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Land market distortion and agricultural green total factor productivity: provincial-level evidence from China

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ABSTRACT

Based on provincial-level agricultural input and output data in China from 2000 to 2019, this study estimates the Luenberger-Hicks-Moorsteen index using the nonparametric method of the directional distance function to obtain agricultural green total factor productivity (AGTFP). The results show that AGTFP in China has increased significantly over the past 20 years, with significant differences between provinces and among the eastern, central, and western regions. Land market distortion has had a significant negative impact on AGTFP. The results suggest that the government needs to promote the market-oriented reform of land factors, solve the price distortion caused by land finance, promote the intensification and modernization of agricultural management, and realize the potential of green agricultural production.

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1. Introduction

Food security remains a long-standing and challenging issue for many developing countries. Among them, China has more difficult problems of feeding 22% of the global population while having only 7% of its arable land. Threatened by the COVID-19 pandemic, global uncertainty, and climate change, China's food security has become a more pressing issue. China's population is estimated to reach 1.5 billion by 2030, necessitating the production of an additional 100 million tons of food annually.¹ In the Global Food Security Index for 2021, out of 113 countries, China is 34th (Kate, 2022). In the face of enormous population pressure and external environmental uncertainty, China must make every effort to increase agricultural productivity (Wang et al., 2020). Therefore, research on agricultural production in China is theoretically and practically significant.

Green total factor productivity (GTFP) is an essential indicator of China's agricultural economic growth and supply-side structural transformation. The concept not only relates to the pace of technological advancement, sometimes referred to as total factor

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productivity (TFP), but is also associated with environmental protection (Su et al., 2022a; Shen et al., 2022). In agricultural production, the output includes both desired and undesired polluting output. China has serious environmental pollution problems in agricultural production (Shen et al., 2022). For instance, China is the world's largest user of chemical fertilizers and pesticides. Wang et al. (2010) posit that over 15% of the total greenhouse gas emissions, around 90% of nitrous oxide, and 60% methane emissions are from agriculture in China. Since the Chinese government announced the goals of carbon peaking and carbon neutrality, GTFP has become a more scientific indicator of capturing the extent of green development in agriculture (Deng et al., 2022). Despite the annual increase in carbon dioxide emissions from agriculture, the trend toward reaching the peak has declined in recent years (Jin et al., 2021; Su et al., 2022b). As noted by the 14th Five-Year Plan, the country is considering setting a new cut-off point for agricultural GTFP (AGTFP) improvement and further improving agricultural development while increasing the carbon constraint target.

Moreover, distortion issues exist in the agricultural land market. Land is an essential and unique production input factor in agricultural production. Problems of poor quality of inputs and inefficient allocation of land factors persist in China (Pingali, 2012). More prominently, in terms of transfer and scale effect, land allocation issues in agricultural production have hampered agricultural growth (Ye, 2015). Under the current land allocation system, the land scale does not correlate with its production efficiency, which means that the allocation of land resources in China might be distorted (Gai et al., 2017). The allocation of land resources affects not only technological progress but also the capitalization and mechanization of agricultural production. Under such circumstances, it is challenging to intensify and increase the scale of farming operations. The agrarian production efficiency per unit of land area is also reduced, and pesticides, chemical fertilizers, and plastic films are used excessively. This then has a significant impact on the polluting output of agricultural production. Thus, reversing regional land resource misallocation and improving land resource utilization efficiency through land market reform is one of the ways to enhance GTFP in agriculture.

Previous literature focuses on the relationship between the distortion of the factor market and AGTFP rather than on the land itself (Yang et al., 2022). Several studies concentrate on the relationship between land market distortions and TFP but do not focus on agriculture or consider the pollution caused by agricultural production (Lu et al., 2020; Yang et al., 2022). Thus, to address this, this study emphasizes the role of land market distortions on AGTFP. We utilize input-output data on Chinese agriculture from 2000 to 2019 to estimate the GTFP using the Luenberger-Hicks-Moorsteen total factor productivity (LHMTFP) index and investigate the impact of distorted land on GTFP in China.

This study makes the following contributions. First, the LHMTFP indicator is introduced to capture the changes in AGTFP in China over the past two decades. The By-Production technique complies with the requirements for material balance, while the LHM indicator considers variations in input and output over time and non-desired outcomes. The methodology of this study provides new insights. Second, we analyze the spatial differences and time variation of AGTFP at a macro level and capture the impact of land market distortions on AGTFP. This allows policymakers

to recognize the importance of land market distortions and improves agricultural green products from the perspective of land factor marketization.

2. Literature review

2.1. AGTFP

One approach to measuring GTFP in agriculture is to consider pollution-causing inputs. For instance, Wang et al. (2012) utilized nitrogen and phosphorus loss in agricultural output as a factor input to calculate the GTFP change index in Chinese agriculture from 1992 to 2010 through a stochastic frontier production function approach. Another method considers undesirable outcomes, such as pollutant emissions and agricultural surface contamination. Xu et al. (2019) quantified agricultural carbon emissions in five ways – namely, agrarian materials, rice cultivation, soil, livestock and poultry rearing, and straw burning – to capture China's AGTFP from 1998 to 2016 by directional distance function (DDF). Xu et al. (2020) included soil nitrogen dioxide emissions to estimate GTFP in agriculture. They found that the productivity with soil nitrogen dioxide emissions is much lower than that without these emissions. Chen et al. (2022) utilized a three-stage data envelopment analysis technique paired with a slack-based metric model to estimate the AGTFP by taking carbon emissions and agricultural surface source pollution as undesirable outputs.

