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Article

Does Digital Financial Inclusion Affect Agricultural Eco-Efficiency? A Case Study on China

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Abstract: Agricultural eco-efficiency can effectively reflect the coordinated green and balanced development of rural resources, and digital financial inclusion provides a strong financial power in the process of long-term balanced development of rural areas. There may be a complex relationship between the two. Therefore, based on the panel data of 30 provinces, autonomous regions, and municipalities in mainland China from 2011 to 2018, this paper explores the impact of digital financial inclusion on agricultural eco-efficiency through the differential GMM method. Further, the paper analyzes how digital financial inclusion influences agricultural eco-efficiency by influencing the agricultural scientific and technological investment. The following conclusions are drawn. First, there is a positive U-shaped nonlinear relationship between digital financial inclusion and agricultural eco-efficiency. Second, the impact of digital financial inclusion on agricultural eco-efficiency is of regional heterogeneity. Digital financial inclusion has a significant positive U-shaped impact on agricultural eco-efficiency in central China but has no significant impact on Eastern and Western China. Third, agricultural R&D investment will intensify the promotion effect of digital financial inclusion on agricultural eco-efficiency.

Keywords: digital financial inclusion; agricultural eco-efficiency; agricultural R&D investment

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1. Introduction

1.1. Background and Research Motivation

With the aggravation of the greenhouse effect crisis, the calls for low-carbon development, green sustainable development, and early realization of carbon neutrality in all countries in the world are increasingly rising. As one of the core industries, the green sustainable development of agriculture also receives the focus of attention. Green and sustainable development of agriculture means that in the process of agricultural production, not only short-term economic benefits should be paid attention to, but also long-term ecological benefits should be emphasized so that agricultural input, agricultural output, and ecological benefits can reach the optimal balance. The basic index to measure the balance of the three is agricultural eco-efficiency [1]. The concept of eco-efficiency was first put forward by German scholars Schaltgger and Sturm in 1990, and it mainly reflects the relationship between input and output. Agricultural eco-efficiency is the extension and expansion of eco-efficiency in the agricultural field. Its deep meaning is that under a certain combination of agricultural input elements, the agricultural output can be obtained as much as possible with as little resource consumption and environmental pollution as possible so as to maximize the output under the condition of limited resource endowment.

In the process of modernization, agriculture gradually forms an industrialized mode of production and management, and its formation and development cannot be separated from the support of rural finance. Due to the practical issues such as scattered population, aging population, lack of collateral for small enterprises and farmers in rural areas, the original financial development concepts, modes, and methods have been hindered frequently in rural areas. In order to solve these problems, the G20 Summit in 2016 formally proposed to break through the original financial development problems through the development and application of digital technology to build a digital inclusive financial system. In the white paper: "Global Standard-setting Institutions and Financial Inclusion—An Evolving Landscape", digital financial inclusion refers to all actions that promote financial inclusion through the use of digital financial services, including the use of digital technology to provide a series of formal financial services for groups without access to financial services or lack financial services [2]. The development of digital financial inclusion can effectively reduce the supply cost of financial services, improve the inclusion of financial services, reduce the threshold of farmers' financing and entrepreneurship, and have a positive impact on farmers' entrepreneurship through information trust upgrading. Under the vigorous promotion of digital financial inclusion, the industrialization and advanced development of agriculture have received abundant financial support; local leading agricultural enterprises can use Internet technology to improve the efficiency of the loan process, which creates conditions for expanding the production scale and improving the level of agricultural technology innovation, as well as creating local characteristic industries. Local farmers can also obtain reasonably priced, safe, and convenient financial services through digital financial inclusion to allocate more high-tech products so as to improve their income [3]. It can be seen that digital financial inclusion can provide sufficient financial power for agricultural industrialization and advanced development and also create conditions for improving agricultural eco-efficiency. As one of the major agricultural countries in the world, China has been continuously strengthening the construction of digital agriculture and rural areas in recent years, enhancing digital productivity, actively implementing the rural revitalization strategy, and striving to build a green new countryside. Therefore, taking China at the present stage as a case, this paper tries to fully reflect the relationship between digital financial inclusion and agricultural eco-efficiency.

1.2. Literature Review and Contribution

Existing literature mainly focuses on two aspects, i.e., the relationship between agricultural eco-efficiency and regional economic development; and the impact of digital financial inclusion on rural development.

The first is to analyze the influencing factors and the spatial effect of agricultural eco-efficiency. Based on China's grain production data from 1997 to 2015, Song et al. [4] used the WF-SFA method to measure China's agricultural eco-efficiency and found that the value of China's agricultural eco-efficiency was within the range of 0.424–0.986. Through the econometric test, it is concluded that GDP per capita, fiscal expenditure level of environmental protection, and other variables have a positive impact on agricultural eco-efficiency. Eder et al. [5] calculated the agricultural eco-efficiency of 135 crop farms in Austria by the DEA method and analyzed the impact of land leasing by using the truncated regression model. The results showed that land leasing would inhibit the improvement of agricultural eco-efficiency, and agricultural tenants would maximize short-term economic efficiency, leading to over-exploitation of the soil and reduction in agricultural eco-efficiency. Zeng et al. [6] used the quantile regression method to analyze the effects of crop diversity on agricultural yield and agricultural eco-efficiency in China, and the results showed that crop diversity had an inverted "U" shaped relationship with agricultural yield but had a positive impact on agricultural eco-efficiency. According to the further regional heterogeneity test they conducted, crop diversity has a positive effect on the agricultural eco-efficiency in the eastern and central regions but has an inhibiting effect on the agricultural eco-efficiency in the northeast and the west. Liu et al. [7] adopted the 1978–2017 provincial panel data of China and the super-SBM model to measure the agricultural eco-efficiency and explore the corresponding influencing factors. The results indicated that there was heterogeneity in the agricultural eco-efficiency of different regions; the agricultural planting structure, agricultural input force, and other factors would promote the impact of agricultural eco-efficiency. Based on the panel data of 31 Chinese provinces from 2006 to 2018, Liao et al. [8] used the Geo-detector model to explore the driving factors of the spatial differences of agricultural eco-efficiency, and the results show that the agricultural eco-efficiency continues to decline year by year; in addition, there is spatial heterogeneity among different regions of agricultural eco-efficiency, and the spatial correlation distribution of agricultural eco-efficiency presents the characteristics of random distribution. Akbar et al. [9] selected the panel data of 31 Chinese provinces from 2007 to 2017 and used the DEA method to calculate the agricultural eco-efficiency of each province, and they also analyzed the influencing factors of agricultural eco-efficiency through the impact of carbon transfer network. It was found that agricultural eco-efficiency was on the rise in general, with significant regional heterogeneity; the information level, agricultural planting structure, and other factors could promote the impact of agricultural eco-efficiency. Zhuang et al. [10] estimated the agricultural eco-efficiency in China based on the two-stage SBM method combined with the entropy method, and they found that the agricultural eco-efficiency was significantly higher than the level of rural economic development, and there was significant heterogeneity in the agricultural eco-efficiency in different regions.

