveals that the digital economy significantly boosts food production capacity in central and primary grain-producing regions, while its impact is comparatively weaker in the eastern and western regions, as well as in non-primary grain-producing areas. In summary, this research sheds light on the pivotal role of the digital economy in augmenting food production capacity, offering valuable insights into regional variations and thresholds in its impact across China.

Keywords Digital economy, Food production capacity, Regional heterogeneity, Threshold effect

Food production capacity, as a cornerstone indicator in the agricultural domain, remains a pivotal concern. According to the latest data from the Food and Agriculture Organization of the United Nations (FAO), over 800 million people globally still endure hunger, with the majority situated in developing nations. The escalating challenges of global climate change, resource scarcity, and population growth compound the urgency of addressing food security. Augmenting food production capacity has thus emerged as a linchpin in resolving this dilemma.

Primarily, the burgeoning global populace imposes escalating demands on food requirements, underscoring the imperative of bolstering production capacity to ensure stable and adequate food provision. Furthermore, environmental vagaries such as climate change engender heightened uncertainty in food production, accentuating the need to fortify agricultural systems against risks and mitigate production downturns stemming from disasters. Moreover, bolstering food production capacity can catalyze agricultural modernization, enhance production efficiency, foster rural economic development, and advance the broader goal of sustainable agricultural practices.

In this context, the emergence of the digital economy provides a significant opportunity to boost food production capacity. The digital economy, characterized by its high efficiency and intelligence, injects fresh vigor and momentum into food production. Leveraging tools such as big data analysis, Internet of Things technology, and artificial intelligence, the agricultural production process can be more precisely monitored and managed, thus boosting efficiency and quality in food production[1]. The development of the digital economy has broadened the horizons for food production, breathing new life into agricultural modernization and sustainable development[2]. However, it's crucial to acknowledge the heterogeneous nature of the digital economy's impact across different regions. While developed regions have embraced advanced digital technology to upgrade the entire food production chain, enhancing its scientific and technological content and value, relatively backward

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regions face challenges such as the digital divide. This gap stems from insufficient digital economy infrastructure and talent reserves, which pose constraints on the enhancement of food production capacity.

Therefore, delving into the mechanism of the digital economy on food production capacity and its regional heterogeneity is paramount. Such analysis not only guides the formulation of food production policies but also fosters overall improvements in food production capacity. Against this backdrop, this paper aims to dissect the mechanism of the digital economy's impact on food production capacity and its regional variances. By uncovering the modes and paths of this impact across different regions, it provides theoretical insights and policy recommendations crucial for promoting agricultural modernization and achieving food security.

Research on food production capacity has emerged as a crucial focus for scholars both domestically and internationally, serving as a core indicator of agricultural development. This emphasis has intensified in recent years due to the twin challenges of global population growth and climate change. Scholars have identified technological progress[3], resource optimization[4], and policy support as primary drivers of improvements in food production capacity[5]. Technological advancements play a pivotal role in enhancing food production efficiency and yield. Mechanization of agriculture, utilization of biotechnology, and implementation of precision agriculture techniques have all significantly contributed to this progress[6]. Resource optimization strategies, such as sustainable land use, water management, and efficient fertilizer application, have garnered attention for their potential to achieve long-term food production sustainability[7]. Policy support is equally crucial for bolstering food production capacity[8]. Studies like Faki et al.[9] have highlighted the potential of targeted policies, such as those in the irrigation sector, to boost food production. Recommendations include setting production targets, implementing pricing and taxation policies, and leveraging comparative advantages in crop production. Moreover, agricultural subsidies[10], price supports[11], and market regulations[12] have been identified as effective mechanisms for incentivizing farmer productivity and ensuring the stable development of grain production. Despite these advancements, challenges persist. Variations in climate, soil, and other natural conditions necessitate region-specific strategies for enhancing food production capacity, making it challenging to formulate a universal model. Additionally, rapid population growth and urbanization exert pressure on land and water resources, further complicating efforts to bolster food production capacity[13].

Research on the impact of the digital economy on food production has been extensively explored in existing literature. Mainly, scholars have focused on the integration of the digital economy into the food supply chain[14], enhancing the high-quality development of the food industry[15], and bolstering food system resilience[16]. Some have delved into leveraging digital technologies for precise crop classification, thereby enhancing production efficiency and ensuring food supply[17]. The closely related literature reflects several key viewpoints: Firstly, the amalgamation of the digital economy with traditional agriculture into smart agriculture stands as a pivotal driver for boosting food production efficiency[18]. Secondly, the digital economy holds significant potential to enhance the food supply chain[19], quality development of the food industry, and resilience of food systems. Thirdly, the digital economy's development can meet production needs in primary grain-producing areas through technological innovation, fostering new modes of agricultural development and business modelsGao, thus leading to continuous improvements in both quantity and quality of grain production. Nevertheless, contrasting perspectives exist. Zhang & Duan[20] argue that the digital economy's advancement has exacerbated the 'siphon effect' of non-agricultural sectors on agricultural production factors, potentially undermining grain production and food security.

