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Green Finance, Chemical Fertilizer Use and Carbon Emissions from Agricultural Production

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Abstract: This study aimed to understand green finance's impact on fertilizer use and agricultural carbon emissions. We selected the macro panel data of 30 provinces (cities) in China from 2000 to 2019. The main research methods are standardized test framework (cross-sectional dependence, unit root and cointegration test), the latest causal test, impulse response, and variance decomposition analysis. Examined the long-term equilibrium relationship between green finance, fertilizer use, and agricultural carbon emissions. The results show: fertilizer consumption and agricultural carbon emissions have a positive correlation. However, green finance can significantly reduce agricultural carbon emissions. The causal test confirmed the bidirectional causal relationship between agricultural carbon emissions and fertilizer use. At the same time, verified one-way causality from green finance to both of them. Interpret the results of impulse response and variance decomposition analysis: among the changes in agricultural carbon emissions, chemical fertilizers contributed 2.45%, green finance contributed 4.34%. In addition, the contribution rate of green finance to chemical fertilizer changes reached 11.37%. Green finance will make a huge contribution to reducing fertilizer use and agricultural carbon emissions within a decade. The research conclusions provide an important scientific basis for China's provinces (cities) to formulate carbon emission reduction policies. China has initially formed a policy system and market environment to support the development of green finance, in 2020, the "dual carbon" goal was formally proposed. In 2021, the national "14th Five-Year Plan" and the 2035 Vision Goals emphasized the importance of green finance. It plays an important supporting role in carbon emission reduction goals, and green finance has become an important pillar of national strategic goals.

Keywords: green finance; chemical fertilizer use; carbon emissions; agricultural production; carbon neutrality

Citation: Guo, L.; Zhao, S.; Song, Y.; Tang, M.; Li, H. Green Finance, Chemical Fertilizer Use and Carbon Emissions from Agricultural Production. *Agriculture* **2022**, *12*, 313. https://doi.org/10.3390/agriculture12030313

Academic Editor: Cláudia Marques dos Santos Cordovil

Received: 6 January 2022
Accepted: 17 February 2022
Published: 22 February 2022

1. Introduction

With increasing greenhouse gas emissions, global warming has become one of the greatest threats faced by countries all over the world, which has brought about melting glaciers, rising sea levels [1], increasing biological morbidity and mortality [2], and increasing frequency of extreme weather including high temperatures and floods [3]. Reducing carbon emissions is a key step to improve the global climate. On 12 December 2015, the 21st Conference of the Parties of the United Nations Framework Convention on Climate Change was held. At the meeting, nearly 200 contracting parties passed the "Paris Agreement" to actively respond to global climate change after 2020. According to the world energy statistics in the 70th edition of the Statistical Yearbook published by the British Petroleum Corporation, in 2020, China is the main carbon emitter in Asia or even the largest carbon emitter in the world, accounting for 30.7%, far exceeding other countries and regions, and China's future carbon emissions will be crucial to global environmental governance. Therefore, China has also taken active actions, making a solemn commitment to achieve the “double carbon” goals of peak carbon dioxide emissions in 2030 and carbon neutrality in 2060, actively exploring ways to reduce carbon simultaneously.

Notably, rural activity is an important source of carbon emissions [4]. Carbon emissions caused by agricultural production and land use account for a quarter of total human emissions [5]. As the largest agricultural country, China has the highest percentage of carbon emissions from agricultural production among all countries in the world. China’s agricultural carbon emissions increased by 18% between 1990 and 2018, from 600 million tons to 710 million tons [6], accounting for 11–12% of the world’s agricultural emissions; in comparison, America only accounted for 6–7% [7]. The relevant research of the World Food and Agriculture Organization (FAO) shows that 75% of carbon dioxide in traditional intensive agriculture comes from fertilizers, feeds and fuels, and the use of fertilizers is the main source of greenhouse gases [8]. Under normal circumstances, in order to increase crop yields and reduce planting costs, farmers in China use more chemical fertilizers [9]. In the past 40 years, China’s sown area has decreased by 100 million hectares, but grain production has increased by 343 million tons, an increase of 107%. The increase in grain output per unit area has also brought about an increase in the use of chemical fertilizers. In 1980, the use of chemical fertilizers was 12.69 million tons and increased to 52.04 million tons in 2019 [10].

Reducing carbon emissions from agricultural production is an effective path and aspect to reduce total carbon emissions in the future and has an important impact on mitigating climate change [11]. Climate change has a negative impact on crops [12]. Therefore, the adoption of energy-saving and renewable technology is one of the solutions to mitigate environmental emissions of agriculture [13,14].The production and planting of green agriculture are required by future agricultural development and will become a trend, which is conducive to the realization of environmentally green and low carbon [15]. In view of the urgency of agricultural emission reduction and the high research value and significance [16], the research on the carbon emission reduction mechanism of agricultural production has gradually become a hot spot [17,18]. Based on some scholars’ views [19–21] that there is a phenomenon of pollution before treatment in society, and there is an inverted U-shaped Kuznets curve relationship between environmental pollution and economic growth, Balsalobre-Lorente et al. [22] explored the relationship between agricultural activities, energy consumption, trade opening, mobile use, and economic growth, pointing out that clean energy can effectively reduce agricultural carbon emissions.

With the increase in measures taken by countries to cope with global climate change, green finance has gradually attracted attention and become a new research focus of scholars [23]. However, there is no clear and specific definition of the concept of green finance, and researchers have not reached a consensus on it [24]. Green finance originated in the 1970s. In 1972, the “Human Environment Conference” was convened by the United Nations in Stockholm, Sweden, and governments around the world jointly discussed environmental issues for the first time. In 2016, the G20 Green Finance Research Group defined green finance as “investment and financing activities that can generate environmental benefits to support sustainable development”. In 2017, the European Commission pointed out green finance is a concept covering climate finance and sustainable finance in a study on green finance, but it is extremely difficult to clearly distinguish between green finance and the latter two. Green finance includes three aspects: funding to support public green policies, investing in green projects through financing activities, and building a green financial system [25]. China has actively become the pioneer of green finance and has basically set up the overall framework of the green financial system, including green bonds, green industry funds, green credit, and green insurance. Green finance can reduce carbon footprint and improve environmental quality, which is environmentally friendly [26]. “Green finance” can effectively support environmentally friendly projects, improve resource utilization efficiency, guide consumers to establish green consumption concepts, promote sustainable social development, and respond to climate change [27].

In the past, the financial sector rarely took the ecological environment and other factors into account, and people chose to invest in projects that caused environmental deterioration to make profits [28]. After considering ecological factors, the financial sector began to pay attention to green sustainable development, make green investment [29], provide more funds and guarantees for farmers using green credit, insurance, subsidies, etc., and encourage farmers to adjust their planting structure and methods by economic benefits, so as to reduce the use of chemical fertilizers. In order to avoid risks, farmers will significantly increase the application of chemical fertilizers [30], while agricultural insurance can smooth the production risks, thus significantly reducing the use of chemical fertilizers [31]. Agricultural subsidies can significantly reduce the use of chemical fertilizers. Studies have shown that agricultural subsidies increased by 100%, the amount of fertilizer used will reduce by an average of 3.4% [32]. In addition, Veelen [11] connects green finance with the social material allocation of the agricultural sector and proposes that low-carbon agricultural energy can be integrated into investment resources, which provides a new way to reshape environmental climate change and its governance.

Green finance has gradually become the best financial strategy to reduce carbon dioxide emissions. Meo and Karim [33] used the QQR method to prove that a negative correlation exists between green finance and CO_2 emissions during a comparative study of the top ten economies (different pollution levels and market conditions) that support green finance. Flammer [34] assessed the environmental impact of green investment and financing projects, and Wang et al. [35] adopted the entropy method, both of which found that green finance was helpful to reduce carbon emissions. Wang et al. [35] also pointed out that China's energy projects funded by green finance are expected to reduce carbon emissions by 12.6 million tons per year. Moreover, the existing research mainly focuses on the influence path of green finance as an influencing factor on some variables and the effect of related policies. Scholars mostly discuss the influence of green finance on high-quality economic development [27], "two high" (high energy consumption and high pollution) enterprises' investment and financing behavior [36] and sustainable development [37]. Existing documents mostly demonstrate the positive effects of green finance on environmental protection from the industrial level [38] and enterprise [36] emission reduction. Little literature relates to green finance and the agricultural sector, and it seldom discusses the influence of fertilizer use and green finance as both control policies on agricultural carbon emissions.

