Research on the influence of rural digital transformation on agricultural carbon emission intensity: Based on Mechanism Tests

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Abstract. This study examines how rural digital transformation impacts agricultural carbon emission intensity, offering insights for synergizing emission reduction and digital rural development. Using the entropy weight method to assess results of digital transformation in agriculture, baseline regression and mediation models are employed, supplemented by heterogeneity analyses across grain-producing and topographically diverse regions. Results reveal that rural digital transformation significantly suppresses agricultural carbon emissions, with stronger effects in mountainous areas compared to plains. Emission reduction efficacy varies regionally, showing greater impact in production-marketing balance zones than in primary grain-producing areas and in livestock areas than plantations. Mechanistically, digitization influences emission intensity primarily through industrial restructuring and secondarily via agricultural water-use efficiency optimization. These findings underscore the importance of region-specific digital strategies, enhanced R&D in central/eastern regions, and cross-regional collaboration to leverage digital industrial upgrades. The study provides actionable pathways for tailoring digitalization policies, advancing green technology integration, and fostering sustainable agricultural transformation through targeted spatial planning and institutional innovation.

Keywords: Rural Digital Transformation, Agricultural Carbon Emission Intensity, Mediating Effects, Regression To The Base.

1. Introduction

As the second largest source of carbon outside of industry, agriculture has a tough task in the reduction of carbon emissions. Ecumenic agricultural production activities, such as large-scale fertilizer application and film mulching, generate large amounts of carbon emissions, which in turn contribute to the global greenhouse effect. As digital technology develops by leaps and bounds, China's countryside is becoming increasingly digitized, providing new ideas for agricultural production. To align with China's carbon peaking and neutrality goals, exploring the emission-reduction potential of rural digitization is imperative.

What is undeniable is that the current research on digitization and agricultural decarbonization pathways and policy design. However, throughout the literature, few scholars have explored rural digitization and agricultural carbon intensity within a unified framework, resulting in a gap in this part of the research. Li et al. (2024) identified an inverted U-shaped relationship between digital inclusive finance and agricultural emissions, mediated by scale expansion and structural optimization [1]. Chen and Li (2024) highlighted agricultural digitalization's decarbonization potential through scaled operations and innovation, while noting regional disparities and threshold effects in emission reduction efficacy[2]. Against this backdrop, our research leverages panel data from 30 Chinese provinces spanning 2013 to 2021. We offer several key contributions. First, we comprehensively explore how digitization impacts agricultural carbon emissions and the underlying mechanisms. Second, we uncover how these effects vary across different terrains, agricultural production targets, and functional regions. Our findings provide new angles and empirical evidence for driving forward agricultural carbon reduction efforts and digital development. This analysis enables more effective policy - making, promoting a sustainable and digital future for China's agricultural sector.Research methodology

1.1. Variable Selection

2.1.1 Dependent variables

Due to the large discrepancies in the scale agricultural production scales across provinces, total agricultural carbon emissions fail to account for output variations, rendering them less persuasive [3]. In this study, agricultural carbon emission intensity serves as the key explained variable. It measures agricultural carbon emissions relative to each unit of gross agricultural output. To determine agricultural carbon emissions, we collated research from various scholars. This approach allows for a thorough evaluation of agricultural carbon emissions across China. Such an approach offers a comprehensive view of the carbon footprint in the agricultural sector, providing a basis for further analysis. [4]. The existing literature outlines three principal approaches to measuring carbon emissions: the emission coefficient method, the model simulation method, and the field measurement method. Among these, the emission coefficient method enjoys the most extensive application in academic research [5]. Consistent with common practice, this study adopts the emission coefficient method to calculate agricultural carbon emissions. This approach ensures compatibility with previous research, strengthening the comparability and reliability of the results obtained in this paper. Referring to Li's research[6], this paper constructs an index system for accounting the total agricultural carbon emissions using carbon emission coefficients as shown in the table.1.

Table 1. Carbon sources and their carbon emission factors

Level 1 indicators	Secondary indicators	Tertiary indicators	Carbon emission factor
Agricultural carbon emissions	Renewable energy	Diesel fuel	0.59kg/kg
	Industrial processes and Product Use	Fertilizers	0.89kg/kg
		Agrochemical	4.93kg/kg
	Agriculture, forestry and Other land use	Agricultural film	5.18kg/kg
		Irrigated	266.48kg/kg
		Plow	312.60kg/kg

Agricultural carbon emissions formula.

$$C_{it} = \sum T_{nit} * \sigma_n (n = 1,2,3,4,5,6) \tag{1}$$

where, C_{it} ,t , σ represent total emissions of the nth carbon source, input quantity, and emission coefficients, respectively. The specific carbon emission coefficients are shown in Table 1.Agricultural carbon emission intensity calculation formula.

$$Aci_{it} = \frac{C_{it}}{AG_{it}} \tag{2}$$

AG denotes agricultural GDP , and Aci is the efficiency of agricultural carbon emissions, higher Aci reflects greater relative emissions.

