Pol. J. Environ. Stud. Vol. XX, No. X (XXXX), 1-13

DOI: *10.15244/pjoes/187165* ONLINE PUBLICATION DATE:

Original Research

The Impact of Digital Inclusive Finance on Agricultural Carbon Emissions: Evidence from China

Chen Li[1], Guohua Chen[1], Xiaoyu Zhang[2], Yajin Li[3], Weichao Ding[2], Xiuxiu Yu[1], Bing He[1*]

[1] School of Business, Jiangsu Ocean University, Lianyungang, China
[2] Graduate Business School, UCSI University, Kuala Lumpur, Malaysia
[3] School of Management, Shanghai University of Engineering Science, Shanghai, China

Received: 07 January 2024
Accepted: 14 April 2024

Abstract

As an important financial instrument, digital inclusive finance (DIF) represents a significant pathway toward achieving sustainable development. Utilizing the fixed-effects, mediation effects, moderation effects, and threshold effects models, this study investigates the influence and detailed mechanism of DIF on agricultural carbon emissions through provincial data in China from 2011 to 2020. The results reveal that: (1) DIF leads to a reduction in agricultural carbon emissions, with the greatest effect observed in the dimension of deep agricultural carbon reduction. (2) The carbon reduction effect can be achieved by enhancing entrepreneurial vitality among farmers, an advanced agricultural industrial structure, and increased levels of agricultural product trade. (3) There is a substitution effect, where large-scale farmland operations weaken the carbon reduction effect. (4) Beyond a certain threshold, DIF exerts a stronger restraining effect on carbon emissions. The conclusions have implications for the government's promotion of digital infrastructure and green development in the agriculture industry. Consequently, this study suggests that the development of DIF should be accelerated.

Keywords: digital inclusive finance, carbon emissions, threshold effect

Introduction

In recent years, the harm caused by global warming has gradually deepened. Carbon emissions caused by inefficient energy consumption are an important factor in global warming, and improving energy efficiency plays a vital role in sustainable environmental development [1]. At the same time, governments around the world are taking measures to achieve carbon neutrality, among which green energy, carbon taxes and environmental policies can support achieving carbon neutrality [2]. In addition, the Chinese government has also become carbon-neutral in various ways in the following decades.

Since 1987, China has undergone a sustained period of rapid economic growth. Simultaneously, China has faced severe environmental problems due to excessive resource consumption and low production efficiency. As an integral part of the open industrial ecosystem, carbon emissions from the agricultural sector account for about 17% of the nation, greatly surpassing the global average

* e-mail: binghe@jou.edu.cn

level. In 2020, President Xi pledged to achieve "carbon peaking by 2030 and carbon neutrality by 2060", which underscores China's resolute commitment to advancing green development. Later, nearly 200 countries on COP26 agreed to keep global warming to 1.5 degrees Celsius to prevent a sharp rise in the frequency of catastrophic climate events around the world. Additionally, the Chinese official document "Opinions on Thoroughly Implementing the New Development Concept and Advancing Carbon Peaking and Carbon Neutrality" articulates a long-term vision of "accelerating green development in agriculture and promoting carbon sequestration". Consequently, reducing agricultural carbon emissions becomes a pivotal strategy for attaining the dual carbon goals and an imperative for realizing high-quality green development within the agricultural sector.

China's digital finance sector is experiencing rapid growth, which has significantly enhanced the accessibility and utility of financial resources. Digital finance has permeated various facets of production and daily life, heralding a new era for business operations and household activities [3]. According to Peking University, China's DIF Index has increased from 33.6 in 2011 to 372.7 in 2021. Digital inclusive finance represents a model where traditional financial institutions leverage digital technology to offer services, giving rise to a novel financial format. Compared to traditional finance, DIF focuses on the integration of the financial sector with technology, augmenting traditional services with network-based, intelligent, and digital elements. Digital inclusive finance removes time and space barriers from the flow of production factors, making financial services available across borders. This is helpful for people who live in remote areas and couldn't get traditional financial services smoothly before. It concurrently reduces the costs associated with financial transactions, effectively mitigating challenges like limited access to financing and high borrowing costs. Therefore, DIF has a pivotal role in advancing the modernization of agriculture.

The development of modern agriculture requires substantial investment, and financial services play important roles in enhancing the efficiency of green agricultural financing. With the evolution of the digital economy, digital inclusive finance products are progressively penetrating the agricultural production sectors, offering precise support to sectors with weaker economic foundations, like agriculture. Possessing both digital and inclusive characteristics, DIF can facilitate the upgrading of rural industrial structures. It introduces digital and intelligent production models, offering significant potential for reducing carbon emissions.

During the development of DIF, the establishment of online financial service platforms minimizes the carbon emissions associated with financial transactions and travel, benefiting both businesses engaged in financing and individuals involved in payment processes. As society progressively adopts a green and low-carbon lifestyle, more production factors are directed toward innovative green industries within the open market. In 2022, China explicitly emphasized the need to "promote the integrated development of inclusive finance and green finance." In this context, the DIF assumes significant importance in addressing issues related to agricultural modernization and green development. Consequently, it is imperative to investigate whether DIF influences China's carbon emissions and comprehend the underlying mechanisms. Research into these questions carries substantial practical significance and theoretical value in the pursuit of sustainable green agriculture.

The possible contributions of this study are: First, a significant portion of research about DIF focuses on regional economic growth, rural vitalization, and rural poverty reduction, while fewer studies link DIF with agricultural carbon emissions. This study links DIF with agricultural carbon emissions and investigates the relationship between them; Second, this paper quantitatively analyzes the effect and mechanism of DIF on agricultural low-carbon development so as to make up for the deficiency of existing literature research scope; Thirdly, the study confirms that DIF reduces carbon emissions by stimulating rural innovation and entrepreneurship, promoting the development of advanced agricultural industrial structures, and enhancing agricultural product trade. Fourthly, the study uncovers a single threshold effect of the digital rural development level, thus filling existing research gaps.

The subsequent sections are structured as such: the second section consists of a literature review, as well as the research gaps and several limitations; the third section shows the theoretical analysis and hypotheses; the fourth section is the research design, including research methods, models, and data collection; the fifth section discusses the empirical results of this paper; and the sixth section summarizes the conclusions, and provides relevant recommendations.