In summary, scholars have conducted thorough analyses of the factors and mechanisms influencing food production capacity from various angles. However, limited empirical evidence exists regarding the role of the digital economy in enhancing food production capacity. This paper aims to fill this gap by (1) quantitatively assessing the digital economy's specific impact on food production capacity through an econometric model; (2) exploring its mechanism on food production capacity from the perspectives of agricultural total factor productivity and resilience, providing insights for policymakers; and (3) further examining the policy effects of the digital economy on food production capacity, thus enriching existing theory and offering a new perspective for research in this field.

Theoretical mechanisms and research hypotheses

Impact of the digital economy on food production capacity

The impact of the digital economy on food production capacity manifests in several key aspects. Firstly, the digital economy enhances the decision-making process in food production by furnishing precise data support[21]. Leveraging big data and cloud computing, agricultural producers access real-time, multi-dimensional information on weather, soil conditions, and crop growth, facilitating accurate perception and prediction of the production environment[22]. This data aids in devising scientific planting programs and judicious resource allocation, thereby reducing production costs and augmenting efficiency. Secondly, the digital economy propels the intelligent and automated facets of food production[23]. Technologies such as the Internet of Things and artificial intelligence empower agricultural equipment with capabilities like remote control, automatic monitoring, and intelligent adjustment[24]. For instance, smart irrigation systems regulate water usage based on crop demand, while intelligent agricultural machinery conducts precise seeding, fertilization, and harvesting operations[25]. These innovations not only alleviate farmers' labor intensity but also enhance the precision and efficiency of food production. Thirdly, the digital economy fosters the marketization and industrialization of food production[26]. Through digital platforms, agricultural producers gain easier access to market information and consumer demand insights, facilitating adjustments in production structure and product strategies. Furthermore, it promotes supply chain integration and synergy within the food industry, optimizing the entire chain from production to sales. This minimizes transaction costs, enhances market competitiveness, and propels sustainable development in the food sector. Lastly, the digital economy facilitates advancements in technological innovation within food production. As digital technology evolves, novel agricultural technologies and management models emerge, offering new possibilities for enhancing food production. Agricultural producers can leverage these advancements to elevate their technical prowess and innovation capabilities, thereby fostering the transformation and upgrading of food production processes[27]. In light of these observations, this paper posits the following hypothesis:

H1: The digital economy can significantly enhance food production capacity.

Mediating effects of agricultural total factor productivity and agricultural resilience

Total factor productivity stands as a pivotal indicator of agricultural efficiency, reflecting the adept utilization of various input factors within the agricultural production process. The advent of the digital economy, facilitated by cutting-edge technologies such as big data, cloud computing, and the Internet of Things, empowers agricultural producers with more precise information access, facilitating optimized resource allocation and heightened efficiency in factor utilization[28]. Specifically, leveraging advanced sensor technologies enables farmers to monitor soil nutrient levels, moisture content, and pest infestations in real-time, facilitating precise fertilization and irrigation practices to maximize crop yield and quality[29]. Furthermore, through the application of artificial intelligence and big data analytics, agricultural producers can make data-driven decisions, refining planting strategies and managing crop growth processes with enhanced precision, consequently amplifying agricultural total factor productivity[30].

Agricultural resilience refers to agriculture's ability to withstand and recover from adverse environmental conditions. Digital economy technologies play a crucial role in enhancing the resilience of agricultural production systems, enabling agriculture to better adapt to environmental changes and withstand disasters[31]. For instance, intelligent weather warning systems can alert farmers to impending weather disasters, allowing them to take timely actions to minimize losses[32]. Moreover, digital economy technology facilitates risk management and insurance for agricultural producers, reducing losses caused by natural disasters or market fluctuations, and bolstering agriculture's resilience to risks[33]. Through digital agricultural production management platforms, farmers can efficiently track and monitor crop growth, identify issues promptly, and implement necessary measures, thus improving the stability and sustainability of agricultural production. These measures collectively enhance agriculture's resilience, ensuring that food production remains relatively stable despite adverse conditions, thereby guaranteeing the continuity and stability of food supply. Based on these insights, this paper proposes the following hypothesis:

H2: The digital economy can augment food production capacity by bolstering agricultural total factor productivity and fortifying agricultural resilience."