2.1.2 Core explanatory variables

Since the broad digital transformation or digitization level is too complex for the agricultural carbon emission pathway, and the evaluation system of rural digitization has not yet formed a consensus, this paper refers to the research of Zhu et al[7],and measures the level of agricultural digitization with the digital village construction index.

Reviewing the existing studies, the variables selected for establishing the measurement system of digital village construction level are different, but there are some common features. When taking data accessibility into account, this research zeroes in on multiple indicators. To evaluate the digital transformation, it adopts the entropy weighting method. This evaluation specifically makes use of the digital village construction index. The paper then builds a measurement system for digital village construction. The system is based on several second - tier indicators. The construction of this system enables a more comprehensive and accurate assessment of the digital village development level.

2.1.3 Control and mechanism variables

After extensively reviewing research on factors influencing agricultural carbon emissions and carbon intensity, it became evident that a diverse range of control variables were being used. When choosing control variables, it's crucial to prevent multicollinearity. Their selection should be grounded in theory rather than relying solely on statistical significance. Similarly, the choice of mediating variables must have theoretical backing.

From the above theoretical analysis, it's clear that apart from the core explanatory variable—rural digital transformation—agricultural carbon emission intensity may be influenced by other factors. Thus, variables that could impact agricultural carbon emissions are included as control variables.

To avoid model covariance issues, this study selects a set of control and mediating variables, drawing insights from relevant literature. This approach ensures that the research framework is both theoretically sound and statistically robust, laying a solid foundation for accurate analysis of the factors affecting agricultural carbon emissions.

1.2. Data acquisition and description

2.2.1 Data acquisition

Panel data (2013–2021) from 30 provinces, cities, autonomous regions, and municipalities are sourced from directly under the central government in China from 2013 to 2021. The digitization measurement data are collected from China Statistical Yearbook, China Rural Statistical Yearbook, Wind database, National Bureau of Statistics of China and related research reports, and the agricultural carbon emission coefficients and other data are from IPCC, Oak Ridge National Laboratory, Oak Ridge National Laboratory, Institute of Resource and Ecological Environment, Nanjing Agricultural University, H P Duan[8] et al. and Li B et al.

2.2.2 Descriptive statistics

The descriptive statistics are shown in Table 2.

Table 2. Descriptive statistics

Variable type	Name	Tickers	Intein	Nota	Max	Min	Aver	Std
Explained variable	cia	y	cia	+	0.28	0.04	0.14	0.06
Core explanatory variables	ld	x		+	0.79	0.03	0.19	0.11
Control variable	ul	a1	riur	+	3.56	1.84	2.53	0.36
	ndo	a2	pala	+	0.70	0.01	0.13	0.11
	lam	a3	gam	+	13353	94	[illegible]442.39	2907.46
	le	a4	ay	+	9.91	5.86	7.84	0.61
	saf	a5	al	+	266.12	3.23	22.01	28.82
	ef	a6	pfs	+	0.35	0.15	0.22	0.04
	acs	a7	gsa	+	14551.3	46.50	3832.99	3112.83

Intermediary variable	ap	m1	tp	+	1.56	0.87	1.093	0.07
	wue	m2	eia	+	92664	1638	3431.3	25515.4
	is	m3	sait	+	0.84	0.33	0.56	0.10
	il	m4	ngu	+	35340	18	911.43	5355.19

Notes: intein: Interpretative indicators; nota: Notation; sams: Sample size; min: Minimum; max: Maximum; std: Standard deviation; cia: Carbon intensity of agriculture; ld: Level of digitization; Rudige: Digital rural development index; ul: Urbanization level; uiur: Urban-rural income ratio; ndo: Natural disaster occurrence; pala: Proportion of agricultural land affected; lam: Agricultural mechanization level; gam: Gross agricultural machinery power; le: Rural education level; ay: Average years of schooling (primary sector); saf: Agricultural finance scale; al: Agricultural loans per capita; ef: Financial support extent to agriculture; pfs: Percentage of financial support to agriculture; acs: Agricultural cropping structure; gsa: Grain sown area; ap: Agricultural productivity; tp: Agricultural total factor productivity; wue: Water use efficiency; eia: Effective irrigated area; is: Industrial structure; sait: Share of agriculture in total production value; il: Innovation level; ngu: Number of green utility model patents.

At the same time, in order to avoid inaccurate model results caused by too large a difference in data magnitude, the data were uniformly standardized in stata before conducting regression and effect calibration.

1.3. Research hypothesis

H1: The promotion in the level of rural digital development can significantly curb the expansion of the scale of agricultural carbon emissions, and its role in promoting agricultural carbon emission reduction is mostly manifested in the two aspects of reducing stock and controlling new generation[9].

