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A Win–Win Scenario for Agricultural Green Development and Farmers' Agricultural Income: An Empirical Analysis Based on the EKC Hypothesis

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Abstract: Due to severe resource and environmental constraints, agricultural green development is a vital step for the low-carbon development of China. How to achieve the goal of a win–win scenario that simultaneously improves agricultural green total factor productivity (GTFP) and farmers' agricultural income was the main focus of this study. Based on the panel dataset for 31 provinces in China from 2000 to 2018, this study calculated the agricultural GTFP using the global Malmquist–Luenberger (GML) index to measure the green development of agriculture. Furthermore, this study investigated the relationship between the agricultural GTFP and agricultural income in an environmental Kuznets curve (EKC) framework, together with the key factors affecting agricultural GTFP. The main results show that, first, driven by technical progress, the agricultural GTFP gradually increased across the country, while there existed a certain degree of heterogeneity in the growth of different regions. Second, the relationships between the agricultural GTFP and agricultural income exhibited a significant U-shape for the whole country and the four regions, indicating that a win–win scenario can be achieved between green development and income level. Third, industrialization and urbanization negatively affected agricultural GTFP, capital deepening played a positive role, and due to the mediated effect of capital deepening, the outflow of the agricultural labor force did not cause substantial harm to agricultural GTFP. The findings of our study provide useful policy implications for the promotion and development of agriculture in China.

Keywords: agricultural green total factor productivity; agricultural income; the global Malmquist–Luenberger index; the environmental Kuznets curve; U-shape

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1. Introduction

Multiple achievements were obtained by China's agricultural reform, making significant contributions to the development of the world's agriculture. However, the early stage of development of China's agricultural sector mainly relied on the substantial consumption of fossil fuels, which brought a large amount of greenhouse gas (GHG) emissions and environmental degradation. The Food and Agriculture Organization (FAO) highlighted that the agricultural sector accounts for 30% of GHG emissions due to human activities [1]. Furthermore, China's agricultural sector accounts for approximately 11% of global agricultural GHG emissions [2]. As the population grows, so do their needs. In 2018, the population of China was 1.4054 billion, and the urbanization rate was 61.50%, but the arable land per capita in China was almost half of the world's average [3]. These situations imply that the conflict over land use as the population rises will intensify with the acceleration of urbanization. At the same time, China's agricultural development relies more heavily on the use of electricity and diesel oil, as well as chemical fertilizers and pesticides to secure food supply. However, this growing demand for energy poses a serious risk to sustainable development and the climate due to the energy-consumption-related GHG (ECR-GHG)

emissions [4]. Additionally, climate change will increase the frequency of natural disasters and exacerbate the possibility of a negative impact of natural disasters on agricultural production [5]. In responding to the challenge of environmental degradation, the net-zero emissions target became a long-term global strategy for sustainable development. China committed to adopting effective policies to realize the peak of carbon emissions by 2030 and carbon neutrality by 2060 [6]. Given that agriculture is a major source of ECR-GHG emissions, stimulating the green development of agriculture will significantly contribute to the carbon neutralization of China. Scholars generally believe that the green total factor productivity (GTFP) is one of the most representative indicators to measure industrial sector green development performance [7]. Therefore, this study took the agricultural GTFP as a proxy variable to measure the green development of the agricultural sector.

Chinese farmers are dependent on agricultural income from farmlands, which has been a concern of the Chinese government [8]. The Chinese government has taken measures to make farming profitable, such as abolishing agricultural tax and providing financial support. In addition, the Chinese government proposed a reform of the household contract responsibility system and the 2010 to 2020 strategy of farmers' income multiplication to improve agricultural income. The 2020 Central No. 1 Document devoted a large amount of attention to agricultural income, as well as agricultural production and supply. For a long period, China's policy emphasis was on ensuring sufficient agricultural output and raising agricultural income, but not all developments were equally positive. Agricultural income in China still increases erratically, and the total amount is much lower than that of non-agricultural income [9]. These issues affect farmers' willingness to participate in agricultural production [10]. For this reason, labor endowments cause farmers to transfer their family labor to non-agricultural sectors [11]. Furthermore, limited by their low agricultural income, farmers are less concerned with environmental conservation. They consider the benefits of abusing farmland to be greater than its costs, particularly as they are not individually responsible for paying the costs for the environmental damage [12]. However, the increase in efforts to boost the agricultural income per capita at the expense of the environment corresponds to an increase in the negative impacts of these efforts on the growth of agricultural income. Thus, can farmers make agricultural income gains without damaging green development performance? This issue warrants careful investigation.

In light of the abovementioned discussions, low income has been established as one of the major causes of environmental degradation as environmental degradation increases with income until a certain income threshold is reached, after which continued increases in income will reduce environmental pressure. This concept is known as the environmental Kuznets curve (EKC) hypothesis expounded by Grossman and Krueger (1992), which postulates an inverted U-shaped relationship between income per capita and environmental degradation [13]. Since then, a large number of studies have tested the validity of the EKC hypothesis using a panel dataset, including the performance of EKC in different pollutants, such as CO₂, NO_x, CH₄, and PM_{2.5} [14–17], regions with different income levels [18], and different stages [19]. However, the major criticism of the EKC is that it is sensitive to the measurement of environmental pollutions, and its empirical results vary depending on the type of the pollutants [20]. Additionally, since pollutants are only outputs of the production process, treating pollutants as an indicator of environmental performance and analyzing the relationship between income and pollutants in such a simplified form cannot reflect the process of converting factor inputs into desirable outputs and undesirable outputs [21]. Even at higher income levels, the modification of the production process may improve environmental quality and efficiency [22]. Furthermore, the common shortcoming of the above-mentioned studies is that the notions of green and sustainability have not been involved, which suggests maximizing economic development performance while maintaining environmental quality. Therefore, this study made efforts to investigate the implications of green development and its possible application in the EKC framework, that is, further investigated the existence of the EKC relationship between GTFP and income growth in the agricultural sector.

The remainder of this paper is structured as follows. In Section 2, a brief review of the relevant literature on the GTFP and EKC hypothesis applied in the agricultural sector is provided. The study area, empirical methodology, and variables' data and sources are explained in Section 3. In Section 4, the spatial–temporal evolution of agricultural GTFP in China is described, and the green growth index is divided into technical efficiency and technical progress. In Section 5, the empirical results of the relationships between agricultural GTFP and agricultural income in the whole country and the four regions are presented. The key factors affecting agricultural GTFP are discussed in Section 6. In Section 7, conclusions are drawn and a discussion of recommendations for agricultural policy is presented.

2. Literature Review

The total factor productivity (TFP), which can measure economic performance that accounts for the influences of technical progress and efficiency, was proposed by Solow (1957) [23]. However, the traditional TFP ignores environmental constraints and thus exaggerates economic performance [24]. As an indicator of green development, GTFP not only takes economic performance but also resource and environmental constraints into consideration. The literature on agricultural GTFP is limited. First of all, using the related data regarding energy from the energy balance sheet, the previous literature calculated agricultural energy consumption by excluding indirect energy consumption; therefore, energy consumption and ECR-GHG emissions of agricultural production were underestimated [25–27]. Apart from direct energy consumption, such as electricity and diesel, the production of diesel, electricity, pesticides, chemical fertilizers, agricultural machinery, and plastic films consumes a large amount of energy and creates ECR-GHG emissions. Second, agricultural GTFP must take the constraints of water resources into consideration. Agriculture occupies more than 70% of global water resources and is the largest user of water resources [28]. However, global freshwater is becoming increasingly scarce [29]. At the same time, FAO (2020) highlighted that the growth of income and urbanization was leading to a rising water demand for industry and services, as well as for water-intensive foods [30]. These issues further aggravate the shortage of agricultural water. In addition, China's agricultural sector accounted for approximately 61.39% of total water consumption in 2018, but the contribution rate to GDP was only 4.2%. Therefore, the low utilization efficiency of water resources is among the key problems that restrict China's green agricultural development.

The application of the EKC hypothesis to agriculture is gaining interest. Scholars have examined the relationship between economic development and carbon emissions in the agricultural sector [14,15]. Nevertheless, green efficiency or productivity in EKC hypothesis literature was rarely analyzed. In addition, the existing literature has ignored the influence of income structure on the green development of agriculture [7]. Undoubtedly, the higher the income from agricultural activities, the more farmers are willing to devote themselves to agricultural production. However, Chinese farmers earn a higher income from non-agricultural activities; at the same time, they care about the urban–rural income gap [31]. Although China's urban–rural income ratio began to decline from the peak of 3.3 in 2009, the relatively lower agricultural income has not reversed the trend of a massive wave of farmers abandoning agricultural production [32]. The net outflow of the rural labor force inevitably must be substituted by agricultural machinery, pesticides, and chemical fertilizers, leading to an increase in energy consumption and ECR-GHG emissions. In conclusion, using an extensive production model to improve agricultural income will cause damage to the environment and reduce agricultural GTFP; on the other hand, agricultural income growth will increase farmers' enthusiasm and improve agricultural GTFP. Therefore, realizing a positive interaction between agricultural income and agricultural GTFP is necessary.

As indicated above, a consensus was reached regarding the importance of green agricultural development. However, few studies have quantified the indirect energy

consumption of agricultural production and thus underestimate ECR-GHG emissions. One contribution of this study is to consider direct and indirect energy consumption, ECR-GHG emissions, and water resources in the calculation of agricultural GTFP. Although there were studies on the EKC hypothesis in the agricultural sector, the empirical evidence on the green development of agriculture and agricultural income is insufficient. Therefore, this study intended to empirically determine the relationships between agricultural income and GTFP in China to fill this gap.

