

Article

An Exploration of the Relationship Between Digital Village Construction and Agroecological Efficiency in China

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Abstract: Whether digital village construction can effectively promote agriculture's green development is essential for modernizing agriculture and rural areas. Using panel data from 30 provinces in China between 2011 and 2022, this study empirically examines the relationship between digital village construction and agroecological efficiency and explores its mechanism of action and threshold effect, contributing to the exploration of agricultural digitization and sustainable development. This study shows that (1) AEE is positively associated with digital village construction; (2) the positive association size varies in regions and construction levels; (3) agricultural land transfer and technological innovation play a mediating role in the positive effect; and (4) there is a single threshold value for the positive effect of digital village construction, and after crossing the threshold value, its marginal effect shows a positive and increasing nonlinear characteristic. This study enhances our comprehension of digital village development to advance agroecological efficiency and offers theoretical insights and policy recommendations for optimizing the rural digital infrastructure and fostering sustainable agricultural growth.

Keywords: digital village; agroecological efficiency; mediation effect; threshold effect; heterogeneity



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1. Introduction

In recent years, China's overall agricultural production capacity has increased. The country's total grain output 2023 reached 1390.82 billion pounds, maintaining a level above 1.3 trillion pounds for nine consecutive years. As a major agricultural country, China has played a crucial role in upholding global food security. However, it also confronts challenges related to resource usage and environmental protection [1]. China has long depended on inputs like fertilizers, insecticides, and other agrochemicals to improve agricultural economic efficiency, but the usage rate remains low. Data from the Food and Agriculture Organization of the United Nations (FAO) indicate that China's usage of fertilizer and pesticides has regularly ranked among the top worldwide for the past 30 years. Despite the utilization rate of fertilizers and insecticides for primary food crops exceeding 40%, there remains a significant gap compared to developed countries [2]. Simultaneously, China is a significant contributor to agricultural carbon emissions. According to estimates from the World Resources Institute, China's carbon emissions have ranked first globally over the past 30 years, with agricultural emissions accounting for 17% of the total. Second National Pollution Source Census Bulletin reveals that China's chemical oxygen demand from agricultural sources totaled 10,671,300 tons, total nitrogen emissions reached 1,414,900 tons, and total phosphorus emissions were 212,000 tons, accounting for 49.77%, 46.52%, and 67.22% of the national total, respectively. Agricultural surface pollution has emerged as a significant source of pollution in China [3]. In this context, optimizing the allocation of agricultural production elements and mitigating the pressures of resource and environmental limits has emerged as a pressing concern for China's agricultural development.

The advancement of digital technology offers new opportunities to address this issue. The widespread adoption of digital technology is driving the fourth industrial revolution,

causing a transformation of the techno-economic paradigm across society [4]. Rural regions have progressively been included in the digital advancement trajectory, resulting in digital villages' emergence. The construction of digital countryside aims to enhance rural production, lifestyle, and ecology by leveraging advanced equipment and technology, demonstrating significant potential in promoting sustainable agricultural development [5]. The Chinese government has continuously released policy documents emphasizing the importance of advancing digital village construction and improving agriculture technology. According to China's Ministry of Agriculture and Rural Development, Internet penetration in Chinese villages reached 58.8% by 2022, agriculture production informatization was 25.4%, and agricultural digital economy penetration was 10.5%. Compared with developed countries, China's village digitization is in its infancy, with a positive development momentum.

Agroecological efficiency (AEE) is an essential indicator of sustainable agricultural development, highlighting the amalgamation of economic advancement, resource conservation, and environmental protection. Enhancing eco-efficiency involves executing techniques to optimize resource input utilization, boosting economic output while reducing resource consumption and environmental damage [6]. Actively promoting green agricultural development represents China's solemn commitment to the international community. By exploring the relationship and mechanism between digital village construction and AEE, this study hopes to contribute internationally to agricultural digital transformation and sustainable development.

2. Literature Review

2.1. Research on Digital Village

Most studies on digital villages concentrate on evaluation levels and impact effects.

(1) Evaluation research. Most scholars have created an indicator system based on panel provincial data and used entropy weighting or principal component analysis to evaluate digital village construction. The primary indicators are village infrastructure construction, digital economic development, life services, and village government [7,8].

(2) Impact effect research. As digitization spreads worldwide, academics have focused increasingly on the digital village. Research has found that the digital village plays a significant role in promoting economic growth, promoting common prosperity, and enhancing economic resilience. Its promotion is closely related to agricultural research and development inputs, credit financial support, non-farm transfer of labor, and other factors [9–11].

2.2. Research on AEE

The research on agroecological efficiency mainly focuses on measurement methods, spatiotemporal heterogeneity, and influence factors.

(1) Methods of measurement. AEE cannot be estimated directly from agricultural systems; hence, evaluation methodologies are needed. AEE can be assessed using the single ratio method, energy-value analysis, ecological footprint analysis, stochastic frontier analysis (SFA), life cycle assessment (LCA), and data envelopment analysis (DEA). Each approach for calculating AEE has pros and cons; thus, the research object and purpose must be chosen best. DEA and its derivative modeling are the primary academic methodologies for assessing AEE [12,13].

(2) Spatiotemporal heterogeneity. Scholars have employed Kernel Density Estimation Analysis, Hotspot Analysis, and other methodologies to study AEE over time and space. The spatial evolution of China's AEE is primarily studied in the east, middle, and west [7,14].

(3) Influence factors. The fundamental characteristic of agriculture is that natural production and economic production are intertwined. Therefore, scholars have mainly studied agricultural resource factors and socio-economic factors at two levels to carry out research. Regarding agricultural resource factors, scholars focus on water, land, labor, and

other input factors [15,16]. Regarding socio-economic factors, scholars research agricultural production services, agricultural policy, urbanization, and other factors to discuss [17–19].

2.3. Research on Digital Village and AEE

Most authors examine the connection between the digital village and AEE from the standpoint of digital agriculture and the digital economy. They generally concur that utilizing digital technology in agriculture can significantly increase total factor productivity and the efficiency of agricultural carbon emissions [20,21]. Advancing scale operations and technical innovation are among the primary ways [22,23]; furthermore, the boost in effectiveness has significant regional heterogeneity [24]. Some scholars have shown that digital village construction promotes agricultural green growth more strongly when rural human capital is high [25]. Fu (2024) found that village digitization and arable land green use efficiency have obvious spatial non-equilibrium. When village digitization crosses the threshold, its promotion effect on arable land green use efficiency is weakened [26].

Overall, the current research predominantly examines the influence of digital agriculture and the digital economy on sustainable agricultural development, with limited studies addressing digital rural areas and agroecological efficiency. Furthermore, the assessment index system for AEE and digital village development needs advancement, alongside a more profound analysis of spatiotemporal evolution and heterogeneity. Therefore, this paper seeks to develop a more comprehensive indicator system to assess the digital village level more accurately and AEE in China, while also analyzing the spatial and temporal evolution of the north–south divide, major grain-producing regions, and non-major producing areas. The relationship between digital village construction and AEE is explored, as well as heterogeneous effects in different regions and at various construction levels. Simultaneously, the mechanism and threshold effect are examined in greater detail.