H2: Digitalization enhance the reduction of agricultural carbon emissions through its influences on industrial structure, level of technological innovation and resource use efficiency.

2. Model building and solving

2.1. Model construction

3.1.1 Model construction based on benchmark regression

The econometric model evaluates digitization’s impact on carbon intensity:

$$Aci_{it} = b_0 + \mathrm{b}_1 Rudige_{it} + \mathrm{b}_2\mathrm{CONTR}_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \tag{3}$$

Aci represents the explained variable, denoting the efficiency of carbon emission in agriculture, Rudige represents the digitization index, measured by entropy weight method. And CONTR denotes covariates. i is the province, t is the time; b is the estimated coefficient, and ε is the error term.

3.1.2 Modeling based on mediating effects

In order to test the mediating effect of digital development and production efficiency, and explore through which pathway this effect is transmitted, this research was carried out using the method of Wen Zhonglin[10], and further discusses the extent of the impact of digital development on the efficiency of agricultural carbon emissions under different pathways, mainly from the perspective of the industrial structure of agricultural production as well as the level of green innovation on the basis of the Ordinary Least Squares (OLS) regression.

The mechanism validation model of this paper is set as follows:

$$Aci_{it} = \alpha_0 + \alpha_1 Rudige_{it} + \alpha_k Z + \mu_i + \delta_i + \varepsilon_{it} \quad (4)$$

$$M_{it} = \beta_0 + \beta_1 Rudige_{it} + \beta_k Z + \mu_i + \delta_i + \varepsilon_{it} \quad (5)$$

$$Aci_{it} = \gamma_0 + \gamma_1 Rudige_{it} + \gamma_2 M_{it} + \gamma_k Z + \mu_i + \delta_i + \varepsilon_{it} \quad (6)$$

2.2. Mechanism Test Outcomes

3.2.1 Baseline regression outcomes

To assess the influence of digitalization on agricultural carbon emission intensity and ensure the robustness of the results, this study employs a step-by-step approach within the baseline framework, with detailed outcomes summarized in Table 3. Column (1) presents univariate regression results for digitization, while Column (2) integrates covariates to establish the comprehensive model.

Regression coefficients for rural digitization consistently demonstrate statistically significant negative correlations, confirming its inhibitory role in agricultural carbon emissions. Model fit progressively improves with incremental variable inclusion. Among covariates, most exhibit positive coefficients and statistical significance across thresholds, except for agricultural cropping structure, which remains insignificant. This implies that current policy frameworks predominantly emphasize "output maximization," as evidenced by variables like financial subsidies and education levels inadvertently fostering high-carbon practices. Such findings reveal a temporal disconnect from the Ministry of Agriculture (MARD)'s "quality-driven transition" strategy, underscoring the urgency of low-carbon incentive realignment.

Table 3. Regression results

Variables	(1)	(2)
cons	0.244^{***} (7.844)	0.029 (1.324)
x	-0.566^{***} (-2.868)	-0.129^{***} (-5.192)
a1		0.062^{***} (-3.157)
a2		0.05^{**} (-2.474)
a3		0.074^{***} (-2.968)
a4		0.095^{***} (-4.014)
a5		0.06^{*} (-1.693)
a6		0.109^{***} (-5.909)
a7		-0.007 (-0.272)
Individual fixed effect	no	no
Time fixed effect	no	no
N	270	270
R^2	0.248	0.293
Adj R^2	0.218	0.271

Note: ***, **, * represent 1%, 5%, and 10% significance levels, respectively, with t-values in parentheses. This rule is continued below.

3.2.2 Mechanism test results

In this paper, a two-step approach is used to develop the test of mediation effects.

The results of the mediation effect test are shown in Table 4. Column (1) shows that the improvement of the development level of digital villages is conducive to the reduction of the intensity of agricultural carbon emissions. Columns (2) to (5) show that the regression coefficients of the effect of digital village development on other intermediary variables are all significantly positive at the 1% level, with the most obvious effect of promoting technological progress, followed by scale operation, and energy conservation and environmental protection last, under the condition of considering the fixed effects and control variables. This may be due to the fact that digital rural development relies on cloud computing, big data, Internet of Things and other emerging technologies to digitally reshape the traditional infrastructure of agriculture, which in turn can change the inherent mode of production to a certain extent. The empirical results show that digital rural development significantly expands the level of appropriate scale operation of agriculture, promotes the process of energy conservation and environmental protection, accelerates the use of agricultural innovation and science and technology, and reduces the consumption of energy and materials and pollutant emissions while enhancing the operational efficiency of agricultural production and the efficiency of the allocation of factor resources, which in turn effectively reduces the intensity of agricultural carbon emissions, and Hypothesis 2 is proved.

