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Can Rural Human Capital Improve Agricultural Ecological Efficiency? Empirical Evidence from China

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Abstract: Agricultural ecological efficiency (AEE) is an important index to measure the coordinated development of agricultural production, resources, and the environment. This study tries to explore the impact of rural human capital (RHC) on AEE, hoping to provide a reference for promoting the green development of agriculture. Data sets (2006–2021) used in this study were gathered from Official Statistics Panel data in 30 provinces in China. Firstly, the super-efficient slacks-based measure model (SBM) with non-expected output is employed to effectively measure AEE. Secondly, the entropy method is used to measure RHC in three dimensions: education, health, and migration. Finally, this study discusses the impact of RHC on AEE using the panel Tobit model and further verifies the moderating effect of Internet popularization on the effect of RHC on AEE using the moderating effect model. The results show that RHC has a significant positive impact on the promotion of AEE, and this positive impact has obvious regional heterogeneity. Specifically, RHC has a greater promoting role on AEE in the eastern and northeastern regions, while it has a smaller promoting role on AEE in the central and western regions. In addition, Internet penetration plays a positive moderating role in the mechanism of the effect of RHC on the AEE. This study may serve as a reference for improving AEE by providing theoretical guidance and policy suggestions for promoting agricultural green development.

Keywords: rural human capital; agricultural ecological efficiency; Internet popularization; moderating effect

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1. Introduction

For a long time, China's agriculture generally adopted an extensive growth mode, which has greatly promoted production but also paid a painful price. Agricultural non-point source pollution such as nitrogen and phosphorus loss, greenhouse gas emissions, decreased land fertility, and other "reverse ecological" problems have become increasingly prominent. The contradiction between agricultural production and resource and environmental constraints is becoming more and more serious [1], which obviously deviates from the concept of "green development". According to "the Second National Pollution Source Census Bulletin" issued by China in 2020, the emissions of chemical oxygen demand (COD), total nitrogen (TN), and total phosphorus (TP) from agricultural sources are 10,671,300 tons, 1,414,900 tons, and 212,000 tons, respectively, accounting for about 50%, 47%, and 67% of the corresponding pollution. It can be seen that agricultural source pollution is quite serious and has caused a serious burden on the ecological environment. Since the implementation of the rural revitalization strategy in China, the protection of the agricultural ecological environment has risen to a particularly important position. Moreover, in the No. 1 Document of the Central Committee in recent years, it has always been emphasized to strengthen agricultural pollution control and promote the green development of agriculture. Green development and sustainable development come down in one continuous line of thought, which is not only the inheritance of sustainable development but also the theoretical innovation of sustainable development in China [2]. Agricultural ecological efficiency (AEE) is an important index to measure the coordinated development of agricultural production, resources, and the environment [3]. AEE means to get as much agricultural output as possible with as little resource consumption and environmental pollution as possible under a certain combination of agricultural input factors, which emphasizes the unity of agricultural production efficiency and environmental benefits [4]. This study tries to explore the impact of rural human capital (RHC) on AEE, hoping to provide a reference for promoting the green development of agriculture.

In recent years, research on AEE has attracted wide attention from scholars [5,6]. AEE can consider both the economic and environmental benefits brought by agricultural production [7,8]. Although the current agricultural economy has achieved rapid development, the overall AEE is still at a low level, which urgently requires seeking new impetus for promoting agricultural green production [9]. Studies have shown that AEE will be affected by various factors such as agricultural mechanization level, regional economic development, urbanization process, agricultural financial expenditure, natural disasters, and so on [6,10–12].

However, the promotion of agricultural green production cannot be separated from the role of farmers themselves. Their knowledge, skills, and production concepts determine their production behavior, which then affects the input and output of agricultural production. Therefore, RHC has an important impact on AEE [13]. Nevertheless, the discussion in this section is still insufficient in the existing studies. Previous studies have paid more attention to the impact of RHC on AEE as measured by the education dimension [14,15]. It is considered that the improvement of farmers' education level means the improvement of agricultural producers' production skills, which can further optimize the efficiency of input factors to promote the improvement of AEE [16]. Moreover, farmers' awareness of environmental protection has been enhanced to a certain extent, which is conducive to the promotion of AEE [17,18]. Of course, some scholars also point out that the RHC has a limited or extremely weak effect on agricultural economic growth [19,20].

Although some scholars have studied the relationship between RHC and AEE, it is obviously limited to discussing the relationship between them only from the educational dimension. It is worth noting that the health status of farmers and the advanced green production concepts and technologies learned in the process of migration and mobility will have a more important impact on agricultural green production. In addition, in the digital age, the popularization of the Internet in rural areas has greatly accelerated the circulation of information in rural areas, which can provide an extremely effective way for the popularization of agricultural green production technology and knowledge [21]. This will inevitably have a subtle influence on the accumulation of RHC, which may better play the role of RHC in promoting agricultural green production. Therefore, this paper primarily focuses on the different dimensions of RHC to explore their impact on AEE. At the same time, the moderating effect of Internet popularization is discussed.

The existing research provides important references for this paper, but there are still the following points that can be supplemented or deepened: First, according to Schultz's definition of human capital, this paper constructs and measures the evaluation index system of RHC from three dimensions, including education, health, and migration. Compared with previous studies using a single dimension of education to measure RHC, this paper's RHC measurement is more comprehensive. Second, this study explores the impact of RHC on AEE and its regional heterogeneity from multiple dimensions, which will help to understand the role of RHC more comprehensively and provide different improvement measures for different regions. Finally, this paper also brings the popularization of the Internet into the research framework so as to explore the moderating effect of Internet popularization on the impact of RHC on AEE. Through this study, we hope to provide new ideas and directions for improving AEE and promoting agricultural green development.

2. Analytical Framework

2.1. Influence of Rural Human Capital on Agricultural Ecological Efficiency

2.1.1. The Role of Educational Human Capital

Farmers decisions dominate the whole agricultural production process, and those decisions are related to the economic and ecological benefits of agricultural production. By educating and training farmers, their production ideas, knowledge and skills, and awareness of environmental protection will be affected, which will change their production decisions and further affect AEE. On the one hand, farmers can not only effectively improve the efficiency of technology use but also enhance their ability to absorb new technologies and knowledge by receiving vocational education and technical training [22]. This has also been proven in other regions. For example, Spielman et al. (2008) found that agricultural education and training can significantly enhance farmers' personal abilities in South Africa [23]. The research of Puskarova et al. (2016) shows that knowledge-based human capital has an important impact on total factor productivity in Europe [24]. On the other hand, farmers who have received education and training can enhance their awareness of environmental protection, which enables them to reduce the use of polluting production factors such as chemical fertilizers and pesticides as much as possible [25]. At the same time, they will be more inclined to use agricultural green production technology [26]. In this way, they will strive to get the maximum benefits with the least pollution and then improve AEE.

Based on the above analysis, the research hypothesis H1a is put forward:

H1a. *Educational human capital has a positive role in promoting AEE.*

2.1.2. The Role of Healthy Human Capital

Health is the premise of the existence and effectiveness of human capital. Farmers' energy, physical fitness, and health status will directly affect personal labor productivity and economic income, which will then affect AEE. Loureiro (2010) found that the difference in farmers' health status can explain the differences in agricultural production efficiency by studying farmers' production in Norway [27]. Compared with farmers with poor health, farmers with good health are more efficient in using input factors such as chemical fertilizers, pesticides, and mechanical equipment [28]. In addition, farmers in good health have relatively higher production enthusiasm and more agricultural labor time, so their labor productivity is higher and it is easier for them to get more economic income [29,30]. They are more inclined to use their economic advantages to invest in advanced production equipment and production skills [31], which is conducive to promoting green agricultural production.