Literature Review

The existing literature related to research on agricultural carbon emissions can be primarily classified into two main categories. Firstly, significant research is focused on estimating agricultural carbon emissions. Johnson et al. (2007) pointed out that methane (CH4) and nitrous oxide (N2O) are mainly produced in agricultural production, while the carbon emission sources are mainly divided into four categories: agricultural waste disposal, livestock raising, agricultural energy use, and plant cultivation [4]. Wu et al. (2023) have presented a novel carbon efficiency model that integrates indices related to water, energy, and food pressure from the standpoint of sustainable development [5]. Agriculture plays a dual role in carbon cycling, serving both as a source and a sink of carbon. Specifically, carbon emissions are generated during human agricultural activities and crop growth, but these emissions are offset during the decomposition of organic matter. Consequently, Li and Wang (2023) argue that agricultural carbon emissions should be measured based on the emissions resulting from human production activities, which encompass the use of pesticides and other contributing factors [6]. The IPCC also provides estimation methods for agricultural carbon emission coefficients, covering various aspects such as fertilizers, pesticides, agricultural machinery power, cropland area, and irrigation.

The second aspect of research delves into the factors that influence carbon emissions. For instance, Han et al. (2018) discovered that economic progress and improvements in agricultural technology had impacts on carbon emissions [7]. Zhao et al. (2018) utilized the LMDI model and found that an increment in resource inputs in agricultural production resulted in a subsequent rise in carbon emissions [8]. Based on provincial data, Wang et al. (2022) uncovered that agricultural specialization can result in excessive fertilizer usage, thus exerting a positive effect on carbon emissions [9]. Moreover, factors such as green agricultural production technologies and integrated urban-rural development have been identified as having influences on agricultural carbon emissions. Researchers have also delved into the influence of relevant policies on Chinese agricultural carbon emissions. For instance, Zhang et al. (2023) have utilized panel data from Chinese counties spanning from 2000 to 2018 and found that agricultural credit subsidy policies can reduce carbon emissions [10]. Du et al. (2023) have examined the effects of national policies on carbon emissions [11].

The studies on the effects of DIF have primarily concentrated on its economic benefits. Chen (2021) has found regional disparities in the influence of China's DIF on the regional income gap [12]. Feng et al. (2022), using panel data from listed Chinese companies, have demonstrated that digital finance development can promote innovation in green technologies for small businesses [13]. In the ecological and environmental domains, Zhong (2022) has observed that digital finance indirectly reduces pollution by promoting the restructuring of green practices [14]. After studying a sample of 285 Chinese cities, Zhang and Liu (2022) discovered a strong connection between digital finance and technology innovation in decreasing carbon emissions [15]. Lin and Zhang (2023), adopting an extreme value theory perspective, have explored the impact of DIF on household consumption [16]. Nevertheless, studies on the impact of DIF on the low-carbon transformation of agriculture are still in their infancy, with limited available literature. For instance, Gao et al. (2022) have suggested that DIF can enhance the level of green technology, subsequently increasing TFP in agriculture, particularly in eastern China [17]. Zhang et al. (2023) have found that in regions with well-established traditional financial systems or more concentrated agricultural industries, DIF can promote green development in agriculture [18].

An examination of the existing literature reveals that there are few studies examining the correlation between DIF and agricultural carbon emissions, especially on the mechanisms by the approach of the fixed effects analysis. Consequently, utilizing province data from 2011 to 2021, this study examines the effect of DIF on carbon emissions. The study investigates the mechanisms through which DIF affects agricultural carbon emissions from the perspectives of rural innovation and entrepreneurship, advanced agricultural industrial structures, and agricultural product trade. This study uses the mediation effects, the moderation effects, and the threshold effects models to examine the factors affecting agricultural carbon emissions, which somewhat fills the methodological research gap.

Theoretical Analysis and Hypotheses

Potential of DIF to Reduce Agricultural Carbon Emissions

DIF offers several pathways through which it can influence agricultural carbon emissions. Firstly, it can address issues related to information asymmetry and limited financial accessibility in rural areas. Traditional rural financial services often grapple with high transaction costs and restricted information channels, resulting in financial exclusion within rural markets. DIF leverages technologies like the internet and big data, enabling precise matching of fund supply and demand and creating new avenues for the flow of agricultural funds. This, in turn, supports farmers in adopting environmentally friendly agricultural technologies, green products, and sustainable practices. Simultaneously, it encourages farmers to embrace financial services, enhances their financial literacy, and fosters environmental awareness (Gomber et al., 2017) [19].

Secondly, digital inclusive finance can help alleviate financing constraints. It pools together dispersed financial resources to provide funding for initiatives related to agricultural pollution control and smart agriculture. Additionally, it attracts a more diverse range of investors, thus spreading the risks associated with agricultural innovation activities. Digital inclusive finance also offers novel financing channels for green innovation enterprises, such as consumer finance (Cao et al., 2021) [20], and these avenues ensure the development of low-carbon technologies.

Furthermore, DIF can empower rural areas to establish environmentally friendly platforms. As digital technology continues to evolve, rural regions are gradually enhancing their information infrastructure, with new media platforms gaining widespread usage. For example, online loans, mobile payments, and mobile banking have become accessible in rural areas, alongside the emergence of second-hand trading platforms that convert idle resources into valuable assets. These platforms enhance the efficiency of rural resource utilization and carbon sequestration capacity, ultimately contributing to carbon emissions reduction. Then, this study proposes Hypothesis 1:

H1: Digital inclusive finance can reduce agricultural carbon emissions.

The Intermediary Effect of Rural Innovation and Entrepreneurship Vitality

DIF plays a pivotal role in mitigating financing constraints and establishing funding pathways for rural entrepreneurs. On one hand, traditional financial services entail relatively high costs for rural households seeking access to financial resources. The advent of digital inclusive finance streamlines transaction processes, providing convenient payment and financing methods, thereby reducing barriers for rural entrepreneurship (Beck et al., 2018) [21]. On the other hand, it also can enhance the entrepreneurial environment, instilling confidence in entrepreneurs by stimulating rural entrepreneurship demand and fostering market dynamism. Big data and the internet serve as platforms for information exchange among rural entrepreneurs, assisting them in understanding market prospects and enriching their choices in entrepreneurial endeavors.

The enhancement of rural innovation and entrepreneurship vitality significantly contributes to reducing carbon emissions in agricultural production. Regional innovation and entrepreneurship capacities influence the level of green development, with technological innovations driving regulatory authorities to enhance environmental governance and oversight mechanisms (Soleas, 2021) [22]. Entrepreneurship and innovation not only stimulate economic growth but also promote advancements in agricultural technology innovation. Improved levels of agricultural technology innovation and entrepreneurship can reshape the prevailing energy consumption structure, fostering the adoption of new energy sources and the conversion of existing ones. Consequently, this reduces energy waste in traditional agricultural production processes, leading to a decline in carbon emissions. Innovative agricultural enterprises tend to favor low-carbon production methods, and their green operational models are more appealing to investors. This, in turn, creates a positive cycle that advances the sustainability of agriculture. This study proposes Hypothesis 2a:

H2a: Farmers' innovation and entrepreneurship vitality mediate the impact of digital inclusive finance on reducing agricultural carbon emissions.