3. Mechanism Analysis and Research Hypotheses

3.1. DV and AEE: Direct Effects

Digital village construction encompasses three parts: digital infrastructure construction, economic development, and life services in rural areas, which provide fundamental support for the digital upgrading of the entire agricultural industry chain [27] when integrated with the green development of agriculture, illustrating the driving rationale of optimizing resource allocation, augmenting agricultural output value, and reducing surface pollution. Specifically, it is manifested in the following aspects: First, according to transaction cost theory, information asymmetry and bounded rationality are two causes of transaction costs. The widespread adoption of the Internet has expanded the avenues through which farmers can acquire information, decreased the expenses associated with information retrieval, and enhanced farmers' access to government policies and market demand information [28], thus optimizing production decisions and minimizing the redundancy of agricultural resource inputs. Precision operating practices, such as agricultural robots, drones, and smart irrigation, reduce energy consumption, increase production efficiency and resource utilization, and minimize ecological damage and pollution [29]. Second, agricultural production is intrinsically dependent on financial support, and the rural digital economy has engendered new forms of the agricultural economy, offering a diverse approach to enhance agricultural output value and foster sustainable agricultural growth. Rural e-commerce has expanded farmers' income channels [30], and digital inclusive finance has boosted the accessibility and efficiency of financial services in rural areas, largely breaking down rural financing constraints, and offering financial assistance for improving production and business environments [31]. Simultaneously, the high security of digital inclusive finance alleviates the trust limitation, making farmers more inclined to exchange production expertise in social activities and achieve the diffusion of green agricultural technology [32]. Third, digital consumption platforms mitigate information asymmetry, facilitating effective linkage between consumer demand and production practices [33]. The in-depth development of digital village construction promotes the consumption upgrade

of rural residents [34], driving farmers' consumption preferences to show environmental protection tendencies [35]. Rational economic agents are motivated to augment the supply of such products to align with the demand for green agricultural products [36]. The optimization of rural distribution facilities and the enhancement of logistics connect the agricultural product circulation network, increasing the circulation rate of green agricultural products and boosting their sales [37]. Additionally, integrating data and traditional production factors elevates the growth rate of marginal compensation, thereby generating a multiplier effect that fosters the growth of output value and green transformation [38]. Hence, the following research hypothesis is posited:

H1. *AEE is positively associated with digital village construction.*

3.2. DV and AEE: Mediation Effect

Induced technological change theory posits that the prices of factors and alternative technologies dictate the allocation of resource factors. As digital village construction progresses, the cost of using digital technology diminishes, providing an advantageous chance for farmers to embrace digital technology in enhancing resource allocation and production techniques. According to the six-element theory of production factors, land, technology, and data are vital production elements. Combining data with land and technological elements is crucial for advancing agricultural large-scale operations and modernization. As previously said, digital village construction has resulted in a novel form of rural economy, boosted non-farm transfer of rural labor, and created an opportunity to transfer agricultural land. Utilizing the smart agriculture management platform enables an exact match between farmers' production capability and underutilized acreage, enabling the conveyance of land to more effective management entities [39]. In the context of moderate-scale operations, farmers have a greater incentive to implement intelligent apparatus and green technology [40], which contributes to the realization of green production [41]. Furthermore, constructing digital villages can produce knowledge spillover effects, which promote the sophisticated technologies developed and implemented, transform agricultural labor and materials, and thus affect agricultural output [42]. For example, using the Internet of Things and remote sensing technology to collect crop growth data can effectively prevent and resist pests and diseases, as well as reduce the input of agrochemicals [43,44]; using intelligent equipment to replace energy-consuming agricultural machinery can improve productivity and decrease carbon emissions [45]. Hence, the following research hypotheses are posited:

H2a. *Digital village construction can positively affect AEE by facilitating agricultural land transfer.*

H2b. *Digital village construction can positively affect AEE by facilitating agricultural technology innovation.*

3.3. DV and AEE: Threshold Effect

Metcalf's Rule and Moore's Law show that Internet value grows as users expand. Digital village construction aligns with the fundamental principle of Metcalfe's law, with varying levels of digital village development between provinces, potentially resulting in non-linear effects on agroecological efficiency. As digital village construction is a long-term project that requires a large amount of capital and technical investment, initial development may be slow, and there will be a certain lag in realizing environmental benefits [46], in which case, the promotion of agroecological efficiency by digital villages will be weaker. Due to the distinctive, powerful sharing, weak exclusivity, and extensive coverage of digital technology, digital village development has an apparent growth rate advantage [47]. As digital village construction continues to be promoted, the link between digital technology and agriculture grows closer; the digital dividend has been fully released, promoting agroecological efficiency more significantly. Hence, the following research hypothesis is posited:

H3. Digital village construction has a threshold effect on the positive effect of AEE.

The specific mechanism analysis diagram is shown in Figure 1.

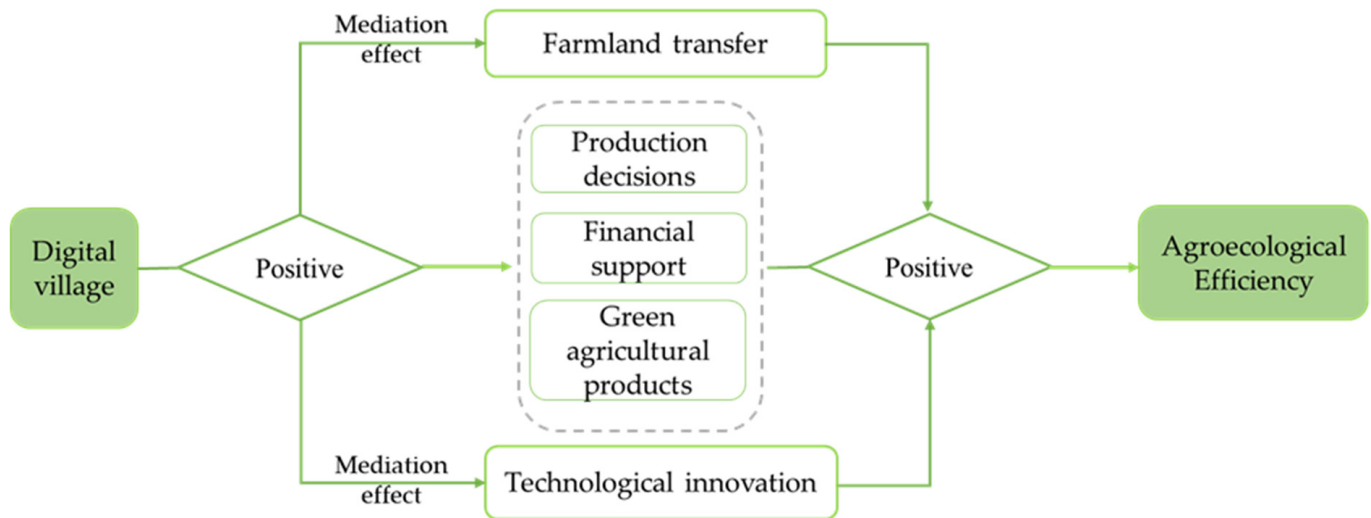


Figure 1. Mechanistic analysis framework.