Based on the above analysis, the research hypothesis H1b is put forward:

H1b. *Healthy human capital has a positive role in promoting AEE.*

2.1.3. The Role of Migratory Human Capital

Lucas believes that the knowledge spillover of human capital helps neighboring groups or regions contact each other and learn new knowledge and technology. The learning effect plays an important role in the popularization of agricultural green production technology. With the improvement of rural transportation facilities, communication between rural areas and cities is closer, which gives farmers more opportunities to communicate and study in cities. They will be influenced by the advanced production concepts of cities, accumulate production management experience, and improve production skills [32]. As Blair's (2008) research on agricultural labor migration in Sierra Leone shows, farmers get more economic income and production technology in the process of migration [33]. De Brauw A. (2019) believes that the mobility of farmers promotes the transformation of agricultural production technology in rural areas, which is more conducive to the efficient production of agriculture [34]. In this way, farmers can bring advanced management experience, production concepts, and production skills gained in mobility into agricultural production, thus improving AEE [35].

Based on the above analysis, the research hypothesis H1c is put forward:

H1c. *Migratory human capital has a positive role in promoting AEE.*

To sum up, this paper puts forward the research hypothesis H1:

H1. *RHC has a positive role in promoting AEE.*

2.2. The Moderating Effect of Internet Popularization

With the gradual popularization of the Internet in rural areas, the Internet has been widely used in agricultural production, which can effectively promote agricultural productivity [36]. On the one hand, the popularization of the Internet provides great convenience for the popularization of agricultural green production technology. The Internet can accelerate the dissemination and diffusion of agricultural green production technology, which greatly reduces the search cost for farmers and provides more opportunities for farmers to understand and learn agricultural green production technology [37]. Moreover, farmers with a higher level of human capital have good learning ability, adaptability, and the possibility of continuing learning, so they can make better use of the convenience of obtaining information brought by the popularization of the Internet to understand and learn agricultural green production technology more quickly [38]. This can greatly improve the application of agricultural green production technology by farmers, which is more conducive to improving AEE. On the other hand, the popularization of the Internet creates an effective way to advocate the concept of ecological environment protection. The government and other relevant departments can more conveniently promote and implement the policies, concepts, rules, and regulations related to agricultural green development through the Internet [39]. Moreover, farmers with higher human capital levels are more likely to accept these policy ideas, which is conducive to enhancing their awareness of ecological and environmental protection, forming the concept of agricultural green production, and changing agricultural production behavior. Therefore, it can give full play to the role of RHC and further enhance AEE.

Based on the above analysis, the research hypothesis H2 is put forward:

H2. *Internet popularization plays a positive moderating role in the process of promoting AEE by RHC.*

This study constructed an analytical framework for the impact of RHC on AEE based on the multi-dimensional impact of RHC and the moderating effect of Internet popularization. The specific impact paths are shown in Figure 1.

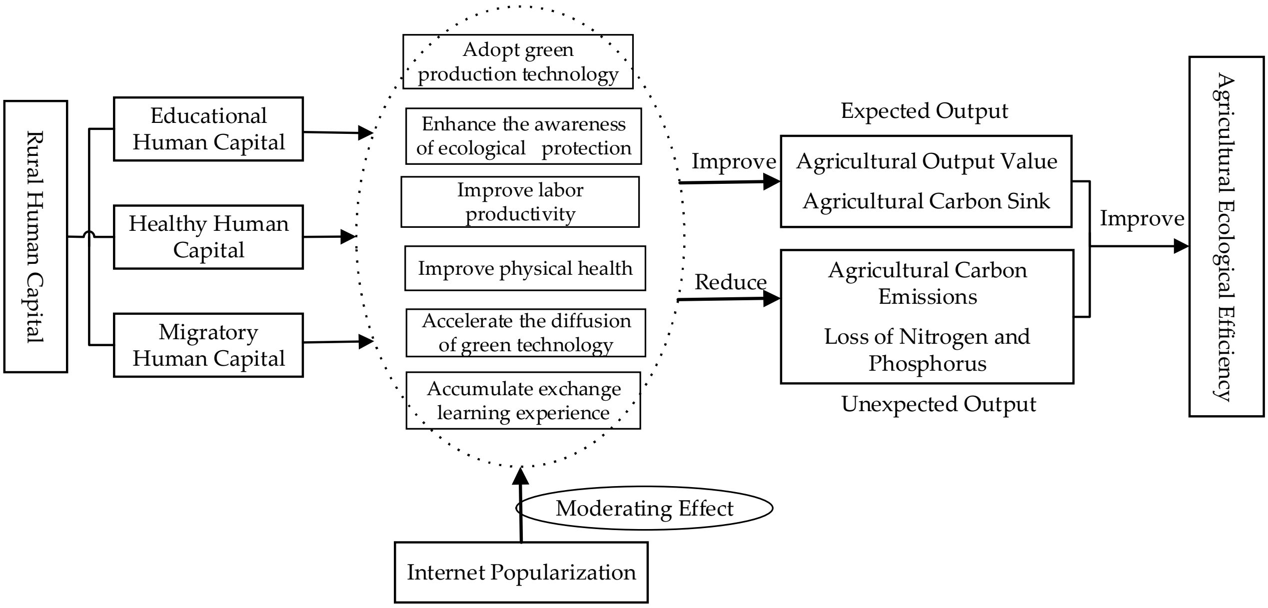


Figure 1. Impact path of rural human capital on agricultural ecological efficiency.

3. Materials and Methods

3.1. Data Sources

Considering the data integrity and availability, this article selects 2006–2021 panel data from 30 provinces in China (excluding Hong Kong, Macao, Taiwan, and Tibet) as the research object. All the data from the "China Statistical Yearbook", "China Rural Statistical Yearbook", "China Labor Statistics Yearbook", "China Population and Employment Statistics Yearbook", "China Internet Development Statistical Report", and the Statistical Yearbook of each province are used to supplement the partially missing data.

3.2. Definition of Variables

3.2.1. Dependent Variable

In this paper, the agricultural ecological efficiency (AEE) is taken as the explained variable and calculated by the super-efficiency SBM model. It reflects the degree of resource utilization and environmental protection in the process of agricultural production. Tone (2001) puts forward the SBM-DEA model with slack variables and takes unexpected output into account [40]. Its advantage lies in that when the input in the system is too high or the output is insufficient, the results measured by the radial DEA model will overestimate the actual efficiency of the decision-making unit (DMU), and the results measured by the angular DEA model will lead to measurement deviation due to ignoring input redundancy or insufficient output, while the non-radial and non-angular SBM-DEA models based on relaxed variables can just overcome these defects [41]. Moreover, in order to better distinguish the efficiency difference between DMUs whose efficiency value is greater than or equal to 1, this paper chooses the super-efficiency SBM-DEA model.

Selection of the input index. The agriculture studied in this paper is narrow agriculture, which refers to the planting industry. Considering the existing research on AEE, labor, machinery, chemical fertilizer, agricultural film, pesticides, land, and irrigation are selected as input indicators. Among them, labor input is the total number of agricultural employees in each province, and machinery input is the total power of agricultural machinery in each province. Since there are no direct statistics on the number of agricultural employees and the total power of agricultural machinery in the existing yearbook statistics, this paper refers to the practice of Huang et al. [42], who convert according to the proportion of agricultural output value to the total output value of agriculture, forestry, animal husbandry, and fishery. The input of chemical fertilizer, agricultural film, and pesticide is the actual consumption of each province; the land input is the total sown area of crops in each province; and the irrigation input is the effective irrigation area of each province.