The Intermediary Effect of Agricultural Industry Structural Upgrading

The transition from lower to higher levels in the agricultural industry structure is known as agricultural industry structural upgrading. DIF plays a pivotal role in facilitating this transition through various mechanisms. Firstly, it injects fresh vitality into economic development by driving industrial structural upgrading through technological innovations, increased productivity, and the influence of consumer demand (Li and Ma, 2021) [23]. Secondly, green products are the cornerstone of the green agricultural industry chain, providing assurance for high-value agricultural products. Digital technology efficiently bridges the gap between the demand for green agricultural products and the related industry chain, creating a robust agricultural ecosystem that fosters the transformation and modernization of agriculture. Digital inclusive finance not only supports the leading industry enterprises but also offers financial accessibility to small-scale farmers, thus promoting the agricultural industry. Moreover, digital platforms for information dissemination simplify access to funds for entrepreneurial enterprises, furthering the enhancement of industrial structures. With the removal of information barriers, communication flows seamlessly, and factors of production, including capital and labor, enrich the service-oriented nature of agriculture and drive structural upgrading in the agricultural industry (Lin, 2016) [24].

In accordance with the Lewis dual economy theory, optimizing the allocation of production factors across industries improves economic efficiency. According to Zhou et al. (2013), carbon emissions can be decreased by optimizing factor proportions and adjusting the structure of the agricultural economy [25]. Agricultural carbon emissions predominantly stem from the use of substances and irrigation. The changes in the agricultural industry structure encourage the transfer of technology between different sectors, influence the division of labor in agriculture, and encourage precise agricultural practices, thereby diminishing carbon emissions. The process of upgrading the agricultural industry structure signifies a move towards greener and more modern agriculture, which contributes to carbon sequestration and reduced emissions in agriculture, ultimately fostering sustainable agricultural development. Then, this study proposes Hypothesis 2b:

H2b: The impact of digital inclusive finance on agricultural carbon emissions reduction is mitigated by upgrading the agricultural industrial structure.

The Intermediary Role of Agricultural Product Trade Level

The influence of the international trade environment has been a central topic. The development of DIF systems becomes paramount in the context of agricultural product trade, particularly when companies heavily rely on external funding for their production. On one hand, the evolution of DIF systems provides essential financial support to agricultural enterprises, ensuring a robust framework for the import and export of agricultural products. A well-established DIF system not only effectively organizes and mobilizes idle social capital but also mitigates risks, offering financial security for the development of novel agricultural technologies and encouraging investments in technology-driven industries. On the other hand, the technological advancements driven by digital inclusive finance have the potential to boost productivity and enhance the international competitiveness of agricultural products. Furthermore, it can stimulate a company's innovative capacity, thus enabling it to maintain a leading market position. Additionally, in line with dynamic international trade theory, technology gaps can impact the distribution of factor endowments across countries, thereby influencing international trade. Consequently, the promotion of DIF serves as an effective catalyst for driving agricultural product trade.

Agricultural product trade plays a pivotal role in influencing carbon emissions (Yang., 2019) [26]. According to the "trade triple impact" theory proposed by Grossman and Krueger (1991) [27], agricultural product trade has environmental repercussions through scale effects, structural effects, and technological effects. To begin with, from a scale perspective, the importation of agricultural products contributes to reducing carbon emissions resulting from the excessive input of production factors. In contrast, the export of agricultural products can lead to an uncritical pursuit of scale expansion, resulting in overinvestment in production factors and environmental pollution. Given China's persistent trade deficit in agricultural products, enhancing agricultural product trade becomes instrumental in reducing agricultural carbon emissions. Furthermore, from a structural viewpoint, as importing countries demand higher product quality, agricultural product trade incentivizes improvements in product quality and a reduction in the input of polluting factors. Lastly, in the process of international agricultural product trade, tangible items like advanced production equipment and high-quality seeds can be exchanged, while intangible elements like green production concepts and agricultural technologies are also transmitted. This results in spillover effects that promote green development in agriculture (Bonato, 2019) [28]. Therefore, this study proposes Hypothesis 2c:

H2c: The level of agricultural product trade mediates the effect of DIF on reducing carbon emissions.

Moderation Effect Analysis

As industrialization and urbanization advance rapidly, agricultural production faces various challenges, including labor shortages and rural-urban disparities. Traditional small-scale farming is not sufficient to meet the demands of modern agricultural development. The transition to large-scale farmland operation is deemed a crucial step toward achieving agricultural modernization. Large-scale farming results in changes to the configuration of agricultural production factors, and consequently, it has much impact on carbon emissions. Enhancing the level of large-scale farmland operation can unlock economies of scale in land management. Generally, farmers engaged in larger-scale operations tend to possess higher levels of agricultural expertise and are more adept at efficiently allocating resources. This often involves reducing fertilizer use and improving energy efficiency. Wu et al. (2018) discovered that an increase in the level of large-scale farmland operation significantly reduces fertilizer application per unit area, leading to decreased production costs per unit area, and enhancing the overall utilization of production resources. These changes result in reduced carbon emissions from agricultural production [29]. Therefore, there may be a substitution effect, which is a specific type of moderation effect. In essence, as the level of large-scale farmland operation increases, the negative influence on carbon emissions may diminish. Then, it proposes Hypothesis 3:

H3: The moderation effect of large-scale farmland operations and an increase in the level of large-scale farmland operations weaken the carbon reduction effect.

Threshold Effect Analysis

As described, DIF holds the potential to ameliorate carbon emissions. Nevertheless, it is worth noting

