agriculture

MDPI

Article

Does Digital Agricultural Technology Extension Service Enhance Sustainable Food Production? Evidence from Maize Farmers in China

Runqi Lun [1,2,3], Wei Liu [4], Guojing Li [1,2] and Qiyou Luo [1,2,*]

1 Institute of Agricultural Resources and Regional Planning, Chinese Academy of Agricultural Sciences, Beijing 100081, China; lunrunqi@hotmail.com (R.L.); liguojing@caas.cn (G.L.)
2 State Key Laboratory of Efficient Utilization of Arid and Semi-arid Arable Land in Northern China, Beijing 100081, China
3 Agricultural Production and Resource Economics, Technical University of Munich, Freising-Weihenstephan, 85354 Munich, Germany
4 China Mobile Group Design Institute Co., Ltd., Beijing 100083, China; david1991caas@sina.com
* Correspondence: luoqiyou@caas.cn

Abstract: This research aims to investigate the average and heterogeneous impacts of digital agricultural technology extension service use on eco-efficiency among 1302 maize-producing farmers from a major maize-producing area in Northeast China in 2022. The slack-based measure model with undesirable outputs is applied to calculate the eco-efficiency of maize production. To obtain an unbiased estimation of the average effect, the self-selection problem generated by observable and unobservable factors is solved by the endogenous switching regression model. Quantile regression is utilized to analyze the heterogeneous effect. Notably, the mediated effects model is utilized to examine the potential mechanism between them. Our findings indicate that digital agricultural technology extension service use can increase maize production's eco-efficiency. Digital agricultural technology extension service users would have reduced the eco-efficiency of the service by 0.148 (21.11%) if they had not used it. Digital agricultural technology extension service nonusers would have improved the eco-efficiency of the service by 0.214 (35.20%) if they had used it. The robustness check reconfirms the results. Moreover, digital agricultural technology extension service use is more helpful for maize farmers who have lower eco-efficiency than those who have higher eco-efficiency. Digital agricultural technology extension service use can improve the eco-efficiency of maize production through the application of organic fertilizers, green pesticides, and biodegradable agricultural films. There are policy implications of these findings: there is an argument for using the publicity of the digital agricultural technology extension service to encourage farmers to use sustainable inputs; additionally, it might be worthwhile to implement a categorized promotion strategy based on the different real-world situations.

Keywords: digital agricultural technology extension service; sustainable food production; eco-efficiency of maize production; endogenous switching regression; potential mechanism

check for updates

Citation: Lun, R.; Liu, W.; Li, G.; Luo, Q. Does Digital Agricultural Technology Extension Service Enhance Sustainable Food Production? Evidence from Maize Farmers in China. *Agriculture* **2024**, *14*, 292. https://doi.org/10.3390/agriculture14020292

Academic Editor: Claudio Bellia

Received: 26 December 2023
Revised: 5 February 2024
Accepted: 8 February 2024
Published: 10 February 2024

1. Introduction

Maize is an important staple food in China and the world [1,2]. As shown in Figure 1, China is now the second maize producer in the world, accounting for 22.54% of the world's total production (277.20 million tons) and 21.06% of its cultivation area (43.36 million ha) in 2022 [3]. Maize is a staple food in China, and its production has been higher than that of rice and wheat for the past decade (as shown in Figure 2), which is important for China's food security; maize has strong adaptability to pests, diseases, climate change, and differences in soil quality. It additionally has high output and is a multipurpose crop, which can be consumed as a vegetable, fodder, and staple food. Maize is a vital food for rural socioeconomic development in China, and is widely distributed in China. It is largely produced in ecologically fragile areas, such as in Northeast and Northwest China, where the realization of sustainable maize production has a positive impact on the local ecosystem [4–6]. Due to the overuse of agricultural production factors, such as chemical fertilizers, chemical pesticides, and plastic films, environmental pollution is currently one of the most prominent challenges facing sustainable maize production and economic development in rural areas [7–11]. The key to achieving sustainable food production is to improve the eco-efficiency (EE) of maize production, attaining higher desirable outputs and lower undesirable outputs [12]. EE was first introduced in 1990 [13] and has been widely used in different sectors and areas to measure sustainability [14–16]. In agriculture, EE refers to the ratio of the economic value created by agricultural production to the environmental impact [12,17–19]. In order to achieve an green agricultural transition and build resource-saving and environmentally friendly agricultural production systems, increasing agricultural efficiency within the restrictions of agricultural pollution discharge is an essential decision. To accomplish sustainable agricultural production practices, it is imperative to enhance EE.

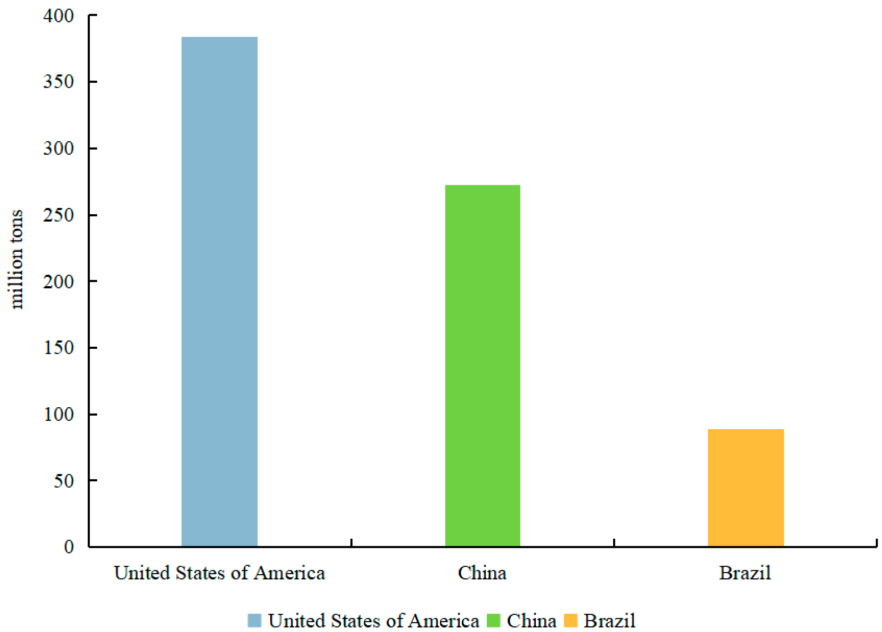

Figure 1. Top three maize producers in the world in 2022.

Digital agricultural technology extension service (DATES) is a new type of agricultural technology extension service, combining the Internet (PC, smart phone, tablet, etc.) with traditional agricultural technology extension services (neighborhood exchange, online guidance, technical training classes, scientific and technological demonstrations, and mass media presence such as newspapers, radio, television, etc.); it has the characteristics of high efficiency, low cost, and high availability [20–22]. DATES can address challenges in traditional agricultural technology extension services, such as poor timeliness, narrow content limitations, time-consuming and labor-intensive offline guidance, and difficulty in carrying out large-scale technical training lectures during the COVID-19 epidemic. This contributes to promoting the sustainable transformation of food production [23]. The Internet has been an efficient way to obtain sustainable production knowledge, especially in rural China [24]. With the implementation of the "Internet Plus" strategy by Chinese government, China's rural netizens have grown from 156 million in 2012 to 308 million in 2022, and the Internet penetration rate in rural areas has increased from less than 23.70% in 2012 to 61.90% in 2022, according to data provided by the China Internet Network Information Center (as shown in Figure 3) [25]. The significant increase in rural Internet penetration rate and the number of rural netizens shows that a large number of rural netizens have become potential target groups for DATES, providing solid support for the application of DATES to farmers. On the other hand, these large numbers of rural netizens are direct beneficiaries of the adoption of sustainable food production practices [20]. Thus, DATES, as one of information and communication technologies (ICTs), has been a key driver for agricultural economics growth, food sustainable production, and the integration of agricultural digitalization and food production.

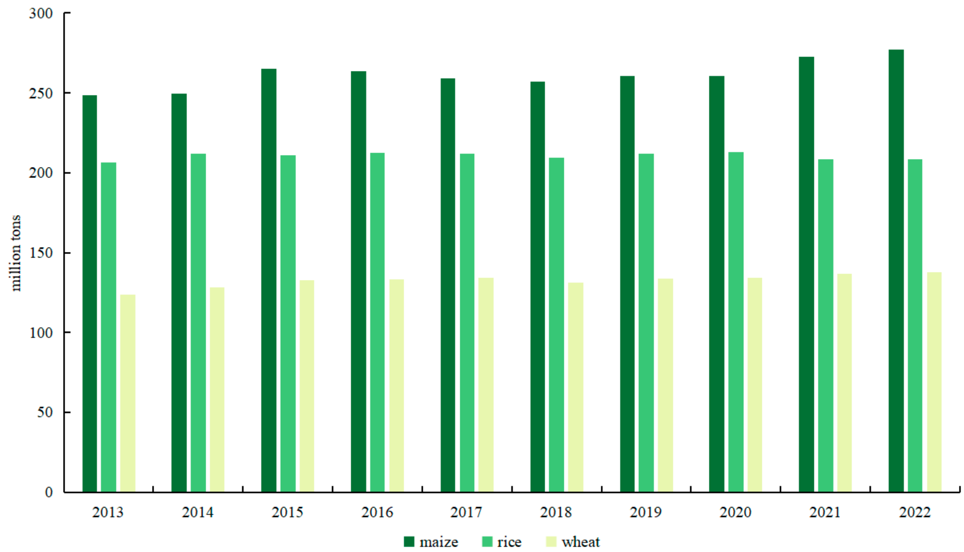

Figure 2. Three staple foods yield in China from 2013 to 2022.

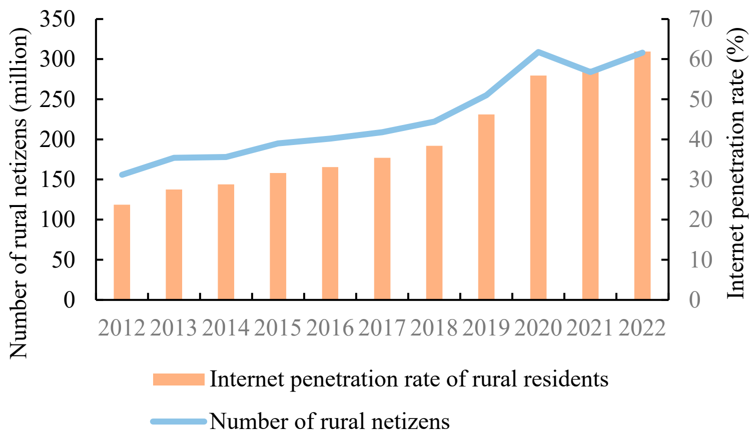

Figure 3. Rural netizens in China from 2012 to 2022.

