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Can Digital Finance Contribute to Agricultural Carbon Reduction? Evidence from China

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Abstract: The existing research covers digital finance's carbon reduction impacts in industrial and urban settings, however, leaving a gap in understanding its effects in agriculture. This study addresses this gap by examining the relationship and mechanism between digital finance and agricultural carbon reduction. Two hypotheses are proposed to guide the study: (1) The development of digital finance could reduce agricultural carbon emissions; (2) The development of digital finance could significantly promote agricultural green innovation, empowering agricultural carbon emission reduction. By employing panel data spanning 31 provinces from 2011 to 2020, we empirically investigate the relationship between digital finance development and a reduction in agricultural carbon emissions. The results indicate that digital financial development significantly reduces agricultural carbon emissions. Mechanism analysis further elucidates the pivotal role of digital finance in facilitating agricultural green innovation, resulting in a decline in agricultural carbon emissions. Additionally, heterogeneity analysis reveals that the impact of digital finance on agricultural carbon emission reduction is particularly pronounced in regions with higher income levels and greater educational attainment. The study offers empirical evidence on the nexus between digital finance and agricultural carbon emissions, from a developing country perspective. It could provide innovative ideas and experiences from China for global agricultural low-carbon development practices.

Keywords: digital finance; agricultural carbon emissions; agricultural green innovation; sustainable agricultural development

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1. Introduction

In recent years, the escalation of greenhouse gas emissions has posed a significant threat to the global biosphere, intensifying the international focus on climate-related issues. Among the factors contributing to climate change, resource consumption, and environmental degradation, agricultural-production-induced carbon emissions play a prominent role [1]. According to data provided by the Food and Agriculture Organization (FAO) of the United Nations, greenhouse gas emissions stemming from agricultural activities surpass 30% of the total global anthropogenic greenhouse gas emissions. As an active participant in and advocate for global climate governance, China made commitments during the 75th session of the United Nations General Assembly, pledging to achieve a peak in carbon dioxide emissions before 2030 and attain carbon neutrality by 2060. To fulfill these ambitious goals, it becomes imperative not only to vigorously promote energy conservation and emissions reduction in the secondary and tertiary sectors but also to expedite the pace of low-carbon transformation within the agricultural sector. Promoting sustainable agricultural development holds significant implications not only for environmental conservation but also for addressing multifaceted issues such as enhancing crop yields, augmenting farmers' income, and ameliorating living standards in rural areas [2,3].

The distinctive nature of agricultural production underscores its substantial reliance on environmental resources. Its growth is intricately linked to the augmentation of resource inputs and the enhancement of production efficiency. Inefficiencies in agricultural production not only lead to wastage of vital resources but also increase carbon emissions. Extant research has underscored the constructive role played by conventional finance in advancing agricultural mechanization, catalyzing agricultural technological innovation, and augmenting farmers' financial well-being. However, traditional financial instruments exhibit inherent limitations, including low efficiency and a propensity for unbalanced urban–rural development [4], constraining their effectiveness in supporting agricultural production. Furthermore, prevailing scholarly discourse predominantly focuses on the economic impact of traditional finance, often overlooking its ecological ramifications [5]. Consequently, there exists a critical gap in comprehending how financial mechanisms can effectively underpin agricultural development while actively contributing to ecological conservation. This necessitates a thorough exploration in the global context, especially in the context of modernizing the worldwide financial system.

In contrast to traditional financial instruments, digital finance emerges as a consequence of profound integration between financial technology and financial products, embodying characteristics such as cost-effectiveness, operational efficiency, and remarkable flexibility [6]. Notably, digital finance significantly amplifies the reach of financial resources while enhancing allocation efficiency [7]. This expansion reduces the transaction costs within agricultural production and enhances farmers' accessibility to credit, fostering tangible potential for diverse resource consumers, including agricultural producers, to transform their production methodologies, curtail their carbon emissions [8], and enhance environmental quality [9].

While some scholars have delved into the ecological implications of finance, few have directly correlated finance with carbon emissions, particularly within the agricultural domain, and scrutinized the specific impact of finance on carbon emission reduction [10]. Furthermore, in an era defined by the prevalence of digital technologies, exploring the avenues through which new financial tools, such as digital finance, can empower low-carbon and sustainable agricultural development constitutes a subject warranting profound research. In the realm of agricultural carbon reduction, digital finance and its environmental implications have attracted limited scholarly attention [11]. Despite existing studies indicating that digital finance development can curtail gross agricultural carbon emissions, these analyses lack an in-depth exploration of carbon emission efficiency. And the agricultural landscape's inherent diversity across provinces complicates direct comparisons utilizing gross level indicators. Moreover, prior empirical investigations into the mechanisms by which digital finance fosters agricultural carbon reduction have often overlooked output factors, particularly the intricate aspects of "non-expected output" such as carbon emissions. This oversight introduces potential measurement biases into the analyses [12].

Consequently, this study seeks to address these issues by integrating digital finance, agricultural green innovation, and agricultural carbon intensity within a unified analytical framework. It aims to empirically analyze the effects of digital finance on carbon emission reduction in the agricultural sector and examine potential mechanisms.

This study distinguishes itself from existing studies in several significant ways, making noteworthy contributions to the field:

Firstly, building upon an analysis of agricultural production activities and a comprehensive review of the existing literature, this study establishes a direct correlation between "digital finance" and "agricultural carbon reduction". We theoretically expound on the positive ecological implications of this emerging financial instrument, digital finance, within the agricultural sector. Additionally, we discuss the potential "agricultural green innovation" mechanisms associated with this correlation.

Secondly, in stark contrast to the preceding research centered on gross agricultural carbon emissions, this study adopts agricultural carbon intensity as a pivotal indicator, considering it as the dependent variable in empirical analysis. This strategic choice not only enhances the comparability of carbon emission data among diverse provinces but also, in substantiating the agricultural carbon reduction impact of digital finance, underscores the capability of digital finance in effectively reducing agricultural carbon emission intensity.

Moreover, this approach sheds light on the intricate interplay between digital finance and agricultural carbon emission efficiency, offering profound and scientifically rigorous empirical substantiation for the environmental ramifications of digital finance initiatives.

Thirdly, this study introduces the "green innovation" mechanism to elucidate how digital finance propels agricultural carbon reduction. Theoretically, this mechanism accentuates ecology-oriented innovation, forging a more nuanced and intuitive linkage between the economical variable of digital finance and the environmental variable of agricultural carbon emissions. Empirically, this study meticulously incorporates both input and output factors when measuring mechanism variables, with special emphasis on the "non-expected output" factor of carbon emissions. Grounded in this comprehensive approach, the analysis of mechanisms not only validates the "green attributes" inherent in digital finance [13] but also provides a robust foundation for understanding its role in fostering environmentally sustainable agricultural practices.

