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Changes in rice yield in China under future climate scenarios

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Changes in rice production in China under future climate scenarios

Abstract

The Levinsohn-Petrin consistent semi-parametric estimation method was used to empirically analyze input-output panel data on rice yields in 30 Chinese provinces from 1990 to 2019 and to predict the level of rice yields at the end of the 21st century. The results show that, in addition to natural disasters and objective natural conditions, rice yields depend mainly on pesticide application, that China's current rice production and operation model is insufficient to match the rapidly growing level of agricultural mechanization, and that promoting large-scale production in rice fields is an effective way to address the waste of agricultural machinery resources. From the prediction results, the model has stronger prediction ability for the central-eastern and southern production areas of China, and very low prediction ability for the northern and western areas. The prediction of rice yield levels in China shows that rice yields in China at the end of the 21st century increase by 9.81% under the RCP8.5 climate scenario.

This paper puts forward targeted suggestions for improving rice yields. The government should strengthen the promotion and training of agricultural technology and increase the channels for farmers to learn rice cultivation techniques; promote large-scale rice production and operation; and improve the education level of rice growers.

Key words: yield of rice; influence factor; Levinsohn-Petrin model

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1 Introduction

Global climate change, mainly characterized by warming, poses a threat to agricultural productivity, with global mean surface temperature projected to increase by 1.5°C - 4°C in 2081-2100 relative to 1850-1900 under various CMIP5 scenarios, with the potential to exceed 4°C under RCP8.5 scenarios (Collins, et al., 2013). As a basic industry, agriculture is directly related to human survival, development, and social stability. With a projected population of 9.1 billion by 2050, annual cereal production needs to increase from the current 2.1 billion tons to about 3 billion tons (FAO, 2018). The global population will further increase to 11.2 billion by 2100. In 2020, China has 18% of the world's population and about 25% of the world's grain production. China's grain production can be divided into cereals, potatoes and legumes by crop species, with cereals dominating, accounting for 92% of China's grain production, in which rice accounting for 34% of cereals production. It is necessary to understand and predict the future rice production in China in the context of the world's population explosion, warming climate, concentrated precipitation, and frequent climate extremes.

Much of the existing research has focused on the effects of climate warming on rice yields. In general, higher temperatures are expected to have a negative impact on rice yields (Li, et al., 2015; Zhao, et al., 2017). However, a study of rice yield in Korea from 1991 to 2011 found that the effect of average temperature on rice yield was positive and negatively correlated with the degree of frost and heavy rainfall (Nam, et al., 2013). Extreme weather greatly affects rice production (Huang, et al., 2018; Chen, et al., 2020), Numerous studies predict that future flood events in most areas of China will occur more frequently, with greater intensity and for longer durations than those currently prevalent (Xu, et al., 2014; Chen, et al., 2013), the magnitude of flooding in many basins is projected to increase dramatically by more than 50% from 2056-2100 compared to 1961-2005 (Yin, et al., 2020). As one of the major natural disasters in China at present, the overall spatial extent of drought in China is expected to decrease significantly in the future, with a decrease in the frequency of drought in most of the northern regions and a slight increase in the frequency of drought in some parts of southern China (Chen, et al., 2013; Li, et al., 2020; Chen, et al., 2021).

On the other hand, total factor productivity in agriculture as an important indicator of agricultural production, many scholars explore the causes of total factor productivity growth in China's agriculture based on the Malmquist index method, concluding that technological progress is the main reason for total factor productivity growth in agriculture and that labor input does not play a significant role in agricultural economic growth (Chen, et al., 2008; Fang & Zhang, 2010; Jin, et al., 2002), however, labor inputs, fertilizer application and diesel fuel are factors that directly affect the technical efficiency of agricultural output (Huang, et al., 2021). With the advancement of agricultural technology, the loss of rice yield caused by climatic conditions can be compensated by agricultural technology. The main socio-economic factors influencing the adoption of agricultural technology by growers are length of residence, land ownership and education level (Fashola, et al., 2007).

In addition, Chinese scholars' research on future rice yield forecasting is mostly based on the Cobb-Douglas form of production function, using the Malmquist-DEA method to measure total factor productivity, and then using gray prediction models and stepwise regression models to estimate yield, but the LP method is less applied in China.

A summary of previous studies on grain yield influencing factors reveals that the current literature mostly focuses on the analysis of the degree of influence of single factors on grain yield, and there are fewer studies that systematically analyze rice yields. China ranks first in the world in total rice production, but only 13th in yield ranking (https://www.atlasbig.com/zh). How to grow high-yielding rice on limited arable land and thus increase rice production is a question that should be thought about today. Based on this, this paper builds on existing research results, combines climatic variables and socioeconomic factor variables to describe the variation of rice yield per hectare in China. This paper achieves two main objectives: 1. To study the effects of climatic conditions and socioeconomic factors on rice yields per hectare from 1990-2019. 2. Changes in rice yields per hectare at the end of the 21st century (2080-2099) relative to the baseline period (1990-2019) under RCP8.5 scenarios.

This paper is structured as follows. Section 2 focuses on the methodology and the model. Section 3 focuses on the variables involved in the model and the processing of the data, Section 3.1 is the processing of the observed data and Section 3.2 is the processing of the data for future climate scenarios. Section 4 presents the changes in rice yield production in China over the past 30 years, the results of the production function, and the prediction of future rice yields

2. Methods

This paper integrates the following two aspects of the study: prognosis of total factor productivity in agriculture and future food production under climate change scenarios. We first analyze the drivers of productivity improvement by a consistent semiparametric approach using agriculture-related data from 1990-2019. For total factor productivity estimation is usually based on macro data starting from estimating the production function. We have integrated biophysical and socio-economic databases to characterize the nature state variables and management factors (Quiroga & Suárez, 2016). The measured TFP is then used to predict future food production in the years 2080-2099.

2.1 Total Factor Productivity in Agriculture

There are several common methods for calculating total factor productivity, such as OLS, FE, IV, OP, LP, and GMM. When the production process is a single factor input, the productivity measure is simple. To more accurately measure the level of variation in input factor productivity, instead of using single factor productivity, the concept of total factor productivity is usually used. The traditional OLS least squares approach to productivity estimation requires that the inputs in the production function are exogenous variables, and that the farmer will optimize productivity by changing factor allocation. In this case, this observable productivity affects factor inputs, which can be endogenous and lead to biased OLS results. To address this problem many scholars have proposed fixed effects estimation and instrumental variables approaches to address it. Fixed effects estimation assumes that the observable TFP component of the firm is unchanged over time and that differences exist only between provinces, and unbiased estimation is performed by adding individual fixed effects dummy variables to address endogeneity. Unlike the fixed effects estimator, IV methods do not rely on strict exogeneity of the inputs for consistent estimation (Beveren, 2012). The choice of the instrument cannot be related to the random error term, which is extremely difficult since the error term is practically unobservable. Also, the IV method cannot handle endogenous exit related problems.

To address the weak instrumental variable problem, Blundell and Bond (2000) use a systematic GMM approach to estimate the production function based on Arellano and Bond (1991) using both lagged first differences of input factors as instrumental variables for their level equations. However, adding lagged terms loses sample information.

Like the instrumental variable method and the fixed effects method, the control function method is also a commonly used method for total factor productivity estimation. Olley and Pakes (1996) were the first to propose a two-step consistent estimation method, which assumes that firms make investment decisions based on their current productivity status, using the firm's current investment level as a proxy for productivity thus solving the simultaneity bias problem. However, the OP method requires companies to have positive investments in the current period (Beveren, 2012).

2.2 Levinsohn–Petrin Estimation Algorithm

After comparing the data prediction, we chose the LP method to calculate the results for analysis. The Levinsohn-Petrin consistent semiparametric estimation method is based on an improvement of the Olley-Pakes method: the LP method develops a new total factor productivity estimation method in response to the problem that samples with zero investment in the OP method are discarded in the estimation process. Rather than using the amount of investment as a proxy variable, the method uses an indicator for intermediate goods inputs instead (Levinsohn & Petrin, 2003).

In this paper, we use the Cobb-Douglas production function and apply the LP method to obtain total factor productivity in agriculture, effectively solving the endogeneity problem of the production function and obtaining consistently valid estimates of the input parameters, which are abbreviated in their logarithmic form as follows:

$$y_{it} = \beta_0 + \beta_{li}l_{it} + \beta_{gi}g_{it} + \beta_{k_i}k_{it} + \beta_{mi}m_{it} + \sum_{\mathrm{j}} \delta_{\mathrm{j}}\mathrm{c}_{\mathrm{jit}} + \omega_{it} + \eta_{it} \qquad 1$$

where i denotes province and t denotes year. $y_{it}$is the logarithm of grain yield production in province in year t. L, G, and K are the logarithms of the rural labor force engaged in rice cultivation, gross domestic product (GDP), and total year-end machinery power, respectively. M is the logarithm of intermediate input agricultural fertilizer use, with climate, agro-climatic zone as the control variable (C). ω_{it} denotes the observable productivity divided in the error term, which is our required TFP. η_{it} denotes the error term.