Selection of the expected output index. There are two expected outputs of agricultural production in this paper: one is carbon sink, which refers to the carbon sequestration effect of various crops in agricultural production (i.e., carbon absorption). The calculation method of carbon absorption draws lessons from the methods commonly used by scholars [43,44]. Its formula is $C_{it} = C_f \times Y_{it} \times (1 - w_f)/H_f$, where C_{it} represents the total amount of carbon sequestration in agricultural production in year t of province i; C_f is the carbon needed to be absorbed in the synthesis of organic matter in the agricultural production process, that is, the carbon absorption rate; Y_{it} is the agricultural output in the t year of province i; w_f is the water content coefficient of each crop; H_f is the economic coefficient of each crop. The second is the output value, which is expressed by the total agricultural output value. In order to eliminate the influence of inflation, the total agricultural output value calculated at comparable prices is selected.

Selection of unexpected output indicators: In this paper, carbon emissions and non-point source pollution in agricultural production processes are considered comprehensively, and carbon emissions and nitrogen and phosphorus losses in agricultural production processes are regarded as unexpected output indicators. Carbon emissions are mainly considered in the context of direct or indirect generation in the process of agricultural production. The carbon sources involved mainly include chemical fertilizers, agricultural films, pesticides, diesel oil, plowing, and irrigation. The carbon emissions are obtained by multiplying the amounts of various carbon sources by their carbon emission coefficients and adding them up [45]. Nitrogen and phosphorus loss coefficients refer to Zhan et al. [46], who obtained them by converting the data in the First National Pollution Census Bulletin.

The construction explanation and sample descriptive statistics of the AEE evaluation index system are shown in Table 1.

Table 1. Evaluation index system for agricultural ecological efficiency.

Indicators	Variables	Variable Description	Mean	SE
Input	Labor input	Number of agricultural employees (ten thousand people)	475.963	(355.061)
	Machinery input	Total power of agricultural machinery (ten thousand kilowatts)	1715.799	(1579.418)
	Land input	The total sown area of crops (thousand hectares)	5421.776	(3704.716)
	Fertilizer input	Fertilizer application amount (ten thousand tons)	185.282	(142.218)
	Pesticide input	Pesticide application amount (ten thousand tons)	5.445	(4.199)
	Agricultural film input	Agricultural film application amount (ten thousand tons)	7.730	(6.547)
	Irrigation input	Effective irrigation area (thousand hectares)	2115.313	(1597.370)
Expected output	Carbon sink	Total agricultural carbon sink (ten thousand tons)	2937.824	(2192.307)
	Output value	Total agricultural output value (100 million yuan)	1581.260	(1257.544)
Unexpected output	Carbon emission	Carbon dioxide (CO_2) emissions (ten thousand tons)	278.734	(194.776)
	Pollutant emission	TN (ten thousand tons)	5.482	(4.059)
		TP (ten thousand tons)	0.408	(0.346)

3.2.2. Explanatory Variables

The explanatory variables of this paper are rural human capital (RHC), which is calculated by the entropy method. The entropy method is weighted according to the amount of information provided by samples or the correlation degree of each index, so the evaluation is more objective, accurate, and credible than the subjective weighting method [47].

Educational human capital (EHC). Considering the research of scholars, this paper selects three indicators to measure EHC: the average education level of rural residents, the per capita education expenditure of rural residents, and the proportion of agricultural workers' training.

Healthy human capital (HHC). Considering the research of scholars, this paper selects three indicators to measure healthy human capital: the per capita medical care expenditure of rural residents, the number of health technicians per thousand population in rural areas, and the number of beds in medical institutions per thousand population in rural areas.

Migratory human capital (MHC). Considering the research of scholars, this paper selects the per capita transportation and communication expenditure of rural residents as the measurement index of MHC.

The construction explanation and sample descriptive statistics of the RHC evaluation index system are shown in Table 2.

Table 2. Evaluation index system for rural human capital.

First Class Index	Second Class Index	Third Class Index	Mean	SE
RHC	EHC	The average education level of rural residents (years)	7.673	(0.666)
		The per capita education expenditure of rural residents (yuan)	817.362	(495.721)
		The proportion of agricultural workers' training (%)	9.462	(14.183)
	HHC	The per capita medical care expenditure of rural residents (yuan)	800.028	(526.590)
		The number of health technicians per thousand people in rural areas (people)	3.911	(1.660)
		The number of beds in medical institutions per thousand people in rural areas (beds)	3.380	(1.505)
	MHC	The per capita transportation and communication expenditure of rural residents (yuan)	1093.424	(771.273)

3.2.3. Moderating Variable

Internet popularization (IP). In this paper, referring to the practices of Cheng and Li [37,38], Internet penetration is used to characterize the Internet's popularization. Since the data in the Statistical Report on Internet Development in China released by the China Internet Network Information Center (CNNIC) is only counted until 2016, the missing data from 2017 to 2021 is filled with the ratio of Internet broadband access ports (ten thousand ports)/total population (ten thousand people) [48].

3.2.4. Control Variables

There are many factors that affect AEE. Combined with the reality of agricultural development and referring to the research of Liang, Ma, and Yang [11,15,26], this paper selects six main influencing factors as control variables, including agricultural disaster rate (Dis), urbanization level (Urb), agricultural structure (Str), agricultural productive service (Ser), and agricultural machinery density (Mac). Among them: (1) The agricultural disaster rate is expressed by the ratio of the affected area to the sown area of crops in each region; (2) The urbanization level is expressed by the proportion of urban population in each province to the total number of the province; (3) The agricultural structure is expressed by the proportion of the output value of planting industry to the total output value of agriculture, forestry, animal husbandry and fishery; (4) Agricultural productive services take the output value of agriculture, forestry, animal husbandry and fishery services as the agency index of agricultural productive services [49]; (5) The density of agricultural machinery is expressed by the total power of agricultural machinery per unit sown area.

Descriptions of variables and descriptive statistics of samples are shown in Table 3.

Table 3. Description of variables and descriptive statistics of samples.

Variables	Variable Description	Obs	Mean	SE
Dependent Variable	AEE	480	0.440	(0.199)
Explanatory Variable	RHC (index)	480	0.254	(0.135)
	EHC (index)	480	0.089	(0.051)
	HHC (index)	480	0.113	(0.058)
	MHC (index)	480	0.042	(0.033)
Moderating Variables	IP (%)	480	45.776	(21.990)
Control Variables	Agricultural disaster rate (%)	480	18.383	(14.352)
	Urbanization level (%)	480	56.349	(13.718)
	Agricultural structure (%)	480	52.410	(8.609)
	Agricultural productive service (100 million yuan)	480	131.657	(141.411)
	Agricultural machinery density (kw/ha)	480	3.141	(1.235)

Note: In order to eliminate the influence of index dimension and ensure the stability of the data, most control variables are logarithmic when regression is carried out later.