Many scholars have studied EE from different perspectives. Some of them evaluated the EE of many agricultural products, i.e., wheat, cotton, soybeans, and rice [26–29], with the average EE of different agricultural products being quite different, ranging from 0.51 to 0.89; this represents different room for improvement in sustainable production of different crops, but only a few studies have explored the EE of maize production. Some studies measured EE from macro, meso, and micro perspectives [30–36]. Although many methods have been developed to evaluate EE, the two most commonly used methods in previous studies are data envelopment analysis (DEA) and stochastic frontier analysis (SFA) [4]. SFA, as a parametric methodology, can handle the impact of uncontrollable factors on inefficiency [37,38], but it is generally only suitable for single-output and multi-input production [39]. DEA is a non-parametric frontier methodology to evaluate EE with multiple inputs and outputs [40]. The method avoids issues related to model setting errors and the impact of nontechnical factors on the EE [41]. In addition, the traditional DEA has a disadvantage in that it can easily overlook undesirable outputs during the calculation process, so it cannot obtain the actual efficiency accurately. Subsequently, the slack-based measure (SBM) model was introduced in 2001, which can overcome the shortcomings of DEA [42]. Hence, this study adopts the SBM model with undesirable outputs.

Existing studies have increasingly concentrated on how DATESs use affects agricultural production practices, especially sustainable agricultural practices (SAPs) selection. First of all, DATESs have become an important channel for farmers to obtain technologies and information related to sustainable food production, meeting their practical needs for solving technical problems and obtaining technical guidance online, and avoiding the shortcomings of inefficiency of technical information transmission and restricted time and space that exist in traditional agricultural technology extensions [43,44]. Secondly, as an efficient information tool, DATES can fill the information gap, reduce information search costs, and accelerate the circulation of agricultural information [45–47]. Thirdly, farmers use DATES to conduct two-way communication with the outside world, improve their decision-making capabilities and risk perception before technology selection, reduce information negotiation costs [48,49], and change farmers' technology adoption preferences in order to maximize the economic benefits of agriculture; in turn, these changes have a potential impact on sustainable food production [50]. However, few studies have focused on the relationship between DATESs and the EE of food production.

The main contribution of this study is to explore the direct effect, heterogeneous effect, and potential mechanism of DATESs on EE while effectively solving the endogeneity problem caused by observable and unobservable variables. This paper offers a possible way to achieve sustainable food production from the perspective of DATESs and build a theoretical bridge between DATESs and sustainable food production. The findings of this paper will present detailed and timely empirical evidence for the expansion of DATESs and a valuable reference for the sustainable development of food production.

The purpose of this paper is to explore the impact of DATESs use on EE of maize production and potential mechanism between them. Differently from existing studies, DATES use is referred to when maize farmers use the DATES to browse and obtain sustainable technologies and input information about maize production rather than only having smart phone apps or following public WeChat accounts. The endogenous switching regression (ESR) model is utilized to address the self-selectivity bias from observable and unobservable variables. An SBM model is employed to evaluate the EE of maize production, which refers to the level of sustainable production. A quantile regression (QR) model is used to investigate the heterogeneous impact of DATES on EE. A mediation model is employed to explore the potential mechanism between them.

The rest of this paper is organized as follows. Section 2 presents the theoretical analysis and research hypothesis. Section 3 describes the data and methodology used in this paper. Section 4 presents the estimation results and Section 5 states the discussion. Section 6 states the conclusions and policy implications.

2. Theoretical Analysis and Research Hypotheses

2.1. Direct Effects of the DATES

According to the new economic growth theory, it is known that technological progress is an important engine for driving sustainable economic growth. DATES, as an important driving force for promoting agricultural economic growth, deeply influences the dissemination and diffusion of information related to the concept, technologies, and inputs of sustainable food production; these contribute to the improvement of the EE of agricultural production. On the one hand, DATES has accelerated the promotion and application of maize sustainable production concepts and technologies. DATES can significantly reduce the cost of searching for information on sustainable maize production, alleviate the asymmetry of agricultural information, deepen farmers' knowledge of sustainable food production, and lead farmers to gradually integrate their knowledge into all process of maize production, thereby improving the EE of maize production. On the other hand, the development of the DATES has facilitated the dissemination and diffusion of knowledge on inputs for sustainable production. DATES has greatly reduced the threshold of maize farmers' access to information on sustainable production inputs, accelerated the speed of information dissemination, broken the traditional information dissemination network based on blood or geography, and improved maize farmers' knowledge of sustainable inputs such as organic fertilizers, green pesticides, and biodegradable films, thus realizing the improvement of the EE of maize production (as shown in Figure 4). Thus, this paper proposes hypothesis 1:

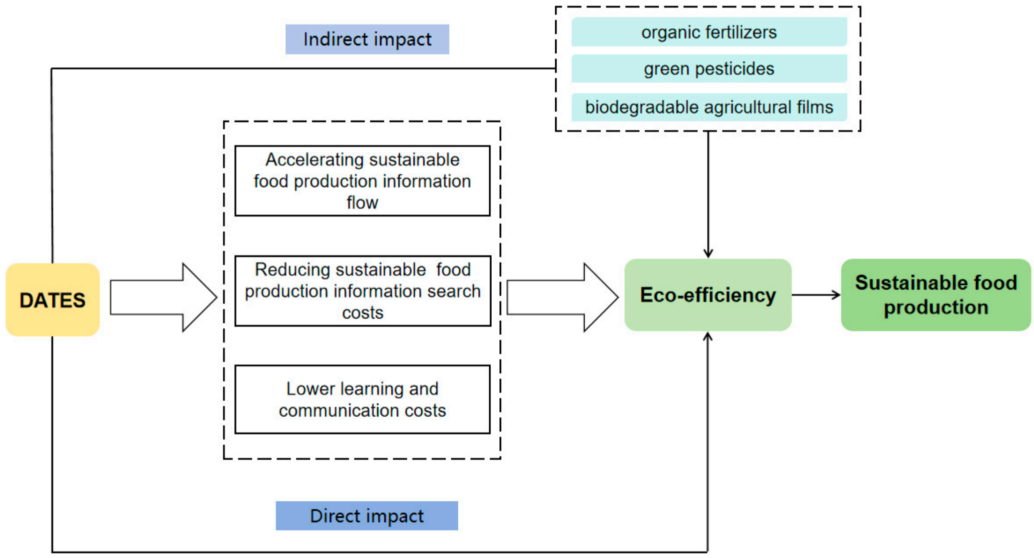

Figure 4. Theoretical framework.

H1. *DATES use can improve the EE of maize production.*

2.2. Heterogeneous Effects of DATES

The impact of DATES use on the EE of maize farmers is heterogeneous. On the one hand, DATES use improves the utilization efficiency of input factors such as capital and land and leads to better allocation efficiency can be achieved in maize production. However, according to the theory of marginal effect, with the continuous improvement of the utilization efficiency of each input factor, the degree of the impact of DATES use on input factors will gradually decrease; in turn, this affects the improvement of the EE of maize production. On the other hand, the DATES will accelerate the accumulation of human capital of maize farmers, but its acceleration effect also has a marginal decreasing trend. The DATES has promoted the accumulation of human capital of maize farmers by spreading sustainable production concepts, technologies, and inputs. The most direct reflection of the accumulation of human capital is the change in the EE of maize production (as shown in Figure 4). With the accumulation of human capital, the impact of DATES use on the EE of maize production has gradually decreased. Based on the analysis, this study proposes hypothesis 2:

H2. *DATES use affects low-EE maize farmers to a greater extent than it affects high-EE maize farmers.*

2.3. Mediation Effects of the DATES

The use of sustainable inputs can improve EE of maize production. As an efficient information acquisition channel, the DATES can help disseminate and diffuse information about sustainable inputs, thereby promoting the improvement of EE in maize production. On the one hand, the DATES can significantly reduce the cost for maize farmers to obtain knowledge related to sustainable inputs. Under the assumption of rational choice theory, if the benefits of sustainable input information are greater than their search costs, maize farmers will actively search for and learn relevant information. This will help stimulate maize farmers' initiative in obtaining information, accelerate the accumulation of knowledge about sustainable inputs, and thus affect the EE of maize production. On the other hand, the DATES can increase the speed of information flow on sustainable inputs. Farmers using the DATES can quickly obtain knowledge about sustainable inputs and the impact on the agricultural environment, deepen their awareness of the environmental benefits brought by sustainable inputs, and increase their willingness to use sustainable inputs; in turn, these affect the EE of maize production (as shown in Figure 4). In view of this, this study proposes hypothesis 3.

H3. *DATES use improves the EE of maize production through the increased use of organic fertilizers, green pesticides, and biodegradable agricultural films.*

3. Materials and Methods

3.1. Data Collection

The farm household cross-sectional data from maize farmers were collected by agricultural layout and regional development research group from September to December 2022 in Heilongjiang, Jilin and Liaoning provinces, China, including 18 researchers. As the three important regions in the main maize-producing area of Northeast China, Heilongjiang, Jilin, and Liaoning provinces were selected as the study regions. Maize output in these three provinces exceeded 92.55 million tons, accounting for 33.39 percent of China's maize total output in 2022. Firstly, Changtu County in Tieling city, Daowai and Acheng Districts in Harbin city, Longjiang and Gannan Counties in Qiqihar city, Gongzhuling, Jiutai, and Yushu Counties in Changchun city, and Lishu County in Siping city were selected from the main maize-producing areas of Northeast China based on the maize production capacity and level of regional economic development. Secondly, 3–4 townships were randomly selected from each sample district and county based on random sampling method, resulting in 28 towns. Thirdly, 3–4 administrative villages were randomly selected from each township, resulting in 107 administrative villages. Finally, 10–16 maize farmers were randomly selected from a complete list of maize farm households, which was provided by the committee within each administrative village. Therefore, the final sample included 1302 maize farmers (as shown in Table 1). The survey was based on a participatory approach, with one-on-one interviews with maize farmers. Thus, the sample is representative.