3. Methods, Indicators, and Data

In this section, first, this study calculated direct and indirect energy consumption and ECR-GHG emissions of agricultural production by sorting out the related conversion coefficients in Section 3.1. Second, the global Malmquist–Luenberger (GML) index was introduced to calculate agricultural GTFP in Section 3.2. Furthermore, panel regression models were implemented to investigate the EKC hypothesis relative to the agricultural GTFP and income in Section 3.3. Finally, the data and indicators were described in all necessary detail in Section 3.4.

3.1. Methods for Determining Agricultural Energy Consumption and ECR-GHG Emissions

The demand for energy of agricultural production consists of direct and indirect energy. First, direct energy consumption includes the diesel oil and electricity used to operate agricultural machinery for sowing, irrigation, fertilization, weeding, and harvesting. Second, indirect energy consumption includes the energy used during the production process of agricultural machinery, pesticides, chemical fertilizers, plastic films, diesel oil, and electricity [33,34]. This paper describes a method that uses the raw data multiplied by related energy conversion coefficients to calculate agricultural energy consumption (except for manpower and animal power) and converts the value of energy consumption into standard coal [31]. The energy conversion coefficients were derived from the China energy statistics yearbook and previous research [35–39].

For the purpose of measuring the environmental pressure caused by agricultural production, ECR-GHG emissions were calculated for each type of energy consumption, including the production or use of diesel oil, electricity, agricultural machinery, pesticides, chemical fertilizers, and plastic films. This study converted the value of ECR-GHG emissions into carbon dioxide equivalents using global warming potential (GWP) parameters [40]. The emissions coefficients were from previous research [41–44].

3.2. Methods for Determining Agricultural GTFP

The GTFP was calculated using the Malmquist–Luenberger (ML) index by several scholars [45]. The ML index and the directional distance function (DDF) were proposed by Chung et al., (1997) to deal with both undesirable outputs and desirable outputs simultaneously [46]. However, the progress of agricultural production is long-term and continuous; meanwhile, the geometric mean of the ML index is not cumulative, meaning that it is unsuitable for measuring long-term changes in GTFP. Moreover, the ML index may face the problem of finding no solution for linear programming and non-transitivity. On the basis of the ML index, Oh (2010) developed the global Malmquist–Luenberger index, which could avoid finding no solution for linear programming [47]. To measure the dynamic trend of agricultural GTFP and further explore the impact of technical progress and efficiency on agricultural GTFP, this study adopted a GML index.

In this study, each province was defined as a decision-making unit (DMU). Based on a panel of $k = 1, \dots, K$ DMUs and $t = 1, \dots, T$ periods, the DMUs use S inputs, $x = (x_1, x_2, x_3, \dots, x_S) \in R_+^S$ to produce N desirable outputs, $y = (y_1, y_2, y_3, \dots, y_N) \in R_+^N$, and M undesirable outputs, $b = (b_1, b_2, b_3, \dots, b_M) \in R_+^M$. Let $g = (g_y, g_b)$ be a direction vector, and $g \in R_+^N \times R_+^M$. Then, the DDF was defined as $D(x, y, b; g_y, g_b) = \max\{\beta \mid (y + \beta g_y, b - \beta g_b) \in P(x)\}$. Since the indices require a heavy dose of additional notations, this study omitted the direction vector $g = (y, b)$ to save space when defining

the indices in the remainder. For example, $D(x, y, b; g_y, g_b)$ was replaced by $D(x, y, b)$ in all places. In defining the GML index, there were two definitions of the production possibility set (PPS): a contemporaneous PPS and a global PPS. The contemporaneous PPS was defined as $P^t(x^t) = \{(y^t, b^t) | x^t \text{ can produce } (y^t, b^t)\}$. Additionally, the global PPS was defined as $P^G(x) = P^1(x^1) \cup P^2(x^2) \cup \dots \cup P^T(x^T)$. By the definition of the global PPS, the model of the GML index at period t and period $t + 1$ can be expressed as follows:

$$GML^{t,t+1}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) = \frac{1 + D^G(x^t, y^t, b^t)}{1 + D^G(x^{t+1}, y^{t+1}, b^{t+1})} \quad (1)$$

where the global DDF was defined as $D^G(x, y, b) = \max\{\beta | (y + \beta y, b - \beta b) \in P^G(x)\}$, $G = t, t + 1$. The $GML^{t,t+1}$ represents the productivity at period $t + 1$ with respect to the period t , where a value of $GML^{t,t+1}$ greater (lower) than 1 indicates an increase (decrease) in GTFP. Additionally, the $GML^{t,t+1}$ was decomposed into technical efficiency (GEC) and technical progress (GTC), as expressed in Equations (2)–(4):

$$GML^{t,t+1}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) = \frac{1 + D^t(x^t, y^t, b^t)}{1 + D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})} \times \left[\frac{1 + D^G(x^t, y^t, b^t)}{1 + D^t(x^t, y^t, b^t)} \times \frac{1 + D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{1 + D^G(x^{t+1}, y^{t+1}, b^{t+1})} \right] \quad (2)$$

$$GEC^{t,t+1} = \frac{1 + D^t(x^t, y^t, b^t)}{1 + D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})} \quad (3)$$

$$GTC^{t,t+1} = \frac{1 + D^G(x^t, y^t, b^t)}{1 + D^t(x^t, y^t, b^t)} \times \frac{1 + D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{1 + D^G(x^{t+1}, y^{t+1}, b^{t+1})} \quad (4)$$

Therefore, the changes in GML include the changes in technical efficiency and technical progress:

$$GML = GEC \times GTC \quad (5)$$

where a value of $GEC^{t,t+1}$ greater or lower than 1 reflects a technical efficiency improvement or loss, respectively, from period t to period $t + 1$; a value of $GTC^{t,t+1}$ greater or lower than 1 reflects technical progress or regress, respectively, from period t to period $t + 1$. Then, the GML and its decomposition across many periods can be expressed as follows:

$$GML^{t,t+1} \times GML^{t+1,t+2} = \frac{1 + D^G(x^t, y^t, b^t)}{1 + D^G(x^{t+1}, y^{t+1}, b^{t+1})} \times \frac{1 + D^G(x^{t+1}, y^{t+1}, b^{t+1})}{1 + D^G(x^{t+2}, y^{t+2}, b^{t+2})} = \frac{1 + D^G(x^t, y^t, b^t)}{1 + D^G(x^{t+2}, y^{t+2}, b^{t+2})} = GML^{t,t+2} \quad (6)$$

$$GEC^{t,t+2} = GEC^{t,t+1} \times GEC^{t+1,t+2} \quad (7)$$

$$GTC^{t,t+2} = GTC^{t,t+1} \times GTC^{t+1,t+2} \quad (8)$$

3.3. Methods for Determining the EKC Relating Agricultural GTFP and Agricultural Income

This study used panel regression models based on the EKC hypothesis to analyze the relationship between agricultural GTFP and farmers' agricultural income. In addition, the quadratic polynomial model was used flexibly to judge the shape of the EKC, and the logarithmic transformation of certain variables was processed to avoid large differences in the magnitude of the variables [48]. The models were as follows:

$$GTFP_{it} = \alpha_0 + \alpha_1 AIPC_{it} + \alpha_2 AIPC_{it}^2 + \alpha_3 Z_{it} + \mu_i + \varepsilon_{it} \quad (9)$$

where i and t indicate the province and year, respectively; the α coefficients represent the parameters to be estimated; μ refers to the individual effect; ε represents the random error term; and $GTFP$ denotes the agricultural GTFP. Given that the GML index is a dynamic index, this study transformed it into a cumulative value for comparability and assumed that the value of GTFP in 2000 was 1, and the GEC and GTC were treated in the same way [49]. Additionally, $AIPC$ denotes the logarithm of agricultural income per capita, and agricultural per capita income was converted into the 2000 base period using the consumer price indices for rural residents; $AIPC^2$ denotes the logarithm of the square of agricultural

income per capita. According to the EKC hypothesis, if $\alpha_1 < 0$ and $\alpha_2 > 0$, then a U-shaped curve is observed between agricultural GTFP and agricultural income, whereas if $\alpha_1 > 0$ and $\alpha_2 < 0$, then an inverse U-shaped curve is observed. Finally, Z denotes the set of control variables, as shown in Table 1.

Table 1. Control variables of panel regression models.

Control Variable	Symbol	Description
Industrial structure	<i>IS</i>	The proportion of the added value of the secondary and tertiary industries to regional GDP.
Proportion of agricultural labor force	<i>PALF</i>	The proportion of agricultural labor force to the total labor force.
Capital deepening	<i>CD</i>	The logarithm of the proportion of agricultural real capital stock to the agricultural labor force; the calculation of agricultural real capital stock is based on Zhang et al., (2004) [50] and Zong et al., (2014) [51].
Educational level	<i>EL</i>	The proportion of the population with a high school degree and above among the population aged 6 years and above to total population.
R&D	<i>RD</i>	The proportion of R&D internal expenditure to regional GDP.
Governmental financial support	<i>GFS</i>	The proportion of agricultural financial expenditure to total financial expenditure.
Relative price	<i>RP</i>	The proportion of the price index of agricultural means of production to the price index of agricultural products.
Environmental regulation	<i>ER</i>	The number of environmental regulations issued.
Agriculture tax	<i>AT</i>	A dummy variable—the timing of the abolition of agricultural tax varies from province to province. When the agricultural tax was completely abolished, $AT = 1$; otherwise, $AT = 0$.
External dependence	<i>ED</i>	The proportion of total import and export of agriculture products to regional GDP.
Natural disaster ratio	<i>NDR</i>	The proportion of sown area affected by natural disaster to the total sown area of agriculture products.

