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Agricultural Production Optimization and Marginal Product Response to Climate Change

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Abstract: This study introduces a non-parametric approach to estimate the marginal products of agricultural inputs (agricultural land, labor, machinery, fertilizers and pesticides) in Jiangsu province, China. To study the effects of climate change on these marginal products, we used a fixed-effects regression model. The results show an upward trend of inefficiency in Jiangsu's agricultural production from 2001 to 2018. The marginal products of agricultural land, labor, machinery, chemical fertilizers and pesticides are 1.54 thousand USD per hectare, 0.32 thousand USD per person, 0.31 thousand USD per kWh, 21.63 thousand USD per ton and 0.88 USD per ton, respectively. Climate change refers mainly to temperature and precipitation, and we analyzed their effects on the marginal products. Temperature has a statistically significant positive effect on the marginal product of fertilizers and machinery, whereas precipitation harms the marginal product of land. Two inputs (i.e., land and fertilizer) are critical driving forces in agricultural production. This study recommends government action to improve agricultural efficiency and ensure climate change adaptation.

Keywords: optimization; marginal product; agricultural input; shadow value; climate change

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1. Introduction

The exploitation of natural resources not only affects the competitiveness of a sector, but also influences its contribution to economic growth [1]. The marginal product reflects the expansion of output resulting from an additional unit of input. Thus, the marginal product can be computed directly by the output to input ratio. This approach may generate biased results, however, as it does not consider the multiple inputs and outputs in production simultaneously.

Economic growth is not only dependent on resources as factors of production, but also on technological progress. Specifically, owing to the law of diminishing marginal returns, technological progress is the primary force behind economic growth, with material and labor investments playing a significant role in this process [2]. In China, agricultural added value increased from 92.7 billion RMB in 1978 to 6616.1 billion RMB in 2018, with an average annual growth rate of 5.3% [3]. This considerable increase was because of technological progress—the most crucial factor in achieving sustainable agricultural development. China has witnessed an average annual growth rate of more than 2% from 1985 to 2013 [4], which is twice the world average [5]. In the context of profound changes in the international and domestic environment, the Chinese government claims that "the bowl of the Chinese people must be held firmly in our own hands at all times", and implements a food security policy of "ensuring basic self-sufficiency of grains and absolute security of staple food".

Despite the rapid growth of agricultural technologies, China's agricultural development faces significant challenges due to the shortage of inputs in production [6]. For example, rapid urbanization has led to farmers' urbanization, continuous occupation of farmland resources and the transfer of a considerable portion of agricultural labor [7,8]. Additionally, China's rural areas have been experiencing a continuous decrease in the supply of agricultural labor due to aging [9,10]. Furthermore, the rapid development of the service industry, such as real estate, has led to the rapid expansion of urban land resources, most of which have been converted from cultivated land [11]. This has caused a shortage of cultivated land in some places [12]. Regarding intermediate resources, the large-scale use of chemical fertilizers has caused soil quality degradation and serious agricultural pollution [1,13,14], thus hindering the long-term green development of agriculture, although it might bring agricultural output growth in the short term [15]. To tackle this problem, some local governments have introduced quantitative fertilizer and pesticide input policies to limit the amount of fertilizer and pesticide input (Department of Agriculture and Rural Affairs of Jiangsu province, Department of Agriculture and Rural Affairs of Zhejiang Province).

Jiangsu is one of the major agricultural provinces in China. In 2013, the total number of permanent agricultural labor resources in Jiangsu was 30.604 million, with 30% (9.675 million) employed outside rural areas [16]; in 2018, however, it ranked first for its output per unit area, and ninth for total grain output. The rapid expansion of secondary and tertiary industries in Jiangsu utilized a large number of land resources for agricultural production. The latest data from the National Bureau of Statistics show that the total sown area of crops in Jiangsu fell from 8582 thousand hectares in 1978 to 7442 thousand hectares in 2019—a decrease of 14%. Furthermore, the sown area of food crops dropped from 6311 thousand hectares in 1978 to 5381 thousand hectares in 2019—a 15% decrease. Previous studies have suggested that changes in land use in Jiangsu show a significant transformation of cultivated land to urban and rural construction land, waters, forests and grasslands [17]. To protect and improve the quality and quantity of cultivated land resources, the Jiangsu Provincial Government issued a series of policies and regulations, such as "Regulations of Jiangsu province on the Quality Management of Cultivated Land" in 2012. Moreover, Jiangsu is facing the pressure of ecological environmental protection. As the Jiangsu province Chemical Fertilizer Reduction and Efficiency Action Implementation Plan (2018–2022) points out, agricultural production requires a great reduction in chemical fertilizer input. The latest data from provincial statistics show that the scalar amount of agricultural chemical fertilizers in Jiangsu declined from 3.38 million tons in 2001 to 2.86 million tons in 2019—a 16% decrease [3]. The current situation of China's agriculture is that the eastern coastal areas are the most developed, gradually lagging behind from east to west, showing a ladder-style development situation, and the agricultural development in Jiangsu province is exactly similar, so there must be similar conclusions between the two, from the research in Jiangsu province to get conclusions, and then analogous to other provinces in the country. Studying the agricultural production status in various regions of Jiangsu province, and the conclusions thereof, are of representative significance.