The second is to study the relationship between financial inclusion and rural development. Liu et al. [3] took the Chinese household database as a sample to conduct an empirical study on the impact of digital financial inclusion on farmers' agricultural production decisions. The results show that digital financial inclusion can encourage rural families to reduce agricultural production, widen the gap between the efficiency of non-agricultural economic activities and agricultural production efficiency, and restrain the improvement of farmers' agricultural output. He and Du [11] made an empirical analysis of financial inclusion and urban-rural income gap based on the economic panel data of 31 provinces in China from 2006 to 2018. The results show that financial inclusion mainly narrows the urban-rural gap by improving the financial quality, but this effect is weaker than the effect of urbanization on the urban-rural income gap; in addition, urbanization and inclusive finance have weakened each other in narrowing the urban-rural income gap. Li et al. [12] used the coefficient of variation method to measure the development level of provincial inclusive finance based on the panel data of China's provinces from 2010 to 2016, and they found that there was large regional heterogeneity in the level of financial inclusion. The panel econometric model is also used to analyze the impact of the development level of financial inclusion on the urban-rural income gap, and it is concluded that the development of financial inclusion can promote the narrowing of the urban-rural income gap. Yang and Fu [13] explored the relationship between the development of financial inclusion and the income of the poor population with different labor abilities in rural China based on the household panel survey data of 21 provinces in China from 2010 to 2016. The results show that the poor population with different labor abilities has different effects on the poverty alleviation of financial inclusion development; the choice of service objects of financial institutions also has a certain influence on it. Li et al. [14] studied the influence of digital financial inclusion on resident consumption based on the survey of Chinese household finance in 2013, 2015, and 2017 and the panel data of the digital financial inclusion index developed by Peking University. The results show that digital financial inclusion can promote resident consumption, and through the heterogeneity analysis, it can be concluded that different levels of assets and financial literacy will affect the promoting effect.

Throughout the above studies, domestic and foreign scholars mainly focus on the analysis of the influencing factors and spatial effects of agricultural eco-efficiency, providing many relevant theories and empirical research methods for the study of eco-efficiency. Many scholars have studied rural development from a micro perspective. Some scholars have analyzed the impact of digital financial inclusion on rural economic development and individual consumption of rural households. However, there are few studies on the impact of digital financial inclusion on rural sustainable development. Under the trend of digitization, the impact of digital financial inclusion on rural ecological efficiency is obvious. However, the form of this influence relationship needs to be further explained through empirical analysis. By exploring the relationship between the two, this paper further shows that digital financial inclusion has a phased impact on rural development. Local governments should make different decisions reasonably according to their own situation to promote the positive role of digital financial inclusion on rural ecological efficiency, rather than blindly developing digital financial inclusion to promote rural sustainable development. Therefore, based on the existing research, this paper explores the impact and mechanism of digital financial inclusion on agricultural eco-efficiency by using the panel data of 30 provinces, autonomous regions, and municipalities in mainland China from 2011 to 2017. Compared with previous studies, the marginal contribution of this paper is mainly reflected in the following three aspects. First, this paper innovatively explores the impact of digital financial inclusion on agricultural eco-efficiency, which enriches the research topic in this field and adds new impetus to the sustainable development of agriculture. This paper uses the super-efficiency SBM-DEA method to measure the agricultural eco-efficiency; through the differential GMM method, this paper explores whether digital financial inclusion can promote the improvement of agricultural eco-efficiency and then explains that digital financial inclusion can promote the sustainable development of rural areas, which provides reasonable support for other countries to promote the digital financial inclusion in rural areas. Second, this paper further expands the research on the regional heterogeneity of digital financial inclusion on agricultural eco-efficiency. Due to the vast territory of China, the development of different provinces and cities is different. In order to further explore whether digital financial inclusion has a significantly different impact on the eco-efficiency of different regions, this paper analyzes the impact of digital financial inclusion on the agricultural eco-efficiency of different regions through sub-sample regression. Thirdly, in order to explore the influence mechanism of digital financial inclusion on agricultural eco-efficiency, this paper analyzes whether the investment of agricultural research and development have a moderating effect on the impact of digital financial inclusion on agricultural eco-efficiency by adding a moderating variable, namely agricultural research and development (R&D) investment.

This paper is divided into five sections: the Section 2 is the introduction of the theory and research methods; Section 3 is the empirical results and analysis; the Section 4 is the further discussion and conclusions.

2. Materials and Methods

2.1. Theoretical Analysis and Research Hypothesis

Digital financial inclusion is the application of a series of related technologies such as computer information processing and big data analysis in the financial field through Internet technology. It promotes the sharing of information, effectively reduces transaction costs and the threshold of financial services, and expands the scope of financial services and coverage; it has the advantages of digital financial sharing, convenience, safety, low cost, and low threshold. Digital financial inclusion well interprets the original intention and goal of financial technology, and it is a digital way to enable people who have long been excluded by the modern financial service industry to enjoy formal financial services [15]. Therefore, digital financial inclusion can reduce transaction costs and the threshold of financial services to make it more convenient for financial services to enter rural areas so that farmers can experience more favorable and safe formal financial services and thus exert a certain impact on agricultural eco-efficiency. In the early development of digital financial inclusion in rural areas, there may be great resistance and some negative effects on agricultural eco-efficiency. Rural infrastructure construction, the farmers' financial literacy, and other factors will make it more difficult for digital financial inclusion to spread widely in rural areas; the cost will increase sharply, and farmers' initial willingness to loan and lack of financial knowledge may lead to a low use rate of capital investment and low return rate. Digital financial inclusion provides a powerful capital impetus for the industrial scale and technological R&D innovation of rural enterprises. However, in the early stage of the technological innovation and development of rural enterprises, R&D, achievement transformation, and promotion are all highly uncertain, which is easy to produce inefficient or even ineffective innovation, and rural enterprises are difficult to obtain expected return. Thus, the investment of enterprises for environmental protection is squeezed out, which can inhibit the improvement of agricultural eco-efficiency. With the development of digital financial inclusion, the relevant construction is becoming more and more mature in rural areas, which may have a positive impact on agricultural eco-efficiency. When the consumption awareness and financial level of farmers are gradually improved, the economic benefits brought by digital financial inclusion will increase, which can effectively stimulate the growth of rural demand and improve the rural consumption level [14]. The mature development of digital financial inclusion can provide more funds and advanced services for the innovation activities and agricultural technology R&D of farmers and rural enterprises. After experiencing the low level of R&D innovation in the initial stage, digital financial inclusion can further improve the level of agricultural innovation, which enables farmers and enterprises to effectively develop and use green production technology and develop green innovation products [16], thus improving the use rate of resources in the production process, reducing the emission of pollutants and improving the agricultural eco-efficiency. Based on the above analysis, Hypothesis 1 is proposed as follows:

Hypothesis 1 (H1). *Digital financial inclusion has a U-shaped nonlinear relationship with agricultural eco-efficiency.*