Existing literature indicates that AGTFP in China presents an upward trend with significant regional differences. Wu and Song (2018), for instance, showed that the AGTFP in the Yangtze River Economic Zone has increased from 1997 to 2015 but remains lower than the average at the national level. Liu and Feng (2019) found that China's AGTFP follows a U-shaped trend, with the turning point occurring in 2010, and that the eastern region had the greatest AGTFP, while the western area had the highest AGTFP growth rate. Ji and Xia (2020) revealed a fluctuating increase in China's AGTFP from 2011 to 2016 with a significant absolute β -convergence trend. Liu et al. (2021) reported that China's AGTFP showed an increasing trend with inter-provincial differences.

The determinants of AGTFP include technological progress (Liu & Feng, 2019), foreign direct investment (Wang et al., 2019), crop insurance (Fang et al., 2021), and agricultural factor endowment and regional characteristics (Liu et al., 2021). Liu and Lv (2021) indicated that rural human capital and GTFP in China have a non-linear connection. Wu and Yao (2021) used a spatial Durbin model to investigate the spatial impact of AGTFP under factor market distortions and showed that factor market distortions inhibit GTFP growth in agriculture. Yin et al. (2022) found that agro-industrial agglomeration has a significant negative effect on AGTFP.

2.2. Land market distortion

A body of studies has addressed the vital role of land distortions in firm investment, industry productivity, and the urban-rural income gap. For instance, Huang et al. (2015) found that industrial land price distortions significantly promote firm overinvestment with different behavior across ownership attributes and industry attributes.

Wang et al. (2021) concluded that government intervention in industrial land concessions causes price distortions of land, further leading to lower productivity of industrial firms. Zhang and Ge (2021) found that land market distortions significantly increase the wealth disparity between cities and rural areas.

A large amount of literature also indicates the significant effect of land misallocation on agricultural production. For example, Chamberlin and Ricker-Gilbert (2016) found that the land lease market has promoted the transfer of land from small-scale farmers with weak abilities to small-scale farmers with strong abilities, which improves agricultural productivity in Malawi and Zambia. Chen (2017) showed that agricultural productivity is lower in economies with a higher proportion of untitled land. Chen et al. (2018) used the price-to-value ratio as an indicator of land distortion. They found that housing activities stimulate farmland price value distortion but do not increase farmland value. Le (2020) concluded that removing all land-use restrictions results in a rise of 8.03% in the GDP per capita. Chen et al. (2022) found that land redistribution increases agricultural productivity at the regional level by an average of 43%. Britos et al. (2022) investigated the influence of land market flaws on agricultural output. They noted that the total output of maize, bean, and coffee is lower than the effective level due to land market imperfections. Our study explored the effect of land distortions on AGTFP from 2000 to 2019 in China.

3. Model

3.1. Environmental production technology

We introduced a set of environmental production options using economic axioms according to sub-production technology (Murty & Russell, 2002; Murty et al., 2012). First, we start with a theoretical definition of the By-Production technique. x^i and x^n represent the number of pollution-free inputs and pollution-producing inputs, respectively. The output vectors y and b indicate desired and unwanted outcomes in the production process, respectively. We can then establish the anticipated production sub-technology T_1 using production economics concepts. The technology describes converting all inputs into desired outputs, which relates to typical production technologies. Here, we ignore the process of production externalities. The definition also has an unintended contamination production sub-technology T_2 . In this case, only the polluting inputs and undesirable outcomes are considered. This technique considers the externalities associated with the production process, thus distinguishing it from the study of traditional efficiency. The intersection of sub-technologies T_1 and T_2 is termed as BP technology, which considers both productivity and environmental efficiency (Shen et al., 2022). In general, after considering the inputs and outputs, the BP technique (TBP) can be expressed as follows:

$$\begin{aligned}
 T_{BP} &= T_1 \cap T_2 \\
 &= \{(x^i, x^n, y, b) \in R_+^{I+N+J+Q} : (x^i, x^n) \text{ can produce } y; x^n \text{ can generate } b\} \\
 T_1 &= \{(x^i, x^n, y) \in R_+^{I+N+J} | f(x^i, x^n, y) \leq 0\} \\
 T_2 &= \{(x^n, b) \in R_+^{N+Q} | g(x^n) \leq b\}
 \end{aligned}$$