All of the sampled maize farmers were given a questionnaire. The survey was limited to only decision makers (in most cases, the head of household is responsible for maize production in Northeast China). This questionnaire employed a multi-criteria decision-making approach. As the main objective of this study is to investigate whether the use of the DATES improves the EE of maize production, we started by measuring the EE of maize production for each maize farmer. Considering the use of the slack-based measure (SBM) model to calculate EE, questions were designed to collect information on inputs, desired outputs, and undesired outputs in maize production. Next, additional questions were designed to determine whether the sample maize farmer households use the DATES to access information on agricultural production technologies and inputs. Given the control variables required for the endogenous switching regression (ESR) model, quantile regression (QR) model, and mediation effects model, we also collected detailed information on individual characteristics, production characteristics, and household characteristics. Before the survey was performed, all of the respondents went through the same training to make sure they understood the purpose of survey.

Table 1. Sample distribution of maize farmers.

Provinces	Cites (Counties and Districts)	Townships	Administrative Villages	Number of Samples and Proportion
Liaoning	Changtu County, Tieling city	Changtu Town	Dongming Village, Sandougou Village, Aiguo Village, Shahezi Village	273 (20.97%)
		Sihe Town	Huajia Village, Qiaobei Village, Jijia Village	
		Dawa Town	Caijia Village, Xiuyan Village, Guangwen Village, Michang Village	
		Guyushu Town	Xingguo Village, Guyushu Village, Dongfeng Village, Dafang Village	
Heilongjiang	Daowai District, Harbin city	Yongyuan Town	Yongyuan Village, Nangang Village, Shuangyuan Village, Dongchuan Village	512 (39.32%)
		Juyuan Town	Juyuan Village, Xinfeng Village, Qianjin Village, Xiaoshan Village	
		Tuanjie Town	Dongxin Village, Xingxing Village, Tuanjie Village, Hongli Village	
	Acehng District, Harbin city	Pingshan Town	Beichuan Village, Suizhong Village, Shuanghe Village, Pingshan Village	
		Hongxing Town	Zhenxing Village, Haixing Village, Haidong Village, Cixing Village	
		Jinlongshan Town	Fuxing Village, Lingxi Village, Yongxing Village, Yudian Village	
	Longjiang County, Qiqihar city	Longjiang Town	Longdong Village, Longxi Village, Xianguang Village, Jiuli Village	
		Longxing Town	Longxing Village, Desheng Village, Wenhua Village, Huayuan Village	
		Shanquan Town	Pingan Village, Daquanzi Village, Longshan Village	
	Gannan County, Qiqihar city	Gannan Town	Dongjiao Village, Xijiao Village, Fuqiang Village, Changsheng Village	
		Dongyang Town	Tongmeng Village, Heping Village, Lianhe Village, Longsheng Village	
		Pingyang Town	Dongsheng Village, Yongli Village, Jianguo Village, Xinglong Village	
Jilin	Jiutai County, Changchun city	Qitamu Town	Liujia Village, Hongqi Village, Xinxin Village	517 (39.71%)
		Xinglong Town	Xingxing Village, Xinglong Village, Jinchuan Village, Hanjia Village	
		Donghu Town	Heilin Village, Shuangshan Village, Wuyi Village, Xinsheng Village	
	Yushu County, Changchun city	Tuqiao Town	Tuqiao Village, Weiguo Village, Baojia Village, Shili Village	
		Xinli Town	Yonghe Village, Taiping Village, Shuangyu Village, Xinli Village	
		Daling Town	Daling Village, Dalong Village, Linjia Village, Linhe Village	
	Gongzhuling County, Changchun city	Xiangshui Town	Wanlong Village, Chifu Village, Pingan Village, Xiangshui Village	
		Daling Town	Cuijia Village, Yonghe Village, Changfa Village, Erdao Village	
		Shuanglong Town	Xinmin Village, Hehe Village, Shifo Village, Yongmao Village	
	Lishu County, Siping city	Lishu Town	Hujia Village Miaopu Village, Gaojia Village, Yangjia Village	
		Wanfa Town	Changsheng Village, Lijia Village, Moujia Village	
		Donghe Town	Donghe Village, Shengli Village, Shuangchengzi Village	

3.2. Methodology

3.2.1. The Slack-Based Measure (SBM) Model

Assuming returns to scale are constant (CRS), the SBM model is as follows:

$$\begin{gathered} min\rho^* = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}^t}}{1+\frac{1}{s1+s2}\left(\sum_{r=1}^{s1}\frac{s_r^g}{y_{r0}^g}+\sum_{r=1}^{s2}\frac{s_r^b}{y_{r0}^b}\right)} \\ \text{s.t.} \\ x_0 = X\lambda + s^- \\ y_0^g = Y^g\lambda - s^g \\ y_0^b = Y^b\lambda + s^b \\ s^- \geq 0,\ s^g \geq 0,\ s^b \geq 0,\ \lambda \geq 0 \\ X = [x_1,\ x_2,\ \cdots,\ x_n] \in R^{m\times n} \\ Y^g = [y_1^g,\ y_2^g,\ \cdots,\ y_n^g] \in R^{s1\times n} \\ vY^b = [y_1^g,\ y_2^g,\ \cdots,\ y_n^g] \in R^{s2\times n} \end{gathered} \tag{1}$$

s represents the slack variable of input and output, and s^-, s^g, and s^b are slack variables denoting input excess, link excess, and output shortfall, respectively. s^-, s^g, and s^b are the variables when estimating the overall EE of DMU. s^-, s^g, and s^b are strictly decreasing. x_{i0} represents the observed input of DMU i, y_{r0} represents the observed output of DMU r, and m represents the number of decision-making units. X, Y^g, and Y^b are the matrices of the input, good output, and bad output, respectively, while X, Y^g, and Y^b are all strictly larger than zero. λ represents the constant vector. ρ^* represents agricultural EE, $\rho^* \in [0,1]$, $\rho^* = 1$ means production units completely efficient, and $s^- = s^g = s^b = 0; \rho^* < 1$ means a production unit is efficiency loss [5,51,52].

3.2.2. Endogenous Switching Regression (ESR) Model

Actually, maize farmers do not make random decisions about using DATES, so there is an issue with self-selection. We employed the ESR model to address this issue, because ESR allows us to figure out self-selection problem caused by both unobservable and observable factors [53–56], and ESR models may perform better than propensity score matching (PSM) that only focus on observable factors [57].

Theoretically, there are two steps in the ESR model. Firstly, a selection equation is created to characterize whether maize farmers search, browse, and acquire sustainable technologies and information through the DATES. It is notable that a maize farmer chooses to use the DATES when the predicted value from doing so exceeds the value from not doing so. S_i is a dummy variable utilized to represent the binary option. Given that it is impossible to observe the predicted value, but it is possible to observe whether a maize farmer uses the DATES, let S_i^* represent the latent variable defining the probability of being DATES user.

Firstly, the decision to use the DATES can be described as shown in Equation (2):

$$S_i^* = \gamma_i Z_{ij} + \nu_i \tag{2}$$

where S_i^* represents the latent variable of the dummy variable S_i, if $S_i^* > 0$, $S_i = 1$; if $S_i^* \leq 0$, then $S_i = 0$. Z_{ij} embodies a vector of independent variables used in the selection equation. Note that the explanatory variables in Z_{ij} can be repeated with X_{ij}, but for better identification, Z_{ij} should contain at least one variable that is not included in X_{ij}, that is, an instrumental variable, which should have a direct impact on whether maize farmers use the DATES but not on their EE; thus, we selected the communication signal strength of the sample villages as the instrumental variable (IV). Considering that the communication signal is the basis for daily communication, each maize farmer may not access WeChat accounts or apps of DATES, but is more likely to access the communication signal, and DATES use and communication signal strength are strongly related. Thus, we believe that the strength of the communication signal influences each maize farmer's decision to use DATES, but has no effect on EE. ν_i represents a random error term assumed to be $\nu_i \sim N\left(0, \sigma_\nu^2\right)$, and γ_i denotes a vector of parameters to be estimated.

Secondly, two different outcome equations are established for DATES users and nonusers in the following:

$$EE_{1i} = \sum_{j=1}^{n} \beta_1 X_{1ij} + \mu_{1i},\ if\ S_i = 1 \tag{3}$$

$$EE_{2i} = \sum_{j=1}^{n} \beta_2 X_{2ij} + \mu_{2i},\ if\ S_i = 0 \tag{4}$$

where DATES users and nonusers are represented by subscripts 1 and 2; X_{ij} represents a vector of independent variables for the outcome equations; β_i is a vector of coefficients to be estimated; and μ_{1i} and μ_{2i} are random error terms assumed to be $\mu_{1i} \sim N\left(0,\ \sigma_1^2\right)$ and $\mu_{2i} \sim N\left(0,\ \sigma_2^2\right)$, respectively.

The error terms in Equations (2)–(4) presume a zero-mean trivariate normal distribution, and the covariance matrix is listed as below:

$$cov(\nu_i,\ \mu_{1i}, \mu_{2i}) = \begin{bmatrix} \delta_\eta^2 & \delta_{\eta 1} & \delta_{\eta 2} \\ \delta_{1\eta} & \delta_1^2 & \delta_{12} \\ \delta_{2\eta} & \delta_{21} & \delta_2^2 \end{bmatrix} \tag{5}$$

where δ_η^2, δ_1^2, and δ_2^2 are the variances of ν_i, μ_{1i} and μ_{2i}, respectively. The covariance between ν_i and μ_{1i} are $\delta_{1\eta}$ and $\delta_{\eta 1}$; the covariance between ν_i and μ_{2i} are $\delta_{2\eta}$ and $\delta_{\eta 2}$; δ_{12} and δ_{21} are the covariance between μ_{1i} and μ_{2i}, but they are not defined since EE_{1i} and EE_{2i} cannot be observed simultaneously.

Given the self-selectivity bias, the random error terms μ_{1i} and μ_{2i} are listed as below:

$$E(\mu_{1i} | S_i = 1) = \delta_{1\eta} \lambda_{1i} = \delta_{1\eta} IMR_{1i} \tag{6}$$

$$E(\mu_{2i} | S_i = 0) = \delta_{2\eta} \lambda_{2i} = \delta_{2\eta} IMR_{2i} \tag{7}$$

where λ_{1i} and λ_{2i} are the inverse Mills ratios, which can correct for the selection bias [56,58].