The fixed effect (FE) and the random effect (RE) models are regression models that are used for panel data, where the difference between the two depends on individual effects. Specifically, individual effects may be present in the form of fixed and random effects and are independent of other explanatory variables. Therefore, it was important to introduce the Hausman test to examine whether there were individual effects and whether these effects were associated with other explanatory variables so as to determine whether the FE or RE model fit the data more accurately in this study [52]. The null hypothesis of the Hausman test is that individual effects are not related to other explanatory variables. If the results reject the null hypothesis, the FE model is adopted. In addition, as the value of the dependent variable (*GTFP*) in this study is non-negative and truncated, the conventional ordinary least squares regression (OLS) would have caused a biased estimation if used. As a censored regression model, the Tobit model can be used to check the regression when the dependent variables are observed only in a restricted way and the explanatory variables are observable [53]. Therefore, this study used the Tobit model to judge whether the empirical results were consistent and observe the reliability of the regression results. Finally, to further analyze the regional differences in the relationship between agricultural GTFP and agricultural income, the FE, RE, and Tobit models were employed for grouped regressions in the same way.

3.4. Indicators and Data

Given the availability and integrity of data, this study used balanced panel data from 2000 to 2018 of 31 provinces in China for the empirical tests, except for Hong Kong, Macao, and Taiwan. According to the standard regional divisions of the National Bureau of Statistics, the 31 provinces are divided into four regions, namely, the northeastern, eastern, central, and western regions (see Figure 1 and Table A2).

Figure 1. China's regional divisions and study areas.

In this study, the indicators of the agricultural GTFP included agricultural input and output. Specifically, agricultural outputs were divided into desirable outputs and undesirable outputs (see Table 2).

Table 2. Input and output indicators of agricultural GTFP.

	Indicator	Description
Input	Energy	Direct and indirect energy consumption
	Water	Water for irrigation
	Land	Sown area of agriculture products
	Labor	Agricultural labor force
Desirable output	Agricultural products	Output of agricultural products
	Added value of agriculture	Added value of agriculture (reference year: 2000)
Undesirable output	ECR-GHG	Direct and indirect ECR-GHG emissions

To ensure the reliability of the original data, the data for this study were collected from the official statistical database and governmental reports, including the China Statistical Yearbook, the China Rural Statistical Yearbook, the China Statistical Yearbook on Science and Technology, the China Agricultural Machinery Industry Yearbook, the China Energy Statistics Yearbook, the China Water Resources Bulletin, the China Environmental Yearbook, and the statistical yearbooks of each province. Additionally, this study converted the total values of the import and export of agricultural products into the average annual price of the RMB exchange rate. To reveal the real economic growth, agricultural income per capita, the added value of the three industries, and regional GDP were all converted into the 2000 base period using the consumer price indices of rural residents and regional gross domestic product indices. The descriptive statistics of all the variables are shown in Table 3.

Table 3. The statistical description of all the variables.

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max
Energy	10 ⁴ tce	589	4170.025	3473.415	88.010	14,690.959
Water	10 ⁸ m ³	589	734.812	561.307	36.390	2681.190
Land	10 ⁴ hm ²	589	399.283	306.031	9.604	1329.025
Labor	10 ⁴ people	589	120.044	100.031	4.200	561.750
Agricultural products	10 ⁴ t	589	513.067	370.701	10.379	1490.272
Added value of agriculture	10 ⁸ CNY	589	968.570	739.538	37.090	3564.000
ECR-GHG	10 ⁴ t CO ₂ eq	589	2369.603	1795.009	49.902	7757.566
Agriculture GTFP	1	589	1.078	0.106	0.782	1.495
Agricultural income per capita	CNY	589	2645.844	1441.147	544.510	7579.670
Industrial structure	1	589	0.878	0.065	0.635	0.997
Proportion of agricultural labor force	1	589	0.401	0.160	0.030	0.883
Capital deepening	CNY per person	589	13,366.334	15,168.976	868.504	140,739.980
Educational level	1	589	0.241	0.104	0.029	0.686
R&D	1	589	1.282	1.058	0.140	6.170
Governmental financial support	1	589	0.096	0.035	0.021	0.190
Relative price	1	589	0.712	0.117	0.392	1.000
Environmental regulation	1	589	1.003	1.717	0.000	18.000
Agriculture tax	1	589	0.745	0.436	0.000	1.000
External dependence	1	589	0.014	0.014	0.001	0.091
Natural disaster ratio	1	589	0.241	0.161	0.000	0.936

4. Empirical Analysis Results for Agricultural GTFP

In this section, the empirical findings based on the overall, regional, and provincial levels were described to confirm the changing trend and driving factors of the agricultural GTFP. Figure 2 shows the values of the GTFP, GEC, and GTC indices.

Figure 2. Agricultural GTFP, GEC, and GTC indices in China and the four regions from 2000 to 2018.

4.1. Analysis of the Overall Agricultural GTFP

As seen from Table A1 and Figure 2, the overall GTFP of agriculture in China showed a gradual increase from 2000 to 2018, with a total growth of 20.61% and an average annual growth rate of 1.15%. Additionally, the technical progress of agricultural production increased by 21.53%, while technical efficiency decreased by 0.52% during this period. Furthermore, there was a modest increase in the overall GTFP by 5.65% from 2000 to 2009, during which time technical efficiency even showed negative growth; the overall GTFP

had a significant increase from 2010 to 2018, during which time technical progress in 2018 was 3.14 times what it was in 2009. The results indicate that technical progress had a positive impact on the overall agricultural GTFP, and the loss of technical efficiency played a negative role.

4.2. Analysis of the Regional Agricultural GTFP

The agricultural GTFP in the northeastern, eastern, central, and western regions increased by 24.12%, 26.39%, 16.49%, and 15.45%, respectively, from 2000 to 2018. Additionally, there were regional differences in the agricultural GTFPs. First, the growth range of the GTFP in the eastern and northeastern regions was higher than that in the central and western regions. Second, the agricultural GTFP in the eastern region was higher than the overall average, while that in the central and western regions was lower than the overall average, which was related to the imbalance of regional economic improvement. The central region was among the main agricultural areas, but its slow agricultural GTFP increase means that the agricultural achievements were likely at the expense of the environment. Furthermore, the green development of agriculture was shown to be an urgent task for the central and western regions. Third, technical efficiency in the northeastern, eastern, central, and western regions changed by -4.98% , 3.61% , -1.18% , and 0.45% , respectively, from 2000 to 2018. Finally, technical progress in all four regions showed a remarkable increase. Therefore, the growth of regional GTFP was due to the facilitation of technical progress greater than the inhibition of technical efficiency loss.

From a temporal perspective, agricultural GTFPs in the regions had a slight increase from 2000 to 2009 and a marked increase from 2010 to 2018. For the northeast region, its agricultural GTFP was higher than the others from 2005 to 2016, during which time both technical progress and technical efficiency promoted GTFP growth; however, its technical efficiency decreased from 1.0462 in 2010 to 0.9502 in 2018, which led to a decline in GTFP from 2016 to 2018. Furthermore, the technical efficiency in the eastern and central regions declined from 2000 to 2009 and gradually became stable after 2014. For the western region, its technical efficiency showed an increasing trend after 2015 with the agricultural GTFP showing development potential.

4.3. Analysis of the Provincial Agricultural GTFP

According to Table A2 and Figure 3, there was one province where the agricultural GTFP had negative growth in 2018, namely, Tibet. In the same year, there were six provinces where the growth range of agricultural GTFP was more than 30%, most of which were in the eastern region. The reasons for this finding were that the eastern region could strengthen technological innovations and rapidly reach the frontier of production technologies.

Furthermore, there were provincial differences in agricultural GTFPs. First, due to the greater promotion of technical progress than the inhibition of technical efficiency loss, the agricultural GTFPs in ten provinces showed an increase from 2000 to 2018, namely, Liaoning, Jilin, Hebei, Guangdong, Shanxi, Anhui, Hubei, Sichuan, Yunnan, and Xinjiang. Second, due to technical progress and fixed technical efficiency, the agricultural GTFPs in eight provinces showed positive growth, namely, Beijing, Tianjin, Shanghai, Shandong, Hainan, Guangxi, Chongqing, and Guizhou. In addition, the rising GTFPs in twelve provinces, namely, Heilongjiang, Jiangsu, Zhejiang, Fujian, Jiangxi, Henan, Hunan, Inner Mongolia, Shaanxi, Gansu, Qinghai, and Ningxia, were due to both the promotion of technical progress and technical efficiency gain. Eventually, due to technical efficiency loss and technical regress, the agricultural GTFP in Tibet showed a decrease in 2018.

In terms of the contribution of provinces to regions, there were sixteen provinces in which the agricultural GTFPs were lower than the related regional average in 2018, which means that more than half of the provinces did not play a significant role in promoting the region's agricultural GTFPs, including major agricultural provinces in China, such as Jilin, Shandong, Guangdong, Anhui, and Hunan. In conclusion, technical efficiency loss

had a mainly inhibitory effect on the provincial GTFPs. Additionally, the main agricultural provinces in China need to improve their agricultural GTFPs.