The marginal contribution of agricultural inputs depends not only on changes in the number of input factors, but also on environmental factors such as climate change [18]. China's agricultural sector provides food for 22% of the world's population, utilizing just 8% of its land, which has caused a series of resource and environmental issues [19]. Climatic changes in temperature and precipitation have significantly influenced agricultural production in China [18]. A favorable environment can promote an increase in agricultural output, whereas a harsh environment will reduce output. Therefore, learning how to deal with the impact of environmental factors, such as climate change, is necessary. Based on this, two hypotheses are proposed. First, because of the limit of arable land resources and intermediate resources, land and fertilizers may be input products that contribute more to agricultural production. Second, good temperature and precipitation will push agricultural production closer to the optimal scale, and high temperature or excessive precipitation will lead to an increase in inefficiency in Jiangsu's agricultural production. Therefore, learning how to deal with the impact of environmental factors, such as climate change, is necessary.

Do reduced inputs increase inefficiency in Jiangsu's agricultural production, or do they push its agricultural production closer to the optimal scale? What role do agricultural inputs (including land, labor, agricultural machinery, fertilizers, and pesticides) play in agricultural production? Does climate change affect the marginal product of agricultural inputs? The answers to these questions can help the government enforce effective policies to ensure the better use of natural resources for agricultural development and environmental protection [1]. This study introduces a non-parametric method to estimate the marginal product of each input resource and efficiency in prefecture-level cities in Jiangsu province from 2001 to 2018 (Figure 1). Then, an econometric model is used to measure the effect of government land policies on the marginal products of inputs and final production.

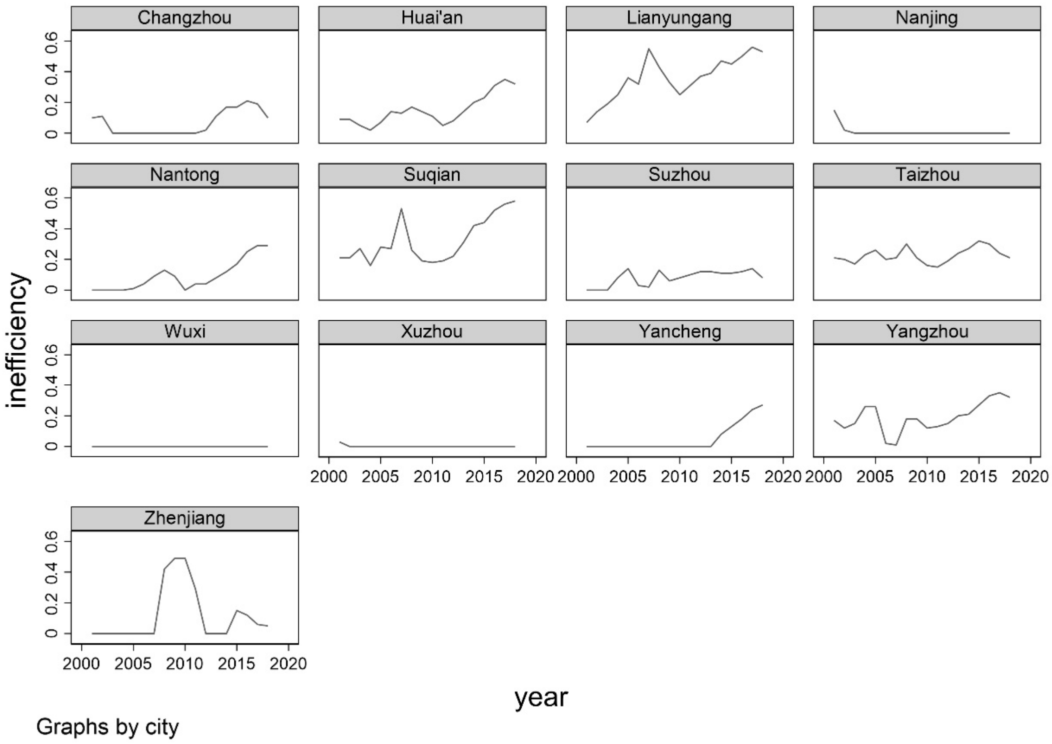

Figure 1. Agricultural inefficiency in different cities of Jiangsu province.