Due to the imbalanced and inadequate regional economic development in China, the level of rural development among different regions varies greatly. There are great differences in agricultural structure, financial development level, and agricultural innovation level among the eastern, central, and western regions of mainland China. Many studies have found that eco-efficiency had strong spatial heterogeneity [17,18]. The development level of digital financial inclusion is also divergent in different regions. In terms of the dimensions of coverage, use depth, and digitization level of digital financial inclusion, there are obvious differences among various regions [19]. Generally speaking, in areas with low levels of financial development and backward agricultural technology, digital financial inclusion is difficult to drive agricultural development in the short term and may even affect the original agricultural structure and cause scale diseconomy, thus inhibiting the improvement of agricultural eco-efficiency, which indicates that the area may be on the left side of the "U"-shaped curve at this time. In areas with a relatively high level of financial development and relatively mature agricultural technology, digital financial inclusion can bring sufficient funds and advanced services to them, improve the local environmental level, increase the effective use of resources, and increase green innovation, which in turn promotes the improvement of agricultural ecological efficiency [20], indicating that the region may be on the right side of the "U" shaped curve at this time. This shows that digital financial inclusion may have a heterogeneous impact on the agricultural eco-efficiency among different regions. Therefore, this paper proposes Hypothesis 2 as follows.

Hypothesis 2 (H2). *There are significant differences in the impact of digital financial inclusion on agricultural eco-efficiency in different regions.*

According to the endogenous growth theory, technological progress is the decisive factor of economic growth. In theory, agricultural R&D investment and agricultural innovation can significantly improve agricultural eco-efficiency [21]. The development of digital financial inclusion can provide sufficient funds and the latest data information for the agricultural R&D technology and technological innovation of rural farmers and enterprises so as to increase the local investment in agricultural R&D, improve the level of agricultural innovation, promote the use of green production technology [20], cultivate more green agricultural products, and achieve both economic and environmental benefits, that is, promoting the high development of agricultural eco-efficiency. Therefore, Hypothesis 3 is proposed as follows.

Hypothesis 3 (H3). *Agricultural R&D investment will intensify the promotion of digital financial inclusion on agricultural eco-efficiency.*

2.2. Research Methods

The focus of this paper is to explore the impact of digital financial inclusion on agricultural eco-efficiency. Specifically, it tests the impact of the Peking University Digital Financial Inclusion Index on agricultural production efficiency measured by super-efficiency SBM-DEA, and this paper also analyzes the moderating effect of digital financial inclusion on agricultural eco-efficiency with agricultural R&D investment as mediating variable. Based on the availability of data, the research samples of this paper are 30 provinces, autonomous regions, and municipalities in China's mainland. Because of the strong heterogeneity, the time trend of agricultural eco-efficiency of these regions, and the endogenous problem between variables, this paper uses the differential GMM method with time control effect for empirical analysis. With Model (1) as the benchmark model, this paper tests whether there is a nonlinear relationship between digital financial inclusion and agricultural eco-efficiency so as to verify Hypotheses 1.

$$\mathrm{AEE}_{it} = \alpha_0 + \alpha_1 DFI_{it} + \alpha_2 DFI2_{it} + \sum_J^N \beta_j CV_{ijt} + \tau_i + \gamma_t + \mu_{it} \tag{1}$$

Secondly, considering the great differences in the economic development level of the Chinese mainland, this paper uses Model (2) to analyze whether there is regional heterogeneity in the relationship between digital financial inclusion and agricultural eco-efficiency through the sub-sample regression method so as to verify Hypotheses 2. Due to the small number of sub-regional samples in this paper, there is a problem that the moment is not rank when using the GMM method. Therefore, this paper selects the 2SLS estimation method to solve the problems of sample size and endogenous variables.

$$\mathrm{RAEE}_{it} = \alpha_3 + \alpha_4 DFI_{i,t-1} + \alpha_5 DFI2_{i,t-1} + \sum_J^N \beta_j CV_{ijt} + \tau_i + \gamma_t + \mu_{it} \tag{2}$$

This paper adds the interaction term of digital financial inclusion and agricultural R&D investment, as well as the interaction term of digital financial inclusion and agricultural innovation level into Model (1), respectively, to build (3) to further analyze the moderating effect of agricultural R&D investment on the impact of digital financial inclusion on agricultural eco-efficiency, thus verifying Hypothesis 3.

$$\mathrm{AEE2}_{it} = \alpha_6 + \alpha_7 FRD_{it} + \alpha_8 DFI_{it} + \alpha_9 DFI2_{it} + \sum_J^N \beta_j CV_{ijt} + \tau_i + \gamma_t + \mu_{it} \tag{3}$$

where AEE_{it} and $\mathrm{AEE2}_{it}$ represent the agricultural eco-efficiency of province (autonomous region or municipality) i in year t; where RAEE_{it} represents the regional agricultural eco-efficiency of province (autonomous region or municipality) i in year t; DFI_{it} represents the degree of digital financial inclusion of province (autonomous region or municipality) i in year t; $DFI2_{it}$ is the square term of DFI_{it}, i.e., $DFI2_{it} = DFI_{it} * DFI_{it}$; FRD_{it} represents the interaction term between digital financial inclusion and agricultural R&D investment of province (autonomous region or municipality) i in year t, specifically, $FRD_{it} = DFI_{it} * ARD_{it}$; CV_{ijt} is the j-th control variable of province (autonomous region or municipality) i in year t; the coefficient α_i (i = 1, 2, 3) is what this paper focuses on. τ_i is the individual fixed effect; γ_t is time effect; α_0 is a constant term, and μ_{it} is a random interference term.

2.3. Variable Description and Data Sources

The explained variable in this paper is agricultural eco-efficiency, which mainly emphasizes maximizing agricultural economic benefits with minimizing agricultural resources and environmental costs, reflecting the effects generated by certain agricultural ecological inputs. In this paper, the super-efficiency SBM-DEA method [22] is adopted to measure agricultural eco-efficiency. The primary premise is to select reasonable input and output indicators systems as well as appropriate characterization variables. First of all, the research object of this paper is agriculture in the narrow sense of each province or autonomous city; that is, it only refers to the planting industry, rather than the broad sense of agriculture, including agriculture, forestry, animal husbandry, and fishing. Secondly, in order to reflect the agricultural ecological efficiency, the input-output indicators selected in this paper will be as close to agricultural production activities as possible. In terms of factor input, this paper selects the crop sown area to represent the land and agricultural practitioners to represent the labor. Since the object of this study is to target the planting industry in Chinese mainland provinces, the selection of crop sown area can effectively reflect the specific land input. It is frequent to select indirect measures to obtain data of agricultural practitioners from the provinces and cities in the Chinese mainland with industrial representation and to represent labor input in the paper. In the process of agricultural production activities, the input factors will inevitably include a series of production inputs such as agricultural machinery, irrigation water, chemical fertilizer, and so on. The total power of agricultural machinery is used to characterize the investment of agricultural machinery in the paper. For agricultural irrigation water, the effective irrigation area is used to measure the input of irrigation water. In terms of chemical fertilizer, pesticide, and agricultural film input, this paper adopts the use of application amount of agricultural chemical fertilizer, pesticide usage, and agricultural membrane usage to characterize the above agricultural production input in turn as the energy use of agricultural production activities is mainly diesel. Therefore, this paper uses agricultural diesel usage to characterize the investment in energy sources. In terms of agricultural factor output, based on the relevant research of other scholars, this paper selects total agricultural production output value to represent the expected output level of agriculture and uses the comprehensive index of agricultural non-point source pollution and agricultural carbon emission to measure the unexpected output at the agricultural level. The reasons for choosing the above characterization variables are as follows. Firstly, these characterization variables are related to agricultural production activities and can effectively reflect the input-output of agricultural ecological efficiency. Secondly, in view of the availability and effectiveness of the data, most of the characterization variables in this paper can be found in the relevant statistical yearbooks of China, and the accuracy of the data is high. The units representing variables and relevant information are mentioned in the relevant yearbooks of China, which reduces the error caused by subjective selection. These input and output indicators, as shown in Table 1, are selected.