3.2. Directional distance function

A distance function can be used to characterize the BP approach discussed in the previous section. The performance gaps of the examined decision units can be identified using the DDF technique. As environmental production techniques include both desired and undesired outputs, the DDF may account for the distinct optimization orientations of the two types of outputs. Desired outputs boost social welfare and should be improved, whereas non-desired outputs cause negative externalities and should be decreased. Input resources are similarly limited and should be minimized to the greatest extent feasible. This environmental production technique can be expressed in the DDF (Chung et al., 1997; Färe et al., 2005). The generalized DDF describes the rise in desirable output and the decrease of the unwanted output and input at the technology level in periods $\alpha \in \{t, t+1\}$ and $\beta \in \{t, t+1\}$. It can be defined as follows:

$$D(x, y, b; g_x, g_y, g_b) = \max \left\{ \omega, \sigma \in R_+ : (x^\alpha - \omega g_x, y + \sigma g_y, b - \sigma g_b) \in T \right\}$$

$(g_x^t, g_y^t, g_b^t) \geq 0$ is the directional vector of inputs, desired outputs, and undesired outputs. $(\alpha, \beta) \in \{t, t+1\} \times \{t, t+1\}$ denotes a mixed periodic DDF.

3.3. LHM indicator and decomposition in the environment

Briec and Kerstens (2004) developed the LHM productivity meter, which may be regarded as an extra full TFP metric (O'Donnell, 2012). The major purpose of our study is to broaden the scope of the LHM indicator by considering non-desired outcomes. We may then use this information to examine the environmentally adjusted TFP indicator (Shen et al., 2019).

Non-desired outputs can be incorporated into TFP measurements in various ways (Dakpo et al., 2016; Ancev et al., 2017; Dakpo & Ang, 2019). Unwanted outputs can be treated as inputs and lowered at the same time. They can also be used as weakly disposable outputs in the model. The former approach is problematic, so we adopted the latter and simultaneously increased desired outputs and decreased non-desired outputs in the optimization process. The environmental LHM indicator measures the change in GTFP by considering the distance between the boundary and observation points within the observation period t and $t+1$. This is done along the direction of (desired and undesired) outputs, keeping the input level constant and the output level stable along the path of inputs (Baležentis et al., 2021). To avoid arbitrariness in the choice of the baseline cycle, we implemented the two cycles sequentially as the baseline cycle. The environmental LHM measure for the base period is defined as t .

$$LHM^t = \left(\begin{array}{l} \left[D^t(x_r^t, y_r^t, b_r^t; 0, g_y^t, g_b^t) - D^t(x_r^t, y_r^{t+1}, b_r^{t+1}; 0, g_y^{t+1}, g_b^{t+1}) \right] \\ - \left[D^t(x_r^{t+1}, y_r^t, b_r^t; g_x^{t+1}, 0, 0) - D^t(x_r^t, y_r^t, b_r^t; g_x^t, 0, 0) \right] \end{array} \right) \quad (1)$$

The first two terms in parentheses denote the gap between the intended and undesirable outputs along the direction of cycle t 's border. The final two terms show

the distance between the inputs and the boundary. We see a GTFP gain when the value of this indicator is greater (lesser) than 0. Similarly, the LHM measure for cycle $t + 1$ is defined as:

$$LHM^{t+1} = \left(\begin{array}{l} \left[D^{t+1}(x_r^{t+1}, y_r^t, b_r^t; 0, g_y^t, g_b^t) - D^{t+1}(x_r^{t+1}, y_r^{t+1}, b_r^{t+1}; 0, g_y^{t+1}, g_b^{t+1}) \right] \\ - \left[D^{t+1}(x_r^{t+1}, y_r^{t+1}, b_r^{t+1}; g_x^{t+1}, 0, 0) - D^{t+1}(x_r^t, y_r^{t+1}, b_r^{t+1}; g_x^t, 0, 0) \right] \end{array} \right) \quad (2)$$

To produce an indicator of the variation in LHM production between periods t and $t + 1$, we use the average score of indicators in (1) and (2) (Baležentis et al., 2022):

$$LHM^{t,t+1} = \frac{1}{2}(LHM^t + LHM^{t+1}) \\ = \frac{1}{2} \left(\begin{array}{l} \left[D^t(x_r^t, y_r^t, b_r^t; 0, g_y^t, g_b^t) - D^t(x_r^t, y_r^{t+1}, b_r^{t+1}; 0, g_y^{t+1}, g_b^{t+1}) \right] \\ - \left[D^t(x_r^{t+1}, y_r^t, b_r^t; g_x^{t+1}, 0, 0) - D^t(x_r^t, y_r^t, b_r^t; g_x^t, 0, 0) \right] \\ + \left[D^{t+1}(x_r^{t+1}, y_r^t, b_r^t; 0, g_y^t, g_b^t) - D^{t+1}(x_r^{t+1}, y_r^{t+1}, b_r^{t+1}; 0, g_y^{t+1}, g_b^{t+1}) \right] \\ - \left[D^{t+1}(x_r^{t+1}, y_r^{t+1}, b_r^{t+1}; g_x^{t+1}, 0, 0) - D^{t+1}(x_r^t, y_r^{t+1}, b_r^{t+1}; g_x^t, 0, 0) \right] \end{array} \right) \quad (3)$$

3.4. Strategy for estimation

Parametric and nonparametric approaches can be used to estimate the DDF. We opted for the nonparametric method, which allows the estimation of production constraints without defining any particular operational form and places *a priori* assumptions on the technique, such as monotonicity and convexity. Murty et al. (2012) proposed an improved sub-production model that keeps the production possibility set convex and returns to the scale variable. We assumed reduced convexity and employed a free disposal hull model.