Furthermore, to address potential endogeneity concerns that could distort the regression results, this study adopts "mobile phone penetration rate" and "internet penetration rate" as instrumental variables, subsequently employing the two-stage least squares method to alleviate endogeneity issues throughout the analytical process.

2. Literature Review and Research Hypotheses

2.1. Literature Review

Finance occupies a pivotal role in addressing environmental challenges and fostering sustainable development [14]. Extensive scholarly inquiries have delved into the ecological impact of finance, employing diverse perspectives such as macro [15,16] and micro [17–19] differentiation, and investigating various countries [20–22] and industries [23–26]. Scholars contend that advancements in financial sectors and the application of diverse financial instruments play a significant role in energy conservation, emission reduction, and sustainable development. However, within academic discourse, there exists a spectrum of opinions regarding the intricate and fluctuating relationship between financial development and the environment [27]. A contingent viewpoint posits that financial development exacerbates environmental pollution [28,29], introducing complexities into the discourse. These divergent perspectives often stem from variances in the spatial scope [30] and temporal span [31] of research endeavors. Furthermore, certain scholars assert that the inherent challenges hindering financial development from effectively promoting environmental amelioration and sustainable progress are rooted in the scarcity of financial resources and the imbalanced development across regions [32,33]. This nuanced analysis underscores the multifaceted nature of the relationship between finance and the environment within the context of sustainable development.

In contrast to traditional finance, digital finance, an offspring of advanced digital technology integrated with financial instruments, presents notable advantages in addressing ecological challenges. It has demonstrated significant progress in advancing carbon reduction objectives. Prior investigations into the nexus between digital finance and carbon reduction have primarily concentrated on the domains of industrial enterprises and urban areas. Scholars contend that digital finance propels carbon reduction by following certain fundamental mechanisms.

First and foremost, digital finance serves as a catalyst for carbon reduction by fostering green technological innovation. This dual-pronged influence is multifaceted. On the one hand, the maturation of digital finance stimulates economic growth and augments income levels [34,35], thereby providing essential support for the development of green technological innovations. Simultaneously, digital finance alleviates the liquidity constraints confronting businesses [36], effectively mitigating barriers to green innovation by reducing the transaction costs and facilitating access to capital [37].

Secondly, digital finance exerts a transformative impact on industries, thereby facilitating carbon reduction. Concretely, digital financial tools channel an increased share of financial resources into sectors that emphasize resource conservation and environmental sustainability [38]. This strategic allocation encourages a shift in the competitive landscape, undermining the comparative advantage enjoyed by energy-intensive [39] and heavily polluting enterprises. Consequently, this reshaping of industrial structures enhances carbon emission efficiency [40] and contributes to a more environmentally sustainable framework.

However, there are also a few scholars who express skepticism about the carbon reduction effects of digital finance. Digital finance is not a "technologically neutral" financial tool; the cost of using digital financial products for financial transactions is high for some social entities [41]. This, in turn, exacerbates the financial constraints faced by the relevant entities. Additionally, the existence of the "digital divide" may intensify the "Matthew effect" in the financial field [42], hindering the ecological effects of digital finance.

An extensive review and synthesis of the existing literature underscore the ongoing academic debate surrounding the ecological implications of digital finance. Notably, there exists a persistent controversy within scholarly circles on this subject. Furthermore, the current body of research pertaining to the intricate relationship and underlying mechanisms connecting digital finance with agricultural carbon reduction is conspicuously lacking in depth and scope. To effectively tackle these pressing issues, it is imperative to delve into further comprehensive research endeavors.

2.2. Research Hypotheses

2.2.1. Digital Finance and Agricultural Carbon Reduction

The concept of digital finance represents the seamless fusion of digital technology and financial instruments, endowing it with qualities akin to traditional finance while also introducing novel functions and roles absent in conventional financial systems. Notably, digital finance plays a pivotal role in advancing agricultural carbon reduction, demonstrating distinct advantages. We posit that the impact of digital finance on agricultural carbon reduction can be discerned across three key dimensions.

Firstly, digital finance addresses the longstanding issue of the financing constraints prevalent in the agricultural sector. Given the dispersed and modest capital requirements of agricultural endeavors, coupled with challenges in aggregating credit information, traditional financial institutions often struggle to support agricultural entities adequately [43]. Digital finance, characterized by its expansive service offerings and minimal transaction costs [44], broadens the utilization and deepens the penetration of financial products and services [45]. By providing diverse financing channels and methods to farmers and agricultural enterprises, digital finance enhances financial accessibility for the so-called "long-tail population" [46]. Consequently, it effectively mitigates financing constraints for agricultural entities under conditions of low cost [47]. This mitigation, in turn, empowers agricultural entities to embrace advanced production techniques and engage in mechanized and intensive agricultural practices, thereby curbing carbon emissions in the agricultural sector.

Secondly, digital finance guides the allocation of agricultural resources in sustainable directions. Through digital platforms, digital finance consolidates financial resources and channels them into eco-friendly agriculture and initiatives aimed at agricultural pollution prevention [48]. By bolstering the comparative advantage of new green agriculture, digital finance facilitates the gradual phasing out of high-pollution and high-energy-consuming agricultural production methods. This strategic redirection enhances the carbon emission efficiency of the agricultural sector.

Lastly, digital finance unleashes the transformative power of information. Leveraging tools such as "big data" and "artificial intelligence", digital finance possesses unique informational advantages not found in traditional financial systems. The application of digital technology dismantles information barriers, empowering farmers to harness the information effect. Small-scale farmers can now seamlessly connect with vast markets. This connectivity not only enables farmers to promptly discern market demands for low-carbon technologies and products but also fosters closer collaboration between farmers and providers of green agricultural technologies [49]. Consequently, it stimulates farmers' inclination toward green and low-carbon production practices, fostering an environment conducive to green innovations.

Based on these assertions, we propose Hypothesis 1:

Hypothesis 1. *The development of digital finance could reduce agricultural carbon emissions.*

2.2.2. The Green Innovation Mechanism of Digital Finance in Promoting Agricultural Carbon Reduction

The efficacious pursuit of environmental solutions within the agricultural sector is intrinsically linked to green innovation [11,50]. We posit that the implementation of digital finance systems holds the potential to foster agricultural green innovation via two distinct mechanisms, consequently engendering agricultural carbon mitigation.