The Levinsohn-Petrin (2003) semiparametric method approach has three basic presuppositions:

> First: the size of intermediate inputs is influenced by the size of capital and productivity, independent of other variables, when the demand function for intermediate inputs can be expressed as: $m_{it} = m(k_{it}, \omega_{it})$
>
> Second: the demand for intermediate inputs is a monotonically increasing function of productivity, and provinces with relatively high productivity will apply more agricultural fertilizer, then the inverse function of the above equation can be taken: $\omega_{it} = \omega(m_{it}, k_{it})$
>
> Third: the productivity k_{it} obeys a Markovian first-order process, that satisfies $\omega_{it} = E(\omega_{it}|\omega_{it-1}) + \xi_{it}$

Under the above three basic assumptions, the above equation (1) is written

$$y_{it} = \beta_{li}l_{it} + \beta_{gi}g_{it} + \sum_{\mathrm{j}} \delta_{\mathrm{j}}\mathrm{c}_{\mathrm{jit}} + \phi(m_{it,}k_{it,}) + \eta_{it} \qquad 2$$

Where,

$$\phi(m_{it,}k_{it,}) = \beta_{0i} + \beta_{mi}m_{it} + \beta_{k_i}k_{it} + \omega_{it}(m_{it,}k_{it,}) \qquad 3$$

The LP estimation scheme consists of two stages. In the first stage, we estimate $\phi(.)$ using OLS with polynomial containing $m_{it}$and k_{it}.

In the second stage, the coefficient β_k of k_{it} and the coefficient β_m of m_{it} are estimated, which leads to the estimate of ω_{it} (Wang & Zhao, 2010).

3 Data

3.1 Data for 1990-2019

The data sources required to measure the total factor productivity of agriculture in each province in this paper are shown in Table 1: details of the variables we use, the units and sources of the data, and the main descriptive statistics are presented. We used the China Rural Statistical Yearbook, compiled by the Rural Social and Economic Survey Department of the China Statistics Bureau, which provided us with information on basic rural conditions and agricultural production conditions in each province (rural population, grain production, grain sown area, total machinery power, fertilizer application). The statistical methods used are census-based (China conducted its first national agricultural census in 1996, which is implemented every 10 years), with sampling survey as the mainstay. Chinese agricultural statistics provide the area affected by agricultural natural disasters in each province.

Table 1. Description and descriptive statistics of the variables used in the analysis (1990-2019).

Type	Variables	Definition	Unit	Source (*)	Mean	Std. Dev.
	YieldRice	Yield of Rice per hectare	Tons/Hectare	CRSY	6.586	1.266
	Population	Rural labor engaged in rice cultivation	per	CRSY	7856247.1	9450877.8
	Fertilizer	Fertilizer used	Tons	NBS	459879.63	544752.17
	Mechanical	Total mechanical power	Kilowatts	CRSY	5905578.9	8139380.7
	GDP	Gross domestic product	100 million Yuan	NBS	10349.706	14797.246
	Per def	Total seasonal precipitation (Dec, Jan, Feb)	mm	(Hersbach, et al., 2019)	101.228	85.594

Per mam	Total seasonal precipitation (Mar, Apr, May)	mm	(Hersbach, et al., 2019)	291.35	199.408
Per jja	Total seasonal precipitation (Jun, Jul, Aug)	mm	(Hersbach, et al., 2019)	573.813	227.407
Per son	Total seasonal precipitation (Sep, Oct, Nov)	mm	(Hersbach, et al., 2019)	230.858	102.446
T def	Average seasonal temperature (Dec, Jan, Feb)	℃	(Hersbach, et al., 2019)	-6.075	6.9
T mam	Average seasonal temperature (Mar, Apr, May)	℃	(Hersbach, et al., 2019)	8.737	4.489
T jja	Average seasonal temperature (Jun, Jul, Aug)	℃	(Hersbach, et al., 2019)	20.382	3.919
T son	Average seasonal temperature (Sep, Oct, Nov)	℃	(Hersbach, et al., 2019)	8.274	5.081
Flood	Dummy variable for Flood	1 or 0 as a function of the area	Emdat	.473	.5

Drought	Dummy variable for Drought	1 or 0 as a function of the area	Emdat	.127	.333
Frost	Dummy variable for frost	1 or 0 as a function of the area	ASPRC	.774	.418
Heat wave	Dummy variable for Heat wave	1 or 0 as a function of the area	GHD	.791	.407
Djclim1	Dummy variable for humid areas	1 or 0 as a function of the area	Own elaboration from Map of wet and dry areas in China	.6	.49
Djclim2	Dummy variable for semi-humid areas	1 or 0 as a function of the area	Own elaboration from Map of wet and dry areas in China	.233	.423
Djclim3	Dummy variable for semi-arid areas and arid areas	1 or 0 as a function of the area	Own elaboration from Map of wet and dry areas in China	.133	.340

N=900

CRSY: China Rural Statistical yearbook, NBS: National Bureau of Statistics; EM-DAT: www.emdat.be (D. Guha-Sapir); ASPRC: Agricultural Statistics of the People's Republic of China

Greenhouse Data (GHD): http://data.sheshiyuanyi.com/

The relevant indicators are described as follows (Statistics, 2019):

1. In general, value added is used as output data for total factor productivity calculation, however, the value added of primary industry covers agriculture, forestry, livestock and fishery. Several scholars believe that the change in unit yield is an important factor affecting the change in total grain production in China (Dai, 2001; Hao, 2009), so in order to obtain accurate total factor productivity in agriculture, we chose the current year's rice unit yield as the output data.

$$YieldRice = \frac{Yield\ of\ Rice\ (10\ kiloTon)}{Area\ of\ rice\ planted\ (kilo\ hectare)}$$

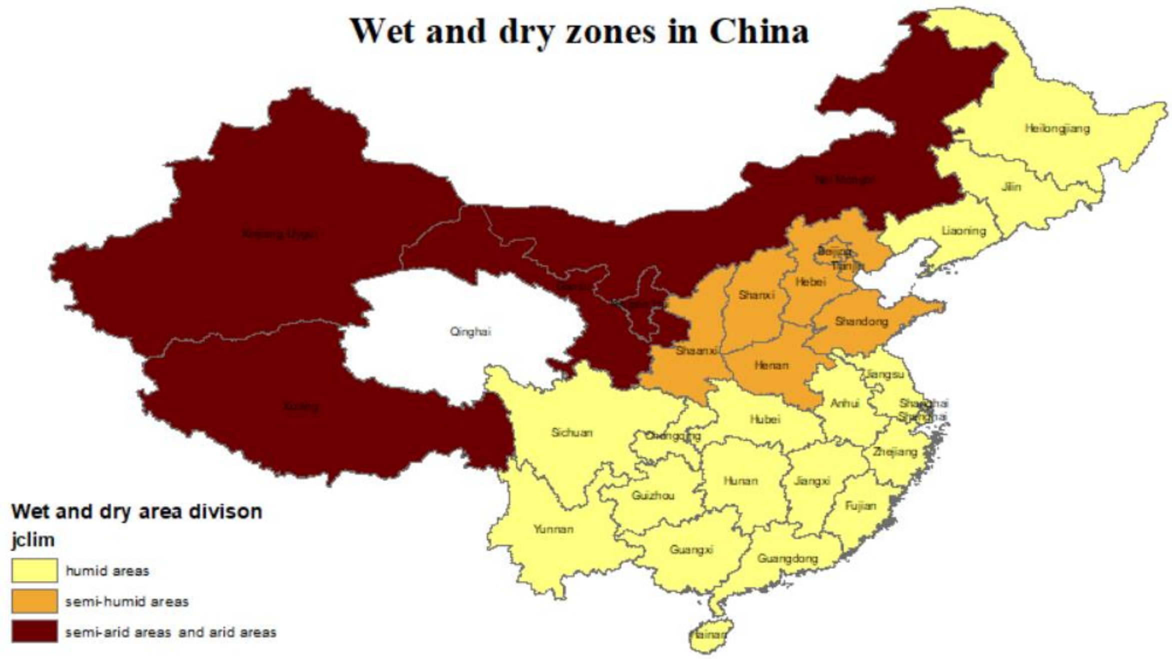
2. The rural labor force engaged in rice cultivation: agricultural production data are not available for the population engaged in agriculture, and this paper uses the percentage of rice cultivation area to the total cultivation area multiplied by the total rural labor force to calculate in order to minimize the scope of the rural labor force engaged in rice cultivation.
3. Agricultural fertilizers include nitrogen, phosphorus, potash and compound fertilizers. The amount of fertilizer used is calculated according to the discounted amount, that is, the amount of nitrogen fertilizer, phosphorus fertilizer and potassium fertilizer respectively according to the composition of nitrogen, phosphorus pentoxide and potassium oxide containing 100 percent of the discounted amount. Compound fertilizers are discounted according to the main components they contain. To estimate the amount of fertilizer applied to rice, we multiplied the percentage of the total planted area with rice by the total agricultural fertilizer application rate.
4. Total farm machinery power, to estimate the amount of fertilizer applied to rice, we multiplied the total farm machinery power by the percentage of the area planted with rice to the total planted area.
5. Precipitation data and temperature data using the ERA5 monthly historical dataset provided by the Climate Data Store (CDS) (Hersbach, et al., 2019).
6. High temperature heat wave data provided by the Institute of Facility Agriculture under the Ministry of Agriculture's Planning and Design Institute, based on daily maximum

temperatures based on the definition of a high temperature heat wave, where the daily maximum temperature reaches or exceeds 35°C for at least four consecutive days (China Meteorological Administration, 2011; You, et al., 2017), Confirm whether province i has experienced a high temperature heat wave in year t. The occurrence is 1 and the occurrence is 0.