Figure 3. Provincial agricultural GTFP in 2001, 2009, 2010, and 2018.

In this study, there was great synchronization between agricultural GTFP and technical progress, but no strong link between agricultural GTFP and technical efficiency, which is consistent with the conclusions drawn by Kumar (2006) [54] and Choi et al., (2015) [55]. Moreover, the average value of technical efficiency was lower than that of the agricultural GTFP and technical progress. In short, technical progress made major contributions to the improvement of agricultural GTFP in China, but technical efficiency loss played a restrictive role.

5. Analysis of Empirical Results of the EKC

5.1. Analysis of the Overall EKC

According to the overall sample regression results in Table 4, regardless of the control variables, the relationship between the agricultural GTFP and agricultural income exhibited a U-shaped curve, which implies a win-win scenario for the green development of agriculture and farmers' agricultural incomes. Additionally, the results of the Hausman tests were at least significant at the 5% level, indicating that the FE models fit the data more accurately than the RE models for this study, and the reliability of FE models was demonstrated by the regression results of the Tobit models.

Considering the control variables, the regression equation was obtained as being $GTFP = -1.442AIPC + 0.094AIPC^2$, and the threshold of the EKC between the agricultural GTFP and agricultural income was approximately CNY 2143.54, which was obtained via the following calculation: $threshold = \exp(-\beta_1/2\beta_2) = \exp[-0.094/2 \times (-1.442)]$. When the agricultural income per capita was lower than CNY 2143.54, the agricultural GTFP decreased with an increase in agricultural income. Above the threshold, agricultural income increased in step with the agricultural GTFP. In the early stages, farmers made agricultural income gains but ignored protecting the environment, and the demand for water, fossil energy, pesticides, and chemical fertilizers increased. Moreover, farmers' awareness

of their effects on the water and air that are public goods was insufficient, further leading to ECR-GHG emissions and resource waste. As agricultural income increased, agricultural GTFP improved as there were more advanced technologies and economic strengths to reduce resource inputs and ECR-GHG emissions. Meanwhile, farmers' awareness of low carbon started to strengthen, driving the sustainable development of agriculture.

Table 4. The overall empirical results of the EKC describing the relationship between agricultural GTFP and agricultural income.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	FE	RE	Tobit	FE	RE	Tobit
<i>AIPC</i>	−1.354 *** (0.139)	−1.403 *** (0.138)	−1.398 *** (0.138)	−1.442 *** (0.144)	−1.458 *** (0.141)	−1.450 *** (0.139)
<i>AIPC</i> ²	0.094 *** (0.009)	0.097 *** (0.009)	0.097 *** (0.009)	0.094 *** (0.009)	0.095 *** (0.009)	0.095 *** (0.009)
<i>IS</i>				−0.566 *** (0.133)	−0.538 *** (0.117)	−0.558 *** (0.119)
<i>PALF</i>				−0.281 *** (0.077)	−0.245 *** (0.066)	−0.252 *** (0.067)
<i>CD</i>				0.028 *** (0.008)	0.022 *** (0.008)	0.024 *** (0.008)
<i>EL</i>				−0.030 (0.105)	−0.026 (0.097)	−0.035 (0.097)
<i>RD</i>				0.031 *** (0.010)	0.023 *** (0.009)	0.025 *** (0.009)
<i>GFS</i>				0.011 (0.150)	0.024 (0.144)	0.022 (0.143)
<i>RP</i>				−0.089 ** (0.036)	−0.084 ** (0.035)	−0.087 ** (0.034)
<i>ER</i>				0.003 * (0.002)	0.003 * (0.002)	0.003 * (0.001)
<i>AT</i>				0.015 * (0.008)	0.018 ** (0.008)	0.017 ** (0.008)
<i>ED</i>				0.401 (0.494)	0.104 (0.441)	0.169 (0.448)
<i>NDR</i>				−0.063 *** (0.021)	−0.065 *** (0.021)	−0.064 *** (0.020)
<i>Constant</i>	5.902 *** (0.541)	6.100 *** (0.538)	6.077 *** (0.537)	6.989 *** (0.575)	7.023 *** (0.567)	7.003 *** (0.558)
<i>R-squared</i>	0.4804	0.4802		0.5681	0.5661	
<i>Hausman Test</i>	7.11 ***			21.57 **		
<i>Obs</i>	589	589	589	589	589	589
<i>N</i>	31	31	31	31	31	31

Note: ***, **, and * indicate that the statistical value was significant at 1%, 5%, and 10%, respectively; the standard errors are in parentheses.

From the perspective of provinces, there are several interesting findings. The number of provinces that passed the threshold increased after 2000. In 2018, more than 90% of provinces' agricultural income per capita was greater than CNY 2143.54, except Beijing and Shanghai. Specifically, the secondary and tertiary industries and the residents' daily life in Beijing and Shanghai occupied the vast majority of land, labor force, and water resources, which played a negative role in agricultural development. Moreover, the two provinces' agricultural products were highly dependent on the supply of other provinces. Therefore, under the shortage of agricultural labor force and farmland, Beijing and Shanghai were bound to heavily depend on agricultural machinery, chemical fertilizers, and pesticides to increase the energy consumption agricultural output per unit to a high level, which reduced their agricultural GTFPs. In conclusion, it is of concern that the industry and services sectors may affect the sustainable development of agriculture.

5.2. Analysis of the Regional EKC

There were regional differences in economic development, industrial structure, and natural environment. Therefore, it was expected that the impacts of agricultural income in the northeastern, eastern, central, and western regions on their agricultural GTFPs would be different.

According to Table 5, the relationships between the agricultural GTFP and agricultural income were U-shaped in the regions, which was consistent with the overall regression results. Thus, agricultural GTFP corresponded to the increase in farmers' agricultural income in the northeastern, eastern, central, and western regions. Second, although the shapes of the regional EKCs were similar, the thresholds in the four regions were different, with the gradual increase from the northeastern region to the central, eastern, and western regions. Particularly, the threshold in the western region was higher than those in the other regions. Third, the western region passed its threshold at the latest in 2014. In contrast, economic development showed a backward trend in the vast majority of provinces in the western region, reflecting the catch-up effect in backward areas. Finally, as China's major agricultural area, the northeastern and central regions realized the simultaneous growth of agricultural GTFP and agricultural income early, which was positive for the green development of China's agriculture.

Table 5. The regional empirical results of the EKC describing the relationship between agricultural GTFP and agricultural income.

Variable	Northeastern			Eastern			Central			Western		
	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	FE	RE	Tobit	FE	RE	Tobit	FE	RE	Tobit	FE	RE	Tobit
<i>AIPC</i>	−0.794 *	−0.384 *	−0.384	−1.457 ***	−2.713 ***	−1.681 ***	−1.664 ***	−1.166 ***	−1.608 ***	−0.935 ***	−0.031	−0.838 ***
	(0.517)	(0.514)	(0.446)	(0.377)	(0.348)	(0.366)	(0.383)	(0.422)	(0.361)	(0.186)	(0.241)	(0.180)
<i>AIPC</i> ²	0.055 *	0.032	0.032	0.090 ***	0.173 ***	0.110 ***	0.113 ***	0.089 ***	0.111 ***	0.057 ***	0.005	0.052 ***
	(0.032)	(0.032)	(0.027)	(0.025)	(0.023)	(0.024)	(0.024)	(0.026)	(0.023)	(0.011)	(0.015)	(0.011)
<i>IS</i>	−0.562 **	−0.886 ***	−0.886 ***	−0.467	−0.284	−0.998 **	0.227	0.367	0.094	−0.595 ***	−0.415 ***	−0.570 ***
	(0.248)	(0.175)	(0.152)	(0.758)	(0.263)	(0.501)	(0.303)	(0.145)	(0.252)	(0.144)	(0.146)	(0.137)
<i>PALF</i>	−1.128 ***	−0.910 ***	−0.910 ***	−1.159 ***	−0.376 **	−0.816 ***	−0.539 ***	−0.205 **	−0.429 ***	0.028	0.008	0.033
	(0.184)	(0.159)	(0.138)	(0.347)	(0.177)	(0.307)	(0.159)	(0.097)	(0.159)	(0.067)	(0.067)	(0.064)
<i>CD</i>	−0.006	−0.005	−0.005	0.028	0.014	0.021	0.005 *	0.014	0.001	0.059 ***	0.024 **	0.050 ***
	(0.032)	(0.032)	(0.028)	(0.019)	(0.014)	(0.017)	(0.013)	(0.013)	(0.012)	(0.012)	(0.009)	(0.011)
<i>EL</i>	−0.187	−0.131	−0.131	−0.103	−0.438 **	−0.200	−0.211	−0.496 ***	−0.304 *	0.107	0.813	0.182
	(0.286)	(0.269)	(0.234)	(0.240)	(0.176)	(0.222)	(0.170)	(0.156)	(0.161)	(0.124)	(0.107)	(0.120)
<i>RD</i>	0.018	0.025	0.025	0.060 **	0.029 **	0.023	0.084 ***	0.107 ***	0.078 ***	0.009	0.004	0.016
	(0.037)	(0.032)	(0.028)	(0.029)	(0.014)	(0.020)	(0.029)	(0.020)	(0.026)	(0.017)	(0.010)	(0.015)
<i>GFS</i>	0.351	0.288	0.288	0.198	1.343 ***	0.612	0.022	−0.342	−0.031	0.142	−0.243	0.112
	(0.427)	(0.447)	(0.388)	(0.433)	(0.376)	(0.400)	(0.286)	(0.316)	(0.270)	(0.139)	(0.173)	(0.134)
<i>RP</i>	−0.142 *	−0.101 **	−0.101 **	−0.081	−0.366 ***	−0.215 **	−0.051	−0.166 ***	−0.094 *	0.016	0.098 **	0.003
	(0.071)	(0.051)	(0.044)	(0.097)	(0.095)	(0.094)	(0.059)	(0.049)	(0.056)	(0.041)	(0.043)	(0.040)
<i>ER</i>	0.008 *	0.009 **	0.009 **	0.002	0.003	0.004	0.001	0.000	0.001	0.000	0.001	−0.000
	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)
<i>AT</i>	−0.026	−0.026	−0.026	−0.098	−0.032	−0.058	0.005	0.009	0.000	0.053 ***	0.039 ***	0.052 ***
	(0.021)	(0.022)	(0.019)	(0.023)	(0.020)	(0.020)	(0.014)	(0.016)	(0.013)	(0.009)	(0.013)	(0.008)
<i>ED</i>	1.845 *	0.589	0.589	0.226	0.660	0.004	4.332	0.440	2.593	−0.709	−0.729	0.596
	(1.085)	(1.008)	(0.875)	(0.866)	(0.626)	(0.801)	(3.461)	(3.100)	(3.241)	(0.809)	(0.731)	(0.759)
<i>NDR</i>	−0.090 ***	−0.100 ***	−0.100 ***	−0.003	−0.121 **	−0.020	−0.062 *	−0.028	−0.057 *	−0.064 ***	−0.042	−0.064 ***
	(0.027)	(0.028)	(0.025)	(0.046)	(0.051)	(0.045)	(0.036)	(0.042)	(0.034)	(0.024)	(0.030)	(0.023)
<i>Constant</i>	5.009 **	3.462 *	3.462 *	7.430 ***	12.247 ***	8.609 ***	7.431 ***	4.576 ***	7.190 ***	4.758 ***	1.376 *	4.390 ***
	(2.189)	(2.181)	(1.895)	(1.753)	(1.351)	(1.534)	(1.584)	(1.688)	(1.490)	(0.725)	(0.960)	(0.703)
<i>R-squared</i>	0.9485	0.9424		0.5939	0.4852		0.7580	0.6751		0.6078	0.4584	
<i>Hausman Test</i>	5.75 ***			58.04 ***			33.76 ***			133.26 ***		
<i>Obs</i>	57	57	57	190	190	190	114	114	114	228	228	228
<i>N</i>	3	3	3	10	10	10	6	6	6	12	12	12