Primarily, the instigation of green innovation endeavors in agriculture necessitates substantial commitments to the development of low-carbon agricultural technologies and the management of agricultural pollution. Such undertakings typically hinge upon the availability of external resources, with external financial backing playing a pivotal role. The advent of digital finance mechanisms can ameliorate the prevalent information asymmetry between agricultural entities and financial institutions, thereby augmenting financial support for agricultural entities engaged in green innovation endeavors. Moreover, digital finance inherently serves as a catalyst for the diminishment of various financial transaction costs, consequently fostering the attraction of additional capital resources for carbon mitigation activities [51].

Conversely, agricultural green innovation activities are typified by a trifecta of defining characteristics, namely high levels of risk, protracted return cycles, and the inadequacy of conventional financial instruments to address the intricacies of such ventures. Traditional financial tools often prioritize economic considerations over the promotion of innovation in agriculture. Digital finance, however, engenders the establishment of a robust risk management framework founded upon extensive big data analytics, which, in turn, serves to effectively mitigate systemic financial risks for financial institutions. This risk mitigation framework augments financial institutions' willingness to support agricultural green innovation.

In light of these considerations, we propose Hypothesis 2:

Hypothesis 2. *The development of digital finance could significantly promote agricultural green innovation, empowering agricultural carbon emission reduction.*

3. Calculation and Analysis of Agricultural Carbon Emissions in China

3.1. Calculation of Agricultural Carbon Emissions in China

This section focuses on the calculation of carbon emissions from agricultural activities, specifically crop cultivation. The methodology employed follows the guidelines recommended in the "2006 IPCC Guidelines for National Greenhouse Gas Inventories". The measurement of agricultural carbon emissions primarily considers six aspects: (1) direct or indirect carbon emissions caused by fertilizer production and use; (2) carbon emissions caused by pesticide production and use; (3) carbon emissions arising from plastic film production and use; (4) carbon emissions generated by the direct or indirect consumption of fossil fuels (mainly agricultural diesel fuels) in agricultural machinery operations; (5) carbon emissions resulting from ploughing, which leads to significant loss of organic carbon into the atmosphere; and finally, (6) carbon emissions resulting from the indirect use of fossil fuels in electricity consumption during irrigation processes. The calculation formula for agricultural carbon emissions is as follows:

$$C = \sum C_i = \sum \delta_i \cdot E_i \quad (1)$$

where C represents the gross carbon emissions from agriculture, C_i represents the carbon emissions from various sources, E_i represents the quantities of carbon emissions from different sources, and δ_i represents the carbon emissions coefficients for each source.

Based on existing research, this study has compiled the agricultural carbon emissions coefficients, as presented in Table 1. These coefficients serve as important parameters for estimating the carbon emissions associated with each specific source in agricultural activities.

Table 1. Carbon emissions coefficient for each source.

Input Element	Coefficient	Reference
Fertilizer	0.8956 kg/kg	West [52]; Oak Ridge National Laboratory, USA
Pesticide	4.9341 kg/kg	Oak Ridge National Laboratory, USA
Agricultural film	5.18 kg/kg	College of Resources and Environmental Sciences, Nanjing Agricultural University
Diesel Fuel	0.5927 kg/kg	Intergovernmental Panel on Climate Change of UN (IPCC)
Ploughing	312.6 kg/km^2	College of Biological Sciences, China Agricultural University
Irrigation	25 kg/Cha	Dubey [53]

The data pertaining to fertilizer, pesticide, plastic film, and diesel fuel usage were extracted from the China Rural Statistical Yearbook, which provides reliable information on the actual quantities of these inputs utilized in China on an annual basis. The recorded figures reflect the specific consumption levels within each respective year. Similarly, the data concerning ploughing activities are derived from the actual planted crop area in China for each corresponding year, while the agricultural irrigation data are based on the real irrigated area in China during the same period. These additional datasets on planted crop area and irrigated area are also sourced from the China Rural Statistical Yearbook. The timeframe for the available data ranges from 2011 to 2020, encompassing a comprehensive overview of the given variables.

3.2. Analysis of Agricultural Carbon Emissions in China

Based on the provided carbon emission calculation formula, we conducted an analysis of agricultural carbon emissions for the period spanning from 2011 to 2020. The results, shown in Figure 1, reveal a distinctive "inverted U-shaped" trend in Chinese agricultural carbon emissions, characterized by an initial increase followed by a subsequent decrease. Specifically, the first phase, covering the years 2011 to 2015, witnessed a rise in China's agricultural carbon emissions from 100.54 million tons in 2011 to 106.91 million tons in 2015, indicating a growth rate of 6.34%. However, the growth rate of agricultural carbon emissions during this phase exhibited an overall deceleration, with an average annual growth rate of 1.55%.

The second phase, spanning from 2016 to 2020, demonstrated varying degrees of reduction in carbon emissions attributed to fertilizer, pesticide, diesel fuel, and plastic film usage. Consequently, the gross agricultural carbon emissions decreased from 106.91 million tons in 2015 to 95.44 million tons in 2020.

Overall, the growth rate of China's agricultural carbon emissions experienced a downward trajectory during the 2011–2020 period, declining from 2.40% in 2012 to 0.67% in 2015. In 2016, agricultural carbon emissions witnessed negative growth for the first time. Subsequently, this trend of negative growth in agricultural carbon emissions continued to expand, indicating significant improvements in the current state of agricultural carbon emissions. China has achieved notable success in reducing agricultural carbon emissions. However, it is important to note that this does not imply the attainment of low-carbon development in agriculture. On the contrary, achieving low-carbon development in agriculture necessitates a continued effort to reduce agricultural carbon emissions and decrease the intensity of such emissions in China.

