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The Inherent Mechanism and Promotion Path of Digital Inclusive Finance Driving Agricultural Carbon Emission Reduction

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Abstract: The green and low-carbon transition in agriculture is an essential prerequisite for building a robust agricultural powerhouse. Utilizing panel data from 31 provinces across China from 2011 to 2023, this study empirically examines the impact of digital inclusive finance (DIF) on agricultural carbon emissions and delves into its underlying mechanisms and influence characteristics. The results demonstrate that DIF significantly reduces agricultural carbon emissions, a finding that holds true after undergoing various robustness tests. The influence of DIF on agricultural carbon emissions displays pronounced heterogeneity, with varying effects observed across different regions and dimensions of DIF on total agricultural carbon emissions. DIF indirectly contributes to agricultural carbon emission reduction by facilitating agricultural land transfer and fostering green technological innovation. Furthermore, the suppressive effect of DIF on agricultural carbon emissions exhibits a dual-threshold characteristic contingent upon rural human capital. As rural human capital levels rise, its efficacy in reducing agricultural carbon emissions continues to intensify. This study underscores that DIF constitutes a pivotal force in driving agricultural carbon emission reduction. Based on the research findings, recommendations are put forth concerning optimizing the provision of DIF, implementing differentiated regional financial support, nurturing rural human capital, and enhancing the supporting infrastructure, thereby providing valuable references for advancing the green and low-carbon transformation of agriculture and constructing a formidable agricultural nation.

1. Introduction

Global warming has become a real challenge affecting human production and life. Agriculture, as a key link between natural ecology and economic systems, is an industry greatly affected by climate change and an important source of greenhouse gas emissions[1]. In April 2025, the Central Committee of the Communist of China and the State Council issued the "Plan for Accelerating the Construction of an Agricultural Power (2024-2035)", which identified "green and low-carbon" as the distinctive background of the construction of an agricultural power. The green and low-carbon transformation of agriculture requires a sound financial system and sufficient financial support at all stages. Compared to traditional finance, digital inclusive finance, with its wide coverage, high efficiency, and low cost, breaks through geographical and information asymmetry limitations, accurately matches the needs of various agricultural management entities, and injects inclusive financial vitality into the green and low-carbon development of agriculture[2].

China's digital inclusive finance has completed a key development accumulation stage from 2011 to 2018, entering a new stage focusing on quality and depth. Research on its impact effects has mostly focused on industrial structure upgrading[3], technological innovation of small and medium-sized enterprises[4], common prosperity[5], and other directions. However, although the academic exploration of financial support for low-carbon development in agriculture has begun, systematic research on the relationship between digital inclusive finance and agricultural carbon reduction is still relatively scarce, and the relevant mechanisms, impact effects, and optimization paths have not yet formed a clear consensus. Based on this, this article empirically tests the overall impact of digital inclusive finance on agricultural carbon emissions using panel data from 31 provinces in China from 2011 to 2023.

The marginal contribution of this article is mainly reflected in the following three aspects: Firstly, based on the bidirectional fixed effects model, this article empirically analyzes the impact of DIF on agricultural carbon emissions and conducts multidimensional heterogeneity analysis. Secondly, a mediation effect model was constructed to empirically test the mediating role of agricultural land transfer rate and green technology innovation in this process, and explore their mechanisms of action. Thirdly, construct a threshold model to clarify the differences in emission reduction intensity of DIF under different levels of human capital, providing a basis for differentiated customization of financial policies. This article innovatively analyzes the impact of DIF on agricultural carbon emissions, focusing on core development issues, with the aim of providing theoretical support and scientific basis for building an agricultural powerhouse and achieving green transformation in agriculture.