7. Climate extremes: frosts, droughts and floods, Using information from Chinese agricultural statistics and Emdat records for the calendar year. Province i is marked as 1 if it has experienced the above extreme climate in year t; conversely, it is 0.
8. For the division of dry and wet regions. Since the variable arid region has only 30 observations, which is not enough for LP estimation, we combined arid and semi-arid regions for estimation (Figure 1). And the arid region Xinjiang was recorded as 0

There are 34 provincial administrative regions in China, and only mainland China is considered in this paper, excluding Hong Kong, Macau and Taiwan. In the same matter, the official data source shows that the rice sown area in Qinghai Province in calendar year is 0, so the provincial unit data here is 30. Since Chongqing, Wanxian, Fuling and Qianjiang areas, which were formerly under Sichuan province, were merged to establish Chongqing municipality in 1997, there are missing data for Chongqing province from 1990 to 1996, so this paper estimates the missing data based on the average proportion of Chongqing and Sichuan province data from 1997 to 2019.

Figure 1: Wet and dry zones in China



Source: Own elaboration from Map of wet and dry areas in China

3.2 Data for 2080-2099: Climate Change Scenarios

We will also analyze the response of rice yields to climate change. Assuming that China's HDI and agricultural fertilizer use remain unchanged from the 2019 data, the change in rice yield production from 2080-2099 is analyzed by simulating the corresponding climate scenarios. These climate scenarios are based on the climate models in CMIP5 adopted by the Intergovernmental Panel on Climate Change (IPCC) in its Fifth Assessment Report (AR5) in 2013.

Table 2: Pathway RCPs

Scenario	Radiative forcing	Greenhouse gas emissions	Agricultural area	Air pollution
RCP8.5	8.5 W m^{-2}	High	Medium for cropland and pasture	Medium-high

Source: https://zhuanlan.zhihu.com/p/113793570

In this paper, only 1 representative concentration pathways are used (Table 2): RCP8.5. (2014) RCP8.5 is a climate scenario without policy intervention, often considered as a worst-case scenario, with increasing greenhouse gas emissions and concentrations. By 2100, atmospheric CO_2 will increase to a value of 936 ppm, CH_4 to 3751 ppb, and N_2O to a value of 435 ppb.

Since 1995, the Coupled Model Intercomparison Project (CMIP), initiated by the WCRP Working Group on Coupled Modeling (WGCM), has been implemented six times, with countries actively developing Earth System Model. There are 35 models participating in CMIP5, six of which are from China (Zhou, et al., 2020). Although the CMIP5 climate model has a much-improved simulation capability in terms of temperature compared to the CMIP3 climate model, the simulated values in terms of extreme temperatures are lower than the observed values. Considering the future warming trend, we chose the CanESM2 model[1], which has a relatively small error for the simulation of the average maximum temperature (Shen & Jiang, 2014), temperature simulation data for 2080-2099 were provided by Pan and Zhang (2020). For the precipitation simulation data, we used the BCC_CSM1.1 model and downloaded the corresponding dataset at CDS Descriptive statistics of future climate are presented in Table 3. Due to the low resolution of this model, Shanghai, Beijing, Tianjin & Hainan cannot be identified. After comparing the observed data from 1990-2019, we decided to replace the corresponding missing values with simulated values from Shandong, Anhui, Sichuan, and Guizhou.

On the other hand, frequent climate extremes are predicted for the end of the 21st century, mainly in terms of extreme heat times and extreme heavy rainfall, with a significant reduction in low-temperature frost damage due to climate warming. Zhao et al (2019) summarized the literature on CMIP5 climate model predictions of future climate extremes in China for the period 2080-2099, (Chen, 2013) The forecast results show that, in addition to the frequency of hairy rain significantly reduced, the frequency and intensity of heavy rain, heavy rain and moderate rain are significantly increased, this situation, resulting in an increase in high-risk areas of flooding, the main high-risk areas for East China, eastern Sichuan, Beijing-Tianjin-Hebei and southeast coastal areas (Xu, et al., 2014). In terms of drought, Zhang and Sun (2012)concluded that the average annual precipitation and evapotranspiration in China will increase in the future, but there is still a surplus of precipitation minus evapotranspiration, and the average frequency of drought in the future is expected to be 24.6% less than that in 1980-2000 (Chen, et al., 2013). In this paper, we assume that future drought events account for 30% of the RCP8.5 scenario, taking into account the variability of the baseline period.

[1] CanESM2 model: the second generation of Canadian Earth System Model.

Table 3: Description and descriptive statistics of the variables used in the analysis (2080-2099).

Variable	Source	RCP8.5	
		Mean	Std. Dev.
Population	(Chen, et al., 2020)	1780399	2382990
Fertilizer	2019	285674.24	353673.31
Mechanical	Own elaboration	15.698	2.448
GDP	IASA	11.928	.908
Per def	BCC	166.206	92.243
Per mam	BCC	426.548	219.604
Per jja	BCC	388.492	181.402
Per son	BCC	163.525	96.467
T def	(Pan & Zhang, 2020)	-3.023	5.687
T mam	(Pan & Zhang, 2020)	11.576	4.936
T jja	(Pan & Zhang, 2020)	26.589	3.533
T son	(Pan & Zhang, 2020)	11.687	4.616
Flood	Own elaboration	.607	.489
Drought	Own elaboration	.3	.459
Frost	Own elaboration	.559	.497
Heat wave	Own elaboration	.923	.266
Djclim1	Own elaboration from Map of wet and dry areas in China	.6	.49
Djclim2		.233	.423

Djclim3	.133	.340
N=600		

Zhou et al (Zhou, et al., 2014)predicted that future weather is characterized by an increase in warm extreme weather climate events and a decrease in cold extreme weather climate events, in other words, an increase in the number of hot heat waves and warm night days and a decrease in the number of frost days. This paper combines the latest IPCC (2021) release of AR6 Climate change. We make the following changes to the heat wave and frost variables, assuming 54% of frost events in 2080-2099, a 19% decrease from the baseline period; 98% of heat wave events, a 0.24% increase from the baseline period; and 62% of flood events.

For the socioeconomic variables, we use the future GDP data of China under the Shared Socioeconomic Pathways SSP2 and SSP5 published by IIASA. We calculate future provincial GDP for 2080-2100 using the distribution of provincial GDP as a percentage of GDP in 2019. on the other hand, considering that the scale of agriculture grows with socioeconomic development, we assume that the growth of total power of farm machinery, a variable representing the scale of agriculture, is consistent with GDP.