Heterogeneity analysis of the digital economy on food production capacity

The impact of the digital economy as an emerging economic force on food production capacity varies significantly across different regions. Geographically speaking, there are noticeable disparities in how the digital economy influences food production capacity. The eastern region, characterized by its developed economy and advanced science and technology, experiences rapid growth in the digital economy[34], resulting in a more pronounced enhancement of food production capacity. Here, advanced technologies like big data and cloud computing have been introduced to achieve precise management and optimization of agricultural processes, thereby boosting efficiency and quality of food production[35]. However, the eastern region may also prioritize the development of secondary and tertiary industries due to the high value-added of land resources, potentially diluting the direct impact of the digital economy on food production capacity[9]. Conversely, the central and western regions, with their emphasis on secondary and tertiary industries due to the high value-added of land resources, lag behind in digital economy development. Consequently, the digital economy's advancement in these regions holds greater potential for enhancing food production capacity compared to the more developed eastern region. Regarding food production functional areas, there are notable differences in how the digital economy affects food production capacity. Major grain-producing regions, pivotal to China's agricultural output, exhibit large-scale production and comprehensive industrial chains, making them prime targets for integrating the digital economy and agriculture[36]. In these areas, digital economy development facilitates intelligent and precise food production, thereby improving efficiency and quality. Moreover, the establishment of digital platforms enables seamless coordination between production and marketing, optimizing resource allocation and bolstering the industry's competitiveness. Conversely, non-major grain-producing areas feature diverse agricultural structures and relatively smaller scales of production. Here, the impact of the digital economy on enhancing grain production capacity may be comparatively limited. Based on these observations, this paper posits the following hypothesis:

H3: Regional heterogeneity exists in the impact of the digital economy on food production capacity.

Research design

Definition of variables

Grain production capacity

Grain production capacity refers to the measure outlined in Xu et al. and Wang et al.'s study[37,38], characterized by the grain production per unit area. This metric is calculated by dividing the total grain production by the total sown area of grain. Standardizing data from different regions or time periods facilitates easy comparison of grain yields per unit area. Higher yields per unit area typically signify more efficient land use, enabling an assessment of the agricultural production potential in a given area. This information is invaluable for agricultural managers in developing planting plans, allocating resources, and devising strategies for technological advancements.

Digital economy

Digital economy: 11 indicators are selected, including The year-end resident population, Internet broadband access subscribers, Urban employment personnel in the information transmission, software, and information technology service industries, Employed personnel in urban units, Total telecommunication services, End-of-year cell phone subscribers, Digital financial inclusion index, Internet users per 100 people, Percentage of employees in computer services and software, and Number of cell phone subscribers per 100 people. The resident population serves as the foundation for the digital economy, indicating the potential service targets and forming the basic population for digital economic activities. Internet usage and penetration rates are key indicators of digital economy development. Metrics such as broadband access and internet users per 100 people reflect the extent of digital information acquisition, communication, and sharing, crucial for advancing the digital economy[39]. Employment ratios in information transmission, software, information technology services, and computer services showcase the workforce and scale of the IT industry, essential for digital economy growth[40]. More and more employed persons in urban units are engaged in digital economy-related industries such as the internet, information technology and e-commerce, and thus the number of employed persons in urban units indirectly reflecting the position and role of the digital economy industry in the urban economy[41]. Telecommunication service volume, year-end mobile phone users, and mobile phone users per 100 people illustrate communication infrastructure development and mobile communication popularity, which underpin the digital economy's infrastructure needs[42]. The Digital Inclusive Finance Index gauges the reach and digitization of financial services, pivotal for fostering financial service accessibility in the digital economy's expansion.

The comprehensive indicator evaluation index system for the digital economy is shown in Table 1. There are currently multiple methods used to evaluate the digital economy, including principal component analysis, entropy weight method, entropy weight TOPSIS method, etc. Due to the involvement of multiple complex factors such as market size, technological innovation, user engagement, etc. in the evaluation of the digital economy, the entropy weight TOPSIS method combines the advantages of entropy weight method in objective weighting and the effectiveness of TOPSIS method in multi-objective decision analysis. It comprehensively considers the advantages and disadvantages of multiple evaluation indicators and objects, and can conduct comprehensive and systematic analysis of these factors[43]. Therefore, this study uses the entropy weight TOPSIS method to comprehensively evaluate the digital economy. The specific calculation steps are as follows:

The first step is to eliminate the influence of dimensionality, and this article adopts the range standardization method to standardize and preprocess the indicator data:

$$d_{ij} = \begin{cases} \frac{x_{ij}-x_{ij(min)}}{x_{ij(max)}-x_{ij(min)}}(positive\ indicator) \\ \frac{x_{ij(max)}-x_{ij}}{x_{ij(max)}-x_{ij(min)}}(negative\ indicator) \end{cases} \tag{1}$$

In Eq. (1), x_{ij} represents the original value of the jth comprehensive evaluation index of the digital economy in the i-th year; d_{ij} represents the standardized value.

Second, the weight of each indicator p_{ij}:

$$p_{ij} = \frac{d_{ij}}{\sum_{i=1}^{m} d_{ij}} \tag{2}$$

Third, calculate the entropy value of the indicator e_j and the redundancy value f_j : (if p_{ij} is 0, then assume $\mathrm{lnp_{ij}}$ is also 0)

$$e_j = -k\sum_{i=1}^{m} p_{ij} \times lnp_{ij} \tag{3}$$

where k = 1/ln m

$$f_j = 1 - e_j \tag{4}$$

Fourth, calculate the entropy weight w_j:

Variable Name	Measurement method	Variable Properties
Digital economy	The year-end resident population	+
	Internet broadband access subscribers	+
	Urban employment personnel in the information transmission, software, and information technology service industries	+
	Employed personnel in urban units	+
	Total telecommunication services	+
	End-of-year cell phone subscribers	+
	Digital financial inclusion index	+
	Internet users per 100 people	+
	Percentage of employees in computer services and software	+
	Number of cell phone subscribers per 100 people	+