This study contributes to the existing literature in two significant ways. First, to the best of our knowledge, it is the first of its kind at the prefectural level in Jiangsu province to identify the contribution of agricultural inputs to agricultural production based on shadow value estimates, including agricultural land, labor, machinery, chemical fertilizers, and pesticides. Second, given that climate change is a long-term factor affecting agricultural production, this research considers the effect of climate change on each agricultural input, and whether there is room for improvement. Moreover, it provides empirical evidence on how climate change affects the marginal products of agricultural inputs.

The remainder of this article is organized as follows. Section 2 elaborates on the literature on the importance of agricultural inputs, the methods of measuring agricultural inputs' marginal products and agricultural efficiency, and the influence of climate change on agricultural production. Section 3 presents the data and methodology of the study. Section 4 describes our empirical results. Finally, Section 5 summarizes the conclusions and provides policy implications.

2. Literature Review

2.1. Agricultural Inputs and Their Importance to Agricultural Growth in China

Many studies have examined the contribution of agricultural inputs (e.g., labor, land, fertilizers, and agricultural machinery) to agricultural production in China, reaching the unanimous conclusion that they play a critical role in China's agricultural growth. For example, Shu et al. (2019) [6] found the elasticity of land input to be the largest in China's agricultural production. However, the marginal product of land in Zhejiang province was lower than those of labor and capital according to Yang (2009) [20]. Nevertheless, because land intensification was still not high, it could be replaced by labor and capital elements. According to Li (2019) [21], labor elasticity has been stable in China, while the elasticity coefficients of capital and land have increased since 2000. Shen et al. (2019) [22] found that fertilizers and agricultural machinery were the primary sources of agricultural economic growth in Sichuan Province. Zhang et al. (2016) [23] suggested that fertilizer, irrigation and mechanical inputs have had a statistically significant positive effect on wheat yield in China, whereas Wu (2010) [24] found that labor and capital were the most critical determinants of provincial agricultural output in the country.

Furthermore, agricultural production efficiency and inputs' use efficiency were also examined. Ma et al. (2021a, 2021b) [25] investigated agricultural production efficiency and fertilizer use efficiency in China, and found that the country's agricultural production efficiency level was relatively low, with a fertilizer use efficiency of only 25.4%. Ye et al. (2020) [26] measured the efficiency of agricultural land use at the county level in China, and showed that land-use efficiency was lower than 70% in more than 70% of counties in the country. Yu et al. (2019) [27] investigated the causal relationship between land use and socio-economic development of urban agglomerations. They found that the average urban land-use efficiency of urban agglomerations in China was not high. Using Germany as a case study to analyze the effects of crop inputs on wheat output under the influence of climatic factors, Albers et al. (2017) [28] showed that changes in inputs explained 49% of wheat yield fluctuations in Germany. However, most studies have focused on estimating the elasticity coefficient or marginal products of each input factor, but did not identify how each decision-making unit (DMU) can improve agricultural production efficiency by increasing a specific input resource during the observation period.

2.2. The Related Methods

Different methods have been employed to investigate the importance or contribution of agricultural inputs to agricultural production. Shen et al. (2019) [22] used the Cobb-Douglas function to calculate the elasticity of agricultural inputs and estimated future agricultural production indicators in Sichuan province by building a grey model (1,1). Shu et al. (2019) [6] employed the constant elasticity of substitution production function to measure the contribution of agricultural inputs to agricultural production in China. Chen and Hu (2016) [29] used the Tobit model to analyze the effect of fertilizer, mechanization, and human capital level on the output of japonica rice. Li et al. (2014) [30] used Griliches' production function to analyze the contribution of input factors to agricultural output in light of significant institutional changes.

Agricultural production efficiency measures the distance between the actual output of agricultural activities and the optimal output (production frontier) using the same amount of agricultural resource input; the closer the distance between them, the higher the overall efficiency of agricultural production. There are two main approaches for measuring the efficiency of agricultural output: parametric and non-parametric. Parametric methods typically use stochastic frontier analysis (SFA), whereas non-parametric methods typically use data envelopment analysis (DEA).