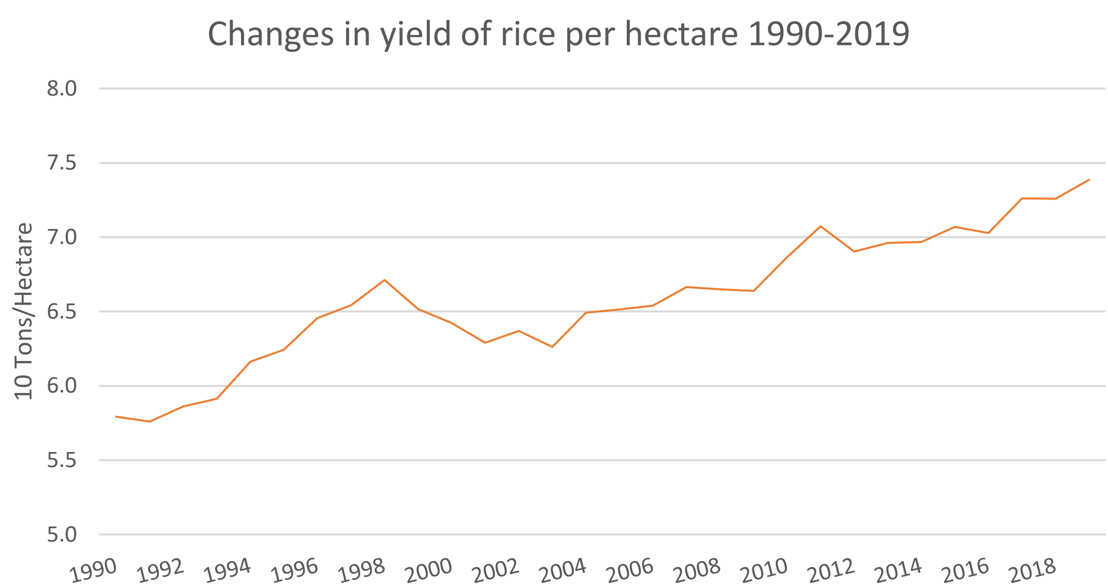
4. Results

4.1 Changes in the past 30 years

4.1.1 Changes in rice yield production

Figure 2 shows that China's rice yield per hectare has grown steadily and maintained an increasing trend since 1990, but there have been sudden decreases in between. The total grain production has been decreasing since 1999 due to the impact of the sudden decrease in grain sown area, and the arable land area has decreased by 4.57%, from 129.3 million hectares in 1998 to 12339.22 million hectares in 2003. The main reason for the decrease in arable land is ecological retreat, which accounted for 77.66% of the decrease in arable land from 28.86% in 1998 to 77.66% in 2003 (Zhou, et al., 2005). With the decrease in total grain production, rice yields slipped from 6,7 tons/ha in 1998 to 6,3 tons/ha in 2003, a decrease of 5.97%. In order to guarantee China's grain production, “the Outline of the Eleventh Five-Year Plan for National Economic and Social Development” adopted at the Fourth Session of the Tenth National People's Congress in 2006 proposed that 1.8 billion mu (120 million hectare) of arable land is a legally binding target and a red line that cannot be crossed. Due to the limitation of arable land area, the only way to improve rice yield is by increasing the yield of rice per unit. After 2004, the improvement of agricultural infrastructure, good policy conditions, and higher input of agricultural factors have greatly contributed to the increase of rice yield, and rice yields have steadily increased, with slight fluctuations but an overall upward trend, with yields of 7,4 tons/ha in 2019.

Figure 2: Changes in yield of rice per hectare 1990-2019

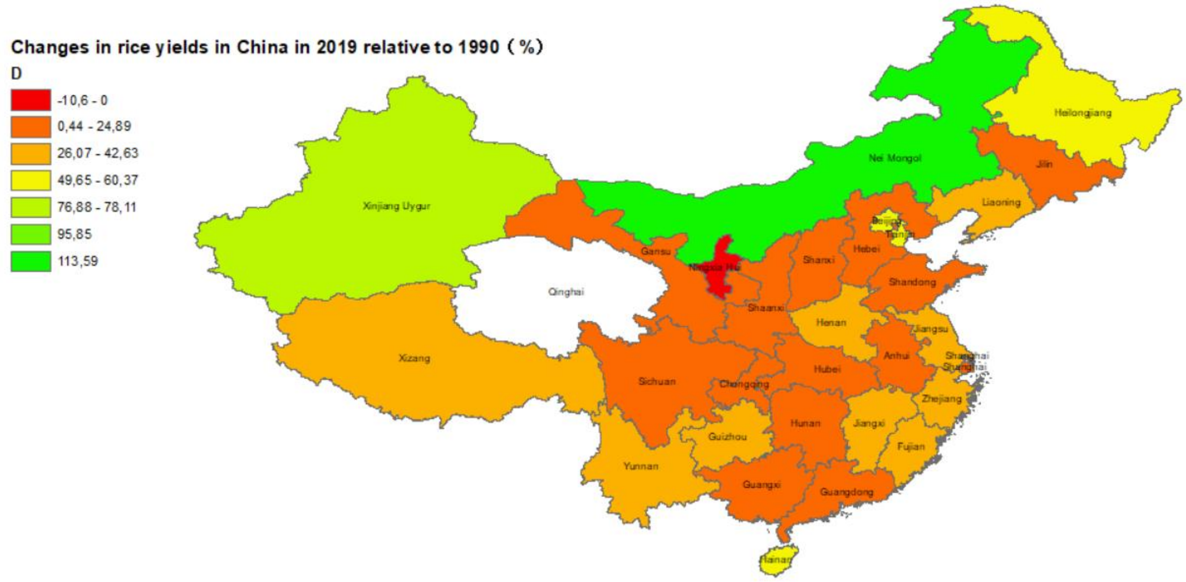


Source: Own elaboration from China Rural Statistical yearbook

We compare the 2019 rice yield production with that of 1990 (Figure 3), it was found that except for Ningxia province, where the yield per unit decreased by 10.6%, all other provinces were positive, In particular, rice yields in Inner Mongolia, Xinjiang and Heilongjiang increased by 114%, 77% and 50%, respectively. The growth in Inner Mongolia and Heilongjiang was mainly due to changes in rice cultivation techniques, these two provinces have applied dry seeded rice technology (China Food, 2020). dry seeded rice can save up to 80% of water compared to traditional rice, and is more suitable for mechanized large-area sowing operations in areas where water resources are not abundant (黑龙江日报, 2018). And the increase of rice yield in Xinjiang is mainly due to the selection and application of excellent varieties. According to Pan et al.'s (2017) analysis of factors influencing rice production in Xinjiang from 1996-2015, each variety renewal increased rice yields by 225-450 kg/hm^2. The decline of rice yield in Ningxia is due to the restructuring of agricultural industrialization. The proportion of grain crops in Ningxia decreases, as shown by the proportion of grain crop area to crop area, which accounted for more than 70% before 2007, decreasing to 58.75% in 2019. At the same time, the area planted with rice decreased, and corn replaced rice as the first major food crop in

Ningxia Province, which is the independent choice of agricultural workers, because the return from planting corn is greater than that of rice (Liu, et al., 2021).

Figure 3:Changes in rice yields in China in 2019 relative to 1990 (%)