Table 1. Comprehensive evaluation index system for digital economy.

$$w_j = f_j / \sum_{j=1}^{n} f_j \tag{5}$$

Fifth, calculate the normalized weight matrix S:

$$S = (s_{ij})_{m\times n}, s_{ij} = w_j \times d_{ij}\,(i = 1,2,3\cdots.,m; j = 1,2,3,\cdots,n) \tag{6}$$

Sixth, determine the positive and negative ideal solutions for each indicator s_j^+ and s_j^- :

$$s_j^+ = max\,\{s_{1j}\,, s_{2j}, s_{3j}, \cdots, s_{ij}\} \tag{7}$$

$$s_j^- = min\,\{s_{1j}\,, s_{2j}, s_{3j}, \cdots, s_{ij}\} \tag{8}$$

Seventh, calculate the Euclidean distances d_i^+ and d_i^- of the positive and negative ideal solutions s_j^+ and s_j^- :

$$d_i^+ = \sqrt{\sum\nolimits_{j=1}^{n} \left(s_{ij} - s_j^+\right)^2} \tag{9}$$

$$d_i^- = \sqrt{\sum\nolimits_{j=1}^{n} \left(s_{ij} - s_j^-\right)^2} \tag{10}$$

Eighth, calculate the closeness C_i :

$$C_i = d_i^- / \left(d_i^- + d_i^+\right)(i = 1,2,3,\cdots,m) \tag{11}$$

where, $0 \leq \mathrm{C_i} \leq 1$; the larger the C_i value, the higher the level of digital economy development.

Mechanism variables

Based on existing literature[44], agricultural total factor productivity was assessed using the global Malmquist index method. Input indicators included the number of people employed in the primary sector, machinery power, sown area, irrigated area, and fertilizer usage. Employment in the primary sector directly relates to agricultural labor input. Machinery power indicates agricultural mechanization. Sown area is crucial for production, while irrigated area signifies water resource utilization, particularly beneficial in arid regions for enhancing crop yield and quality. Proper fertilizer usage improves soil fertility and crop output. Output is measured by the value of agricultural products, reflecting economic efficiency. Agricultural resilience is gauged by crop-affected area, indirectly indicating system resilience. Strong resilience implies minimal disaster impact and output loss, while weak resilience suggests vulnerability to disasters with significant output reduction.

Control variables

Based on existing literature[45,46], this study includes several key variables as control factors. Firstly, local financial expenditure on agriculture, forestry, and water affairs (lnLfe) is chosen to gauge government investment in these sectors. Secondly, the area of soil erosion control (lnAsec) serves as an indicator of regional soil protection efforts. Thirdly, the effective irrigated area (lnIa) reflects the extent of irrigation infrastructure coverage and water resource utilization. Additionally, the Engel's coefficient (Engel) is utilized to assess rural residents' income levels and consumption structure dynamics. Meteorological factors, namely precipitation (Pre) and sunshine (Sun), are crucial for agricultural production, directly influencing crop growth and yield. It's worth noting that the logarithmic treatment is applied to lnAsec due to its potential minimum value being zero. These selected variables provide a comprehensive framework for understanding the complex dynamics between agricultural carbon emissions and economic growth, ensuring a robust analysis while controlling for pertinent factors.

Data sources

The data for this article were gathered from multiple sources including the China Statistical Yearbook, China Rural Statistical Yearbook, China Regional Statistical Yearbook, statistical yearbooks from various provinces and cities in China, and the Peking University Digital Finance Research Center. Any missing data were supplemented using interpolation techniques. Descriptive statistics for specific variables are presented in Table 2.

Modeling

To explore the impact of the digital economy on food production capacity, a benchmark regression model is constructed as follows:

$$Gpc_{it} = \alpha_0 + \alpha_1 Dig_{it} + \alpha_2 C_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{12}$$

In order to delve into the potential mediating effect of agricultural total factor productivity and agricultural resilience, the following mediating effect model is formulated:

$$Tfpa_{it} = \beta_0 + \beta_1 Dig_{it} + \beta_2 C_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{13}$$

$$Gpc_{it} = \gamma_0 + \gamma_1 Dig_{it} + \gamma_2 Tfpa_{it} + \gamma_3 C_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{14}$$

Variable	Obs	Mean	Std.Dev	Min	Max
Gpc	330	0.358	0.111	0.183	0.700
Dig	330	0.240	0.182	0.049	1.000
lnLfe	330	6.186	0.575	4.519	7.200
lnAsec	330	7.655	1.848	0	9.678
lnIa	330	7.286	1.049	4.694	8.729
Engel	330	33.715	5.484	23.800	51.810
Pre	330	0.003	0.001	0.001	0.006
lnSun	330	7.594	0.274	6.838	8.209
Tfpa	330	1.002	0.070	0.800	1.387
Asr	330	762.399	752.959	1.600	42,237.000
Ur	330	59.591	12.137	35.030	89.600

Table 2. Descriptive characteristics of used variables.