3.3. Model Setting

3.3.1. Tobit Model

Considering that the dependent variable (AEE) in this paper is calculated by the SBM-DEA model, which is between 0 and 2, the Tobit model obviously has the characteristics of a two-sided broken tail. For this kind of regression with few explained variables, the Tobit model has obvious advantages over the OLS method. However, for panel data regression, it is difficult to obtain consistent and unbiased estimators by using a fixed effect model [50]. Therefore, this paper chooses the panel Tobit model of random effects to explore the impact of RHC on AEE, which is constructed as follows:

$$AEE_{it} = \beta_0 + \beta_j H_{j,it} + \sum_{k}^{n} \beta_k lnZ_{k,it} + \mu_i + \varepsilon_{it}, \varepsilon_{it} \sim N\left(0,\ \delta^2\right) \tag{1}$$

where AEE_{it} denotes AEE in the province i at year t; β_0 denotes constants; $H_{j,it}$ denotes RHC, including RHC, EHC, HHC, and MHC; β_j represents the coefficient to be estimated of RHC; $lnZ_{k,it}$ denotes the logarithmic term of the control variables of AEE, including agricultural disaster rate, agricultural structure, agricultural productive service, local environmental regulation, and agricultural machinery density; β_k denotes the coefficients to be estimated for logarithmic terms of control variables; μ_i denotes individual fixed effects; ε_{it} denotes the random error.

3.3.2. Moderating Effects Mode

In order to further explore the moderating effect of Internet penetration on the impact of RHC on AEE, the interactive terms ($c\_H \times c\_I$) of RHC (c_H) and Internet penetration rate (c_I) after Decentralization are introduced into the model. The specific model is as follows:

$$AEE_{it} = \beta_0 + \beta_1 c_{Hit} + \beta_2 c_{Iit} + \beta_3 c_{Hit} \times c_{Iit} + \sum_{k}^{n} \beta_k lnZ_{k,it} + \mu_i + \varepsilon_{it},\ \varepsilon_{it} \sim N\left(0,\ \delta^2\right) \tag{2}$$

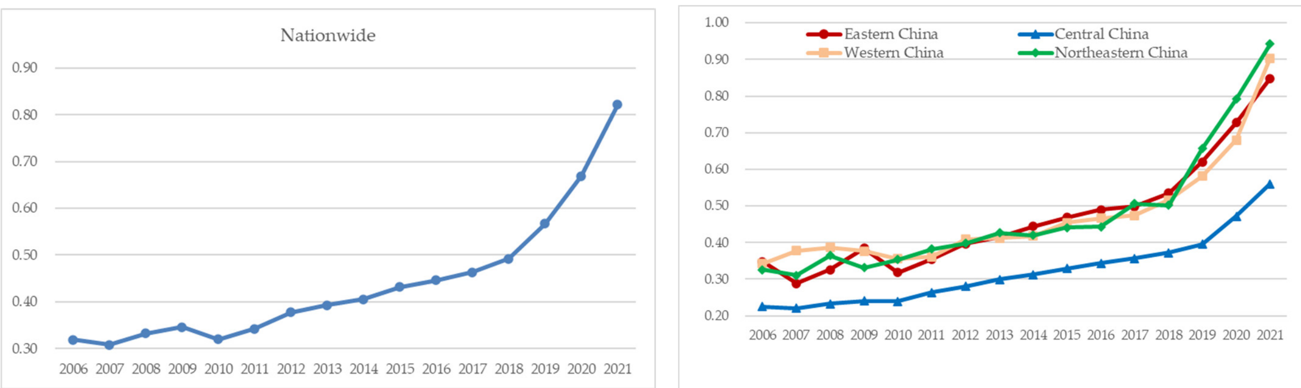
where β_1, β_2, and β_3 are the coefficients to be estimated of the decentralized RHC comprehensive index (c_H), Internet penetration rate (c_I), and their interactive term ($c\_H \times c\_I$), respectively, and others are the same as those expressed by Equation (1).

4. Results

4.1. Measurement of Agricultural Ecological Efficiency

Based on MaxDEA 8.0 software and using the super-efficiency SBM model, this study calculates AEE in 30 provinces from 2006 to 2021.

It can be seen from Figure 2a that the change trend of AEE in China can be basically divided into three stages: a fluctuating growth stage in the early stage from 2006 to 2010, a stable growth stage in the middle stage from 2011 to 2015, and a rapid growth stage in the late stage from 2016 to 2021. In the early stages, China's AEE rose from 0.319 in 2006 to 0.346 in 2009 and then fell back to 0.320 in 2010, with relatively slow growth during this period. The possible reason is that during this period, China's agricultural production pays more attention to economic benefits but less attention to ecological protection. In order to increase the agricultural output value, the production mode of high input and high emission is adopted. According to statistics, although the total grain output in China increased by 12.26% during this period, the input of petrochemical production factors also increased a lot, such as the application of chemical fertilizers, which increased by 16.69%, and the use of pesticides, which increased by 20.43%, which caused great pollution to the environment, so the AEE increased slowly. In the middle stage, China's AEE increased from 0.343 in 2011 to 0.432 in 2015, with an average annual growth rate of 2.24%, showing stable growth. This may have a great relationship with the implementation of policies such as strengthening agriculture and benefiting farmers, promoting green development, and building a resource-saving and environment-friendly society during the 12th Five-Year Plan period. During this period, agricultural ecological protection was greatly strengthened, which reduced agricultural non-point source pollution while stabilizing agricultural economic benefits, thus making AEE grow stably. In the late stage, China's AEE increased from 0.447 in 2016 to 0.822 in 2021, with an average annual growth rate of 7.50%, achieving rapid growth. This shows that during the 13th Five-Year Plan period, the measures taken to actively respond to climate warming, such as advocating the production and lifestyle of low-carbon life and implementing the zero-growth action of chemical fertilizer and pesticide use, have achieved remarkable results. While ensuring the steady growth of agricultural production, it further reduces the negative effects of agricultural production and promotes the very rapid growth of AEE.



(**a**) (**b**)

Figure 2. (**a**) Average time trend of agricultural ecological efficiency in China; (**b**) Average time trend of agricultural ecological efficiency in the four regions in China.

As shown in Figure 2b, the mean values of AEE in the eastern, central, western, and northeastern regions all showed slow growth in the early stages and rapid growth in the middle and late stages. In the early stages, the AEE in the western region was in a leading position, while the AEE in the eastern and northeastern regions lagged behind that in the western region, which may be due to the fact that the eastern and northeastern regions paid more attention to the rapid development of the agricultural economy and neglected the protection of the agricultural environment during this period. In the middle stage, the AEE in the eastern region grew relatively fast and gradually led other regions, which indicated that the eastern region paid more and more attention to agricultural ecological protection during this period and made use of its economic advantages to give back to agriculture. In the late stage, the AEE in Northeast China grew rapidly and gradually took a leading position, which may be closely related to the fact that the country attaches great importance to the protection of black land. China's black soil region is mainly distributed in Northeast China, where agricultural resources are abundant, soil is fertile, and land productivity is relatively high. However, the AEE in the central region has been lagging behind other regions, which means that it still has a lot of room to optimize the input-output structure and improve AEE, and it can promote the improvement of AEE in terms of agricultural technological progress and agricultural technical efficiency. The reasons for this phenomenon may be that the eastern region is relatively developed in its economy and has a high level of agricultural production technology, so it can use its technological advantages to reduce resource consumption. The population in western and northeast China is relatively small, so their demand for production is relatively low, and the resources paid per unit of production are relatively small. However, the central region is neither economically developed like the eastern region nor has a small population like the western and northeastern regions. Therefore, the central region uses more resources per unit of production and produces more pollution, so the ecological efficiency is relatively low.