The ESR model can help us to estimate the expected EE for DATES users and nonusers in the counterfactual and actual contexts:

$$E(\mu_{1i} | S_i = 1) = \delta_{1\eta} \lambda_{1i} = \delta_{1\eta} IMR_{1i} \tag{8}$$

$$E(\mu_{2i} | S_i = 0) = \delta_{2\eta} \lambda_{2i} = \delta_{2\eta} IMR_{2i} \tag{9}$$

$$E(Y_{1i} | S_i = 0) = \beta_{2j} X_{2ij} + \delta_{2\eta} IMR_{2i} \tag{10}$$

$$E(Y_{2i} | S_i = 1) = \beta_{1j} X_{1ij} + \delta_{1\eta} IMR_{1i} \tag{11}$$

We can also estimate the average treatment effect on the treated group (ATT), which is the difference between Equations (8) and (10), and the average treatment effect on the untreated group (ATU), which is the difference between Equations (9) and (11).

$$ATT = E(Y_{1i} | S_i = 1) - E(Y_{2i} | S_i = 0) \tag{12}$$

$$ATU = E(Y_{1i} | S_i = 0) - E(Y_{2i} | S_i = 0) \tag{13}$$

Due to the self-selectivity bias is accounted for through this computation, ATT and ATU indicate unbiased estimation.

3.2.3. Quantile Regression (QR) Model

After measuring the average impact of using the DATES to access sustainable technologies and information on the EE of maize production, the heterogeneous impact on the EE of maize production is further explored. The quantile regression model has two main characteristics: one is that the model is not strongly constrained by the assumptions of the error term, which can effectively avoid the influence of extreme values in the data, and the estimation results tend to be more robust; and the other is constructed by using the weighted average of the absolute values of the residuals to minimize the objective function, which can estimate the regression coefficients of the explanatory variables under different quantile points [59]. The specific model is as follows:

$$Q_q = a_q + b_q X_i + c_q W_i + \varepsilon_i \tag{14}$$

where Q_q denotes the EE of maize production of maize farmers; vector X_i represents the explanatory variables, vector W_i represents the control variables; a_q, b_q, and c_q denotes the parameters to be estimated; and ε_i denotes the error term.

3.2.4. Mediation Effects Model

Combining the stepwise regression method and bootstrap method, the mediating role of green inputs in the impact of using the DATES on the EE of maize production was tested. The mediating effect model is as follows:

$$Y_i = a_0 + a_1 X_i + a_2 N_i + \varepsilon_1 \tag{15}$$

$$M_i = b_0 + b_1 X_i + b_2 N_i + \varepsilon_2 \tag{16}$$

$$Y_i = c_0 + c_1 X_i + c_2 M_i + c_3 N_i + \varepsilon_3 \tag{17}$$

where Y_i denotes the EE of maize production; vector X_i represents the explanatory variables; vector M_i represents the mediating variables; vector N_i represents the control variables; a, b and c denotes the parameters to be estimated; and ε is the error term.

4. Results

4.1. Descriptive Statistics

The variables are composed of two parts: (1) inputs, desirable output, undesirable outputs, and related emission coefficients in the SBM model; (2) dependent variables, control variables, instrumental variables, and treatment variables for the ESR model.

In terms of the SBM model, the desirable output is maize gross revenue per ha, and the inputs consist of land, seed, fertilizer, labor, and others (including pesticides, agricultural film, and machinery). The undesirable output is composed of carbon emissions and nitrogen and phosphorus losses.

EE, as the dependent variable for the ESR model, is evaluated based on the SBM model, ranging from 0 to 1.

The treatment variable for the ESR model is DATES use. DATES use is regarded as maize farmers acquire sustainable production technologies and information through WeChat public accounts or smart phone apps. See the following question from the questionnaire: “Do you use WeChat public accounts of DATES to access sustainable production technologies and information?” Here, if the answer is “yes”, then it equals 1; otherwise, it equals 0.

The instrumental variable (IV) in this paper is denoted as the communication signal strength of the sample villages. Considering that the communication signal is the basis for daily communication, each maize farmer may not access WeChat accounts or apps of DATES, but is more likely to access the communication signal, and DATES use and communication signal strength are strongly related. Thus, we believe that the strength of the communication signal influences each maize farmer’s decision to use DATES, but has no effect on EE. On a 5-point Likert scale (very poor, poor, average, good, and outstanding, equal to 1, 2, 3, 4, and 5, respectively), a question was devised to measure each maize farmer's satisfaction level of communication signal strength.

The control variables for the ESR model consist of two parts. The first part states maize farmers' characteristics, such as gender, age, health status, years of education, whether they are village leaders, whether they participate in off-farm work, and whether they participate in digital technology training. The second part is the production characteristics, involving farm size, income from other crops production, the number of laborers in maize production, degree of specialization, and distance from households to the nearest central market.

In this study, total carbon emissions of maize production process should include carbon emissions caused by carbon sources such as fertilizers, pesticides, diesel fuel (including sowing and harvesting), agricultural films, deep plow, and irrigation. The calculation formula can be specified as follows:

$$C = \sum C_i = \sum n_i \times \gamma_i \tag{18}$$

where C denotes the quantity of carbon emissions, C_i represents the emissions from different carbon sources, n_i denotes the usage amounts of inputs and diesel fuel and the deep plowed area, and γ_i is the emission coefficient of different carbon sources in agriculture; Table 2 presents the agricultural carbon emission coefficient and reference sources.

Table 2. Agricultural carbon emission source, coefficient, and reference sources.

Source	Carbon Emission Coefficient	References
Fertilizer	0.896 kg/kg	Oak Ridge National Laboratory
Pesticide	4.934 kg/kg	Oak Ridge National Laboratory
Diesel fuel	0.593 kg/kg	Intergovernmental Panel on Climate Change (IPCC)
Agricultural film	5.180 kg/kg	Institute of Resource, Ecosystem and Environment of Agriculture, Nanjing Agricultural University
Deep plow	312.600 kg/km^2	College of Biological Sciences, China Agricultural University
Irrigation	25 kg/ha	Dubey [60]

In this study, the total nitrogen and total phosphorus produced in the maize production process should be calculated using Formula (19):

$$E = m_i \times (\rho_i + \delta_i) \tag{19}$$

where E is the total nitrogen and total phosphorus losses in the maize production process; m_i is the nitrogen and phosphorus used in maize production process, which mainly come from the chemical fertilizer input in the production process, expressed in pure amount of chemical fertilizer; and ρ_i and δ_i are the nitrogen and phosphorus loss coefficients, respectively, as presented in Table 3 [61].

Table 3. Chemical fertilizer loss rate in study areas.

Region	Loss Rate (%)	
	Nitrogen Fertilizer	Phosphate Fertilizer
Liaoning and Jilin	20	4
Heilongjiang	10	7

Table 4 presents the descriptive statistics of desirable outputs, inputs, and undesirable outputs for the SBM model. From the perspective of maize production, we select the cost of land, seed, fertilizer, labor, and others (including pesticides, agricultural film, and machinery) as inputs and maize gross revenue as the desirable output. As shown in Table 3, compared to the DATES nonuser group, desirable output and most inputs in DATES user group are higher than DATES nonuser group, except for seed.

Table 4. Descriptive statistics of inputs, desirable output, and undesirable outputs.

Variable	Total	DATES Users	DATES Nonusers	Difference
Desirable output (CNY/ha)	26,025.579	27,526.312	22,874.039	4652.272 ***
Land (CNY/ha)	1494.617	1550.556	1377.147	173.409 *
Seed (CNY/ha)	753.073	669.033	84.040	753.073
Fertilizer (CNY/ha)	2460.384	2508.372	2358.552	149.821 **
Labor (CNY/ha)	7658.409	7519.770	7952.627	−432.857 **
Others (CNY/ha)	1197.574	1232.485	1124.271	108.214 **
Total carbon emission (kg/ha)	1387.381	1467.790	1216.716	276.073 **
Total nitrogen loss (kg/ha)	170.3187	176.4504	157.302	19.1484
Total phosphorus loss (kg/ha)	34.3683	34.8462	33.3639	1.4823

Note: CNY is Chinese currency, 1 USD = 6.726 CNY in 2022, ***, **, and * denote significance at the 1%, 5%, and 10% significance levels, respectively.

Table 5 displays descriptive statistics for the ESR model variables. There are 882 DATES users and 420 nonusers among the 1302 samples, indicating that 67.13% of maize farmers use the DATES to obtain sustainable technologies and information about maize production (as shown in Figure 5). The comparison between DATES users and nonusers reveals obvious differences in several variables. For instance, the education years in DATES users' group are significantly higher than those in the nonusers group. Compared to the DATES nonusers, DATES users are younger, more healthy, well-educated, more willing to be village leaders, have a larger farm size, earn more from other crops, and have more digital technology training. Notably, these significant differences between the two groups suggest the possibility of a self-selection issue in DATES use.

Table 5. Descriptive statistics of variables for the ESR model.

Variables	Definition	Total	DATES Users	DATES Nonusers	Difference
EE	Ranges from 0 to 1	0.671	0.702	0.608	0.094 ***
DATES use	1 = yes, 0 = no	0.677	1.000	0.000	1.000 ***
Communication signal strength	Very bad, bad, average, good and excellent equal to 1–5, respectively	2.535	2.799	1.979	0.820 ***
Age	Age of respondents	48.479	46.786	52.036	−5.250 ***
Gender	1 = male, 0 = female	0.749	0.820	0.600	0.220 ***
Health status	1 = very poor, 2 = poor, 3 = fair, 4 = better, 5 = very good	3.858	4.051	3.665	0.386 ***
Education	Years of education	11.044	11.772	9.514	2.258 ***
Off-farm work	1 = yes, 0 = no	0.523	0.541	0.486	0.055
Village leader	1 = yes, 0 = no	0.157	0.197	0.071	0.126 ***
Farm size	Maize planted area (hectare)	0.730	0.860	0.519	0.340 ***
Income from other crops	Other crops gross revenue in 2022 (ten thousand CNY [1]/ha)	5.300	5.345	5.025	0.320 **
Labor	Number of laborers per household	2.320	2.452	2.213	0.239
Degree of specialization	Maize production area/all arable area, %	0.515	0.515	0.513	0.002
Digital technology training	1 = yes, 0 = no	0.468	0.476	0.451	0.025 *
Market distance	Distance from the household to the nearest central market (km)	9.949	10.035	9.830	0.205

Note: [1] CNY is yuan, Chinese currency (1 USD = 6.99 CNY in 2022). ***, **, and * denote significance at the 1%, 5%, and 10% significance levels, respectively.

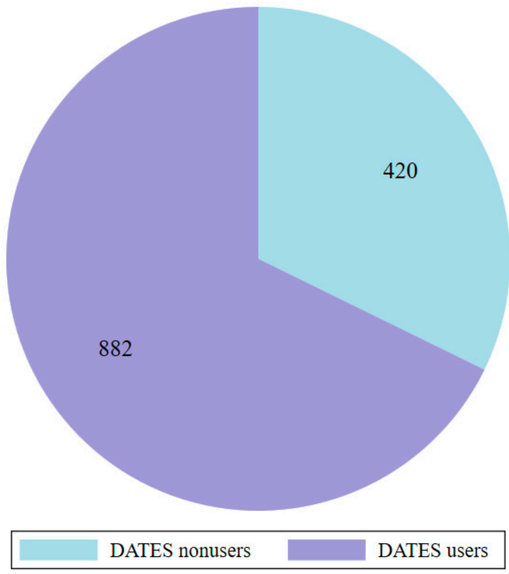

Figure 5. DATES use of samples.