Note: ***, **, and * indicate that the statistical value is significant at 1%, 5%, and 10%, respectively; the standard errors are in parentheses.

6. Discussion

According to Section 4, all four regions in China achieved their agricultural GTFPs gains during the sample period and had significant heterogeneity, which is consistent with the recent works of Liu et al., (2021) [7] and Liu and Feng (2019) [56]. According to Section 5, the relationship between the agricultural GTFP and agricultural income exhibited a U-shaped curve. Green production is conducive to reducing environmental pollutants, growing agricultural products, and thus increasing farmers' income. At the same time, this perceived gain will encourage farmers to engage in environmentally friendly production. Farmers with higher agricultural income are more likely to invest more time and money to adopt and master new technologies to improve GTFP; then, a win-win scenario can be achieved between agricultural green development and income growth. This result is in line with conclusions of Li et al., (2021) [10], Trujillo-Barrera et al., (2021) [57], and Li et al. (2021) [58].

This study further discussed key factors affecting China's agricultural GTFP from the perspectives of the whole country and the four regions.

From the perspective of the overall sample: The estimated coefficient of *IS* was -0.566 at the 1% significance level, which means that the rising added value of the industry and services in regional GDP had a significant inhibitory effect on the agricultural GTFP. First, with the rapid growth of industrialization and urbanization, large-scale farmland was occupied. Second, economic growth is associated with the transfer of the labor force from the countryside to the cities and from the agriculture sector to the industrial and service sector, which led to a decline in the quality and quantity of the agricultural labor force. Furthermore, more pesticides and chemical fertilizers were used to relieve the pressure of agricultural labor outflow, increasing energy consumption per unit of output. The findings are consistent with those postulated by Wang et al., (2016) [59].

The coefficients of *PALF* and *CD* were -0.281 and 0.028 , respectively, which were significant at the 1% level. The results indicate that the outflow of the rural labor force had not caused substantial harm to China's agricultural GTFP. Additionally, capital deepening played a significant positive role due to the research and development of agricultural machinery, equipment, infrastructure, and new breeds with high quality and production. Under the shortage of farmland and the rural labor force, the rational division of agriculture, rising degree of specialization, and intensification of agricultural production typically drove the sustainable growth of agriculture, which all benefited from capital deepening. Therefore, capital deepening could be an effective factor substitution for the outflow of the agricultural labor force. To confirm this speculation, this study used the FE model to further estimate the mediated effect of the variable of *CD* [60]. According to Table A3, capital deepening played a significant mediating role in the relationship between the proportion of agricultural labor force and agricultural GTFP, approximately 60%, which is consistent with the finding reported by Li et al., (2016) [61].

The coefficient of *RD* was 0.031 and significant at the 1% level; R&D investment could promote the innovation of green agricultural technology, which is in line with the conclusion of Adetutu and Ajayi (2020) [62]. The coefficient of *RP* was -0.089 at the 5% significance level; the agricultural production cost reduction and farmers' disposable income growth improved farmers' enthusiasm for farming. However, the variables of *EL* and *GFS* did not have a significant positive effect on agricultural GTFP, which was different from our expectations. Farmers in education had more opportunities to hold non-agricultural jobs, which caused the outflow of high-quality rural labor, thus hindering the growth of agricultural GTFP. Additionally, governmental financial support must pay further attention to the field of green and sustainable development of agriculture. Studies by Yang et al., (2017) [63] and Xu et al., (2020) [64] support this study's outcomes.

According to Table 4, the coefficients of *ER* and *AT* were 0.003 and 0.015 , respectively, which were significant. First, environmental regulation was an important means for production management and pollutant supervision, with the advantages of convenient operation and quick effects. Second, the abolition of agricultural tax increased farmers'

enthusiasm for agricultural production. In addition, the coefficient of *NDR* was -0.063 and significant at the 1% level, indicating that the rising natural disaster ratio played a significantly negative role in agricultural GTFP. These findings are aligned with those of Zhan and Xu (2019) [65], Wang and Shen (2014) [66], and Xu et al., (2017) [5]. Finally, the variable of *ED* positively affected the agricultural GTFP, as China could leverage external trade to increase the import of virtual water and land to relieve the native pressure of the resource shortage, which is consistent with the recent work of Li et al., (2021) [67].

From the perspective of the regional sample: First, the coefficient estimates indicating the impact of *IS* on agricultural GTFP were found to be negative in most regions, but positive and not statistically significant in the central regions, as the urbanization and industrialization were lower than those in the eastern region [7]. Second, the coefficients of *PALF* in the northeastern, eastern, and central regions were -1.128 , -1.159 , and -0.539 , respectively, at the 1% significance level, which was consistent with the whole country. However, the variable of *PALF* in the western region played a weak role, which was related to the fact that the western region was the main area of rural labor force output [61]. Moreover, capital deepening played a greater role in agricultural GTFP in western regions than it did in the others, as the western region did not show obvious advantages in infrastructure and technological innovation [7]. In addition, the coefficients of *EL* and *GFS* were not significant in the four regions, which agreed with the overall regression results. At the same time, R&D in the eastern and central regions played a significant role in improving their agricultural GTFPs.

The role of *RP* in improving the GTFP was significant in most regions but not in the western region. Although financial subsidies could reduce the price of agricultural means of production, they inevitably caused farmers to use extensive amounts of chemical fertilizers, pesticides, and agricultural plastic films to maintain agricultural output growth, which caused ECR-GHG emissions [12]. Furthermore, the abolition of agricultural tax played a greater role in promoting the GTFP in the central and western regions, due to which the incentive effect on farmers was greater in the backward and major agricultural regions, which is consistent with the finding reported by Xu et al., (2012) [68]. Finally, the rising natural disaster ratio had a significant negative impact on agricultural GTFP, which was corroborated in the four regions. This finding further summarizes that green development is an essential way to realize the sustainable development of agriculture.

7. Conclusions and Suggestions

For most countries, energy conservation and GHG emissions reduction and improvement of farmers' agricultural income are the footholds of main policies in the agricultural sector [31]. Thus, it is meaningful to discuss the relationship between green development and income growth in the agricultural sector, especially for China, which is a large agricultural country. In addition, since the regional development in China is imbalanced, a further study of the regional EKC is necessary to determine their spatial-temporal characteristics. Different from current EKC literature, this study incorporated agricultural GTFP into the EKC framework, providing insights into the planning of effective mitigation measures for diminishing natural resources and deteriorating environment, together with the driving factors of the regional differences. Using the panel dataset from 2000 to 2018 of China's 31 provinces, this study first calculated the direct and indirect energy consumption and ECR-GHG emissions during agricultural production. Next, the GML index was employed to calculate the agricultural GTFP and its decompositions. Based on the EKC hypothesis, this study used panel regression models to analyze the relationship between agricultural GTFP and agricultural income, as well as the key factors affecting agricultural GTFP. The main conclusions drawn from the empirical analysis are as follows:

(1) The overall agricultural GTFP in China increased by 20.61% from 2000 to 2018, indicating China's agricultural green performance followed a progression during the sample period. There were regional and provincial differences in agricultural GTFPs. The agricultural GTFPs in the central and western regions were lower than the overall average

level. Additionally, the provinces with a higher growth range of agricultural GTFP were mainly in the eastern region rather than the main agricultural regions. Hence, the central and western regions should be the focus of improving the agricultural GTFP. Furthermore, technical progress was the main driving force of China's agricultural GTFP growth, while technical efficiency loss played a restrictive role.