2. Literature Review

2.1. The Effects of DIF

The concept of Inclusive Finance was first proposed by the United Nations during the promotion of the "International Year of microcredit" in 2005. It aims to solve the problems such as the widening gap between the rich and the poor and the increasing imbalance in the allocation of financial resources[6]. At present, the research on the impact of DIF mainly focuses on poverty reduction and income increase, technological innovation and regional economic growth. In terms of the effect of poverty reduction and income increase, DIF can improve the availability of financial services, accurately identify service objects, stimulate farmers' willingness to consume and improve farmers' income level by relying on the advantages of channels and data; At the level of technological innovation, DIF can significantly improve the regional innovation output by improving the development level of higher education and improving infrastructure construction, and can effectively alleviate the financing constraints of enterprises to promote enterprise innovation; In terms of economic growth effect, directly, DIF can reduce the threshold of financial services, provide loans, insurance, financial services and other services for farmers, help improve their risk resistance, and cultivate the development of small, medium and micro enterprises.

2.2. Influencing Factors of Agricultural Carbon Emissions

There have been numerous theoretical achievements in the study of factors affecting agricultural carbon emissions, mainly focused on industrial structure, technological innovation, and agricultural policies. Wu Xianrong et al. (2014)[7] believe that compared to low-carbon industries such as forestry and fisheries, agriculture requires a large amount of high carbon inputs such as fertilizers and pesticides. Therefore, the increase in its proportion in the industrial structure will reduce carbon emission efficiency, which is not conducive to agricultural carbon reduction. Tamazian et al. (2009) [8] found that financial development can improve resource utilization efficiency through technological progress, thereby reducing carbon emissions. Yang Chen et al. (2021) [9] found that the policies implemented in 2013 for major grain producing areas not only increased grain production, but also significantly reduced the total agricultural carbon emissions, emission density, and emission intensity, and the inhibitory effect continued to increase over time.

3. Research Hypothesis

3.1. The Carbon Emission Reduction Effect of DIF

In the digital age, the deep integration of inclusive finance and digital technology has injected new financial impetus into carbon reduction and green development. Firstly, traditional agriculture generally suffers from problems such as scattered management, cumbersome processes, and low production efficiency. DIF supported by digital technology can accurately meet financial needs, cultivate and strengthen new types of agricultural management entities, promote large-scale agricultural land management and optimize resource allocation. Secondly, compared to traditional financial services with high costs, low efficiency, and credit bias, DIF has the advantages of low cost, wide coverage, and strong inclusiveness. It can effectively lower the "wealth threshold" of traditional finance, improve the efficiency of financial markets and information transmission and provide solid support for green production. Finally, its popularization has significantly increased the enthusiasm of farmers to participate in environmental protection. Farmers can easily report complaints and participate in environmental governance through relevant platforms, effectively addressing their lack of participation and further enhancing their environmental awareness. Based on the above analysis, hypothesis 1 is proposed as follows:

H1: DIF can effectively mitigate agricultural carbon emissions.

3.2. Impact Mechanism of DIF on Agricultural Carbon Emissions

3.2.1. The Role of Green Technology Innovation

Reducing agricultural carbon emissions cannot be achieved without technological innovation and progress. Su Peitian et al. (2023)[10] believe that DIF has the potential to deeply integrate into the process of agricultural industry organizational change, and can play a positive role in key areas such as agricultural technology innovation, optimization and improvement of production equipment, and effective transformation of human capital. Innovation in agricultural green technology is a powerful tool for reducing anthropogenic greenhouse gas emissions and a significant means of addressing climate change. Due to factors such as rising labor costs and scarce water and soil resources, future agricultural production growth will rely more on intensive, large-scale, and mechanized management methods. With DIF, farmers can adopt more green technologies and production methods, thereby reducing carbon emissions. Based on the above analysis, hypothesis 2 is proposed:

H2: DIF can reduce agricultural carbon emissions by promoting green technology innovation.