4.2. The Impact of Rural Human Capital on Agricultural Ecological Efficiency

4.2.1. Overall Regression Analysis

Based on the theoretical analysis of the impact of RHC on AEE, this paper uses the Tobit model to empirically analyze the impact of RHC on AEE and verify the rationality of the hypothesis. Table 4 shows the regression results. We can see that when the model (1) does not add control variables, the estimated coefficient of RHC is positive and significant at the level of 1%. In the model (2), the estimated coefficient of RHC is still positive and significant at the level of 1%, which shows that RHC has a significant role in promoting the improvement of AEE, thus verifying that the hypothesis H1 is valid. Generally speaking, the higher the level of RHC, it means that farmers have a higher education level, higher production skills, and healthier physical fitness, and they are more likely to learn and communicate with each other through migration and mobility so as to acquire new agricultural production technology and management experience, which is conducive to improving the efficiency of input factors and improving labor productivity. Moreover, well-educated and trained farmers will take the initiative to realize the problem of ecological environment protection and reduce the use of polluting production factors such as chemical fertilizers and pesticides as much as possible, thus effectively reducing pollution emissions in the process of agricultural production. This makes the efficiency among the input, expected output, and unexpected output of agricultural production factors more balanced, so as to meet the requirements of "high economic efficiency" and "green sustainability" and promote the green development of agriculture.

Table 4. The impact of rural human capital on agricultural and ecological efficiency.

Variables	Dependent Variable: AEE				
	(1) Coefficients	**(2) Coefficients**	**(3) Coefficients**	**(4) Coefficients**	**(5) Coefficients**
RHC	1.000 *** (0.040)	1.118 *** (0.102)			
EHC			1.617 *** (0.260)		
HHC				2.255 ***(0.217)	
MHC					3.057 ***(0.329)
lnDis		−0.030 *** (0.008)	−0.039 *** (0.009)	−0.033 *** (0.008)	−0.032 *** (0.008)
Ubr		−0.286 * (0.155)	0.328 ** (0.160)	−0.117 (0.146)	0.287 ** (0.139)
lnStr		−0.107 (0.079)	−0.096 (0.088)	−0.121 (0.079)	−0.067 (0.084)
lnSer		0.001 (0.012)	0.032 ** (0.013)	0.004 (0.012)	0.026 ** (0.012)
lnMac		−0.086 *** (0.030)	−0.081 ** (0.033)	−0.089 *** (0.030)	−0.088 *** (0.032)
cons	0.186 *** (0.024)	0.910 *** (0.321)	0.542 (0.348)	0.893 *** (0.321)	0.481 (0.330)
Log likelihood	340.149	347.600	313.607	342.218	334.910
sigma_u	0.118 *** (0.016)	0.110 *** (0.015)	0.124 *** (0.018)	0.107 *** (0.015)	0.125 *** (0.018)
sigma_e	0.108 *** (0.004)	0.106 *** (0.004)	0.113 *** (0.004)	0.107 *** (0.004)	0.108 *** (0.004)
LR test	281.550 ***	248.630 ***	229.500 ***	237.090 ***	266.100 ***
Wald test	613.450 ***	678.780 ***	521.810 ***	649.980 ***	620.520 ***

Note: ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively.

In order to further explore the impact of different dimensions of RHC on AEE, education human capital (EHC), health human capital (HHC), and migration human capital (MHC) are substituted into models (3)–(5) for estimation, and the estimation results are shown in Table 4.

From the estimation results of model (3), we can see that the estimation coefficient of EHC is positive and significant at the level of 1%, which shows that EHC has a significant role in promoting the improvement of AEE and verifies the hypothesis H1a is valid. The higher the education level of farmers, the more expenditure there is on education and training, and the trained farmers will have a relatively higher level of agricultural production skills, and at the same time, they will have a stronger awareness of ecological protection. They will not only have a higher understanding and adoption of agricultural green production technology but also use factor resources more reasonably and scientifically, which will reduce resource waste and environmental pollution. Under the same input level, farmers with higher EHC will have a relatively higher output efficiency and profit rate because of the rational use of production factors, which will significantly promote AEE.

From the estimation results of model (4), we can see that the estimation coefficient of HHC is positive and significant at the level of 1%, which shows that HHC also has a significant role in promoting the improvement of AEE and verifies the hypothesis H1b is valid. With the gradual improvement of investment in farmers' health in China, farmers' expenditure on health has gradually increased, which makes rural HHC better. This means that the health conditions of farmers have been greatly improved, and healthy farmers will be more proficient in the application of agricultural production technology and equipment, which will help them improve their labor productivity. Therefore, it is beneficial to improve AEE.

From the estimation results of model (5), we can see that the estimation coefficient of MHC is positive and significant at the level of 1%, which shows that MHC also has an obvious promotion effect on the improvement of AEE and verifies the hypothesis H1c is valid. With the gradual improvement of rural transportation facilities and the popularization and application of communication equipment in rural areas, farmers' travel is becoming more and more convenient, and communication between rural areas and cities becomes more frequent. This gives farmers more opportunities to contact and learn knowledge and skills related to agricultural production, participate in training and study more conveniently, and help them learn and adopt agricultural green production technology, while at the same time helping them gain advanced production knowledge and management experience in neighboring areas. Through the "learning imitation effect", agricultural technology spreads more smoothly, and then the learned experience and technology are applied to agricultural production by farmers, which is conducive to improving AEE.

4.2.2. Heterogeneity Analysis: Subregional Regression

In order to further explore the heterogeneity of the impact of RHC on AEE in different regions of China, a regression analysis of different regions was carried out. According to the estimation results in Table 5, the impact of the comprehensive index of RHC in the four major regions of China on their respective AEE is consistent with that in the whole country, and they all show significant promotion, but there are certain differences in the degree of action and the impact of different dimensions of RHC.

Table 5. Heterogeneity analysis: subregional regression.

Variables	**Dependent Variable: AEE**			
	Eastern China Coefficients	**Central China Coefficients**	**Western China Coefficients**	**Northeastern China Coefficients**
RHC	1.226 *** (0.168)	0.634 *** (0.099)	0.987 *** (0.300)	1.007 *** (0.273)
EHC	1.814 *** (0.395)	1.144 *** (0.224)	1.103 (0.680)	1.673 ** (0.772)
HHC	2.051 *** (0.379)	1.731 *** (0.243)	1.982 *** (0.561)	2.663 *** (0.532)
MHC	2.432 *** (0.464)	2.203 *** (0.478)	2.781 ** (1.146)	3.863 *** (1.384)
Control variables	yes	yes	yes	yes

Note: *** and ** represent the significance levels of 1% and 5% respectively.

Specifically, RHC has the greatest promotional effect on AEE in the eastern region, which is related to the relatively high level of economic development in the eastern region. It has performed relatively better in the research, development, and promotion of agricultural green production technology and has higher investment in rural education and training, health care, transportation, and communication than other regions. Therefore, farmers in the eastern region have comparative advantages in learning and adopting agricultural green production technology, which is more conducive to agricultural green development. Followed by the northeast region. As an important grain production base in China, its agricultural foundation is relatively good, and the quality of farmers is relatively high, which is conducive to the application and popularization of agricultural green production technology, so its RHC promotes AEE relatively greatly. In contrast, although RHC has a significant positive impact on AEE in central and western China, the impact degree is lower than that in eastern and northeastern China, so they need to make further efforts to improve the level of RHC in order to give full play to the promotion role of RHC.

From the impact of different dimensions of RHC, we can see that EHC has the greatest impact on AEE in the eastern region, followed by the northeast region and the central region, while its influence in the western region is not significant. HHC has the greatest influence on AEE in the northeastern region, followed by the eastern region, and finally the western and central regions. MHC also has the greatest impact on AEE in the northeast region, followed by the western, eastern, and central regions in turn.