The measurement methods of agricultural eco-efficiency are complex and varied. Compared with other methods, the data including analysis (DEA) can not only carry out dimensionless data processing but also can measure the relative efficiency of agriculture scientifically without assigning weight to relevant input-output indicators artificially. What is more, the super-efficiency SBM-DEA can more effectively solve the problem that the traditional DEA model cannot sort effective decision-making units; therefore, this paper adopts the super-efficiency SBM-DEA model to calculate the agricultural eco-efficiency of 30 provinces and autonomous regions or municipalities in mainland China from 2011 to 2018 with the help of the DEA software according to the input and output indicators shown in Table 1. In this paper, the formula of super-efficiency SBM-DEA is placed in Appendix A so that readers can further understand the method to calculate AEE.

It is worth mentioning that the units of these input-output indicators do not contain specific significance. These input-output indicators represent the measurement values of all aspects in the calculation of AEE. Their numerical multiple conversion will not affect the value of AEE calculated by super-efficiency SBM-DEA. Therefore, this paper only selects one unit of these input-output indicators, which does not include all cases. The values of AEE calculated by them are the same.

Table 1. Description of the input-output indicators.

Primary Indicators	Secondary Indicators	Characterization Variables	Variable Description
Input	Land	Crop sown area (one thousand hectares)	None
	Labor	Agricultural practitioners (ten thousand people)	Agricultural personnel in the primary industry will be converted according to the proportion of the agricultural output value accounting for the total output value of agriculture, forestry, animal husbandry, and fishery
	Agricultural machinery	Total power of agricultural machinery (ten thousand kW)	None
	Irrigation water	Effective irrigation area (one thousand hectares)	None
	Chemical fertilizer	Application amount of agricultural chemical fertilizer (ten thousand tons)	None
	Pesticides	Pesticide usage (ton)	None
	Agricultural membrane	Agricultural membrane usage (ton)	None
	Energy sources	Agricultural diesel usage (ten thousand tons)	None
Expected output	Total output agricultural value	Total agricultural production output value (RMB 100 million)	Unified conversion into the constant price-output value in 2011;
Unexpected output	Agricultural pollution emissions	Comprehensive index of agricultural non-point source pollution	It is calculated by entropy method; chemical fertilizer application is multiplied by fertilizer loss index, pesticide and agricultural membrane residue by corresponding residual coefficient; fertilizer loss coefficient, pesticide residual coefficient, and pesticide membrane residual coefficient are 0.65, 0.5, 0.1, respectively
	Agricultural carbon emissions	Agricultural carbon emissions (ten thousand tons)	The number of carbon emission sources of chemical fertilizer, pesticide, agricultural membrane, agricultural diesel, agricultural irrigation, and tillage loss is multiplied by the corresponding emission coefficient; the corresponding emission coefficient, i.e., 0.8956, 4.934, 5.18, 0.5927, 20.476, 312.6

The original data are mainly derived from the "China Rural Statistical Yearbook", "China Agricultural Statistical Yearbook", "China Statistical Yearbook", and statistical yearbooks of various regions. The calculation results of agricultural eco-efficiency are consistent with the descriptive statistics of agricultural eco-efficiency in Table 2. See Table 2 for details.

Table 2. Descriptive statistics of variables of the whole sample and sub-samples.

	The Whole Sample			Eastern China			Central China			Western China		
VarName	**Obs**	**Mean**	**SD**	**Obs**	**Mean**	**SD**	**Obs**	**Mean**	**SD**	**Obs**	**Mean**	**SD**
AEE	240	0.83	0.28	96	0.96	0.19	72	0.62	0.19	72	0.87	0.30
DFI	240	1.84	0.85	96	2.06	0.87	72	1.79	0.83	72	1.72	0.82
DFI2	240	4.26	3.09	96	5.02	3.47	72	3.88	2.77	72	3.62	2.63
DAM	240	0.65	0.25	96	0.81	0.29	72	0.57	0.29	72	0.53	0.14
PS	240	2.67	2.88	96	2.07	1.08	72	4.25	1.08	72	1.90	0.75
FSA	240	0.11	0.03	96	0.09	0.03	72	0.12	0.03	72	0.13	0.02
ARD	240	4.26	2.94	96	4.96	3.53	72	4.49	3.53	72	3.10	1.91
AIL	240	73.20	86.32	96	91.82	98.41	72	90.28	98.41	72	31.31	35.54
ER	240	62,785.53	50,316.19	96	79,702.24	66,851.97	72	67,029.40	66,851.97	72	35,986.06	18,236.78

The core explanatory variable of this paper is digital financial inclusion, which is represented by the digital inclusive financial index of Peking University from 2011 to 2018 [23]. The digital financial inclusion index used in this paper is preprocessed, which reduces the data by 100 times, which will not change the significance of the explanatory variable DFI, but only change the size of its estimation coefficient. The reason why this paper uses data preprocessing for DFI is to facilitate the intuition of the later empirical results so as to enlarge the estimation coefficient of DFI by 100 times. It is worth mentioning that since the sub-index of DFI in the following does not directly participate in the empirical regression, this paper does not process the data of the sub-index of DFI. This may occur when the value of the sub-index is much larger than the DFI index, which is caused by data preprocessing.

This paper further analyzes how digital financial inclusion affects agricultural eco-efficiency through agricultural R&D investment [7]. Agricultural R&D investment is one of the important bridges between digital financial inclusion and agricultural ecological efficiency. The development of digital financial inclusion can inject more financial capital into agricultural development, increase investment in agricultural R&D, improve the level of technological innovation in agricultural production, reduce pollution and waste in the production process, improve resource use efficiency and technological progress, so as to improve AEE. Among them, agricultural R&D investment is measured by multiplying scientific and technological investment by the proportion of agricultural gross output value in regional GDP; the unit is 100 million yuan.