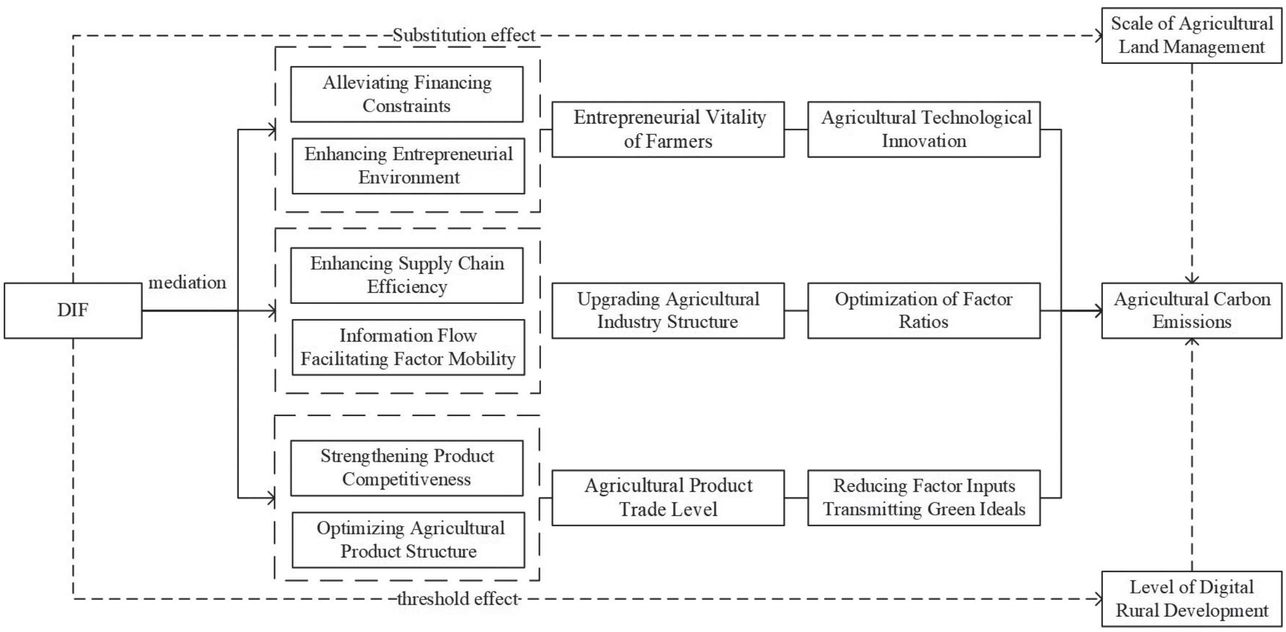

Fig. 1. Logical framework for theoretical analysis

that there may be a threshold for the impact. In comparison to traditional finance, DIF can transcend temporal and spatial constraints to efficiently deliver financial services to marginalized populations in remote areas. The underpinning of DIF hinges on a robust digital infrastructure, encompassing internet-based communication technologies, digital resources, and the Internet of Things. Hence, it follows that the influence of DIF on the reduction of carbon emissions exhibits heterogeneity at varying levels of digital rural development. Presently, there is a pronounced imbalance in digital rural development across the nation. Regions situated in the eastern part of the country leverage their advantageous geographic positioning and relatively economic capabilities to harness advanced digital technologies more readily. Consequently, DIF in the eastern region can manifest a more prominent role in mitigating carbon emissions. In contrast, in the other two regions grapple with delayed progress in digital rural development. Consequently, the influence of DIF on the reduction of carbon emissions is of lesser magnitude in these regions. Therefore, it proposes Hypothesis 4:

H4: The influence of DIF on agricultural carbon emissions has a threshold effect, and the degree of digital rural development determines the threshold.

Research Design

Model Specification

Baseline Regression Model

This study employs a fixed-effects model to verify Hypothesis 1, as in Equation (1):

$$CEI_{it} = \alpha + \beta_1 DIF_{it} + \beta_2 Controls_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (1)$$

Here, CEI_{it} signifies the agricultural carbon emissions intensity in province i at year t; DIF_{it} stands for the DIF index in province i during time t; *Controls* encompass potential influencing control variables; μ_i and δ_t represent province and year fixed effects, respectively; and ε_{it} is the error term.

Mediation Models

To examine the influencing mechanisms, the mediation models are as follows:

$$CEI_{it} = \alpha_0 + \alpha_1 DIF_{it} + \alpha_2 Controls_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (2)$$

$$M_{it} = \beta_0 + \beta_1 DIF_{it} + \beta_2 Controls_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (3)$$

$$CEI_{it} = \gamma_0 + \gamma_1 DIF_{it} + \gamma_2 M_{it} + \gamma_3 Controls_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (4)$$

M_{it} signifies the mediating variables, consisting of farmers' innovation and entrepreneurship vitality (*Entre*), the enhancement of agricultural industrial structure (*Aisu*), and the level of agricultural product trade (*Atrade*). α, β, and γ denote the coefficients, while μ_i and δ_t represent year and province fixed effects, respectively. ε_{it} accounts for the error term.

Moderation Effects Model

This study constructs the moderation effects model to investigate the moderating role of agricultural land scale operation level (*Lscale*).

$$CEI_{it} = \alpha_0 + \alpha_1 DIF_{it} + \alpha_2 Controls_{it} + \alpha_3 Lscale_{it} + \alpha_4 DIF_{it} \times Lscale_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (5)$$

The determination of the existence of moderation effects relies on the significance level of the interaction term.

Threshold Effects Model

Considering that DIF may have differential effects on CEI, this study introduces the threshold variable (digital rural development level) to examine whether DIF has varying effects on CEI under different levels of digital rural development. Hence, the following threshold model is formulated:

$$CEI_{it} = \alpha_0 + \alpha_1 DIF_{it} \times I(Drd \le \lambda_1) + \alpha_2 DIF_{it} \times I(\lambda_1 < Drd \le \lambda_2) + \dots + \alpha_n DIF_{it} \times I(\lambda_{n-1} < Drd \le \lambda_n) + \alpha_{n+1} DIF_{it} \times I(Drd > \lambda_n) + \alpha_\phi Controls_{it} + \varepsilon_{it} \quad (6)$$

Drd represents the threshold variable, digital rural development level; I (*) denotes the indicator function of the threshold model, with I equal to 1 if the condition in parentheses is true, and 0 otherwise.

Variable Selection

Dependent Variable: Agricultural Carbon Emissions Intensity (*CEI*). Before calculating the agricultural CEI, this study first estimates the carbon emissions resulting from factor inputs in agriculture. According to the IPCC calculating method, carbon emissions originate from six aspects: fertilizers, pesticides, diesel, plastic film, irrigation, and tillage. The formula is as follows:

$$TC = \sum C_i = \sum S_i P_i \quad (7)$$

In equation (7), *TC* represents the total carbon emission, C_i stands for the emissions from different sources, S_i denotes the coefficients for these sources, and P_i represents their quantities. Specific information is provided in Table 1.

Following that, the following formula is used to determine the carbon emission based on agricultural output value:

$$CEI = TC / AGDP \quad (8)$$

In equation (8), *CEI* represents agricultural carbon emissions intensity, and *AGDP* corresponds to agricultural output value.

Table 1. Sources of agricultural carbon emissions and coefficients

Carbon Source	Carbon Emission Coefficients	Sources
Chemical fertilizer	0.89kg/kg	ORNL
Pesticide	4.93kg/kg	ORNL
Diesel fuel	0.59kg/kg	IPCC
Plastic sheeting	5.18kg/kg	IREEA
Irrigation	266.48kg/hm^2	Ding et al.[32]
Ploughing	312.60kg/hm^2	IABCAU

Independent Variable: DIF index (*DIF*). This study employs the DIF index calculated by Peking University for the years 2011 to 2020 to measure DIF. The index comprises three dimensions: breadth of coverage (*CB*), depth of usage (*UD*), and degree of digitalization (*DL*).

