frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 22 November 2024
DOI 10.3389/fenvs.2024.1492454

OPEN ACCESS

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RECEIVED 06 September 2024
ACCEPTED 11 November 2024
PUBLISHED 22 November 2024

CITATION
Li W, Guo J, Tang Y and Zhang P (2024) The impact of digital rural construction on agricultural carbon emission intensity. *Front. Environ. Sci.* 12:1492454.
doi: 10.3389/fenvs.2024.1492454

The impact of digital rural construction on agricultural carbon emission intensity

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Reducing agricultural carbon emissions is critical to achieving green agricultural development and the “dual carbon” goals. The present study conducts empirical analysis using provincial panel data from 29 provinces in China from 2011 to 2022 combined with econometric models based on the mechanism of the impact of digital rural construction on agricultural carbon emission intensity. The entropy method and carbon emission factor method are used to determine the level of digital rural construction and agricultural carbon emission intensity. The fixed effect and intermediary effect models are used to empirically analyze the impact of digital rural construction on agricultural carbon emission intensity. The results indicate that (1) digital rural construction significantly inhibits agricultural carbon emission intensity, and there are differences in different regions and dimensions of digital rural construction; (2) the construction of digital rural areas can indirectly reduce the intensity of agricultural carbon emissions by promoting the level of rural human capital; (3) financial support for agriculture played significant positive regulatory effect. The policy recommendations are proposed to provide a reference for promoting agricultural carbon reduction and digital rural construction in other countries.

KEYWORDS

digital rural construction, agricultural carbon emission intensity, human capital, financial support for agriculture, impact

1 Introduction

Food production and total agricultural output have grown in recent years, but the accompanying problem of agricultural carbon emissions is becoming increasingly serious. According to the “Global Agriculture Outlook 2022–2031” report, greenhouse gas emissions directly generated by agriculture are projected to increase by 6% over the next decade. As a major agricultural country, China actively undertakes the significant responsibility of reducing agricultural carbon emissions and has introduced various plans to strengthen carbon reduction in agriculture. For instance, in September 2020, China set the goals of “peaking carbon emissions by 2030” and achieving “carbon neutrality by 2060”. In 2022, China issued the “Collaborative Implementation Plan for Pollution Reduction and Carbon Reduction”, which emphasized deepening the implementation of actions to reduce the quantity and improve the efficiency of fertilizers and pesticides to meet carbon reduction requirements. Reducing agricultural carbon emissions while ensuring food security has become a common concern for China and the world.

Agricultural carbon emission refers to the greenhouse gas emissions directly or indirectly generated by various activities in the process of agricultural production. Research on agricultural carbon emissions mainly focuses on carbon sources, carbon emission measurement, influencing factors, and carbon reduction measures. There are six primary sources of carbon emissions (Zhang et al., 2022). The calculation methods for agricultural carbon emissions primarily include the default coefficient of the IPCC (Sperow, 2020) and the life cycle assessment method (Jana and De, 2016). Agricultural carbon emissions influence economic development, urbanization, and energy use (Qing and Yuhang, 2022; Xu and Lin, 2017; Wei Z. et al., 2023). Land use patterns, farmland ecosystems, and soil erosion can affect the carbon balance of agricultural systems (Woomer et al., 2004; Lal, 2003; Kindler et al., 2011). Measures for agricultural carbon reduction mainly involve technological innovation, technological progress, industrial structure optimization (Li G. et al., 2024; Li J. et al., 2024; Wang et al., 2023), collecting environmental taxes (Iyke-Ofoedu et al., 2024), encouraging farmers to join rural cooperatives and adopt socialized services (Wang and Qiu, 2024; Chen et al., 2022), adjusting fertilizer use (Ji et al., 2024), promoting large-scale agricultural land management (Bai et al., 2023), and implementing crop rotation and fallow practices (Zhang et al., 2024). Financial support for agriculture, industrial upgrading and clean agricultural production technologies are effective for reducing agricultural carbon emissions (Wei S. et al., 2023; Du et al., 2023; Guo et al., 2022).

"The Outline of the Strategy for the Development of Digital Countryside" points out that the construction of digital rural countryside refers to the application of networking, informatization and digitalization in agricultural and rural development and the process of promoting the modernization and transformation of agriculture and rural areas, which is not only the strategic direction of rural revitalization but also an important content of the construction of digital China. "The Action Plan for Digital Rural Development (2022–2025)" emphasizes the application of digitalization in rural areas, positioning data as an essential input factor in modern agricultural production. In this context, exploring the impact of digital rural construction on agricultural carbon emission intensity can offer new insights into agricultural carbon reduction and assess the role of digital rural strategies in agricultural development. The Internet can facilitate land circulation among farmers and help them adopt agricultural productive services, thereby improving agricultural green total factor productivity (Liu et al., 2022). Digital inclusive finance can optimize resource allocation and reduce agricultural carbon emissions (Hong et al., 2024; Liu et al., 2024). The higher the level of digital finance development, the stronger its role in financial agglomeration and reducing agricultural carbon emissions (Li, 2023; Zhao et al., 2023). Digitalization can lower carbon intensity by enhancing agricultural technology, human capital levels, and urbanization rates, with regional variations (Wang et al., 2024). The relationship between digital agriculture growth and agricultural green total factor productivity exhibits an inverted U-shaped curve (Zhou et al., 2023).