4. Research Design

4.1. Model Selections

4.1.1. Tobit Model

The agroecological efficiency derived from the super-efficient SBM model is a constrained variable, with values ranging from [0, 2]. Tobit regression provides more consistent and unbiased estimates than OLS regression. Consequently, this study employed the Tobit panel random effects model for the benchmark regression [48].

$$aee_{it} = \beta_0 + \beta_1 dv_{it} + \beta_2 controls_{it} + \varepsilon_{it} \quad (1)$$

aee_{it} represents agroecological efficiency; dv_{it} represents digital village construction, β_1 is the coefficient of dv_{it} ; β_2 is the coefficient of the control variable; β_0 is the constant term; and ε_{it} is the random error term. The variables are transformed logarithmically to mitigate the effects of heteroskedasticity and multicollinearity on the regression analysis.

4.1.2. Mediated Effects Model

To further explore the impact mechanism of digital village construction on AEE, a “two-step” model of the mediated effect test is constructed based on the baseline regression model [49]:

$$med_{it} = \theta_0 + \theta_1 dv_{it} + \theta_2 controls_{it} + \varepsilon_{it} \quad (2)$$

The mediating variables med_{it} include the degree of agricultural land transfer (alc) and agricultural technological innovation (ati). θ_0 is a constant term, θ_1 is the coefficient of dv ; and θ_2 is the coefficient of the control variable.

4.1.3. Threshold Effect Model

To test H3, a panel threshold regression model is constructed as follows [50]:

$$aee_{it} = \varphi_0 + \varphi_1 dv_{it} \times I(dv_{it} \leq \gamma_1) + \varphi_2 dv_{it} \times I(\gamma_1 < dv_{it} \leq \gamma_2) + \varphi_3 dv_{it} \times I(dv_{it} > \gamma_n) + \varphi_4 controls_{it} + \varepsilon_{it} \quad (3)$$

The threshold variable set in the model is dv_{it} ; φ represents the regression coefficient; γ is the threshold to be estimated; and $I(\cdot)$ is the indicator function.

4.2. Description of Variables

4.2.1. Explained Variable: Agroecological Efficiency

This study examines the plantation sector. Within the agricultural transformation and enhancement framework, agroecological efficiency underscores the integration of “resource conservation, environmental protection, and economic development”. “Resource conservation” aims to enhance the efficiency of agrochemical usage and mitigate surface contamination, “environmental protection” seeks to decrease carbon emissions and improve carbon sink functionality, and “economic development” highlights the enhancement of economic output. An evaluation system for agroecological efficiency was developed based on the requirements of social, economic, and ecological development [18]. Table 1 presents specific indications and descriptions.

Table 1. Assessment Index System for AEE.

Dimension Layer	Indicator Layer	Indicator Description
Input indicators	Labor Inputs	Number of people working in agriculture (ten thousand people)
	Land Inputs	Crops sown area (thousand hectares)
	Fertilizer Inputs	Fertilizer application amount (ten thousand tons)
	Pesticide Inputs	Pesticide application amount (ten thousand tons)
	Agricultural Film Inputs	Agricultural film application amount (ten thousand tons)
	Machinery Inputs	Total power of agricultural machinery (ten thousand kilowatts)
	Energy inputs	Agricultural Diesel Usage (ten thousand tons)
	Irrigation Inputs	Effective irrigation area (thousand hectares)
	Capital Inputs	Investment in Agricultural Fixed Assets (billions of RMB)
Desired outputs	Agricultural outputs	Total agricultural output value (billions of RMB)
	Agricultural carbon sinks	Total agricultural carbon sink (ten thousand tons)
Undesired outputs	Agricultural surface pollution	Composite index of surface pollution
	Agricultural carbon emissions	Total carbon emissions (ten thousand tons)

Input indicators include labor, land, fertilizer, pesticide, agricultural film, machinery, energy, irrigation, and capital. Agricultural labor input is calculated by multiplying the number of primary sector employees by the proportion of agricultural output to agricultural, forestry, animal husbandry, and fisheries outputs.

Expected outputs include economic outputs, characterized by gross agricultural output, and ecological outputs, characterized by agricultural carbon sinks. The calculation of carbon sinks refers to a related study [51]; the formula is: $C = \sum_i^k C_i = \sum_i^k c_i * Y_i * (1 - r) / H_i$. C is the total amount of carbon uptake by crops; C_i is the amount of carbon uptake by a certain kind of crop; k is the amount of crop species; c is the amount of carbon absorbed by the crop through the synthesis of organic matter per unit; and Y_i , r , H_i are the economic output, water content, and economic coefficient of the crop, respectively. The main crops cover ten crops, including rice, wheat, maize, etc.

The non-desired output contains two parts: agricultural surface source pollution and agricultural carbon emissions. Referencing existing research [18], we calculated agricultural surface source pollution by multiplying the nitrogen and phosphorus content of fertilizers, pesticide application, and agricultural film usage by their respective wastage coefficients and synthesized these factors into a single pollution index using the entropy method. The equation for calculating agricultural carbon emissions is: $E = \sum E_i = \sum T_i * \delta_i$. E is the total agricultural carbon emissions, E_i is the carbon emissions of different carbon sources, and T_i and δ_i are the carbon emissions and carbon emission coefficients of each carbon source, respectively.

4.2.2. Core Explanatory Variables: Digital Village Construction Level

Taking the Action Plan for the Development of Digital Villages (2022–2025) as the policy blueprint, based on the principles of comprehensiveness, science, and data availability,

an assessment system for a digital village is constructed based on previous research [52]. Due to the varying measurements of the indicators, the entropy value approach is employed to standardize and assess them, with specific indicators and descriptions shown in Table 2.

Table 2. Assessment Index System for DV.

Dimensional Layer	Indicator Layer	Indicator Description
Digitalization Foundations	General equipment	Optical fiber density Rural Internet penetration rate Rural Computer Penetration rate Rural cell phone penetration rate
	Production facility	Length of rural delivery routes (kilometers) Number of agrometeorological observation stations Taobao Village/Administrative Village (%)
Digital Economy Development	E-commerce	E-commerce Sales (billions of RMB) E-commerce Purchases (billions of RMB)
	Digital Inclusive Finance	Depth of Digital Financial Inclusion Usage Breadth of digital financial inclusion coverage
Digital Life Services	Farmers' Mobile Payment Level	Digital Inclusion Level of Financial Digitization
	Farmers' Transportation and Communication Level	Percentage of rural residents' per capita expenditure on transportation and communication
	Rural Logistics Service Level	Average population served per postal outlet (ten thousand people)
	Level of rural electrification	Rural electricity consumption/rural population (kWh/person)

4.2.3. Intermediary Variables

The degree of agricultural land circulation (alc) and agricultural technology innovation (ati) were selected as mediating variables [53]. The degree of agricultural land transfer is characterized by the proportion of the transferred area of contracted arable land to the total area of family-contracted operated arable land, and agricultural technological innovation is represented by the ratio of agricultural science and technology patents to the workforce in the primary industry.