4.3. Moderating Effect Analysis

Theoretical analysis shows that Internet popularization (IP) can play a regulatory role in the process of RHC affecting AEE. Therefore, further empirical analysis is needed to verify the RHC and IP of the AEE of the common impact mechanism. Firstly, the decentralized RHC (c_H) and Internet penetration rate (c_I) are substituted into the model (6), and the regression results are shown in Table 6. We can see that the estimated coefficients of (c_H) and (c_I) are both positive and significant at the level of 1%, which shows that both

RHC and IP have a positive impact on AEE. Furthermore, bringing the interaction items of c_H and c_I ($c\_H \times c\_I$) into the model (7), we can see that the estimated coefficients of c_H, c_I, and $c\_H \times c\_I$ are all positive and significant at the level of 1%, which shows that RHC and IP can not only promote the improvement of AEE alone, but also that IP plays a positive role in the process of RHC promoting the improvement of AEE; Finally, the control variables are substituted into the model (8), and the estimated coefficients of c_H, c_I, and $c\_H \times c\_I$ are still significant, thus further verifying the hypothesis H2.

Table 6. Moderating effect analysis.

Variables	Dependent Variable: AEE		
	(6) Coefficients	**(7) Coefficients**	**(8) Coefficients**
c_H	0.768 *** (0.091)	0.701 *** (0.084)	0.499 *** (0.122)
c_I	0.168 *** (0.059)	0.197 *** (0.054)	0.116 * (0.069)
$c\_H \times c\_I$		1.472 *** (0.159)	1.658 *** (0.214)
lnDis			−0.023 *** (0.008)
Ubr			0.313 (0.215)
lnStr			−0.006 (0.077)
lnSer			0.033 ** (0.013)
lnMac			−0.060 ** (0.030)
cons	0.440 *** (0.022)	0.402 *** (0.023)	0.230 (0.349)
Log likelihood	344.182	383.339	385.223
sigma_u	0.115 *** (0.016)	0.119 *** (0.016)	0.120 *** (0.018)
sigma_e	0.108 *** (0.004)	0.099 *** (0.003)	0.097 *** (0.003)
LR test	266.410 ***	320.350 ***	263.230 ***
Wald test	630.550 ***	837.970 ***	891.450 ***

Note: ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively.

4.4. Robustness Test

From the test results of the model itself, we can see that both the LR test and the Wald test have passed the significance test at the 1% level, which shows that it is reasonable to choose the panel Tobit model with random effects in this paper. In order to further analyze the robustness of the above results, this paper continues to use the instrumental variable method (IV) and panel fixed effect model (FE) to test them. In the instrumental variable method (IV), the first-order lag term of RHC is used as the instrumental variable. Table 7 shows that the test results are basically consistent with the previous results, which shows that the research conclusion of this paper is robust.

Table 7. Robustness test.

Variables	Dependent Variable: AEE	
	IV Coefficients	**FE Coefficients**
L.RHC	1.156 *** (0.115)	
RHC		1.111 *** (0.119)
lnDis	−0.024 *** (0.008)	−0.028 ** (0.008)
Ubr	−0.259 (0.165)	−0.230 (0.252)
lnStr	−0.143 * (0.085)	−0.197 ** (0.099)
lnSer	0.013 (0.014)	−0.005 (0.020)
lnMac	−0.054 * (0.032)	−0.064 * (0.036)
cons	0.951 *** (0.343)	1.228 *** (0.378)

Note: ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively. The estimation results of other models have also passed the robustness test.

5. Discussion

As a special kind of capital, RHC is embodied in farmers' own knowledge, skills, health, and so on. Promoting agricultural green production cannot be separated from farmers' own roles. Their knowledge, skills, and production concepts determine their production behavior, which then affects the input and output of agricultural production. Therefore, RHC has an important impact on AEE. The existing research mainly focuses on the impact of RHC on AEE as measured by the education dimension [14,15], which confirms the impact of EHC on AEE [16,26]. However, there is a lack of systematic analysis of other dimensions of RHC in the literature. Based on existing research, this paper uses the Tobit model to analyze the impact of different dimensions of RHC on AEE. At the same time, this paper examines the moderating role of Internet popularization in the process of RHC affecting AEE. Under the background of promoting agricultural green development, it is expected to provide ideas and directions for promoting agricultural green production from the perspective of farmers.

This study comprehensively analyzes the impact of RHC on AEE from three dimensions of RHC, namely, EHC, HHC, and MHC. The results showed that RHC could significantly promote AEE. Specifically, EHC plays a significant role in promoting AEE. Education can improve farmers' application of technology and improve productivity, which is consistent with the research of M. Reimers, Wu Y., and others [51,52]. Through education and training, farmers have improved their production skills and awareness of environmental protection, thus improving the efficiency of input factors and reducing the use of polluting production factors such as chemical fertilizers and pesticides, which is conducive to improving AEE [22,26]. The difference is that both HHC and MHC also have a significant promotional effect on AEE. As mentioned in the previous theoretical analysis, the research of Wang (2016) and Lu (2017) shows that farmers in good health are more efficient in using input factors such as chemical fertilizers, pesticides, machinery, and equipment [28,31]; Sun (2016) and Brauw (2019) prove that farmers can learn more production technology and management experience in the process of mobility [32,34]. On the basis of them, this study further verified the influence of HHC and MHC on AEE. The improvement of rural HHC means that the health conditions of farmers can be greatly improved, which further improves labor productivity. The improvement of rural MHC means that it is easier for farmers to acquire production technology and management experience. In this way, farmers can do better in agricultural resource management, agricultural production, and pollution control, which can further improve AEE.

Through further subregional regression, we can know that there is regional heterogeneity in the influence of RHC on AEE. Its promoting effect is greatest in the eastern region of China, followed by the northeast region, the central region, and the western region in turn. Different dimensions of RHC also have regional heterogeneity in AEE. For example, the promotion effect of EHC is greater in eastern China; the promotion effect of HHC and MHC is more effective in the northeast region. This result can provide some guidance for policy making, and the improvement of RHC needs to make corresponding policies according to local conditions. Another noteworthy finding is that Internet popularization (IP) plays a positive role in moderating the influence of RHC on AEE. Previous studies have paid little attention to what factors affect RHC in the process of RHC affecting AEE. Some scholars have tested the positive effect of IP on technology diffusion [21,38]. Based on them, this study further verifies the moderating effect of IP, which can further play the role of RHC in promoting AEE. It can provide a new reference for promoting the green development of agriculture.

This study provides a valuable reference for the impact of RHC on AEE. In order to further improve AEE and promote the green development of agriculture, we can formulate corresponding policies from the perspective of improving RHC. However, some studies have shown that social capital can stimulate economic growth through network relations and social trust [53,54]. In areas with abundant social and human capital, more technological innovation will be produced, which has made a great contribution to productivity growth [55,56]. Therefore, it is speculated that there may be an influence relationship between social capital and human capital, and their interaction may be more conducive to the improvement of AEE. This is also the limitation of this study.