As a predominantly agricultural country, China serves as a typical representative of global digital rural construction (Zhang et al., 2023). With the promotion of relevant national policies, several critical questions arise: How does the construction of digital rural areas affect the intensity of agricultural carbon emissions? Is there heterogeneity in the effects between different regions? What are the intermediate transmission mechanisms? What factors can regulate the carbon emission reduction effect of digital rural construction on agriculture? Clarifying these issues is essential for evaluating the impacts of rural digital construction, seizing the opportunities it presents, and exploring new strategies for agricultural carbon reduction.

Previous studies on agricultural carbon emissions mainly focused on the measurement of carbon emissions and the decomposition of influencing factors. Compared with previous studies, this paper makes several contributions. First, it innovates in research by exploring the impact of digital rural construction on agricultural carbon emission intensity, aligning with the "dual carbon" strategy, "digital countryside" strategy, thus providing new insights into reducing global agricultural carbon emissions,The construction of digital countryside brings new opportunities for agricultural carbon emission reduction. Second, it innovates in research content by constructing the index system, calculating the levels of digital rural construction and agricultural carbon emission intensity through an index system and clarifying the logical mechanisms between these systems using a combination of literature review and relevant theories. The study empirically analyzes the impact of digital rural construction on agricultural carbon emission intensity. It examines the intermediary effect of rural human capital, the regulatory implications of financial support for agriculture. This is conducive to understanding the logical mechanism behind the construction of digital rural construction to reduce agricultural carbon emission and the direction of policy regulation in various countries. The research provides suggestions for leveraging digital rural construction to achieve low-carbon agricultural development so as to promote the achievement of global carbon reduction targets.

The rest of chapters are arranged as follows: Section 2 offers literature review and research hypotheses. Section 3 introduces the methods, variable selection and description and data source. The results of the study are presented in the Section 4. Section 5 presents the discussion and several policy recommendations. The last section summarizes the conclusions.

2 Literature review and research hypotheses

2.1 Concept of digital rural construction and index system construction

Foreign scholars have explored the concept of the digital countryside primarily from the perspectives of digital agriculture or technology (Rotz et al., 2019; Engås et al., 2023). In 2019, China issued the "Digital Rural Development Strategy Outline", providing a specific definition: digital rural construction refers to the application of networking, informatization, and digitization in agricultural and rural development, aiming to promote the modernization and transformation of agriculture and rural areas. There is yet to be a unified standard for evaluating digital rural construction. The calculation method is mainly based on the comprehensive evaluation model using the entropy method. Indicators typically involve the construction of digital rural information infrastructure, digital rural financial infrastructure, and digital rural service platforms (Ping et al., 2024; Hao and Tan, 2022). Some approaches replace the level of digital rural construction with a single indicator, such as the county-level digital rural index (Linghui and Yongxin, 2022).

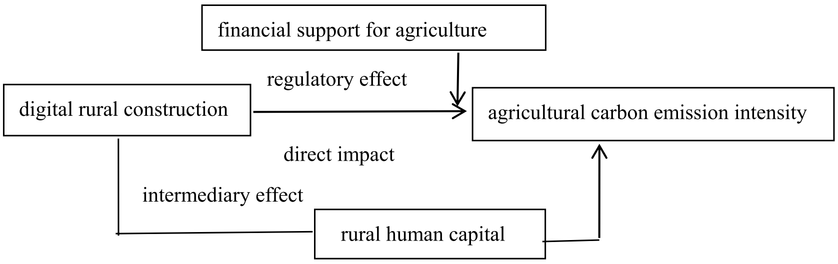

FIGURE 1
Theoretical framework diagram.

2.2 The impact mechanism of digital rural construction on agricultural carbon emission intensity

2.2.1 Direct impact mechanism of digital rural construction on agricultural carbon emission intensity

With the implementation of the "Broadband China" and "Digital Rural" strategies, digital technology has become a significant input factor in agricultural production in the new era. Based on the theory of the digital economy, the construction of a digital rural construction can leverage the substitution and integration effects of the digital economy to alleviate the mismatch of agricultural resource factors and improve agriculture's total green factor productivity (Honghai and Xinmin, 2023). Digital rural construction can reduce farmers' transaction costs and alleviate market information asymmetry, effectively lowering agricultural production costs and environmental pollution (Rolandi et al., 2021). This construction has accelerated the widespread dissemination of advanced technologies in rural areas (Popescu et al., 2020), and technological innovation is a crucial measure to promote agricultural carbon reduction. It facilitates the recombination and efficient allocation of various production factors, thereby improving production efficiency (Acemoglu and Restrepo, 2018). Due to specific differences in resource endowments among different regions, the impact of digital rural construction on agricultural carbon emission intensity varies across areas.

Hypothesis 1: Digital rural construction is beneficial for reducing agricultural carbon emission intensity.

Hypothesis 2: The impact of digital rural construction on agricultural carbon emission intensity has regional differences.