Variable	(1)	(2)
Dig	0.196*	0.220**
	(0.097)	(0.096)
Constant	0.289***	0.700
	(0.024)	(0.439)
Control variable	No	Yes
Area FE	Yes	Yes
Year FE	Yes	Yes
N	330	330
R^2	0.212	0.364

Table 3. Benchmark regression. *Notes:* Symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. All models are estimated using a double fixed effects model. Robust standard errors for clustering with individuals (provinces) as the clustering variable are in parentheses in each column. Same as below.

$$Asr_{it} = \alpha_0 + \alpha_1 Dig_{it} + \alpha_2 C_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{15}$$

$$Gpc_{it} = b_0 + b_1 Dig_{it} + b_2 Asr_{it} + b_3 C_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{16}$$

Currently, as urbanization accelerates, the agricultural workforce continues its migration to urban centers. This shift prompts changes in rural land use and agricultural practices, potentially impacting food production capacity. Consequently, this study employs the population urbanization rate as a proxy indicator to develop a threshold effect model. The goal is to investigate the nonlinear impact of agricultural population migration and the digital economy on food production capacity, aiming for a comprehensive understanding of the intricate effects of rural demographic shifts on food production.

$$\begin{aligned} &Gpc_{it} = \rho_0 + \rho_1 Dig_{it} * I\left(Ur \leq q_1\right) + \\ &\rho_2 Dig_{it} * I\left(q_1 < Ur \leq q_2\right) + \rho_3 Dig_{it} * I\left(q_2 < Ur \leq q_3\right) + \\ &\cdots + \rho_n Dig_{it} * I\left(Ur > q_n\right) + \rho C_{it} + \mu_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{17}$$

Here, i is the province, and t is the year; *Gpc* is the food production capacity; *Dig* is the digital economy; *Tfpa* is total factor productivity in agriculture. *Asr* is agricultural resilience, and *Ur* is urbanization rate; *C* denotes control variables; α, β, γ, a, b, and ρ are the regression coefficients; μ_i and δ_t denote controls for individual and temporal heterogeneity, and ε_{it} is the random error term.

Empirical results and analysis

Baseline regression

Table 3 presents the results of the baseline regression of the digital economy on food production capacity. Column (1) represents the analysis without considering the control variables, while column (2) includes these controls. The findings reveal a significantly positive regression coefficient for the digital economy at the 5% significance level. This suggests that the digital economy plays a substantial role in fostering the development of food production capacity, with an estimated impact of 0.220 units for each change in the digital economy. The paper posits that the rapid advancement of the digital economy not only optimizes resource allocation and enhances factor efficiency but also fosters the intellectualization and modernization of food production, thereby bolstering food production capacity, thus validating H1.

Robustness tests

To ensure the robustness of the test results, this study employs three approaches for robustness testing, as shown in Table 4: Variable Replacement: Replacing the explanatory variables. Both food output and agricultural economic output encompass production considerations and, to some extent, reflect the productivity and efficiency of agriculture. Hence, food output per unit area is substituted with the logarithmic value of agricultural economic output per unit area (column (1)). Shrinkage treatment: one percent right-hand side indentation of explanatory variables (column (2)). Addressing Endogeneity: Considering the omission of important variables or the possible existence of bidirectional causality between digital economy development and food production capacity capacity thus leading to endogeneity problems, in order to further mitigate the interference of endogeneity problems, this paper uses the lagged one period of the level of digital economy development (L.Dig) as an explanatory variable on the basis of a fixed-effects model, however, it should be noted that the use of lagged variables may still bring about a bias, the Especially when the omitted variables exhibit serial correlation, therefore, this paper simultaneously employs the instrumental variable method for endogeneity. Following Huang Qunhui et al.'s approach[47], the number of telephone calls in each province in 1984 is selected as an instrumental variable to reduce the endogeneity problem of the model. Since traditional communication technology is closely linked to the digital economy, historical telephone call data exerts negligible impact on present agricultural mechanization and meets the exogeneity criterion. To handle the cross-sectional nature of the data, we adopt Zhao Tao et al.'s treatment, utilizing the logarithm of the interaction term between lagged-period Internet broadband access users and 1984 telephone call data (lnIv) as an instrumental variable. Column (3) reveals that digital economy development, even with a lagged one-period explanatory variable, remains statistically significant. Column (4) shows the regression coefficients for the instrumental variables, which pass the 1% significance test, indicating that the instrumental variables and the endogenous explanatory variables are significantly correlated.The CraggDonald Wald F statistic is 115.28, which is greater than the Stock-Yogo critical value at the 10% level, the AR statistic has an F value of 13.01 ($p = 0.0011$) , the chi-square value of 14.20 ($p = 0.0002$) supports the validity of the instrumental variables and the rejection of the presence of weak instrumental variables by the instrumental variables In addition, the p-value of the Kleibergen-Paap rk LM statistic is less than 0.01 rejecting the hypothesis that the instrumental variables are under-identified. Column (5) demonstrates a significantly positive impact of the digital economy on food production capacity at the 5% level. In conclusion, the selected instrumental variables validate our findings, indicating that digital economy development substantially enhances food production capacity. This confirms the robustness of our benchmark regression results.