3.2.2. The Role of Agricultural Land Circulation

The development of finance can promote farmers' land circulation activities[11]. Firstly, the development of DIF provides a solution to the credit constraints that limit the transfer of agricultural land and the expansion of agricultural production, such as "difficult and expensive financing" and "where to get money" for farmers; secondly, DIF provides farmers with a new channel to obtain accurate, comprehensive, and timely financial knowledge, which enables farmers to make family decisions that are more in line with their own interests, which is conducive to land circulation; thirdly, DIF, with its characteristics of convenient information access and efficient sharing, significantly improves the transparency and symmetry of information when farmers communicate with relevant institutions. This not only significantly reduces transaction costs but also effectively breaks farmers' excessive dependence on traditional financial institutions, thereby providing strong information support for land circulation decisions. The circulation of agricultural land can expand the scale of agricultural operations, improve agricultural production efficiency, and thus achieve agricultural carbon emission reduction. Based on the above analysis, Hypothesis 3 is proposed:

H3: DIF can reduce agricultural carbon emissions by promoting agricultural land circulation.

4. Empirical Research Design

4.1. Variable Description

4.1.1. Dependent Variable

This paper takes the total agricultural carbon emissions (ACE) as the dependent variable and performs a logarithmic transformation on it. Focusing on agriculture in the narrow sense, namely crop farming, this study mainly examines the direct and indirect carbon emissions generated by six major carbon sources—chemical fertilizers, pesticides, agricultural plastic films, diesel oil, irrigation and tillage—during the crop farming production process. The carbon emissions from crop farming are calculated based on the relevant carbon emission coefficients of each carbon source, with the calculation formula as follows:

$$E = \sum E_i = \sum T_i \times \varepsilon_i \tag{1}$$

Where E represents the total carbon emissions from the planting industry, T_i represents the input amount of the ith carbon source, and ε_i represents the carbon emission coefficient of the ith carbon source.

4.1.2. Core Explanatory Variable

This article takes digital inclusive finance (DIF) as the core explanatory variable. The measurement of the development level of provincial-level DIF adopts the PKU_DFIIC compiled by the Digital Finance Research Center of Peking University. This index covers data at the provincial, municipal, and county levels in China from 2011 to 2023. It includes one primary indicator of the DIF Index and three secondary indicators of coverage_breadth, usage_depth, and digitization_level, which together provide a comprehensive view of the development status of China's DIF.

4.1.3. Mediating Variables

There are two mediating variables studied in this paper: one is agricultural land circulation (Land), which is measured by the ratio of the total area of household contracted farmland circulation to the total area of household contracted farmland in each province for the current year and is used to verify Hypothesis 3; the other is green technology innovation (Pgreentech), which is measured by the per capita number of green invention patent applications in each province and is used to verify Hypothesis 2.

4.1.4. Threshold Variable

Using rural human capital level (RHC) as the threshold variable, I adopt the logarithm of the actual per capita labor human capital in rural areas of each province from the China Human Capital Report published by the China Human Capital and Labor Economics Research Center of Central University of Finance and Economics as the threshold variable.

4.1.5. Control Variables

This article selects the following indicators as control variables:(1) Government support intensity (Intervene). This article selects the proportion of agricultural expenditure in local fiscal expenditure as the measurement indicator for this variable;(2) Population education level (Education). This article uses the average years of education per capita in each province to characterize this variable;(3) Economic development level (Economic). This article measures the level of economic development using the logarithm of per capita GDP at the provincial level;(4) Agricultural infrastructure (Facility). This article selects the total power of agricultural machinery to measure the level of agricultural infrastructure. To eliminate the interference of dimensional differences in variables on the regression results, this indicator is linearly transformed by dividing the original value of total power of agricultural machinery by 10000 to unify the variable scale;(5) Ecological environment condition (Environment). This article uses the forest coverage rate to measure the ecological environment of each province.