Table 4. Mechanism test results

	(1) Total effect	(2) Scale operation effect	(3) Energy saving and environmental protection effect	(4) Structural optimization effect	(5) Technological progress effect
x	-0.168*** (-5.43)				
m1		0.388*** (3.38)			
m2			0.028*** (6.12)		
m3				0.041 (0.92)	
m4					0.723*** (17.21)
Control variables	yes	yes	yes	yes	yes
Time/individual fixed effect	yes	yes	yes	yes	yes
N	270	270	270	270	270
Adj R^2	0.379	0.1199	0.6614	0.0787	0.6702

2.3. Robustness validation

Table 5. Robustness validation results

	(1)	(2)	(3)
x	-0.157*** (0.028)	-0.198*** (0.039)	-0.169*** (0.033)
Control variables	yes	yes	yes
Time/individual fixed effect	yes	yes	yes
N	270	270	270
Adj R^2	0.24	0.292	0.275

Table 5 outlines robustness evaluations conducted via temporal sample restriction, alternative explained variable operationalization (adopting Ding Baogen's [11] plantation-centric carbon accounting framework), and 1% data truncation. Columns (1)-(3) correspond to regressions excluding 2013–2014 data, revising variable quantification methodologies, and tail-trimmed datasets, respectively. Core variables retain significance at the 1% threshold, robustly corroborating baseline conclusions.

2.4. Heterogeneity test

To unravel geographic disparities in ecological consumption's role in rural revitalization, heterogeneity analyses are performed across grain functional zones and topographic divisions (Table 6), drawing methodologies from Tian et al.

3.4.1 spatial divergence analysis based on functional grain zone areas

Despite nationwide carbon mitigation from rural digitization, regional discrepancies in resource endowments, economic development, and production practices induce spatial divergence. Classifying 30 regions into primary production zones, marketing zones, and balanced zones (per China Statistical Yearbook criteria), results reveal significant emission suppression in production and balanced zones but minimal impact in marketing zones, likely due to divergent resource allocation frameworks and technology diffusion barriers. This suggests that in China, the results of digital village construction have a stronger inhibitory effect on agricultural carbon emissions in areas with larger agricultural production scale, while the inhibitory effect is relatively insignificant in areas with smaller scale. Moreover, the coefficients do not seem to be a simple linear relationship between the larger scale of production and the stronger inhibition.

Table 6. Heterogeneity test results

	(1) Major agricultural region	(2) Main grain marketing area	(3) Balance of production and marketing area	(4) Flat terrain	(5) Uneven terrain	(6) Plantation	(7) Livestock areas
x	-0.212*** (-4.389)	-0.003 (-0.047)	-0.564*** (-4.68)	-0.125*** (-4.284)	-0.374*** (-4.373)	-0.129*** (0.025)	-0.157*** (0.028)
Control variables	yes	yes	yes	yes	yes	yes	yes
Time/ Province fixed effect	yes	yes	yes	yes	yes	yes	yes
N	117	63	90	99	171	45	225
Adjusted R^2	0.432	0.298	0.557	0.231	0.656	0.752	0.24

3.4.2 Topography-based heterogeneity tests

Digitalization significantly reduces emissions in both flat and mountainous regions, yet coefficient magnitudes are notably larger in mountainous areas. While uneven terrain complicates digital infrastructure deployment, successful implementation drives innovative production practices and stronger emission suppression. In contrast, flat regions, with pre-existing infrastructure saturation, exhibit diminishing marginal returns. Additionally, policy resource incline and diversified production modes in mountainous areas enhance carbon reduction efficacy.

3.4.3 Heterogeneity of agricultural production objects

Using the 400-mm isoprecipitation line referring to Yang Xue et al.'s study[12] to demarcate crop and livestock zones, results (Columns 6-7) show significant emission reduction in both sectors at the 1% level, with larger absolute coefficients in livestock zones. This highlights digitization's stronger carbon mitigation potential in pastoral systems, likely due to optimized resource integration and policy prioritization. It shows that digital rural development can reduce the intensity of agricultural carbon emissions in both plantation and livestock zones, and the effect is better in livestock zones than in plantation zones.

3. Conclusions

Leveraging provincial panel data (2013–2021), this study demonstrates rural digitization's suppression of agricultural carbon intensity via industrial restructuring and water-use efficiency gains, and the effect is more significant in mountainous areas, production and marketing balance areas and livestock areas, but the emission reduction effect is weaker in main grain production areas, and the tilting of policy resources and the appropriateness of production methods are the key. However, the current financial support to agriculture and education inputs still favor the traditional high-carbon mode, which may exacerbate carbon emissions in the short term. Policy recommendations include: (1) differentiated digital infrastructure investments targeting mountainous and pastoral regions; (2)cross-regional collaboration platforms to foster technology spillovers; (3) green technology integration into agricultural subsidies and education systems to accelerate low-carbon transitions.

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