2.2.2 The impact of digital rural construction on agricultural carbon emission intensity through rural human capital

The government can disseminate information on agricultural low-carbon production technologies to farmers through rural digital platforms. Farmers can utilize the Internet and social media to access high-quality educational resources, enabling them to acquire advanced green production technology quickly to enhance their labor skills, knowledge level, and environmental awareness. This can influence rural labor behavior, encouraging farmers to adopt green production practices beneficial for agricultural carbon emission reduction (Ma et al., 2022). The construction of digital rural areas can overcome the limitations of traditional rural areas in terms of talent, resources, time, and space, thereby improving resource allocation efficiency, promoting the enhancement of green total factor productivity in agriculture, and exerting a substitution effect on the rural labor force, alleviating issues related to insufficient rural labor. Digital technology, as a fundamental driver in digital rural area construction, can catalyze changes in agricultural workers' skills and other elements, forming digital agrarian productivity (Junge and Qinmei, 2023). In promoting digital rural construction, digital technology can lower the cost of farmers' access to market information (Mary George et al., 2016; Song et al., 2020), enhance human capital by focusing on farmers' digital literacy, reinforce environmental awareness, and encourage green production practices (Aldieri et al., 2019). The proliferation of rural digitization has paved new pathways for developing low-carbon agriculture.

Hypothesis 3: The construction of digital agriculture can reduce the intensity of agricultural carbon emissions by promoting the level of rural human capital.

2.2.3 The regulatory of financial support for agriculture in the impact of digital rural construction on agricultural carbon emission intensity

Currently, agricultural management entities in China predominantly consist of small-scale operations, and the construction of digital rural areas constitutes projects with significant externalities and essential public welfare attributes. It is a comprehensive undertaking involving various components, such as network infrastructure construction and the enhancement of rural human capital, which necessitate financial backing. However, farmers typically need more financial resources to undertake such endeavors. The level of economic development and the availability of financial support are critical factors influencing the effectiveness of digital rural construction (Xing et al., 2023). Moreover, financial support for agriculture can facilitate the aggregation of information, technology, and talent, thereby aiding in the high-level development of digital rural areas (Chunlin et al., 2024).

Hypothesis 4: financial support for agriculture can positively influence the impact of digital rural construction on agricultural carbon emission intensity. Based on the above theoretical analysis, the theoretical framework diagram of the impact of digital rural construction on agricultural carbon emission intensity was constructed, as shown in Figure 1.

3 Methods

3.1 Model setting

3.1.1 Entropy method

AHP and Delphi methods are commonly employed to determine indicator weights, yet they entail significant subjectivity. Therefore, the entropy method is utilized to ascertain the weights of each indicator, enhancing the scientific validity of the evaluation results, which boast high credibility and accuracy. The specific application methods of the entropy method can be found in some literature (Chen and Zhang, 2023).

①Dimensionless treatment of indicators

converting the indicator values of each indicator to 0–1, which can avoid the impact of different indicator dimensions.

$$\text{Positive indexes: } X'_{tij} \frac{X'_{tij} - X_{jmin}}{X'_{jmax} - X_{jmin}}$$

$$\text{Negative indexes: } X'_{tij} \frac{X'_{jmax} - X_{tij}}{X'_{jmax} - X_{jmin}}$$

②Standardized processing of raw indicators

The dimensionless processed indicators are standardized and translated to obtain the standardized indicator values:

$$X''_{tij} = 0.99 \times X'_{tij} + 0.01$$

③Calculate the proportion of indicator value

$$P_{tij} = \frac{X''_{tij}}{\sum_t \sum_i X''_{tij}}$$

④Calculate the entropy value of the indicator

$$S_j = -\ln(kn)^{-1} \sum_t \sum_i P_{tij}\, ln\left(P_{tij}\right)$$

⑤Calculate the differentiation coefficient of the indicator

$$G_j = 1 - S_j$$

⑥Calculate the weight of the indicator

$$W_j = \frac{G_j}{\sum_j G_j}$$

⑦Calculate the comprehensive evaluation value in each province

$$H_{ti} = \sum_j \left(W_j \times X''_{tij}\right)$$

3.1.2 Carbon emission coefficient method

The carbon emission measurement method based on IPCC (Intergovernmental Panel on Climate Change) carbon emission coefficient is the common method to estimate carbon emission at present with the advantages of simple calculation process, easy popularization and less data demand. In china there are six primary sources of agricultural carbon emissions (Li et al., 2011), including pesticides, chemical fertilizers, agricultural fuel, agricultural plastic film, agricultural sowing areas, and agricultural irrigation areas. The corresponding carbon emission coefficients are as follows (Li et al., 2011; West and Marland, 2002; Zhi and Gao, 2009; Wu et al., 2007; Dubey and Lal, 2009): 4.9341 kg/kg,0.8956 kg/kg, 0.5927 kg/kg, 5.180 kg/kg, 312.60 kg/km^2, 25 kg/hm^2. The total agricultural carbon emissions are calculated as follows:

$$ac = \Sigma ac_i = \Sigma T_i \times \delta_i \tag{1}$$

Where ac represents the total agricultural carbon emissions, ac_i represents the carbon emissions of various carbon sources, T_i and δ_i respectively represent the actual consumption of multiple carbon sources and their corresponding carbon emission coefficients.

3.1.3 Benchmark regression model

To test the impact of digital rural construction on agricultural carbon emission intensity, the benchmark regression model constructed is as follows:

$$acintensity_{it} = a_0 + a_1 digcounty_{it} + a_2 controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

Where $acintensity_{it}$ is the agricultural carbon emission intensity of Province i in year t, $digcounty_{it}$ is the digital rural construction level of Province i in year t, and controls is a series of control variables. μ_i and λ_t refer to the fixed province effect and time effect, respectively, and ε_{it} refers to the random disturbance term.