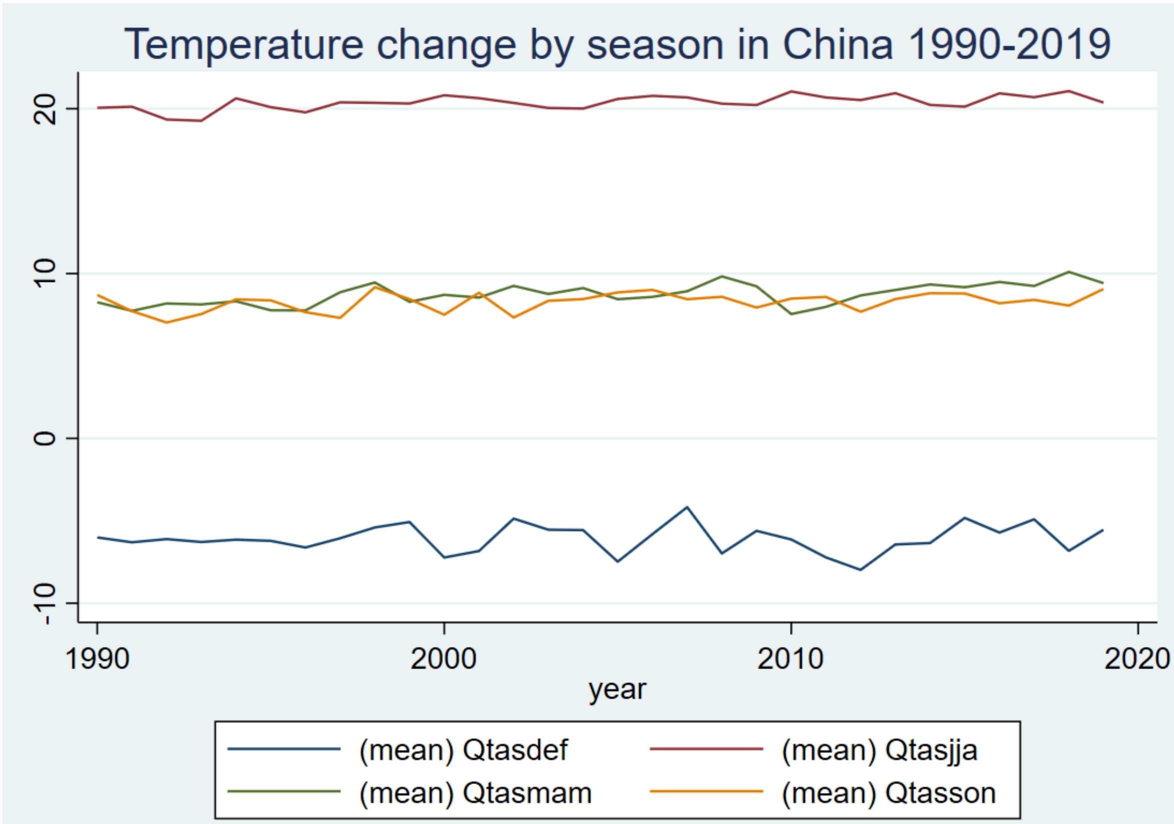


Source: Own elaboration from China Rural Statistical yearbook

4.1.2 Climate Change

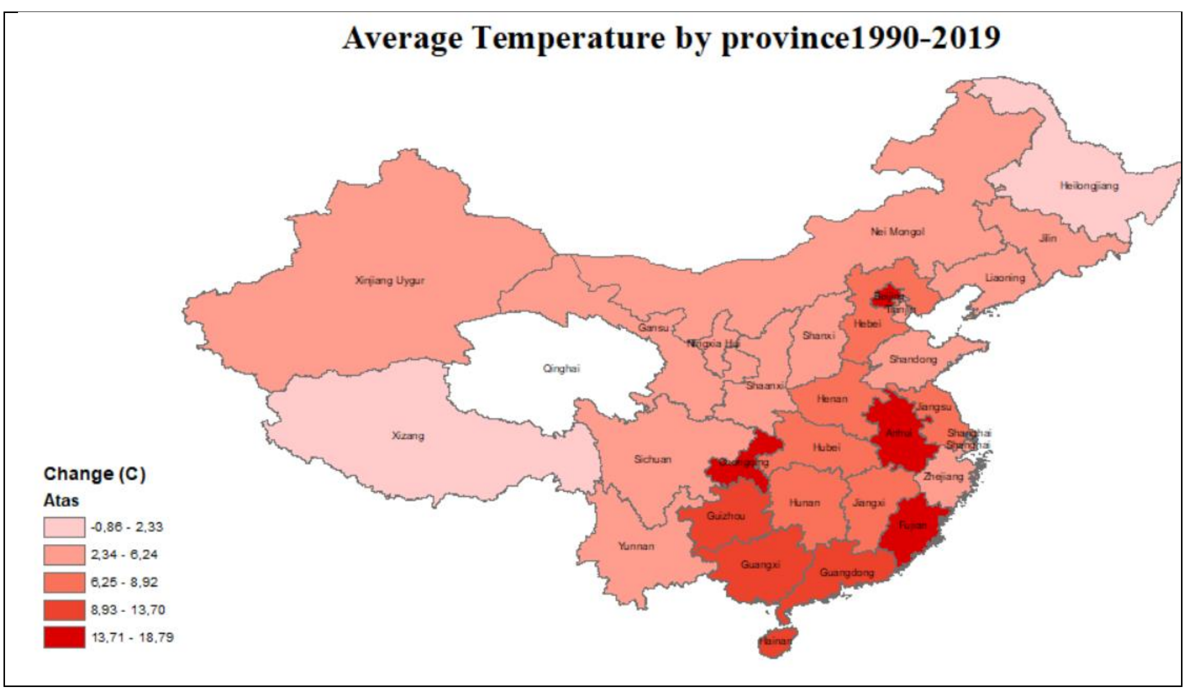
The national average temperature shows a fluctuating upward trend by season during 1990-2019 (Figure 4). The average spring temperatures ranged from 7.54°C to 10.10°C, with an average temperature of 8.74°C The average summer temperature is 19.27°C ~ 21.07°C, and the average temperature is 20.38°C. The summer temperature is a bit too low compared to other countries, which is due to the fact that the temperature in the northeastern provinces and Inner Mongolia pulls down the average; Autumn temperatures are similar to those of spring, with average temperatures of 7.03°C ~ 9.17°C and an average of 8.27°C; Average winter temperatures of -7.98°C ~ 4.17°C, with an average of -6.07. In terms of fluctuations, winter temperatures fluctuate the most and are unstable, but there is an overall warming trend, while summer fluctuates the least and grows steadily. Figure 5 shows us the temperature distribution of each province from 1990-2019, Beijing, Anhui, Chongqing and Fujian had the highest average temperatures.

Figure 4: Temperature change by season in China 1990-2019



Source: Own elaboration from (Hersbach, et al., 2019)

Figure 5: Average Temperature by province1990-2019



Source: Own elaboration from (Hersbach, et al., 2019)

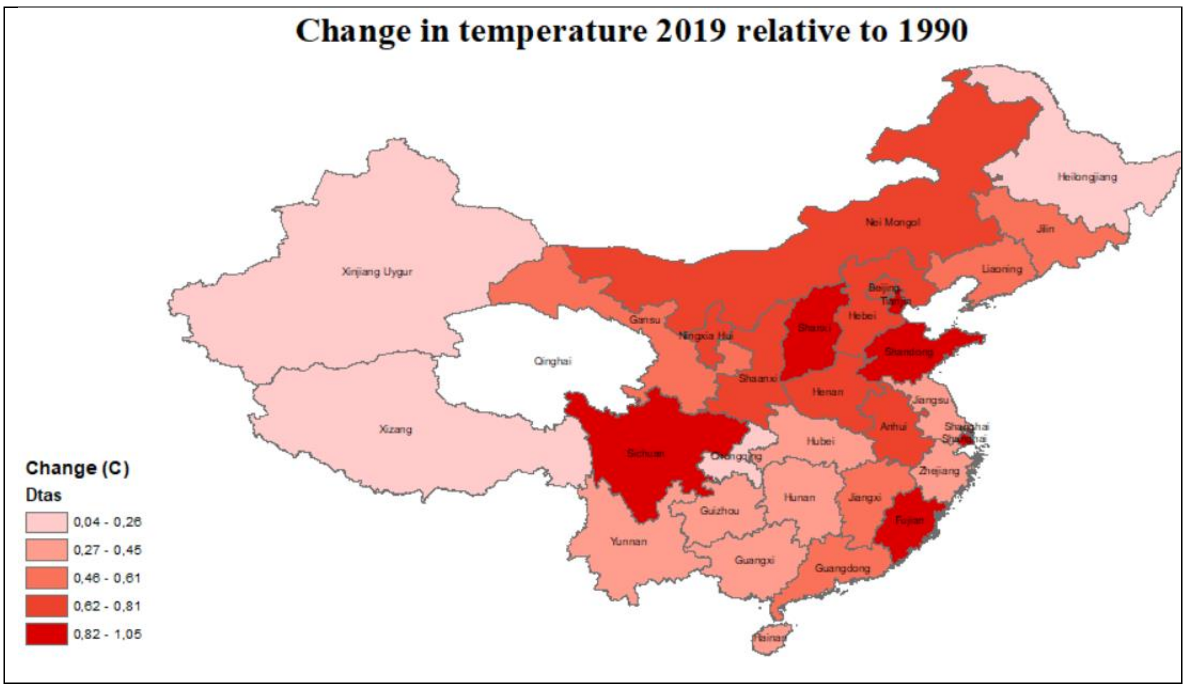
Comparing the change in temperature between 2019 and 1990 (Table 4), the average spring temperature is significantly warmer with an increase of 1.15°C, followed by the winter with an increase of 0.47°C. From the provincial level (Figure 6), the warming varies from season to season and from region to region. The temperature increase is mainly concentrated in central and northern China

Table 4:Climate change in China in 2019 relative to 1990

	1990		2019	
	Mean	SD	Mean	SD
Qtasdef	-6.01	6.793	-5.541	6.779
Qtasjja	20.056	4.183	20.373	3.936
Qtasmam	8.259	4.608	9.415	4.533
Qtasson	8.703	5.061	9.065	5.008

Source: Own elaboration from (Hersbach, et al., 2019)