In view of this, this study attempts to test the long-term relationship among green finance, fertilizer use, and carbon emissions in the agricultural sector by using the provincial data of China from 2000 to 2019. This study considers provincial data, not national data, and provides a broader understanding of the relationship among variables. We think that this research has contributed to the existing literature in the following aspects: Firstly, based on provincial data, this study estimates the amount of agricultural carbon emissions in each province (city) and studies the influence of green finance and fertilizer use on agricultural carbon emissions in various provinces of China. Next, this paper solved the causality test among chemical fertilizer, green finance, and agricultural carbon emissions and deepened the understanding of the long-term influence of chemical fertilizer use and green finance on agricultural carbon emissions. Finally, the article can enrich the theoretical research on green finance and the use of chemical fertilizers, as well as provide a basis and reference for the government to formulate carbon emission reduction policies.

2. Materials and Methods

2.1. Data and Index

2.1.1. Total Agricultural Carbon Emission

Chemical fertilizers, agricultural plastic films, pesticides, and agricultural activities can be regarded as the main sources of agricultural carbon emissions [39]. This study focuses on agricultural production and planting in a narrow sense. When considering the factors that may lead to carbon emissions in the process of agricultural production activities, we pay more attention to carbon emissions caused by input factors, so we take chemical fertilizers, pesticides, agricultural plastic films, agricultural diesel oil, agricultural cultivation, and agricultural irrigation as carbon emission sources to estimate the total agricultural carbon emission of each province. To quantify the above carbon sources, we select data such as the pure amount of agricultural chemical fertilizer application, pesticide consumption, agricultural plastic film consumption, agricultural diesel oil consumption, the total sown area of agriculture, and the effective irrigated area of agriculture to measure. The composition of fertilizers is a compound fertilizer, which contains nitrogen, phosphorus, and potassium. Table 1 shows the data sources of the above variables. The left column is the name of the main variable, the middle column is the data unit, and the right column is the data source corresponding to each variable.

Table 1. The data sources.

Variables	Unit	Data Sources
Pure amount of agricultural chemical fertilizer application	kg	China Rural Statistical Yearbook
Pesticides consumption	kg	
Agricultural plastic films consumption	kg	
Agricultural diesel oil consumption	kg	
The total sown area of agriculture	hm^2	
The effective irrigated area of agriculture	hm^2	

Note: They are provincial data from 2000 to 2019.

We calculate the total agricultural carbon emission of each province (city) by multiplying the carbon source usage and carbon emission coefficient based on the collected data. The measurement formula adopted in this paper is as follows:

$$E = \sum E_{\mathrm{i}} = \sum T_i \bullet \delta_i$$

In which E represents total agricultural carbon emission, T_i denotes the amount of carbon source used. δ expresses the carbon emission coefficient of each carbon source, i refers to species of carbon sources ($i = 1, 2, \ldots, 6$). The carbon emission calculation method adopts the emission coefficient method, that is, the carbon emission is equal to the carbon source consumption multiplied by the corresponding carbon emission coefficient. Each carbon source emission coefficient and the main reference sources are shown in Table 2. All GHG emissions in this study are considered to be caused by the input factors of agricultural production activities. The unit in the second column, the former is the carbon dioxide emission unit kg, and the latter is the calculation unit of each carbon source.

Table 2. Carbon emission coefficient reference.

Carbon Source	Carbon Emission Coefficient	Refer to the Main Source
Fertilizer	0.895 6 kg/kg	Oak Ridge National Laboratory [40]
Pesticide	4.934 1 kg/kg	Oak Ridge National Laboratory
Agricultural plastic films	5.18 kg/kg	Institute of Resource, Ecosystem and Environment of Agriculture, Nanjing Agricultural University
Agricultural diesel oil	0.592 7 kg/kg	Intergovernmental Panel on Climate Change IPCC
Agricultural cultivation	3.126 kg/hm^2	College of Biological Sciences, China Agricultural University
Agricultural irrigation	25 kg/hm^2	[40,41]

Note: kg/kg means that for each additional kilogram of carbon source used, the increase in carbon emission is the value corresponding to the carbon emission coefficient, and the unit is kg. Taking fertilizer as an example, for every additional kilogram of fertilizer use, carbon emissions increase by 0.8956.

Among the above carbon sources, the statistical problem of the concept of the agricultural ploughing process may not involve the use of machinery, or the proportion is extremely small, so the double calculation between agricultural diesel oil and agricultural cultivation is ignored here.

2.1.2. Green Financial Index Construction Method

Table 3 lists the four main indicators of constructing the green financial index in this paper. In order to measure the development of green finance more comprehensively, the positive development indicators such as green insurance and green investment are selected as well as the reverse indicators such as green credit and government support. The data used come from the China Statistical Yearbook, Statistical Yearbook of each province, China Insurance Yearbook, and the index is calculated by entropy method.

Table 3. The definition and attribute of the green financial index.

Primary Index	Characterization Index	Indicator Description	Index Attribute
Green credit	The proportion of interest expenditure of energy-intensive industries	Interest expenditure of six high energy consumption industries/Industrial interest expense	−
Green investment	Environmental pollution control investment as a proportion of GDP	Investment in environmental pollution control/GDP	+
Green insurance	Agricultural insurance depth	Agricultural insurance income/Total agricultural output value	+
Government support	The proportion of financial environmental protection expenditure	Financial environmental protection expenditure/General budget expenditure	−
Green credit	The proportion of interest expenditure of energy-intensive industries	Interest expenditure of six high energy consumption industries/Industrial interest expense	−
Green investment	Environmental pollution control investment as a proportion of GDP	Investment in environmental pollution control/GDP	+

Notes: "+" indicates the positive attribute of the index. "−" indicates the negative attribute of the index. Because of the missing data, the missing values of some years are replaced by the average values of the data of adjacent five years.

Green credit refers to a brand-new credit policy which was put forward by the People's Bank of China, the Ministry of Environmental Protection, and China Banking Regulatory Commission on 30 July 2007. The purpose of this new policy is to curb the blind expansion of industries with high energy consumption and high pollution, which will realize environmental protection control through financial leverage. In this article, the situation of green credit is reflected by the ratio of interest expenditure of six high energy-consuming industrial industries to total industrial interest expenditure.

Green investment refers to the practice of investing in companies that are producing "green" technologies that are beneficial to the environment or recycling other environmentally responsible activities. People who are interested in socially responsible investment have the opportunity to support companies that implement energy efficiency, build green buildings, reduce waste generation and use recyclable materials in manufacturing or transportation. The ratio of investment in regional environmental pollution control to GDP can reflect the importance that local governments attach to green development.

Green insurance refers to all the ecological risk management activities and fund utilization activities that are carried out by applying insurance concepts and means, focusing on ensuring the service of national ecological security and ecological high-quality development and serving the government's ecological governance. Green insurance is the concentrated embodiment of insurance social management function. Here, the growth of regional green insurance reflects the protection degree of the green industry with the ratio of agricultural insurance income to the total agricultural output value.

Government support means that the government supports and guarantees the growth of green finance through fiscal policies. The 2016 China Green Finance Development Report released by China Green Finance Summit in 2017 pointed out that although there are no clear green finance support projects in the national budget, the government funds, general public budgets, and state-owned capital operating budgets all contain green finance-related projects, such as environmental protection expenditures, agriculture, forestry and water expenditures, etc. Here, the ratio of fiscal expenditure on environmental protection to fiscal general budget expenditure is selected to reflect the government's support for green finance.