A series of linear programs must be solved in computing the LHM indicators and their components in expressions (1) and (2). Only two uncommon situations are presented here. This study compared the input and output vectors of cycle $\alpha \in \{t, t + 1\}$ with the cycle $\beta \in \{t, t + 1\}$. The relevant output or input DDF is defined in our technique. We assumed decision-making units R , where $r = 1, 2, \dots, R$. Next, we constructed an empirical bound using these units' input and output vectors. Specifically, we derived the output DDF $D^\beta(x^\alpha, y^\alpha, b^\alpha; 0, g_y^\alpha, g_b^\alpha)$ by solving the linear algorithm shown below (LP1).

$$D(x, y, b; 0, g_y, g_b) = \max_{\sigma, \phi, \varphi} \sigma \\ \text{s.t. } \sum_{r=1}^R \phi_r y_r^j \geq y^j + \sigma g_y^j, \forall j; \\ \sum_{r=1}^R \phi_r x_r^i \leq x^i, \forall i;$$

$$\begin{aligned}
\sum_{r=1}^R \phi_r x_r^n &\leq x^n, \forall n; \\
\sum_{r=1}^R \varphi_r b_r^q &\leq b^q - \sigma g_b^q, \forall q; \\
\sum_{r=1}^R \varphi_r x_r^n &= \sum_{r=1}^R \phi_r x_r^n, \forall n; \\
\sum_{r=1}^R \phi_r &= 1; \\
\sum_{r=1}^R \varphi_r &= 1; \\
\phi_r &= \{0, 1\}, \forall r; \\
\varphi_r &= \{0, 1\}, \forall r.
\end{aligned} \tag{LP1}$$

ϕ and φ are vectors of intensity variables. $(0, g_y^\alpha, g_b^\alpha)$ shows the maximum increase in desired output and maximum decrease in undesired output. The input DDF $D^\beta(x^\alpha, y^\alpha, b^\alpha; g_x^\alpha, 0, 0)$ could be acquired by solving the linear algorithm below (LP2).

$$\begin{aligned}
D(x, y, b; g_x, 0, 0) &= \max_{\omega, \phi, \varphi} \omega \\
s.t. \sum_{r=1}^R \phi_r y_r^j &\geq y^j, \forall j; \\
\sum_{r=1}^R \phi_r x_r^i &\leq x^i - \omega g_x^i, \forall i; \\
\sum_{r=1}^R \phi_r x_r^n &\leq x^n - \omega g_x^n, \forall n; \\
\sum_{r=1}^R \varphi_r b_r^q &\leq b^q, \forall q; \\
\sum_{r=1}^R \varphi_r x_r^n &= \sum_{r=1}^R \phi_r x_r^n, \forall n; \\
\sum_{r=1}^R \phi_r &= 1; \\
\sum_{r=1}^R \varphi_r &= 1; \\
\phi_r &= \{0, 1\}, \forall r; \\
\varphi_r &= \{0, 1\}, \forall r.
\end{aligned} \tag{LP2}$$

ϕ and φ are vectors of intensity variables. ω represents the input value in DDF. $(g_x^\alpha, 0, 0)$ denotes the maximum reduction in the direction of the input defined in period $\alpha \in \{t, t + 1\}$.

Table 1. Description of variables.

Indicator	Variable	Metrics	Unit
Input	L	Employees working in the primary industry	Ten thousand people
	T	Agricultural seeded area	Thousands of hectares
	K1	Agricultural mechanization	Million kilowatts
	K2	Amount of fertilizer used	Million tons
	K3	Number of pesticides used	Million tons
Output	K4	Amount of plastic film used	Million tons
	GDP	Total agricultural output	Hundred million RMB
	CO2	Agricultural carbon emissions	Million tons

Source: Authors' calculation.

Table 2. Statistical descriptions.

Variable	Obs.	Mean	Std. Dev.	Min	Max
L	600	983.540	721.612	37.090	3564
T	600	5327.101	3588.664	88.600	14783.400
K1	600	2809.442	2683.849	94	13353
K2	600	175.131	137.603	6.200	716.100
K3	600	5.266	4.224	0.140	17.346
K4	600	6.955	6.330	0.060	34.352
GDP	600	1335.769	998.232	56.980	4845.954
CO2	600	969.680	603.784	23.360	2417.750

Source: Authors' calculation.

3.5. Data

To estimate the AGTFP, we employed input and output data from 30 provinces in mainland China (excluding Tibet). The inputs were labor, land, and capital, among which capital inputs included mechanical power, fertilizer use, pesticide use, and agricultural film use. We measured desired output using gross agricultural output. To reduce the impact of pricing factors, we used prices in the year 2000 as the benchmark and corrected the data of gross agrarian output for all years. Agrarian carbon emissions, including the carbon emissions of fertilizer, pesticide, agricultural film, diesel, and irrigation combined, measured undesired output. Data were obtained from the China Stock Market & Accounting Research Database, the National Bureau of Statistics, and the China Rural Statistical Yearbook (2000–2019). Tables 1 and 2 give specific indicator descriptions and descriptive statistics.