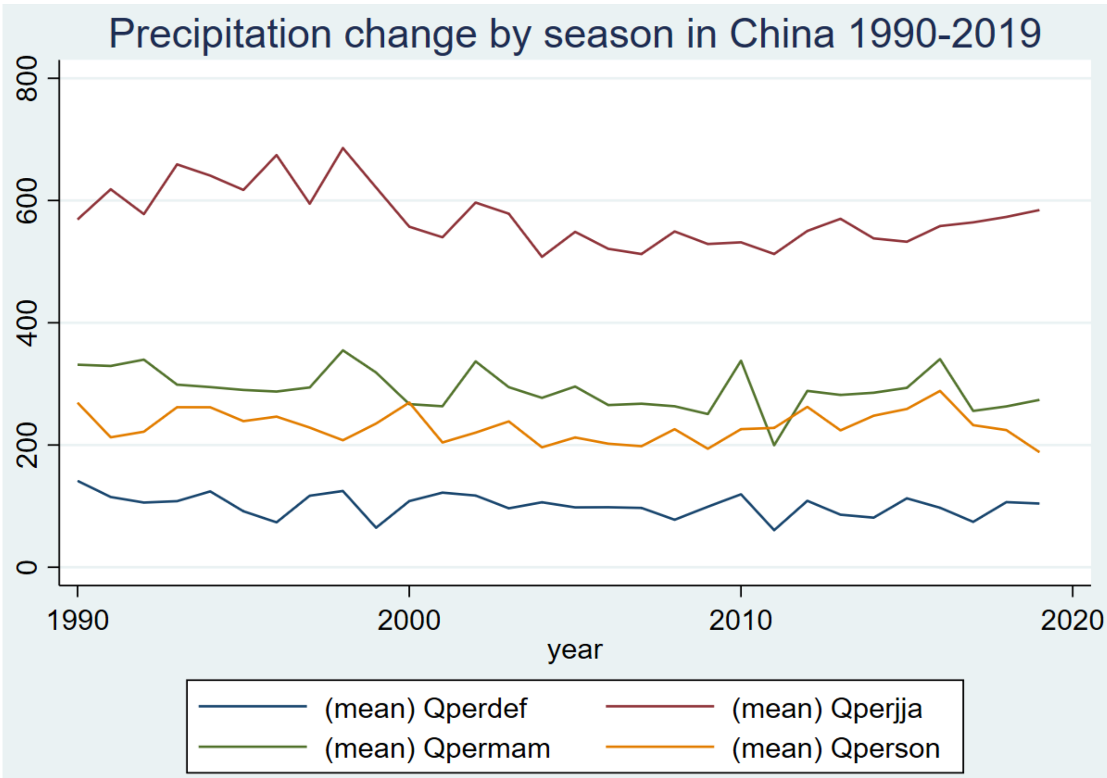
Figure 6: Change in temperature 2019 relative to 1990



Source: Own elaboration from (Hersbach, et al., 2019)

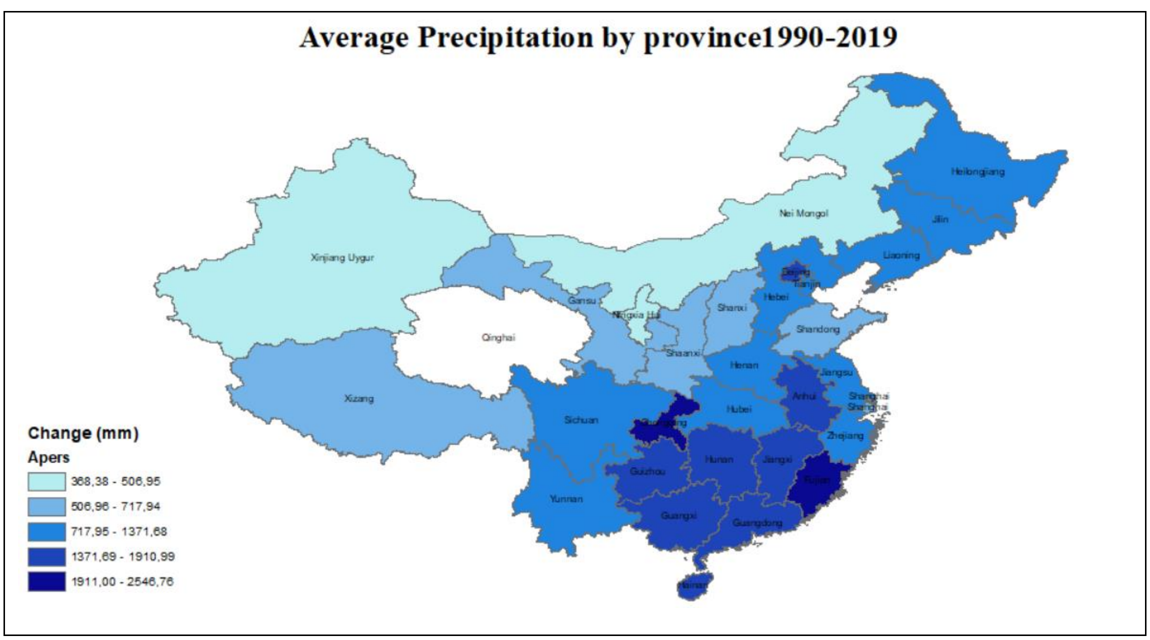
China's precipitation is mainly influenced by the monsoon in summer. During 1990-2010, the national average summer precipitation showed a fluctuating decrease and then an upward trend, while the other seasons became a decreasing trend during 1990-2019 (Figure 7). The average precipitation range in spring is 273mm-331mm, in summer is 568mm-584mm, in autumn is 188mm-269mm, and in winter is 104mm-141mm. Figure 8 shows us the distribution of precipitation by province for the years 1990-2019. It is basically consistent with Figure 1, in which the precipitation is larger in Beijing, Anhui, Chongqing and Fujian.

Figure 7: Precipitation change by season in China 1990-2019



Source: Own elaboration from (Hersbach, et al., 2019)

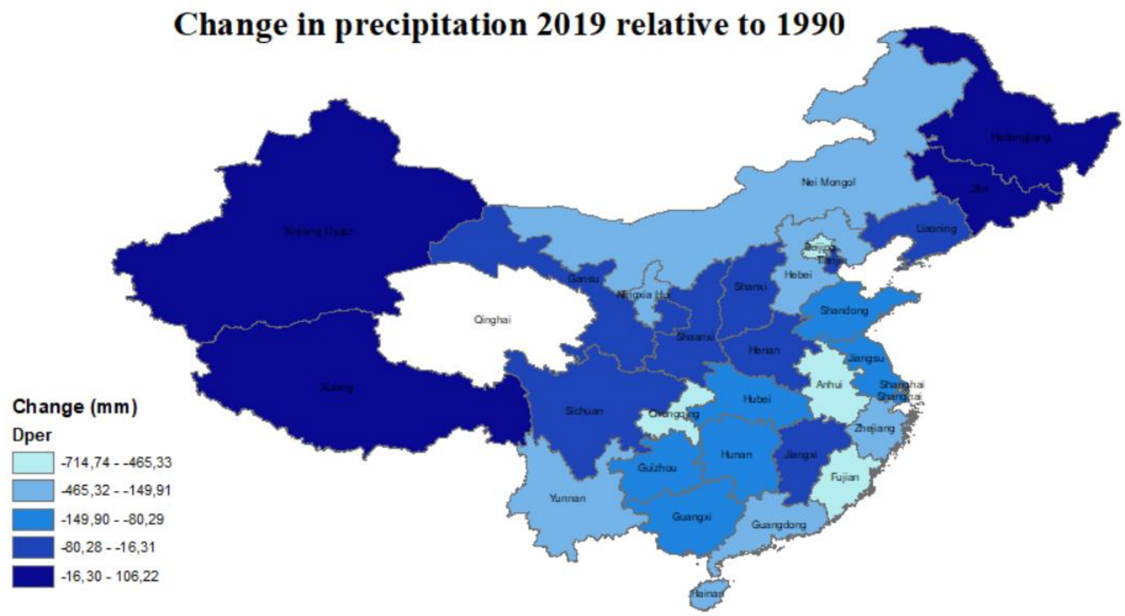
Figure 8: Average Precipitation by province1990-2019



Source: Own elaboration from (Hersbach, et al., 2019)

Table 5: Precipitation change in China in 2019 relative to 1990

	1990		2019	
	Mean	SD	Mean	SD
Per def	141.362	116.335	104.191	89.546
Per mam	331.360	213.660	273.844	180.746
Per jja	568.990	177.086	584.405	226.343
Per son	269.291	134.564	188.197	73.876



Source: Own elaboration from (Hersbach, et al., 2019)

4.2 Levinsohn-Petrinproduction functions' estimates

Based on the Table 7 elasticity coefficients, we ran a regression to assess the predictive power of the model. The average rice yield predicted within the sample for the past 30 years is 6.431 t/ha (Table 6), 2.58% lower than the actual average unit yield, but the predicted SD is larger than the true observed value. Considering that China's vast land area and complex and diverse topography create large differences in China's climatic resources, different policy priorities among provinces, and varying agricultural technologies, the conditions faced cannot be generalized, so we believe that a variation of the model's in-sample predictions can be accepted. We further analyze the predictive ability of average yields at the province level and find that the prediction ability for central eastern and southern

China is found to be better, with the best simulation ability for Jiangsu, Henan, Hubei, Sichuan, Zhejiang, Hunan and Jiangxi, within 10% difference, especially for Yunnan and Hebei provinces, within 2% difference.

Table 6: Comparison of predicted and observed values within the sample

Variable	Mean	Std. Dev.	Min	Max
yieldRice	6.586	1.266	0.667	10.146
yieldRice estimated	6.431	2.704	1.815	22.802

We used the PRODEST command of STATA 15 for LP estimation, and Table 7 illustrates the elasticity coefficients of the role of drivers on rice yields. It can be seen that all variables, except labor, precipitation and flood and drought in natural disasters, have key effects on the enhancement or suppression of rice yields.