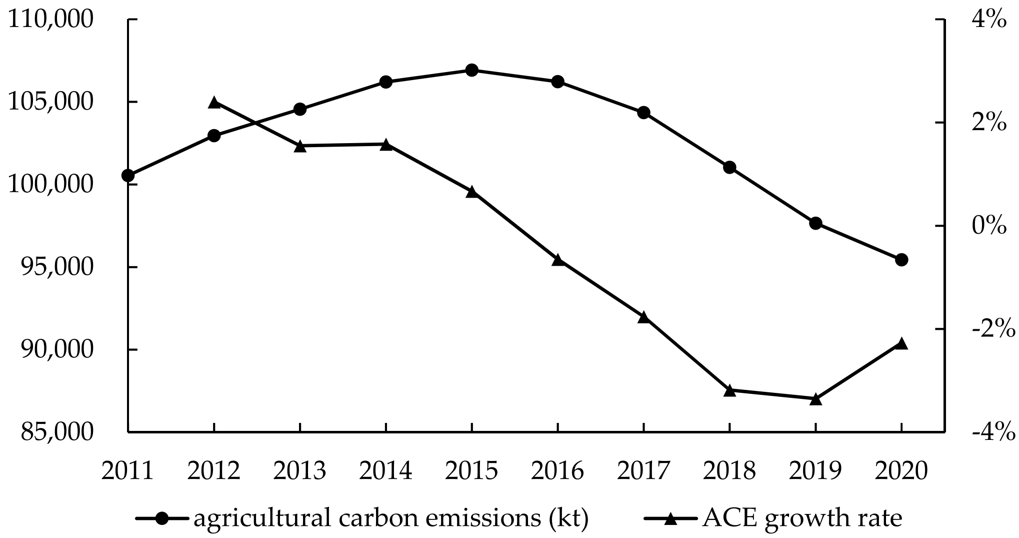

Figure 1. Agricultural carbon emissions and ACE growth rate in China during 2011−2020.

Calculation of agricultural carbon emission intensity can be performed by dividing the gross agricultural carbon emissions, as presented in the previous section, by the corresponding gross agricultural output value of each province in the given year. Figure 2 illustrates the gross agricultural carbon emissions and intensity by province in China for the year 2020. The analysis reveals substantial variation in agricultural carbon emissions among provinces.

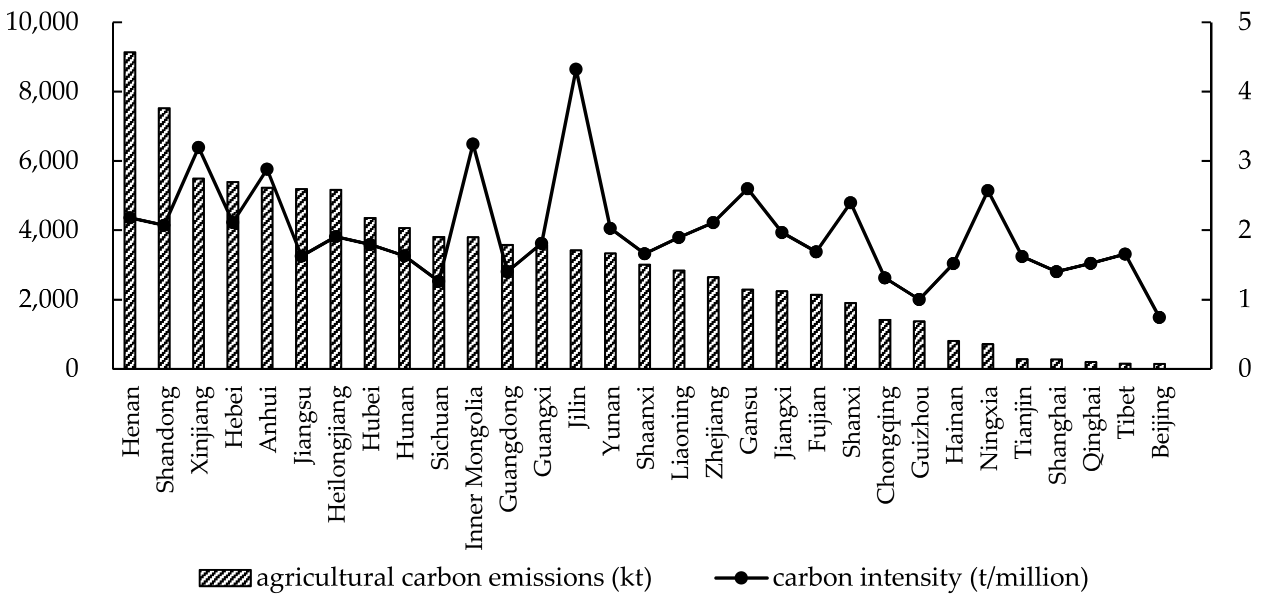

Figure 2. Agricultural carbon emission and carbon intensity of 31 provinces in China in 2020.

Regarding the provincial ranking of agricultural carbon emissions in 2020, the Henan province exhibits the highest gross agricultural carbon emissions, reaching 9.13 million tons, whereas Beijing demonstrates the lowest emissions at a mere 0.13 million tons, which demonstrates a staggering 68-fold difference between these two regions. Furthermore, the top five provinces contribute to 34.33% of the national gross agricultural carbon emissions. This disparity highlights significant variations in agricultural carbon emissions across different regions. Notably, major agricultural provinces, particularly those specializing in grain production, play a crucial role in driving agricultural carbon emissions in China. Among the 13 major grain-producing provinces, the carbon emissions of 10 provinces rank among the top 10 nationwide. Consequently, reducing carbon emissions in these key grain-producing regions holds significant implications for achieving the national carbon reduction goals.

Regarding carbon intensity, it is observed that areas with higher carbon emissions are primarily concentrated in economically less developed regions. For instance, the Jilin province, despite having the highest carbon intensity, ranks only 14th in terms of gross carbon emissions. This phenomenon can be attributed to the fact that regions with higher levels of economic development often possess more favorable conditions for agricultural production technology innovation and low-carbon production practices compared to regions with lower economic development levels.

4. Empirical Research

4.1. Benchmark Regression Model

To examine the impact of digital finance on agricultural carbon emission, we established the following regression model:

$$carbon_{it} = \alpha_0 + \alpha_1 dfi_{it} + \sum \alpha_k control_{k,it} + \mu_t + \lambda_i + \varepsilon_{it} \tag{2}$$

where i and t denote i-th province and t-th year; $carbon$ represents the agricultural carbon emission; dfi represents digital finance; and $control$ represents the control variables. μ_t denotes year-fixed effects, λ_i denotes province-fixed effects, and ε_{it} represents the random error term.

4.2. Variable Description

4.2.1. Dependent Variable

Agricultural carbon emission ($carbon$): it is represented by the agricultural carbon intensity, as calculated in the previous section. To account for the influence of price changes on output, this study employs the year 2011 as the base year and utilizes the agricultural output index to normalize the annual agricultural output values, rendering them comparable to the year 2011.