2.1.3. Descriptive Statistics Analysis

The level value, logarithm value, and first-order differential value descriptive statistics of total agricultural carbon emission, chemical fertilizer use, and green financial index are shown in Table 4. The average carbon dioxide emissions reached 969.68, with a range of 2394.39, and the data fluctuated widely. The average amount of chemical fertilizer used is 175,129, and the regional standard deviation is 1,376,030 tons. The average value of the green finance index is only 0.141, with a range of 0.751, which shows that the green financial index fluctuates greatly in different regions.

Table 4. The descriptive statistics of the main variables.

Variable	Mean	Std. Dev.	Min	Max
Carbon	969.68	603.784	23.36	2417.75
Fertilizer	175.129	137.603	6.17	716.09
Green	0.141	0.093	0.042	0.793
Lncarbon	6.568	0.934	3.151	7.791
Lnfertilizer	4.746	1.084	1.82	6.574
Lngreen	−2.108	0.509	−3.175	−0.232
Dlncarbon	−0.004	0.054	−0.269	0.24
Dlnfertilizer	0.01	0.051	−0.296	0.263
Dlngreen	0.055	0.045	−0.208	0.25

2.2. Cross-Sectional Dependence Tests

In the early research [42–44], the panel unit root test and panel stationarity test assumed that each cross-sectional body is independent, but this assumption was limited in practical operation [45]. Affected by common shocks, such as macroeconomic shocks, the unit entities in panel data will be interdependent [46]. Under the condition of cross-section correlation, the size of the panel test will be seriously distorted, so the cross-section dependence test is the key problem of the panel test. Breusch and Pagan put forward the Breusch–Pagan LM test in 1980 to test the cross-section correlation, and Pesaran [47] improved it and put forward Pesaran CD and standardized La Grange multiplier (LM) tests. Breusch–Pagan LM test is given by:

$$LM = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T_{ij}\mu_{ij}^2 \rightarrow \chi^2(N(N-1)/2) \quad (1)$$

Small samples N and T are suitable for Equation (1), but with the increase in N, the test will be distorted in size, and the larger the N, the greater the uncertainty of LM statistics. Finally, the test will be inapplicable in large samples. Pasaran repaired the above problems, the cross-section inspection he proposed can be used for large sample N and variable/fixed time T:

$$LM = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+}^{N} (T_{ij}\mu_{ij}^2 - 1) \to N(0,1) \tag{2}$$

$$CD = \sqrt{2/N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T_{ij}\mu_{ij}^2 \to N(0,1) \tag{3}$$

In Equation (3), μ_{ij}^2 is the correlation coefficient of residual error, its calculation expression is as follows:

$$\mu_{ij} = \mu_{ij} = \frac{\sum_{t-1}^{T} \varepsilon_{ij}\varepsilon_{ji}}{\left(\sum_{t-1}^{T} \varepsilon_{ij}^2\right)^{\frac{1}{2}} \left(\sum_{t-1}^{T} \varepsilon_{jt}^2\right)^{1/2}} \tag{4}$$

where ε_{ij} and ε_{ji} are standard errors.

2.3. Unit Root Test

2.3.1. LLC

The LLC [44] test (applicable to common root cases) is a left unilateral test, and the LLC test principle adopts the ADF test form. The LLC test is based on the following ADF inspection formula:

$$\Delta y_{it} = \rho y_{i\ t-1} + \sum_{j=1}^{k_i} \gamma_{ij}\Delta y_{i\ t-j} + Z_{it}'\varnothing + \varepsilon_{it},\ i = 1,2,\ldots,N; t = 1,2,\ldots,T$$

However, the standardized proxy variables influenced by the auto-correlation of Δy_{it} and y_{it} and the deterministic items are used. Specifically, it can be divided into two steps: (1) estimate the proxy variable. Make the following two regression equations after determining the number of additional terms *k*:

$$\Delta y_{it} = \sum_{j=1}^{k_i} \hat{\gamma}_{i\ j}\Delta y_{i\ t-j} - Z_{it}'^{\hat{\varnothing}} + \hat{\varepsilon}_{it},\ \Delta y_{i\ t-1} = \sum_{j=1}^{k_i} \widetilde{\gamma}_{i\ j}\Delta y_{i\ t-j} + Z_{it}'\widetilde{\varnothing} + \widetilde{\varepsilon}_{it-1}$$

transposition of terms:

$$\widetilde{\varepsilon}_{it} = \Delta y_{it} - \sum_{j=1}^{k_i} \hat{\gamma}_{i\ j}\Delta y_{i\ t-j} - Z_{it}'^{\hat{\varnothing}},\ \widetilde{\varepsilon}_{it-1} = \Delta y_{it} - \sum_{j=1}^{k_i} \widetilde{\gamma}_{ij}\Delta y_{i\ t-j} - Z_{it}'\widetilde{\varnothing}$$

Standardize $\widetilde{\varepsilon}_{it}$ and $\widetilde{\varepsilon}_{it-1}$:

$$\widetilde{\varepsilon}_{ij}^* = \hat{\varepsilon}_{it}/s_i\ ,\ \widetilde{\varepsilon}_{ij}^* = \widetilde{\varepsilon}_{it-1}/s_i$$

s_i (i = 1, 2, ..., N) refers to the standard deviation of regression residuals of each individual, so as to obtain the proxy variables $\hat{\varepsilon}_{ij}^*$ and $\widetilde{\varepsilon}_{ij}^*$ of Δy_{it} and Δy_{it-1}.

(2) Make the following regression with proxy variables $\hat{\varepsilon}_{ij}^*$ and $\widetilde{\varepsilon}_{ij}^*$,

$$\hat{\varepsilon}_{ij}^* = \rho\widetilde{\varepsilon}_{ij}^* + v_{it}$$

Furthermore, LLC proves that the following $\widetilde{t}_p$ which is the estimator $\hat{\rho}$ modified statistic gradually obeys the standard normal distribution.

$$\widetilde{t}_{\hat{\rho}} = \frac{t_{\hat{\rho}} - \left(N\widetilde{T}\right)S_N\hat{\sigma}^2 s(\hat{\rho})\mu_{m\widetilde{T}}^*}{\sigma_{m\widetilde{T}}^*} \to N(0,1)$$

In which $t_{\hat{\rho}}$ and N respectively represent the standard T statistic and interface capacity; $\widetilde{T} = T - \left(\sum_i k_i/N\right) - 1$ (T is individual capacity); S_N, $\hat{\sigma}^2$, $S(\rho)$ respectively represent the average of the ratio of long-term standard deviation to information standard deviation of each individual, the variance of the error term v_{it} and the standard error of ρ; what is more, $\mu_{m\widetilde{T}}$ and $\sigma_{m\widetilde{T}}$ are the adjustment items of the mean and standard deviation, respectively.

