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Research article

Capital deepening and land average grain yield convergence: Evidence from China

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A B S T R A C T

The shift of agricultural labor force to non-agricultural sectors has paralleled China's economic development, leading to a substantial rise in labor costs relative to capital. Consequently, the agricultural production has witnessed a shift towards capital-intensive practices. The capital deepening coincides with the significant increase in China's grain output while the main cause of capital deepening in China's grain production is poorly understood. This study examines the effect of increasing in various capital investments on the grain yield growth and growth convergence in China's main production areas, based on the data collected from the data set of the Compilation of Cost-Benefit Data of Agricultural Products (CCBDAP). Results show that the increases of chemical fertilizer, pesticide and machinery input have played key roles in the increase of grain yield. For early indica rice, japonica rice, wheat and maize, the average land output bears a β convergence. These findings suggest that more capital investments are supposed to accelerate the growth of grain yield per unit of land, take the opportunity of practicing the cross-provincial balance system of occupation and compensation of cultivated land. Moreover, strategic adjustments to the spatial distribution of grain cultivation are recommended to maximize the utilization of limited arable land resources while upholding national food security objectives.

1. Introduction

Since the reform and opening-up in 1970s, China's grain production has made remarkable progresses with grain output has more than doubled, e.g. the total grain production increased from 300 million tons in 1978 to 669 million tons in 2020. The Chinese government has made great contributions to ensure the food security and implemented a series of policies to support the agricultural development, such as the household responsibility system [1], the reform of the grain distribution system [2]; [3], the exemption of agricultural taxes [4], improvement of agricultural subsidy system [5], and the most stringent farmland protection institution [6]. These policies have improved farmers' incentive for grain planting and encouraged them to adjust the planting structure, expand the grain sown area, and finally increase total grain yield.

With the rapid growth of grain output, the input structure of grain production has changed significantly (Figs. 1 and 2). From 1978 to 2020, China's grain planting area decreased slightly, but remained at about 110 million hectares over years. During the same period, the overall number of agricultural labor force showed a downward trend, reducing from 283 million to 177 million. In contrast, the

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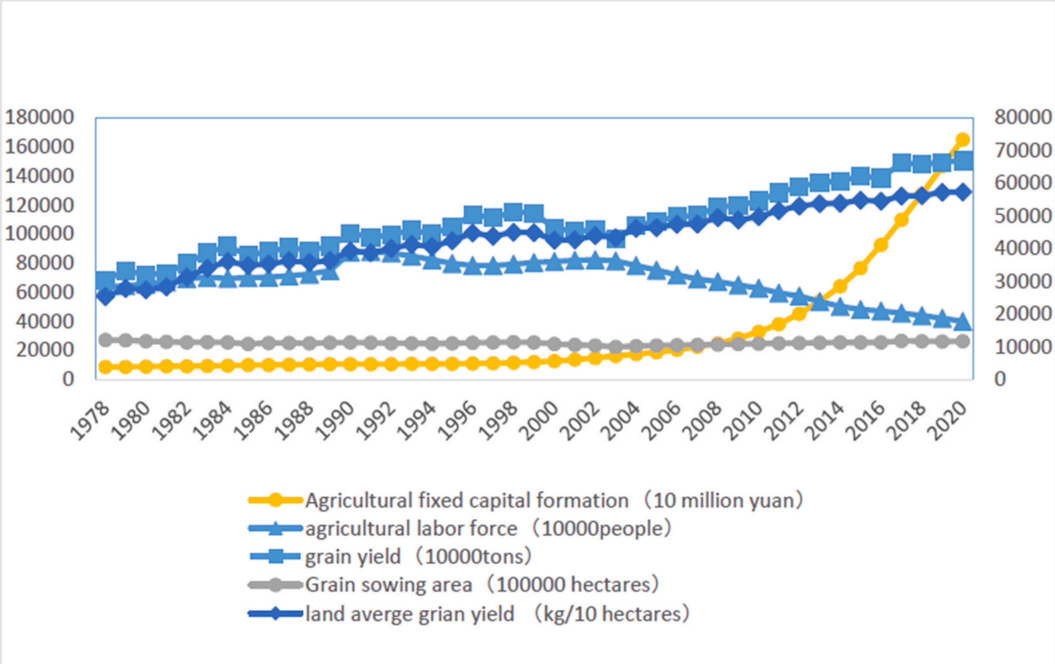

Fig. 1. Food input-output since 1978.

agricultural capitals increased rapidly from 86.8 billion yuan[1] to 1.65 trillion yuan. Overall, the input structure of China's grain production shows a changing trend of stable grain sowing area, continuous decline in labor input while growth in capital input. That is the so-called 'Capital deepening', defining as the introduction of labor-saving technologies with intensive capitals, such as machinery, chemical fertilizer, and improved seeds. The trend of capital deepening at the input side shows a strong synchronization with the rapid growth of grain production. The trend of production towards capital deepening may also be an important incentive for China's grain output growth [7].

Given that the planting area remains stable, the sharp increase in Chinese total grain output suggests that the output per unit land has increased significantly. From a state level, the rice yield increased by 66 % from 302.4 kg/mu[2] in 1980 to 481.1 kg/mu in 2017. During the same period, wheat and maize yield increased more than doubled with an increase from 147.8 kg/mu to 423.5 kg/mu and 242.4 kg/mu to 501.5 kg/mu, respectively. Therefore, the following discussion on the difference of grain yield per unit land in different regions will distinguish the grain types, starting by further analyzing the grain yield per unit land at the provincial level. Taking maize as an example, in 1980, the maize yield in Xinjiang province was 230.5kg/mu and that in Liaoning province (356.2 kg/mu) was almost 1.5 times of Xinjiang (Fig. 2). In 2017, the figure was 714.7kg/mu in Xinjiang with 50 % higher than its counterpart Liaoning (473.8 kg/mu). Although the maize yield per unit land in both provinces showed an increasing trend, he maize yield per unit land in Xinjiang increased more rapidly and caught up with that in Liaoning (Fig. 2). Thus, the variation of grain yield per unit land between provinces is also undergoing changes. It is important to analyze the variation to better understand the rapid growth of national grain yield. In this sense, two hypotheses are proposed.

H1. Since the capital deepening coincides with the significant increase in China's grain output. And that the total grain output has significantly increased simultaneously with the yield per unit land in China. Capital deepening could be the main cause for the progress of China's grain production, the increase of capital investment per unit land can promote the growth of grain yield per unit land.

H2. Considering that the land average grain yield gap between different provinces within China is narrowing. Grain yield per unit land has growth convergence in main production area in China.

The convergence analysis is used to study the economic growth gap between different regions. In principle, convergence can be divided into β Convergence and δ Convergence ([8]). The β Convergence signifies that the economic growth rate of regions with low initial per capita GDP is more rapid, catching up with regions with high per capita GDP; while δ Convergence means that with the economic development, the variance of labor average GDP per capita among different countries and regions decreases, and the level of economic development tends to convergence. The convergence used afterwards refers to β Convergence. That is the growth rate of grain yield in areas with low initial yield is higher, and its catch-up rate of grain yield in areas with high yield is defined as the

[1] Yuan is the Chinese currency unit, 1 Yuan ≈ 0.14 US dollars in 2024.
[2] Mu is the Chinese area unit, 1 Mu = 1/15 ha.