4.2. Eco-Efficiency Scores

Table 6 presents the EE scores of maize production. The average EE for 1302 maize farmers is 0.671, ranging from 0.397 to 1. There is a significant difference in EE between DATES users and nonusers. The average EE of 881 people who use DATES is 0.702, while that of 421 nonusers is 0.608. This shows that the average EE of maize production in DATES users group is about 15.46% higher than that in DATES nonusers group, which is more clear in Figure 6.

Table 6. Descriptive summary of EE scores.

Group	Mean	Standard Deviation	Min	Max
DATES users	0.702	0.187	0.481	1
DATES nonusers	0.608	0.189	0.397	0.9
All	0.671	0.192	0.397	1

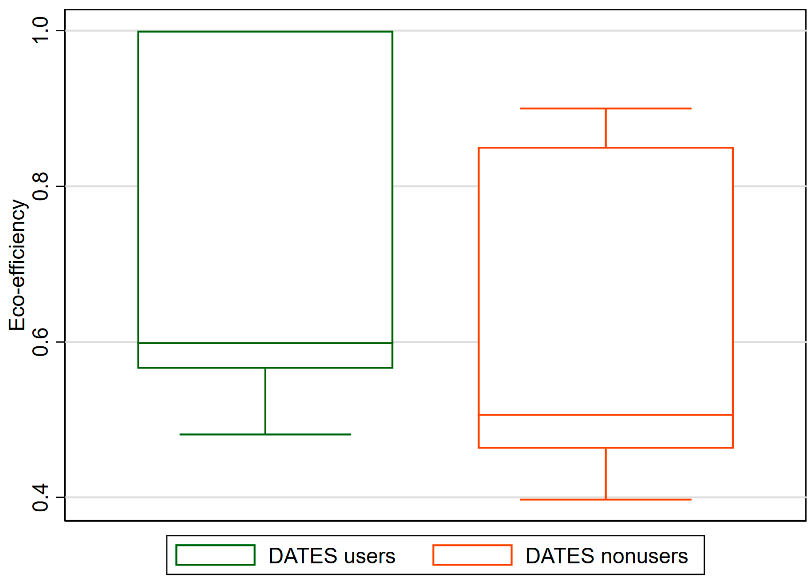

Figure 6. The difference in EE of maize production between DATES users and nonusers.

4.3. Results of the ESR Model

As shown in Table 7, 16.66 is a significant value at the 1% level for the LR test of independent equations, which implies that the selection and outcome equations are unrelated. Meanwhile, $\ln \sigma_1$ and $\ln \sigma_0$ are both significant, implying that there is a self-selection problem [58,62]. Therefore, it is appropriate to adopt the ESR model.

Table 7. Estimation results of the ESR model.

Variable	Selection Equation	ESR Outcome Equations (EE) DATES Users	DATES Nonusers
Age	−0.003 *** (0.004)	−0.002 *** (0.001)	−0.003 ** (0.001)
Gender	0.613 *** (0.094)	0.079 *** (0.017)	0.011 (0.022)
Health status	0.156 *** (−0.058)	−0.076 (0.076)	−0.079 (0.184)
Education	0.041 *** (0.015)	−0.001 (0.002)	0.002 (0.004)
Off-farm work	0.248 *** (0.081)	−0.011 (0.012)	0.030 (0.019)
Village leader	0.319 ** (0.130)	0.068 *** (0.017)	−0.053 (0.035)
Farm size	0.167 ** (0.042)	−0.025 *** (−0.005)	−0.029 *** (0.010)
Income from other crops	−0.695 ** (0.298)	0.252 *** (0.043)	0.194 ** (0.077)
Labor	−0.049 (0.042)	−0.016 *** (0.006)	−0.012 (0.010)
Specialization degree	−0.127 (0.134)	-0.015 (0.020)	−0.108 *** (0.031)
Market distance	−0.078 (0.054)	−0.023 *** (0.008)	0.007 (0.011)
Digital technology training	0.070 (0.083)	−0.031 ** (0.013)	−0.058 *** (0.018)
Communication signal strength	0.355 *** (0.039)		
Constant	−0.652 * (0.372)	0.995 *** (0.057)	0.767 *** (0.092)
$\ln \sigma_1$		−1.712 *** (0.031)	
$\ln \sigma_0$			−1.748 *** (0.050)
ρ_1		−0.505 *** (0.107)	
ρ_0			−0.253 (0.250)
Durbin–Wu–Hausman	30.009 ***		
Cragg–Donald Wald F Statistic	70.965		
Stock–Yogo critical values under 10% bias	16.380		
LR test of independentequations	16.660 ***		

Note: Figures in parentheses are robust standard error, ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively.

4.3.1. Determinants of DATES Use

The estimated coefficient of the IV (communication signal strength) is significant at 1% level, and it met our expectation. This indicates that, the stronger the communication signal, the more likely that maize farmers are to obtain sustainable technology and information through DATES. The Cragg–Donald Wald F statistic was 70.97, indicating that the null hypothesis of weak instrumental variables (IV) was rejected. Therefore, IV is valid (Table 7).

Table 7 also demonstrates that a number of variables have a significant impact on whether a maize farmer uses DATES or not. The variables of gender, health status, education, off-farm work, village leader, farm size and communication signal strength have significant positive effects on DATES use, but the variables of age and income from other crops have a significant negative effect on DATES use.

4.3.2. Determinants of EE

Table 7 provides the coefficients for outcome equations. In general, the coefficients of the independent variables for DATES users and DATES nonusers have quite different statistical significance, which shows that these observable factors account for various impacts of EE on maize production between the two groups, such as age, gender, village leader, income from other crops, labor, specialization degree, and market distance.

There is a negative correlation between age, farm size, labor, specialization degree, and market distance and the EE for DATES users and nonusers. The gender and village leader factors have a positive impact on EE for only DATES users, and income from other crops has a significant positive impact on EE for both groups.

4.3.3. Average Treatment Effects

Table 8 reports the predicted EE in the actual and counterfactual contexts, as well as the treatment effects of DATES use by DATES users and nonusers. The ATT and ATU are unbiased results after addressing the self-selection problem.

Table 8. Average treatment effects of DATES use on EE.

Group	Use	No Use	ATT	ATU
DATES users	0.701	0.553	0.148 ***	—
DATES nonusers	0.822	0.608	—	0.214 ***

Note: *** indicates significance at the 1%, 5%, and 10% significance levels, respectively.

The value of ATT and ATU show that DATES use can improve EE of maize production for both groups (Table 7). Specifically, EE of maize production would reduce by 0.148 (21.11%) for DATES users if they had not used DATES to obtain sustainable technology and information about production. EE would increase by 0.214 (35.20%) for DATES nonusers if they had used DATES (as shown in Figure 7). According to the average difference in EE between DATES users and nonusers (approximately 0.093), ATT indicates that ignoring self-selection bias would significantly underestimate the effect of DATES use on EE.

4.4. Robustness Check

The robustness test is conducted in treatment effects model (TEM) and ordinary linear squares (OLS) regression to ensure the accuracy of the analytical findings (as shown in Table 9). The results of the OLS show an underestimation of the impact of the use of DATES due to the neglect of self-selection issues, but DATES use has a positive and significant effect on the EE of maize production. TEM was first proposed by Maddala [62]. TEM results support the reliability of the existing results, as shown in Table 7. Notably, the estimated coefficients for DATES use in the outcome equation are significant and positive, indicating that DATES use does increase EE. For the sake of simplicity, no more information about the TEM and OLS is provided in this study. Therefore, hypothesis H1 is verified.

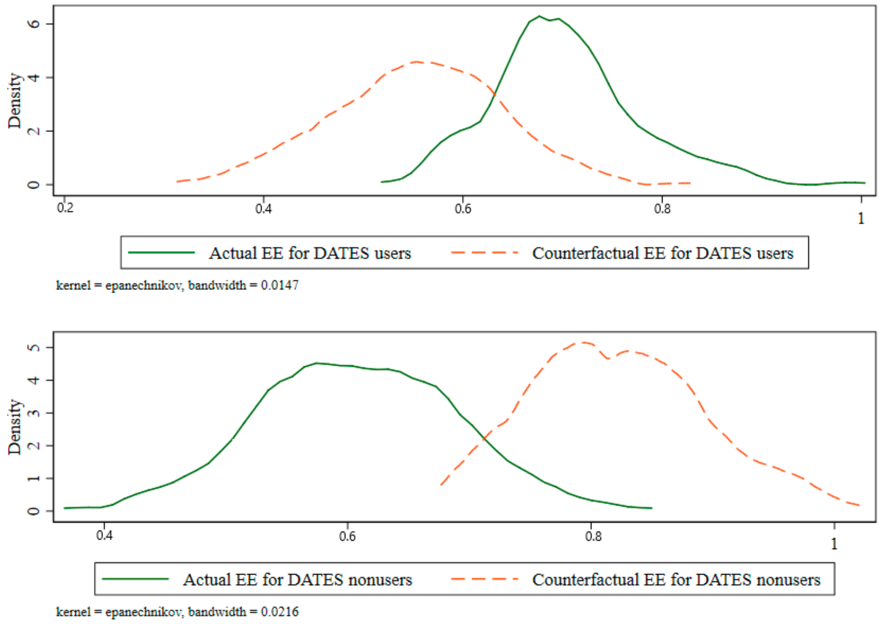

Figure 7. Probability density of EE for two regimes.

Table 9. Robustness check based on the ESR, TEM, and OLS.

Items	ESR	TEM	OLS
Coefficient of DATES use	—	0.188 *** (0.026)	0.076 *** (0.011)
ATT	0.148 *** (0.004)	—	—
ATU	0.214 *** (0.005)	—	—
Control variables	Yes	Yes	Yes

Note: Figures in parentheses are robust standard error, *** indicates significance at the 1%, 5%, and 10% significance levels, respectively.