2.3.2. ADF

In the Choi [43] test (Fisher-ADF) (used in different root cases), a combined p_i test statistic is proposed. The test method is based on the Fisher principle. First, the ADF test is performed on each individual, and ADF-Fisher statistics are constructed by the sum of probability p_i corresponding to ADF statistics. Under the original hypothesis, assuming that H_0 is the root of existence unit:

$$ADF - Fisher = -2\sum_{i=1}^{N} log(p_i) \to \chi^2(2N)$$

2.3.3. PP

Phillips and Perron used σ^2 and σ_s^2 [48,49], which is the estimated value of makes nonparametric correction to the T statistic of the ADF test, and the corrected statistic is as follows:

$$Z(\tau) = \tau\left(\hat{\sigma}^2/\hat{\sigma}_{Sl}^2\right) - (1/2)\left(\hat{\sigma}_{Sl}^2 - \hat{\sigma}^2\right)T\sqrt{\hat{\sigma}_{Sl}^2\sum_{t=2}^{T}(x_{t-1} - \overline{x}_{T-1})^2}$$

In which $\hat{\sigma}^2$ is the unconditional variance sample estimator of σ^2, that is:

$$\hat{\sigma}^2 = T^{-1}\sum_{t=1}^{T}\hat{\varepsilon}_t^2$$

Assume $\{\varepsilon_t\}$ that the delay order of significant autocorrelation can be estimated to be 1, which $\hat{\sigma}_{Sl}^2$ is the estimated value of conditional variance sample $\hat{\sigma}_S^2$:

$$\hat{\sigma}_{Sl}^2 = T^{-1}\sum_{t=1}^{l}\hat{\varepsilon}_t^2 + 2T^{-1}\sum_{j=1}^{t}\varnothing_j(l)\sum_{t=j+1}^{T}\hat{\varepsilon}_t\hat{\varepsilon}_{t-j}$$

In the formula, $\varnothing_j(l) = 1 - \frac{1}{l-1}$, this weight is guaranteed $\hat{\sigma}_{Sl}^2$ tobe positive.

$$\overline{x}_{T-1} = \frac{1}{T-1}\sum_{t=1}^{T-1}x_t$$

2.4. Panel Cointegration Test

We use the residual-based ADF test (Kao test) to correct panel cointegration test. For panel regression model:

$$y_{it} = x_{it}\beta + z_{it}\gamma + e_{it}$$

Among them, e_{it} is a non-cointegration I (1) process. Kao [50] used the DF and ADF unit root test to test the zero hypothesis without cointegration. For the ADF test, Kao proposed the following equation for regression:

$$\hat{e}_{it} = \rho\hat{e}_{i,t-1} + \sum_{j=1}^{p}\theta_j\Delta\hat{e}_{i,t-j} + v_{itp}$$

At the same time, ADF statistics without cointegration null hypothesis are constructed:

$$ADF = \frac{t_{ADF} + \frac{\sqrt{6N}\hat{\sigma}_v}{2\hat{\sigma}_{0v}}}{\sqrt{\frac{\hat{\sigma}_{0v}^2}{2\hat{\sigma}_v^2} + \frac{3\hat{\sigma}_v^2}{10\hat{\sigma}_{0v}^2}}}$$

Among them, $\hat{\sigma}\sigma_v^2 = \sum\limits_{yy} - \sum\limits_{yx} \sum\limits_{xx}^{-1}$, $\hat{\sigma}_{0v}^2 = \hat{\Omega}_{yy} - \hat{\Omega}_{yx}\hat{\Omega}_{xx}^{-1}$.

2.5. Causality Test

After the cointegration test, we pay attention to the causality among agricultural carbon emission, green finance, and chemical fertilizer use. Granger [51] pioneered the method of analyzing the causality of time series data. On the basis of the above, Dumitrescu-Hurlin [52] expanded it, and provided a method of testing the causality of panel data which can judge the causality through the impact of the past value of X on the present value of Y. The regression model is as follows:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_{ik} y_{i,t-k} + \sum_{k=1}^{K} \beta_{ik} x_{i,t-k} + \varepsilon_{i,t}$$

In which, i = 1, 2, . . . , N; t = 1, 2, . . . , T; $x_{i,t}$ and $y_{i,t}$ is the observed value of two stationary series at individual i and time t; a_i is the individual fixation effect. The regression coefficient of each section element in this equation is variable. The equation assumes that the panel must be stationary and the lag order k of all individuals is the same.

2.6. FMOLS and DOLS

OLS regression can obtain the super-uniform estimator of cointegration parameters [53]. However, because the OLS estimator neglects short-term dynamics, it may lead to a large, limited sample deviation [54] and the asymptotic distribution is usually nonstandard, and it will be affected by noise parameters, which will lead to the ineffectiveness of common inspection procedures and make statistical inference difficult. Therefore, Phillips and Hansen [55] put forward the nonparametric correction of the OLS estimator, the so-called FMOLS estimator, and the DOLS estimator also has the above correction effect. Estimates from either or DOLS are asymptotically equivalent [56,57].

It is worth mentioning that FMOLS and DOLS are both group average estimation methods between dimensions. They can solve the problems of sequence correlation and endogenous explanatory variables in the study of long-term relationships.

For panels with i = 1, 2, . . . , N regions at time t = 1, 2, . . . , M, consider the following cointegration system:

$$\begin{gathered} Y_{it} = \alpha_{it} + \beta X_{it} + \varepsilon_{it} \\ X_{it} = X_{it-1} + \varepsilon_{it} \end{gathered}$$

$Z_{it} = (Y_{it}, X_{it})' \sim I(1)$ and $\omega_{it} = (\varepsilon_{it}, \mu_{it})' \sim I(0)$ with a long run covariance matrix $\Omega_i = L_i L_i'$, L_i is the lower triangular decomposition of Ω_i which can also be decomposed as $\Omega_i = \Omega^0 + \Gamma_i + \Gamma_i'$, Ω^0 and Γ_i are the contemporaneous covariance and a weighted sum of autocovariances, respectively.

The panel FMOLS estimator for the coefficient β is given by:

$$\beta_{NT}^* = N^{-1} \sum_{i=1}^{N} \left(\sum_{i=1}^{T} \left(X_{it} - \overline{X}_i\right)^2 \right)^{-1} \left(\sum_{i=1}^{T} \left(X_{it} - \overline{X}_i\right) Y_{it}^* - T_{\widehat{\tau}_i} \right.$$

$$Y_{it}^* = \left(Y_{it} - \overline{Y_i}\right) - \frac{\widehat{L_{21i}}}{\widehat{L_{22i}}} \Delta X_{it},\ \widehat{\tau}_i \equiv \widehat{\Gamma_{21i}} + \widehat{\Omega_{21i}^0} - \frac{\widehat{L_{21i}}}{\widehat{L_{22i}}} \left(\widehat{\Gamma_{22i}} + \widehat{\Omega_{22i}^0} \right)$$

The DOLS is written as follows:

$$Y_{it} = \alpha_i + \beta_i X_{it} + \sum_{j=-ji}^{jl} \theta_{ij} \Delta X_{it-j} + \varepsilon_{it}^*$$

where the estimated coefficient β is given by:

$$\beta_{dols}^* = N^{-1} \sum_{i=1}^{N} (\sum_{t=1}^{T} Z_{it} Z_{it}^i)^{-1} \left(\sum_{t=1}^{T} Z_{it} Y_{it}^* \right)$$

where $Z_{it} = \left(X_{it} - \overline{X_i}, \Delta X_{it-j}, \ldots, \Delta X_{it+k} \right)$ is $2(K+1)$ vector of regressors.

2.7. Variance Decomposition and Impulse Response Approach

We adopted variance decomposition and impulse response methods to obtain the relative importance of the dependent variables of different factors and examine the response of each endogenous variable to the changes of itself and all other endogenous variables. This kind of shock can also be described by the model structure. In the impulse response function (which is based on stable VAR model), the change of variable means that an endogenous variable is disturbed or impacted (called "impulse"), that is, its error changes. The response of variable refers to the influence of error change on itself and other endogenous variables. By observing the image of the impulse response function, we can more effectively reflect the time lag and intensity change of the transmission effect of each influencing dependent variable on the fluctuation of the dependent variable. As proposed by Lanne [58], the VAR model can be written in the following style:

$$y_t = \sum_{j=0}^{p} \phi_i y_{t-i} + \varepsilon_t$$

where ε_t is the independent identically distributed (iid) error term with 0 mean and 0 covariance matrix as well as ϕ_i is a simple impulse response function. ϕ_i can be changed into an infinite vector moving average according to the following formula [59]:

$$\phi_i = \begin{cases} I_k, i = 0 \\ \sum_{j=1}^{i} \phi_{t-j} A_j, i = 1, 2, .. \end{cases}$$

I_k and A_j are the unit elements of the companion matrix and the coefficient matrix of the transformed VAR into infinity VMA form, respectively.

In the initial formula, assuming weak stationarity, y_t obtains an infinite moving average representation:

$$y_t = \sum_{j=0}^{\infty} A_j \varepsilon_{t-j}$$

In this paper, the lag interval selected is 14.