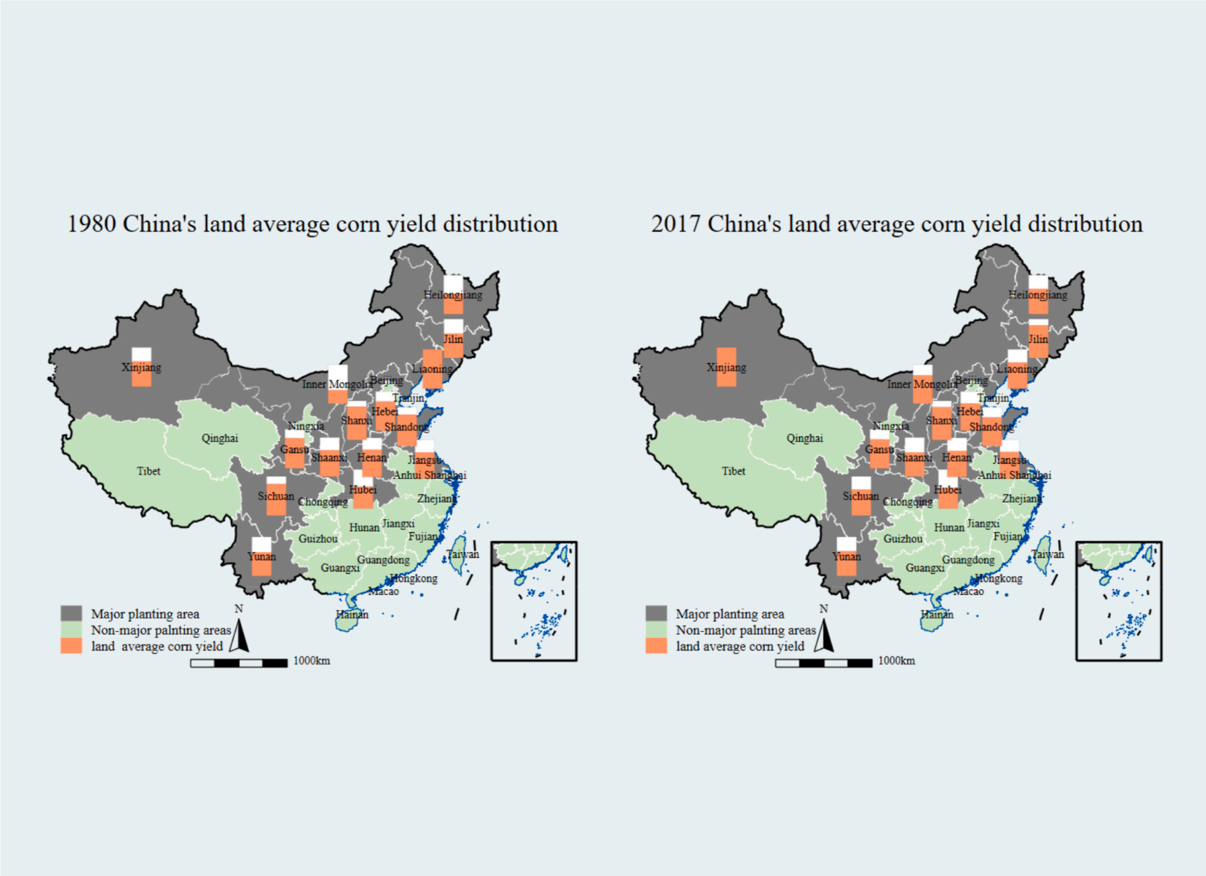

Fig. 2. Land average corn yield distribution in 1980 and 2017. The bars in the figure indicate the ratio of land average maize yields in the corresponding province to the highest yielding province of the year.

convergence of grain yield.

A large body of literatures have analyzed the convergence of agricultural productivity in different countries in a specific region (Suhariyanto & thirtle, [9]; [10–12]) and different regions within a country (Thirtle et al., [13]; [14]). Similarly, studies on the convergence of agricultural productivity in China mostly focus on the convergence analysis of labor productivity [15] and total factors productivity [16–18], but few had examined the convergence of grain yield per unit land. The grain yield per unit land is directly related to the grain planting area. If there is a trend of convergence of grain output per unit land within China, the spatial adjustment of grain planting will become one of the important ways to increase grain production. Furthermore, in the context of smallholder-oriented farming system, few studies have analyzed the difference of grain output growth between regions from the perspective of the change of input structure.

The contribution of the study to the existing literature are twofold. First, it addresses the mechanism underlying the convergence of land-average output from a capital deepening perspective, thereby improving the understanding of agricultural economic growth. Unlike the previous studies, this article focuses on analyzing the convergence of grain yield per land in different provinces of China, which helps us to better understand the rapid growth of grain output from a spatial perspective. Second, this study employed multiple econometric methods for robustness check to verify the growth convergence of land-average grain output in China, providing rigorous evidences to support the theoretical hypothesis.

The follow-up structure is arranged as follow. Section 2 introduces the impact mechanism and research hypothesis, Section 3 specifying model, Section 4 is data and variables, Section 5 presents empirical results and discussions, and concludes and make policy implications in Section 6.

2. Theoretical framework

With China's economic development and social structure adjustment, a significant portion of the agricultural labor force have migrated to non-agricultural sectors and off-farm income has rapidly increased. From 2000 to 2020, the disposable income of rural residents increased more than 4 times from 3088 yuan to 16,823 yuan. As one of the important components of disposable income, wage income increased over 10 times in the period, from 702 yuan to 9364 yuan.[3] In 2020, wage income accounted for over 50 % of the disposable income of rural residents and had already become their main source of revenue growth. As the off-farm income is usually regarded as the opportunity cost for agricultural labor input, the increase of off-farm income is often accompanied by the decrease of agricultural labor input, and grain production is facing stronger labor input constraints [19]. As can be seen from Fig. 1, the number of agricultural labor force reduced by 183.8 million from 2000 to 2020. At the same time, farmers' income has also increased steadily because of non-agricultural income growth and this in turn released farmers' investment constraints to access more capitals.

According to the induced technological innovation theory [20]; [21], technological progress is a dynamic process to approach the factors with relatively low prices. It is expected that after the sharp rise of rural labor costs, production technology favor capital factors and agricultural production use more capitals. Studies had found that even though the smallholders with fragmentated farm size are still dominating at present in Chinese agricultural production, operators had already coped with shocks through the outsourcing services provided by the professional agricultural companies. For instance, some studies have found that agricultural machinery companies that provide outsourcing services effectively coping with the impact of the reduction of rural labor force [22,23]. At the same time, to address the rapid increase of agricultural wages, farmers had adjusted their grain planting from maize and wheat to rice that uses more chemical fertilizers [24].