4.2.2. Independent Variable

Digital finance (dfi): referring to the existing research, we adopt the China Digital Finance Index, compiled by Peking University Digital Finance Center as the core explanatory variable, and divide its actual value by 100 before introducing it into the model. The index system involves multiple dimensions and a wide range, covering the new features and situations of digital financial services from an innovative perspective. Through cooperation with Ant Group, it ensures the objectivity and authenticity of the data sources and is currently the most commonly used indicator for studying the development of digital finance in China [54,55]. The index encompasses data from 31 provinces in China spanning the years 2011 to 2020. It comprises one primary indicator, namely the overall Digital Finance Index, along with three secondary indicators that collectively depict the development of digital finance in China. This study primarily examines the overall level of digital finance and tests the robustness of the impact of the three secondary indicators on agricultural carbon emissions.

4.2.3. Control Variables

To account for factors beyond digital finance that influence agricultural carbon emissions, building upon prior research [56,57], this study includes several important indicators reflecting agricultural production conditions as control variables. These variables encompass:

1. Financial support for agriculture (finance): It signifies the level of financial assistance directed toward the agricultural sector.

2. Proportion of grain crop planting (structure): It represents the relative share of grain crops in total crop planting.
3. Transportation conditions (trans): It measures the quality and accessibility of transportation infrastructure.
4. Level of agricultural mechanization (machine): It reflects the extent to which agricultural tasks are performed using mechanized equipment.

Nominal variables expressed in monetary units are adjusted using corresponding price indices. Table 2 provides the definitions and descriptions of the relevant variables used in this study.

Table 2. Definition of variables used.

Type	Variables	Symbol	Definition
Dependent Variable	Agricultural Carbon Emission	carbon	Gross agricultural carbon emissions/gross agricultural output value
Independent Variable	Digital Finance	dfi	Digital Finance Index/100
Control Variables	Proportion of Grain Crop Planting	structure	Grain cultivation area/crop cultivation area
	Financial Support for Agriculture	finance	Agriculture, forestry, and water affairs expenditure/gross financial expenditure $\times 100$
	Transportation Conditions	trans	(Total railway mileage + total highway mileage)/province area
	Level of Agricultural Mechanization	machine	Total power of agricultural machinery/crop cultivation area
Mechanism Variable	Agricultural Green Innovation	gtfp	Green total factor productivity in agriculture

The dataset utilized in this study encompasses the period from 2011 to 2020, incorporating data from all 31 provinces in China. The sample size consists of 310 observations. The data sources employed include the "China Agricultural Yearbook", "China Rural Statistical Yearbook", and annual statistical yearbooks from different provinces. Table 3 presents the descriptive statistics of the pertinent variables used in this analysis.

Table 3. Descriptive statistics to the variables.

Variable	N	Mean	STDEV	Min	Max
carbon	310	2.259	0.671	0.742	5.560
dfi	310	2.162	0.970	0.162	4.319
structure	310	0.653	0.140	0.355	0.971
finance	310	11.611	3.363	4.110	20.384
trans	310	0.953	0.541	0.052	2.225
machine	310	6.871	3.501	2.638	24.513
gtfp	310	1.074	0.109	0.755	2.362

4.3. Empirical Results and Analysis

4.3.1. Benchmark Regression Results and Analysis

The baseline model investigates the impact of digital finance and crop-planting structure on agricultural carbon emissions. The Hausman test suggests that the fixed effects model (FE) is appropriate for the baseline regression analysis. Moreover, in agricultural production practices, carbon emissions are highly correlated with agricultural activities, displaying strong persistence. Many behaviors in agricultural practices become ingrained habits that are challenging to alter in the short term. Considering the panel data employed in this study, which encompass a relatively limited time span and extensive cross-sectional coverage, to enhance the credibility of the estimation results, this study additionally employs the SYS-GMM model for regression and compares the estimation results of the two models. The specific regression results are presented in Table 4.

Table 4. Benchmark regression results.

	FE		SYS-GMM	
	(1)	**(2)**	**(3)**	**(4)**
dfi	−0.960 *** (−4.000)	−0.693 *** (−2.826)	−0.049 *** (−3.101)	−0.047 ** (−2.160)
carbon(−1)			0.985 *** (68.337)	0.917 *** (12.265)
structure		2.784 *** (4.663)		0.044 (0.099)
trans		−0.475 * (−1.847)		0.011 (0.023)
finance		0.029 * (1.908)		−0.004 (−0.415)
machine		0.039 ** (2.086)		−0.006 (−0.438)
Constant	2.840 *** (26.279)	0.756 (1.304)	0.110 * (1.808)	−1.975 (−0.423)
Year-fixed effect	YES	YES	YES	YES
Province-fixed effect	YES	YES	YES	YES
R^2	0.239	0.307		
N	310	310	248	248

Note: *, **, and *** indicate that the estimated coefficients passed the *t*-test at the 10%, 5%, and 1% levels of significance, respectively.

The regression results in Table 4 demonstrate that the coefficient of digital finance consistently exhibits statistical significance at the 1% level in columns (1), (2), and (3), and it is statistically significant at the 5% level in column (4). Moreover, the coefficients are negative, indicating that digital finance has a significant and negative effect on agricultural carbon emissions. This result provides empirical support for hypothesis 1, suggesting that digital finance can effectively reduce agricultural carbon emissions.

Regarding the control variables, the regression results indicate that as the level of financial support for agriculture and agricultural mechanization increases, agricultural carbon emissions also increase. This phenomenon can be attributed to several factors. Firstly, agricultural machinery, as a tool for agricultural modernization, has a substitution effect on labor and animal power. However, as the number of agricultural machines increases, the consumption of agricultural energy, such as diesel fuel, also rises, leading to an overall increase in agricultural carbon emissions. Additionally, financial support for agriculture, while promoting agricultural production and increasing farmers' income, may inadvertently encourage excessive resource use and excessive development of farmland, subsequently resulting in elevated agricultural carbon emissions.

On the other hand, the results reveal that improvements in transportation conditions significantly contribute to agricultural carbon reduction. This result can be explained by the fact that the construction of railway and road transportation infrastructure facilitates the input of low-carbon production factors and advanced production techniques into agricultural processes. Consequently, this leads to a reduction in agricultural carbon emissions.

4.3.2. Robustness Test

1. Changing the Measurement Method of the Dependent Variable

In the benchmark regression model, the gross agricultural carbon emissions for the 31 provinces in China from 2011 to 2020 were initially calculated based on the carbon accounting formula provided by the IPCC, focusing on input factors. To further ensure the robustness of the results, this study conducted a re-measurement of agricultural carbon emissions using data from the Carbon Emission Accounts and Datasets (CEADs). This database incorporates information from 30 provinces in China spanning the years 2011 to 2019. It provides comprehensive carbon emissions data based on 17 energy consumption-related indicators, encompassing 47 economic sectors, including agriculture, within the national economic accounting framework. The database offers the advantages of high accuracy and strong continuity.