In order to control the influence of other characteristics at the provincial level on agricultural eco-efficiency, after referring to the research and analysis of many scholars [24], the following control variables are selected. From an economic point of view, this paper selects the level of financial support for agriculture as the corresponding control variable. The level of financial support for agriculture can effectively reflect the level of funds supporting agricultural development. Digital financial inclusion can promote the improvement of the level of financial support for agriculture and then have an impact on AEE. In agriculture, this paper selects the density of agricultural machinery, planting structure, and agricultural innovation level as relevant control variables. The density of agricultural machinery can effectively reflect the efficiency of mechanization in agricultural production. The planting structure reflects the rationality of agricultural production. The level of agricultural innovation reflects the degree of technological innovation in agricultural development. In the aspect of the environment, this paper selects the cost environmental regulation as the control variable, which can effectively reflect the regional awareness of environmental protection so as to achieve high-quality economic development. The above control variables are related to digital financial inclusion and agricultural ecological efficiency. The specific variable characterizations are shown in Table 3.

Table 3. Variable characterization and data sources.

Variable	Abbreviation	Characterization Variable	Source
Agricultural eco-efficiency	AEE	Calculated with the Super-efficiency SBM-DEA model	China Agricultural statistical yearbook, China Rural Statistical Yearbook, China financial statistical yearbook, China Statistical Yearbook
Digital financial inclusion	DFI	Peking University digital financial inclusion index	Peking University
The level of fiscal support for agriculture	FSA	Local fiscal expenditure on agriculture, forestry, and water conservancy/local fiscal expenditure in general budget	China Agricultural statistical yearbook, China Rural Statistical Yearbook, China financial statistical yearbook
Density of agricultural machinery	DAM	Total power of agricultural machinery/total sown area of crops	China Agricultural statistical yearbook, China Rural Statistical Yearbook
Planting structure	PS	Grain crop acreage/(crop sown acreage − grain crop acreage)	China Agricultural statistical yearbook, China Rural Statistical Yearbook
agricultural research investment	ARD	Multiplying scientific and technological investment by the proportion of agricultural gross output value in regional GDP	China Agricultural statistical yearbook, China Rural Statistical Yearbook, China financial statistical yearbook
agricultural innovation level	AIL	The number of applications for new varieties of agricultural plants	China Agricultural statistical yearbook, China Rural Statistical Yearbook, China Science and technology statistical yearbook
Cost-based environmental regulation	ER	The total amount of income from pollutant discharge fee of each province	China Environmental Statistical Yearbook, Statistical Yearbook of Provinces

The research samples of this paper are 30 provinces, autonomous regions, and municipalities in mainland China from 2011 to 2018. Due to too many missing data of some variables in Xizang, the data cannot be kept consistent, so it is finally deleted from the sample. In this paper, the interpolation method is used to supplement the missing data of some provinces. Data are from "China Statistical Yearbook", "China Rural Statistical Yearbook", "China Agricultural Statistical Yearbook", "China Energy Statistical Yearbook", "China Science and Technology Statistical Yearbook", "China Environmental Statistical Yearbook", the EPS database, and the statistical yearbook of 30 provinces.

Table 2 displays the descriptive statistics of the main research variables in this paper, including the full sample of mainland China, eastern China, central China, and western China. In order to eliminate the problem of heteroscedasticity, this paper preprocesses the data of existing variables and takes the natural logarithm of the control variables whose data form is the absolute logarithm.

It is worth noting that in the above data, agricultural R&D investment, agricultural innovation level, and cost-based environmental regulation are shown in absolute numbers; they are not treated by logarithm in descriptive statistics, and they are treated by natural logarithm in the follow-up empirical process.

In order to better describe the nonlinear relationship between AEE and DFI, this paper makes a scatter diagram of the nonlinear fitting relationship between them based on the data in Table 2. It is shown in Figure 1 below:

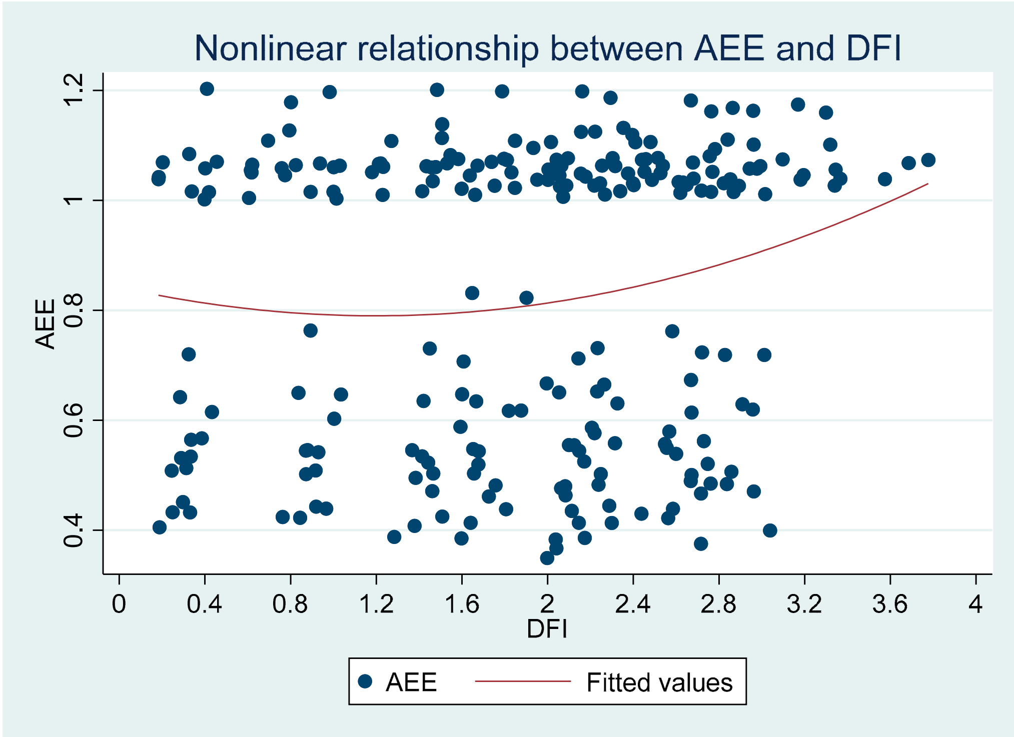

Figure 1. Scatter diagram of AEE and DFI.

It can be seen from Figure 1 that there may be some nonlinear relationship between AEE and DFI. According to the fitted nonlinear curve in Figure 1, there may be a "U"-shaped nonlinear relationship between AEE and DFI. Based on this, there is a "U" relationship between AEE and DFI, both from the theoretical analysis and data fitting. This paper further tests the relationship between them through empirical regression analysis.

3. Empirical Results and Analysis

Tests of the Benchmark Model

Due to China's vast territory and distinctive resource distribution, as well as great differences in development strategy, economic structure, and financial development level among different regions, the whole sample of mainland China is divided into the eastern region, central region, and western region in the regional heterogeneity test. Based on the benchmark regression Model (1) and Model (2), using the differential GMM method and 2SLS estimation method, this paper constructs regression analysis on the whole sample as well as three sub-samples to obtain the regression results as shown in Table 4, where Columns (1) shows the regression results of the differential GMM method, and Columns (2)–(4) show the regression results of 2SLS estimation.

Table 4. Benchmark model regression results of the full sample and sub-samples.