4.2.4. Control Variables

The following control variables are selected to mitigate bias from omitted variables [27,54,55]. The urbanization level (ur) is described by the ratio of a province's urban population to its total population. Agricultural disaster rate (dr) is the ratio of impacted area to crop sown area in each region. The level of science and technology (st) is defined as the ratio of internal expenditure on research and experimental development funding to fiscal expenditure. The level of financial support for agriculture (fs) is defined as the ratio of expenditure on agriculture, forestry, and water affairs to fiscal expenditure. The rural human capital level (rhc) is described by the per capita years of schooling in rural regions. Agricultural machinery density (amd) is defined as the total power of agricultural machinery per unit of the sown area.

4.3. Data Description

Based on data availability and completeness rules, panel data from 30 Chinese provinces (not including Hong Kong, Macao, Taiwan, and Tibet) from 2011 to 2022 were chosen as research samples. The data were sourced from the China Rural Statistical Yearbook, the National Bureau of Statistics, and pertinent reports, with some missing numbers addressed by linear interpolation. Table 3 displays the descriptive statistics results.

Table 3. Descriptive statistical results of the main variables.

Variables	Observed	Mean	Standard Error	Min	Max
are	360	0.713	0.264	0.247	1.256
dv	360	0.172	0.092	0.061	0.580
ur	360	60.12	12.06	35.04	89.58
dr	360	14.10	11.58	0.415	69.59
st	360	1.050	0.621	0.122	3.216
fs	360	11.35	3.338	4.041	20.38
rhc	360	7.859	0.628	5.878	10.115
amd	360	6.520	2.353	2.516	13.87
alc	360	0.327	0.168	0.034	0.911
ati	360	0.001	0.002	0.000	0.019

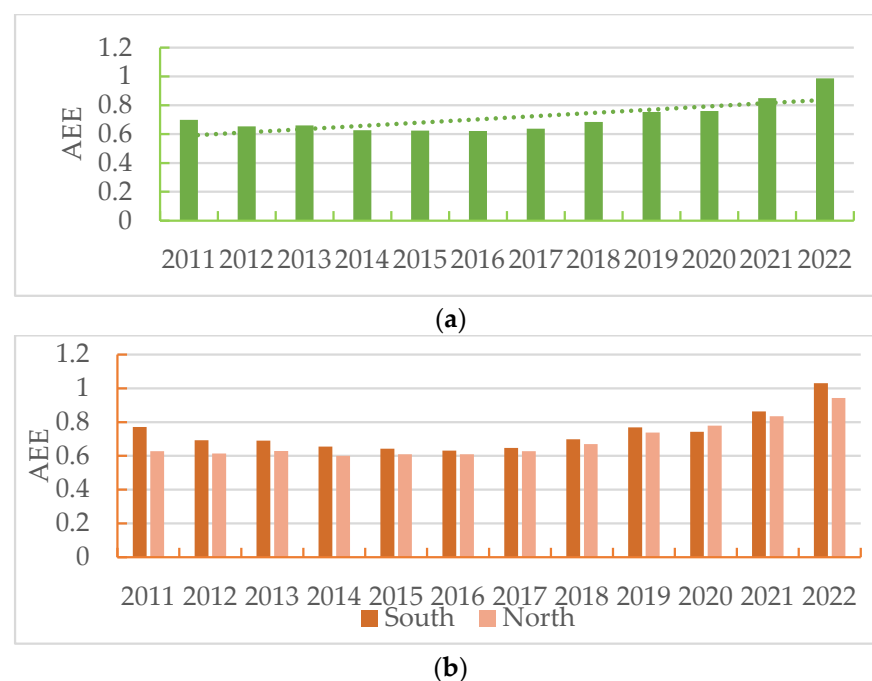
5. Results

5.1. Measurement Results of Agroecological Efficiency and Digital Village Construction

5.1.1. Measurement Results of Agroecological Efficiency

From the national level (Figure 2a), agroecological efficiency shows a fluctuating upward trend, but compared with the distance from the optimal production frontier, there remains potential for enhancement, indicating that agroecological efficiency could be improved under the non-desired output constraints.

From the regional level (Figure 2b,c), the agroecological efficiency of each region shows an upward trend and demonstrates significant spatial differentiation. The distribution pattern is “south (0.736) > north (0.690)” and “major grain-producing areas (0.797) > non-major grain-producing areas (0.649)”. The southern regions, including Shanghai and Jiangsu, and the major grain-producing areas of Henan and Shandong, which may leverage their geographic advantages, exhibit elevated agroecological efficiency values (Figure 2d). The southern region has a relatively better economic foundation, better infrastructure, and technical conditions for developing digital agriculture, which provides a first-mover advantage in realizing cleaner production. The main grain-producing areas have vast and flat lands with a high level of large-scale operation, which is conducive to agroecological efficiency.