4.2. Model Construction

4.2.1. Two-way Fixed Effects Model

To verify Hypothesis 1, this paper constructs a two-way fixed effects model of region (province) and time to estimate the impact of DIF development on agricultural carbon emissions. The model is as follows:

$$\ln ACE_{it} = \alpha_0 + \alpha_1 DF_{it} + \sum \alpha \times Control_{it} + \sigma_i + \mu_t + \varepsilon_{it} \tag{2}$$

In Equation (2), i represents the province and t represents the time. The dependent variable ACE_{it} indicates the agricultural carbon emissions (in ten thousand tons) of the i-th province in the t-th year. The independent variable DIF_{it} represents the level of DIF development of the i-th province in the t-th year. $Control_{it}$ represents a series of control variables, including the level of government support ($Intervene_{it}$), the level of economic development ($Economic_{it}$), the status of agricultural infrastructure ($Facility_{it}$), the ecological environment ($Environment_{it}$), and the educational attainment of the employed population ($Education_{it}$). σ_i is the fixed effect of the province, μ_t is the fixed effect of the year, and ε_{it} is the random disturbance term.

4.2.2. Mediation Effect Model

Green technology innovation and agricultural land circulation may have a mediating effect on agricultural carbon emissions. Therefore, following the approach of Wen Zhonglin et al. (2014)[12], a mediating effect model is constructed to verify Hypotheses 2 and 3 in this paper. Based on

Equation (2), the model is set as follows:

$$M_{it} = \beta_0 + \beta_1 DF_{it} + \sum \beta \times Control_{it} + \sigma_i + \mu_t + \varepsilon_{it} \quad (3)$$

$$\ln ACE_{it} = \gamma_0 + \gamma_1 DF_{it} + \gamma_2 M_{it} + \sum \gamma \times Control_{it} + \sigma_i + \mu_t + \varepsilon_{it} \quad (4)$$

In equation, M_{it} serves as the mediating variable, encompassing green technology innovation ($Pgreentech_{it}$) and agricultural land circulation ($Land_{it}$).

4.2.3. Panel Threshold Model

To examine the nonlinear impact of DIF on agricultural carbon emissions, based on the panel threshold model proposed by Hansen and Bruce (1999), this paper establishes a model with a double threshold as an example, as follows:

$$\ln ACE_{it} = \tau_0 + \tau_{i1} DF_{it} \times I(q_{it} \leq \lambda_{i1}) + \tau_{i2} DF_{it} \times I(\lambda_{i1} < q_{it} \leq \lambda_{i2}) +$$
$$\tau_{i3} DF_{it} \times I(q_{it} > \lambda_{i3}) + \sum \tau_{in} \times Control_{it} + \sigma_i + \mu_t + \varepsilon_{it} \quad (5)$$

Among them, the core explanatory variable, the DIF index, is influenced by the threshold variable, denoted as q, which represents the rural human capital level (RHCit). I(*) is an indicator function, meaning that when the threshold variable satisfies the condition within the parentheses, I(*) takes the value of 1; otherwise, it takes the value of 0. The meanings of the remaining variables are the same as in equation (2).

4.3. Data Sources

Table 1: Descriptive statistics of variables

variable name	sample size	mean	SD	min	max
ACE	403	5.163	1.173	1.889	6.766
DIF	403	254.5	111.3	16.22	473.8
coverage_breadth	403	239.2	116.1	1.960	466.5
usage_depth	403	245.5	109.6	6.760	510.7
digitization_level	403	321.0	117.8	7.580	476.9
payment	403	202.3	88.68	0	379.5
insurance	403	503.6	206.2	0.250	951.9
credit	403	164.9	74.69	1.160	303.7
Intervene	403	11.46	3.439	3.870	20.38
Economic	403	10.93	0.462	9.706	12.21
Facility	403	0.338	0.294	0.00940	1.335
Environment	403	32.96	18.09	4.020	66.80
Education	403	9.209	1.123	4.222	12.78
FS	403	0.114	0.0341	0.0387	0.204
TF	403	158,811	85,176	12,545	424,725
Land	390	0.339	0.174	0.0335	0.922
Pgreentech	403	0.770	1.322	0	10.96
RHC	403	11.51	0.427	10.65	13.35