3. Results

3.1. Cross-Sectional Dependence and Unit Root Tests Results

In Table 5, the cross-sectional dependency test results show that the original assumption that there is no dependency between regions is rejected at the significance level of 1%, which means that cross-regional dependency exists. We selected three test methods (LLC, ADF, and PP) to guarantee the correctness of the unit root test, Table 6 reflects the test results. The results obtained by the three test methods are consistent. At a 1% significance level, only lngreen can reject the original hypothesis of unit root, and the level values of other variables cannot reject the original hypothesis. However, all variables can reject the original hypothesis at a 1% significance level after the first-order difference. This indicates that there may be a false regression, so the next step is to adopt the cointegration test. Therefore, Kao's residual panel cointegration test (ADF) is used to test whether there is a long-term cointegration relationship between variables and correct the error model.

Table 5. Cross-sectional dependence test results.

Test	Statistic	Prob.
Breusch–Pagan LM	2370.873	0.0000 ***
Pesaran scaled LM	65.63224	0.0000 ***
Pesaran CD	30.14657	0.0000 ***

Notes: *** Significant at 1% level.

Table 6. Panel unit root tests results.

Variables	Level		First-Difference	
	None	Intercept and Trend	None	Intercept and Trend
LLC test				
Lncarbon	0.3258	0.9982	0.0000 ***	0.0000 ***
Lnfertilizer	0.0003 ***	1.0000	0.0000 ***	0.0000 ***
Lngreen	0.0000 ***	0.0000 ***	0.0001 ***	0.0000 ***
ADF-Fisher chi-square test:				
Lncarbon	0.3596	0.8194	0.0000 ***	0.0000 ***
Lnfertilizer	0.1385	1.0000	0.0000 ***	0.0000 ***
Lngreen	0.0000 ***	0.0000 ***	0.0033 ***	0.0000 ***
PP-Fisher chi-square test				
Lncarbon	0.3823	0.9558	0.0000 ***	0.0000 ***
Lnfertilizer	0.7219	1.0000	0.0000 ***	0.0000 ***
Lngreen	0.0000 ***	0.0025 ***	0.0000 ***	0.0000 ***

Notes: *** Significant at 1% level.

3.2. Panel Cointegration Test Results

According to Kao's residual panel cointegration test (ADF), the result is reflected in Table 7. The results show that the *p*-value is 0.0069, which is far less than 0.01, so we can reject the original hypothesis that there is no cointegration relationship at the significance level of 1%, which means that the cointegration relationship exists. After the co-integration test is passed, we can examine the causality among agricultural carbon emissions, fertilizer use, and green finance through the Granger causality test, which is helpful for us to study the influence of fertilizer use and green finance on agricultural carbon emissions.

Table 7. Kao panel cointegration test results.

	Null Hypothesis	t-Statistics	Probability
ADF	No co-integration	−2.4601	0.0069 ***

Notes: *** Significant at 1% level.

3.3. Results of DOLS and FMOLS

Table 8 gives the estimation results of dynamic OLS and FMOLS. In the long run, chemical fertilizer consumption in various regions has a positive impact on carbon emissions. In contrast, green finance has a significant negative effect on agricultural carbon emission, and all parameters reject the original assumption that the parameter is equal to 0 at the significance level of 5%. Our findings are similar to the research conclusion of Flammer [34] and Wang et al. [35], who both found that with the support of green investment and financing projects, carbon emissions have decreased. This paper focuses on agricultural carbon emissions, showing that green orientation also plays a significant role in agricultural investment and financing, which can significantly reduce agricultural carbon emissions.

Table 8. Benchmark results.

Variables	Coefficient	SE	t-Statistic	Prob.
DOLS (1)				
LNFERTILIZER	0.4890	0.0331	14.7671	0.0000 ***
LNGREEN	−0.1448	0.0166	−8.7152	0.0000 ***
FMOLS (2)				
LNFERTILIZER	0.3682	0.0431	8.5526	0.0000 ***
LNGREEN	−0.0560	0.0258	−2.1677	0.0311 **

Notes: ** Significant at 5% level. *** Significant at 1% level.

Specifically, under the DOLS method, the use of chemical fertilizers increases by 1%, the agricultural carbon emission increase by about 0.49%, while the green financial index increases by 1%, and the agricultural carbon emission decrease by about 0.14%. Under the FMOLS method, the agricultural carbon emissions increase by about 0.37% for every 1% increase in fertilizer usage and decrease by about 0.06% for every 1% increase in the green financial index. From the level of parameter significance, the fitting effect of DOLS is better.

3.4. Causality Test Results

The paired causality test results among agricultural carbon emission, chemical fertilizer use, and green finance are shown in Table 9. Meo and Karim [33] pointed out that different countries supporting green finance show bi-directional causations or one-way directional causation between green finance and carbon dioxide due to different environmental pollution levels and market conditions. However, we found one-way causality between green finance and agricultural carbon emissions. This shows that there is great potential for developing green finance in our country, which can significantly reduce agricultural carbon emissions. Moreover, we notice one-way causality between green finance and fertilizer use and two-way causality between fertilizer use and carbon emissions.

Table 9. Pairwise Granger causality tests.

Null Hypothesis	Obs	F-Statistic	Prob.
LNCARBON does not Granger Cause LNGREEN	510	0.6198	0.5384
LNGREEN does not Granger Cause LNCARBON		34.5480	0.0000 ***
LNFERTILIZER does not Granger Cause LNGREEN	510	1.9076	0.1495
LNGREEN does not Granger Cause LNFERTILIZER		56.3713	0.0000 ***
LNFERTILIZER does not Granger Cause LNCARBON	540	26.4542	0.0000 ***
LNCARBON does not Granger Cause LNFERTILIZER		4.9600	0.0073 ***

Notes: *** Significant at 1% level.

All the parameter test results rejected the original hypothesis of no causality at the significance level of 1%, which means that the implementation of green finance policy can reduce fertilizer consumption and carbon emissions, which are the reasons for the mutual reduction in fertilizer use and carbon emissions.

3.5. VAR Diagnostic Test

In this study, the VAR model of green finance, chemical fertilizer use, and agricultural carbon emission is constructed, and the optimal index is obtained when the lag period is 14. The results of the causality test show that there are bi-directional or one-way directional causations among them. On the basis that all three variables are endogenous variables, we test the stationarity of the VAR model, and obtain the ideal results (see Figure 1). By observing the inverse roots of the AR characteristic polynomial, we can draw the conclusion that the VAR model has good stability, for all the dots are within the circle. The results of variance decomposition and the impulse response which are based on this VAR model will be given in 4.6.

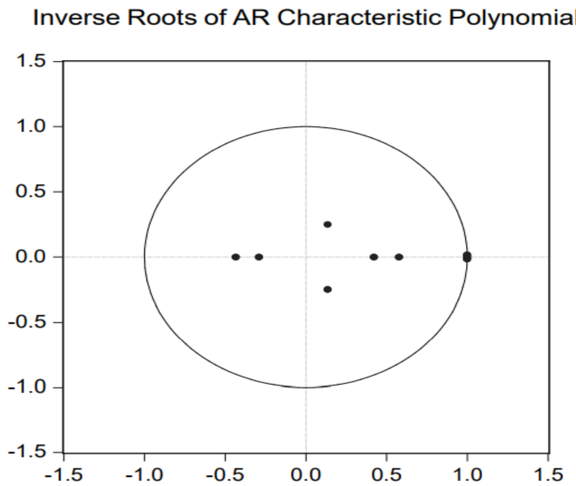

Figure 1. The inverse roots of the AR characteristic polynomial.