**Figure 2.** Cont.

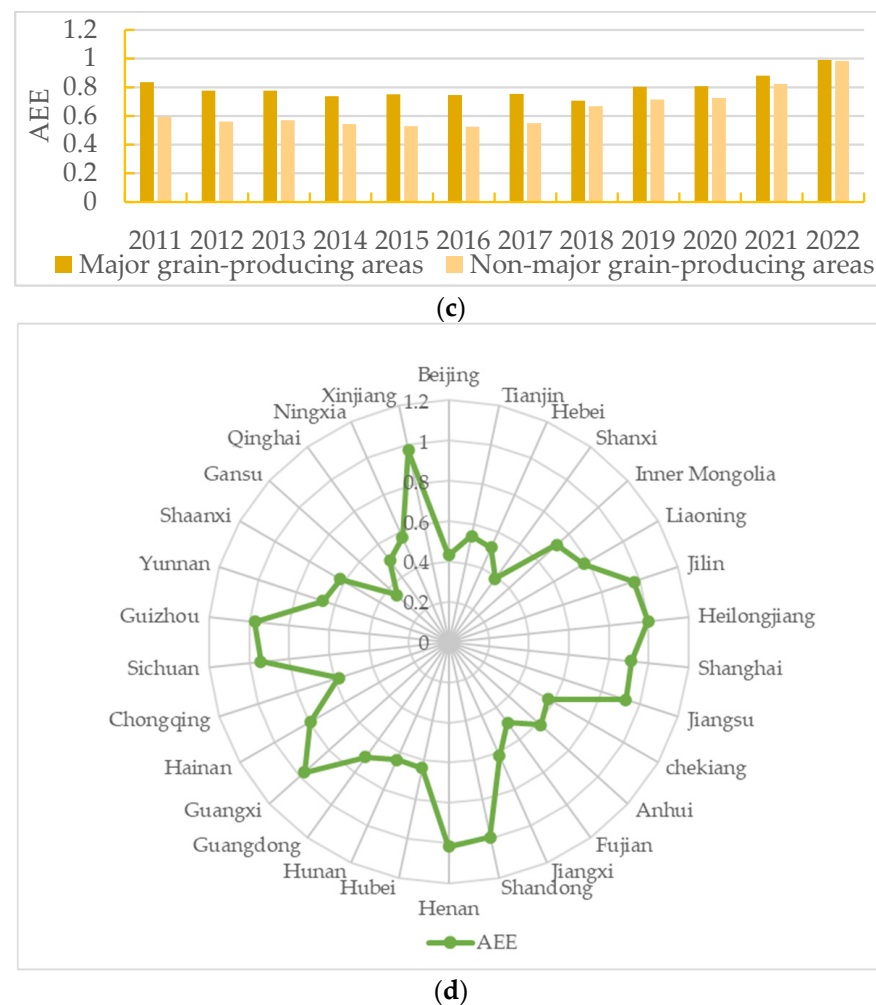


Figure 2. Evolution trend of agroecological efficiency (2011–2022). (a) Overall agroecological efficiency annual average for the study area; (b) South–North agroecological efficiency annual averages; (c) Major grain-producing areas—non-major grain-producing areas agroecological efficiency annual averages; and (d) Provincial agroecological efficiency averages.

5.1.2. Measurement Results of Digital Village Construction

From the national level (Figure 3a), the overall level of digital village construction shows a continuous upward trend, with substantial growth, reflecting that the digital village construction strategy has achieved significant results.

From the regional level (Figure 3b,c), the level of digital village construction in all regions shows an upward trend. The distribution pattern is “south (0.173) > north (0.171)” and “non-major grain-producing areas (0.195) > major grain-producing areas (0.142)”. The digital village construction level in economically advanced regions like Beijing and Shanghai exceeds the average, with no substantial general disparity between the north and south (Figure 3d). The possible reason is that as Internet penetration deepens, the rural digital infrastructure has become more comprehensive, alongside the ongoing implementation of national policies, which has expedited the digitalization of agriculture and rural areas across all provinces. However, the level of digital countryside construction significantly differs among functional grain-production regions, exhibiting lower levels in major grain-producing areas such as Hunan, Jiangxi, Sichuan, and Anhui, while non-major grain-producing areas like Beijing, Shanghai, Zhejiang, and Tianjin demonstrate higher levels. This disparity is attributed to the reliance of digital countryside construction on financial, technological, and human resource support. The significant disparity in the degree

of digital village construction is 0.269, signifying the coexistence of spatial differentiation and spatial agglomeration in China's digital village construction.

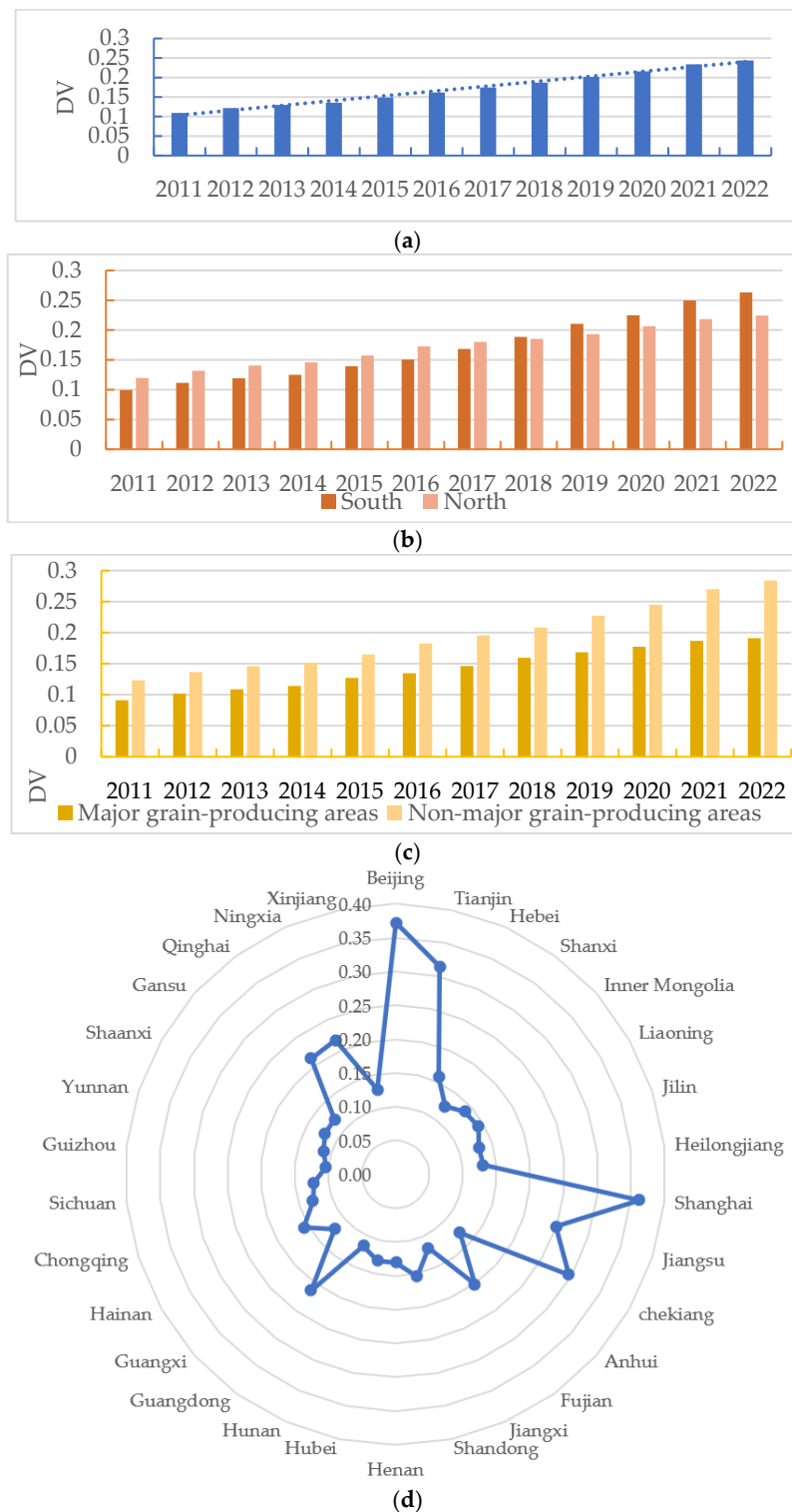


Figure 3. Evolution trend of digital village index (2011–2022). (a) Overall digital village index annual average for the study area; (b) South–North digital village index annual averages; (c) Major grain-producing areas—non-major grain-producing areas digital village index annual averages; and (d) Provincial digital village index averages.