3.6. Specification of the econometric model

Land distortion refers to factor market prices differing from their potential costs owing to imperfect markets or government regulation, resulting in the non-optimal distribution in production. China's land market reform has been slow and characterized by the eastern region reforming at a significantly faster pace than the western region in recent years. As essential inputs for agricultural production, land scale, and quality profoundly impact agricultural productivity. Resource allocation and market-based transactions in the land market significantly impact farming efficiency and agricultural green development. Therefore, one of the primary purposes of this study is to capture the effect of land distortion on agricultural productivity in China. This study uses a multiple linear regression model, and the econometric model is

Table 3. Definition of variables.

	Variable name	Variable definition
AGTFP	Agricultural green total factor productivity	Green total factor productivity in agriculture
Distortion	Land market distortion	Share of land premiums in regional revenues as a proxy variable for land market distortions.
Base	Agricultural foundation	The agricultural base is expressed as the actual gross agricultural product per capita.
Structure	Agricultural structure	The percentage of grain seeded to the total area planted for crops is used to describe the agricultural structure.
Ln(human)	Ln (rural human capital)	Rural human capital is estimated using the average rural educational attainment.
Capital	Degree of capitalization of agriculture	The ratio of agriculture machinery's total output power to the amount of cultivated land in a region represents the degree of capitalization of agriculture.
Industrialize	Industrialization level	The ratio of secondary industry value added to regional GDP is used to determine the extent of industrialization.
Urban	Level of Urbanization	The ratio of urban to total population is used to measure the amount of urbanization.
Expenditure	Agriculture-related financial expenditure	Agricultural-related fiscal expenditure is the ratio of government agricultural-related fiscal cost to regional GDP.
Tax	Agricultural tax burden	The ratio of rural tax to total agricultural production is used to calculate the farm tax burden.
Trade	Agricultural terms of trade	The ratio of the agrarian production price index to the agrarian production material price index is used to calculate agricultural terms of trade.

Source: Authors' calculation.

constructed as follows:

$$\begin{aligned}
 GTFP_{it} = & \beta_0 + \beta_1 distortion_{it} + \beta_2 base_{it} + \beta_3 structure_{it} + \beta_4 \ln(human_{it}) \\
 & + \beta_5 capital_{it} + \beta_6 industrialize_{it} + \beta_7 urban_{it} + \beta_8 expenditure_{it} \\
 & + \beta_9 tax_{it} + \beta_{10} trade_{it} + \mu_i + \nu_t + \lambda_{it},
 \end{aligned}$$

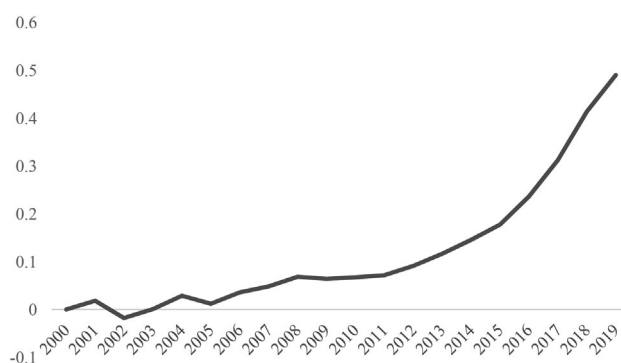
where $GTFP_{it}$ is agricultural productivity in province i at year t . The main explanatory variable is land factor market distortion, denoted by $distortion_{it}$. Local governments expropriate land from farmers and strategically transfer it to supply land resources between industrial land and commercial and residential land. In this process, the government has a two-way monopoly on the non-agricultural land market and the primary market for urban land. This ultimately manifests in large land transfer fees being dominated by local governments (Sun et al., 2014; Wu et al., 2015). Therefore, we used the share of land concessions in regional fiscal revenue as a proxy variable to measure land market distortions (Xie, 2017). The data are obtained from the CSMAR database and the China Land and Resources Statistical Yearbook (2000–2019).

This study selected control variables based on previous research and data availability (Liang & Long, 2015; Wu & Yao, 2021). We used the following variables as control variables: agricultural development level, agricultural structure, rural human capital, degree of agricultural capitalization, level of industrialization, level of urbanization, agriculture-related financial expenditure, agricultural tax burden, and agricultural terms of trade. Table 3 lists the definitions of the specific variables. Among all variables, agricultural tax refers to several agriculture-related taxes in general.