3.1.4 Intermediary effect model

Utilizing the stepwise regression method (Wen and Ye, 2014) for testing, the model is constructed as follows:

$$acintensity_{it} = a_0 + c digcounty_{it} + a_2 controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

$$lnhuman_{it} = b_0 + a digcounty_{it} + b_2 controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{4}$$

$$acintensity_{it} = c_0 + c' \, digcounty_{it} + b lnhuman_{it} + c_3 controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{5}$$

Where rural human capital is the intermediary variable, c is the total effect coefficient of digital rural construction affecting agricultural carbon emission intensity; a is the effect of the core explanatory variable of digital rural construction on the intermediary variable of rural human capital; c' is the direct effect of digital rural construction on agricultural carbon emission intensity after controlling the influence of rural human capital; b is the indirect effect of the intermediary variable rural human capital on agricultural carbon emission intensity after controlling the impact of the core explanatory variable digital rural construction.

3.1.5 Regulatory effect model

To further analyze the regulatory effect of financial support for agriculture on the impact of digital rural construction on agricultural carbon emission intensity, the regulatory effect model is developed as follows:

$$\begin{aligned} acintensity_{it} = m_0 + m_1 digcounty_{it} + m_2 financialsupport_{it} \\ + m_3 digcounty_{it} financialsupport_{it} + m_4 controls_{it} \\ + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{6}$$

TABLE 1 Index system of digital rural countryside.

Primary indicators	Secondary indicators	Unit	Attribute
Construction of digital rural information infrastructure	Rural broadband access users	10,000 households	+
	Average mobile phone ownership per 100 rural households	number	+
Financial infrastructure	Digital inclusive finance index		+
Construction of digital service platform	Rural delivery route length	kilometre	+

3.2 Variable selection and description

(1) Explained Variable. The explained variable in this paper is agricultural carbon emission intensity (variable: acintensity). Agricultural carbon emission is calculated by carbon emission coefficient method (see Equation 1). Agricultural carbon emission intensity is the total agricultural carbon emission ratio to total agricultural output value (Xueqiang et al., 2023).
(2) Explanatory Variable: The primary explanatory variable in this study is digital rural construction (variable:digcounty). As the establishment of "Taobao Villages" has been prevalent in numerous provinces for several years, it is not considered in this paper. The construction of digital rural information infrastructure primarily indicates the transformation of information dissemination and the proliferation of modern information technology in rural areas. Financial infrastructure mainly represents the digital economic infrastructure. Establishing a digital service platform predominantly reflects the state of digital logistics. The specific index system is outlined in Table 1.
(3) Intermediary Variables: The intermediary variable in this paper is rural human capital (variable: lnhuman), with *per capita* years of education in rural areas chosen to represent the development level of rural human capital in each province.
(4) Regulatory Variables: The regulatory variable in this paper is financial support for agriculture (variable:financialsupport), measured by the proportion of local financial expenditures on agriculture, forestry, and water affairs, local general budget expenditures.
(5) Control Variables: To account for the influence of other factors on agricultural carbon emission intensity and avoid interference, the following control variables are selected: Urbanization (variable:urbanization): Measured by the proportion of the urban population in different regions at the end of the year. Disaster rate (variable:disasterrate): Measured by the proportion of the affected area as a percentage of the planted crop area. Technological innovation development (variable:lntechnology): Measured by the number of patents granted. Agricultural industry structure (variable:agrstructure): Reflects the development of various industries in the region, measured by the proportion of the primary industry in the regional economy. Agricultural mechanization strength (variable: lnmachstrength): Measured by dividing the total power of agricultural machinery by the cultivated land area. Intensity of science and technology expenditure (variable:tcf): Measured by the proportion of science and technology expenditure to local general public budget expenditure.

3.3 Data source and descriptive analysis

The research sample comprises 29 provinces in China. Due to a significant number of missing values for specific indicators of digital countryside in Xizang and Shanghai, these provinces are temporarily excluded from the calculation to ensure the accuracy of the research. The study period spans from 2011 to 2022. Data sources include the China Statistical Yearbook, China Rural Statistical Yearbook, and the Peking University Digital Financial Inclusion Index. For individual missing data, the interpolation method is employed for completion. The statistical characteristics of essential variables are presented in Table 2.

A scatter plot and fitting line illustrating the relationship between digital rural construction and agricultural carbon emission intensity were generated using the sample data, as depicted in Figure 2. It is evident that as the level of digital rural construction increases, agricultural carbon emission intensity decreases, indicating a negative correlation between the two variables. This preliminary observation suggests that digital rural construction may reduce agricultural carbon emission intensity, aligning with the theoretical derivation presented earlier in this paper. Further analysis will involve the inclusion of control variables and the adoption of multiple models for verification.

4 Results

4.1 Baseline regression results

Prior to conducting the baseline regression, the variance inflation factor (vif) was utilized to test for collinearity among variables. The testing revealed that the minimum vif value for each variable was 1.43, the maximum was 4.06, and the average was 2.71,which is significantly less than 10. Therefore, there was no collinearity issue among the variables. Table 3 presents the benchmark regression results of "Digital rural construction-agricultural carbon emission intensity". The calculation results are obtained by referring to Equation 2. Columns (1) and (2) display the outcomes of the fixed effects model, indicating that digital rural construction significantly reduces agricultural carbon emission intensity. Without control variables, the coefficient of digital rural construction is −0.090, exhibiting a substantial correlation at the 1% significance level. Even after incorporating a series of control variables, the coefficient remains −0.087, still significantly correlated at the 1% level. This suggests that digital rural

TABLE 2 Descriptive statistical results.