3.6. Variance Decomposition and Impulse Response Analysis Results

We use the variance decomposition and impulse response analysis method proposed by Lanne [58] to obtain the influence degree of chemical fertilizer and green finance on carbon emissions from the agricultural sector of 30 provinces (cities) in China. Table 10 and Figure 2 show the variance decomposition and impulse response analysis results of the 14-year forecast period, respectively. The results show that, in the fourteenth forecast period, 80.11% of agricultural carbon dioxide changes can be explained by the impact of agricultural carbon dioxide itself, while chemical fertilizer and green finance contribute 7.78% and 12.11%, respectively, and the contribution of green finance will gradually exceed that of chemical fertilizer, which indicates that the impact of green finance on carbon emissions will be greater and greater. We are concerned that the contribution rate of green finance to chemical fertilizers in the 14-year forecast period reaches 20.46% simultaneously, which means that chemical fertilizer use and green finance will continue to significantly affect the changes in agricultural carbon emissions in the next decade, and the implementation of green finance policy will also continue to affect the use of chemical fertilizers, which is consistent with our causality test results.

Namahoro et al. [60] used the impulse response function to estimate the influence of economic growth, renewable energy, and energy intensity on carbon emissions in different regions and different income levels. They found that the impact of economic growth and energy intensity on carbon dioxide emissions is increasing. In addition, renewable energy has considerable potential to reduce CO_2 emissions. In our research results (Figure 2), we are concerned that after a shock of the new interest rate which gives green finance a standard deviation, the agricultural carbon emissions did not respond in the first period, and gradually declined from the second period. As far as the overall response is concerned, it shows a significant long-term downward trend, and it continues to decline for a long time. This shows that the shock of green finance has a significant long-term negative effect on agricultural carbon emissions; that is, green finance also has great potential to reduce carbon emissions. Moreover, given a shock of chemical fertilizer, agricultural carbon emissions did not respond in the first period, slowly increased from the second period, and showed a stable positive effect after the fourth period. In addition, chemical fertilizers did not respond to the shock of green finance in the first phase. Like agricultural carbon emissions, the impulsive response has been declining since the second phase, showing a long-term downward trend. This shows that the shock of green finance also has a long-term significant negative effect on chemical fertilizers and green finance has a significant positive effect on reducing chemical fertilizer consumption.

Table 10. The impulse response and variance decomposition results.

Period	S.E.	LNCARBON	LNFERTILIZER	LNGREEN
		Variance Decomposition of LNCARBON:		
1	0.0453	100.0000	0.0000	0.0000
2	0.0712	98.4829	1.4334	0.0836
3	0.0916	97.0158	2.6695	0.3147
4	0.1085	95.7503	3.5618	0.6880
5	0.1229	94.5617	4.2379	1.2004
6	0.1357	93.3585	4.7885	1.8530
7	0.1472	92.0885	5.2641	2.6475
8	0.1577	90.7227	5.6922	3.5851
9	0.1675	89.2460	6.0881	4.6660
10	0.1767	87.6513	6.4602	5.8885
11	0.1855	85.9370	6.8132	7.2497
12	0.1939	84.1051	7.1498	8.7451
13	0.2021	82.1604	7.4711	10.3686
14	0.2102	80.1100	7.7774	12.1126
		Variance Decomposition of LNFERTILIZER:		
1	0.0414	8.9496	91.0504	0.0000
2	0.0676	10.6340	89.0487	0.3174
3	0.0890	10.8311	88.2015	0.9674
4	0.1074	10.4105	87.7005	1.8891
5	0.1238	9.7244	87.2207	3.0549
6	0.1389	8.9302	86.6269	4.4429
7	0.1533	8.1060	85.8641	6.0299
8	0.1672	7.2946	84.9152	7.7902
9	0.1808	6.5215	83.7821	9.6964
10	0.1942	5.8024	82.4770	11.7206
11	0.2077	5.1472	81.0179	13.8350
12	0.2213	4.5615	79.4256	16.0129
13	0.2350	4.0482	77.7222	18.2295
14	0.2490	3.6081	75.9298	20.4621
		Variance Decomposition of LNGREEN:		
1	0.0439	0.0007	0.0078	99.9915
2	0.0697	0.0026	0.0126	99.9849
3	0.0898	0.0121	0.0230	99.9649
4	0.1065	0.0296	0.0311	99.9393
5	0.1210	0.0545	0.0372	99.9083
6	0.1341	0.0860	0.0420	99.8719
7	0.1460	0.1238	0.0462	99.8300
8	0.1571	0.1676	0.0500	99.7824
9	0.1675	0.2171	0.0535	99.7293
10	0.1773	0.2721	0.0571	99.6708
11	0.1866	0.3323	0.0606	99.6071
12	0.1955	0.3974	0.0643	99.5383
13	0.2040	0.4674	0.0680	99.4646
14	0.2121	0.5418	0.0720	99.3862

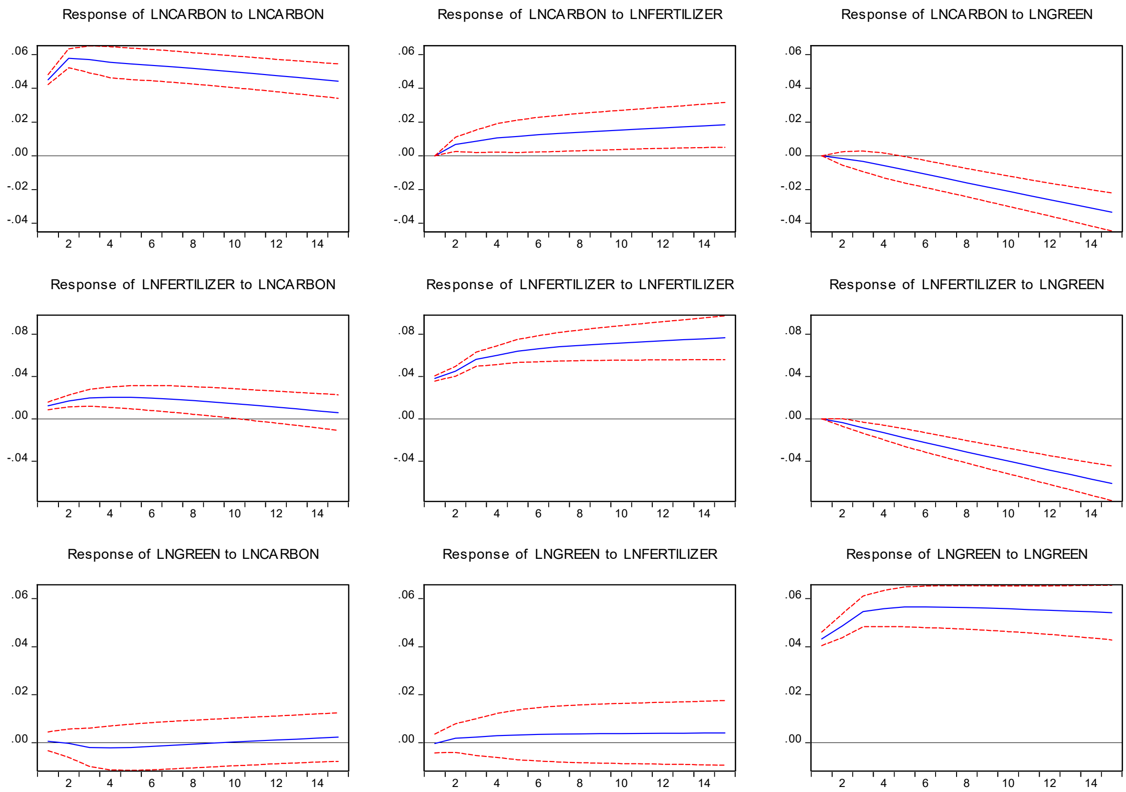

Figure 2. Impulse response of lncarbon, lngreen, and lnfertilizer for prediction of 14 years (blue color) with 95% of confidence interval (red color).

Furthermore, the shock of agricultural carbon emissions on chemical fertilizers shows a long-term stable positive effect. The shock of agricultural carbon emissions on green finance fluctuates greatly in the short term, even shows a weak negative response, and shows a weak positive response in the long term. As far as the overall response is concerned, the impact of agricultural carbon emissions on green finance is very weak. Similarly, the shock of chemical fertilizers has a long-term positive effect on green finance, but overall, its impact is very weak.