5.2. Benchmark Regression Analysis

Table 4 shows the results of the benchmark regression with stepwise addition of control variables, and the results of models (1)–(7) show that there is a positive association between AEE and digital village construction, which is significant at 1% level. The regression coefficients and significance levels remained unchanged during the incremental addition of control variables, validating H1.

Table 4. Benchmark regression.

Variables	LNAEE						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Indv	0.036 *** (3.70)	0.065 *** (3.72)	0.043 ** (2.48)	0.059 *** (3.10)	0.060 *** (3.14)	0.058 ** (3.12)	0.076 *** (3.94)
lnur		−0.093 *** (−2.08)	−0.088 *** (−2.16)	−0.119 ** (−2.54)	−0.124 *** (−2.61)	−0.153 *** (−3.06)	−0.177 *** (−3.63)
ln dr			−0.012 *** (−3.17)	−0.010 ** (−2.60)	−0.010 ** (−2.54)	−0.009 ** (−2.44)	−0.011 *** (−2.85)
lnst				0.022 *** (2.29)	0.023 ** (2.33)	0.022 ** (2.21)	0.024 *** (2.76)
lnfs					−0.010 (−0.59)	−0.008 (−0.45)	−0.002 (−0.10)
lnahc						0.163 ** (1.83)	0.171 ** (2.13)
lnamd							0.639 *** (2.58)
Constant	0.040 ** (2.15)	0.472 *** (2.26)	0.441 *** (2.30)	0.592 *** (2.70)	0.642 *** (2.74)	0.412 *** (2.61)	0.639 ** (2.58)
Wald test	13.70 ***	17.42 ***	28.65 ***	32.64 ***	32.64 ***	35.62 ***	44.80 ***
Lr test	53.06 ***	52.74 ***	30.92 ***	37.71 ***	36.35 ***	38.58 ***	28.10 ***

Note: ***, ** represent the significance levels of 1%, 5%, respectively **/***.

According to model (7) results, the impact of control variables on agroecological efficiency is mainly manifested as follows: ① Urbanization levels negatively affect AEE, which may be because as the urbanization level increases, more rural laborers move to the cities. To fill manpower shortages, farm machinery will increase. The overuse of agricultural machinery increases unexpected output, reducing AEE. ② Agricultural disaster rate negatively affects AEE, the reason of which is that agricultural production's inherent vulnerability to the natural environment results in diminished output during natural disasters, thereby hindering the enhancement of eco-efficiency. ③ Science and technology levels positively affect AEE, indicating that the enhancement and implementation of agricultural production technology can optimize the allocation of agricultural resources, and improve resource utilization, thereby increasing desired output and reducing undesired output. ④ Agricultural financial support has a negative but not statistically significant impact on AEE, which may be related to the description of agricultural financial support. ⑤ The positive regression coefficient for rural human capital indicates that farmers with high levels of environmental awareness, digital literacy, and technology use can promote green production, thus contributing to agroecological efficiency. ⑥ Agricultural machinery density negatively affects AEE, probably due to substantial inputs of high energy-consuming agricultural machinery generating considerable greenhouse gas emissions, thereby exacerbating agricultural carbon emissions and surface pollution, which hinders the enhancement of eco-efficiency.

5.3. Endogeneity Treatment

Based on theory and judgment, endogeneity may exist between digital village construction and AEE. One is that more factors can influence agroecological efficiency, this study cannot control for all the influencing factors, so there may be omitted variables. Secondly,

regions exhibiting greater agroecological efficiency may possess a favorable policy climate and robust economic basis, facilitating the advancement of digital village construction; this may lead to reverse causality between the two, resulting in biased modeling. Therefore, the panel instrumental variables method is used to deal with the endogeneity problem.

Firstly, using the panel fixed-effects model to avoid endogeneity bias from omitted variables, the regression results in column (1) of Table 5 show that digital village construction still improves AEE. Secondly, based on the study of Wang (2023) et al. [56], appropriate instrumental variables are chosen to mitigate the model's endogeneity issue: ① The number of Internet domain names (IDNs) serves as a significant metric for assessing Internet development, reflecting the extent of a province's investment in the digital infrastructure, while having no direct influence on agroecological efficiency, thereby satisfying the criteria of relevance and conciseness. ② Digital village construction is a long-term dynamic development process, wherein early-stage construction accumulation is intricately linked to current developmental progress, independent of the agroecological efficiency of the present time. Therefore, the two-stage lagged digital village construction index meets the correlation and exogeneity criteria. As can be seen from two-stage least squares (2SLS) test results, as shown in Table 6 columns (2) and (3), the instrumental variables pass the unidentifiable test, weak instrumental variable test, and over-identification test with reasonableness. Column (3) results show that digital village construction still significantly and positively affects agroecological efficiency after considering endogeneity issues.

Table 5. Endogeneity test.

Variables	AEE		
	(1)	(2)	(3)
dv	0.695 ** (1.76)		0.706 *** (2.73)
L2.dv		1.049 *** (18.28)	
idn		0.442 *** (3.23)	
Constant	1.869 ** (2.11)		
Year	yes	yes	yes
Province	yes	yes	yes
Kleibergen–Paap rk LM *			23.2250 [0.000]
Cragg–Donald Wald F *			311.356 [19.93]
Hansen- <i>p</i> -value			0.120
Observed	360	300	300
R ²	0.265	0.711	0.558

* Kleibergen–Paap rk LM statistic of 23.225, corresponding to a *p*-value of 0.000, indicating that it passes the test of non-identifiability; and the Cragg–Donald F statistic of 311.356, which is much larger than the Stock–Yogo weak instrumental variable identification test at 10% significance level with a critical value of 19.93, indicating that it passes the weak instrumental variable test. Note: ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively **/***.

Table 6. Mediation effect test.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	alc	dv	alc	ati	dv	ati
dv	0.472 *** (4.54)		1.888 ** (2.58)	0.016 *** (12.13)		0.028 *** (4.43)
dv-IV		0.923 *** (4.28)			0.923 *** (4.28)	

Table 6. Cont.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	alc	dv	alc	ati	dv	ati
Controls	yes	yes	yes	yes	yes	yes
First-stage F-value		100.17			141.82	
Endogenous wald χ^2			346.00 ***			636.25 ***
Wald exogeneity test			0.0364			0.0265
Observed	360	360	360	360	360	360

Note: ***, ** represent the significance levels of 1%, 5%, respectively.

5.4. Mediation Effect Analysis

To investigate the mechanism of digital village construction on AEE, agricultural land transfer degree, and technology innovation are selected as intermediary variables to be incorporated into the model. IV-Tobit is used to test the causality between the core explanatory variables and the intermediary variables [57], utilizing the number of Internet domain names as the instrumental variable. Table 6 reports the regression results.