Capital deepening directly affects grain production. On the one hand, the widely use of agricultural machinery in China has accelerated the transfer of rural labor force and reduced the possibility of increasing grain yield per unit land through increasing labor input. On the other hand, the extensively use of chemical fertilizer, improved varieties and other factors has effectively enhanced the grain production capacity. Although the machinery services had few impacts on farmers with higher labor efficiency, it has significantly improved the resource allocation of farmers with lower labor efficiency [25]. Therefore, this paper holds that the increase of capital investment will promote grain yield.

At the same time, for a given grain crop, its main production area is often located in one or several relatively concentrated areas. Due to their adjacent or similar geographical locations, the agricultural natural production conditions in these areas have some similarities. There is a "peer effect" in the adjustment of input structure and the adoption of advanced technology. Therefore, in a specific grain crop production, the capital deepening process in different regions can be regarded as gradually synchronize, and this process has also made great contribution to the growth of grain yield. Since the capital deepening process in different regions happens simultaneously for a given crop, increasing of capital investment leads to slow growth of yield per unit land in areas with relatively high level of capital input, according to the law of diminishing marginal return of capital input, and vice versa. Thus, the convergence trend of average output per unit land of the same crop in different regions may be further strengthened.

3. Model specification

In the following section, econometric models are used to verify the two theoretical hypotheses proposed above. First, the two-way fixed effect model is used to test hypothesis 1, namely the impact of capital deepening on grain output. Second, the OLS model, the two-way fixed effect model and dynamic panel model are used to further verify the conditional convergence of average grain output. In addition, the subsequent measurement models are clustered according to crop types for regression analysis, and the subscripts in the specific model also have a unified meaning. T represents different periods, i indicates different regions, j represents the category of capital inputs, k represents other control variables, r represents regional dummy variables, and s represents time dummy variables. It should be noted that, since the regression models are for different kinds of crops, the regression model only includes two dimensions, namely the time dimension and region dimension.

3.1. OLS convergence model

In equation (1), Yield_{it} is the yield per unit land of a given crop in region i in period t, Yield_{it0} denotes the yield per unit land at the first period of region i, and $\ln\mathrm{Yield}_{it}$ to $\ln\mathrm{Yield}_{it0}$ represents the growth rate of a given crop in region i from period 0 to period t. The OLS is directly carried out for Equation (1). If the estimated coefficient β is negative, it indicates that the initial yield per unit land of a given crop is negatively correlated with its growth rate. That is, the lower the initial yield per unit land is, the faster the yield per unit land increases, and there is a convergence trend in the average yield per unit land of this crop.

$$\ln\mathrm{Yield}_{it} - \ln\mathrm{Yield}_{it0} = \alpha + \beta\ln\mathrm{Yield}_{it0} + \varepsilon_{it} \tag{1}$$

[3] The data source is China Statistical Yearbook, https://www.stats.gov.cn/sj/ndsj/. We have already excluded inflation factors from the income data, mainly based on GDP deflator at constant prices 2000.

3.2. Two-way fixed effect convergence model

The OLS regression in Eq. (1) can only offer a preliminary estimation in whether the grain yield per unit land increases and whether it converges in the main production area. While the convergence of a grain crop in its main production area is also affected by other factors. To reduce the potential risk of missing variables, we include regional dummy variables and other factors to construct the following panel data model:

$$\Delta \mathrm{Yield}_{it} = \alpha + \beta_1 \ln \mathrm{Yield}_{it-1} + \sum_j \beta_j X_{ijt} + \sum_k \gamma_k Z_{ikt} + \eta_s \sum_s \mathrm{TIME}_s + \delta_r \sum_r \mathrm{REGION}_r + \mu_i + \varepsilon_{it},$$

$$\Delta \mathrm{Yield}_{it} = \ln \mathrm{Yield}_{it} - \ln \mathrm{Yield}_{it-1} \tag{2}$$

Where $\ln \mathrm{Yield}_{it-1}$ is the grain yield per unit land in t-1 period, and $\Delta \mathrm{Yield}_{it} = \ln \mathrm{Yield}_{it} - \ln \mathrm{Yield}_{it-1}$ represents the growth rate of average output per unit land from t-1 period to t period. The regression equation in Eq. (2) is a two-way fixed effect model. When average investment intensity of various types of capital per unit land (X_{ijt}), individual characteristics of different provinces (REGION_r), various policy shocks (TIME_t), and other control variables (Z_{ikt}) are included, we estimate Eq. (2) to determine whether there is a conditional convergence trend. If the coefficient β_1 is significant and negative suggesting that the lower the yield per unit land in the previous period was, the higher the growth rate in this period will be. In other words, there exists a conditional convergence trend.

3.3. Convergence model of dynamic panel data

equation (2) can be rewritten as:

$$\ln \mathrm{Yield}_{it} - \ln \mathrm{Yield}_{it-1} = \alpha + \beta_1 \ln \mathrm{Yield}_{it-1} + \sum_j \beta_j X_{ijt} + \sum_k \gamma_k Z_{ikt} + \delta_i \sum_i \mathrm{REGION}_i + \mu_i + \varepsilon_{it}$$

$$\ln \mathrm{Yield}_{it} = \alpha + (1+\beta_1) \ln \mathrm{Yield}_{it-1} + \sum_j \beta_j X_{ijt} + \sum_k \gamma_k Z_{ikt} + \delta_i \sum_i \mathrm{REGION}_i + \mu_i + \varepsilon_{it} \tag{3}$$

The independent variable in Eq. (3) includes the lagged term of dependent variable, which is a typical dynamic panel data model. Studies like Caselli et al. [26] and [27] had used the dynamic panel model to study the economic convergence. There are some differences in the estimation methods of the dynamic panel model. Arellano and Bond [28] proposed a method for estimating dynamic panel data using the first-order difference generalized method of moments (DIF-GMM). This method first calculates the first-order difference to the model, then uses the lagged term of exogenous variables as instrumental variables to estimate the model and reduce the potential of endogeneity. However, this estimation method could also lead to weak instrumental variables when sample size is relatively small. To address it, Arellano and Bover [29] and Blundell and Bond [30] proposed another dynamic panel data estimation method of system generalized method moments (SYS-GMM). It combines the first-order difference equation and horizontal equation and possesses superior finite sample properties. In the study, we used both of DIF-GMM and SYS-GMM to estmate Eq. (3) and the results of the two estimation methods are reported as a robustness check.

4. Data and variables

4.1. Grain and plant area

In Chinese statistical caliber,[4] grain includes cereals (rice, maize, and wheat), potato and bean. In 2020, China's total grain output was 669.5 million tons, including 616.7 million tons of cereals. Cereals output accounted for 92.1 %[5] of grain output, making it the most important concern to the food security of China. Therefore, this study focus on the cereal crops. Since rice contains many varieties, with great differences in spatial distribution and planting methods, rice varieties are clustered into japonica rice and early indica rice.

Regarding the main grain planting area (Table 1), we excluded those provinces that the sown area of wheat and maize accounted for less than 1 % of the total country's sown area in 2017. The dataset from National Statistical Bureau can provide the detailed information (including sown areas) of the main grain crops expect for the sown area of japonica rice and early indica rice. Therefore, we export data from the Compilation of Cost-Benefit Data of Agricultural Products[6](CCBDAP) as additional source. The CCBDAP dataset includes the input-output and cost-benefit information of major crops in its main planting province and is also the main source of input-output data of the crops studied in this paper.