Based on abundant empirical methods, the results are remarkable. Although the data only ends in 2019, the data over the last two years have not been reflected, but the research conclusion is reliable.

4. Conclusions

Through the panel data analysis of 30 provinces (cities) in China for 20 years (2000–2019), this study examined the role of green finance and fertilizer usage as determinants of agricultural carbon emissions. In this study, the cross-sectional correlation and data stationarity of variables were first checked by the Pesaran [47] test and unit root test, and then the Kao [50] test was used to test the long-term co-integration relationship between the three variables. The long-term co-integration relationship between green finance, fertilizer use, and agricultural carbon emissions was shown in the empirical results. In the case of the long-term cointegration relationship, the causality test confirmed a bidirectional causal relationship between agricultural carbon emission and chemical fertilizer use. In contrast, a one-way causal relationship that runs from green finance to CO_2 and from green finance to chemical fertilizer was strictly verified simultaneously. In addition, in the variance decomposition and impulse response based on the VAR model, it was found that green finance has established a positive relationship with agricultural carbon emissions. Moreover, as far as China is concerned, fertilizer consumption is positively correlated with agricultural carbon emissions. In contrast, the impact of green finance and agricultural carbon emissions is negative, and the development of the former will reduce the latter.

In light of the above research results, we put forward the following policy suggestions: Firstly, local governments should implement the concept of sustainable development, promote the wide application of green finance in the agricultural sector, broaden the ways of green agricultural production investment, to achieve low-carbon agricultural development. Secondly, strengthen the government's top-level design, improve agricultural production efficiency through technological innovation and innovation, promote organic fertilizers to replace chemical fertilizers, and carry out agricultural "fertilizer loss" action to achieve a negative increase in chemical fertilizer use. Thirdly, strengthen the supervision of carbon emissions in agricultural fields. Local governments can restrict farmers' input of agricultural factors by improving the carbon tax system. Furthermore, setting up a reward and punishment system is an effective way to encourage farmers to carry out green production. Finally, strengthening extensive cooperation with the international community, learning from the advanced experience of other countries, introducing advanced energy-saving and emission-reduction technologies and tools will help China achieve its goal of carbon neutrality at an early date.

The research of this paper has made innovations on the basis of predecessors, focusing on the important problem existing in agricultural production—carbon emission, but there are also some limitations: the transmission of "green finance—reducing fertilizer use—agricultural carbon emission reduction" process research is not systematic enough; in addition, The economic development levels of different provinces and cities in China are different, and there are differences in agricultural production. The impact of green finance on different regions is also different. The differences in the impact of green finance on agricultural carbon emissions in different regions have not been fully studied in the article. It is suggested that future research can focus on the multi-level, wide-coverage, and sustainable green carbon reduction road, refine the policy requirements for energy conservation and emission reduction, and implement differentiated management according to local conditions.

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

Funding: This research was funded by the National Social Science Fund of China (No. 20CMZ037, 21BGL022).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available within the article.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Shukla, J.; Verma, M.; Misra, A. Effect of global warming on sea level rise: A modeling study. *Ecol. Complex.* **2017**, *32*, 99–110. [CrossRef]
2. Calleja-Agius, J.; England, K.; Calleja, N. The effect of global warming on mortality. *Early Hum. Dev.* **2020**, *155*, 105222. [CrossRef] [PubMed]
3. Zhang, G.-W.; Zeng, G.; Iyakaremye, V.; You, Q.-L. Regional changes in extreme heat events in China under stabilized 1.5 °C and 2.0 °C global warming. *Adv. Clim. Chang. Res.* **2020**, *11*, 198–209. [CrossRef]
4. Sharma, G.D.; Shah, M.I.; Shahzad, U.; Jain, M.; Chopra, R. Exploring the nexus between agriculture and greenhouse gas emissions in BIMSTEC region: The role of renewable energy and human capital as moderators. *J. Environ. Manag.* **2021**, *297*, 113316. [CrossRef] [PubMed]
5. Laborde, D.; Mamun, A.; Martin, W.; Piñeiro, V.; Vos, R. Agricultural subsidies and global greenhouse gas emissions. *Nat. Commun.* **2021**, *12*, 1–9. [CrossRef]

6. FAO. The State of Agricultural Commodity Markets. Agricultural Trade, Climate Change and Food Security, Rome. 2018. Available online: http://www.fao.org/3/I9542EN/i9542en.pdf (accessed on 20 December 2021).
7. Bai, Y.; Deng, X.; Jiang, S.; Zhao, Z.; Miao, Y. Relationship between climate change and low-carbon agricultural production: A case study in Hebei Province, China. *Ecol. Indic.* **2018**, *105*, 438–447. [CrossRef]
8. Wang, X.L.; Meng, Y.X.; Shan, Y.H.; Gong, Y.T. Carbon Emissions and Influencing Factors of Farmers' Agricultural Production Taking Some Areas in Hubei Province as Examples. *Bull. Soil Water Conser.* **2020**, *40*, 160–167, 174. (In Chinese)
9. Jiang, Y.; Li, K.; Chen, S.; Fu, X.; Feng, S.; Zhuang, Z. A sustainable agricultural supply chain considering substituting organic manure for chemical fertilizer. *Sustain. Prod. Consum.* **2021**, *29*, 432–446. [CrossRef]
10. National Bureau of Statistics of the People's Republic of China. Statistics Database. 2020. Available online: stats.gov.cn (accessed on 20 December 2021).
11. Van Veelen, B. Cash cows? Assembling low-carbon agriculture through green finance. *Geoforum* **2021**, *118*, 130–139. [CrossRef]
12. Elahi, E.; Khalid, Z.; Tauni, M.Z.; Zhang, H.; Lirong, X. Extreme weather events risk to crop-production and the adapta-tion of innovative management strategies to mitigate the risk: A retrospective survey of rural Punjab, Pakistan. *Technovation* **2021**, 102255, *in press*. [CrossRef]
13. Elahi, E.; Zhang, Z.; Khalid, Z.; Xu, H. Application of an artificial neural network to optimise energy inputs: An energy- and cost-saving strategy for commercial poultry farms. *Energy* **2022**, *244*, 123169. [CrossRef]
14. Elahi, E.; Khalid, Z.; Zhang, Z. Understanding farmers' intention and willingness to install renewable energy technology: A solution to reduce the environmental emissions of agriculture. *Appl. Energy* **2022**, *309*, 118459. [CrossRef]
15. Cui, Y.; Khan, S.U.; Deng, Y.; Zhao, M.; Hou, M. Environmental improvement value of agricultural carbon reduction and its spatiotemporal dynamic evolution: Evidence from China. *Sci. Total Environ.* **2020**, *754*, 142170. [CrossRef] [PubMed]
16. Wu, X.; Zhang, J.; Cheng, L.; Tian, Y. Potential of agricultural carbon reduction under climate change and its spatial correlation characteristics in China: Based on the spatial Durbin model. *China Popul. Resour. Environ.* **2015**, *25*, 53–61.
17. Bracmort, K. Nitrous oxide from agricultural sources: Potential role in greenhouse gas emission reduction and ozone recover. *Congr. Res. Serv.* **2010**, *1*, 1–9.
18. Burney, J.A.; Davis, S.; Lobell, D. Greenhouse gas mitigation by agricultural intensification. *Proc. Natl. Acad. Sci. USA* **2010**, *107*, 12052–12057. [CrossRef]
19. Kuznets, S. Economic Growth and Income Inequality. *Am. Econ. Rev.* **1955**, *45*, 1–28.
20. Grossman, G.M.; Krueger, A.B. *Environmental Impacts of a North American Free Trade Agreement*; National Bureau of Economic Research Working Paper 3914; NBER: Cambridge, MA, USA, 1991. [CrossRef]
21. Panayotou, T. *Empirical Tests and Policy Analysis of Environmental Degradation at Different Stages of Economic Development (No. 992927783402676)*; International Labour Organization: Geneva, Switzerland, 1993.
22. Balsalobre-Lorente, D.; Driha, O.M.; Bekun, F.V.; Osundina, O. Do agricultural activities induce carbon emissions? The BRICS experience. *Environ. Sci. Pollut. Res.* **2019**, *26*, 25218–25234. [CrossRef]
23. Peng, B.; Yan, W.; Elahi, E.; Wan, A. Does the green credit policy affect the scale of corporate debt financing? Evidence from listed companies in heavy pollution industries in China. *Environ. Sci. Pollut. Res.* **2021**, *29*, 1–3. [CrossRef]
24. Zhang, D.; Zhang, Z.; Managi, S. A bibliometric analysis on green finance: Current status, development, and future directions. *Financ. Res. Lett.* **2019**, *29*, 425–430. [CrossRef]
25. Lindenberg, N. *Definition of Green Finance*; Social Science Electronic Publishing: London, UK, 2014.
26. Khan, M.A.; Riaz, H.; Ahmed, M.; Saeed, A. Does green finance really deliver what is expected? An empirical perspective. *Borsa Istanb. Rev.* **2021**. [CrossRef]
27. Yang, Y.; Su, X.; Yao, S. Nexus between green finance, fintech, and high-quality economic development: Empirical evidence from China. *Resour. Policy* **2021**, *74*, 102445. [CrossRef]
28. Sachs, A. Completeness, interconnectedness and distribution of interbank exposures—A parameterized analysis of the stability of financial networks. *Quant. Financ.* **2013**, *14*, 1677–1692. [CrossRef]
29. Falcone, P.M.; Morone, P.; Sica, E. Greening of the financial system and fuelling a sustainability transition. *Technol. Forecast. Soc. Chang.* **2018**, *127*, 23–37. [CrossRef]
30. Pope, R.D.; Kramer, R.A. Production Uncertainty and Factor Demands for the Competitive Firm. *South. Econ. J.* **1979**, *46*, 489. [CrossRef]
31. Zhang, C.; Lv, K.Y.; Cheng, X.Y. Dose agricultural insurance affect farmers' application of pesticides? Empirical evidence from grain farmers in 4 provinces. *J. China Agric. Univ.* **2019**, *24*, 184–194. (In Chinese)
32. Guo, L.; Li, H.; Cao, X.; Cao, A.; Huang, M. Effect of agricultural subsidies on the use of chemical fertilizer. *J. Environ. Manag.* **2021**, *299*, 113621. [CrossRef]
33. Meo, M.S.; Karim, M.Z.A. The role of green finance in reducing CO_2 emissions: An empirical analysis. *Borsa Istanb. Rev.* **2021**, *3*, 1–10. [CrossRef]
34. Flammer, C. Corporate green bonds. *J. Financ. Econ.* **2021**, *142*, 499–516. [CrossRef]
35. Wang, M.-X.; Zhao, H.-H.; Cui, J.-X.; Fan, D.; Lv, B.; Wang, G.; Li, Z.-H.; Zhou, G. Evaluating green development level of nine cities within the Pearl River Delta, China. *J. Clean. Prod.* **2018**, *174*, 315–323. [CrossRef]
36. Zhang, S.; Wu, Z.; Wang, Y.; Hao, Y. Fostering green development with green finance: An empirical study on the environmental effect of green credit policy in China. *J. Environ. Manag.* **2021**, *296*, 113159. [CrossRef] [PubMed]