(2) There were U-shaped relationships between the agricultural GTFP and agricultural income in the whole country and the four regions, indicating that agricultural income gains were at the expense of the environment and the overexploitation of natural resources at the early stage. With economic growth and technical progress, agricultural GTFP and agricultural income growth could achieve a win-win scenario. Furthermore, the turning point of the overall EKC was calculated, which corresponded to an agricultural income per capita of CNY 2143.54. The thresholds of the regional U-shaped curves were different, increasing from the northeastern region to the central, eastern, and western regions.

(3) The results suggest that several factors affected agricultural GTFP. First, there was a significant negative correlation between industrial structure and agricultural GTFP, indicating that the rising added value of the secondary and tertiary industries in regional GDP had a significant negative impact on agricultural GTFP. Second, owing to capital deepening, the outflow of the agricultural labor force did not cause substantial harm to the agricultural GTFP. Second, capital deepening promoted the agricultural GTFP development; at the same time, it played a mediating role in the relationship between the outflow of agricultural labor and agricultural GTFP. Then, R&D investment, governmental financial support, the relative price, external dependence, environmental regulation, and agriculture tax all positively affected agricultural GTFP, but the growth of the educational level and natural disasters were not conducive to agricultural GTFP development. Finally, due to imbalanced development, there were differences in the factors affecting the agricultural GTFP in the regions.

Based on the above and empirical conclusions, China's agriculture sector is on a path to resource conservation and environmental friendliness. However, different regions should implement measures in agricultural green development based on specific circumstances as indicated by differences in the GTFP. Furthermore, local government should strengthen regional cooperation, especially emissions-reduction technologies transfer to the central and western regions. Since the rapid development of industrialization and urbanization negatively affected the agricultural sector, it is of great significance to optimize the efficient allocation of resources between industries, build an efficient connection between agriculture and industry, and encourage the technologies and capabilities of the industrial and service sector to flow into the agriculture sector.

Technical progress is the main contributor to the agricultural GTFP growth across China and in each region. Therefore, to increase investment and technological innovation can make sense in energy conservation and emissions reduction and achieve the continuous growth in the agricultural economy. China should take measures to optimize agricultural machinery and facilitate the research and development of energy-saving and emissions-reduction technologies.

Furthermore, the Chinese government could provide subsidies to encourage farmers to purchase and use agricultural machinery that can save energy and reduce emissions, with the purpose of phasing out energy-intensive and emissions-intensive agricultural machinery. Meanwhile, the government needs to accelerate the production and effective application of energy-efficient agricultural machinery, while also pay attention to the degree of farmers' acceptance of agricultural machinery. Thus, it is necessary to actively cultivate scientific and technological talents, make advanced technologies of agricultural green development effectively absorbed, and adopt policies suitable for different regions to absorb agricultural labor with high quality and skill.

Besides agricultural machinery, the use of chemical fertilizers and pesticides is also the main cause of ECR-GHG emissions. Hence, China should encourage the use of organic fertilizers and pesticides, as well as agricultural plastic film recycling. In addition, China

can strengthen international cooperation to expand the use of organic agricultural technologies, such as biological pesticides and fertilizers. Eventually, supervising and providing subsidies for enterprises to produce organic fertilizers will be necessary.

This study mainly focused on the relationship between green development and income growth in the agricultural sector based on the historical data. However, the trend prediction for the energy consumption and ECR-GHG emissions of agricultural production has not been taken into consideration, which is of significance in pushing for China's carbon neutrality by 2060. Future research on this aspect can be taken up.

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

Appendix A

Table A1. The growth rate (%) of the GTFP, GEC and GTC indices in China and the four regions.

Year	Northeastern			Eastern			Central			Western			China		
	GTFP	GEC	GTC	GTFP	GEC	GTC	GTFP	GEC	GTC	GTFP	GEC	GTC	GTFP	GEC	GTC
2001	1.18	−4.95	6.61	3.74	−0.24	4.25	−1.28	−4.30	3.16	−0.07	−1.63	1.65	0.89	−2.78	3.92
2002	4.25	−0.04	4.33	6.23	−0.12	6.61	1.61	−0.95	2.59	1.52	−0.67	2.31	3.40	−0.44	3.96
2003	4.17	−5.12	10.22	6.87	−0.66	8.18	1.69	−2.30	4.10	1.83	−0.90	2.90	3.64	−2.24	6.35
2004	3.11	1.25	3.01	7.68	0.81	7.10	2.44	−1.04	3.54	2.61	0.24	2.48	3.96	0.32	4.03
2005	6.49	2.00	5.04	6.26	1.97	4.67	2.95	−0.11	3.14	2.73	0.93	1.92	4.61	1.20	3.69
2006	7.35	3.80	3.91	2.70	1.84	1.31	1.68	−0.46	2.27	2.05	1.06	1.16	3.45	1.56	2.16
2007	6.90	2.03	5.54	4.62	1.45	3.88	4.80	−2.32	7.37	2.94	−0.08	3.20	4.82	0.27	5.00
2008	12.98	3.42	9.87	7.04	0.91	6.54	3.96	−3.19	7.71	4.49	0.04	4.69	7.12	0.30	7.20
2009	8.20	0.88	8.00	6.74	−0.64	7.80	2.90	−3.89	7.43	4.74	0.81	4.18	5.65	−0.71	6.85
2010	12.97	4.62	8.68	9.68	1.73	8.33	4.23	−2.34	7.06	4.22	0.27	4.10	7.78	1.07	7.04
2011	17.74	4.48	13.20	10.65	2.17	8.77	5.13	−2.35	8.00	3.98	−0.24	4.43	9.38	1.02	8.60
2012	20.87	6.26	14.37	12.00	4.04	8.16	5.91	−2.45	8.87	4.46	−1.68	6.31	10.81	1.54	9.43
2013	25.62	7.79	17.09	14.70	5.01	9.82	6.05	−2.75	9.44	5.61	−1.26	7.00	13.00	2.20	10.84
2014	25.41	7.06	17.59	17.83	3.86	13.87	11.18	−1.00	12.38	6.92	−1.21	8.29	15.34	2.18	13.03
2015	29.53	7.33	20.99	17.95	3.83	13.85	10.21	−0.63	11.18	6.83	−1.04	8.04	16.13	2.37	13.52
2016	31.36	5.46	24.82	22.16	3.70	18.03	11.48	−1.06	12.93	9.11	−0.57	9.83	18.53	1.88	16.4
2017	23.59	−1.22	25.27	24.55	3.56	20.53	14.11	−0.97	15.43	11.19	0.66	10.75	18.36	0.51	18.00
2018	24.12	−4.98	30.76	26.39	3.61	22.25	16.49	−1.18	18.11	15.45	0.45	15.01	20.61	−0.52	21.53

Note: the values of the GTFP, GEC, and GTC indices in 2000 were set to 1.

Table A2. The cumulative values of the GTFP, GEC, and GTC indices in the provinces.