The estimation results of the robustness test are presented in Table 5. Following the change in the measurement method of the dependent variable, it is observed that the coefficient of the independent variable (dfi), representing digital finance, remains significantly negative at the 1% level. This signifies that digital finance continues to exert a substantial and statistically significant effect in reducing agricultural carbon emissions, even after the alteration in the measurement approach. These results reaffirm the robustness of the initial conclusion that digital finance plays a pivotal role in mitigating agricultural carbon emissions.

Table 5. Results of robustness analysis: changing the measurement method of the dependent variable.

	(1)	**(2)**
dfi	−0.266 *** (−1.663)	−0.176 *** (−2.023)
Constant	2.693 *** (37.523)	2.745 *** (2.650)
Control variable	NO	YES
Year-fixed effect	YES	YES
Province-fixed effect	YES	YES
R^2	0.220	0.243
N	270	270

Note: *** indicate that the estimated coefficients passed the *t*-test at the 1% level of significance.

2. Replacing the Core Explanatory Variable

The three secondary indicators of digital finance, namely breadth, depth, and digitization, are utilized as replacements for the original independent variable in the regression analysis. This approach enables further exploration of whether these dimensions of digital finance have a significant impact on agricultural carbon emissions. The results of this robustness test are presented in Table 6.

Table 6. Results of robustness analysis: replacing the core explanatory variable.

	(3)	**(4)**	**(5)**
Breadth	−0.955 *** (−2.713)		
Depth		−0.403 *** (−3.171)	
Digitization			−0.053 *** (−2.835)
Constant	0.845 (1.422)	0.494 (0.892)	0.379 (0.693)
Control variable	YES	YES	YES
Year-fixed effect	YES	YES	YES
Province-fixed effect	YES	YES	YES
R^2	0.306	0.312	0.215
N	310	310	310

Note: *** indicate that the estimated coefficients passed the *t*-test at the 1% level of significance.

Among the three dimensions of digital finance, all exhibit a statistically significant negative impact on agricultural carbon intensity. Specifically, an increase in breadth extends inclusive finance to areas and populations that have traditionally been underserved by traditional financial institutions. This extension of financial services facilitates the adoption of new technologies and varieties by farmers, thereby effectively unleashing a "digital dividend" in rural areas. Furthermore, an increase in depth provides farmers with diverse channels for fundraising, ensuring financial support for intensive, green, and low-carbon agricultural production. Additionally, an improvement in digitization reduces the cost of financial services, activates capital flow in rural areas, and motivates farmers to adopt modern agricultural production methods.

However, it is worth noting that there are variations in the coefficients representing the impact of the different dimensions of digital finance on agricultural carbon reduction. In terms of the absolute values of the regression coefficients, breadth has the greatest impact, followed by depth, and then digitization. This suggests that in future development processes, while continuing to leverage the inclusive nature of digital finance and extending digital financial services to more underserved populations, greater emphasis should be placed on expanding the depth of digital finance usage. This entails focusing on improving multi-level, inclusive, digitized, and intelligent financial products and service systems. Additionally, local governments should accelerate the construction of rural digital infrastructure, enhance the overall level of digitalization in society, and promote the integration of digital elements into agricultural production and management activities. These efforts are particularly crucial for facilitating green and low-carbon development in agriculture.

3. Panel Quantile Regression

To account for heteroscedasticity and provide more robust estimation results, this study employs the panel quantile regression method. This method allows for the estimation of regression coefficients at different quantile levels, thus capturing potential variations across the distribution of the dependent variable. For this analysis, three quantile levels were selected: 0.25, 0.50, and 0.75. These levels enable a deeper exploration of the impact of digital finance on agricultural carbon emissions across provinces. The regression results are presented in Table 7.

Table 7. Results of robustness analysis: panel quantile regression.

	(6)	(7)	(8)
dfi	−0.163 ***	−0.121 **	−0.062
	(−5.771)	(−2.433)	(−0.977)
Constant	1.298 ***	0.842 **	1.157 **
	(5.974)	(2.497)	(2.144)
Control variable	YES	YES	YES
pseudo R^2	0.157	0.190	0.226
N	310	310	310

Note: **, and *** indicate that the estimated coefficients passed the *t*-test at the 5% and 1% levels of significance, respectively.

From the results in Table 7, it can be observed that the quantile estimation results differ from those of the fixed effects model estimation. The effects of variables on agricultural carbon emissions exhibit variations at different quantile levels, indicating greater diversity compared to the panel regression results. Specifically, the impact of digital finance on agricultural carbon emissions is consistently negative across all three quantile levels. It is statistically significant at the 1% level for the 0.25 quantile and at the 5% level for the 0.50 quantile. These results reaffirm that the development of digital finance leads to significant reductions in agricultural carbon emissions.

Furthermore, when comparing the coefficients of digital finance at different quantile levels, it is observed that as the quantile level increases, the negative impact of digital finance on agricultural carbon emissions gradually decreases. The absolute value of the estimated coefficient decreases from 0.163 at the 0.25 quantile to 0.062 at the 0.75 quantile, and the coefficient becomes progressively insignificant. One possible explanation for this phenomenon is that the areas experiencing a more pronounced effect of digital finance are often regions with higher levels of agricultural development. In these regions, farmers possess a stronger subjective awareness of low-carbon production and benefit from favorable green production conditions. They are also more adept at utilizing new technologies and tools such as digital finance to support their green production practices, thereby facilitating agricultural carbon reduction.

Overall, the panel quantile regression analysis further reinforces the result that the development of digital finance has a significant negative impact on agricultural carbon emissions. The results demonstrate variations in the effects at different quantile levels, indicating the presence of diverse dynamics in the relationship between digital finance and agricultural carbon emissions across provinces.

4.3.3. Endogeneity Analysis

This study encounters two potential endogeneity issues. Firstly, there is the concern of omitted variables, as numerous factors can influence agricultural carbon emissions. Despite controlling for a range of possible factors, it is difficult to guarantee the complete exclusion of all potential omitted variables from the error term. Secondly, there is the issue of reverse causality. In agricultural production practice, farmers utilize digital finance products and services to improve agricultural methods, enhance resource allocation efficiency, and achieve agricultural carbon reduction. The economic and ecological benefits derived from agricultural carbon reduction further incentivize stakeholders to actively raise and utilize funds for intensive operations and improved resource utilization, thereby promoting the development of digital finance.