The integration of the benchmark regression findings with the analysis of columns (1)–(3) in Table 6 demonstrates a mediating effect of agricultural land transfer on the impact of digital village building on AEE, confirming H2a. The construction of digital villages enables the integration of data as a production factor in agriculture, facilitating effective feedback on agricultural land usage to farmers. This alignment of land production requirements with farmers' capabilities fosters conditions for large-scale and intensive production, thereby enhancing agricultural productivity. The rational transfer of agrarian land simultaneously enables farmers to overcome scale limitations, promotes the adoption of agricultural green technology, reduces surface pollution, and enhances agroecological efficiency.

The integration of the benchmark regression findings and the examination of columns (4)–(6) in Table 6 demonstrates that agrotechnological innovation mediates the impact of digital village building on agroecological efficiency, hence confirming H2b. Digital technology is not only the primary driver of digital village development but also an important component of agricultural technology. Innovations in agricultural technology will yield welfare benefits in agricultural production and farmers' lives. For instance, disseminating and implementing advanced farming equipment can enhance farmers' technical literacy and environmental consciousness. Additionally, novel agricultural products can significantly improve resource utilization efficiency, while cultivating pest-resistant crop varieties can diminish agrochemical inputs at the source. Technological innovation can significantly boost agricultural laborers and objects, augmenting desired agricultural output, diminishing undesired output, and fostering improvements in agroecological efficiency.

5.5. Robustness Tests

5.5.1. Robustness Tests for Benchmark Regressions

To further guarantee the robustness of the results, three methods are used for re-testing. First, the explanatory variables must be replaced. Based on the super-efficient SBM-GML index to measure agroecological efficiency and re-test empirically, the results are shown in column (1) of Table 7; the regression coefficient of digital village construction remains significantly positive. Second, the four municipality samples must be excluded. Considering the special characteristics of the four municipalities directly under the central government, including Beijing, Shanghai, Tianjin, and Chongqing, their policy support levels, digital infrastructure strengths, and main agricultural functions are different from those of other provinces. Consequently, after eliminating the municipal samples and doing re-tests, the results in column (2) of Table 7 indicate that the regression coefficients for digital rural construction are statistically significant at the 5% level. Third, the regression results are not substantially changed by tailoring the data. Therefore, the regression results of digital village construction for agroecological efficiency improvement remain robust.

Table 7. Benchmark regression robustness test.

Variables	AEE-GML	AEE	AEE
	(1)	(2)	(3)
Indv	0.225 *** (4.43)	0.050 ** (3.10)	0.016 ** (2.24)
Constant	0.111 *** (2.78)	0.466 ** (2.20)	0.013 *** (2.56)
Controls	yes	yes	yes
Wald test	61.51 ***	31.99 ***	26.83 ***
Lr test	8.77 ***	28.80 ***	35.48 ***
Observed	330	312	360

Note: ***, ** represent the significance levels of 1%, 5%, respectively.

5.5.2. Robustness Tests for Intermediation Effects

The robustness test for mediation effects. This study employs the Bootstrap technique to analyze the mediation model through regression [58]. Table 8 demonstrates that the confidence intervals for both indirect and direct effects exclude 0, signifying that agricultural land transfer and agricultural technology innovation exert a significant mediating influence in the advancement of AEE within the context of the digital village.

Table 8. Robustness test for mediation effect.

Mediating Variables	Pathway	Effect Coefficient	Standard Error	Confidence Interval
Land	indirect effect	0.312 **	0.135	[0.047, 0.577]
	direct effect	0.465 ***	0.065	[0.234, 0.659]
Inn	indirect effect	0.476 **	0.187	[0.110, 0.843]
	direct effect	0.625 ***	0.220	[0.195, 1.056]

Note: ***, ** represent the significance levels of 1%, 5%, respectively.

5.6. Heterogeneity Analysis

5.6.1. Geographic Heterogeneity

Different climates, temperatures, and precipitation patterns have created various crop maturation systems in China, and there are great regional differences in agricultural production. The Qinling–Huaihe River line is the demarcation line between drylands and paddy fields in China, as well as the demarcation line of agricultural maturation systems. This study used this line to divide the north–south region and conduct a subsample regression analysis. Results are shown in Table 9, columns (1) and (2). The table shows that the positive effects of digital village construction on AEE are greater in the northern region than southern region. The likely explanation is that the southern region commenced digital rural construction earlier, resulting in more favorable conditions for advancing digital agriculture and establishing a more structurally stable agricultural system, thereby preventing the full realization of the digital village dividend. While the northern region is in the stage of agricultural upgrading, the latecomer advantage is obvious. The advancement of digital rural infrastructure facilitates the integration of digital technology with agricultural production, transforming traditional agricultural practices and fostering the potential for sustainable agricultural development.

Table 9. Regional Heterogeneity test.

Variables	(1)	(2)	(3)	(4)
Indv	0.039 ** (2.44)	0.045 *** (2.66)	0.003 (0.27)	0.069 *** (2.86)
Constant	0.087 (1.25)	0.113 (1.47)	−0.020 (−0.33)	0.296 ** (2.47)

Table 9. Cont.

Variables	(1)	(2)	(3)	(4)
Controls	yes	yes	yes	yes
Wald test	13.53 **	37.49 ***	19.11 ***	20.75 ***
Lr test	3.63 **	18.94 ***	13.51 ***	13.20 ***
Observed	180	180	156	204

Note: ***, ** represent the significance levels of 1%, 5%, respectively.

5.6.2. Heterogeneity of Production Structure

Different agricultural production functions produce different environmental effects; this study conducted a subsample regression analysis according to the Chinese Ministry of Agriculture and Village's division of agricultural production functional areas. The results of Table 7, columns (3) and (4), indicate that the positive effect of digital village construction on AEE is more significant in the non-major grain-producing regions than in the major grain-producing regions. The possible reason is that the major grain-producing areas possess a substantial advantage in agricultural production capacity, and the tendency to "tend food" is significant, thereby constraining the beneficial influence of digital village construction on AEE. Conversely, non-major grain-producing areas exhibit a more diverse agricultural industry structure, providing a solid foundation for rural digitization. This facilitates the effective realization of digital technology dividends in agricultural production, consequently exerting a more pronounced influence on enhancing agroecological efficiency.

5.6.3. Heterogeneity of Digital Village Construction Level

Considering the heterogeneous effects of resource endowment, economic scale, and infrastructure construction level on AEE in different regions, this paper refers to previous studies and conducts quantile regression, to test the effects of village construction on AEE under different digital village levels [58].

Table 10 reports the estimation results of the quantile regression model. The impact of digital village development on AEE varies significantly at different levels of digital village development, with significantly positive coefficients at the 25%, 50%, and 75% magnitudes. However, the positive effect of digital village construction on AEE decreases with increasing magnitude. The marginal effect of digital village building on AEE is higher at lower levels of digital village building. At higher levels of digital village construction, the facilitating effect diminishes, which suggests that digital village construction can reduce the gap in AEE in different regions, in line with the goal of sustainable agricultural development.

Table 10. Quantile Regression.