Region	GTFP			GEC			GTC		
	2001	2010	2018	2001	2010	2018	2001	2010	2018
Liaoning (LN)	1.0239	1.1304	1.2613	0.9042	1.0002	0.8992	1.1324	1.1303	1.4027
Jilin (JL)	1.0038	1.1090	1.1322	0.9778	1.1578	0.9198	1.0265	0.9575	1.2305
Heilongjiang (HLJ)	1.0078	1.1497	1.3301	0.9695	0.9807	1.0315	1.0395	1.1725	1.2895
Beijing (BJ)	1.0678	0.9869	1.1663	1.0000	1.0000	1.0000	1.0678	0.9869	1.1663
Tianjin (TJ)	1.1241	1.1241	1.1241	1.0000	1.0000	1.0000	1.1241	1.1241	1.1241
Hebei (HEB)	1.0179	1.0484	1.2712	0.9703	1.0137	0.9957	1.0490	1.0342	1.2769
Shanghai (SH)	1.0809	1.4345	1.2925	1.0000	1.0000	1.0000	1.0809	1.4346	1.2926
Jiangsu (JS)	1.0299	1.1895	1.4947	1.0364	1.2202	1.3281	0.9937	0.9749	1.1255
Zhejiang (ZJ)	1.0012	1.0571	1.4396	1.1256	1.1258	1.1258	0.8895	0.9391	1.2790
Fujian (FJ)	1.0113	1.0425	1.3258	1.0000	0.8956	1.0001	1.0113	1.1641	1.3258
Shandong (SD)	0.9932	1.1016	1.2629	0.9309	1.0000	1.0000	1.0670	1.1016	1.2629
Guangdong (GD)	0.9850	1.0085	1.1308	0.9128	0.9180	0.9116	1.0790	1.0983	1.2399
Hainan (HN)	1.0627	0.9747	1.1315	1.0000	1.0000	1.0000	1.0627	0.9747	1.1315
Shanxi (SX)	0.9331	0.9460	1.0210	0.9109	0.8380	0.8344	1.0244	1.1293	1.2242
Anhui (AH)	0.9868	1.0240	1.1110	0.9502	0.9362	0.9379	1.0385	1.0937	1.1845
Jiangxi (JX)	1.0105	1.0436	1.2114	0.9738	1.0427	1.0825	1.0377	1.0010	1.1193
Henan (HEN)	0.9688	1.1748	1.3225	0.9731	1.0954	1.0954	0.9956	1.0727	1.2076
Hubei (HUB)	1.0155	1.0206	1.1824	0.9661	0.9186	0.9642	1.0512	1.1112	1.2265
Hunan (HUN)	1.0086	1.0446	1.1410	0.9678	1.0285	1.0145	1.0422	1.0156	1.1247
Inner Mongolia (INN)	0.9890	1.0519	1.2361	0.9526	1.0094	1.0482	1.0382	1.042 2	1.1794
Guangxi (GX)	1.0265	1.0915	1.1629	1.0000	1.0000	1.0000	1.0265	1.0915	1.1629
Chongqing (CQ)	0.9582	1.0855	1.1238	1.0000	1.0000	1.0000	0.9582	1.0855	1.1238
Sichuan (SC)	0.9915	1.1005	1.2404	0.9713	1.0304	0.9917	1.0208	1.0681	1.2509
Guizhou (GZ)	1.0025	1.0510	1.3079	0.9179	0.9051	1.0000	1.0921	1.1613	1.3077
Yunnan (YN)	0.9978	0.9860	1.1462	0.9739	0.9065	0.9524	1.0246	1.0877	1.2033
Tibet (XZ)	0.9681	0.8421	0.9413	1.0000	0.9519	0.9050	0.9681	0.8847	1.0401
Shaanxi (SAX)	1.0063	1.0856	1.1444	0.9954	1.0436	1.0089	1.0110	1.0403	1.1342
Gansu (GS)	1.0059	1.0031	1.0990	0.9877	0.9912	1.0134	1.0185	1.0122	1.0843
Qinghai (QH)	1.0437	1.0877	1.2008	1.0325	1.1312	1.1277	1.0109	0.9615	1.0647
Ningxia (NX)	1.0035	1.0370	1.1394	0.9869	1.0269	1.0583	1.0169	1.0099	1.0770
Xinjiang (XJ)	0.9984	1.0846	1.1121	0.9864	1.0360	0.9479	1.0121	1.0468	1.1729

Note: the values of GTFP, GEC, and GTC indices in 2000 were set to 1.

Table A3. Empirical results of the mediated effect of capital deepening.

Explained Variable	Explanatory Variable	(19)	(20)	(21)	(22)
		GTFP	CD	GTFP	GTFP
	<i>PALF</i>	−0.716 *** (0.042)	−8.964 *** (0.282)	−0.282 *** (0.066)	
	<i>CD</i>			0.048 *** (0.006)	0.069 *** (0.004)
	<i>Constant</i>	1.365 *** (0.017)	12.653 *** (0.115)	0.753 *** (0.077)	0.456 *** (0.033)
	<i>R-squared</i>	0.3473	0.6454	0.4175	0.3984
	<i>Obs</i>	589	589	589	589
	<i>N</i>	31	31	31	31

Note: *** indicates that the statistical value is significant at 1%, respectively; the standard errors are in parentheses.

References

- Food and Agriculture Organization (FAO). *Climate Change, Agriculture and Food Security*; Food and Agriculture Organization of the United Nations: Rome, Italy, 2016.
- Olivier, J.G.J.; Peters, J.A.H.W. *Trends in Global CO₂ and Total Greenhouse Gas Emissions*; PBL Netherlands Environmental Assessment Agency: The Hague, The Netherlands, 2020.
- World Bank Data. Available online: <https://data.worldbank.org/indicator/AG.LND.ARBL.HA.PC?end=2016&start=1961> (accessed on 1 July 2020).
- Yuan, S.; Peng, S. Trends in the economic return on energy use and energy use efficiency in China's crop production. *Renew. Sustain. Energy Rev.* **2017**, *70*, 836–844. [\[CrossRef\]](#)
- Xu, Z.; Tang, Y.; Connor, T.; Li, D.; Li, Y.; Liu, J. Climate variability and trends at a national scale. *Sci. Rep.* **2017**, *7*, 3258. [\[CrossRef\]](#)
- Mallapaty, S. How China could be carbon neutral by mid-century. *Nature* **2020**, *586*, 482–483. [\[CrossRef\]](#) [\[PubMed\]](#)
- Liu, D.; Zhu, X.; Wang, Y. China's agricultural green total factor productivity based on carbon emission: An analysis of evolution trend and influencing factors. *J. Clean. Prod.* **2021**, *278*, 123692. [\[CrossRef\]](#)
- Zhou, Z.; Liu, J.; Zeng, H.; Zhang, T.; Chen, X. How does soil pollution risk perception affect farmers' pro-environmental behavior? The role of income level. *J. Environ. Manag.* **2020**, *270*, 110806. [\[CrossRef\]](#) [\[PubMed\]](#)
- China Economic Net. Available online: http://paper.ce.cn/jjrb/html/2020-07/13/content_423397.htm (accessed on 13 July 2020).
- Li, M.; Wang, J.; Zhao, P.; Chen, K.; Wu, L. Factors affecting the willingness of agricultural green production from the perspective of farmers' perceptions. *Sci. Total Environ.* **2020**, *738*, 140289. [\[CrossRef\]](#)
- Al-Amin, A.K.M.A.; Hossain, M.J. Impact of non-farm income on welfare in rural Bangladesh: Multilevel mixed-effects regression approach. *World Dev. Perspect.* **2019**, *13*, 95–102. [\[CrossRef\]](#)
- Van Wessenbeeck, C.F.A.; Keyzer, M.A.; van Veen, W.C.M.; Qiu, H. Can China's overuse of fertilizer be reduced without threatening food security and farm incomes? *Agric. Syst.* **2021**, *190*, 103093. [\[CrossRef\]](#)
- Grossman, G.M.; Krueger, A.B. Environmental impacts of a north American free trade agreement. *CEPR Discuss. Papers* **1992**, *8*, 223–250.
- Liu, X.; Zhang, S.; Bae, J. The impact of renewable energy and agriculture on carbon dioxide emissions: Investigating the environmental Kuznets curve in four selected ASEAN countries. *J. Clean. Prod.* **2017**, *164*, 1239–1247. [\[CrossRef\]](#)
- Ridzuan, N.H.A.M.; Marwan, N.F.; Khalid, N.; Ali, M.H.; Tseng, M.-L. Effects of agriculture, renewable energy, and economic growth on carbon dioxide emissions: Evidence of the environmental Kuznets curve. *Resour. Conserv. Recycl.* **2020**, *160*, 104879. [\[CrossRef\]](#)
- Haider, A.; Bashir, A.; Husnain, M.I.U. Impact of agricultural land use and economic growth on nitrous oxide emissions: Evidence from developed and developing countries. *Sci. Total Environ.* **2020**, *741*, 140421. [\[CrossRef\]](#)
- Luo, J.; Du, P.; Samat, A.; Xia, J.; Che, M.; Xue, Z. Spatiotemporal pattern of PM_{2.5} concentrations in mainland China and analysis of its influencing factors using geographically weighted regression. *Sci. Rep.* **2017**, *7*, 40607. [\[CrossRef\]](#) [\[PubMed\]](#)
- Awaworyi Churchill, S.; Inekwe, J.; Ivanovski, K.; Smyth, R. The environmental Kuznets curve in the OECD: 1870–2014. *Energy Econ.* **2018**, *75*, 389–399. [\[CrossRef\]](#)
- Lin, B.; Zhu, J. Changes in urban air quality during urbanization in China. *J. Clean. Prod.* **2018**, *188*, 312–321. [\[CrossRef\]](#)
- Rashid Gill, A.; Viswanathan, K.K.; Hassan, S. The environmental Kuznets curve (EKC) and the environmental problem of the day. *Renew. Sustain. Energy Rev.* **2018**, *81*, 1636–1642. [\[CrossRef\]](#)
- Guo, H.; Liu, X. Time-space evolution of China's agricultural green total factor productivity. *Chin. J. Manag. Sci.* **2020**, *28*, 66–75.
- Zaim, O.; Taskin, F. A Kuznets curve in environmental efficiency: An application on OECD countries. *Environ. Resour. Econ.* **2000**, *17*, 21–36. [\[CrossRef\]](#)
- Solow, R.M. Technical change and the aggregate production function. *Rev. Econ. Stat.* **1957**, *39*, 312–320. [\[CrossRef\]](#)
- Shen, Z.; Baležentis, T.; Ferrier, G.D. Agricultural productivity evolution in China: A generalized decomposition of the Luenberger-Hicks-Moorsteen productivity indicator. *China Econ. Rev.* **2019**, *57*, 101315. [\[CrossRef\]](#)
- Yan, Q.; Yin, J.; Baležentis, T.; Makutėnienė, D.; Štreimikienė, D. Energy-related GHG emission in agriculture of the European countries: An application of the Generalized Divisia Index. *J. Clean. Prod.* **2017**, *164*, 686–694. [\[CrossRef\]](#)
- Qiu, G.Y.; Zhang, X.; Yu, X.; Zou, Z. The increasing effects in energy and GHG emission caused by groundwater level declines in north China's main food production plain. *Agric. Water Manag.* **2018**, *203*, 138–150. [\[CrossRef\]](#)
- Ma, X.; Wang, C.; Dong, B.; Gu, G.; Chen, R.; Li, Y.; Zou, H.; Zhang, W.; Li, Q. Carbon emissions from energy consumption in China: Its measurement and driving factors. *Sci. Total Environ.* **2019**, *648*, 1411–1420. [\[CrossRef\]](#)
- Li, M.; Fu, Q.; Singh, V.P.; Liu, D.; Li, T. Stochastic multi-objective modeling for optimization of water-food-energy nexus of irrigated agriculture. *Agric. Water Manag.* **2019**, *127*, 209–224. [\[CrossRef\]](#)
- Zheng, J.; Wang, W.; Liu, G.; Ding, Y.; Cao, X.; Chen, D.; Engel, B.A. Towards quantification of the national water footprint in rice production of China: A first assessment from the perspectives of single-double rice. *Sci. Total Environ.* **2020**, *739*, 140032. [\[CrossRef\]](#)
- Food and Agriculture Organization (FAO). *The State of Food and Agriculture 2020. Overcoming Water Challenges in Agriculture*; Food and Agriculture Organization (FAO): Rome, Italy, 2020.
- Chen, J.; Cheng, S.; Song, M. Changes in energy-related carbon dioxide emissions of the agricultural sector in China from 2005 to 2013. *Renew. Sustain. Energy Rev.* **2018**, *94*, 748–761. [\[CrossRef\]](#)