37. Cheung, F.M.; Hong, Y.Y. (Eds.) *Green Finance, Sustainable Development and the Belt and Road Initiative*; Routledge: London, UK, 2021.
38. Muganyi, T.; Yan, L.; Sun, H.-P. Green finance, fintech and environmental protection: Evidence from China. *Environ. Sci. Ecotechnol.* **2021**, *7*, 100107. [CrossRef]
39. Cui, H.; Zhao, T.; Shi, H. STIRPAT-Based Driving Factor Decomposition Analysis of Agricultural Carbon Emissions in Hebei, China. *Pol. J. Environ. Stud.* **2018**, *27*, 1449–1461. [CrossRef]
40. West, T.; Marland, G. A synthesis of carbon sequestration, carbon emissions, and net carbon flux in agriculture: Comparing tillage practices in the United States. *Agric. Ecosyst. Environ.* **2002**, *91*, 217–232. [CrossRef]
41. 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]
42. Hadri, K. Testing for stationarity in heterogeneous panel data. *Econ. J.* **2001**, *3*, 148–161. [CrossRef]
43. Choi, I. Unit root tests for panel data. *J. Int. Money Financ.* **2001**, *20*, 249–272. [CrossRef]
44. Levin, A.; Lin, C.-F.; Chu, C.-S.J. Unit root tests in panel data: Asymptotic and finite-sample properties. *J. Econ.* **2002**, *108*, 1–24. [CrossRef]
45. O'Connell, P.G. The overvaluation of purchasing power parity. *J. Int. Econ.* **1998**, *44*, 1–19. [CrossRef]
46. Andrews, D.W.K. Cross-Section Regression with Common Shocks. *Econometrica* **2005**, *73*, 1551–1585. [CrossRef]
47. Pesaran, M.H. *General Diagnostic Tests for Cross-Section Dependence in Panels*; IZA Discussion Paper Series; Cambridge University: Cambridge, UK, 2004.
48. Phillips, P.C.B. Time Series Regression with a Unit Root. *Econometrica* **1987**, *55*, 277. [CrossRef]
49. Phillips, P.C.B.; Perron, P. Testing for a Unit Root in Time Series Regression. *Biometrika* **1988**, *75*, 335. [CrossRef]
50. Kao, C. Spurious regression and residual-based tests for cointegration in panel data. *J. Econ.* **1999**, *90*, 1–44. [CrossRef]
51. Granger, C.W.J. Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica* **1969**, *37*, 424. [CrossRef]
52. Dumitrescu, E.-I.; Hurlin, C. Testing for Granger non-causality in heterogeneous panels. *Econ. Model.* **2012**, *29*, 1450–1460. [CrossRef]
53. Stock, J.H. Asymptotic Properties of Least Squares Estimators of Cointegrating Vectors. *Econometrica* **1987**, *55*, 1035. [CrossRef]
54. Banerjee, A.; Dolado, J.J.; Hendry, D.; Smith, G. Exploring equilibrium relationships in econometrics through static models: Some Monte-Carlo evidence. *Oxf. Bull. Econ. Stat.* **1986**, *48*, 253–277. [CrossRef]
55. Phillips, P.C.B.; Hansen, B.E. Statistical Inference in Instrumental Variables Regression with I(1) Processes. *Rev. Econ. Stud.* **1990**, *57*, 99–125. [CrossRef]
56. Banerjee, A. Panel Data Unit Roots and Cointegration: An Overview. *Oxf. Bull. Econ. Stat.* **1999**, *61*, 607–629. [CrossRef]
57. Dreger, C.; Reimers, H.E. Health care expenditures in OECD countries: A panel unit root and cointegration analysis. *Int. J. Appl. Econom. Quant. Stud.* **2005**, *2*, 5–20. [CrossRef]
58. Lanne, M.; Nyberg, H. Generalized Forecast Error Variance Decomposition for Linear and Nonlinear Multivariate Models. *Oxf. Bull. Econ. Stat.* **2016**, *78*, 595–603. [CrossRef]
59. Dong, K.; Dong, X.; Jiang, Q. How renewable energy consumption lower global CO_2 emissions? Evidence from countries with different income levels. *World Econ.* **2019**, *43*, 1665–1698. [CrossRef]
60. Namahoro, J.; Wu, Q.; Zhou, N.; Xue, S. Impact of energy intensity, renewable energy, and economic growth on CO_2 emissions: Evidence from Africa across regions and income levels. *Renew. Sustain. Energy Rev.* **2021**, *147*, 111233. [CrossRef]