Mechanism discussion

To delve deeper into understanding the mechanism of the digital economy's role in bolstering grain production capacity, this article introduces agricultural total factor productivity and agricultural resilience as mediating variables. By constructing an intermediary effect model to scrutinize their interplay, the results are presented in Table 5. In column (1), the impact of the digital economy on agricultural total factor productivity is notably positive, indicating a significant enhancement in agricultural productivity due to digital interventions. Furthermore, the regression coefficients of the digital economy and agricultural total factor productivity in

	(1)	(2)	(3)	(4)	(5)
Variable	Variable replacement	Shrinkage treatment	The Dig of lag one period	Instrumental variable	
Dig	1.011**	0.220**			0.703**
	(0.386)	(0.096)			(0.308)
lnIv				0.067***	
				(0.020)	
L. Dig			0.215**		
			(0.086)		
Constant	9.018***	0.700	0.963*	-0.575	0.671
	(1.400)	(0.439)	(0.553)	(0.666)	(0.542)
Control variable	Yes	Yes	Yes	Yes	Yes
Area FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	330	330	330	330	330
R^2	0.824	0.364	0.310	0.256	
Cragg-Donald Wald F				127.17	
Stock-Yogo 10% threshold				16.38	
Kleibergen-Paap rk LM				9.30***	

Table 4. Robustness test.

Variable	(1) Tfpa	(2) Gpc	(3) Asr	(4) Gpc
Dig	0.348*	0.204**	-1,654.927*	0.197*
	(0.172)	(0.091)	(907.112)	(0.100)
Tfpa		0.048**		
		(0.023)		
Asr				-0.0001***
				(3.80e-06)
Constant	0.770	0.663	-5,264.366	0.627
	(1.311)	(0.393)	(3996.121)	(0.424)
Control variable	Yes	Yes	Yes	Yes
Area FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	330	330	330	330
R^2	0.210	0.375	0.213	0.411

Table 5. Mechanism of action analysis.

Threshold variables	Threshold number	RSS	MSE	F-value	P-value	Threshold value	95% Confidence interval
Ur	Single-threshold	0.1488	0.0005	104.39	< 0.0001	65.6900	(64.1800, 66.0400)
	Dual-threshold	0.1424	0.0004	14.34	0.3233	82.2900	(74.6300, 83.5700)
	Triple-thresholds	0.1374	0.0004	11.68	0.3467	83.5700	(71.8100, 86.6150)

Table 6. Threshold estimation results.

column (2) are all significantly positive at the 5% level, respectively, suggesting that the digital economy can augment food production capacity by elevating agricultural total factor productivity.

Moving to column (3), we examine the influence of the digital economy on agricultural resilience. Given that this study employs the extent of crop disasters as a metric for agricultural resilience, a significant negative effect of the digital economy on agricultural resilience is expected. As depicted in Table 5, the regression coefficient of the digital economy is significantly negative at the 10% level, implying that digital advancements can mitigate the occurrence of crop disasters, thus fortifying agricultural resilience. In column (4), the impact of the digital economy on grain production capacity is significant at the 10% level, while the regression coefficient of agricultural resilience is notably negative at the 1% level. Consequently, the digital economy can amplify grain production capacity by bolstering agricultural resilience, thereby validating H2. Assuming the role of a US-based individual, I have refined the passage for clarity and conciseness while maintaining the original content's integrity.

Analysis of threshold effects

To explore the nonlinear impact of the digital economy on food production capacity across varying circumstances, this study examines the shift in agricultural demographics and employs panel threshold model regression. The population urbanization rate serves as the threshold variable in this analysis. As shown in Table 6, the P-value of the single-threshold model using urbanization level as the threshold variable is less than 0.0001, significant at the 1% level. However, the P-values of the double-threshold and triple-threshold models are both greater than 0.1, indicating no significance. Therefore, a single-threshold model with a threshold of 65.6900 is chosen.

Table 7 reports the results of regression estimation between the variables under different threshold effects. In column (1), it is shown that when the urbanization level is lower than 65.6900, the coefficient of the impact of the digital economy on food production capacity is 0.105, which is not significant, suggesting that the potential of the digital economy in food production is not effectively utilized when urbanization levels are lower. However, when the urbanization level is higher than 65.6900, the impact coefficient of the digital economy on food production capacity is 0.555, significant at the 1% level. This indicates that the impact of the digital economy on food production capacity increases significantly after the urbanization level crosses the threshold, suggesting that the advantages of the digital economy have been more fully exploited in the area of food production as urbanization accelerates.

Heterogeneity analysis

Geographic heterogeneity

Considering the differences in economic level among provinces in China, 30 provinces are divided into eastern, central and western regions, and the specific regression results are shown in Table 8. The regression coefficient of the digital economy in the eastern region is 0.183, but it is not significant. The reason is that the eastern region, as the most active and developed region of China's economic development, has a relatively mature and stable

Variable	(1)
Dig	0.105
(Ur ≤ 65.6900)	(0.067)
Dig	0.555***
(Ur > 65.6900)	(0.108)
Constant	0.058
	(0.334)
Control variable	Yes
Area FE	Yes
Year FE	Yes
N	330
R^2	0.372

Table 7. Threshold effect regression results.