32. Wang, G.; Qian, L. Grain security strategy in the 70 years since the founding of new China: Evolution path and internal logic. *Chin. Rural Econ.* **2019**, *9*, 15–29.
33. Zhang, X.; Pan, H.; Cao, J.; Li, J. Energy consumption of China's crop production system and the related emissions. *Renew. Sustain. Energy Rev.* **2015**, *43*, 111–125. [[CrossRef](#)]
34. Zhen, W.; Qin, Q.; Wei, Y.-M. Spatio-temporal patterns of energy consumption-related GHG emissions in China's crop production systems. *Energy Policy* **2017**, *104*, 274–284. [[CrossRef](#)]
35. Yin, J.; Gao, Z.; Zhang, B.; Zheng, Y. A study of the energy conversion system in farming. *J. Shanxi Agric. Univ. Nat. Sci. Ed.* **1998**, *2*, 95–98.
36. Xu, J. *A Study on the Energy Use and Energy Efficiency of Grain Production: Empirical Analyse Based on DEA*; Zhejiang University: Hangzhou, China, 2011.
37. Hu, L.; Niu, S.; Ma, L.; Zhang, X.; Ding, Y. Relationship between agricultural energy consumption and economic growth based on panel data model in China. *Trans. CSAE* **2011**, *27*, 1–6.
38. Wang, J.; Rothausen, S.G.S.A.; Conway, D.; Zhang, L.; Xiong, W.; Holman, I.P.; Li, Y. China's water-energy nexus: Greenhouse-gas emissions from groundwater use for agriculture. *Environ. Res. Lett.* **2012**, *7*. [[CrossRef](#)]
39. Department of Energy Statistics, National Bureau of Statistics. *The China Energy Statistics Yearbook*; China Statistics Press: Beijing, China, 2018.
40. Intergovernmental Panel on Climate Change (IPCC). *Greenhouse Gas Inventory: 2006 IPCC Guidelines for National Greenhouse Gas Inventories*; United Kingdom Meteorological Office: Bracknell, UK, 2006.
41. Yuan, B.; Lie, Z.; Di, X.; Zuo, T. Life cycle inventories of fossil fuels in China (II): Final life cycle inventories. *Mod. Chem. Ind.* **2006**, *4*, 59–61.
42. Kaltsas, A.M.; Mamolos, A.P.; Tsatsarelis, C.A.; Nanos, G.D.; Kalburtji, K.L. Energy budget in organic and conventional olive groves. *Agric. Ecosyst. Environ.* **2007**, *122*, 243–251. [[CrossRef](#)]
43. Zhi, J.; Gao, J. Analysis of carbon emission caused by food consumption in urban and rural inhabitants in China. *Prog. Geogr.* **2009**, *28*, 429–434.
44. Tian, Y.; Li, B.; Li, J. Research on stage characteristics and factor decomposition of cultivated land carbon emission in China. *J. China Univ. Geosci. Soc. Sci. Ed.* **2011**, *11*, 59–63.
45. Liu, Z.; Xin, L. Has China's Belt and Road Initiative promoted its green total factor productivity? Evidence from primary provinces along the route. *Energy Policy* **2019**, *129*, 360–369. [[CrossRef](#)]
46. Chung, Y.H.; Färe, R.; Grosskopf, S. Productivity and undesirable outputs: A directional distance function approach. *J. Environ. Manag.* **1997**, *51*, 229–240. [[CrossRef](#)]
47. Oh, D.-H. A global Malmquist-Luenberger productivity index. *J. Prod. Anal.* **2010**, *34*, 183–197. [[CrossRef](#)]
48. Wooldridge, J.M. *Introductory Econometrics: A Modern Approach*, 6th ed.; Cengage Learning: Boston, MA, USA, 2016.
49. Jiang, Y.; Wang, H.; Liu, Z. The impact of the free trade zone on green total factor productivity: Evidence from the Shanghai pilot free trade zone. *Energy Policy* **2021**, *148*, 112000. [[CrossRef](#)]
50. Zhang, J.; Wu, G.; Zhang, J. The estimation of China's provincial capital stock: 1952–2000. *Econ. Res. J.* **2004**, *10*, 35–44.
51. Zong, Z.; Liao, Z. Estimates of fixed capital stock by sector and region: 1978–2011. *J. Guizhou Univ. Financ. Econ.* **2014**, *3*, 8–16.
52. Hausman, J.A. Specification tests in econometrics. *Econometrica* **1978**, *46*, 1251–1271. [[CrossRef](#)]
53. Shuai, S.; Fan, Z. Modeling the role of environmental regulations in regional green economy efficiency of China: Empirical evidence from super efficiency DEA-Tobit model. *J. Environ. Manag.* **2020**, *261*, 110227. [[CrossRef](#)] [[PubMed](#)]
54. Kumar, S. Environmentally sensitive productivity growth: A global analysis using Malmquist-Luenberger index. *Ecol. Econ.* **2006**, *56*, 280–293. [[CrossRef](#)]
55. Choi, Y.; Oh, D.-H.; Zhang, N. Environmentally sensitive productivity growth and its decompositions in China: A metafrontier Malmquist-Luenberger productivity index approach. *Empir. Econ.* **2015**, *49*, 1017–1043. [[CrossRef](#)]
56. Liu, Y.; Feng, C. What drives the fluctuations of “green” productivity in China's agricultural sector? A weighted Russell directional distance approach. *Resour. Conserv. Recycl.* **2019**, *147*, 201–213. [[CrossRef](#)]
57. Trujillo-Barrera, A.; Pennings, J.M.E.; Hofenk, D. Understanding producers' motives for adopting sustainable practices: The role of expected rewards, risk perception and risk tolerance. *Eur. Rev. Agric. Econ.* **2016**, *43*, 359–382. [[CrossRef](#)]
58. Li, B.; Ding, J.; Wang, J.; Zhang, B.; Zhang, L. Key factors affecting the adoption willingness, behavior, and willingness-behavior consistency of farmers regarding photovoltaic agriculture in China. *Energy Policy* **2021**, *149*, 112101. [[CrossRef](#)]
59. Wang, C.; Gao, Q.; Wang, X.; Yu, M. Spatially differentiated trends in urbanization, agricultural land abandonment and reclamation, and woodland recovery in Northern China. *Sci. Rep.* **2016**, *6*, 37658. [[CrossRef](#)]
60. Wen, Z.; Ye, B. Analyses of mediating effects: The development of methods and models. *Adv. Psychol. Sci.* **2014**, *22*, 731–745. [[CrossRef](#)]
61. Li, G.; Li, Y.; Zhou, X. Agricultural mechanization, labor transfer and the growth of farmer's income: A re-examination of causality. *Chin. Rural Econ.* **2018**, *11*, 112–127.
62. Adetutu, M.O.; Ajayi, V. The impact of domestic and foreign R&D on agricultural productivity in sub-Saharan Africa. *World Dev.* **2020**, *125*, 104690.
63. Yang, Z.; Cai, J.; Qi, W.; Liu, S.; Deng, Y. The Influence of income, lifestyle, and green spaces on interregional migration: Policy implications for China. *Popul. Space Place* **2017**, *23*, e1996. [[CrossRef](#)]

-
64. Xu, B.; Chen, W.; Zhang, G.; Wang, J.; Ping, W.; Luo, L.; Chen, J. How to achieve green growth in China's agricultural sector. *J. Clean. Prod.* **2020**, *271*, 122770. [[CrossRef](#)]
 65. Zhan, J.; Xu, Y. Environmental regulation, agricultural green TFP and grain security. *China Popul. Resour. Environ.* **2019**, *29*, 167–176.
 66. Wang, X.; Shen, Y. The effect of China's agricultural tax abolition on rural families' incomes and production. *China Econ. Rev.* **2014**, *29*, 185–199. [[CrossRef](#)]
 67. Li, Z.; Jin, M.; Cheng, J. Economic growth of green agriculture and its influencing factors in China: Based on emergy theory and spatial econometric model. *Environ. Dev. Sustain.* **2021**. [[CrossRef](#)]
 68. Xu, C.; Holly Wang, H.; Shi, Q. Farmers' income and production responses to rural taxation reform in three regions in China. *J. Agric. Econ.* **2012**, *63*, 291–309. [[CrossRef](#)]