	Full Sample (1)	Eastern China (2)	Central China (3)	Western China (4)
	AEE	**RAEE**	**RAEE**	**RAEE**
DFI	−0.1877 *** (−4.7094)			
DFI2	0.0171 ** (2.9159)			
L.DFI		0.1932 (1.52)	−0.0461 * (−1.68)	0.0088 (0.41)
L.DFI2		−0.0081	0.0146 *	−0.0034

Table 4. *Cont.*

	Full Sample (1)	Eastern China (2)	Central China (3)	Western China (4)
	AEE	**RAEE**	**RAEE**	**RAEE**
		(−0.58)	(1.72)	(−0.45)
DAM	−0.1466 ***	−0.2182 ***	0.0039	−0.1586 *
	(−5.2370)	(−5.04)	(0.08)	(−1.79)
PS	−0.0010	0.0100 *	−0.0001	−0.0655 **
	(−0.8153)	(1.68)	(−0.09)	(−2.47)
FSA	−0.0523	−1.6225 ***	−0.6904	−0.3457
	(−0.3481)	(−2.78)	(−1.36)	(−1.17)
lnARD	0.0045	0.0467	0.0336	0.0635
	(1.6271)	(0.50)	(0.18)	(0.61)
lnAIL	−0.0070	0.0150	0.0104	−0.0000
	(−1.4033)	(1.35)	(1.39)	(−0.00)
lnER	0.0059 *	0.0281 ***	0.0570 *	0.0027
	(2.1764)	(3.42)	(1.82)	(0.14)
Individual effect	YES	YES	YES	YES
Time effect	YES	YES	YES	YES
_cons	1.1011 ***	0.2972	−0.1408	0.5322 **
	(4.5404)	(0.84)	(−0.31)	(2.37)
N	176	84	63	60

t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In addition, in order to reflect the empirical regression results in Table 4, this paper takes (1) in Table 4 as an example to describe the "U"-shaped nonlinear relationship between AEE and DFI. The specific graph is shown in Figure 2 below:

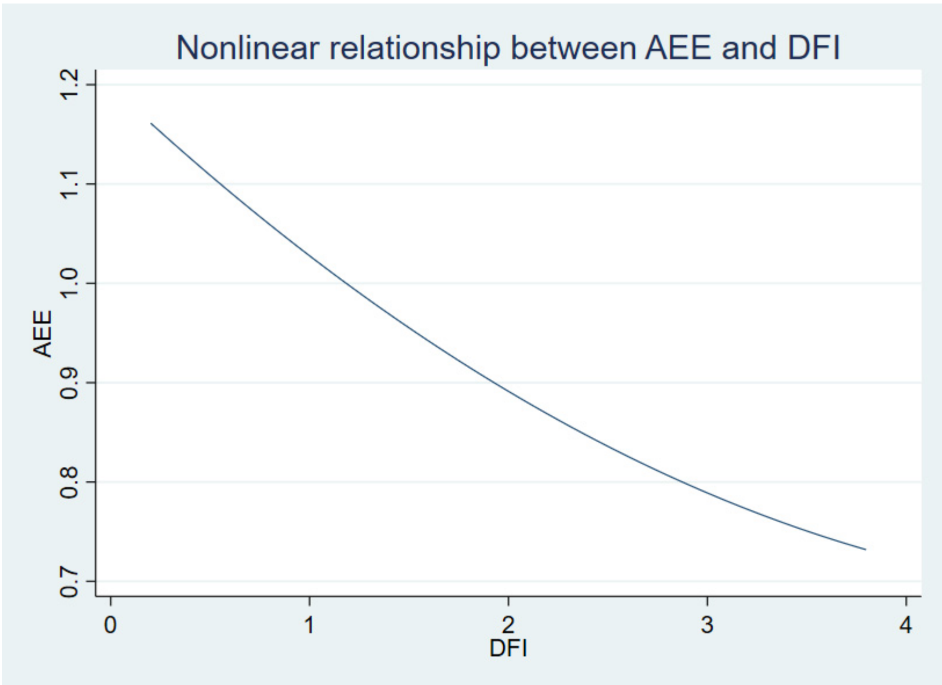

Figure 2. "U"-shaped curve of empirical regression results.

Table 4 illustrates the empirical results of the impact of digital financial inclusion on agricultural eco-efficiency of the whole sample and different regions in mainland China. According to Columns (1) in Table 4, the first-order regression coefficients of the key explanatory variable digital financial inclusion are negative, while the regression coefficients of the quadratic terms are positive, and both are significant at the 5% level, which indicates that the digital financial inclusion has a positive "U"-shaped nonlinear relationship with agricultural eco-efficiency, that is when the development of digital financial inclusion is on the left side of the "U"-shaped turning point, it will inhibit the development of rural eco-efficiency, and when it is on the right side of the "U"-shaped turning point, it will promote the development of rural eco-efficiency. Further, the "U"-shaped nonlinear relationship between DFI and AEE is intuitively reflected in Figure 2. In addition, the inflection point of the curve is located at DFI = 5.4833, which exceeds the maximum value of DFI, so only the left side of the "U" curve can be seen in Figure 2.

The main reason for the above results is that the development of digital financial inclusion in rural areas needs the accumulation of financial technology and financial knowledge to play a real role, and the positive impact of digital financial inclusion on the sustainable development of agriculture is not achieved overnight. It can be found from the coverage width and usage depth of the Peking University Digital Financial Inclusion Index [23] that the average values of these two indicators in 2011 are 34.28 and 46.93, respectively, while in 2018, the values of these two indicators are 281.92 and 287.50, respectively. From the huge changes of coverage width and use depth of this index, we can see that the development of digital financial inclusion in rural areas has stage characteristics. In the early stage of the development of digital financial inclusion, the lack of agricultural production factors and the imperfection of agricultural technology have greatly increased the difficulty of the promotion and implementation of digital financial inclusion in rural areas. Due to the lack of financial knowledge and financial development, it is difficult for farmers and rural enterprises to use the financial help and technical support provided by digital financial inclusion to improve productivity [3], and the use rate of funds and technical efficiency is extremely low at this time. In addition, the enterprises' innovation and technology R&D require much capital investment, but their R&D and achievements are highly uncertain. The R&D failure or ineffective innovation will lead to the cost of funds and unable to obtain the expected profits, resulting in the stagnation of the agricultural technology level, lower level of output, resulting in the decline of agricultural eco-efficiency. Therefore, during this period, the impact of digital financial inclusion on agricultural eco-efficiency lies on the left side of the "U"-shaped curve; that is, digital financial inclusion inhibits the improvement of agricultural eco-efficiency. The maturity of digital financial inclusion is reflected in the digital level. According to the digital level index in the digital financial inclusion Index of Peking University, the average level of each province rose from 46.32 to 383.70 from 2011 to 2018. After the development of digital financial inclusion gradually matures in rural areas, local farmers and enterprises can better enjoy the financial services and financial help brought by digital financial inclusion. Relevant studies have shown that digital financial inclusion can stimulate and improve the consumption of rural residents [15] and drive the development of the rural economy. Along with the development of digital financial inclusion, enterprises in rural areas have broadened the sources of funds, reduced financing costs, expanded the amount and scale of funds raised, thus increasing the investment in agricultural R&D, which is conducive to improving agricultural innovation ability, developing more new energy technologies to be applied in agricultural production [16], and improving the use rate of input resources, so that the emissions of undesired output will be reduced and further the agricultural eco-efficiency will be improved. Therefore, the impact of digital financial inclusion on agricultural eco-efficiency in rural areas in this period lies on the right side of the "U"-shaped curve; that is, digital financial inclusion promotes the improvement of agricultural eco-efficiency. Therefore, Hypothesis 1 of this paper is valid. Digital financial inclusion has a "U"-shaped nonlinear relationship with agricultural eco-efficiency.