Variable classification	Variable	Number	Mean	Standard error	Maximum	Minimum
Explained variable	acintensity	348	0.150	0.052	0.349	0.031
Explanatory variable	digcounty	348	0.426	0.165	0.858	0.060
Mediating variable	lnhuman	348	2.056	0.079	2.314	1.771
Regulatory variable	financialsupport	348	0.116	0.032	0.204	0.040
Controls	urbanization	348	0.586	0.109	0.876	0.350
	disasterrate	348	0.141	0.112	0.618	0.004
	lntechnology	348	10.259	1.480	13.679	6.219
	lnmachstrength	348	2.045	0.472	2.917	0.950
	agrstructure	348	9.961	4.960	26.100	0.300
	tcf	348	0.021	0.014	0.068	0.004

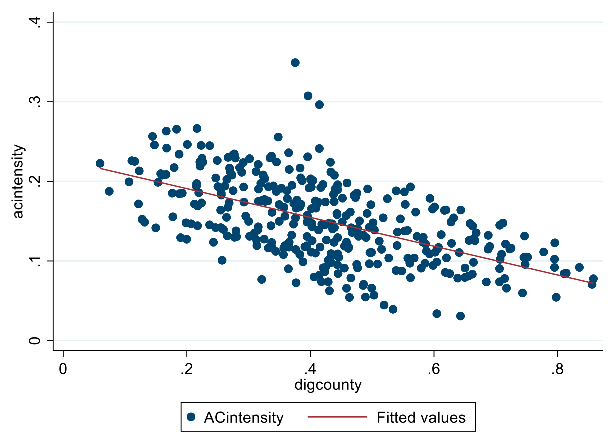

FIGURE 2
Scatter plot and fitting line of digital rural construction and agricultural carbon emission intensity.

construction exerts a significant carbon reduction effect on agriculture. Columns (3) and (4) present the results of the random effects model. The Hausman test indicates that chi2 (6) = 25.85, Prob > chi2 = 0.0002, thereby rejecting the null hypothesis and affirming that the fixed effects model is more suitable. The baseline regression results unequivocally demonstrate that digital rural construction significantly diminishes the intensity of agricultural carbon emissions, thereby confirming hypothesis 1.

4.2 Robustness and endogeneity test results

4.2.1 Robustness test results

(1) Replace Core Explanatory Variables. Carbon emissions from food production are a significant component of agricultural carbon emissions. To test robustness, the intensity of agricultural carbon emissions is replaced with the carbon emission intensity from food production, and the baseline regression is performed again. The results are presented in Table 4 (1).
(2) Reduce Sample Size. Municipalities like Beijing, Chongqing, and Tianjin differ markedly from other provinces regarding government resource support and agricultural development. Therefore, these municipalities are excluded from the sample, and the regression analysis is conducted again with the remaining samples. The results, shown in Table 4 (2), indicate that the estimated coefficient of digital rural construction is significantly negative at the 5% level.
(3) Indentation of Sample Variables. To avoid the interference of extreme values on regression results, all variables are winsorized at the 1% level. The suffix _w is used to denote variables after winsorization. The results are shown in Table 4. After this data adjustment, the estimated coefficient of digital rural construction remains significantly negative at the 5% level, further demonstrating the robustness of the baseline regression results.

The findings from these three robustness tests consistently show a negative and significant coefficient for digital rural construction, affirming the robustness of the baseline regression conclusion: the construction of digital countryside can significantly reduce agricultural carbon emission intensity.

4.2.2 Endogeneity test results

Using the second lag of digital rural construction (L2. digcounty) as an instrumental variable helps avoid endogenous estimation bias caused by two-way causality. The initial phase of digital rural construction creates favorable conditions for subsequent stages, satisfying the relevance requirement. Early-stage digital countryside construction reduces agricultural carbon emission intensity in the current period, meeting the homogeneity requirement. The two-stage least squares method (IV_2SLS) was employed to re-examine the impact of digital rural construction on agricultural carbon emission intensity (see Table 5). In the first-stage regression results, the instrumental variable L2. digcounty is positively correlated with the endogenous variable (discount) at

TABLE 3 Results of benchmark regression.

Variable	Acintensity			
	(1) Fe	(2) Fe	(3) Re	(4) Re
digcounty	−0.090***	−0.087***	−0.243***	−0.145***
	(-3.07)	(-2.62)	(-32.23)	(-8.68)
urbanization		−0.170**		−0.246***
		(-2.30)		(-5.34)
disasterrate		0.022*		0.018*
		(1.83)		(1.66)
lntechnology		−0.004*		−0.007***
		(-1.84)		(-3.54)
lnmachstrength		0.007		−0.001
		(0.99)		(-0.16)
agrstructure		−0.003**		−0.005***
		(-2.51)		(-6.42)
tcf		−0.274		−0.220
		(-1.49)		(-1.14)
_cons	0.189***	0.346***	0.254***	0.479***
	(15.10)	(6.79)	(33.17)	(17.42)
Year/Province	YES	YES		
N	348	348	348	348
R^2	0.917	0.925		
Adj.R^2	0.907	0.914		
F	9.452	3.478		

$^*p < 0.1$ $^{**}p < 0.05$ $^{***}p < 0.01$.

TABLE 4 Results of robustness test.