Mediating Variables: (1) Farmers' Innovation and Entrepreneurship Vitality (*Entre*), measured by the ratio of rural individual employment and private enterprise employment to the annual urban population. A higher ratio indicates greater entrepreneurship vitality. (2) Upgrading of Agricultural Industrial Structure (*Aisu*), determined by dividing the total output value of the primary industry by the output value of forestry, animal husbandry, and fishery. (3) Level of Agricultural Product Trade (*Atrade*), expressed as the total trade volume of agricultural products divided by the value-added output of the primary industry.

Moderating Variable: Large-Scale Land Operation Level (*Lscale*), determined by dividing the total area planted with crops by the number of workers in the primary industry.

Threshold Variable: Level of Rural Digital Development (*Drd*), measured by using the ratio of the number of rural broadband users to the rural population.

Control Variables: (1) Level of Agricultural Industry (*Indus*), determined by dividing the value of agricultural output by the value of agriculture, forestry, animal husbandry, and fishery. (2) Rural Economic Development Level (*Agdp*) computed utilizing the value ratio of agricultural output to the population in rural areas. (3) Level of Agricultural Modernization (*Amode)*, symbolized by the total power of agricultural machinery. (4) Planting Structure (*Stru*), expressed as the proportion of the grain planting area to the total crop planting area. (5) Industrial Structure (*Isu*), demonstrated by the secondary industry's output value as a percentage of GDP.

Data Sources

Given data availability and the observability of research outcomes, this study utilizes Chinese provincial data from 2011 to 2020. Data on agricultural CEI are from the China Agriculture Yearbook and the China Rural Statistics Yearbook. Data on DIF come from the DIF Index by Peking University. Mechanism variables, moderating variables, and control variables are from the China Population and Employment Statistics Yearbook, the EPS database, and the China Research Network. Table 2 presents descriptive statistics.

Table 2. Descriptive Statistics

Variable	Obs	Mean	Std.	Min	Max
CEI	310	0.198	0.062	0.049	0.399
lnDIF	310	5.212	0.677	2.786	6.068
CB	310	196.7	96.56	1.960	397
UD	310	211.1	98.19	6.760	488.7
DL	310	290.1	117.3	7.580	462.2
Indus	310	0.523	0.085	0.302	0.721
Agdp	310	0.975	0.499	0.208	3.708
Amode	310	7.637	1.125	4.543	9.499
Stru	310	0.662	0.144	0.355	0.971
Isu	310	0.457	0.125	0.159	0.850
Phone	310	4.564	0.242	3.952	5.244
Atrade	310	0.816	2.427	0.006	15.50
Entre	310	0.071	0.054	0.008	0.328
Aisu	310	0.436	0.094	0.182	0.673
Lscale	310	1.871	0.450	0.736	3.322
Drd	310	0.974	1.750	0.003	13.48

Empirical Results

Benchmark Regression

Table 3 presents the findings of this study, which examines how DIF development affects the intensity of agricultural carbon emissions. Additionally, the result of the Hausman test indicates the use of fixed effects. The findings show that the coefficient of DIF is continuously significant and negative. This supports Hypothesis 1 by indicating a considerable reducing influence of the growth of DIF on the intensity of agricultural carbon emissions. On one hand, DIF, characterized by its low entry barriers and cost-effectiveness, alleviates financing constraints in rural financial markets. It effectively broadens financing channels for farmers, achieving economies of scale and reducing CEI. On the other hand, farmers utilize these funds to introduce green agricultural technologies, enhancing production efficiency and thus effectively reducing CEI. Furthermore, the development of DIF indirectly enhances financial literacy among farmers and accelerates the empowerment of agriculture's low-carbon development.

As indicated in column (6) of Table 3, the coefficient of the level of agricultural modernization is significantly positive, signifying that the advancement of agricultural mechanization intensifies CEI. The coefficients for agricultural industry level, rural economic development level, planting structure, and industrial structure are

Table 3. Benchmark Regression Result

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
lnDIF	-0.042***	-0.031***	-0.028**	-0.035***	-0.037***	-0.029***
	(0.016)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
Indus		-0.347***	-0.313***	-0.288***	-0.302***	-0.352***
		(0.064)	(0.073)	(0.070)	(0.068)	(0.064)
Agdp			-0.013*	-0.0262***	-0.025***	-0.035***
			(0.007)	(0.009)	(0.009)	(0.010)
Amode				0.036***	0.036***	0.037***
				(0.009)	(0.009)	(0.010)
Stru					-0.077	-0.128***
					(0.049)	(0.047)
Isu						-0.077***
						(0.024)
Constant	0.373***	0.471***	0.446***	0.284***	0.343***	0.379***
	(0.066)	(0.053)	(0.055)	(0.074)	(0.073)	(0.074)
Observations	310	341	341	341	341	310
R-Squared	0.918	0.930	0.932	0.936	0.937	0.942
Province FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

-0.352, -0.035, -0.128, and -0.077, respectively, and all are statistically significant, demonstrating their capacity to reduce agricultural CEI.

Heterogeneity Analysis

Heterogeneity Test for DIF

This section further investigates whether DIF exhibits agricultural carbon reduction effects across three dimensions: coverage breadth (CB), usage depth (UD), and digitization level (DL). The results, as presented in Table 4, are examined. As indicated by columns (1) and (2), the reduction in agricultural carbon emission intensity is significantly attributed to coverage breadth and usage depth. As the scope of DIF continues to expand, the "digital dividend" is effectively harnessed in remote areas, assisting farmers in adopting green technologies and products to enhance production efficiency. Increased usage depth broadens financing channels for rural farmers, thereby providing financial support for low-carbon production. In column (3), the impact of digitization level on CEI is significantly positive. This may be attributed to the relatively weak state of digital infrastructure development in rural China. Therefore, expediting the development of digital infrastructure in remote rural areas is of paramount importance for reducing agricultural carbon emission intensity.

Table 4. Heterogeneity Test: the dimensional regression of digital inclusion financial

	(1)	(2)	(3)
VARIABLES	CEI	CEI	CEI
CB	-0.016***		
	(0.003)		
UD		-0.020***	
		(0.007)	
DL			0.019***
			(0.006)
Controls	YES	YES	YES
Constant	0.314***	0.380***	0.231***
	(0.062)	(0.076)	(0.063)
Observations	310	310	310
R-squared	0.944	0.941	0.941

Regional Function Classification Heterogeneity Test

China is home to 13 major grain-producing regions, including provinces like Heilongjiang, Henan, and Shandong. These grain-producing regions, as opposed to non-grain-producing areas, exhibit differences in the proportion of cereal crop cultivation. Therefore, to determine whether there is heterogeneity in the influence of DIF on agricultural CEI, this study conducts separate regressions using the remaining 18 regions, and results are presented in columns (1) to (2) of Table 5.