6. Conclusions and Recommendations

6.1. Conclusions and Policy Recommendations

Based on the statistical data of 30 provinces in China from 2006 to 2021, this paper uses the super-efficiency SBM model to measure AEE and the Tobit model to empirically analyze the influence of RHC on AEE. At the same time, we further verified the moderating effect of Internet popularization on the effect of RHC on AEE using the moderating effect model. Through this study, we hope to provide policy suggestions for improving AEE and promoting agricultural green development. The main conclusions are as follows: (1) At the national level, RHC and its three dimensions can significantly promote the improvement of AEE. (2) In terms of regional heterogeneity, the impact of RHC and its three dimensions on AEE in the four regions is different. Among them, it has a greater promoting effect on the eastern and northeastern regions and a smaller promoting effect on the central and western regions. (3) In addition, Internet popularization can have a significant positive moderating effect on the process of RHC promoting the improvement of AEE. The above research results show that it can provide a feasible reference for improving AEE and promoting agricultural green development from the perspective of RHC. Therefore, this paper proposes the following policy recommendations:

Improve RHC in multiple dimensions. The development of education and health systems has always been an important social problem that rural China faces. Attaching great importance to this aspect can not only improve RHC but also solve social problems. Therefore, in the educational dimension, the government should increase financial support for rural education and training, optimize the allocation of education and training resources, gradually improve the rural education and training system, and improve the quality of rural education and training. In the health dimension, the government should improve rural medical and health support facilities and focus on supporting areas with relatively poor medical service levels so as to improve the rural medical service level. The new rural cooperative medical system needs to be further improved. Government departments can enhance rural residents' awareness of chronic disease prevention and medical care through publicity. In addition, in the migratory dimension, the government should further improve the rural transportation and communication infrastructure and promote communication between villages and between rural and urban areas. It can give full play to the "demonstration effect" between cities and well-developed rural areas and promote the popularization of agricultural green production technology. Relevant departments should also pay attention to reasonably guiding high-quality farmers to return home.

Improve RHC according to local conditions. Each region should take appropriate measures to improve the level of RHC according to the degree of influence of each dimension of RHC on its AEE, so as to give full play to the promotion role of RHC. For example, the eastern region should focus on improving rural EHC so as to give full play to the promotion of EHC to AEE; the northeast region should focus on improving rural HHC and MHC in order to better play the role of HHC and MHC in promoting AEE.

Make use of the popularization of the Internet to further play the role of RHC. Social innovation has brought many network platforms, which can bring better services to rural areas. Therefore, it is necessary to comprehensively promote the construction of rural information and constantly improve the rural Internet infrastructure. Make full use of the convenience of the network platform, provide online education and training services for farmers, and accelerate the popularization of green production technologies and concepts. In addition, we should actively carry out the integration of RHC and Internet technology. Train a group of new farmers with culture and technology as soon as possible so that they can master new production technologies such as agricultural remote sensing, intelligent agricultural machinery, and efficient pesticide application by unmanned aerial vehicles and further enhance AEE.

6.2. Limitations and Future Prospects

This study has some limitations, and further work needs to be carried out in these areas. First of all, the conclusions obtained by using the data analysis at the provincial level are relatively general. Therefore, the follow-up research will obtain microdata at the farmer level through investigation so as to make a more specific and detailed analysis. Secondly, the moderating effect test results in this study showed that Internet popularization plays a positive role in moderating the influence of RHC on the AEE, and there may be other influence paths that play a role in the impact of RHC on the AEE, which needs to be further analyzed in future studies. In addition, as mentioned in the previous discussion, this study does not consider the role of social capital. There may be interaction between social capital and human capital, which may have a positive impact on AEE. This will be considered in the follow-up study.

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References

1. Wei, M.S.; Yan, T.W.; Luo, S.X. The Impacts of Scale Management and Technological Progress on Green and Low-carbon Development of Agriculture: A Quasi-natural Experiment Based on the Establishment of Major Grain-producing Areas. *Chin. Rural. Econ.* **2023**, *458*, 41–65.
2. Li, Z. The Green Development of Agriculture in China: Innovation and Evolution. *Chin. Rural. Econ.* **2023**, *458*, 2–16.
3. Wu, G.; Xie, Y.; Li, H.; Riaz, N. Agricultural Ecological Efficiency under the Carbon Emissions Trading System in China: A Spatial Difference-in-Difference Approach. *Sustainability* **2022**, *14*, 4707. [CrossRef]
4. Hou, M.Y.; Yao, S.B. Spatial-temporal evolution and trend prediction of agricultural eco-efficiency in China: 1978-2016. *Acta Geogr. Sinica.* **2018**, *73*, 2168–2183.
5. Scuderi, A.; Cammarata, M.; Branca, F.; Timpanaro, G. Agricultural production trends towards carbon neutrality in response to the EU 2030 Green Deal: Economic and environmental analysis in horticulture. *Agric. Econ.* **2021**, *67*, 435–444. [CrossRef]
6. Bethwell, C.; Sattler, C.; Stachow, U. An analytical framework to link governance, agricultural production practices, and the provision of ecosystem services in agricultural landscapes. *Ecosyst. Serv.* **2022**, *53*, 101402. [CrossRef]
7. Thanawong, K.; Perret, S.R.; Basset-Mens, C. Eco-efficiency of paddy rice production in Northeastern Thailand: A comparison of rain-fed and irrigated cropping systems. *J. Clean. Prod.* **2014**, *73*, 204–217. [CrossRef]
8. Guo, H.H.; Liu, X.M. Spatial and Temporal Differentiation and Convergence of China's Agricultural Green Total Factor Productivity. *J. Quant. Technol. Econ.* **2021**, *38*, 65–84.
9. Wu, G.; Riaz, N.; Dong, R. China's agricultural ecological efficiency and spatial spillover effect. Environment. *Dev. Sustain.* **2022**, *25*, 3073–3098. [CrossRef]
10. Li, G.; Tang, D.; Boamah, V.; Pan, Z. Evaluation and Influencing Factors of Agricultural Green Efficiency in Jianghuai Ecological Economic Zone. *Sustainability* **2022**, *14*, 30. [CrossRef]
11. Liang, J.; Long, S.B. China's Agricultural Green Total Factor Productivity Growth and Its Affecting Factors. *J. South China Agric. Univ. Soc. Sci. Ed.* **2015**, *14*, 1–12.