4.5. Heterogeneous Analysis

The QR model's findings illustrate the impact of DATES use on EE varies significantly across different quantiles. If we only examine the homogenous or mean-based effects of DATES use on EE of maize production, we cannot observe the results of this heterogeneity. Table 10 shows a positive and statistically significant correlation between DATES use and EE of maize production for the 15th, 30th, 50th, and 60th quantiles. Notably, DATES use had the greatest effect on EE at lower quantiles, denoting that DATES use is more beneficial to maize farmers with lower EE than to those with higher EE (as shown in Figure 8). It is more clearly presented in Therefore, hypothesis H2 is verified.

Table 10. Heterogeneous impact of DATES use on EE.

Items	EE				
	15th	30th	50th	60th	75th
DATES users	0.097 *** (0.005)	0.098 *** (0.005)	0.079 *** (0.011)	0.073 *** (0.019)	0.033 (0.028)
Control variables	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.193	0.141	0.083	0.115	0.156

Note: Figures in parentheses are robust standard error, *** indicates significance at the 1%, 5%, and 10% significance levels, respectively.

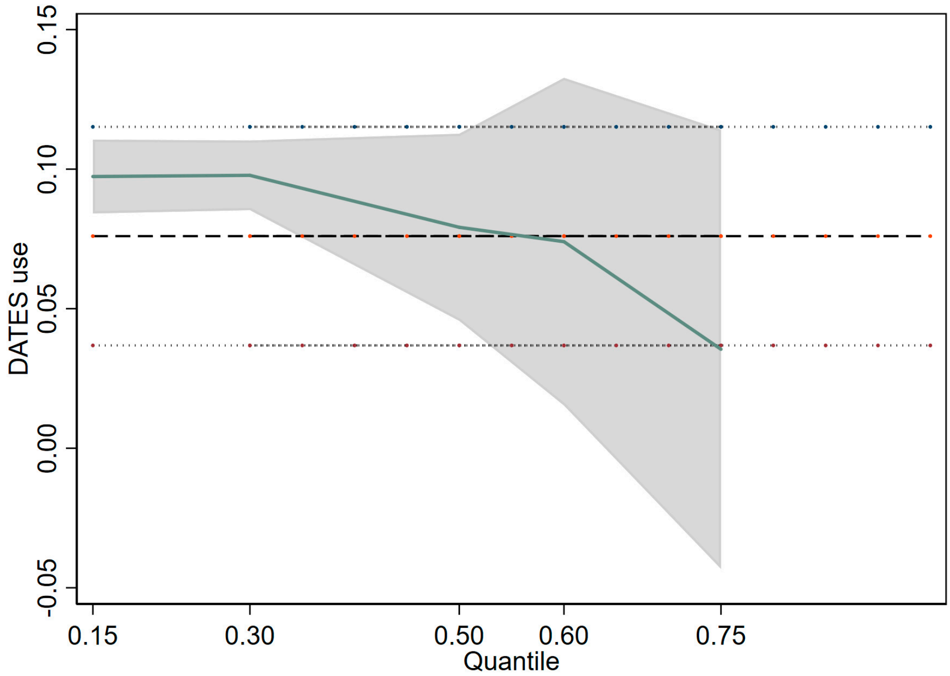

Figure 8. Variation of coefficients with different quantiles.

4.6. Mechanism Analysis

The results of the mediation effects model are shown in Table 11.

Table 11. Estimation of mediation effect model.

Variable	EE	Adoption of Organic Fertilizer	Adoption of Green Pesticide	Adoption of Biodegradable Agricultural Films	EE
DATES use	0.094 *** (0.011)	0.171 *** (0.029)	0.188 *** (0.029)	0.180 *** (0.029)	
Adoption of organic fertilizer					0.094 *** (0.010)
Adoption of green pesticide					0.068 *** (0.010)
Adoption of biodegradable agricultural films					0.058 *** (0.011)
Control variables	Yes	Yes	Yes	Yes	Yes
Number of observations	1302	1302	1302	1302	1302

Note: Figures in parentheses are robust standard error, *** indicates significance at the 1%, 5%, and 10% significance levels, respectively.

According to the second column of Table 10, the estimated coefficient of DATES use is significant at 1% level, which means that DATES use significantly increases the EE of maize production. In the third column, the estimated coefficient of DATES use is significantly positive, implying that DATES use significantly increases the likelihood of maize farmers adopting organic fertilizer. From the results of column 6, it can be seen that, after adding the mediator variables, DATES use and application of organic fertilizer are both significantly positively correlated with EE, which means that application of organic fertilizer plays a part of the mediator effect in the effect of DATES use on sustainable maize production, which accounts for 17.10% of the total effect; in other words, 17.10% of the improving effect of DATES use on EE of maize production is achieved through the application of organic fertilizer. In order to further test the robustness of the results of the mediation effect model, the bootstrap method was used to test the mediation effect of organic fertilizer application between DATES use and EE. The results showed that the direct effect was

0.077 and the indirect effect was 0.016, which were both significant at the 1% statistical level; the confidence interval of the indirect effect did not include 0, which indicated that the application of organic fertilizer played a mediating role in the influence of DATES use on the EE of maize production.

As can be seen from the results in column 4, the estimated coefficient of DATES use is significantly positive, implying that DATES use significantly increases the likelihood of using green pesticides by maize farmers. From the results in column 6, it can be seen that after adding the mediator variables, DATES use and the use of green pesticides are both significantly positively correlated with the EE of maize farmers' production, indicating that the use of green pesticides plays a part of the mediator effect in the impact of DATES use on the EE of production, which accounted for 13.63% of the total effect; in other words, 13.63% of the effect of the use of the DATES in enhancing the EE of maize farmers' production is realized through the use of green pesticides. This is realized through the use of green pesticides. In order to further test the robustness of the results of the mediation effect model, the bootstrap method was utilized to test the mediation effect of the use of green pesticides in the relationship between DATES use and the EE of maize production. The results showed that the direct effect was 0.081 and the indirect effect was 0.013, both of which were significant at the 1% statistical level; the confidence interval of the indirect effect did not include 0, indicating that the use of green pesticides plays a mediating role in the impact of DATES use on the EE of maize production, and hypothesis H4 was verified.

Similarly, from the results in column 5, the estimated coefficient of DATES use is significantly positive, implying that DATES use significantly increases the likelihood that maize farmers will use biodegradable agricultural films. From the results in column 6, it can be seen that after adding the mediator variables, both DATES use and the use of biodegradable films are significantly positively correlated with the EE of maize farmers' production, indicating that the use of biodegradable films plays a part in the mediating effect of the impact of DATES use on the EE of production, which accounts for 11.16% of the total effect, i.e., 11.16% of the effect of DATES use on improving the EE of maize farmers' production is through the use of biodegradable films. A proportion of 11.10% of the total effect, that is, 11.10% of the effect of DATES use in improving the EE of maize farmers' production, is realized through the use of biodegradable agricultural film. In order to further test the robustness of the results of the mediated effect model, the bootstrap method was utilized to test the mediated effect of using biodegradable agricultural film between DATES use and the EE of maize production. The results showed that the direct effect was 0.083 and the indirect effect was 0.010, which were significant at the statistical levels of 1%, respectively; the confidence interval of the indirect effect did not include 0, which indicated that the use of biodegradable agricultural film played a mediating role in the influence of DATES use on the EE of maize production. Therefore, hypothesis H3 is verified.

5. Discussion

For eco-efficiency scores, the average EE is 0.671, ranging from 0.397 to 1. There is a significant difference in EE between DATES users and nonusers. The findings imply that there is still room for EE improvement for all maize farmers; the level is lower than the EE of wheat production in Japan [27], but it is higher than the EE of rice production in China [29]. The average EE of maize production in DATES users group is about 15.46% higher than that in DATES nonusers group. In other words, DATES use may lead to better sustainable production performance. At the same time, it is necessary to improve farmers' awareness of EE, especially in rural and ecologically fragile areas.

For factors influencing DATES use, the estimated coefficient of the age of the maize farmer is significantly negative, implying that it is less likely for older maize farmers to use DATES. This result is in line with existing research [34,58,63,64]. The coefficient of gender of maize farmers is statistically significantly positive, implying that male maize farmers are more likely to obtain sustainable technology and information through DATES use. The better a maize farmer's health status, the more energy and capacity they have to learn how to use the DATES, the more likely they are to obtain sustainable production information [65]. The more years of education the maize farmers have, the stronger their ability to acquire new information and learn, the more inclined they will be to use the DATES to access sustainable production technology and information. This is consistent with the findings of existing studies [50]. Maize farmers with off-farm employment may be more likely to use DATES because they may have broader horizons and be more likely to investigate new sustainable technologies and information; this finding differs from the findings of related studies [66]. There is a significant and positive correlation between DATES use and farm size. Compared with farmers with small farm size, farmers with larger farm size pay more attention to the long-term economic benefits of agricultural production, so they have a greater incentive to enhance the sustainability of their agricultural production by using DATES to obtain timely and useful technologies and information. Thus, larger-scale maize farmers are much more likely to use DATES; this finding is inconsistent with the conclusion of existing studies [58,66]. Furthermore, income from other crops has a negative impact on the use of DATES, indicating that, the higher the income from other crops, the more dependent maize farmers are on the current production methods and the lower their willingness to choose to use DATES to change their production models. However, the existing literature did not note this variable [20,47,67].

For the determinants of EE, at the 1% and 5% levels, the coefficient of age for DATES users and nonusers are both significant and negative. It illustrates that the EE of maize production decreases by between 0.002 and 0.003 for every ten-year increase in age, assuming all other variables remain constant. The significant and positive gender coefficient for DATES users indicates that the EE of male maize farmers is 0.079, which is significantly higher than that of female maize farmers; this finding is consistent with findings on technical efficiency in the literature [66]. For DATES users, the village leader coefficient is statistically significant and positive, indicating that the EE of village leaders who use DATES is 0.068 higher than that of normal maize farmers who use DATES. This result is primarily attributable to the responsibility of village leaders for transferring technologies and information from the local government and relevant departments to farmers, enhancing village leaders' DATES use experience and leading to an increased likelihood of obtaining sustainable information about superior technology and high-quality inputs; an existing study supported this result [58].

Keeping other variables constant, the findings indicate that maize farmers with a larger farm size would have decreased EE among maize farmers by between 0.025 and 0.029. Basically, maize production in China is usually labor-intensive and land-intensive. Therefore, the production of a large-scale farm has become a challenge for maize farmers to manage with precision; this may impede the improvement of EE [67].