Meeusen and Broeck (1977) [31] proposed and developed stochastic frontier production functions under specific technical conditions; Aigner et al. (1977) [32] and Battese and Coelli (1993) [33] studied the functional relationship between input factors and the maximum yield, and a combination of production factors was given. In particular, it is often combined with the translog production function, which is a variable elastic production function model, and can be easily estimated with strong tolerance [34]. From a structural perspective, it is classified as a quadratic response surface model. This means that it can better capture the relationship among inputs in the production function, the differences in technological progress of various inputs, and changes in technological advancement over time [34]. For example, Wang and Wu (2015) [34] employed SFA to investigate the production efficiency of the corn industry in different provinces in China, whereas Cheng et al. (2016) [35] used an SFA model beyond the logarithmic production function to examine the efficiency loss caused by factor misplacement in agricultural production in the country.

Charnes et al. (1978) [36] proposed the non-parametric DEA method based on Farrell's (1957) [37] theory. This typically uses a set of input and output datasets to build parametric segmentation surfaces on data points to obtain boundary production and distance functions that estimate productivity. Jiao (2013) [38] used a three-stage DEA model to calculate the pure technical efficiency, scale efficiency, and comprehensive efficiency of agricultural production in Shandong province. In addition, spatial measurement models were employed to measure agricultural production efficiency. For example, Wu (2010) [24] used the spatial lag and spatial error models to explore the output elasticity of agricultural inputs in China. Ma et al. (2021a) [25] employed a spatial econometric model to calculate the production efficiency of China's agricultural production and its temporal changes between 1990 and 2017.

In summary, both parametric and non-parametric methods have been widely applied to calculate technical efficiency by constructing production frontier models in the field of agricultural research. On one hand, the parametric approach uses a predefined production function to build the production frontier, and employs a conditional expectation of the technical inefficiency term as technical efficiency. On the other hand, the non-parametric approach can calculate efficiency through linear programming, with one of its advantages being that only input-output data are required, and it precludes the need for functional forms of production boundaries. As the actual production function is always unknown, this study employs a non-parametric method to calculate the efficiency of agricultural production in Jiangsu province.

2.3. The Effect of Climate Change on Agricultural Production

Recently, the effect of climate change on agricultural production has attracted widespread attention from governments and academia. Climate change could affect the production environment, which might lead to changes in agricultural production inputs and outputs [39]. For example, increases in temperature and carbon dioxide levels can enhance the yields of some crops, while climatic changes that cause severe drought and floods are harmful to agricultural production. In particular, temperature and precipitation are two of the most critical indicators used to study the influence of climate change on agricultural production [40]. Previous studies have shown that climate change has a negative effect on total factor production, and furthermore, high temperature has a negative effect on labor and fertilizers, but has no effect on machinery in the short term [18]. Yi et al. (2021) [19] found that agricultural research investment has regional differences in addressing the effect of climate change on agricultural productivity, and the annual average temperature has a positive effect on agricultural productivity. The existing research on climate change on agricultural production pays more attention to agricultural production efficiency, or a certain agricultural input factor, but few studies focus on the effect of climate change on each agricultural input. Studying the contribution of each agricultural input (including land, labor, agricultural machinery, fertilizers and pesticides) to agricultural production when climate changes can determine the room for improvement in agricultural production, which can help the government and farmers respond to changes in the production environment in a more targeted manner. Despite many studies on the effect of climate change on agricultural output, few have examined the effect of climate change on the marginal contribution of inputs in agricultural production. This study focuses on the relationship between climate change and the marginal product of agricultural inputs, providing a new research perspective.

3. Materials and Methods

3.1. Data

This study examines balanced panel data of the main prefecture-level cities in Jiangsu province from 2001 to 2018. The data were divided into input and output. Inputs includes labor force (10,000 people), cultivated land area (1000 hectares), total power of agricultural machinery (10,000 kWh), chemical fertilizer (10,000 tons), and pesticides (10,000 tons). Output represents the agricultural gross output value (billion USD) of the prefecture-level city and has been deflated based on the 2011 level. All data were obtained from the Statistical Yearbook of Jiangsu province from 2001 to 2018.

Table 1 presents the summary statistics of the variables used in the analysis. The results show that labor, fertilizers and pesticides have a downward decreasing trend, whereas land has an upward trend, first increasing and then decreasing over the same period. The total power of agricultural machinery and agricultural gross output value increases over the analysis period.