From the perspective of digital financial inclusion, this paper further analyzes the eastern, central, and western regions of China to explore whether there is regional heterogeneity of the impact of digital financial inclusion on agricultural eco-efficiency. Comparing the results in Columns (2)–(4) in Table 4, it can be seen that the regression coefficients of the first-order term of digital financial inclusion in eastern and central China are positive, while the regression coefficients of the quadratic terms in both regions are negative. Only the regression coefficients of digital financial inclusion in central China pass the significant test of 10% level. In the western region, the regression coefficient of the first-order term is positive, and that of the quadratic term is negative, but they do not pass the significant test. This shows that the relationship between digital financial inclusion and agricultural eco-efficiency in the western region of China presents an inverted "U" shape, while the relationship between digital financial inclusion and agricultural eco-efficiency in the eastern and central regions presents a positive "U" shape. However, only the relationship between digital financial inclusion and agricultural eco-efficiency in the central region is significant.

First of all, for the eastern region, its digital financial inclusion has no significant effects on agricultural eco-efficiency, which may be due to the fact that the eastern economic and financial development levels are far ahead of the other two areas, so, relatively speaking, digital financial inclusion in eastern China is difficult to rapidly improve the original technical level of agriculture in the short term, and it is impossible to promote the improvement of agricultural eco-efficiency by providing more funds and technical help, thus resulting in the situation that digital financial inclusion has no significant impact on agricultural eco-efficiency in eastern China [25]. Secondly, for the central region, its digital financial inclusion has significantly "U" shaped relationship with the agricultural eco-efficiency, and this situation may be because of the relatively stable economic and financial development in central China, which provides much room to improve its agricultural R&D and technical level compared with the developed eastern region. Therefore, digital financial inclusion can bring help to the agricultural development in the central region, but the effect is a "U" shaped effect; that is, in the early stage of agricultural development in the central region, digital financial inclusion cannot effectively promote agricultural science and technology and the transformation of agricultural innovation achievements through capital and digital information technology, on the contrary, this inefficient investment results in the waste of resources, reduces the agricultural production efficiency of local enterprises and inhibits the improvement of agricultural eco-efficiency. When digital financial inclusion develops to a certain stage in the central region, the capital investment and high-end digital information technology provided by it can improve the production efficiency and reduce the operating costs of local enterprises, as well as promote the development of agricultural technology innovation by increasing the investment in agricultural R&D, making green technology more efficient and reasonable in the production process, so as to reduce pollution emissions, and then improve the eco-efficiency of agriculture [26]. Finally, for the western region, the impact of digital financial inclusion on the agricultural eco-efficiency in the western region is not significant, which indicates that the development of digital financial inclusion in the western region almost does not affect the local agricultural eco-efficiency. This may be due to the relatively backward level of economic and financial development in the western region, whose industrial structure is dominated by agriculture. Due to the limited level of financial development, digital financial inclusion is difficult to enter the western region, and the resistance it meets is much greater than that in the eastern or central region. Therefore, the impact of digital financial inclusion on the agricultural eco-efficiency of the western region is limited. Through the analysis of the above reasons, Hypothesis 2 is tenable; that is, digital financial inclusion has a regional heterogeneous impact on agricultural eco-efficiency in China [6].

4. Further Discussion and Conclusions

4.1. Mechanism Analysis

Based on regression Models (3), we employ the differential GMM method to further analyze the moderating effect of agricultural R&D investment on the impact of digital financial inclusion on agricultural eco-efficiency. In Table 5, Columns (1) shows the empirical regression results of exploring the moderating effect of agricultural R&D investment.

Table 5. Regression results of mechanism analysis and robustness test.

	DGMM (1)	DGMM (2)	SGMM (3)
	AEE	AEE	AEE
FRD	0.0059 *		
	(2.1764)		
DFI	−0.1825 ***	−0.1877 ***	−0.1497 ***
	(−5.0325)	(−4.7094)	(−5.4450)
DFI2	0.0189 **	0.0171 **	0.0321 ***
	(2.8406)	(2.9159)	(5.8425)
Control variables	YES	YES	YES
Individual effects	YES	YES	YES
Time effect	YES	YES	YES
_cons	1.1011 ***	1.1984 ***	0.3586 *
	(4.5404)	(7.0545)	(2.2372)
N	176	176	207

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

As can be seen from Columns (1) of Table 5, the key explanatory variables DFI and DFI2, as well as the interaction term FRD between digital financial inclusion and agricultural R&D investment, all pass the significance test at the 10% level, and the coefficient of the interaction term is positive. This indicates that agricultural R&D investment has a moderating effect on the impact of digital financial inclusion on agricultural eco-efficiency, and it will strengthen the promoting effect of digital financial inclusion on agricultural eco-efficiency [7]. The reason for the above situation may be that the sustainable development of digital financial inclusion in rural areas can provide effective and convenient financial services for local farmers and enterprises, improve the level of agricultural R&D investment and agricultural innovation through a large amount of capital investment [26], and effectively promote the transformation of agricultural technology progress and scientific research achievements into social productivity, so as to reduce the emission of agricultural pollutants caused in the production process, improve agricultural productivity and then promote the improvement of agricultural eco-efficiency. What is more, digital financial inclusion can promote the digital level of rural areas, promote the development of rural informatization, help the application and promotion of advanced technology in rural areas, reduce the cost of learning, and introducing advanced technology in rural areas, so as to effectively help farmers and enterprises improve the ability of green technological transformation and innovation of agricultural products [27], improve the conversion rate of agricultural scientific and technological achievements, and finally realize the green sustainable development of agriculture. Based on the above analysis, Hypotheses 3 of this paper are tenable; that is, the investment of agricultural R&D aggravates the promotion effect of digital financial inclusion on agricultural eco-efficiency.

4.2. Robustness Test

In order to further verify the robustness of the conclusion of this paper, referring to studies such as the work of [28,29], this paper adds system GMM method compare the regression results with the differential GMM method [29], so as to test whether the conclusion of this paper is robust. The regression results of the model are shown in Table 5.

From the regression results in Table 5, it can be seen that in the different methods, the first-order terms of the coefficients of the key explanatory variable, digital financial inclusion, are negative, and the quadratic terms are positive, and they all have passed the 5% level of significance test [30], indicating that digital financial inclusion and agricultural eco-efficiency have a positive "U"-shaped nonlinear relationship, which is consistent with the previous conclusions. The conclusions of this research are robust.