Many researchers have not included the income from other crops in their analysis, which is positively correlated with EE among DATES users. Maize farmers with higher income from other crops are more able to invest in sustainable technologies and inputs into maize production to improve EE. The number of laborers in maize production has a significantly negative impact on EE for DATES users; this illustrates that, the greater the number of laborers engaged in maize production, the greater the barriers to adopting sustainable technologies and inputs. This makes it difficult to increase EE, but there is no such evidence among DATES nonusers; this result is different to those presented in a previous study [58]. Moreover, for DATES nonusers, the significant and negative coefficients of specialization degree implies that, the larger the proportion of maize-production area maize farmers manage, the lower EE they have. This is because maize farmers cannot understand sustainable technology and information in a timely manner without the help of the DATES, which limits EE improvement. The coefficient of market distance is negative and significant at the 1 % level, indicating that the presence of a long distance between maize farmers and the market will impede the diffusion of sustainable technologies and information and hinder the improvement of EE. Notably, digital technology training has a significantly negative impact on EE for both of the groups, implying that the current technical training is mainly aimed at e-commerce, socialization, etc., and does not meet the sustainable development needs of agricultural production. Accordingly, farmers' time is used up through use of DATES to learn sustainable production technologies and information, which negatively affects EE; this finding is different from those presented in a previous study [58].

Overall, this study has several limitations. First, the analysis only focuses on maize production; thus, the conclusion should be applied to other staple or cash crops with caution. This is because of the fact that agricultural technologies and inputs for different crops have fundamentally different requirements. Second, due to a lack of available funds for research, the sample size in this study remains relatively small. All the farm households in the sample were selected from Northeast China. In this context, caution needs to be taken when generalizing the conclusions of this study to other regions in China. Third, using cross-sectional data makes it difficult to examine the dynamic impact of DATES on the EE of production.

Therefore, there are some areas for further research. Firstly, further study should try to investigate the impact of DATES on EE and the mechanisms between them for different staple or cash crops; even for different planting structures or crop combinations, it may reveal thought-provoking results. Secondly, further study should seek more funding and organize larger teams to collect as many samples as possible. Thirdly, further study should construct a panel database to observe the long-term dynamic impacts of the DATES on EE.

6. Conclusions and Policy Implications

This study reveals the average and heterogeneous impacts of DATES use on the EE of maize production and its potential mechanism; the study uses survey data from 1302 farmers in the main maize-producing areas of Northeast China. The main conclusions are as follows: First, the average EE of maize production is 0.67, and the loss of EE reaches 0.33, indicating that there is still significant room for sustainable development in maize production. Second, DATES nonusers would improve the EE of maize production by 35.20% if they had used it, indicating that DATES use can improve sustainable maize production. The decision to use the DATES is significantly affected by age, gender, health status, education, off-farm work, village leader status, farm size, income from other crops, and communication signal strength; meanwhile, the EE of maize production is significantly affected by age, gender, village leader status, farm size, income from other crops, number of laborers, degree of specialization, market distance, and digital technology training. Third, DATES use is more helpful for maize farmers with lower EE than it is for those with higher EE, implying that the effect of DATES use gradually slows down as EE increases. Fourth, the application of organic fertilizer, green pesticides, and biodegradable agricultural films are significantly positively correlated with DATES use, indicating that DATES use can promote the use of green inputs. At the same time, DATES use can contribute to sustainable maize production through the application of organic fertilizers, green pesticides, and biodegradable agricultural films.

Above all, relevant policy implications can be proposed. First, the government should join hands with universities, colleges, and research institutions to popularize the concept of sustainable food production through a combination of online and offline methods; additionally, farmers should be encouraged to adopt sustainable production technologies and sustainable inputs. Secondly, governments should continue to expand their investments in information and communication technology infrastructures in rural areas to empower sustainable food production. Relevant departments should utilize all kinds of public accounts, agricultural extension apps, and websites to accelerate the flow of information on sustainable food production and, subsequently, accelerate the accumulation of human capital. Thirdly, the government should implement a categorized promotion strategy based on the actual situations of different production entities. They should pay more attention to farmers with low EE and provide them with targeted digital technology training to achieve sustainable food production. Finally, it is important to use the publicity of DATES to encourage farmers to use more sustainable inputs; additionally, technical guidance and training lessons should be provided to accelerate the transition to sustainable food production.

Author Contributions: Conceptualization, R.L., W.L., G.L. and Q.L.; methodology, R.L. and G.L.; software, R.L. and G.L.; validation, R.L. and W.L.; formal analysis, R.L., W.L. and G.L., investigation, R.L. and Q.L.; data curation, R.L. and W.L.; writing—original draft preparation, R.L. and W.L.; writing—review and editing, R.L., W.L., G.L. and Q.L.; visualization, R.L. and G.L.; supervision, Q.L. and G.L.; project administration, R.L. and Q.L.; funding acquisition, R.L. and Q.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by China Agriculture Research System—Potato Industrial Economics (CARS-9) and the China Scholarship Council (202103250054).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: Special thanks are given to the farmers who were eager to cooperate in the survey.

Conflicts of Interest: Author Wei Liu was employed by the company China Mobile Group Design Institute Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. Yang, J.; Jiang, R.; Zhang, H.; He, W.; Yang, J.; He, P. Modelling maize yield, soil nitrogen balance and organic carbon changes under long-term fertilization in Northeast China. *J. Environ. Manag.* **2023**, *325*, 116454. [CrossRef]
2. Zhang, W.; Qiao, Y.; Lakshmanan, P.; Yuan, L.; Liu, J.; Zhong, C.; Chen, X. Combing public-private partnership and large-scale farming increased net ecosystem carbon budget and reduced carbon footprint of maize production. *Resour. Conserv. Recycl.* **2022**, *184*, 106411. [CrossRef]
3. FAO. FAO Statistical Databases. Available online: https://www.fao.org/faostat/en/#data/QCL (accessed on 1 March 2023).
4. Liu, Y.S.; Zou, L.L.; Wang, Y.S. Spatial-temporal characteristics and influencing factors of agricultural eco-efficiency in China in recent 40 years. *Land Use Policy* **2020**, *97*, 10. [CrossRef]
5. Pang, J.X.; Chen, X.P.; Zhang, Z.L.; Li, H.J. Measuring Eco-Efficiency of Agriculture in China. *Sustainability* **2016**, *8*, 15. [CrossRef]
6. Wu, F.; Zhan, J.Y.; Guneralp, I. Present and future of urban water balance in the rapidly urbanizing Heihe River Basin, Northwest China. *Ecol. Model.* **2015**, *318*, 254–264. [CrossRef]
7. Shen, Z.; Qiu, J.; Hong, Q.; Chen, L. Simulation of spatial and temporal distributions of non-point source pollution load in the Three Gorges Reservoir Region. *Sci. Total Environ.* **2014**, *493*, 138–146. [CrossRef]
8. Hu, L.L.; Guo, L.; Zhao, L.F.; Shi, X.Y.; Ren, W.Z.; Zhang, J.; Tang, J.J.; Chen, X. Productivity and the complementary use of nitrogen in the coupled rice-crab system. *Agr. Syst.* **2020**, *178*, 102742. [CrossRef]
9. Lazaridou, D.; Michailidis, A.; Trigkas, M. Socio-economic factors influencing farmers' willingness to undertake environmental responsibility. *Environ. Sci. Pollut. Res. Int.* **2019**, *26*, 14732–14741. [CrossRef]
10. Li, F.; Yang, P.; Zhang, K.; Yin, Y.; Zhang, Y.; Yin, C. The influence of smartphone use on conservation agricultural practice: Evidence from the extension of rice-green manure rotation system in China. *Sci. Total Environ.* **2022**, *813*, 152555. [CrossRef]
11. Zou, L.; Liu, Y.; Wang, Y.; Hu, X. Assessment and analysis of agricultural non-point source pollution loads in China: 1978–2017. *J. Environ. Manag.* **2020**, *263*, 110400. [CrossRef]
12. Zhong, F.L.; Jiang, D.W.; Zhao, Q.Q.; Guo, A.J.; Ullah, A.; Yang, X.; Cheng, Q.P.; Zhang, Y.N.; Ding, X.J. Eco-efficiency of oasis seed maize production in an arid region, Northwest China. *J. Clean. Prod.* **2020**, *268*, 10. [CrossRef]
13. Schaltegger, S.; Sturm, A. Ökologische Rationalität: Ansatzpunkte zur Ausgestaltung von ökologieorientierten Managementinstrumenten. *Unternehm.* **1990**, *44*, 273–290.
14. Caiado, R.G.G.; de Freitas Dias, R.; Mattos, L.V.; Quelhas, O.L.G.; Leal Filho, W. Towards sustainable development through the perspective of eco-efficiency—A systematic literature review. *J. Clean. Prod.* **2017**, *165*, 890–904. [CrossRef]
15. Deng, X.Z.; Gibson, J. Improving eco-efficiency for the sustainable agricultural production: A case study in Shandong, China. *Technol. Forecast. Soc. Chang.* **2019**, *144*, 394–400. [CrossRef]
16. Mickwitz, P.; Melanen, M.; Rosenstrom, U.; Seppala, J. Regional eco-efficiency indicators—A participatory approach. *J. Clean. Prod.* **2006**, *14*, 1603–1611. [CrossRef]
17. Rebolledo-Leiva, R.; Angulo-Meza, L.; Iriarte, A.; Gonzalez-Araya, M.C.; Vasquez-Ibarra, L. Comparing two CF+DEA methods for assessing eco-efficiency from theoretical and practical points of view. *Sci. Total Environ.* **2019**, *659*, 1266–1282. [CrossRef]