Table 1. Descriptive statistics of agricultural inputs and outputs.

Year	Labor	Land	Machinery	Fertilizers	Pesticides	Output
2001	111.69	590.29	228.81	26.00	0.70	2.18
2002	104.16	588.77	229.53	25.95	0.66	2.22
2003	94.64	576.11	233.75	25.68	0.68	1.78
2004	87.47	582.07	234.37	25.89	0.71	2.04
2005	81.41	586.81	242.78	26.22	0.79	1.97
2006	75.54	584.62	261.18	26.38	0.76	2.09
2007	71.55	567.76	260.95	26.31	0.74	2.06
2008	68.95	584.60	279.30	26.21	0.72	2.26
2009	67.41	591.81	293.12	26.46	0.71	2.62
2010	66.14	601.31	302.87	26.24	0.69	2.79
2011	63.21	603.76	315.85	25.94	0.67	2.97
2012	61.23	606.37	324.20	25.46	0.64	3.33
2013	59.70	606.08	339.53	25.14	0.62	3.63
2014	58.62	603.75	357.69	24.89	0.61	3.90
2015	56.62	603.51	371.37	24.61	0.60	4.17
2016	55.59	595.53	377.43	24.04	0.59	4.25
2017	55.59	583.64	383.95	23.37	0.56	4.33
2018	54.46	578.50	387.87	22.49	0.54	4.45

Notes: A fixed exchange rate is employed; 1 USD is equal to 6.5 RMB. Data sources: Statistical yearbook of Jiangsu province.

3.2. Method of Estimating Marginal Product by Shadow Price Ratio

Assume that there are K DMUs, namely, cities in the Jiangsu province of China. The production technology includes inputs and outputs of the agricultural sector, and $x = (x_1, \ldots, x_n) \in R_+^N$ represents N types of inputs (e.g., labor, land), $y = (y_1, \ldots, y_m) \in R_+^M$ are M types of outputs (e.g., GDP), and T is the production technology defined as follows:

$$T = \{(x, y) : x \; can \; produce \; y\} \tag{1}$$

To eliminate the influence of heterogeneity in the sample, we assumed variable returns to scale (VRS) for the agricultural sector's production technology, which could be represented based on an output-oriented directional distance function. The inefficiency score was computed by the directional distance function, which is the difference between the evaluated DMUs and their benchmarks. For instance, 1% inefficiency suggests that the evaluated DMU can increase its agricultural output by 1%, given a certain level of inputs, whereas zero inefficiency implies that the evaluated city is on the production frontier serving as the benchmark. The directional distance function (D) can be defined as

$$\hat{D}\left(x, y; g_x, g_y\right) = \sup_{\delta}\left\{\delta \in \Re_+ : \left(x - \delta g_x, y + \delta g_y\right) \in \hat{T}\right\} \tag{2}$$

where δ is the inefficiency score that represents the potential expansion of the outputs and the reduction in inputs. By applying the output-oriented directional distance function, the direction vectors of $\left(g_x, g_y\right) = \left(0, y_k^m\right)$ are initialized. λ_k is the activity variable that represents the reference set. For instance, "k" cities are included in the reference set of the evaluated DMU if λ_k is greater than 0.

The linear program of estimating the shadow price is given as

$$
\begin{aligned}
D(x,\ y;\ g_x, g_y) \ &= \min_{\pi_y,\pi_x,\phi} \phi - \left(\sum_{m=1}^{M} \pi_y^m y_{k\prime}^m - \sum_{n=1}^{N} \pi_x^n x_{k\prime}^n \right) \\
s.t. &\sum_{m=1}^{M} \pi_y^m y_k^m - \sum_{n=1}^{N} \pi_x^n x_k^n \le \phi, k = 1, \ldots, K \\
&\sum_{m=1}^{M} \pi_y^m g_y^m + \sum_{n=1}^{N} \pi_x^n g_x^n = 1 \\
&\pi_y^m \ge 0, m = 1, \ldots, M \\
&\pi_x^n \ge 0, n = 1, \ldots, N
\end{aligned} \tag{3}
$$

where ϕ is the shadow profit to be computed, which also allows for VRS; and π_y^m and π_x^n are the shadow output and input values, respectively. The objective function is set to minimize the difference between the shadow profit (ϕ) and the evaluated profit $\left(\sum_{m=1}^{M} \pi_y^m y_{k'}^m - \sum_{n=1}^{N} \pi_x^n x_{k'}^n \right)$. $\sum_{m=1}^{M} \pi_y^m g_y^m + \sum_{n=1}^{N} \pi_x^n g_x^n = 1$ is the constraint on the directional distance function.