This paper selects 31 provinces from 2011 to 2023 as the research subjects (excluding Chinese Hong Kong, Chinese Macao, and Chinese Taiwan, due to data availability constraints). The data on agricultural carbon emissions are sourced from the China Rural Statistical Yearbook for each year from 2011 to 2023, as well as the provincial statistical yearbooks of 31 provinces (cities, autonomous regions) in Chinese Mainland. The data on DIF are obtained from the Digital Finance Research Center of Peking University. The data on the number of green invention patent applications are sourced from the patent search website of the China National Intellectual Property Administration (https://pss-system.cponline.cnipa.gov.cn/). The data on the level of rural human capital are derived from the China Human Capital Report published by the China Human Capital and Labor Economics Research Center of Central University of Finance and Economics. All other data are sourced from public information such as the China Statistical Yearbook, China Leisure Agriculture Yearbook, and China Environmental Statistics Yearbook over the years. Descriptive statistics for each variable are presented in Table 1.

5. Empirical Analysis

5.1. Benchmark Regression Results

Before the benchmark regression, a two-way fixed effects model was used for estimation through stationarity test, multicollinearity test (VIF<10), and Hausman test (χ^2=47.47, p<0.001). The benchmark regression results are shown in Table 2. The first list shows the regression results without control variables. It can be seen that DIF significantly reduces the total agricultural carbon emissions at the 1% level, with an impact coefficient of -0.0048, which preliminarily verifies hypothesis 1 of this article. After adding control variables, the goodness of fit of the model was improved, with an impact coefficient of -0.00437, indicating that for every 1% increase in DIF, the total agricultural carbon emissions decreased by 0.437 units.

Table 2: Benchmark regression results

VARIABLES	(1)ACE	(2)ACE
DIF	-0.00480***	-0.00437***
	(0.00154)	(0.00128)
Control variables	YES	YES
Constant	6.385***	5.334***
	(0.392)	(1.269)
Observations	403	403
R-squared	0.995	0.996

Note: ***, **, * represent significance levels of 1%, 5%, and 10%, respectively. The standard errors are provided in parentheses, the same below.

5.2. Robustness Test

Based on the above benchmark regression analysis, it can be concluded that DIF has a significant inhibitory effect on agricultural carbon emissions. To further verify the robustness of the model, this paper adopts methods such as winsorization, adding control variables, replacing the dependent and core explanatory variables, and reducing the sample size. As shown in Table 3, column (1) shows the result after tail reduction, and the regression coefficient is still significantly negative; Column (2) in the table shows the regression results after adding two control variables: financial support for agriculture (FS), expressed as the proportion of agriculture, forestry and water conservancy expenditure in the general public budget expenditure; Another control variable is the traffic facility level (TF), which is expressed by the sum of railway and highway mileage. After adding two control variables, the regression coefficient is still significantly negative, indicating that the model fitting effect is still good. Column (3) is the result of replacing the dependent variable with agricultural per capita carbon emissions; Column (4) shows the result of replacing the core explanatory variable with the digital inclusive financial index divided by 100. Column (5) is the result of ranking the average gross agricultural output over the years, excluding the top three major agricultural provinces, namely Henan, Shandong and Hebei. Based on the above robustness test results, it can be concluded that the regression coefficient of DIF on agricultural carbon emissions is significantly negative, which verifies the strong robustness of the benchmark regression model.

Table 3: Robustness test

VARIABLES	(1)Winsorization ACE	(2)Add control variables ACE	(3)Replace the dependent variable ACEPC	(4)Replace explanatory variable ACE	(5)Exclude regions ACE
DIF (or DIF/100)	-0.00437***	-0.00384***	-0.000896***	-0.437***	-0.00463***
	(0.00128)	(0.00124)	(0.000210)	(0.128)	(0.00130)
Control variables	YES	YES	YES	YES	YES
Province fixed	YES	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES	YES
Constant	5.334***	5.644***	0.579**	5.334***	5.136***
	(1.269)	(1.309)	(0.263)	(1.269)	(1.400)
Observations	403	403	403	403	364
R-squared	0.996	0.996	0.956	0.996	0.996