18. Bianchi, M.; del Valle, I.; Tapia, C. Measuring eco-efficiency in European regions: Evidence from a territorial perspective. *J. Clean. Prod.* **2020**, *276*, 123246. [CrossRef]
19. Zeng, L.L.; Li, X.Y.; Ruiz-Menjivar, J. The effect of crop diversity on agricultural eco-efficiency in China: A blessing or a curse? *J. Clean. Prod.* **2020**, *276*, 13. [CrossRef]
20. Gao, Y.; Zhao, D.; Yu, L.; Yang, H. Influence of a new agricultural technology extension mode on farmers' technology adoption behavior in China. *J. Rural. Stud.* **2020**, *76*, 173–183. [CrossRef]
21. Mahmood, N.; Arshad, M.; Mehmood, Y.; Faisal Shahzad, M.; Kächele, H. Farmers' perceptions and role of institutional arrangements in climate change adaptation: Insights from rainfed Pakistan. *Clim. Risk Manag.* **2021**, *32*, 100288. [CrossRef]
22. Oyinbo, O.; Chamberlin, J.; Abdoulaye, T.; Maertens, M. Digital extension, price risk, and farm performance: Experimental evidence from Nigeria. *Am. J. Agric. Econ.* **2022**, *104*, 831–852. [CrossRef]
23. Buehren, N.; Goldstein, M.; Molina, E.; Vaillant, J. The impact of strengthening agricultural extension services on women farmers: Evidence from Ethiopia. *Agric. Econ.* **2019**, *50*, 407–419. [CrossRef]
24. Hudson, H.E.; Leclair, M.; Pelletier, B.; Sullivan, B. Using radio and interactive ICTs to improve food security among smallholder farmers in Sub-Saharan Africa. *Telecommun. Policy* **2017**, *41*, 670–684. [CrossRef]
25. CNNIC. *The 51th China Statistical Report on Internet Development*; CNNIC: Beijing, China, 2023.
26. Mohammadi, A.; Rafiee, S.; Jafari, A.; Dalgaard, T.; Knudsen, M.T.; Keyhani, A.; Mousavi-Avval, S.H.; Hermansen, J.E. Potential greenhouse gas emission reductions in soybean farming: A combined use of Life Cycle Assessment and Data Envelopment Analysis. *J. Clean. Prod.* **2013**, *54*, 89–100. [CrossRef]
27. Masuda, K. Measuring eco-efficiency of wheat production in Japan: A combined application of life cycle assessment and data envelopment analysis. *J. Clean. Prod.* **2016**, *126*, 373–381. [CrossRef]
28. Ullah, A.; Perret, S.R.; Gheewala, S.H.; Soni, P. Eco-efficiency of cotton-cropping systems in Pakistan: An integrated approach of life cycle assessment and data envelopment analysis. *J. Clean. Prod.* **2016**, *134*, 623–632. [CrossRef]
29. Huang, M.L.; Zeng, L.L.; Liu, C.J.; Li, X.Y.; Wang, H.L. Research on the Eco-Efficiency of Rice Production and Its Improvement Path: A Case Study from China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 20. [CrossRef]
30. Rashidi, K.; Saen, R.F. Measuring eco-efficiency based on green indicators and potentials in energy saving and undesirable output abatement. *Energ. Econ.* **2015**, *50*, 18–26. [CrossRef]
31. Yang, L.; Zhang, X. Assessing regional eco-efficiency from the perspective of resource, environmental and economic performance in China: A bootstrapping approach in global data envelopment analysis. *J. Clean. Prod.* **2018**, *173*, 100–111. [CrossRef]
32. Xin, Y.; Tao, F. Optimizing genotype-environment-management interactions to enhance productivity and eco-efficiency for wheat-maize rotation in the North China Plain. *Sci. Total Environ.* **2019**, *654*, 480–492. [CrossRef] [PubMed]
33. Oliveira, R.; Camanho, A.S.; Zanella, A. Expanded eco-efficiency assessment of large mining firms. *J. Clean. Prod.* **2017**, *142*, 2364–2373. [CrossRef]
34. Yang, L.; Yang, Y. Evaluation of eco-efficiency in China from 1978 to 2016: Based on a modified ecological footprint model. *Sci. Total Environ.* **2019**, *662*, 581–590. [CrossRef] [PubMed]
35. Zeng, J.J.; Han, J.Y.; Qu, J.S.; Maraseni, T.N.; Xu, L.; Li, H.J.; Liu, L.N. Ecoefficiency of China's agricultural sector: What are the spatiotemporal characteristics and how are they determined? *J. Clean. Prod.* **2021**, *325*, 11. [CrossRef]
36. He, G.J.; Ma, Z.G.; Wang, X.N.; Xiao, Z.; Dong, J.R. Does the improvement of regional eco-efficiency improve the residents' health conditions: Empirical analysis from China's provincial data. *Ecol. Indic.* **2021**, *124*, 107387. [CrossRef]
37. Aigner, D.; Lovell, C.A.K.; Schmidt, P. Formulation and estimation of stochastic frontier production function models. *J. Econom.* **1977**, *6*, 21–37. [CrossRef]
38. Meeusen, W.; van Den Broeck, J. Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. *Int. Econ. Rev.* **1977**, *18*, 435–444. [CrossRef]
39. Jin, G.; Li, Z.; Deng, X.; Yang, J.; Chen, D.; Li, W. An analysis of spatiotemporal patterns in Chinese agricultural productivity between 2004 and 2014. *Ecol. Indic.* **2019**, *105*, 591–600. [CrossRef]
40. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
41. Angulo-Meza, L.; González-Araya, M.; Iriarte, A.; Rebolledo-Leiva, R.; Soares de Mello, J.C. A multiobjective DEA model to assess the eco-efficiency of agricultural practices within the CF + DEA method. *Comput. Electron. Agric.* **2019**, *161*, 151–161. [CrossRef]
42. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [CrossRef]
43. Adamides, G.; Stylianou, A. Evaluation of the Radio as an Agricultural Information Source in Rural Areas. *J. Agric. Food Inf.* **2018**, *19*, 362–376. [CrossRef]
44. Li, B.; Zhuo, N.; Ji, C.; Zhu, Q. Influence of Smartphone-Based Digital Extension Service on Farmers' Sustainable Agricultural Technology Adoption in China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 9639. [CrossRef]
45. Norton, G.W.; Alwang, J. Changes in Agricultural Extension and Implications for Farmer Adoption of New Practices. *Appl. Econ. Perspect. Policy* **2020**, *42*, 8–20. [CrossRef]
46. Ma, Q.; Zheng, S.; Deng, P. Impact of Internet Use on Farmers' Organic Fertilizer Application Behavior under the Climate Change Context: The Role of Social Network. *Land* **2022**, *11*, 1601. [CrossRef]

47. Fabregas, R.; Kremer, M.; Schilbach, F. Realizing the potential of digital development: The case of agricultural advice. *Science* **2019**, *366*, eaay3038. [CrossRef] [PubMed]
48. Steinke, J.; Achieng, J.O.; Hammond, J.; Kebede, S.S.; Mengistu, D.K.; Mgimiloko, M.G.; Mohammed, J.N.; Musyoka, J.; Sieber, S.; van de Gevel, J.; et al. Household-specific targeting of agricultural advice via mobile phones: Feasibility of a minimum data approach for smallholder context. *Comput. Electron. Agric.* **2019**, *162*, 991–1000. [CrossRef]
49. Fernando, A.N. Seeking the treated: The impact of mobile extension on farmer information exchange in India. *J. Dev. Econ.* **2021**, *153*, 102713. [CrossRef]
50. Zheng, Y.; Fan, Q.; Jia, W. How Much Did Internet Use Promote Grain Production?—Evidence from a Survey of 1242 Farmers in 13 Provinces in China. *Foods* **2022**, *11*, 1389. [CrossRef] [PubMed]
51. Nodin, M.N.; Mustafa, Z.; Hussain, S.I. Eco-efficiency assessment of Malaysian rice self-sufficiency approach. *Socio-Econ. Plan. Sci.* **2023**, *85*, 101436. [CrossRef]
52. Liu, Z.; Zhang, M.; Li, Q.; Zhao, X. The impact of green trade barriers on agricultural green total factor productivity: Evidence from China and OECD countries. *Econ. Anal. Policy* **2023**, *78*, 319–331. [CrossRef]
53. Hou, J.; Huo, X.; Yin, R. Does computer usage change farmers' production and consumption? Evidence from China. *China Agric. Econ. Rev.* **2018**, *11*, 387–410. [CrossRef]
54. Khanal, A.R.; Mishra, A.K. Financial performance of small farm business households: The role of internet. *China Agric. Econ. Rev.* **2016**, *8*, 553–571. [CrossRef]
55. Di Falco, S.; Veronesi, M.; Yesuf, M. Does Adaptation to Climate Change Provide Food Security? A Micro-Perspective from Ethiopia. *Am. J. Agric. Econ.* **2011**, *93*, 829–846. [CrossRef]
56. Huang, J.K.; Wang, Y.J.; Wang, J.X. Farmers' Adaptation to Extreme Weather Events through Farm Management and Its Impacts on the Mean and Risk of Rice Yield in China. *Am. J. Agric. Econ.* **2015**, *97*, 602–617. [CrossRef]
57. Läpple, D.; Hennessy, T.; Newman, C. Quantifying the Economic Return to Participatory Extension Programmes in Ireland: An Endogenous Switching Regression Analysis. *J. Agric. Econ.* **2013**, *64*, 467–482. [CrossRef]
58. Zhu, X.; Hu, R.; Zhang, C.; Shi, G. Does Internet use improve technical efficiency? Evidence from apple production in China. *Technol. Forecast. Soc. Chang.* **2021**, *166*, 120662. [CrossRef]
59. Dubey, A.; Lal, R. Carbon footprint and sustainability of agricultural production systems in Punjab, India, and Ohio, USA. *J. Crop Improv.* **2009**, *23*, 332–350. [CrossRef]
60. Lai, S.Y.; Du, P.F.; Chen, J.N. Evaluation of non-point source pollution based on unit analysis. *J. Tsinghua Univ. (Sci. Technol.)* **2004**, *44*, 1184–1187. [CrossRef]
61. Song, C.; Liu, R.; Oxley, L.; Ma, H. The adoption and impact of engineering-type measures to address climate change: Evidence from the major grain-producing areas in China. *Aust. J. Agric. Resour. Econ.* **2018**, *62*, 608–635. [CrossRef]
62. Maddala, G.S. *Limited-Dependent and Qualitative Variables in Econometrics*; Cambridge University Press: Cambridge, UK, 1983.
63. Ma, W.; Nie, P.; Zhang, P.; Renwick, A. Impact of Internet use on economic well-being of rural households: Evidence from China. *Rev. Dev. Econ.* **2020**, *24*, 503–523. [CrossRef]
64. Huang, Y.; Luo, X.; Liu, D.; Du, S.; Yan, A.; Tang, L. Pest control ability, technical guidance, and pesticide overuse: Evidence from rice farmers in rural China. *Environ. Sci. Pollut. Res.* **2021**, *28*, 39587–39597. [CrossRef] [PubMed]
65. Zheng, H.; Ma, W.; Wang, F.; Li, G. Does internet use improve technical efficiency of banana production in China? Evidence from a selectivity-corrected analysis. *Food Policy* **2021**, *102*, 102044. [CrossRef]
66. Rajkhowa, P.; Qaim, M. Personalized digital extension services and agricultural performance: Evidence from smallholder farmers in India. *PLoS ONE* **2021**, *16*, e0259319. [CrossRef] [PubMed]
67. Desiere, S.; Jolliffe, D. Land productivity and plot size: Is measurement error driving the inverse relationship? *J. Dev. Econ.* **2018**, *130*, 84–98. [CrossRef]