[4] The main source of the classification standard is the Announcement of the National Bureau of Statistics on Grain Yield in 2018.

[5] Data sources: Announcement of the National Bureau of Statistics on Grain Yield in 2020.The "Compilation of Cost-Benefit Data of Agricultural Products" dataset includes the provincial and national production cost and income data of China's main agricultural products over the years and managed by the National Development and Reform Commission of China.

[6] The "Compilation of Cost-Benefit Data of Agricultural Products" dataset includes the provincial and national production cost and income data of China's main agricultural products over the years and managed by the National Development and Reform Commission of China.

Table 1
Main crops and planting areas.

Crops	Planting area
Japonica rice	Anhui, Henan, Hebei, Heilongjiang, Hubei, Jilin, Liaoning, Shandong, Zhejiang, Jiangsu, Yunnan and Ningxia (12 provinces)
Early indica rice	Hunan, Hainan, Fujian, Guangdong, Guangxi, Hubei, Jiangxi, Zhejiang and Anhui (9 provinces)
Wheat	Inner Mongolia, Sichuan, Anhui, Shandong, Shanxi, Xinjiang, Jiangsu, Hebei, Henan, Gansu and Shaanxi (13 provinces)
Maize	Inner Mongolia, Jilin, Shandong, Shaanxi, Hebei, Henan, Gansu, Liaoning, Shanxi, Heilongjiang, Yunnan, Sichuan, Jiangsu, Hubei and Xinjiang (15 provinces)

Source: Calculations based on the grain sown area of each province from 1984 to 2017.

Table 2
Input and output variables description.

Category	Variable name	Description	Data sources
Yield variable	Yield (kg/mu)	The average yield of grain per unit land (mu)	Compilation of Cost-Benefit Data of Agricultural Products (CCBDAP)
Input variables	Labor (day/mu)	The average labor input per unit land	CCBDAP
	Chemical (yuan/mu)	The actual cost of chemical fertilizer and pesticide per unit land	CCBDAP
	Machinery (yuan/mu)	The average level of machinery input per unit land	CCBDAP
	Irrigation (yuan/mu)	The average irrigation input level per unit land	CCBDAP
	Seeds (yuan/mu)	The average seed input cost per unit land	CCBDAP
	Manure (yuan/mu)	The average farmyard manure per unit land	CCBDAP

Note: The price of input factors is inevitably affected by inflation. This paper uses the price index of agricultural means of production over the years in different regions to reduce the average input of chemical fertilizer and pesticide per mu.

4.2. Variables description

We collected the provincial level dataset from 1984 to 2017 with detailed information of input-output variables and other control variables (Table 2). The data of input and output variables were calculated as the per unit of land area. Notably, the capital investment had been decomposed into agro-chemicals, machinery, irrigation, seed, and manure to accommodate the functional difference of capital investment.

Regarding the control variables (Table 3), the natural disaster impact, grain planting preference, development of non-agricultural sector, irrigating capability, rural power consumption, and policy shocks had been included.

5. Results and discussion

5.1. Descriptive statistics

We first group the cereal types into four categories: early indica rice, japonica rice, wheat, and maize. Then we divide the period of 1984–2017 into three phases, i.e. 1984-1993, 1994–2003, and 2004–2017.

Overall, crop yields have undergone significant growth with the unit land yield growing almost continuously. The unit land yield of japonica rice was significantly higher than that of early indica rice in each period, which was due to the northern distribution of japonica rice and longer maturity period. Second, in terms of input factors, numerous types of capital input have increased in the process of grain production, while labor input has been declining. The chemical fertilizer input of rice increased rapidly. Within the rice crop, the land average fertilizer input of japonica rice is higher than that of early indica rice. The land average chemical fertilizer input of japonica rice reached 181.9 yuan during the period of 2004–2017, which was more than five times that of 1984–1993. In addition, the chemical fertilizer input of wheat and maize also shows an increasing trend, but it is lower than that of rice.

Regarding machinery input, the machinery input of rice was higher than that of wheat and maize per unit of land. The machinery input of early indica rice increased from 8.5 yuan to 124.9 yuan between 2004 and 2017. In the land average irrigation input, the japonica rice is the highest, followed by wheat, maize and early indica rice. Japonica rice is mostly distributed in the northern plains and high-altitude areas in the south. The irrigation water consumption of rice crops is high, while natural precipitation in the north is insufficient, thus the irrigation cost is the highest. On the contrary, early indica rice is mostly distributed to the south of the Yangtze River. Although the water consumption is high, the land average irrigation cost is the lowest among the four crops due to the greater natural precipitation. Inputs of farmyard manure were not high for all four crops. For example, the organic fertilizer of early indica rice used per unit of land was 7.2 yuan from 1984 to 1993, then this value rose to 10.9 yuan from 2004 to 2017, showing an insignificant increase. The rapid increase of capital input corresponds to the continuous decline of agricultural labor input. The land average labor input of wheat decreased from 13.7days in the first period to 6.2days in the third period, the land average labor input decreased by 54.363 %, and that of early indica rice with higher mechanical input decreased by 61.08 %, thus indicating that the crops with superior

Table 3
Control variables description.

Category	Variable name	Description	Data sources
Control variables	ND (%)	Natural disaster impact (affected area/disaster area)	Compilation of Statistical Data of PRC 60 years (CSDP60) & China Rural Statistical Yearbook (CRSY)
	CA (%)	Proportion of grain planting area (grain planting area/ crop planting area)	CSDP60 & CRSY
	NAD (%)	Development of non-agricultural sector (non-agricultural sector GDP/GDP)	CSDP60 & CRSY
	IRR (%)	Proportion of effective irrigation area (effective irrigation area/crop planting area)	CSDP60 & CRSY
	ELE ($KWh*10^{10}$)	Rural power consumption	CSDP60 & CRSY
	TIME	Policy variables (time dummy for exogenous policy shocks)	–

machinery substitution exhibit a faster decline of labor input.

In addition to input-output variables, other provincial variables also exhibit certain characteristics. First, although natural disaster impact variable (ND) contains some man-made disaster resistance factors, this variable does not decrease with time from the perspective of descriptive statistical results. On the contrary, the negative impact of natural disaster impact is the most obvious in the second period (1994–2003), while being relatively small in the other two periods. This also reveals that disaster relief can only reduce the losses caused by natural disasters to a certain extent yet cannot fundamentally change this trend. Second, the proportion of output value of secondary and tertiary industries continues to increase over time, and the proportion of grain planting area gradually decreases. The rising proportion of non-agricultural output value is the trend of economic development, while the decline of the proportion of grain planting area reflects the fact that the proportion of cash crop planting increased, and farmers' planting preference has altered to a certain extent.

5.2. Regression estimation results

The convergence estimation results of four cereal crops in their main production areas are present in Table 6 and Table 7. The first column of each crop reports the preliminary convergence results estimated by the OLS method. Deltaly0 is the growth rate of per unit

Table 4
Descriptive statistics of variables (early indica rice and japonica rice).