The results show that DIF has a negative impact on agricultural CEI in both regions. This could be attributed to the high frequency of agricultural activities in grain-producing regions, resulting in higher agricultural CEI compared to non-grain-producing regions. Therefore, carbon reduction policies should be oriented towards grain-producing regions, emphasizing the integration of policy implementation with digital inclusive finance to create complementary advantages, effectively mitigating agricultural carbon emissions.

Regional Characteristic Heterogeneity Test

Given the significant differences in geographic location, resource conditions, and climate among China's grain-producing regions, agricultural carbon emission intensity varies. Thus, these grain-producing regions are categorized into the Yellow River Basin (Hebei, Shandong, Henan, Inner Mongolia), the Yangtze River Basin (Jiangxi, Anhui, Hubei, Hunan, Jiangsu, Sichuan), and the Songhua River Basin (Jilin, Liaoning, Heilongjiang) for separate regressions. The results are shown in columns (3) to (5) of Table 5.

In the grain-producing provinces of the Yangtze River Basin, the results show that DIF significantly lowers carbon emission intensity. However, the results for the Songhua River Basin and the Yellow River Basin fail the significance test. An explanation for this might be that the Yangtze River Basin grain-producing provinces have relatively well-developed digital infrastructure, fostering rapid growth in green and low-carbon agricultural practices. This has facilitated the deep integration of DIF with the agricultural industry, effectively reducing agricultural carbon emission intensity in the Yangtze River Basin. In contrast, the Yellow River Basin and the Songhua River Basin grain-producing provinces lag in terms of digital infrastructure development and service quality. However, with the continued expansion and penetration of digital inclusive finance services, both the Yellow River Basin and the Songhua River Basin grain-producing provinces can reduce agricultural CEI.

Influence Mechanism Test

Table 6 presents the results of the mediation effect test. In column (1), the coefficient for DIF is 0.037 and statically significant, indicating that DIF can enhance farmers' innovation and entrepreneurial vitality. In column (2), the coefficient for farmers' innovation and entrepreneurial vitality is significantly negative. This implies that farmers' innovation and entrepreneurial vitality can significantly restrain carbon emissions. Farmers' innovation and entrepreneurial vitality partially mediate the relationship between DIF and agricultural carbon emissions, supporting hypothesis H2a. DIF, characterized by low cost and broad coverage, facilitates financial convenience for farmers' innovation and entrepreneurship. Innovation and entrepreneurship can enhance agricultural productivity, reducing carbon emissions from traditional, less efficient production methods.

In column (3), the coefficient for DIF is positive, indicating that DIF promotes the upgrading of the agricultural industry structure. In column (4), the coefficient for the upgrading of the agricultural industry structure is negative and significant. This suggests that DIF can reduce carbon emissions by promoting the upgrading of the agricultural industry structure, with the upgrading of the agricultural industry structure playing a partial mediating role, supporting hypothesis H2b. Digital inclusive finance provides efficient information communication and capital flow channels, which promote the allocation of production factors, thereby reducing carbon emissions.

In column (5), DIF positively influences the level of agricultural product trade. In column (6), the level of agricultural product trade significantly negatively affects agricultural CEI at the 5% level. This indicates that DIF can reduce carbon emissions by increasing the level of agricultural product trade, with the level of agricultural product trade serving as a partial mediator, supporting hypothesis H2c. DIF provides financial support for agricultural technology development and increases the level of agricultural product trade, thereby reducing carbon emissions.

Moderation Effect Test

Table 7 reports the moderation test results, where the scale of farmland management (Lscale) is used as a moderating variable. The interaction term (LnDIF×Lscale)

Table 5. Heterogeneity Test: location and function positioning and regional characteristics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Major grain producing areas	Non-major grain producing areas	Yellow River	Yangtze River	Songhua River
lnDIF	-0.076**	-0.034***	-0.082	-0.144**	-0.018
	(0.037)	(0.009)	(0.048)	(0.063)	(0.110)
Controls	YES	YES	YES	YES	YES
Constant	0.715***	0.498***	0.077	0.846*	-0.009
	(0.221)	(0.092)	(0.279)	(0.420)	(0.948)
N	130	180	40	60	30
R-squared	0.964	0.941	0.986	0.985	0.989
Province FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Table 6. Influence Mechanism Test

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLE	Entre	CEI	Aisu	CEI	Atrade	CEI
lnDIF	0.037**	-0.028***	0.010**	-0.019**	1.980***	-0.052***
	(0.017)	(0.009)	(0.005)	(0.008)	(0.609)	(0.018)
Entre		-0.121*				
		(0.070)				
Aisu				-1.006***		
				(0.102)		
Atrade						-0.003**
						(0.001)
Province FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Constant	-0.127	0.373***	1.014***	1.399***	1.693	0.474***
	(0.091)	(0.072)	(0.022)	(0.138)	(3.204)	(0.090)
Observations	310	310	310	310	310	310
Controls	YES	YES	YES	YES	YES	YES
R-squared	0.826	0.943	0.995	0.953	0.954	0.931

is positive and significant, indicating that the scale of farmland management plays a negative moderating role in the impact of DIF on agricultural CEI. When the scale of farmland management is higher, the effect of DIF on reducing carbon emissions is correspondingly weakened, supporting hypothesis H3. The coefficient for the moderating variable, the scale of farmland management, is significantly negative, suggesting that a higher scale of farmland management can significantly reduce carbon emissions. Overall, there is a substitution relationship between DIF and the scale of farmland management, and their respective effects on agricultural carbon reduction offset each other.

Table 7. Moderating Effects Estimation

VARIABLES	CEI
lnDIF	-0.058***
	(0.013)
Lscale	-0.149***
	(0.031)
LnDIF×Lscale	0.024***
	(0.005)
Province FE	YES
Year FE	YES
Constant	0.549***
	(0.079)
Controls	YES
Observations	310
R-squared	0.950

Threshold Effect Test

Under varying levels of digital rural development, the impact of DIF on carbon emissions may exhibit heterogeneity. Therefore, this study utilizes bootstrapping with 300 samples to investigate the threshold effect of digital rural development. The results in Table 8 indicate that the p-values for a single threshold and a double threshold are 0.033 and 0.167, respectively. This implies that the influence of DIF on agricultural CEI has a single threshold effect when the degree of digital rural development is employed.

Table 8. Threshold Effect Analysis

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	0.085	0.0003	44.47**	0.033	32.001	39.103	49.867
Double	0.076	0.0003	36.91	0.167	61.430	83.227	108.993

Table 9 presents the results of the threshold effect regression analysis concerning the level of digital rural development and the threshold value of 0.0178 divides the influence into two intervals. In the first interval (CEI≤0.0178), the coefficient representing the impact is -0.006. In the second interval (CEI > 0.0178), the coefficient representing the impact is -0.022. As the level of digital rural development increases, DIF enhances its inhibitory effect. This phenomenon can be explained by the fact that in the early stages, rural digital development lagged, thereby weakening the inhibitory effect of DIF on agricultural CEI. However, with the improvement of digital infrastructure and the expansion of the depth and breadth of DIF, rural farmers' access to financial resources has broadened. This, in turn, led to advancements in green agricultural technologies and production efficiency.