Variable	Eastern Region	Central Region	West Region	Main grain-producing Region	Non-main grain-producing Region
Dig	0.131	0.360**	0.154	0.198*	0.197*
	(0.157)	(0.120)	(0.105)	(0.102)	(0.111)
Constant	-0.400	0.974	0.663	1.524**	0.040
	(0.546)	(0.845)	(0.367)	(0.583)	(0.408)
Control variable	Yes	Yes	Yes	Yes	Yes
Area FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	121	88	121	143	187
R^2	0.596	0.442	0.332	0.429	0.432

Table 8. Regional heterogeneity.

industrial structure. Since land elements have higher added value in these regions, the eastern region is more inclined to invest resources in secondary and tertiary industries, such as manufacturing and service industries, in order to obtain higher economic returns. This bias in industrial structure makes the proportion of agriculture in the overall economy relatively low, which in turn affects the effect of the digital economy in the field of food production. The impact of the digital economy on food production capacity in the western region is positive, but again, not significant. This result stems from the fact that the western region is rich in agricultural resources, but traditional agricultural production methods are often limited by the level of technology and management, leading to low production efficiency, and the relatively poor level of agricultural resource endowment and economic development in the western region. In contrast, the regression coefficient of the central region passes the 5% significance level. The central region is in a critical period of economic transformation and upgrading, and its industrial structure is in transition from traditional agriculture to modern agriculture, which provides a broad space for the penetration and integration of the digital economy. With the continuous development and popularization of information technology, the agricultural production methods in the central region have begun to gradually get rid of the traditional constraints and move towards a new stage of intelligence and precision. This inter-regional heterogeneity reflects the impact of different economic foundations and industrial structures on the attractiveness of the digital economy, which in turn provides valuable references for policymakers, who should formulate differentiated strategies according to regional characteristics when promoting the development of the digital economy in the future, in order to maximize its benefits in the field of food production. H3 was initially validated.

Heterogeneity of functional grain-production areas

Considering that provinces have different positioning of agricultural functional zones, the role of digital economy may be different, in order to test the heterogeneity of the impact of policy implementation in different agricultural functional zones, the sample is divided into main grain-producing and non-grain-producing regions for the regression. The results are shown in Table 8, and we find that the digital economy shows obvious regional heterogeneity in the effect of food production increase. In the main grain-producing regions, the regression coefficient of digital economy is 0.198, showing its significant effect on the increase of grain production per unit area, while in the non-main grain-producing regions this coefficient is 0.197, which is lower than that of the main grain-producing region. This difference is mainly due to the fact that the main grain-producing regions tend to have more concentrated agricultural resources and more mature agricultural production systems, and due to historical and policy influences, the main grain-producing regions tend to have higher inputs and development in digital infrastructure construction and agricultural science and technology promotion. This makes it easier for farmers and enterprises to access advanced digital technologies and effectively utilize them in their daily production. Through the application of digital technologies such as precision agriculture and smart farm machinery, the main grain-producing regions s are able to realize the refined management of the agricultural production process and improve production efficiency, thus significantly increasing the yield per unit area. In contrast, the planting structure of the non-main grain-producing area was affected by the division of the functional food production area in 2001, which led to the fact that this area was mostly used for the production of high value-added cash crops, which, due to the formation of the profit drive relative to grain production, led to the fact that the farmers reduced their inputs to grain production to some extent, which in turn affected the role of the digital technology in enhancing the production capacity of grain.H3 Further be verified. This heterogeneity suggests that when formulating and implementing agricultural policies, we should take into full consideration the functional positioning and development stages of agriculture in different regions, so as to more accurately utilize the potential and benefits of the digital economy and promote the sustainable development of agricultural production in different regions. In the long run, the effective design of digital economy promotion strategies for non-main grain-producing regions will help guide them to optimize their agricultural structure, achieve the coordinated development of food production and cash crop cultivation, and thus enhance overall agricultural competitiveness.

Conclusions

Main conclusion

The profound advancement of the digital economy is progressively reshaping the traditional landscape of food production. Through technological innovation and model enhancement, it effectively boosts food production capacity, thereby establishing a robust foundation for both food security and national development. Drawing upon panel data spanning 2011 to 2021 from 30 provinces in China, this study investigates the mechanism through which the digital economy influences food production capacity. Employing a double fixed effect model, mediation effect model, and panel threshold model, the analysis reveals several key insights: The impact of the digital economy on food production capacity is notably positive, significant at the 10% level. This effect persists even after robustness checks, including the replacement of random effects model, tail treatment reduction, incorporation of control variables, and consideration of instrumental variables. Mechanism analysis indicates two pathways through which the digital economy affects food production capacity. Firstly, it enhances agricultural total factor productivity, and secondly, it strengthens agricultural resilience, consequently increasing food production capacity. A threshold effect is observed in urbanization levels. When the urbanization rate surpasses 65.6900, the impact of the digital economy on food production capacity escalates significantly from 0.105 to 0.555. Heterogeneity analysis highlights the influence of geographic region and functional location on the role of the digital economy in enhancing food production capacity. Regarding geographic regions, the digital economy's effect on boosting food production capacity is more pronounced in the central region compared to the east and west regions. In terms of functional areas of food production, the digital economy has a slightly stronger impact on the food production capacity of main food-producing areas compared to non-main food-producing areas.