	Early indica rice		Japonica rice	
	Group = 1 N = 90		Group = 1 N = 120	
Variable	Mean	S.D.	Mean	S.D.
Yield (kg/mu)	367.0	29.1	415.3	72.7
LaborInput (days/mu)	20.0	2.8	22.4	7.6
Chemical (yuan/mu)	31.6	12.9	32.9	15.9
Machinery (yuan/mu)	8.5	4.6	8.4	9.5
Irrigation (yuan/mu)	3.3	1.9	8.9	8.3
Seeds (yuan/mu)	9.2	8.0	10.5	8.3
OrganicManure (yuan/mu)	7.2	3.2	6.0	5.1
	Group = 2 N = 90		Group = 2 N = 120	
Variable	Mean	S.D.	Mean	S.D.
Yield (kg/mu)	365.7	29.6	470.8	65.7
LaborInput (days/mu)	14.6	3.1	16.7	6.9
Chemical (yuan/mu)	74.0	17.5	92.2	28.1
Machinary (yuan/mu)	28.9	14.7	26.6	13.1
Irrigation (yuan/mu)	8.1	2.7	29.3	20.5
Seeds (yuan/mu)	15.9	5.8	19.0	10.6
OrganicManure (yuan/mu)	8.7	3.5	8.4	6.7
	Group = 3 N = 126		Group = 3 N = 168	
Variable	Mean	S.D.	Mean	S.D.
Yield (kg/mu)	406.9	25.0	535.6	63.5
LaborInput (days/mu)	7.8	2.6	9.2	4.4
Chemical (yuan/mu)	146.9	39.9	181.9	56.5
Machinary (yuan/mu)	124.9	62.3	115.2	62.7
Irrigation (yuan/mu)	8.7	2.7	47.3	30.1
Seeds (yuan/mu)	37.7	18.5	38.4	25.3
OrganicManure (yuan/mu)	10.9	21.2	11.6	13.0

Notes: Group = 1, Group = 2, and Group = 3 refers to the period between 1984 and 1993, 1994–2003, and 2004–2017, respectively. Because of the space limitation, Table 2 only presents the mean and standard deviation of variables. For its detailed information and other variables, please check Table A1 in the Appendix.

Table 5
Descriptive statistics of variables (wheat and maize).

	Wheat		Maize	
	Group = 1 N = 110		Group = 1 N = 150	
Variable	Mean	SD	Mean	SD
Yield (kg/mu)	241.4	42.1	341.4	76.7
LaborInput (days/mu)	13.7	4.8	16.7	7.3
Chemical (yuan/mu)	25.5	11.4	20.5	9.8
Machinery (yuan/mu)	6.7	5.8	4.4	9.2
Irrigation (yuan/mu)	4.5	4.8	3.2	5.9
Seeds (yuan/mu)	10.2	3.5	6.7	5.8
OrganicManure (yuan/mu)	7.6	3.8	6.6	4.2
	Group = 2 N = 110		Group = 2 N = 150	
Variable	Mean	SD	Mean	SD
Yield (kg/mu)	283.9	50.4	367.8	92.9
LaborInput (days/mu)	11.0	3.6	14.7	9.0
Chemical (yuan/mu)	67.2	18.0	63.6	19.5
Machinery (yuan/mu)	29.6	13.0	12.6	10.9
Irrigation (yuan/mu)	19.3	13.8	11.3	12.2
Seeds (yuan/mu)	26.5	9.7	18.2	4.8
OrganicManure (yuan/mu)	10.6	5.4	11.4	7.7
	Group = 3 N = 110		Group = 3 N = 210	
Variable	Mean	SD	Mean	SD
Yield (kg/mu)	368.8	64.3	472.7	83.1
LaborInput (days/mu)	6.2	2.3	8.2	3.8
Chemical (yuan/mu)	139.8	59.3	128.5	31.8
Machinery (yuan/mu)	94.4	37.3	65.8	42.2
Irrigation (yuan/mu)	34.1	25.4	18.3	17.5
Seeds (yuan/mu)	52.3	22.2	49.9	60.6
OrganicManure (yuan/mu)	13.7	11.2	14.2	12.1

Notes: Group = 1, Group = 2, and Group = 3 refers to the period between 1984 and 1993, 1994–2003, and 2004–2017, respectively. Because of the space limitation, Table 3 only presents the mean and standard deviation of variables. For its detailed information and other variables, please check Table A2 in the Appendix.

land yield in phase t relative to the beginning of the period, LnY_0 is the logarithm of per unit land yield in each province at the beginning of the period, and its coefficient is the absolute convergence coefficient. The second, third and fourth columns show the convergence test results obtained by the panel data regression method, in which deltaLY is the growth rate of output in t period relative to output in t-1 period, and LnY_{t-1} is the logarithm of average grain output per unit land in t-1 period, the coefficient of which is the convergence coefficient. The second column lists the two-way fixed effect regression results, the third column the first-order difference generalized method of moments (DIF-GMM) regression results, and the fourth column the system generalized method of moments (SYS-GMM) regression results.

A series of statistical tests must be conducted on the model before using GMM. First, it is necessary to test the choice of lag period of the model. According to the description in the model setting part, the first-order lag term of the dependent variable in the regression model determines the convergence of land average crop yield, while the second-order lag term must be used as the instrumental variable of the first-order lag term to eliminate the endogenous problem of the first-order lag term. According to this, the standard of dependent variable sequence correlation test is that the first-order correlation is significant, while the second-order correlation is not significant. This is because the first-order lag of the dependent variable has a strong correlation with the dependent variable itself, which can explain the change of the dependent variable to a certain extent. The second-order lag term is not related to the dependent variable itself, and it is an instrumental variable that meets the exogenous assumption. Second, the independent variables other than the dependent variable lag term in the model should be over-identified. If the test results cannot reject the original hypothesis, then the other variables in the model are exogenous. According to the test results in Tables 4 and 5, all tests of the convergence model have been passed, and the setting of the convergence model of four types of crops is reasonable.

According to the OLS estimation, the land average yield of the four crops exhibits a convergence trend, namely, without considering any other conditions, the average yield per unit land of the four food crops bears a convergence trend in their main production areas. After considering the individual characteristics, policy impact and other socio-economic conditions in the various regions during the panel data convergence, it is observed that the average output per unit land of a crop in its main production area still exhibits the convergence characteristics. After considering the characteristics of other provinces, the convergence of yield per unit land of japonica rice, early indica rice, maize and other crops has increased, while the convergence trend of land average yield of wheat crops has weakened after considering other effects. In the respective convergence regressions of japonica rice, early indica rice, maize and wheat, the lagged term of dependent variables is significant at the level of 1 %, and the convergence trend of crop yield per unit land in its main production area is relatively stable.

Based on the description in the theoretical mechanism part, the increase of average capital investment per unit land and the decline of marginal return on capital are important reasons for the convergence of grain crops. In the regression analysis, the heterogeneous impact of the increase of different types of land average capital investment on land average grain yield was considered. First, the

Table 6
Convergence analysis of Japonica rice and early indica rice.