5.3. Heterogeneity Analysis

5.3.1. The Impact of the Development Level of DIF in Different Regions on the Total Agricultural Carbon Emissions

Due to the influence of regional economic development level, there are differences in the development level of DIF. This article conducts heterogeneity analysis on 31 provincial samples divided into coastal and non coastal, high-income and low-income, eastern, central and western regions to explore the degree of suppression of agricultural carbon emissions by DIF in different regions. The results are shown in Tables 4 and 5. Columns (1) and (2) of Table 4 show that the development of DIF in coastal areas has a significant inhibitory effect on agricultural carbon emissions, while non-coastal areas did not pass the significance test. The reason is that coastal areas have developed economies, complete digital infrastructure, high DIF penetration rate, and superior natural endowments, and the combination of the two amplifies the emission reduction effect.

Columns (3) and (4) of Table 4 show that the impact coefficient of DIF in high-income areas is significantly negative, while low-income areas did not pass the test. This is because high-income areas have better economic and digital infrastructure, and farmers have stronger financial literacy and green production capabilities, which can rely on DIF to achieve emissions reduction; Low income areas are constrained by factors such as insufficient digital coverage and weak financial participation of farmers, making it difficult to fully utilize the DIF emission reduction mechanism.

Tables (1), (2), and (3) in Table 5 indicate that DIF has a significant negative impact on agricultural carbon emissions in the eastern region, while the central and western regions did not pass the test. This is because farmers in the eastern region have higher digital literacy, and the scale of agricultural management entities is larger, which can better undertake DIF resource support and implement low-carbon production models; However, farmers in the central and western regions have weak digital usage capabilities, making it difficult to utilize digital financial resources to promote low-carbon production transformation.

Table 4: Regional heterogeneity results(I)

VARIABLES	(1)coastal areas	(2)non-coastal areas	(3)Low-income areas	(4)High-income level regions
DIF	-0.00567**	-0.00101	-0.000685	-0.00587***
	(0.00184)	(0.00141)	(0.00104)	(0.00131)
Control variables	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES
Province fixed	YES	YES	YES	YES
Constant	4.152*	7.517***	6.083***	4.192*
	(2.282)	(0.814)	(0.571)	(2.157)
Observations	156	246	200	202
R-squared	0.996	0.998	0.999	0.997

Table 5: Regional heterogeneity results(II)

VARIABLES	(1)eastern area	(2)western area	(3)central area
DIF	-0.00363***	0.00159	-0.00180
	(0.000725)	(0.00145)	(0.00127)
Control variables	YES	YES	YES
Year fixed	YES	YES	YES
Province fixed	YES	YES	YES
Constant	4.524*	7.912***	6.767***
	(2.400)	(1.231)	(0.832)
Observations	143	156	104
R-squared	0.997	0.998	0.996

5.3.2. The Impact of Different Dimensions of DIF on Total Agricultural Carbon Emissions

DIF is a multidimensional indicator that includes three dimensions: coverage breadth, usage depth, and digitalization level, as well as sub indicators such as payments, insurance, and credit under the usage depth index. Further research will be conducted on its impact on agricultural carbon emissions. As shown in columns (1), (2), and (3) of Table 6, both the depth of use and the degree of digitization have significant inhibitory effects on agricultural carbon emissions. The use of deep enhancement can accurately embed financial services into various aspects of agricultural production, providing continuous financial support for low-carbon technology application and green transformation, and achieving agricultural emission reduction. The improvement of digitalization can optimize service efficiency, reduce the financing threshold and cost of green agriculture, and promote the low-carbon and intelligent transformation of agriculture. The coverage breadth coefficient is negative but not significant, indicating that expanding service coverage alone will still be difficult to achieve significant emissions reductions if it does not effectively match the low-carbon demand in agriculture.

As shown in Table 7, columns (1), (2), and (3) report the impact of three financial models: digital credit, digital payments, and digital insurance, on agricultural carbon emissions. The results indicate that both digital payments and digital insurance can significantly reduce agricultural carbon emissions, while digital credit failed the significance test. Digital payments have improved the capital turnover efficiency of agricultural production and transactions, reducing the consumption of intermediate resources. Digital insurance provides risk protection for low-carbon agricultural technology and green projects, alleviates farmers' concerns about transformation, and promotes the implementation of emission reduction. Digital credit did not pass the significance test, possibly due to its investment still leaning towards traditional agriculture, insufficient matching with low-carbon projects, and low efficiency in the use of credit by some farmers, making it difficult to translate into actual emission reduction effects.