Table 4. Descriptive statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
AGTFP	510	0.030	0.069	-0.580	0.304
Distortion	510	0.012	0.017	0.000	0.217
Base	510	0.284	0.178	0.052	1.131
Structure	510	0.658	0.134	0.354	0.971
Ln(human)	510	2.159	0.115	1.798	2.548
Capital	510	0.725	0.376	0.154	1.783
Industrialize	510	0.431	0.082	0.160	0.620
Urban	510	-0.540	0.140	0.269	0.942
Expenditure	510	0.024	0.020	0.002	0.110
Tax	510	0.090	0.115	0.014	0.661
Trade	510	1.014	0.055	0.821	1.355

Source: Authors' calculation.

**Figure 1.** National Cumulative AGTFP in China during 2000–2019.

Source: Authors' calculation.

Specifically, it is the sum of slaughter, farming, special agricultural production, deed, pastoral, and cropland occupation taxes before 2007 and the sum of the deed, tobacco leaf, and cropland occupation taxes since 2007. Due to data limitations, we obtained the data from 2003 to 2019 for 30 provinces in mainland China excluding Tibet. The data are obtained from the dataset of the National Bureau of Statistics and CSMAR. The descriptive results of all variables are shown in [Table 4](#).

4. Results

4.1. Agricultural green productivity changes in China during 2000–2019

[Figure 1](#) shows the national cumulative AGTFP in China. In general, the level of AGTFP has risen steadily. Against the background of resources and the environment increasingly becoming a hard constraint for economic growth, technological progress in agriculture is an essential factor for agricultural development. Amid increasing ecological and environmental pressure, the key to achieving agricultural carbon emission reduction lies in technical efficiency.

[Figure 2](#) presents the average AGTFP of each province from 2000 to 2019. The AGTFP varies widely between provinces. From the numerical point of view, the average AGTFP of the 30 provinces in the past 20 years reaches a maximum of 0.096 and a minimum of -0.131. From the perspective of the provinces, economic belts such as Beijing-

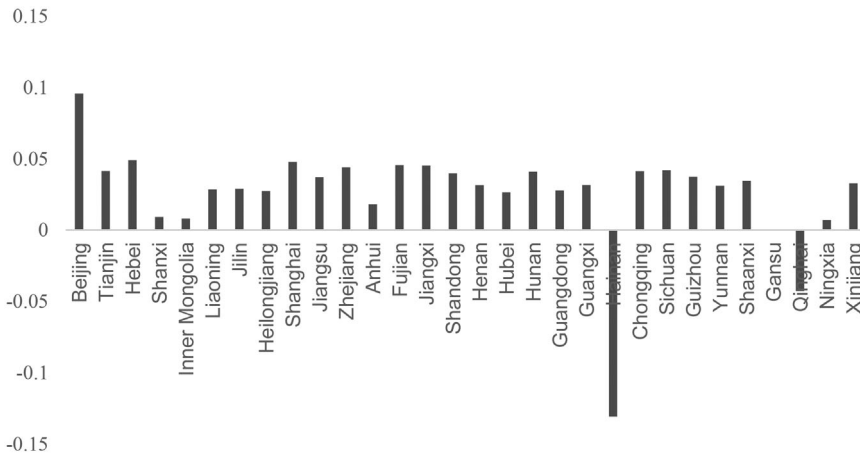


Figure 2. Average AGTFP by province (2000–2019).

Source: Authors' calculation.

Tianjin-Hebei and Jiangsu-Zhejiang-Shanghai have higher AGTFP values. In contrast, Hainan, Gansu, Qingdao, and other underdeveloped inland provinces have lower AGTFP values. The results show that Hainan, Gansu, and Qinghai have a negative AGTFP. In the case of Hainan, this might be due to limited land resources, tight arable land resources, small-farmer and low-efficiency agricultural operations, and extensive environmental losses in agricultural development (Song et al., 2020). Gansu, located in northwestern China, has insufficient water resources, a weak ecological environment, and low environmental capacity, which limit the development of agriculture and technical efficiency improvement. Qinghai, in the northeastern region of the Qinghai-Tibet Plateau, has a high altitude, cold climate, and fragile ecological environment. Only a small number of cold-tolerant crops are suitable for growth there. Furthermore, agricultural research and technology are underdeveloped in this area. All of these factors caused slow development and expansion of the agricultural economy.

AGTFP is higher in Beijing, Tianjin, and Hebei, with Beijing having the highest AGTFP. Agricultural green technological progress is the driving force of AGTFP growth in Beijing, Tianjin, and Hebei. The latest data from the National Bureau of Statistics show that agriculture in Beijing contributes to innovative and green development, owing to the enormous contribution (72%) of agriculture science and technological progress that exceeds the national average by 14 percentage points (Li & Lu, 2019). Moreover, fertilizer and pesticide applications decreased by 46% and 30%, respectively, from 2013 to 2018 (National Bureau of Statistics of China 2019). Another finding is the significant variation of AGTFP between regions.

Figure 3 shows the average AGTFP in different regions from 2000 to 2019. The results show that the eastern region has the highest AGTFP and the fastest growth. The central region has the second highest AGTFP, followed by the northeast region. The western region has the lowest AGTFP. We also observe a significant spatial divergence in productivity growth, with the overall distribution trend rising from west to east. Meanwhile, it rises and then falls from south to north, corresponding with previous results (Yang et al., 2019).