Although the shadow values have no intrinsic meaning, their ratio between inputs and outputs may provide useful information for policymakers. The marginal product between output (π_y) and input (π_x) can be expressed as:

$$\frac{dy}{dx} = -\frac{\frac{\partial D}{\partial x}}{\frac{\partial D}{\partial y}} = \frac{\pi_x}{\pi_y} \tag{4}$$

In the empirical analysis, the shadow price ratios between the inputs and outputs are investigated. Table 2 presents the shadow price ratios and their economic interpretations.

Table 2. Economic interpretation of shadow price ratios.

Notation	Economic Interpretation	Formula
SP_{Labor}	The GDP expansion resulting from an extra unit of labor use, or the marginal product of labor.	$\frac{\pi_{Labor}}{\pi_{GDP}}$
SP_{Land}	The GDP expansion resulting from an extra unit of land use, or the marginal product of land.	$\frac{\pi_{Land}}{\pi_{GDP}}$
$SP_{Machinery}$	The GDP expansion resulting from an extra unit of machinery use, or the marginal product of machinery.	$\frac{\pi_{Machinery}}{\pi_{GDP}}$
$SP_{Fertilizer}$	The GDP expansion resulting from an extra unit of fertilizer use, or the marginal product of fertilizers.	$\frac{\pi_{Fertilizer}}{\pi_{GDP}}$
$SP_{Pesticide}$	The GDP expansion resulting from an extra unit of pesticide use, or the marginal product of pesticides.	$\frac{\pi_{Pesticide}}{\pi_{GDP}}$

It is noteworthy that some inputs' shadow value might be zero because of multiple solutions in linear programming. The zero value suggests that such inputs may be less important during the production process. The high frequency of a non-zero value indicates that this input plays a significant role in producing the corresponding output—in other words, it is scarce.

3.3. Econometric Strategy

One of this study's significant purposes is to capture the effect of climate change on the marginal products of land and other agricultural input factors. The empirical model was formulated as follows

$$spinput_{it} = \alpha + \beta climate_{it} + \gamma X_{it} + \mu_t + \varepsilon_{it} \tag{5}$$

where $spinput_{it}$ is the marginal product of land or the fertilizer factor in city i in year t, and $climate_{it}$ is a climatic variable, including temperature and precipitation. This study selected annual average temperature (°C) and annual precipitation to measure the climate changes. X_{it} is the control variable which included the proportion of crop output value in the output value of agriculture and the amount of each agricultural input, μ_t is the fixed year effect, and ε_{it} is the random disturbance term.

A fixed-effect model was employed to estimate Equation (5). Given that limited variables are used in the regression model, we chose the fixed-effects model instead of the random-effects model, as the results of the fixed-effect model are always consistent regardless of whether the invariant omitted estimators are correlated with the error terms. When the invariant omitted estimators are associated with the error terms, random-effects models are inconsistent.

4. Results

The estimation results show that, as a whole, agricultural inefficiency in Jiangsu province increased from 2001 to 2018, despite some sharp fluctuations (Figure 2). The average annual growth rate was 6.6%, and reached a maximum of 21% in 2017. In particular, agricultural inefficiency moved by approximately 10% from 2001 to 2012. After 2012, it showed a rapid upward trend, especially after 2015. From 2016 to 2018, agricultural inefficiency remained at approximately 20%. These results suggest that there is still room for improving agricultural productivity in Jiangsu province.

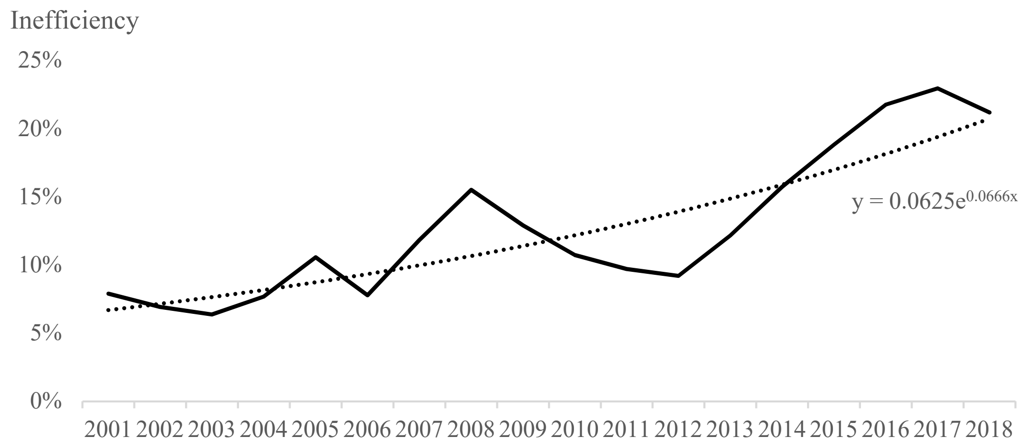

Figure 2. Changes in agricultural inefficiency in Jiangsu province.