Table 6: Heterogeneous results of different dimensions of DIF(I)

VARIABLES	(1)ACE	(2)ACE	(3)ACE
coverage_breadth	-0.000299		
	(0.00109)		
usage_depth		-0.00242***	
		(0.000648)	
digitization_level			-0.00147***
			(0.000444)
Control variables	YES	YES	YES
Year fixed	YES	YES	YES
Province fixed	YES	YES	YES
Constant	5.323***	5.275***	5.713***
	(1.515)	(1.281)	(1.337)
Observations	403	403	403
R-squared	0.996	0.996	0.996

Table 7: Heterogeneous results of different dimensions of DIF(II)

VARIABLES	(1)ACE	(2)ACE	(3)ACE
credit	0.000437		
	(0.00104)		
payment		-0.00181**	
		(0.000820)	
insurance			-0.000538**
			(0.000234)
Control variables	YES	YES	YES
Year fixed	YES	YES	YES
Province fixed	YES	YES	YES
Constant	5.312***	5.527***	5.597***
	(1.484)	(1.434)	(1.468)
Observations	403	403	403
R-squared	0.996	0.996	0.996

5.4. Mediating Effect Analysis

Through theoretical analysis, it can be seen that DIF can affect agricultural carbon emissions through land transfer and green technology innovation. This section will use the mediation effect model to test hypotheses 2 and 3, and the results are shown in Table 8. According to the results in column (1), DIF has a positive impact on agricultural land transfer, with a significance level of 1%. When both DIF and land transfer return to agricultural carbon emissions, the results are shown in column (2). The transfer of agricultural land has a significant negative impact on agricultural carbon emissions at a level of 10%, with an impact coefficient of -0.252; The negative impact of DIF on agricultural carbon emissions reaches a significant level of 1%, with an impact coefficient of -0.00406. Therefore, the transfer of agricultural land plays a partial mediating role between DIF and agricultural carbon emissions, thus verifying hypothesis 3 of this article.

According to the results in Column (3), DIF has a positive impact on green technological innovation at the 1% significance level. When DIF and green technological innovation are regressed on agricultural carbon emissions simultaneously, the results are shown in Column (4): green technological innovation exerts an inhibitory effect on agricultural carbon emissions at the 1% significance level with an impact coefficient of -0.0584; DIF exerts an inhibitory effect on agricultural carbon emissions at the 10% significance level with an impact coefficient of -0.00245. Green technological innovation plays a partial mediating role between DIF and agricultural carbon emissions, thus verifying Hypothesis 2 of this paper.

Table 8: Mediating effect analysis

VARIABLES	(1)Land	(2)ACE	(3)Pgreentech	(4)ACE
DF	0.00275***	-0.00406***	0.0328***	-0.00245*
	(0.000744)	(0.00118)	(0.0114)	(0.00132)
Mechanism variable		-0.252*		-0.0584***
		(0.137)		(0.0113)
Control variables	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES
Province fixed	YES	YES	YES	YES
Constant	2.041***	5.477***	-5.348	5.021***
	(0.475)	(1.298)	(4.451)	(1.340)
Observations	390	390	403	403
R-squared	0.936	0.996	0.896	0.997

5.5. Threshold Effect Analysis

Benchmark regression and robustness tests have confirmed the significant inhibitory effect of DIF on agricultural carbon emissions. This effect relies on rural labor's ability to use digital financial tools and their acceptance of green production technologies, with rural human capital (RHC) being a core manifestation of this ability. It can be inferred that the emission reduction effect of DIF is not linear and constant, but may undergo qualitative changes as rural human capital levels cross critical thresholds. Based on this, this paper uses rural human capital (RHC) as the threshold variable to construct a panel threshold model to further explore the nonlinear impact of DIF on agricultural carbon emissions and clarify the differences in the strength of the emission reduction effect across different human capital ranges. First, I determine whether there is a threshold effect by repeatedly sampling 300 times under the assumptions of single threshold, double threshold, and triple threshold. The F values are 27.31, 20.51, and 11.60, respectively, with corresponding P values of 0.05, 0.0933, and 0.2333, respectively. The double threshold model is selected. The results of the double threshold effect test and the threshold values are shown in Tables 9 and 10.