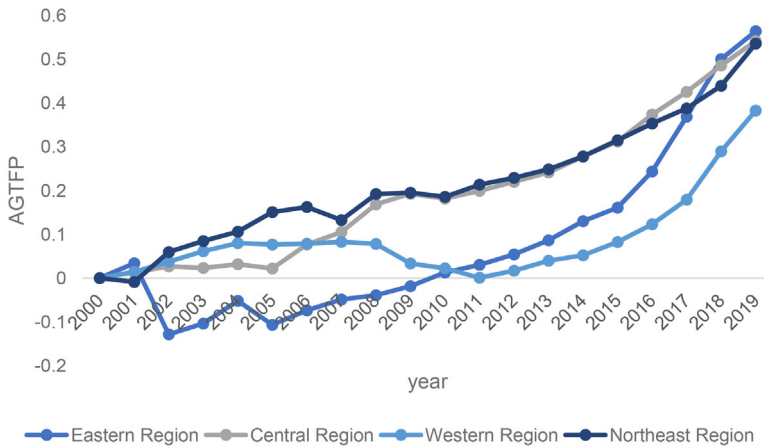


Figure 3. AGTFP by region (2000–2019).

Source: Authors' calculation.

Table 5. Results of impact of land distortion on agricultural green productivity.

Variable	Model 1 FE	Model 2 RE	Model 3 FE	Model 4 RE	Model 5 FE ¹
Distortion	−0.594*** (−2.75)	−0.395** (−1.99)	−0.375* (−1.81)	−0.449** (−2.28)	−0.375* (−1.72)
Base			0.079* (1.94)	−0.059** (−2.33)	0.079** (2.12)
Structure			−0.247*** (−3.63)	−0.047 (−1.54)	−0.247* (−1.78)
Ln(human)			0.184** (2.32)	0.164*** (3.32)	0.184* (1.85)
Capital			−0.067*** (−2.99)	−0.002 (0.14)	−0.067** (−2.42)
Industrialize			−0.182** (−2.27)	−0.073 (−1.42)	−0.182** (−2.44)
Urban			0.019 (0.43)	0.003 (0.08)	0.019 (0.50)
Expenditure			0.183 (0.59)	−0.268 (−1.20)	0.183 (0.57)
Tax			−0.031 (−1.21)	−0.052** (−2.02)	−0.031** (−0.92)
Trade			−0.055 (−1.11)	−0.054 (−1.06)	−0.055 (−1.47)
Constant	0.037 *** (9.47)	0.035*** (6.48)	−0.053 (−0.29)	−0.211* (−1.87)	−0.053 (−0.22)
Hausman Test	0.021		0.000		
N	510	510	510	510	510
R-sq	0.016	0.016	0.176	0.130	0.176

Note. 1. *** $p < .01$, ** $p < .05$, * $p < .1$. 2. FE¹ indicates the Fixed Effect model with clustering.

Source: Authors' calculation.

4.2. Impact of land distortion on agricultural green productivity

The impact of land distortion on green productivity in China's agriculture is shown in Table 5. The Hausman test disqualifies the models with random effects. The results of White's test indicate a heteroskedasticity problem, so we also regress the equation with clustering standard errors. With and without adding other control variables, the results show that land market distortion negatively and significantly impacts

agricultural green productivity. Moreover, the impact is still significant with clustering standard errors. To enhance the credibility of the regression model, we run the regressions with a quality bilateral tail shrinkage of 1% and quality bilateral truncation of 1%. The regression results still show a significant negative impact of land market distortion on green productivity in agriculture.

The distortion of the land market marks the deviation of land price from opportunity cost, leading to the misallocation or suboptimal allocation of land, which then harms the improvement of AGTFP. The results of this study indicate that if land can be effectively allocated and if the distortion of the land market can be improved by 1%, China's AGTFP will increase by 37.5%. This finding is generally consistent with previous research, but there are subtle differences. This study measures the impact of land distortion alone, whereas previous literature measured the combined effects of three types of distortions: land, capital, and labor. Using provincial data from 1997 to 2018, Wu and Yao (2021) concluded that a 1% reduction in factor market distortion, which is the average of capital market distortion, labor market distortion, and land market distortion, would lead to an increase in about 19.7% in AGTFP. Similarly, Yang et al. (2022) calculated a 15.7% improvement using provincial data from 1997 to 2020. Changes in the land factor market alone can lead to more significant green productivity gains. This also illustrates the importance of considering land market distortions. Britos et al. (2022) found that due to land market distortions, the total production of corn and beans was 19% lower than their efficient levels, and coffee was 31% lower.

The importance of land distortion in influencing green productivity is that distortion of land resource prices is related to economic and social development, such as land finance, local government investment attraction, and urban construction. This study takes the share of land concessions in regional fiscal revenue as a proxy variable for land market distortion. When the number of agricultural lands is reduced due to land finance and land transfer, village communal land is more likely to be confiscated in large quantities for economic development. This might result in extensive land use and a waste of land resources. It is not easy to form large-scale and intensive management. Using pesticides, fertilizers, and agricultural films leads to a wide range of pollution, high carbon emission levels, and difficulty in improving agricultural green productivity. The main reasons for this are the existence of land financial problems and the virtual land ownership caused by the unclear subject of land property rights in rural collective-owned land and the existing fiscal and tax system (Table 6).