	Japonica rice				Early indica rice			
	OLS	FE twoway	DIF GMM	SYS GMM	OLS	FE twoway	DIF GMM	SYS GMM
	deltaLY0	deltaLY	deltaLY	deltaLY	deltaLY0	deltaLY	deltaLY	deltaLY
LnYieldt0	−0.61***				−0.42***			
	(-13.21)				(-4.36)			
LnYieldtm1		−0.68***	−0.71***	−0.51***		−0.8***	−0.8***	−0.67***
		(-14.43)	(-4.95)	(-0.68)		(-10.28)	(-3.19)	(-4.75)
Lnlaborinput		−0.07	−0.11***	−0.02		0.03	−0.02	0.01
		(-1.73)	(-4.26)	(-0.65)		(0.77)	(-0.37)	(0.5)
lnchemical		0.09**	0.11***	0.08***		0.02	−0.003	−0.004
		(2.4)	(3.83)	(3.29)		(0.62)	(-0.12)	(-0.21)
lnmachine		0.03*	0.04***	0.04**		0.01	0.07***	0.05*
		(1.86)	(2.71)	(2.39)		(0.38)	(2.69)	(1.95)
lnirr		0.02*	0.03***	0.03**		0.04*	−0.002	0.004
		(1.84)	(3.12)	(2.05)		(2.09)	(-0.1)	(0.3)
lnseeds		0.01	0.004	0.03		−0.01	0.01	0.02
		(0.43)	(0.22)	(1.38)		(-0.84)	(0.42)	(1.49)
lnOrganicM		0.001	−0.001	0.02*		0.02**	0.02***	0.01
		(0.04)	(-0.06)	(1.87)		(2.39)	(3.88)	(1.41)
NAD		−0.18	−0.05	0.05		−0.15	0.01	0.15
		(-0.93)	(-0.33)	(0.28)		(-1.1)	(0.04)	(1.38)
ND		−0.02	−0.04*	−0.02		−0.05	−0.07*	−0.06
		(-0.53)	(-1.73)	(-1.12)		(-0.98)	(-1.79)	(-1.45)
CA		0.19*	0.24**	0.09		0.1	−0.02	−0.04
		(1.83)	(2.28)	(1.35)		(0.82)	(-0.15)	(-0.76)
ELE		$-0.23^{*}\ 10^{-4}$	$-0.93^{*}\ 10^{-3}$	$-0.25^{*}\ 10^{-5}$		$-0.23^{*}\ 10^{-4**}$	$-0.15^{*}\ 10^{-4}$	$-0.29^{*}\ 10^{-4**}$
		(-1.42)	(-1.43)	(-0.22)		(-2.64)	(-0.9)	(-2.15)
Constant	3.81***	3.92***	4.43***	3.76***	2.5***	4.52***	4.64***	3.67***
	(13.87)	(10.89)	(13.53)	(13.62)	(4.38)	(11.25)	(10.97)	(9.28)
Individual fixed effect[a]	NO	YES	NO	NO	NO	YES	NO	NO
Time fixed effect	NO	YES	NO	NO	NO	YES	NO	NO
First stage	–	–	−2.89***	−2.98***	–	–	−2.66***	−2.59***
Second stage	–	–	−0.97	−0.57	–	–	−0.02	0.41
sargan	–	–	389.81	664.99	–	–	275.82	524.3
N	408	396	384	396	306	297	288	297
R^2	0.3	0.5	–	–	0.06	0.58	–	–
F	174.37	–	–	–	18.99	–	–	–

Note: *t* statistics are in parentheses (*p $<$ 0.1, **p $<$ 0.05, ***p $<$ 0.01). a clustering standard error at provincial level.

chemical fertilizer and pesticide inputs were significantly positive in the three models for the japonica rice crop. The two-way FE model was significant at 5 % level, while the significance level of the other two types of GMM models was 1 %. The inputs of machinery and irrigation were also significant and positive in the three models, with the marginal effect on the increase of land average yield was smaller than that of the input of chemical fertilizer and pesticide. Therefore, the increases use of chemical fertilizer and pesticide, machinery and irrigation are the main reasons for the increase of japonica rice land average yield, with the yield increasing effects of chemical fertilizer and pesticide input being particularly prominent. Second, for the early indica rice crops, the machinery input variables are significantly positive in the two types of GMM models, in which the significance level of the differential GMM model is 1 %, that of the system GMM model is 10 %, and the coefficient of two-way FE model is positive, yet not significant. Organic fertilizer variables were significantly positive in the two-way FE model and differential GMM model yet had no significant positive effect in the system GMM model.

In the three models, the sign of coefficients of the three capital variables (chemical fertilizer, pesticide, irrigation) and seed are inconsistent and insignificant. Therefore, the main factors promoting the growth of per unit land yield are machinery and manure. Finally, seeds, machinery, and chemical fertilizer are the main capital factors contributing to the wheat yield growth while machinery and chemical fertilizer are responsible for the maize yield growth.

The estimated coefficients of the labor input variables in the early indica rice and maize crop models are inconsistent and statistically insignificant. They have a negative impact in japonica rice crop model and have a significance of 1 % in the two types of GMM models, while having a positive effect in wheat crop regression, and are only significant in the two-way FE model. These results suggest that the per unit grain yield can hardly rely on the increase of labor and it cannot explain the convergence of land average grain yield. Holding other control variables constant, the impact of non-agricultural output value on the growth rate of per unit land yield of different crops exhibits large differences. This variable may have positive and negative effects on per unit land yield of grain and the regression results are basically as we expected.

Regarding the natural disasters, it plays a negative role in the regression models of all four crops and have statistical significance in the partial regression of early indica rice and wheat crops, which shows that the negative effect of natural disasters on grain yield

Table 7
Convergence analysis of wheat and maize yield.