Table 9: Threshold effect test

threshold variable	threshold number	threshold estimate	F-value	P-value	95% confidence interval
RHC	Threshold1	11.7233	27.31	0.0500	[11.6836,11.7355]
	Threshold2	12.3907	20.51	0.0933	[11.8998,12.5800]

Table 10: Threshold regression results

threshold variable	Threshold variable range	ACE
RHC	RHC<11.7233	-0.00241**
		(0.000990)
	11.7233<RHC<12.3907	-0.00265**
		(0.00102)
	RHC>12.3907	-0.00298***
		(0.000966)
Constant	4.832***	
	(1.292)	
Control variables	YES	
Observations	403	
R-squared	0.689	
Number of prov_id	31	

The threshold regression results in Table 10 indicate that, influenced by differences in rural human capital levels, the inhibitory effect of DIF on agricultural carbon emissions presents a three-stage threshold feature: when the level of rural human capital is low (RHC<11.7233), due to the weak financial literacy and green technology application ability of farmers, the emission reduction inhibitory effect of DIF is weak, showing only a weak negative impact; When at a moderate level (11.7233<RHC<12.3907), with the improvement of farmers' education and production skills, the funding support and information empowerment effects of DIF gradually become apparent, and the emission reduction inhibitory effect is significantly enhanced; When the level of human capital is high (RHC>12.3907), DIF and high-quality labor form a synergistic effect, accurately empowering agricultural green technology innovation and low-carbon scale production, further strengthening the inhibitory effect on agricultural carbon emissions, and fully releasing the potential for carbon reduction.

6. Conclusions and Suggestions

DIF can promote green and low-carbon development in agriculture, which is of great significance for accelerating the construction of a strong agricultural country and achieving the "dual carbon" goal. The main conclusions of this article are as follows:

Firstly, DIF has a significant inhibitory effect on agricultural carbon emissions; Secondly, the inhibitory effect exhibits significant regional and dimensional heterogeneity. At the regional level, it is significant in coastal, eastern, and high-income areas, but not significant in non coastal, central western, and low-income areas. At the dimensional level, usage_depth and digitalization_level can significantly suppress agricultural carbon emissions, while coverage_breadth did not show a significant inhibitory effect. In terms of specific financial models, digital payments and insurance have significant carbon reduction effects, while the impact of credit is not significant; Thirdly, from a mechanism perspective, DIF mainly promotes agricultural land transfer and green technology innovation to achieve agricultural carbon reduction; Fourthly, the inhibitory effect of DIF on agricultural carbon emissions exhibits phased characteristics and is regulated by the dual threshold of rural human capital. With the improvement of rural human capital, the inhibitory effect of DIF on agricultural carbon emissions will continue to intensify.

Based on the above analysis, the following policy recommendations are proposed:

Firstly, optimize DIF supply, launch characteristic credit products, and build a digital information platform to reduce the financing costs of new agricultural operating entities; Secondly, we should implement differentiated support based on regional differences, deepen financial digitization in the eastern and coastal regions, and strengthen digital infrastructure and service coverage in low-income areas and central and western regions; Thirdly, strengthen the cultivation of rural human capital, popularize digital tools and green technologies, and comprehensively improve farmers' financial literacy and production skills; Finally, improve the supporting system, standardize land transfer procedures, strengthen the research and development of green technologies and the application of low-carbon technologies, activate key links in agricultural emissions reduction, and promote the green and low-carbon transformation of agriculture.

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