To address the potential bias arising from endogeneity in the regression results, this study employs instrumental variables for the core explanatory variable. The selection of instrumental variables must meet the requirements of exogeneity and relevance. Drawing on relevant research, this study selects "mobile phone penetration rate" (mobile) and "internet penetration rate" (net) as instrumental variables and employs the two-stage least squares (2SLS) estimation method for testing.

The choice of these instrumental variables is based on their relevance to digital finance. The internet serves as a crucial channel for accessing digital finance products and services. The development of wireless communication devices and mobile internet has overcome the temporal and spatial constraints of traditional finance, enabling more people to access financial services such as mobile payments through their mobile devices. Mobile phones have become a significant driver in promoting the development of digital finance. Furthermore, after controlling for other macro factors that influence agricultural carbon emissions, no direct relationship is observed between mobile phone penetration rate or internet penetration rate and agricultural carbon emissions. This strengthens their suitability as instrumental variables.

The testing results are presented in Table 8. By employing "mobile phone penetration rate" and "internet penetration rate" as instrumental variables, the significant agricultural carbon reduction effect of digital finance remains, reaffirming the robustness of the baseline regression results. This provides further support for the hypothesis that digital finance plays a significant role in reducing agricultural carbon emissions.

Table 8. Results of endogeneity test.

	(1)	(2)
dfi	−0.073 **	−0.084 **
	(−2.157)	(−2.575)
Constant	0.317	0.236
	(0.550)	(0.413)
Control variable	YES	YES
Year-fixed effect	YES	YES
Province-fixed effect	YES	YES
R^2	0.221	0.222
N	310	310

Note: ** indicate that the estimated coefficients passed the *t*-test at the 5% level of significance.

4.3.4. Heterogeneity Analysis

The previous results indicate that digital finance contributes to a reduction in agricultural carbon emissions. Given the significant economic and social differences among regions, this section conducts a heterogeneity analysis focusing on two aspects: income level heterogeneity and education level heterogeneity.

1. Income Level Heterogeneity Analysis

To investigate whether the impact of digital finance on agricultural carbon emissions varies across different income levels, the sample is divided into regions with relatively higher and lower levels of rural residents' per capita disposable income, using the median as the threshold. Separate analyses are conducted for these two groups, and the results are presented in Table 9.

Table 9. Results of the heterogeneity analysis.

	High-Income Area	Low-Income Area	High Education Level	Low Education Level
dfi	−0.202 ***	−0.036	−1.000 **	−0.078 **
	(−8.137)	(−0.988)	(−2.541)	(−2.090)
Constant	3.429	0.870	−0.315	0.886
	(5.503)	(1.179)	(−0.326)	(1.252)
Control variable	YES	YES	YES	YES
Year-fixed effect	YES	YES	YES	YES
Province-fixed effect	YES	YES	YES	YES
R^2	0.574	0.234	0.248	0.292
N	129	181	155	155

Note: ** and *** indicate that the estimated coefficients passed the *t*-test at the 5% and 1% levels of significance, respectively.

The results indicate that there is heterogeneity in the impact of digital finance on agricultural carbon emissions due to significant differences in the level of economic development between regions. Specifically, while the coefficient of digital finance is negative in both high-income and low-income regions, it achieves statistical significance at the 1% level only in high-income regions. In comparison, the coefficient of digital finance in low-income regions is both less significant and smaller in absolute value. This suggests that the impact of digital finance on agricultural carbon reduction is primarily observed in high-income regions, whereas its effect is less pronounced in low-income regions.

Several reasons can explain this phenomenon, considering both objective environmental and subjective motivational factors. On the one hand, low-income regions often have lower levels of economic development and lower rates of digital finance adoption compared to high-income regions. This objective condition hampers farmers in low-income regions from utilizing digital finance tools to optimize agricultural production, management, and resource allocation. On the other hand, farmers in low-income regions generally face lower income levels, making it challenging to expand production and adopt digital technologies. Relative to relatively impoverished households, they may lack the motivation to utilize digital finance tools for agricultural production, management, and resource optimization. These factors, either directly or indirectly, contribute to the structural differences in the impact of digital finance on agricultural carbon reduction.

2. Education Level Heterogeneity Analysis

Education level serves as an internal factor affecting rural residents' learning and utilization of digital technology. To examine whether the impact of digital finance on agricultural carbon emissions varies across different levels of education, the sample is divided into regions with relatively higher and lower levels of rural residents' average years of education, using the median as the threshold. Separate analyses are conducted for these two groups, and the results are presented in Table 9.

The results indicate that digital finance significantly reduces carbon emissions at the 5% significance level for both categories of education levels. However, in regions with higher education levels, the carbon reduction effect of digital finance is stronger compared to regions with lower education levels. Several factors can account for this observation. Firstly, residents in regions with higher education levels tend to have higher acceptance and application levels of digital finance due to their better education. They are more likely to understand and utilize digital finance tools for agricultural purposes. Secondly, residents who prioritize education are often more environmentally conscious and place a greater emphasis on environmental protection. The low-carbon development facilitated by digital finance aligns with their expectations and goals, leading to a stronger carbon reduction effect in regions with higher education levels.

4.3.5. Mechanism Analysis

To analyze the mechanism through which digital finance affects agricultural carbon emissions, this section conducts a theoretical analysis based on the previous findings. Building upon prior research [58], this study explores whether digital finance influences agricultural carbon emissions by promoting agricultural green innovation.

To investigate this mechanism, the study adjusts the baseline regression model as follows: Firstly, the mechanism variable, agricultural green innovation (gtfp), is introduced as the dependent variable, with digital finance (dfi) serving as the explanatory variable for regression analysis. Subsequently, the mechanism variable, agricultural green innovation, is added to the baseline regression model as an additional control variable. The specific regression model is as follows:

$$\begin{gathered} gtfp_{it} = \beta_0 + \beta_1 dfi_{it} + \sum \beta_k control_{k,it} + \mu_t + \lambda_i + \varepsilon_{it} \\ carbon_{it} = \gamma_0 + \gamma_1 dfi_{it} + \gamma_2 gtfp_{it} + \sum \gamma_k control_{k,it} + \mu_t + \lambda_i + \varepsilon_{it} \end{gathered} \tag{3}$$

where gtfp represents agricultural green innovation, dfi represents digital finance, and *control* denotes the same control variables as in the baseline model.