With the progress of time and technology, the application of agricultural fertilizers, agricultural labor has been gradually replaced by machinery and is no longer a key factor affecting agricultural production.

The elasticity coefficient of the effect of the amount of agricultural fertilizer input on rice yield is 0.107, and the role of chemical fertilizer in increasing rice yield is irreplaceable. However, the increase in the amount of fertilizer application may cause ecological damage. (Figure 9) Fertilizer application started to decline from 2017 and still had a non-negligible effect on rice yields despite the reduction in fertilizer use, suggesting that the techniques and methods of fertilizer application can better improve rice yields at the same fertilizer dose. Rice growers should adopt different fertilization methods according to the production of rice and focus on the development of fertilizer application techniques to improve the efficiency of fertilizer application. For example, in Shaanxi Province, the best fertilizer application amount suitable for Shaanxi was developed by combining soil nutrients (Hao, 2018).

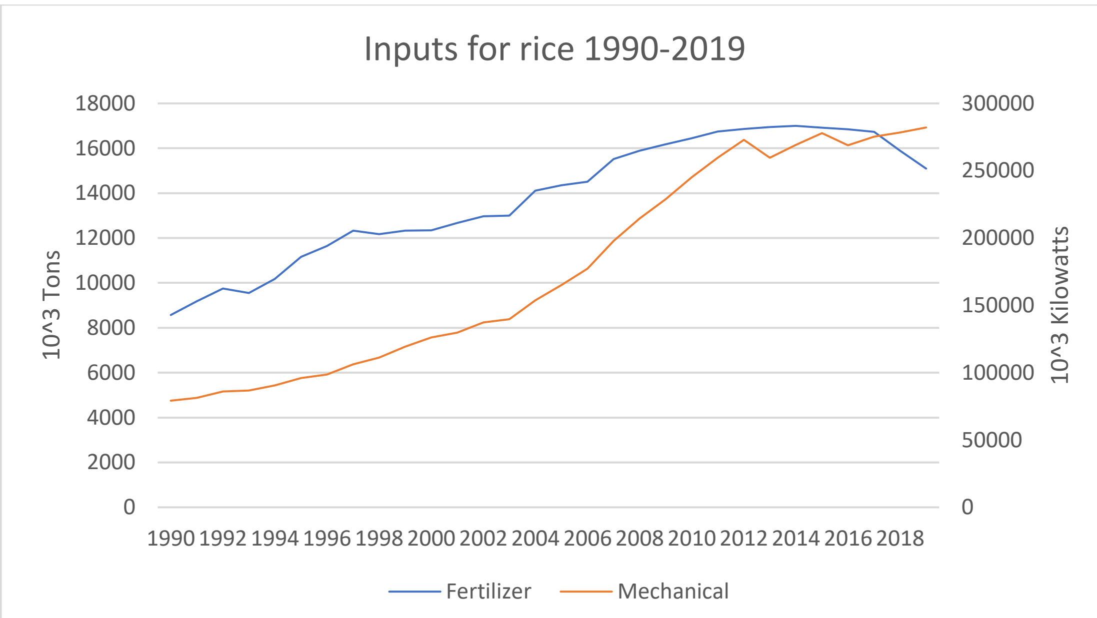
Surprisingly, the impact of input farm machinery power on rice yields was negative with an elasticity coefficient of -0.043 (Table 7), a result that does not make economic sense. In fact, mechanized tillage, seedling planting and fertilization are all beneficial to the improvement of rice yields. In previous studies by scholars have concluded that the impact of agricultural machinery power on grain yield is negative (He, 2009). The main reasons for this conclusion are: On the one hand, due to the large differences in China's geographical environment and level of economic development, the average area of cultivated land per household in different provinces also varies significantly, and the area of rice fields operated by farmers in different provinces varies greatly. The largest province, Heilongjiang, has an average household size of 17.72 hectares, while the smallest province, Guizhou, has only 0.18 hectares. Provinces with too small arable land per household are unable to form large-scale operations and have low efficiency in the use of agricultural machinery. In order to promote large-scale land management, the Standing Committee of the National People's Congress passed the Law of the People's Republic of China on Land Contracting in 2002 to clarify the legality of the transfer of farmers' contractual land management rights in the form of legislation. That is, farmers who have the right to contract land management transfer the right to use land to other farmers or economic organizations in accordance with the law and the principle of voluntary compensation. The large average arable land area per household in Heilongjiang and Zhejiang provinces is the result of land transfer. On the other hand, agricultural mechanization is becoming more and more popular, and it can be seen through Figure 9 that agricultural machinery power is growing rapidly since 1990 until it leveled off in 2012. However, planters do not have a clear understanding of the operation points and precautions of mechanized rice transplanting and nursery technology, so that the advantages of rice mechanization cannot be brought into play (He, 2021). And from the statistical caliber, the total power of agricultural machinery includes a series of agricultural machinery power of agriculture, forestry, animal husbandry, fishery and agricultural products processing, etc., and only a part of it is really used in rice production, so the data is not highly representative.

On the other hand, the estimates of climatic factors are not in line with our expectations. Rice is grown in China from early April to mid-October. Before the study, we predicted that warmer temperatures during the growing season would negatively affect rice yields, but the results showed that warmer temperatures in summer would enhance rice yield production. Such as the study of temperature changes and rice yields in southern China by Scholars (Zeng, 2021), which showed that a 1°C increase in average temperature decreased rice yields by 2.61%-3.57%. It has also been shown that an increase in temperature is positively correlated with rice yield (Nam, et al., 2013). By understanding the temperature conditions for rice growth, I believe that the summer temperature conditions in China today are positively correlated with rice yields until they increase to a temperature threshold.

Rice as a crop that likes high temperature and high humidity, although the precipitation factor did not have a significant effect on rice yield in this study estimation, it was significant at the 0.1% level in both humid and semi-humid areas. In fact, rice generally requires between 700-1200 mm of water for the full growing season, and these two areas are more suitable for rice growth. However, due to the limitation of the research instrument, this paper uses the provincial capital location to divide the dry and wet areas, and does not link the spatial resolution data with the rice yield information, which is one of the shortcomings of this paper.

And the arid/semi-arid region is located in the western part of China, which has been a key area for development by the government. In 2000, the State Council established the Western Development Office. In 2006, the State Council adopted the "Western Development" Eleventh Five-Year Plan, Since the implementation of the Western Development Plan, efforts have been made to solve the two "short board" problems of transportation and water conservancy in the western region. The elasticity coefficient of precipitation is too low to have a negligible effect on yields, indicating that farmland water facilities have been improved in most of China. On the other hand the region has applied the dry rice cultivation earlier (Section 3.1.1). It also focused on improving rice varieties and selecting and breeding rice varieties suitable for local climatic conditions.

Figure 9: inputs Fertilizer and Mechanical for rice 1990-2019



Source: Own elaboration from China Rural Statistical yearbook

Among the four natural disasters, flood, drought, frost and heat wave, heat wave had the strongest suppression on rice yield with an elasticity coefficient of -0.073, which was significant at the 0.1% level. While floods surprisingly have a positive effect on rice yields, the production impact of natural disasters on agricultural yields is unquestionable, with a flood-affected area of 7,190 thousand hectares and a flooded area of 3,040 thousand hectares in 2020 (NBS). Although rice is a water-loving crop, when the inundation depth is greater than the critical value, rice respiration will be affected, causing rice yield reduction or even crop failure (Wang, 2008). The reason for this unconventional result, the flood elasticity coefficient of 0.013, is that the paper does not classify the intensity and frequency of flood hazards.

Table 7: Levinsohn-Petrin estimates for the factors' elasticities of the statistical function of TFP response for yield of rice per hectare

	Coef	SE
Poplation	0.012	(0.057)
GDP	0.066***	(0.005)
Mechanical	-0.043***	(0.004)
Fertilizer	0.107***	(0.005)
Per def	0.002	(0.005)
Per jja	0.000	(0.001)
Per mam	-0.002	(0.005)
Per son	0.002	(0.005)
T def	0.034***	(0.004)
T jja	0.037***	(0.007)
T mam	-0.021***	(0.005)
T son	-0.010	(0.005)
Flood	0.005	(0.005)
Drought	-0.008	(0.005)
Frost	-0.013**	(0.004)
Heat wave	-0.073***	(0.005)
Djclim1	-0.152***	(0.005)
Djclim2	-0.102***	(0.003)
Djclim3	-0.002	(0.006)
Obs	900	

Note: standard errors (SEs) in LP model are bootstrapped using 50 replications. *** Significant at the 0.1% level, ** Significant at the 1% level, * Significant at the 5% level. Coef denotes the coefficient.