	(1)	(2)	(3)
	Fcintensity	Acintensity	acintensity_w
digcounty	−0.355***	−0.074**	
	(-3.88)	(-2.18)	
digcounty_w			−0.078**
			(-2.45)
Controls	YES	YES	YES
Year/Province	YES	YES	YES
_cons	0.469	0.432***	0.311***
	(1.49)	(7.26)	(6.59)
N	348	312	348
R^2	0.953	0.929	0.935
Adj.R^2	0.946	0.918	0.924
F	2.909	4.677	3.531

$^*p < 0.1$ $^{**}p < 0.05$ $^{***}p < 0.01$.

the 1% level, indicating that the chosen instrumental variable is sufficiently associated with the endogenous variable. In the under identification test, the LM value is 112.230, passing the 1% significance test, which confirms the absence of under identification issues. The Cragg-Donald Wald F-value is 4,276.309, exceeding the critical value of 16.38 at the 10% significance level for the Stock-Yogo weak instrumental variable test, indicating no weak instrumental variable issues. The Hansen J statistic indicates no over identification problem, affirming the appropriateness of the selected instrumental variable. After addressing the endogeneity problem using the instrumental variable method, digital rural construction continues to show a significant negative correlation with agricultural carbon emission intensity at the 1% level, confirming the robustness of the result.

4.3 Heterogeneity analysis results

4.3.1 Heterogeneity analysis of agricultural functional attributes

Divide the country into two categories based on whether it is a major grain-producing area. The regression results are shown in Table 6. The regression coefficients for digital rural construction are negative and pass the significance tests at 1% and 5%. However, the degree of influence varies across different regions. Digital rural construction significantly inhibits agricultural carbon emission intensity in major grain-producing areas. This effect is due to the country's favorable resource allocation towards these grain-producing areas. On the one hand, the major grain-producing areas bear the heavy responsibility of maintaining national food security, the state attaches great importance to the development of major grain-producing areas, and has introduced a series of targeted policies to promote the construction of digital countryside, such as providing a number of financial funds for the construction of digital countryside in major grain-producing areas for infrastructure construction, digital technology research and development and application promotion. The main grain-producing areas have relatively good network coverage and perfect infrastructure, which provides the necessary basic conditions for the construction of digital countryside. On the other hand, major grain-producing areas usually have large areas of farmland which facilitate the large-scale application of digital technology in agricultural production. The observed regional differences, attributed to varying resource endowments, confirm hypothesis 2.

4.3.2 The dimensional heterogeneity analysis of digital rural construction

This part analyzes the impact of the sub-dimension of digital rural construction on agricultural carbon emission intensity (see Table 7). Rural broadband access users and the average mobile telephone ownership per 100 rural households significantly reduce agricultural carbon emission intensity, each passing the 1% significance test. The total index of digital inclusive finance within the construction of digital rural finance and the length of rural delivery routes within the construction of digital rural service

TABLE 5 Regression results of instrumental variables.

		(1) 1st	(2) 2nd
		Digcounty	Acintensity
L2.digcounty		0.924***	
		(73.08)	
digcounty			−0.135***
			(-5.98)
Controls		YES	YES
Year/Province		YES	YES
_cons		0.174***	0.357***
		(7.51)	(9.37)
N		290	290
R^2		0.973	0.367
Adj.R^2		0.972	0.351
F		1772.387	
Underidentification test	Kleibergen-Paap rk LM statistic	112.230	
	Chi-sq (1) P-val	0.000	
Weak identification test	Cragg-Donald Wald F statistic	4,276.309	
	Kleibergen-Paap rk Wald F statistic	5,340.880	
Stock-Yogo weak ID test critical	values: 10% maximal IV size	16.38	
Hansen J statistic	overidentification test of all instruments	0.000	

$^*p < 0.1$ $^{**}p < 0.05$ $^{***}p < 0.01$.

TABLE 6 Results of regional heterogeneity analysis.

	Acintensity	
	(1) Main grain-producing areas	(2) Non grain-producing areas
digcounty	−0.167***	−0.094**
	(-3.14)	(-2.49)
Controls	Yes	Yes
Year/Province	Yes	Yes
_cons	0.511***	0.284***
	(3.10)	(5.62)
N	156	192
R^2	0.938	0.942
Adj.R^2	0.924	0.930
F	8.523	2.756

$^*p < 0.1$ $^{**}p < 0.05$ $^{***}p < 0.01$.

platforms show no significant effect on carbon emissions. But when the level of digital inclusive finance is above the 0.25 quartile value (lndigfi ≥ 5.106) and the length of rural delivery route is above the 0.75 quartile value (lndelroute ≥ 12.154), the agricultural carbon emission intensity is also significantly reduced, and both pass the significance test of 10%. In other words, with the continuous improvement of digital inclusive finance and the length of rural delivery routes, the effect on agricultural carbon emission reduction will gradually increase, and there is a nonlinear relationship between them. The sub-dimensional construction level is related to the

TABLE 7 Results of dimensional heterogeneity.