Comparing the changes in agricultural inefficiency in each city of Jiangsu province from 2001 to 2018, the trends in most cities are consistent with the overall trend of Jiangsu province (Figure 1). In only a few cities, such as Nanjing and Wuxi, the inefficiency level remained at 0%. However, in Lianyungang, Suqian, and Huai'an, the inefficiency level exhibited an upward trend. The results indicate that there is great potential for agricultural growth in many cities in Jiangsu province. They also suggest that each city should treat itself as a DMU to determine the possible policies or measures to improve its production efficiency.

Given that agricultural inefficiency in most cities in Jiangsu province increased from 2001 to 2008, we then identified which input factors could improve production efficiency. The average marginal products of agricultural inputs in Jiangsu province from 2001 to 2018 are presented in Table 3. The marginal products of agricultural land, labor, machinery, chemical fertilizers, and pesticides are 1.54 thousand USD per hectare, 0.32 thousand USD per person, 0.31 thousand USD per kWh, 21.63 thousand USD per ton and 0.88 USD per ton, respectively. In particular, in Changzhou, where the marginal contribution rate of land elements is the highest, the marginal product of land is 3.58 thousand USD per ha. Yancheng has the highest marginal product of labor (1.77 thousand USD per person), namely, labor productivity. Taizhou has the highest marginal product of machinery (1.05 thousand USD per kWh). In Zhenjiang City, which has the highest marginal contribution rate of fertilizer elements, every additional ton of fertilizer input could increase agricultural GDP by 243.73 thousand USD.

Table 3. The marginal products of inputs at the city level.

City	SPLand	SPLabor	SPMachinery	SPFerilizer	SPPesticide
Unit	**10^3\$/ha**	**10^3\$/Person**	**10^3\$/kwh**	**10^3\$/ton**	**\$/ton**
Changzhou	3.58	0.00	0.08	15.18	0.00
Huai'an	1.39	0.47	0.16	2.88	3.83
Lianyungang	3.79	0.00	0.19	0.00	3.83
Nanjing	1.21	1.21	0.07	2.99	0.00
Nantong	0.05	0.00	0.00	7.74	0.00
Suqian	1.88	0.14	0.44	3.33	0.00
Suzhou	3.56	0.00	0.04	1.00	3.83
Taizhou	0.13	0.05	1.05	0.54	0.00
Wuxi	2.90	0.02	0.41	1.47	0.00
Xuzhou	1.06	0.00	0.00	1.31	0.00
Yancheng	0.34	1.77	0.00	0.79	0.00
Yangzhou	0.00	0.40	1.04	0.28	0.00
Zhenjiang	0.15	0.09	0.52	243.73	0.00
Average	1.54	0.32	0.31	21.63	0.88

Notes: A fixed exchange rate is employed; 1 USD is equal to 6.5 RMB.

It is worth noting that a high marginal product value suggests a lack in the corresponding input, while a zero value indicates a relatively abundant resource. Thus, the zero value of the marginal product of pesticides indicates that this input is not scarce in Jiangsu province.

We utilized an econometric model to identify the effect of climate change, in terms of temperature and precipitation, on marginal products of agricultural inputs. Table 4 shows the regression results of the average annual temperature on marginal products. In the short term, the increase in temperature significantly enhances the marginal products of fertilizers and machinery. In the short term, the increase in ambient temperature will accelerate the loss of nutrients. To cope with this, farmers will increase the input of fertilizers and other chemicals; therefore, in the short term, as the investment in fertilizers increases, the marginal fertilizer product will increase. It is worth noting that changes in temperature also have a significant effect on the marginal products of agricultural machinery, and a possible explanation is that as the temperature rises, the uncertainty of agricultural production increases, and farmers will invest more in mechanical technology to maintain production stability. Therefore, in the short term, as the machinery input increases, so too will the marginal machinery product. Table 5 shows the effect of annual precipitation on marginal products. The regression results indicate that the increase in annual precipitation reduces the marginal contribution of land significantly, which may be because of the increase in precipitation destroying the soil structure. The marginal contribution of temperature and precipitation to other agricultural inputs does not have a significant effect in the short term.