Consequently, the carbon reduction effect brought about by DIF strengthens. As a result, hypothesis H4 is validated.

Table 9. Regression Results of the Threshold Effects

VARIABLES	CEI
lnDIF(≦0.0178)	-0.006*
	(0.004)
lnDIF (> 0.0178)	-0.022***
	(0.002)
Controls	YES
R-squared	0.815

Sensitivity Analysis

Replacement of Explanatory Variables

Considering that the impact of DIF on agricultural CEI may exhibit lag effects, this study conducted regressions with digital inclusive finance lagged by one period and two periods to ensure the accuracy of the results. The results in columns (1) and (2) of Table 10 indicate that the coefficients for the first-order and second-order lag terms are both negative and significant. Hypothesis 1 is once again confirmed.

Exclusion of Specific Regions

Recognizing that the development levels of DIF and agriculture in direct-administered municipal areas may differ from other regions, we excluded samples from the four direct-administered municipal areas and conducted the regression again. The results are shown in column (3) of Table 10. It is evident that the coefficient for DIF is -0.030 and significant, reaffirming the robustness of the baseline results.

Table 10. Robustness test results

VARIABLES	(1) CEI	(2) CEI	(3) CEI
L.lnDIF	-0.023**		
	(0.010)		
L2.lnDIF		-0.024**	
		(0.011)	
LnDIF			-0.030***
			(0.009)
Controls	YES	YES	YES
Constant	0.357***	0.361***	0.398***
	(0.082)	(0.094)	(0.120)
Observations	279	248	270
R-squared	0.941	0.943	0.953

Quantile Regression

To effectively analyze the asymmetric impact of DIF, panel quantile regression with quantiles set at 0.25, 0.5, and 0.75 is employed. The results are in Table 11 and reveal that the effect of DIF is significantly negative at all quantiles. This is consistent with the baseline results. Furthermore, as the quantile level increases, the coefficients exhibit a decreasing trend, although the significance level remains at a 1% level. This suggests that the inhibitory effect of DIF is slightly weakened as the level of carbon emissions in agriculture increases.

Table 11. Robustness test results:quantile regression

VARIABLES	(1)q25	(2)q50	(3)q75
lnDIF	-0.029***	-0.032***	-0.037***
	(0.006)	(0.007)	(0.006)
Indus	-0.065**	0.070	0.164**
	(0.032)	(0.073)	(0.078)
Agdp	-0.037***	-0.020***	-0.034**
	(0.011)	(0.006)	(0.014)
Amode	0.007*	-0.008***	-0.008**
	(0.004)	(0.003)	(0.003)
Stru	0.168***	0.102***	0.096*
	(0.032)	(0.032)	(0.054)
Isu	0.054	0.138***	0.110***
	(0.033)	(0.038)	(0.037)
Constant	0.195***	0.270***	0.306***
	(0.053)	(0.057)	(0.044)
Observations	310	310	310

Endogeneity Test

Due to the possibility of reverse causality, omitted relevant explanatory variables, and other endogeneity issues between DIF and agricultural CEI, the results may be subject to errors. Hence, an instrumental variable (IV) approach to mitigate endogeneity issues is applied. First, the one-period lag and two-period lag of DIF are chosen as instrumental variables. Second, mobile phone penetration rates are used as instrumental variables in a 2SLS regression analysis. Table 12 presents the findings from the endogeneity test. When the one-period and two-period lags of DIF are employed as instruments, the impact of DIF on agricultural CEI is significantly negative. In column (3), when mobile phone penetration rates are used as instruments, the coefficient for DIF remains negative and is significant.

Table 12. Endogeneity Tset

VARIABLES	(1)CEI	(2)CEI	(3)CEI
L.lnDIF	-0.067**		
	(0.026)		
L2.lnDIF		-0.117**	
		(0.046)	
Phone			-0.081*
			(0.048)
Controls	YES	YES	YES
Constant	0.572***	0.890***	0.552***
	(0.167)	(0.287)	(0.173)
N	279	248	310
R-squared	0.942	0.944	0.934

Conclusions

This study utilized Chinese provincial data from 2011 to 2020 and examined the impact mechanisms of DIF on agricultural carbon emissions. The conclusions are as follows: (1) DIF significantly lowers the carbon emissions associated with agriculture. When examining sub-dimensions, both coverage breadth and usage depth exhibit negative effects on carbon emissions, with usage depth having the strongest effect. Regarding regional heterogeneity, the impact is stronger in non-grain-producing areas. Furthermore, within the grain-producing areas, there is a significant negative impact in the Yangtze River basin. (2) The impact of DIF on agricultural CEI operates through the mediation of enhanced entrepreneurial vigor among rural households, the advancement of the agricultural industry structure, and the level of agricultural product trade. (3) The scale of agricultural land operations and DIF exhibit a substitution effect in inhibiting carbon emissions. (4) DIF exhibits a single threshold effect when considering the level of digital rural development as the threshold. (5) Robustness tests were conducted and confirmed the consistency of the research findings.

Considering the findings, this study provided these recommendations. On one hand, governments should intensify their support for the development of DIF to enhance its role in reducing carbon emissions. This point is similar to some scholars' research views [30]. Policymakers can utilize digital technologies to remove traditional financial barriers, thereby promoting carbon reduction in agriculture. This could be achieved through continued efforts in building digital infrastructure, expanding rural access to the Internet, and increasing public awareness of DIF's benefits. On the other hand, the innovative and entrepreneurial effects of DIF should be fully harnessed to support green agricultural innovations. This includes optimizing the allocation of production factors, advancing the sophistication of the industry structure, and facilitating technological advancements in agriculture to improve international trade in agricultural products.

Nevertheless, this study also has several limitations. First, the availability of data was restricted to the provincial level due to missing data in many prefecture-level cities. Second, this research considered six aspects when measuring agricultural carbon emissions, including fertilizers, pesticides, diesel, plastic film usage, irrigation, and plowing. However, factors such as agricultural cultivation practices and crop types may also influence agricultural carbon emissions and warrant further exploration. Third, some studies have analyzed the impact of sustainable energy policies on environmental quality [31, 32]. However, this paper does not consider the impact of related policies and this can be analyzed in further studies.

Conflicts of Interest

The authors declare no conflict of interest.