	Acintensity					
	(1)	(2)	(3)	(4)	(5)	(6)
lntel	−0.065***					
	(-4.32)					
lnbroadb		−0.012***				
		(-6.14)				
lndigfi			0.010			
			(0.88)			
lndelroute				0.003		
				(0.98)		
lndigfi (≥5.106)					−0.103*	
					(-1.66)	
lndelroute (≥12.154)						−0.027*
						(-1.94)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/Province	Yes	Yes	Yes	Yes	Yes	Yes
_cons	0.650***	0.344***	0.316***	0.319***	0.835**	0.916***
	(7.74)	(8.13)	(4.80)	(5.56)	(2.51)	(3.30)
N	348	348	348	348	261	87
R^2	0.927	0.931	0.923	0.923	0.934	0.979
Adj.R^2	0.916	0.920	0.912	0.912	0.921	0.970
F	5.787	7.772	2.903	3.067	1.822	7.905

*$p < 0.1$ **$p < 0.05$ ***$p < 0.01$.

overall level of digital rural construction. The mobile phones and the Internet enables farmers to obtain weather information and information of agricultural materials products earlier, so they can implement scientific and reasonable irrigation and fertilization, and avoid environmental problems caused by excessive use of agricultural materials. The popularization of digital inclusive finance and the construction of express routes require a large amount of investment in the early stage, then the carbon reduction effect will gradually appear in the later stage, so as to achieve the purpose of reducing agricultural carbon emission intensity.

4.4 Intermediary effect results

The theoretical analysis indicates that digital rural construction can directly reduce agricultural carbon emission intensity and indirectly do so by enhancing the knowledge and skills of laborers, thereby leveraging the "human capital effect". This paper employs a three-step method to build an intermediary effect model, with the measurement test results shown in Table 8, the calculation results refer to Equations 3–5. The coefficients in columns (1), (2), and (3) are all significantly correlated, suggesting that rural human capital plays a partial mediating role in the carbon reduction effect of digital rural construction on agriculture. The Sobel test was used to verify the robustness of the results of the intermediary effect further. The total utility coefficient of digital rural construction on agricultural carbon emission intensity was −0.087, the effect coefficient of digital rural construction on the intermediary variable rural human capital was 0.113, and the total utility coefficient of rural human capital on agricultural carbon emission intensity was −0.126. These correlations were significant at the 1%, 1%, and 5%, respectively. The direct effect coefficient is −0.073, significantly correlated at 5%, while the indirect effect coefficient is −0.014, accounting for 16.3% of the total effect. The direct effect accounts for 83.7%. The intermediary effect passed both the stepwise test of the three-step method and the Sobel test, demonstrating the robustness of the intermediary effect and confirming hypothesis 3.

4.5 Regulatory effect results

Theoretical analysis indicates that financial support for agriculture influences the effect of digital rural construction on agricultural carbon emission intensity. An interaction term

10.3389/fenvs.2024.1492454

TABLE 8 Results of intermediary effect.

	(1)	(2)	(3)	
	Acintensity	Lnhuman	Acintensity	
digcounty	−0.087***	0.113***	−0.073**	
	(-2.62)	(2.70)	(-2.33)	
lnhuman			−0.126**	
			(-2.55)	
Controls	Yes	Yes	Yes	
Year/Province	Yes	Yes	Yes	
_cons	0.346***	2.115***	0.612***	
	(6.79)	(34.86)	(4.98)	
N	348	348	348	
R^2	0.925	0.952	0.927	
Adj.R^2	0.914	0.944	0.915	
F	3.478	2.798	3.255	
Sobel test				
	Est	Std_err	z	$p>\|z\|$
a_coefficient	0.113	0.042	2.699	0.007
b_coefficient	−0.126	0.049	−2.553	0.011
Indirect_effect_a*b	−0.014	0.008	−1.855	0.064
Direct_effect_c’	−0.073	0.031	−2.332	0.020
Total_effect_c	−0.087	0.033	−2.618	0.009
Proportion of total effect that is mediated:			0.163	
Direct effect to Ratio of total			0.837	

*$p < 0.1$ **$p < 0.05$ ***$p < 0.01$.

TABLE 9 Results of regulatory effect.

	Acintensity	
	(1)	(2)
digcounty	−0.082**	−0.118***
	(-2.53)	(-3.75)
financialsupport	0.242***	0.421***
	(2.78)	(4.55)
c_digcountyc_financialsupport		−1.676***
		(-5.47)
Controls	Yes	Yes
Year/Province	Yes	Yes
_cons	0.338***	0.153**
	(6.84)	(2.56)
N	348	348
R^2	0.927	0.934
Adj.R^2	0.916	0.923
F	3.267	5.988

*$p < 0.1$ **$p< 0.05$ ***$p < 0.01$.

between financial support for agriculture and digital rural construction was introduced to test this hypothesis, avoiding collinearity between variables. After decentralizing the data, the variables of financial support for agriculture and digital rural construction were combined to form the interaction term c_ digcounty *c_financialsupport. Columns (1) and (2) in Table 9 compare the results before and after introducing the interaction term, the calculation results refer to Equation 6. The coefficients of the main effect of digital rural construction are negative in both cases. After introducing the interaction term, its coefficient is −1.676. The original coefficient of digital rural construction changes from −0.082 to −0.118, showing a more significant effect. This indicates that the negative impact of digital rural construction on agricultural carbon emission intensity is amplified with increased financial support for agriculture, thereby verifying hypothesis 4.

5 Discussion

This study not only elucidated the logical mechanism between digital rural construction and agricultural carbon emission intensity through a literature review and related theories but also comprehensively analyzed the impact path and degree from intermediary effect and regulatory effect. Future development suggestions were proposed to enhance the study’s applicability. The primary regression results indicate that digital rural construction significantly and negatively affects agricultural carbon emission intensity, with regional differences, aligning with previous scholarly findings. Digital rural development can reduce agricultural carbon emissions and improve total factor productivity in agriculture. The higher the level of economic growth, the stronger the carbon emission reduction effect of digital rural construction.