	Wheat				Maize			
	OLS	FE Two-way	DIF GMM	SYS GMM	OLS	FE Two-way	DIF GMM	SYS GMM
	deltaLY0	deltaLY	LnYield	LnYield	deltaLY0	deltaLY	LnYield	LnYield
LnYieldt0	−0.6*** (-6.75)				−0.98*** (-20.53)			
LnYieldtm1		−0.64*** (-11.98)	−0.65*** (-5.16)	−0.58*** (-7.95)		−0.77*** (-13.82)	−0.73*** (-6.08)	−0.65*** (-8.17)
Lnlaborinput		0.11* (1.82)	0.01 (0.37)	0.05 (1.22)		0.09* (2.09)	−0.02 (-0.63)	−0.03 (-0.81)
lnchemical		0.1** (2.42)	0.05 (1.42)	0.1*** (3.61)		0.2*** (4.25)	0.14*** (3.39)	0.13*** (3.60)
lnmachine		0.06** (2.88)	0.07** (2.36)	0.1*** (2.78)		0.01 (0.88)	0.08*** (3.37)	0.01*** (3.74)
lnirr		0.031 (0.9)	0.05* (1.67)	0.01 (0.22)		0.02 (1.14)	−0.02 (-0.91)	0.01 (0.67)
lnseeds		0.22** (2.48)	0.26*** (4.57)	0.12*** (2.71)		0.003 (0.14)	0.05** (2.47)	0.02 (0.1)
lnOrganicM		0.001 (0.06)	0.01 (0.34)	0.01 (0.83)		0.01 (0.52)	0.01 (0.99)	0.03 (1.62)
NAD		−0.28 (-1)	0.34 (1.4)	0.2* (1.95)		0.12 (0.31)	0.1 (0.68)	−0.14 (-1.13)
ND		−0.151 (-1.705)	−0.143** (-2.145)	−0.155** (-2.056)		−0.002 (-0.049)	−0.012 (-0.232)	0.027 (0.541)
CA		0.146 (0.738)	−0.103 (-0.630)	−0.207*** (-3.028)		−0.185 (-0.896)	−0.264 (-1.244)	−0.122 (-1.013)
ELE		−0.182* 10^{-4} (-0.562)	−0.230* 10^{-4} (-0.716)	−0.213* 10^{-4} (0.613)		−0.720* 10^{-4}*** (-3.146)	−0.351* 10^{-4} (-1.224)	−0.518* 10^{-4}* (-1.850)
Constant	3.488*** (7.248)	2.496*** (8.776)	2.636*** (9.284)	2.461*** (8.661)	5.842*** (22.387)	3.708*** (5.777)	3.915*** (10.224)	3.557*** (11.997)
Individual fixed effect	NO	YES	NO	NO	NO	YES	NO	NO
Time fixed effect	NO	YES	NO	NO	NO	YES	NO	NO
First stage	–	–	−2.620***	−2.627***	–	–	−3.177***	−3.205***
Second stage	–	–	1.552	1.533	–	–	1.245	1.184
Sargan	–	–	316.0781	607.858	–	–	442.3469	811.3122
N	374	363	352	363	510	495	480	495
R2	0.109	0.582	–	–	0.453	0.652	–	–
F	45.497	–	–	–	421.472	–	–	–

Note: *t* statistics are in parentheses (*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$). [a] clustering standard error at provincial level.

cannot be ignored. With the exception that the proportion of grain sown area has a consistent positive impact and partially significant in the three japonica rice regression models, in the other crop models it is either negative and not significant, or the direction of coefficient symbols is inconsistent. This suggests excluding japonica rice crops, the improvement of grain planting preference cannot effectively promote the growth of land average grain yield. The coefficients of rural electricity consumption variables in all regression models are negative and have a significant negative effect in the partial regression of early indica rice and maize crops. This is because more petrochemical energy and less power resources are used in agricultural production. The development of non-agricultural industry is the main driver for the increase of power consumption in rural areas. The development of rural non-agricultural industry reduces farmers' incentives for agricultural production, which will in turn exert a negative effect on the growth of per unit land grain yield.

6. Conclusion and policy implications

China's grain production has made remarkable progresses in the last decades and the total grain output has more than doubled as compared to that in the end of 1970s. At the same time, with the continuous development of non-agricultural economy, a large portion of the agricultural labor force has migrated to non-agricultural sectors, and grain production become more capital intensive oriented (i. e. capital deepening). This study analyzes the effects of capital investments on the growth of grain yield per unit land and the convergence of grain crops in their main planting areas.

Three main finding emerge from the empirical analysis. First, chemical fertilizer, pesticide and machinery were important factors to increase the growth of grain yield in the per unit land perspective. Second, for all four crops (early indica rice, japonica rice, wheat and maize), the per unit land yield witnessed a convergence trend in the main production areas. When including control variables of individual region characteristics, the development of non-agricultural industries, the impact of natural disasters and various exogenous policies, the convergence of per unit land yield is still hold. Specifically, the convergence of japonica rice, wheat and maize increased while the convergence trend of indica rice crops weakened. Third, increasing the grain yield per unit land in areas with lower initial levels is an important way to maintain China's food security. In terms of spatial distribution of grain production, the convergence of grain yield per unit land between regions also facilitates spatial adjustment of grain cultivation.

Several policies can be drawn from the findings. First, considering the continuous promotion of China's spatial urbanization process in the future, the plan to ensure grain production by expanding the grain planting area is not feasible. Instead, to increase grain per unit land yield will be the primary means by which to ensure food security in the future. Although the technological progress contained in capital elements has effectively promoted the growth of grain land average yield, capital deepening itself also has some limitations, such as soil degradation caused by the abuse of chemical fertilizers and pesticides and the increasingly pollution of rural water sources. Therefore, the government should guide farmers to make more reasonable capital investments, through advocating technologies such as the soil testing and formula fertilization and introducing new varieties.

Second, the finding of per unit land of grain output among provinces is narrowing providing a theoretical explanation of the Chinese land policy. For instance, since the implementation of the "Cultivated land balancing system" policy in 1997, China has banned the cross-provincial cultivated land occupation and compensation and this regulation ended up by the end of 2016. If the variation of per unit land yield of a specific grain crop in different provinces is increasing, the cross-provincial cultivated land occupation and compensation are expected to be "unbalanced". In other words, if one mu of cultivated land is occupied in areas with higher grain yield per mu, then the compensation in areas with lower grain yield per unit land must be greater than one mu. However, if there is a convergence trend in the yield of a given cereal crop between provinces, then the "Cross-provincial cultivated land balancing system" will be closer to the "balanced". That is, the occupied areas and compensated areas area tend to be equal. In this way, the "Cross-provincial cultivated land balancing system" is conducive to the more effective use of limited cultivated land resources and to maintain national food security under the context of industrialization and urbanization. It should be noted that the spatial distribution of grain cultivation is not only determined by the grain yield per unit land and the comparative benefits of grain cultivation, but also directly influenced by regional non-agricultural economic development and the national development strategy. And this is not the main concern of the study and will be the possible direction of relevant research in the future.

7. Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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CRediT authorship contribution statement

Sicheng Zhao: Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization. **Yu Hong:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Guogang Wang:** Writing – review & editing, Validation, Supervision, Software.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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If applicable.

Appendix

Table A1
Descriptive statistics of variables (Early indica rice, Japonica rice)

	Early indica rice				Japonica rice			
	Group = 1 N = 90				Group = 1 N = 120			
Variable	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Yield (kg/mu)	367.0	29.1	268.1	447.5	415.3	72.7	272.0	615.1
LaborInput (days/mu)	20.0	2.8	13.9	26.6	22.4	7.6	11.4	42.1
Chemical (yuan[a]/mu)	31.6	12.9	8.4	73.7	32.9	15.9	0.0	73.7

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Table A1 (*continued*)