Theoretical contributions

This study contributes in the following ways: (1) It explores the impact of digital economy on food production capacity from a relatively new research perspective. Traditionally, research on food production capacity has focused on agricultural technology, natural resources, and policy environments, while the potential impact of the digital economy, as an emerging field, has not been thoroughly examined. This paper enriches the existing literature; (2) The study not only addresses the direct effects of the digital economy on food production capacity but also delves into the underlying mechanisms. For instance, the digital economy may empower the food industry through total factors productivity in agriculture and agricultural resilience, thereby indirectly enhancing food production capacity. This mechanism analysis contributes to a more comprehensive understanding of the complex effects of the digital economy on food production capacity; (3) Given China's vast territory, there are significant differences among regions in terms of digital economy development, agricultural resource endowments, and economic structures. Therefore, this study analyzes the impact and differences of the digital economy on food production capacity across the eastern, central, and western regions, which is crucial for formulating differentiated agricultural policies and digital economy development strategies.

Practical implications

Enhancing the application of the digital economy in agriculture holds immense promise. The government should ardently advocate for the deep integration of the digital economy with agricultural practices, thereby unlocking further growth potential for food production. Primarily, bolstering rural Internet infrastructure is imperative, augmenting network coverage and quality in rural locales to establish a robust foundation for digital economy applications. Additionally, proactive promotion of intelligent agricultural equipment is crucial, encouraging farmers to adopt advanced tools like smart farm machinery and irrigation systems to enhance automation and intelligence in agricultural production. Strengthening the utilization of agricultural big data is also paramount, offering scientific decision support for production optimization and resource allocation through comprehensive data collection, analysis, and application.

Efforts to optimize agricultural total factor productivity and resilience are essential. Increased investment in agricultural science and technology innovation is imperative. Supporting scientific research institutions and enterprises in advancing agricultural technologies and management models, such as precision fertilizer application and water-saving irrigation, can significantly elevate total factor productivity. Concurrently, fortifying agricultural disaster prevention and mitigation systems is crucial. Establishing a robust disaster early warning system, enhancing farmland water conservancy infrastructure, and promoting agricultural insurance are pivotal strategies to bolster agriculture's resilience against natural calamities, ensuring food production stability and security.

Emphasizing regional disparities and functional positioning is paramount. Recognizing the varying impact of the digital economy on food production across regions and functional agricultural areas is crucial when formulating policies. Consideration of regional resource endowment, economic development levels, and food production functional positioning is imperative to tailor policies that align with local conditions. Providing increased policy support and financial investment for the rapid development of the digital economy in western regions and major food production areas is essential.

Highlighting the significance of the urbanization threshold effect, it's imperative for governments to closely monitor its impact on the digital economy's role in food production capacity. Adjustments in policy direction and investment strategies should be made promptly when indicators surpass this threshold. For instance, in highly urbanized areas, fostering integrated urban–rural development can enhance resource sharing and exploit complementary advantages between urban and rural sectors, thus facilitating broader digital economy application in agriculture. Similarly, in regions experiencing rapid rural economic growth, bolstering investment in agricultural science, technology innovation, and workforce training can elevate agricultural production's digitalization and intelligence. By implementing precise policies and dynamically adapting to changing circumstances, the digital economy can effectively contribute to bolstering food production capacity.

However, this study still has some limitations. Firstly, the data completeness and lack of statistics on digitalized agricultural production methods due to limitations in macro statistical data may impact the portrayal of digital agriculture in this paper, hindering a full reflection of the level of digital economic development. Second, there are also limitations in the choice of variables, for example, measuring agricultural disaster resilience by the area affected by agricultural disasters, although it directly reflects the impact of natural disasters on agricultural production, it may not fully reflect all dimensions of disaster resilience. Therefore, future research should explore more comprehensive indicators to measure agricultural resilience. Finally, in this study, we conducted a preliminary analysis for the heterogeneity of the effect of digital economy on food production increase. Although meaningful results have been obtained, we expect to be able to fully utilize the advantages of causal forest modeling to contribute new insights to the research on digital transformation in agriculture in our subsequent work, considering its unique advantages in exploring complex causality and heterogeneity effects.

Data availability

It can be obtained directly from the first author.

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Author contributions

Conception and design:J. W.; Provision of study material: J. W.; Data analysis and interpretation: J. W., Y. D.; Manuscript writing: J.W., Y.D.; Manuscript revision: J.W., Y.D. and H.W.; All authors read and approved the final manuscript.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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