4.3 The forecast of the yield of rice

Based on the assumptions made in the previous section 3.2 for each influencing factor and the Cobb-Douglas production function model finalized in section 2.2 above, rice yields were projected for 2080-2099 under the RCP4.5 and RCP8.5 climate scenarios. We projected rice yields for 2080-2099 under the RCP4.5 and RCP8.5 climate scenarios (Table 8). Based on the results of this projection, it can be seen that under certain natural conditions and the current rice cultivation area, rice yields at the end of the 21st century increase by 9.81% over the estimated baseline period under the RCP8.5 climate scenario.

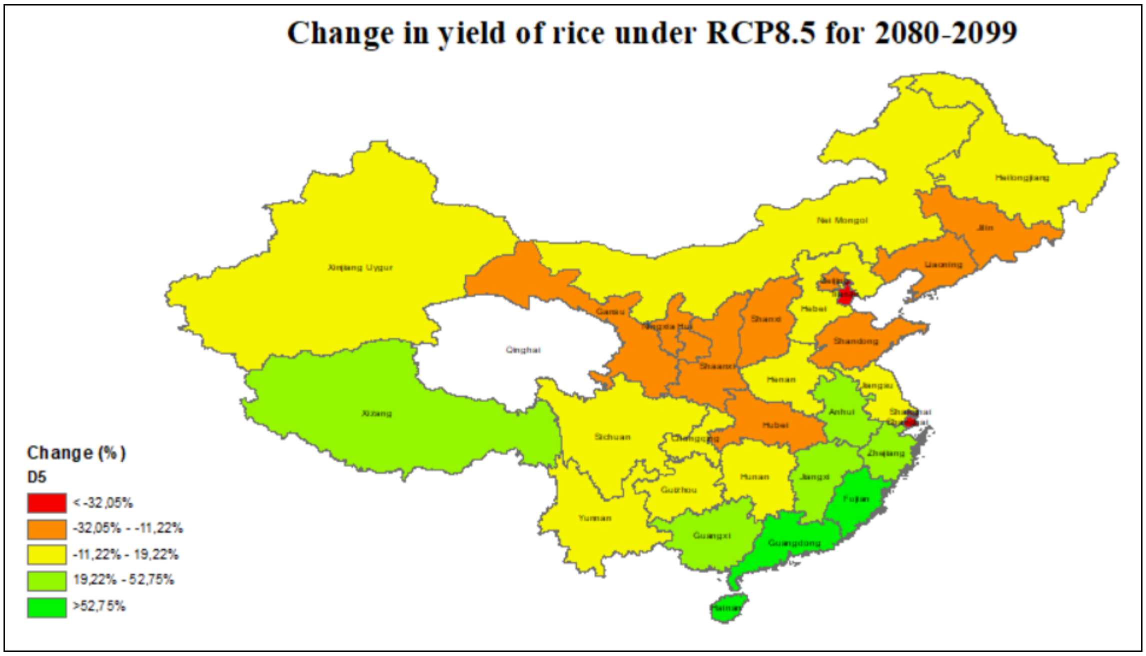
Table 8: The forecast of the yield of rice 2080-2099

Variable	Mean	Std. Dev.	Min	Max
YieldRiceRCP8.5	7.062	3.581	1.602	43.264

Source: Own elaboration

At the provincial level, the current rice production areas in China are mainly located in Hunan, Hubei, Jiangxi, Anhui, and Jiangsu in the central south, Sichuan in the southwest, Guangdong and Guangxi in the south, and the northeast. As the weather and climate change, the distribution of rice production areas in China will be adjusted again by the end of the 21st century. The increase in rice yield was mainly concentrated in the central east and south of China, especially in Fujian Province (Figure 10). Under the RCP8.5 scenario, rice yields increased by about 153%, and there is still significant potential for improving yields of major grain crops in China.

Figure 10: Change in yield of rice for 2080-2099



Source: Own elaboration from China Rural Statistical yearbook

Here we study the impact on rice yields under future climate scenarios, we do not explicitly analyses the impact of adaptation measures on rice, such as crop rotation, varietal improvement, fertilization practices, etc. Growers can make important decisions on their own to adapt to harsh climate change and increase rice yields to increase profitability. This cannot be predicted, but humans tend to make decisions based on expected returns. And this paper does not take into account farmers' earnings, as the sources of their earnings cannot be differentiated by food type.

Also to accommodate the complex and diverse climatic conditions in China, rice growing areas have been divided according to climatic resources and this analysis faces the challenge of spatially resolved data. The analysis of rice growing areas faces the challenge of spatially resolved data, which is one of the research limitations of this paper.

5. Discussion and conclusions

Scholars in various countries have been concerned with research in this area of agricultural production, and the factors affecting grain yield have been key to the field. Previous authors have provided a rich literature on the factors affecting grain yield, grain yield prediction, and other issues. Based on previous studies, this paper selects rice yield, an important grain crop in China, combined with the objective fact that the current arable land in China is stable, and borrows the Cobb Douglas production function theory to study the impact of climate change on rice yield. The LP estimation method was used to derive the elasticity coefficients of each factor and to predict rice yields at the end of the 21st century under the RCP8.5 climate scenario, leading to the following main conclusions:

1. The eventual outcomes of this paper are acquired through model development and plan. From the outcomes, it is essentially reliable with the current truth of rice development, and the outcomes can logically and successfully clarify the inward laws of rice development advancement and future improvement patterns, and furthermore the forecast of future normal rice yield in China is inside the scope of logical development.
2. Based on the basic principles of the Cobb Douglas production function, the influencing factors affecting rice yields in China between 1990 and 2019 were analyzed, and the results showed that the current rice yields in China are mainly dependent on the use of agricultural fertilizers. With the improvement of the modern level of agriculturalization, the dependence of rice yield on the quantity of labor is getting smaller and smaller, and the quality of agricultural labor is putting forward higher requirements, but at present, there is a lack of Chinese agricultural science and technology talents, and most of them are single-type talents with mainly theoretical knowledge (Jiang, 2016). However, the fragmentation of land use cannot match the current level of agricultural mechanization, and the low efficiency of agricultural machinery utilization causes waste of resources.
3. Assumptions were made on various factors affecting rice yields, and then rice yield levels in China at the end of the 21st century were projected based on the established rice yield production function model, with an average rice yield increase of 9.81% in 2080-2099 compared to 1990-2019 under the RCP8.5 climate scenario.

Based on the above research on the level of rice yield in China and the influencing factors, this paper proposes the following countermeasures on how to further improve rice yield production:

1. Strengthen agricultural technology promotion and training
   China has entered the modernization of agriculture, which refers to the mechanization of agriculture, scientific production technology, industrialization of agriculture and informatization of agriculture. At present, the utilization rate of agricultural machinery is too low due to the terrain, scale and other reasons, resulting in a waste of resources. The results of agricultural science and technology, which can effectively improve the efficiency of rice production, have not been applied to the grassroots in a rational way. Increasing agricultural technology promotion and training and encouraging support for institutions engaged in agricultural technology-related businesses to actively participate in the establishment of an

agricultural technology promotion system will help farmers learn modern agricultural technology and clarify technical points.

2. Encourage rice scale and industrialized operation.

   There is a general problem in China that rural land is operated on a family basis and the scale of operation is too small to give full play to the advantages of modern agriculture, and it is difficult to fully realize the role of the level of agricultural mechanization in promoting rice yields. Although the government has implemented the policy of separation of rights and land transfer, it has only solved the problem of farmers who have moved to the city to work and abandoned their farming. Most families still choose to farm on their own, and the disadvantages of small-scale decentralized operation, such as high input and low output, low level of specialization and low scale efficiency, are increasingly prominent. In this case, realizing the scale of rice production and industrialization can effectively improve the rice output rate. However, at present, farmers have a low level of education, no autonomy, and still use traditional labor methods of farming. Realizing the scale of rice production requires government promotion, the leadership of village cadres, and the spontaneity of farmers. The government can set up experimental villages for large-scale rice production and use the Internet to publicize them, thus causing villages to spontaneously imitate them. However, this requires the leadership and decision-making power of village cadres, who should not just imitate and ignore the objective conditions of the villages.

3. Increase the educational level of the workforce

   Human capital is a key element in production. Since China entered the modernization of agriculture, the quantity of labor force has played a minimal role in improving rice yields, while the quality of education determines the level of acceptance of new technologies and varieties of rice cultivation by rice growers. But on the one hand, people with higher education are reluctant to engage in agriculture-related fields when choosing a university major, and on the other hand, highly qualified rural laborers mostly choose to go out to work. Therefore, changing the conceptual thinking of labor force and allowing them to voluntarily stay in their hometowns to build new rural areas is an uncrossable step in developing modern agriculture.

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