For control variables, the results indicate that agricultural development level, agricultural structure, rural human capital, degree of agricultural capitalization, and industrialization also significantly affect AGTFP. The level of local agricultural growth reflected in the agricultural base has a positive impact. Provinces with higher levels of agricultural development are more likely to achieve increased green agriculture output. Similarly, rural human capital has a positive influence on GTFP. This is because an increase in the average years of schooling enhances rural human capital, which leads to the modernization of agricultural production and operation and improves agricultural production efficiency.

Table 6. Results of impact of land distortion on agricultural green productivity.

Variable	Model 1	Model 2
	Quality bilateral shrinkage 1%	Quality bilateral truncated tail 1%
Distortion	−0.349** (−2.02)	−0.274* (−1.74)
Base	0.070** (2.07)	0.072** (2.34)
Structure	−0.202*** (−3.56)	−0.142*** (−2.72)
Ln(human)	0.210*** (3.17)	0.187*** (3.07)
Capital	−0.070*** (−3.70)	−0.065*** (−3.81)
Industrialize	−0.186*** (−2.78)	−0.156** (−2.59)
Urban	−0.000 (−0.01)	0.023 (0.70)
Expenditure	0.097 (0.37)	0.058 (0.25)
Tax	−0.024 (−1.12)	−0.003 (−0.15)
Trade	−0.068 (−1.63)	−0.021 (−0.54)
Constant	−0.106 (−0.69)	−0.173 (−1.23)
N	510	510
R-sq	0.213	0.209

Source: Authors' calculation.

Moreover, the agricultural structure negatively impacts AGTFP. The higher the ratio of food to cash crops, the lower the efficiency of land cultivation tends to be. With the same degree of carbon emission, the higher the share of grain sowing, the lower the GTFP. Likewise, the degree of agricultural capitalization negatively affects AGTFP. The higher the proportion of total agricultural machinery power and the greater the pollution-causing inputs, the lower the level of AGTFP. The level of regional industrialization also has a negative effect on AGTFP. During the growth of secondary industry-oriented economies, the government tends to supply industrial production factors at low prices, hindering the development of AGTFP. The negative impact of agricultural taxation on GTFP in agriculture is not significant. An agricultural tax burden reduces farmers' burdens and promotes agricultural technological progress and production efficiency to a certain extent. However, since 2006, agricultural taxes have been discontinued, and other related taxes have been drastically reduced, making the effect of the agricultural tax burden on green agricultural productivity insignificant.

5. Conclusion

This study combines the environmental DDF and nonparametric method to estimate the AGTFP at the provincial level from 2000 to 2019. It then further examines the impact of land market distortion on AGTFP.

The findings indicate that China's AGTFP steadily increased during 2000–2019. Although there are fluctuations, the overall increase is considerable. Taking 2000 as the benchmark, it rose to 0.49 in 2019. The absolute and change values of AGTFP

vary greatly among Chinese provinces and regions. The eastern regions have the highest AGTFP and the fastest growth. The central region has the second highest AGTFP, followed by the northeast area. The western region has the lowest AGTFP. Productivity growth differs significantly among regions.

We also confirm the negative influence of land price distortion on GTFP in agriculture. The distortion of the land market leads to the failure of optimal allocation of land resources, which hinders the improvement of AGTFP. Moreover, we also identify the significant positive impact of the agricultural base and rural human capital on the AGTFP level. Agricultural structure, degree of agricultural capitalization, and industrialization have a markedly detrimental effect on the AGTFP level.

Therefore, we formulate the ensuing policy suggestions. First, the government should build a perfect institutional system for market-oriented land factor allocation and promote market-oriented land factor reform. The specific power of land acquisition and management should be decentralized. The management of the balance between occupancy and compensation in urban and rural regions, as well as the growth and decline of productive land use, should be put into place by the authorities. Second, the government should clarify the main body and the fundamental principles of land ownership. The ambiguous right of land ownership is the root cause of the direct distortion of land resource prices and various problems related to land transactions. Legal solutions must be applied. Third, the government should adjust the central-to-local revenue distribution ratio to solve the price distortion caused by land finance. Adjusting the fiscal and taxation system can solve the mismatch between financial and service powers faced by Chinese local governments, help avoid over-reliance on land finance, and change the asymmetry between land supply and demand such that prices conform to the equilibrium level of the market.

This article is not without limitations. There is no subdivision of various industries within agriculture, and high-pollution agriculture and low-pollution agriculture are indistinguishable.

Note

1. Dipanjan Roy Chaudhury. 2020. 'With rising population and declining arable land, China may be staring at a major food crisis', *The Economic Times*. <<https://economictimes.indiatimes.com/news/international/world-news/with-rising-population-and-declining-arable-land-china-may-be-staring-at-a-major-food-crisis/articleshow/77942570.cms?from=mdr>>

Disclosure statement

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