	Early indica rice				Japonica rice			
Machinery (yuan/mu)	8.5	4.6	3.0	27.0	8.4	9.5	0.0	57.7
Irrigation (yuan/mu)	3.3	1.9	0.4	8.0	8.9	8.3	1.5	41.5
Seeds (yuan/mu)	9.	8.0	2.8	33.7	10.5	8.3	2.7	59.9
OrganicManure (yuan/mu)	7.2	3.2	0.8	20.2	6.0	5.1	0.2	30.9
Development level of non-agricultural industry (NAD)	0.7	0.1	0.4	0.8	0.7	0.1	0.6	0.9
Natural disaster impact (ND)	0.4	0.2	0.0	0.9	0.5	0.1	0.3	0.9
Proportion of grain sown area (CA)	0.7	0.0	0.6	0.8	0.8	0.1	0.7	0.9
Rural power consumption (100 million kWh) (ELE)	26.1	24.9	0.0	127.7	39.5	32.3	1.8	169.2
	Group = 2 N = 90				Group = 1 N = 120			
Variable	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Yield (kg/mu)	365.7	29.6	286.5	421.8	470.8	65.7	331.1	614.8
LaborInput (days/mu)	14.6	3.1	6.7	22.9	16.7	6.9	6.8	38.1
Chemical (yuan/mu)	74.0	17.5	32.0	122.3	92.2	28.1	44.3	178.7
Machinary (yuan/mu)	28.9	14.7	6.6	80.6	26.6	13.1	5.5	67.1
Irrigation (yuan/mu)	8.1	2.7	2.7	14.8	29.3	20.5	5.4	98.1
Seeds (yuan/mu)	15.9	5.8	8.1	33.7	19.0	10.6	8.0	60.3
OrganicManure (yuan/mu)	8.7	3.5	2.6	21.1	8.4	6.7	0.2	30.9
Development level of non-agricultural industry (NAD)	0.8	0.1	0.6	0.9	0.8	0.1	0.7	0.9
Natural disaster impact (ND)	0.5	0.1	0.3	0.8	0.5	0.1	0.2	0.9
Proportion of grain sown area (CA)	0.6	0.1	0.5	0.7	0.7	0.1	0.5	0.9
Rural power consumption (100 million kWh) (ELE)	96.7	130.6	1.2	714.3	108.5	102.4	2.0	529.5
	Group = 3 N = 126				Group = 3 N = 168			
Variable	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max
Yield (kg/mu)	406.9	25.0	326.5	455.9	535.6	63.5	363.5	717.1
LaborInput (days/mu)	7.8	2.6	3.5	14.7	9.2	4.4	3.0	25.7
Chemical (yuan/mu)	146.9	39.9	54.9	224.9	181.9	56.5	69.4	299.6
Machinary (yuan/mu)	124.9	62.3	19.3	270.6	115.2	62.7	12.0	269.1
Irrigation (yuan/mu)	8.7	2.7	0.4	17.8	47.3	30.1	5.3	157.8
Seeds (yuan/mu)	37.7	18.5	11.5	83.2	38.4	25.3	10.8	146.1
OrganicManure (yuan/mu)	10.9	21.2	1.0	129.1	11.6	13.0	0.0	49.5
Development level of non-agricultural industry (NAD)	0.9	0.1	0.7	1.0	0.9	0.0	0.8	1.0

Note: Group = 1 signifies the period between 1984-1993, Group = 2 is 1994–2003, and Group = 3 is 2004–2017. [a] yuan is Chinese currency.

Table A2
Descriptive statistics of variables (wheat, maize)

	Wheat				Maize			
	Group = 1 N = 110				Group = 1 N = 150			
Variable	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Yield (kg/mu)	241.4	42.1	122.1	358.9	341.4	76.7	218.0	562.9
LaborInput (days/mu)	13.7	4.8	3.6	25.9	16.7	7.3	6.4	61.4
Chemical (yuan/mu)	25.5	11.4	6.9	55.2	20.5	9.8	0.2	51.0
Machinary (yuan/mu)	6.7	5.8	0.3	33.2	4.4	9.2	0.0	49.0
Irrigation (yuan/mu)	4.5	4.8	0.1	23.6	3.2	5.9	0.0	29.7
Seeds (yuan/mu)	10.2	3.5	4.8	21.6	6.7	5.8	1.3	35.7
OrganicManure (yuan/mu)	7.6	3.8	0.5	23.9	6.6	4.2	0.0	19.7
Development level of non-agricultural industry (NAD)	0.7	0.1	0.6	0.9	0.7	0.1	0.6	0.9
Natural disaster impact (ND)	0.5	0.1	0.1	0.9	0.5	0.1	0.1	0.8
Proportion of grain sown area (CA)	0.8	0.1	0.6	0.9	0.8	0.1	0.6	0.9
Rural power consumption (100 million kWh) (ELE)	37.4	31.0	5.6	169.2	33.6	28.4	5.6	169.2
	Group = 2 N = 110				Group = 2 N = 150			
Variable	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Yield (kg/mu)	283.9	50.4	183.9	389.2	367.8	92.9	185.9	611.6
LaborInput (days/mu)	11.0	3.6	5.0	20.6	14.7	9.0	4.7	101.0
Chemical (yuan/mu)	67.2	18.0	14.4	98.6	63.6	19.5	29.7	131.1
Machinary (yuan/mu)	29.6	13.0	2.5	54.8	12.6	10.9	0.0	65.4
Irrigation (yuan/mu)	19.3	13.8	0.5	51.7	11.3	12.2	0.0	50.4
Seeds (yuan/mu)	26.5	9.7	11.2	52.2	18.2	4.8	7.9	37.8
OrganicManure (yuan/mu)	10.6	5.4	0.0	23.8	11.4	7.7	1.3	59.9
Development level of non-agricultural industry (NAD)	0.8	0.1	0.7	0.9	0.8	0.1	0.7	0.9
Natural disaster impact (ND)	0.5	0.1	0.2	0.8	0.5	0.1	0.2	0.9
Proportion of grain sown area (CA)	0.7	0.1	0.4	0.9	0.7	0.1	0.4	0.9
Rural power consumption (100 million kWh) (ELE)	97.4	93.9	0.2	529.5	84.0	85.2	0.2	529.5
	Group = 3 N = 154				Group = 3 N = 210			
Variable	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Yield (kg/mu)	368.8	64.3	216.5	494.3	472.7	83.1	250.0	714.7
LaborInput (days/mu)	6.2	2.3	2.7	14.2	8.2	3.8	2.5	19.6

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Table A2 (*continued*)

	Wheat				Maize			
Chemical (yuan/mu)	139.8	59.3	44.8	539.0	128.5	31.8	60.2	197.7
Machinary (yuan/mu)	94.4	37.3	5.0	165.5	65.8	42.2	1.0	160.1
Irrigation (yuan/mu)	34.1	25.4	0.0	88.6	18.3	17.5	0.0	84.5
Seeds (yuan/mu)	52.3	22.2	17.2	108.5	49.9	60.6	14.9	523.3
OrganicManure (yuan/mu)	13.7	11.2	0.0	63.8	14.2	12.1	0.0	47.8
Development level of non-agricultural industry (NAD)	0.9	0.0	0.8	1.0	0.9	0.0	0.8	1.0
Natural disaster impact (ND)	0.5	0.1	0.1	0.8	0.5	0.1	0.1	0.8
Proportion of grain sown area (CA)	0.7	0.1	0.3	0.9	0.7	0.1	0.3	1.0
Rural power consumption (100 million kWh) (ELE)	297.3	413.8	26.7	1888.0	251.5	369.0	23.7	1888.0

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