Variables	(1) 25%	(2) 50%	(3) 75%
Indv	0.613 ** (5.20)	0.520 *** (4.12)	0.504 *** (3.21)
Constant	3.560 ** (2.51)	4.685 *** (3.08)	4.898 ** (2.59)
Controls	yes	yes	yes
Observed	360	360	360
R ²	0.3138	0.3051	0.1246

Note: ***, ** represent the significance levels of 1%, 5%, respectively.

5.7. Threshold Effect Analysis

This study utilizes digital village building as a threshold variable to examine the threshold effect. After repeated sampling 1000 times using the Bootstrap method, the single threshold is significant at the 5% confidence level, and the double threshold does not pass the significance test, indicating that the positive effect of digital village construction on AEE

is characterized by a significant single threshold, with a threshold value of 0.193 (Table 11). Among the 30 provinces in China, 16 provinces have not crossed the threshold value in 2022, digital villages are yet to be raised to a higher level.

Table 11. Threshold regression.

Variables	Threshold Variable
	(1)
$dv \times I(dv \leq 0.193)$	0.431 *** (9.22)
$dv \times I(dv > 0.193)$	0.548 *** (10.87)
Controls	yes
R^2	0.266
Observed	360

Note: *** represents the significance levels of 1%, respectively.

Table 10 shows that the influence of digital village construction on AEE all pass the significance test at the 1% level, as the digital village construction level increases, it exhibits the nonlinear characteristics of positive and increasing marginal effects. Specifically, when the level of digital village construction is below the threshold value of 0.193, the effect coefficient of digital village construction on AEE is 0.431; when the level of digital village construction crosses the threshold value of 0.193, the impact coefficient increases to 0.548. This indicates that the positive effect of digital village construction on AEE gradually increases as the digital village construction level increases. H3 is verified.

6. Discussion

Digital village construction is a fresh boost for agricultural sustainability. Academic interest in both has grown in recent years. Diverse scholars have studied digital villages and sustainable agricultural development from diverse viewpoints, and studies on the indicator system and enhancement path are distinct.

Compared to previous studies, the possible marginal contributions of this study are as follows: First, this study examines how digital village construction affects agricultural eco-efficiency. Unlike previous studies, this paper quantifies the simultaneous effects of digital advancements in farmers' production and lifestyle on agricultural economic efficiency and eco-efficiency, providing a scientific foundation to recognize rural digitalization's role in sustainable agriculture. Secondly, this article enhances an evaluation system for digital village development and agroecological efficacy. Traditional information fundamental indicators cannot adequately indicate how rural residents use digital resources, and it is difficult to capture the full extent of digital village creation. This study integrates indicators that represent the status of rural digital life services into the evaluation system, seeking to represent the development status of the digital village accurately and comprehensively. Agricultural capital and carbon sinks are essential for agricultural production inputs and outputs. Scarce literature has simultaneously integrated both components into the agroecological efficiency assessment system, which this study covers, potentially improving the evaluation of digital village development and agroecological efficiency. Third, this study examines the varied effects of digital village construction on AEE. The effect of different regions and levels of digital village construction on AEE is scientifically studied, given regional resource endowments to support regionally appropriate development plans. Fourth, the threshold effect model is used to explore the nonlinear influence of digital village construction on AEE and provide decision-making references for better using digital villages' environmental effects.

This paper has some theoretical contributions in enriching the evaluation system of digital village and AEE as well as the influence mechanism between the two. Global agricultural development patterns indicate that agriculture is undergoing sustainable

modernization. However, China's agricultural development is still plagued by rough operation and endogenous pollution, and technologies like agricultural Internet of Things (IoT) and Artificial Intelligence (AI) are limited by cost and need to be widely promoted. This paper explores the spatial non-equilibrium characteristics of China's digital village construction and AEE, which is conducive to proposing locally adapted development strategies to scientifically promote agriculture digitalization and sustainable development.

However, this study has drawbacks. When studying the impact of digital villages on agroecological efficiency, Ren (2024) focuses on the importance of digital village governance and finds that strong village governance enhances the positive impact of digital villages on AEE [59]. In contrast, this paper neglected the role of village governance, which can be further explored in future research.

7. Conclusions

7.1. Research Conclusions

This study examined the effect of digital village development on AEE, with the primary conclusions outlined as follows:

- (1) Agroecological efficiency is correlated with digital village construction and shows a positive direct effect.
- (2) The positive effect of digital villages on agroecological benefits varies by region and digital village construction level. More positive effects are evident in the north than south, non-major grain-producing areas than major grain-producing areas, and low-level digital village construction than high-level.
- (3) Agricultural land transfer and technological innovation are the two paths for digital village construction to exert positive effects.
- (4) A single threshold exists for the exertion of digital village construction's positive effect, and after the digital village construction level crosses the threshold, its marginal effect presents a positive and increasing non-linear characteristic.

7.2. Recommendations

(1) Thoroughly advancing the digital village development and entirely harnessing the digital dividend. The government ought to establish a dedicated fund to finance the development of digital infrastructure in rural areas and enhance the coverage of 5G networks in villages. They ought to enhance collaboration with network operators and financial institutions to ensure secure and dependable online lending services, encouraging farmers' engagement in the digital advancement of rural industry.

(2) Advocating for digital village development tailored to local circumstances and addressing the digital divide. A national online network of agricultural technology information services should be established to facilitate real-time sharing of agricultural production data, enhance communication among farmers across different regions, support advancements in underdeveloped digital village areas, and reduce disparities in the modernization of agriculture.

(3) Facilitating agricultural land transfers and technological innovation. Complying with agricultural land property rights regulations, encouraging non-agricultural employment for excess rural laborers, improving farmers' readiness to transfer land, and optimizing arable land and farmers' production capabilities enable large-scale, intensive operations. Training centers ought to be established in collaboration with higher education institutions to nurture agricultural digital innovators, provide incentives to agricultural technicians, and improve research on critical agricultural technologies and research findings transformation.

(4) Lowering the threshold of digital technology adoption and fostering digital literacy among agricultural practitioners. The government should offer tax incentives or subsidies to farmers who implement digital services to alleviate their financial strain. It should also offer farmers complimentary training in digital services to facilitate their proficiency in utilizing digital tools and improve the practical implementation of agricultural technology, thereby amplifying the beneficial impacts of digital village development.

7.3. Limits and Research Proposals for Future

Future research may be expanded in three distinct ways. First, the relevance of indicators in digital village evaluations might be improved. This study used the digitization degree index within the digital financial inclusion index to indicate the extent of farmers' mobile payment usage, which may exhibit some discrepancies from the actual circumstances. As the availability of pertinent data enhances, future studies can refine the digital village evaluation index system to achieve more precise assessment results. Secondly, considering data granularity, conclusions derived from province data may be generalized; future studies could utilize county-level data to better reflect regional disparities in digital villages. Third, the agroecological efficiency measured in this study focuses on the plantation industry; however, the impact of digital village construction on agroecology is also likely to be reflected in the animal husbandry industry. Future studies could consider, for example, the ecological efficiency of the animal husbandry industry in the research framework.

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