The mechanism variable for agricultural green innovation (GTFP) is represented by the agriculture green total factor productivity calculated in this study. In agricultural production activities, the output factors include not only the "expected output" but also the "non-expected output" such as carbon emissions. This study incorporates both the "expected output" factors and "non-expected output" factors into the system, using the SBM-GML index to measure and evaluate the agricultural green total factor productivity. The input and output factors are shown in Table 10.

Table 10. Factor system of agricultural green total factor productivity.

Type	Indicator	Definition
Input Factor	Land input	Crop cultivation area
	Labor input	Number of employees in primary industry
	Pesticide input	Amount of pesticides used
	Fertilizer input	Amount of fertilizer used
	Irrigation input	Effective irrigation area
	Agricultural film input	Amount of agricultural plastic film used
	Machinery input	Total power of agricultural machinery
	Draft animal input	Number of large livestock at year-end
Output Factor	Expected output	Gross agricultural product
	Non-expected output	Agricultural carbon emission

The results of the mechanism test are shown in Table 11. The regression results in column (1) demonstrate that the coefficient of digital finance (dfi) is significantly positive at the 1% level. This result suggests that digital finance effectively promotes agricultural green innovation.

Table 11. Results of the mechanism analysis.

	(1) gtfp	(2) Carbon	(3) Carbon	(4) Carbon
dfi	0.049 ***	−0.746 ***	−0.725 **	−0.720 **
	(4.572)	(−3.040)	(−2.457)	(−2.552)
gtfp		−0.309 *	−0.404 ***	−0.405 ***
		(−1.943)	(−2.741)	(−2.763)
Constant	1.176 ***	1.176 *	1.236 **	1.239 ***
	(5.138)	(1.909)	(2.568)	(2.600)
Control variable	YES	YES	YES	YES
Year-fixed effect	YES	YES	YES	YES
Province-fixed effect	YES	YES	YES	YES
R^2	0.131	0.317	0.236	0.236

Note: *, **, and *** indicate that the estimated coefficients passed the *t*-test at the 10%, 5%, and 1% levels of significance, respectively.

Upon introducing the mechanism variable (gtfp) into the baseline regression model, it is observed that agricultural green innovation is significantly negative at the 10% level. This indicates that agricultural green innovation significantly contributes to agricultural carbon reduction. When comparing the coefficients of digital finance before and after introducing agricultural green innovation, it becomes evident that the coefficient of digital finance remains significantly negative at the 1% level. This implies that agricultural green technological innovation not only directly affects agricultural carbon emissions but also serves as an important mechanism variable mediating the relationship between digital finance and agricultural carbon emissions. The carbon reduction effect of digital finance in agriculture is partially achieved through the promotion of agricultural green innovation. These results confirm the hypothesis that agricultural green innovation plays a mediating role in the relationship between digital finance and agricultural carbon emissions.

To address the potential endogeneity issue arising from introducing the new variable of agricultural green innovation (gtfp), this study applies a similar approach as previously used to mitigate endogeneity concerns. Two instrumental variables, “mobile phone penetration rate (mobile)” and “internet penetration rate (net)”, are utilized, and regression analysis is conducted using the two-stage least squares (2SLS) method. The regression results are presented in columns (3) and (4) of the Table 11.

Upon controlling for endogeneity, the significance level of the coefficient of digital finance (dfi) slightly decreases but remains significantly negative at the 5% level. Additionally, the significance level of agricultural green innovation (gtfp) increases from 10% to 1% while remaining negative. These results further confirm that a portion of the carbon reduction effect of digital finance in agriculture is achieved via the promotion of agricultural green innovation.

By employing instrumental variables and the 2SLS method to address potential endogeneity concerns, the regression analysis provides more robust results and supports the conclusion that digital finance influences agricultural carbon emissions partly via its impact on agricultural green innovation. The results underscore the importance of agricultural green innovation as a mediating mechanism in the relationship between digital finance and agricultural carbon emissions.

5. Conclusions and Policy Implications

5.1. Conclusions

The integration of digital finance with agricultural economic development is progressively emerging as a novel catalyst and propellant for fostering high-quality advancements in agriculture. Against the backdrop of strategies aimed at carbon peaking and carbon neutrality, it is imperative to ascertain whether the progression of the digital economy has facilitated agricultural carbon reduction and harnessed the carbon reduction potential inherent in digital finance. To this end, this study leverages panel data encompassing 31 provinces in China, spanning the period from 2011 to 2020. By calculating the provincial level of agricultural green and low-carbon development, the study empirically investigates the influence of digital finance development on agricultural carbon emissions. Particular attention is given to elucidating the mechanism of green innovation. The econometric results unveil the subsequent outcomes:

The benchmark regression result highlights that the advancement of digital finance plays a pivotal role in significantly diminishing agricultural carbon emissions, thereby fostering agricultural carbon reduction. This result proves the validity of hypothesis 1 in this study. Remarkably, this conclusion remains robust even when subjecting the analysis to stringent tests, such as altering the measurement methodology of the dependent variable and employing panel quantile regression as a substitute for the core explanatory variable.

Moreover, this research endeavors to shed light on and provide clarity regarding the mechanism of green technological innovation, particularly in the context of the influence exerted by the development of digital finance. The results reveal a substantial and noteworthy enhancement in the levels of agricultural green technological innovation, attributable to the progression of digital finance, which provides empirical evidence to prove the validity of hypothesis 2 in this study. This, in turn, leads to a tangible reduction in agricultural carbon emissions, owing to the mechanism of green technological innovation.

Furthermore, using heterogeneity analysis, it becomes evident that the effects of digital finance on agricultural carbon reduction are more pronounced in areas characterized by higher income levels and greater educational attainment. These specific regions exhibit a heightened sensitivity and responsiveness to the agricultural carbon reduction benefits offered by digital finance.

5.2. Policy Implications

Based on the aforementioned findings, this study puts forth the following policy implications: Firstly, there is a need to actively facilitate the establishment of digital infrastructure in rural areas, thereby enhancing digitization levels and social service capabilities. Secondly, emphasis should be placed on further enhancing agricultural green innovation and increasing the conversion rate of scientific achievements. To support the development of green, low-carbon, and high-quality agriculture, it is necessary to increase fiscal support for green technology research. Thirdly, regional differences should be taken into account when formulating low-carbon agricultural development strategies. Localized approaches and differentiated strategies are recommended to address the specific needs and challenges of different regions. Implementing preferential tax policies and providing proactive fiscal policy support can encourage the development of digital finance in these regions, foster the adoption of green production and consumption practices, and further propel agricultural production toward environmentally friendly and low-carbon practices.

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