Funding

This work was supported by the Research Start-up Fund Project by Jiangsu Ocean University (KQ19060) and the Project of Haiyan by Lianyungang City (KK22006)

References

1. ADEBAYO T.S., ÖZKAN O., EWEADE B.S. Do energy efficiency R&D investments and information and communication technologies promote environmental sustainability in Sweden? A quantile-on-quantile KRLS investigation. Journal of Cleaner Production, **440**, 140832, **2024**.
2. AKRAM R., IBRAHIM R.L., WANG Z., ADEBAYO T.S., IRFAN M. Neutralizing the surging emissions amidst natural resource dependence, eco-innovation, and green energy in G7 countries: Insights for global environmental sustainability. Journal of Environmental Management, **344**, 118560, **2023**.
3. HUANG S.J. Digital finance development and household leverage in China: evidence from the CFPS. World Scientific Research Journal, **7** (2), 103, **2021**.
4. JOHNSON J., FRANZLUEBBERS A., WEYERS S., REICOSKY D. Agricultural opportunities to mitigate greenhouse gas emissions. Environmental pollution, **150**, 107, **2007**.
5. WU D., ZHANG Z.W., LIU D., ZHANG L.L., LI M., KHAN M.I., LI X., CUI S. Calculation and analysis of agricultural carbon emission efficiency considering water-energy-food pressure: Modeling and application. Science of The Total Environment, **907**, 167819, **2023**.
6. LI S., WANG Z. Time, Spatial and Component Characteristics of Agricultural Carbon Emissions of China. Agriculture, **13,** 214, **2023**.
7. HAN H.B., ZHONG Z.Q., GUO Y., XI F., LIU S.L. Coupling and decoupling effects of agricultural carbon emissions in China and their driving factors. Environmental Science and Pollution Research, **25**, 25280, **2018**.

8. ZHAO R., LIU Y., TIAN M., DING M., CAO L., ZHANG Z., CHUAI X., XIAO L., YAO L. Impacts of water and land resources exploitation on agricultural carbon emissions: The water-land-energy-carbon nexus. Land Use Policy, **72**, 480, **2018**.
9. WANG R., ZHANG Y., ZOU C. How does agricultural specialization affect carbon emissions in China? Journal of Cleaner Production, **370**, 133463, **2022**.
10. ZHANG Z., TIAN Y., CHEN Y.H. Can agricultural credit subsidies affect county-level carbon intensity in China? Sustainable Production and Consumption, **38**, 80, **2023**.
11. DU Y.Y., LIU H.B., HUANG H., LI X. The carbon emission reduction effect of agricultural policy—evidence from China. Journal of Cleaner Production, **406**, 137005, **2023**.
12. CHEN M. Research on threshold effect of digital inclusive finance and regional urban-rural income gap. Frontier in Economics and Management, **2** (8), 255, **2021**.
13. FENG S.L., ZHANG R., LI G.X. Environmental decentralization, digital finance, and green technology innovation. Structural Change and Economic Dynamics, **61**, 70, **2022**.
14. ZHONG K.Y. Does the digital finance revolution validate the Environmental Kuznets Curve? Empirical findings from China. PLOS ONE, **17** (1), e0257498, **2022**.
15. ZHANG M.L., LIU Y. Influence of digital finance and green technology innovation on China's carbon emission efficiency: empirical analysis based on spatial metrology. Science of The Total Environment, **838** (10), 156463, **2022**.
16. LIN H., ZHANG Z. The impacts of digital finance development on household income, consumption, and financial asset holding: an extreme value analysis of China's microdata. Personal and Ubiquitous Computing, **27**, 1607, **2023**.
17. GAO Q., CHENG C., SUN G., LI J.F. The Impact of Digital Inclusive Finance on Agricultural Green Total Factor Productivity: Evidence from China. Frontiers in Ecology and Evolution, **10**, 905644, **2022**.
18. ZHANG W., HUANG M., SHEN P.C., LIU X.M. Can digital inclusive finance promote agricultural green development? Environmental Science and Pollution Research, 1, **2023**.
19. GOMBER P., KOCH J.A., SIERING M. Digital Finance and FinTech: current research and future research directions. Journal of Business Economics, **87** (5), 537, **2017**.
20. CAO S., NIE L., SUN H.P., SUN W.F., TAGHIZADEH-HESARY F. Digital finance, green technological innovation, and energy-environmental performance: Evidence from China's regional economies. Journal of Cleaner Production, **327**, 129458, **2021**.
21. BECK T., PAMUK H., RAMRATTAN R., URAS B.R. Payment Instruments, Finance and Development. Journal of Development Economics, **133**, 162, **2018**.
22. SOLEAS E. Environmental factors impacting the motivation to innovate: a systematic review. Journal of Innovation Entrepreneurship, **10** (1), 17, **2021**.
23. LI Y., MA K. Research on the Path of Digital Inclusive Finance's Influence on Industrial Structure Upgrade. 2021 International Conference on Economic Development and Business Culture (ICEDBC 2021), 77, **2021**.
24. LIN Y. Travel Costs and Urban Specialization Patterns: Evidence from China's High Speed Railway System. Journal of Urban Economics, **98** (5), 98, **2016**.
25. ZHOU X., ZHANG J., LI J. Industrial Structural Transformation and Carbon Dioxide Emissions in China. Energy Policy, **57**, 43, **2013**.
26. YANG J. Does International Agricultural Trade Matter for Carbon Emissions: A Case Study of the Area Along "the Belt and Road Initiative". IOP Conference Series: Earth and Environmental Science, **310** (5), **2019**.
27. GROSSMAN G., KRUEGER A.B. Environmental Impacts of a North American Free Trade Agreement. C.E.P.R. Discussion Papers, **1991**.
28. BONATO M. Realized correlations, betas, and volatility spillover in the agricultural commodity market: What has changed? Journal of International Financial Markets Institutions and Money, **62**, 184, **2019**.
29. WU Y.Y., XI X.C., TANG X., LUO D.M., GU B.J., LAM S.K., VITOUSEK P.M., CHEN D.L. Policy distortions, farm size, and the overuse of agricultural chemicals in China. Proceedings of the National Academy of Sciences, **115** (27), 7010, **2018**.
30. ADEBAYO T.S., ÖZKAN O. Investigating the influence of socioeconomic conditions, renewable energy and eco-innovation on environmental degradation in the United States: A wavelet quantile-based analysis. Journal of Cleaner Production, **434**, 140321, **2024**.
31. LIU X., ADEBAYO T.S., RAMZAN M., ULLAH S., ABBAS S., OLANREWAJU V.O. Do coal efficiency, climate policy uncertainty and green energy consumption promote environmental sustainability in the United States? An application of novel wavelet tools. Journal of Cleaner Production, **417**, 137851, **2023**.
32. ADEBAYO T.S., KARTAL M.T., ULLAH S. Role of hydroelectricity and natural gas consumption on environmental sustainability in the United States: Evidence from novel time-frequency approaches. Journal of Environmental Management, **328**, 116987, **2023**.