Compared to previous studies, this research has made the following improvements:

(1) It combines theoretical mechanism analysis with scientific demonstration, verifying digital rural construction’s overall carbon reduction effect and further analyzing its dimensions.
(2) It emphasizes the critical role of digital rural construction in enhancing rural human capital and underscores the importance of financial support from government.

This study uses China as a case study to analyze the impact of digital rural construction on agricultural carbon emission intensity, providing a valuable reference for other countries aiming for agricultural low-carbon emission reduction. While emphasizing the importance of rural human capital, further analysis is needed on how to promote these aspects in different regions better. Enhancing rural human capital to bolster the role of digital rural construction in reducing agricultural carbon emissions. With the intensification of global climate change, reducing carbon emissions has become a global goal, which requires joint efforts of all countries. Carbon emissions come mainly from human activities and natural processes, such as the burning of fossil fuels (Baoguo et al., 2022), development of industrialization (Zhenshuang et al., 2022), urban land use (Xueqiang et al., 2023) and development of agriculture. About one-fifth of the world's greenhouse gases come from agriculture according to a report by the United Nations Food and Agriculture Organization. Agriculture must do something active to fight climate change because it is closely related to global sustainable development. Agriculture is an important industry in many countries, especially in developing countries. Digital rural construction can improve agricultural production efficiency by improving the human capital level of farmers, and reduce agricultural carbon emission intensity. Financial support for agriculture played significant positive regulatory effect. Promote the international exchange of China's digital countryside construction and agricultural carbon emission reduction experience can contribute to the low-carbon development and sustainable development of global agriculture.

Some policy recommendations are proposed according to empirical results:

(1) Pay more attention to the carbon reduction impact of digital rural construction in agricultural development and accelerate the pace of digital rural construction. Enhancing internet accessibility in rural areas is foundational for the digital rural construction. Cornwall region is the representative of the implementation of the comprehensive strategy of rural digitalization in the United Kingdom, mainly implementing broadband access and digital training to strengthen the construction of digital countryside. The application of digital technology in agriculture can be optimized by the network infrastructure. For example, in the United States, farmers can accurately fertilize, irrigate according to precise data such as soil conditions and crop growth, avoiding the waste of resources and reducing carbon emissions in agricultural production.
(2) Focus on enhancing rural human capital, recognizing its long-term significance in agricultural productivity. Empowering rural labor with skills enhances productivity. Given the pivotal role of the "human capital effect" in carbon reduction, efforts should promote low-carbon concepts among small and medium-sized farmers. Initiatives like "technology to the countryside" should encourage farmers to adopt new technologies and agricultural methods, ensuring a smooth transmission path for the human capital effect of the digital countryside.
(3) Increase central financial support for digital agriculture development. Such support plays a vital role in regulating digital countryside construction. Recognizing the infancy of digital agriculture in certain areas, especially those with weak financial resources and infrastructure, the central government should provide targeted subsidies and investments to bolster development. Securing financial investment is paramount for the ambitious project of digital rural construction.
(4) Formulating differentiated countermeasures to heterogeneity results. In view of regional heterogeneity, major grain-producing areas should play an exemplary role for other regions. For example, integrate agricultural production data, market information and technical services to provide digital services for farmers. From the sub-dimension of digital rural construction, the mobile phones and the Internet played a significant role in promoting agricultural carbon emission reduction which need supportting. But the governments also need to actively promote digital financial inclusion in rural areas. Digital inclusive finance is the product of the combination of digital technology and inclusive finance, which has an important impact on farmers' employment and production.

6 Conclusion

Drawing on provincial panel data from 2011 to 2022, this study employed the entropy and carbon emission factor methods to gauge China's digital rural construction and agricultural carbon emission intensity. Through panel fixed effect, intermediary effect, regulatory effect, the study explored the impact of digital rural construction on agricultural carbon emission intensity, yielding the following key conclusions:

(1) Digital rural construction significantly reduces agricultural carbon emission intensity, indicating its potential to agricultural carbon emission reduction. This conclusion remains robust even after accounting for endogeneity and robustness testing.
(2) The impact of digital rural construction on agricultural carbon emission intensity varies across regions, with a more pronounced effect observed in major grain-producing areas. Among digital rural construction subdimensions, digital infrastructure construction notably curbs agricultural carbon emissions.
(3) Intermediary effect analysis reveals that digital rural construction indirectly reduces agricultural carbon emissions by elevating rural human capital, harnessing the "human capital effect" to achieve emission reduction. The direct and indirect effects account for 83.7% and 16.3% of the total impact, respectively. Enhanced rural human capital influences planting decisions and behaviors, affecting agricultural carbon emissions. Digital rural construction transcends temporal and spatial constraints, facilitating farmer access to new technologies and bolstering environmental awareness.
(4) Regulatory effect analysis demonstrates that government financial support for agriculture positively adjusts the impact of digital rural construction, with varying effects across regions based on different levels of financial support.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

WL: Methodology, Writing–original draft, Writing–review and editing. JG: Conceptualization, Methodology, Writing–review and editing. YT: Software, Writing–review and editing. PZ: Methodology, Writing–review and editing.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This study was supported by the following project: Dongying Science Development Fund Project (DJB2023014).

Acknowledgments

The authors thank the institutions that provided funding.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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