4.3. Conclusions and Suggestions

Based on the data of 30 provinces, autonomous regions, and municipalities in mainland China from 2011 to 2018, this paper analyzes the overall and regional impact of digital financial inclusion on agricultural eco-efficiency [31], and it further explores the moderating effect of agricultural R&D investment on the impact of digital financial inclusion on agricultural eco-efficiency [32], and the following conclusions are drawn.

(1) Digital financial inclusion has a positive "U"-shaped nonlinear relationship with agricultural eco-efficiency, which indicates that digital financial inclusion has two stages of impact on agricultural eco-efficiency. In the early stage of the development of digital financial inclusion, due to the low level of rural financial development, backward infrastructure, and other factors, digital financial inclusion is difficult to improve agricultural eco-efficiency by driving agricultural technological progress and innovation [33]. With the increasingly mature development of digital financial inclusion in rural areas, a large amount of capital input and advanced digital information level will improve the efficiency of agricultural technology, enhance the ability of green innovation in agriculture, reduce pollutant emissions in the process of agricultural production, and thus promote the improvement of agricultural eco-efficiency [34].

(2) Digital financial inclusion has heterogeneous effects on agricultural eco-efficiency in different regions of China. Among them, digital financial inclusion has a stronger "U" -shaped nonlinear relationship with the agricultural eco-efficiency in the central region of mainland China, while its influence on the agricultural eco-efficiency in the other two regions is not obvious [35], indicating that digital financial inclusion has regional differences in the impact on agricultural eco-efficiency [36].

(3) In the mechanism analysis, by introducing agricultural R&D investment as moderating variable, it is found that agricultural R&D investment significantly enhances the promotion effect of digital financial inclusion on agricultural eco-efficiency [35,37].

In view of the above conclusions, this paper puts forward the following suggestions. First, when implementing digital financial inclusion in rural areas, governments of all countries should pay close attention to whether it can be compatible with sustainable agricultural development [38]. When the development level of digital financial inclusion is low, that is, it is on the left of the turning point of the "U" shaped curve, countries should strengthen the development of digital financial inclusion in rural areas so that it can be transferred to the right of the turning point of the "U" shaped curve as soon as possible, so as to effectively and fully play the promoting role of digital financial inclusion in agricultural eco-efficiency [39]. Second, as digital financial inclusion has a heterogeneous impact on agricultural eco-efficiency in different regions, local governments should give priority to rural financial development and infrastructure construction rather than blindly strengthen the development of digital financial inclusion in rural areas [40]. When promoting digital financial inclusion in rural areas in various regions, more attention should be paid to the introduction of high-tech talents and the development of agricultural green technology, especially in areas with low levels of technology and finance [41], the local financial technology level and transportation should be improved first, and the development experience of other regions with mature digital financial inclusion should be referred to [42]. Third, both theoretical analysis and empirical results show that agricultural R&D investment and agricultural innovation level have significant effects in promoting the improvement of agricultural eco-efficiency [43]. At the same time, the government should also pay attention to the integrated development of financial technology and agriculture [44], speed up the construction of digital level in rural areas, give full play to the positive effect of digital financial inclusion, and drive the green and sustainable development of agriculture [45].

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Appendix A

AEE Measures

This paper calculates AEE based on the super-efficiency SBM-DEA model [46], in which the basic principle of the SBM-DEA model is as follows:

It is assumed that there are n decision units (DMUs) in agricultural production, each DMU contains M types of input elements, a types of expected output, and b types of unexpected output. In this paper, matrices X, Y^d and Y^{ud} are used to represent input elements, expected output, and unexpected output, respectively. The specific matrix form is as follows:

$$\begin{gathered} X = [x_1, x_2, \ldots, x_n] \in R^{m\times n} \\ Y^d = \left[{y_1}^d, {y_2}^d, \ldots, {y_n}^d\right] \in R^{a\times n} \\ Y^{ud} = \left[{y_1}^{ud}, {y_2}^{ud}, \ldots, {y_n}^{ud}\right] \in R^{b\times n} \end{gathered} \tag{A1}$$

At the same time, assuming that the above matrices are greater than zero. Under the condition of constant return to scale (CRS), the production possibility set (PPS) can be defined as:

$$p = \left\{ \left(x, y^d, y^{ud}\right) \middle| x \geq X\lambda, y^d \leq Y^d\lambda, y^{ud} \leq Y^{ud}\lambda, \lambda \geq 0,\ \lambda \in R^n \right\} \tag{A2}$$

Limiting conditions $\lambda \geq 0,\ \lambda \in R^n$ means constant return to scale. Based on this, the SBM-DEA model can be expressed as follows:

$$\rho^* = min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{D_i^-}{x_{i0}}}{1 + \frac{1}{a+b}\left(\sum_{r=1}^{a} \frac{D_r^d}{{y_{r0}}^d} + \sum_{h=1}^{b} \frac{D_h^{ud}}{{y_{h0}}^{ud}}\right)} \tag{A3}$$

$$s.t.\ x_0 = X\lambda + D^-,\ {y_0}^d = Y^d\lambda - D^d, {y_0}^{ud} = Y^{ud}\lambda + D^{ud}$$

Among them, D^-, D^d, and D^{ud} are relaxation variables, which respectively represent excessive input, insufficient expected output, and excessive undesired output. ρ^* is the ecological efficiency of DMU, which is between 0 and 1. When ρ^* = 1 and D^-, D^d, and D^{ud} are all 0, the evaluation unit is fully efficient. On the contrary, there is efficiency loss and room for adjustment and improvement. Therefore, based on (A3), the super-efficiency SBM-DEA model can make the ecological efficiency value greater than 1. The specific equation is as follows (A4):

$$\rho^*{}_S = min \frac{1 + \frac{1}{m}\sum_{i=1}^{m} \frac{D_i^-}{x_{i0}}}{1 - \frac{1}{a+b}\left(\sum_{r=1}^{a} \frac{D_r^d}{{y_{r0}}^d} + \sum_{h=1}^{b} \frac{D_h^{ud}}{{y_{h0}}^{ud}}\right)}$$

$$s.t.\ x_i^k \geq \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j + D_i^-$$

$$
\begin{gathered}
{y_{rk}}^{d} \le \sum_{j=1, j\neq k}^{n} {y_{rk}}^{d} \lambda_j + D_r^d \\
{y_{hk}}^{ud} \ge \sum\nolimits_{j=1, j\neq k}^{n} {y_{hk}}^{ud} \lambda_j + D_h^d \\
1 - \frac{1}{a+b}\left(\sum_{r=1}^{a} \frac{D_r^d}{{y_{rk}}^{d}} + \sum_{h=1}^{b} \frac{D_h^{ud}}{{y_{hk}}^{ud}} \right) > 0 \\
\lambda, Y^d, Y^{ud} \ge 0 \\
i = 1, 2, \ldots, n;\ r = 1, 2, \ldots, a; h = 1, 2, \ldots, b
\end{gathered}
\tag{A4}
$$

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