12. Guo, X.; Huang, S.; Wang, Y. Influence of Agricultural Mechanization Development on Agricultural Green Transformation in Western China, Based on the ML Index and Spatial Panel Model. *Math. Probl. Eng.* **2020**, *2020*, 6351802. [CrossRef]
13. Zhang, S.H. The Influence of Heterogeneous Rural Human Capital on Agricultural Green Total Factor Productivity: Based on Provincial Panel Data in China. *J. Shanxi Univ. Philos. Soc. Sci. Ed.* **2017**, *40*, 127–138.
14. Liu, F.; Lv, N. The threshold effect test of human capital on the growth of agricultural green total factor productivity: Evidence from China. *Int. J. Electr. Eng. Educ.* **2021**. [CrossRef]
15. Ma, G.Q.; Tan, Y.W. Impact of Environmental Regulation on Agricultural Green Total Factor Productivity—Analysis Based on the Panel Threshold Model. *J. Agrotech. Econ.* **2021**, *5*, 77–92.
16. Han, H.B.; Zhao, L.F.; Zhang, L. The Influence of Heterogeneous Human Capital on Agricultural Environmental Total Factor Productivity: Empirical Research Based on Rural Panel Data. *J. Cent. Univ. Financ. Econ.* **2014**, *5*, 105–112.
17. Yang, H.; Wang, X.; Peng, B. Agriculture carbon-emission reduction and changing factors behind agricultural eco-efficiency growth in China. *J. Clean. Prod.* **2022**, *334*, 130193. [CrossRef]
18. Chen, F.; Yang, M.J. Influence of International Trade in Agricultural Products on Agricultural Green Total Factor Productivity in China. *J. South China Agric. Univ. Soc. Sci. Ed.* **2021**, *20*, 94–104.
19. Attanasio, O.; Meghir, C.; Nix, E.; Salvati, F. Human Capital Growth and Poverty: Evidence from Ethiopia and Peru. *Rev. Econ. Dyn.* **2017**, *25*, 234–259. [CrossRef]
20. Yin, C.J. Agricultural R&D, Human Capital and Agricultural Total Factor Productivity. *J. South China Agric. Univ. Soc. Sci. Ed.* **2017**, *16*, 27–35.
21. Li, Q.N.; Li, G.C. The Impact of Internet Development on Agricultural Total Factor Productivity Growth. *J. Huazhong Agric. Univ. Soc. Sci. Ed.* **2020**, *4*, 71–78+177.
22. Zhang, Z.; Hou, L.; Qian, Y.; Wan, X. Effect of Zero Growth of Fertilizer Action on Ecological Efficiency of Grain Production in China under the Background of Carbon Emission Reduction. *Sustainability* **2022**, *14*, 15362. [CrossRef]
23. Spielman, D.J.; Ekboir, J.; Davis, K.; Ochieng, C.M. An innovation systems perspective on strengthening agricultural education and training in sub-Saharan Africa. *Agric. Syst.* **2008**, *98*, 1–9. [CrossRef]
24. Puskarova, P.; Piribauer, P. The impact of knowledge spillovers on total factor productivity revisited: New evidence from selected European capital regions. *Econ. Syst.* **2016**, *40*, 335–344. [CrossRef]
25. Fei, H.M.; Chang, X.Y.; Jiang, H.M. Government Regulation, Social Norms, and Farmer's Farmland Quality Protection Behavior: Based on Survey Data in the Black Soil Area of Jilin Province. *Rural. Econ.* **2021**, *10*, 53–61.
26. Yang, Z.Q. How does Education affect Agricultural Green Agricultural Productivity?—An Empirical Study Based on Different Educational Forms in Rural China. *China Soft Sci.* **2019**, *8*, 52–65.
27. Loureiro, M.L. Farmers' health and agricultural productivity. *Agric. Econ.* **2010**, *40*, 381–388. [CrossRef]
28. Wang, Y.Q.; Chen, Y.Z. The Impacts of Labor Migration on Farm Households' Cropping Structure. *Issues Agric. Econ.* **2016**, *37*, 41–48+111.
29. Wang, Y.; Yin, Z.C. Capital accumulation of Healthy Human Resources and Growth of Farmers' Income. *Chin. Rural. Econ.* **2009**, *300*, 24–31+66.
30. Cheng, M.W.; Jin, Y.H.; Gai, Q.E.; Shi, Q.H. Department of Agricultural, Food and Resource Economics. *Econ. Res. J.* **2014**, *49*, 130–144.
31. Lu, J.; Su, Y. Empirical Study on Human Capital, Economic Growth and the Difference of Regional Economic Development: Based on Semi-parametric Additive Mode. *Popul. J.* **2017**, *39*, 89–101.
32. Sun, Y.M. Rural Human Capital Accumulation under Rural Urban Labor Migration: Theoretical Analysis and Enlightenment. *Jiang-Huai Trib.* **2016**, *1*, 17–26.
33. Blair, J.A.S. Migration of agricultural manpower in Sierra Leone. *Tijdschr. Econ. Soc. Geogr.* **2008**, *68*, 198–210. [CrossRef]
34. De Brauw, A. Migration Out of Rural Areas and Implications for Rural Livelihoods. *Annu. Rev. Resour. Econ.* **2019**, *11*, 461–481. [CrossRef]
35. Ma, W.W.; Yang, S.L. An Empirical Study on the Poverty Alleviation Effect of Multidimensional Human Capital in Rural China. *Inq. Econ. Issues* **2017**, *8*, 39–49.
36. Zhu, X.K.; Hu, R.F.; Zhang, C.; Shi, G. Does internet use improve technical efficiency? Evidence from apple production in China. *Technol. Forecast. Soc. Chang.* **2021**, *166*, 120662. [CrossRef]
37. Cheng, M.W.; Zhang, J.P. Internet Popularization and Urban-rural Income Gap: A Theoretical and Empirical Analysis. *Chin. Rural. Econ.* **2019**, *2*, 19–41.
38. Li, G.C.; Cai, M.N.; Ye, F. Internet, human capital and the agricultural TFP growth. *J. Hunan Agric. Univ. Soc. Sci.* **2021**, *22*, 16–23.
39. Wang, J.M. Research into Protection Mechanisms of Rural Water Environment in View of Ecological Civilization: A Case Study of Northern Area of Jiangsu Province. *J. Hehai Univ. Philos. Soc. Sci.* **2016**, *18*, 87–93, 96.
40. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 49. [CrossRef]
41. Ge, P.F.; Wang, S.J.; Huang, X.L. Measurement for China's agricultural green TFP. *China Popul. Resour. Environ.* **2018**, *28*, 66–74.
42. Huang, S.A.; Sun, S.M.; Gong, M.B. The Impact of Land Ownership Structure on Agricultural Economic Growth: An Empirical Analysis on Agricultural Production Efficiency on the Chinese Mainland (1949–1978). *Soc. Sci. China* **2005**, *3*, 38–47, 205–206.
43. Tian, Y.; Zhang, J.B.; Luo, X.F. Regional Comparative Analysis on the Coordination Degree between Net Carbon Benefit and Economic Benefit of Plant Industry in China. *Econ. Geogr.* **2014**, *34*, 142–148.

44. Wu, H.Y.; He, Y.; Huang, H.J.; Chen, W.K. Estimation and spatial convergence of carbon compensating rate of planting industry in China. *China Popul. Resour. Environ.* **2021**, *31*, 113–123.
45. Li, B.; Zhang, J.B.; Li, H.P. Research on Spatial-temporal Characteristics and Affecting Factors Decomposition of Agricultural Carbon Emission in China. *China Popul. Resour. Environ.* **2011**, *21*, 80–86.
46. Zhan, J.T.; Xu, Y.J.; Ge, J.H. Change in agricultural green productivity in China considering the cost of carbon emissions. *Resour. Sci.* **2019**, *41*, 884–896.
47. Liu, Y.F.; Li, H.M.; Ma, H.Y. Evaluation of Agricultural Modernization of State Farms: Based on Entropy Weight Method and TOPSIS Method. *Issues Agric. Econ.* **2021**, *2*, 107–116.
48. Fang, D.C.; Pei, M.D. Study on the Measurement of New and Old Driving Force Conversion and Its Influencing Factors. *Contemp. Econ. Manag.* **2021**, *43*, 26–32.
49. Gao, W.L. The Effect and Its Mechanism of Agricultural Servitization on High-quality Development of Grain Industry. *J. Guangdong Univ. Financ. Econ.* **2021**, *36*, 61–76.
50. Chen, Q. *Advanced Econometrics and Stata Applications*, 2nd ed.; Higher Education Press: Beijing, China, 2014.
51. Reimers, M.; Klasen, S. Revisiting the Role of Education for Agricultural Productivity. *Am. J. Agric. Econ.* **2013**, *95*, 131–152. [CrossRef]
52. Wu, Y.; Li, X. Is human capital investment necessary to modernization? The effect of rural polytechnic training in dual agriculture. *Int. J. Financ. Econ.* **2020**, *26*, 3028–3039. [CrossRef]
53. Beugelsdijk, S.; Schaik, T.V. Social capital and growth in European regions: An empirical test. *Eur. J. Political Econ.* **2005**, *21*, 301–324. [CrossRef]
54. Jia, S.S.; Xu, X. Community-level social capital and agricultural cooperatives: Evidence from Hebei, China. *Agribusiness* **2021**, *37*, 804–817. [CrossRef]
55. Akçomak, I.S.; Ter Weel, B. Social capital, innovation and growth: Evidence from Europe. *Eur. Econ. Rev.* **2009**, *53*, 544–567. [CrossRef]
56. Paula, P. Trust or bust: Growth effects of knowledge, human and social capital revisited. *Econ. Syst.* **2022**, *46*, 101036.