Table 4. The effect of temperature on the marginal product.

	(1)	(2)	(3)	(4)
Variables	**Spland**	**Lnspfertilize**	**Lnsplabor**	**Lnspmachinery**
temperature	0.203	0.366 *	0.208	0.328 **
	(1.22)	(1.81)	(0.75)	(2.38)
share	4.941 *	1.460	7.866 *	0.494
	(1.79)	(0.63)	(1.84)	(0.22)
land	0.002			
	(0.81)			
fertilizer		−0.007		
		(−0.13)		

Table 4. *Cont.*

	(1)	(2)	(3)	(4)
Variables	**Splnd**	**Lnspfertilize**	**Lnsplabor**	**Lnspmachinery**
labor			−0.020	
			(−0.79)	
machinery				−0.012 **
				(−2.55)
Constant	−133.543 ***	−193.468 ***	−64.797	−192.545 ***
	(−3.09)	(−3.43)	(−0.42)	(−3.21)
Year Fe	YES	YES	YES	YES
Observations	106	105	36	76
R-squared	0.168	0.207	0.411	0.223

Notes: t-statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5. The effect of precipitation on the marginal product.

	(1)	(2)	(3)	(4)
Variables	**Spland**	**Lnspfertilize**	**Lnsplabor**	**Lnspmachinery**
precipitation	−0.009 **	−0.007	−0.001	0.002
	(−2.15)	(−1.52)	(−0.22)	(0.52)
share	5.443 **	1.901	8.192 *	1.326
	(2.02)	(0.81)	(1.82)	(0.57)
land	0.001			
	(0.45)			
fertilizer		−0.007		
		(−0.14)		
labor			−0.018	
			(−0.71)	
machinery				−0.012 **
				(−2.51)
Constant	−137.493 ***	−209.977 ***	−73.755	−188.414 ***
	(−3.23)	(−3.66)	(−0.47)	(−2.94)
Year Fe	YES	YES	YES	YES
Observations	106	105	36	76
R-squared	0.195	0.198	0.398	0.155

Notes: t-statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. Conclusions

This study first investigates the efficiency of Jiangsu province's agricultural production in China from 2001 to 2018. Then, a robust non-parametric model is introduced to explore the shadow price and marginal products of inputs. Finally, an econometric model was utilized to examine the effect of climate change on the marginal product of agricultural inputs. The empirical results show an increasing trend of agricultural production inefficiency in Jiangsu province from 2001 to 2018, despite the existence of significant differences in performance among different prefectures. Land and fertilizer inputs are the two most important driving forces in agricultural production, as their maximum shadow values are non-zero. Most prefectures improve their production efficiency by increasing land and fertilizer inputs. The marginal products of agricultural land, labor, machinery, chemical fertilizers, and pesticides are 1.54 thousand USD per hectare, 0.32 thousand USD per person, 0.31 thousand USD per kWh, and 21.63 thousand USD per ton and 0.88 USD per ton, respectively. Finally, higher temperature increased the marginal fertilizer and machinery products significantly, whereas increased precipitation decreased the marginal land product.

There are some clear lessons for the government in Jiangsu province. First, improving agricultural factor productivity is key to promoting high-quality agricultural development in Jiangsu province and ensuring the security of food supply. As an important agricultural province, Jiangsu plays a vital role in ensuring a stable supply of agricultural products, and increasing agricultural productivity can help ensure food security. Therefore, under the constraints of limited land resources, further enhancement of the marginal products of agricultural inputs is of great importance to the strategy of "reserving grain on the ground and storing grain on technology". The empirical results show that agricultural productivity in Jiangsu province still has room for improvement. For example, Jiangsu province can further increase financial support, such as increasing investment in arable land infrastructure, soil improvement, soil fertility cultivation, and dynamic monitoring. Furthermore, it is essential to continuously strengthen and improve the agricultural technology extension system to increase the productivity of inputs by providing subsidies for agricultural production resources.

Second, the government can better allocate inputs to improve agricultural production efficiency in Jiangsu province. Each prefecture should consider itself a DMU to determine the possible policies or measures to improve its production efficiency. Given the differences in the marginal output of agricultural inputs in various regions of Jiangsu province, the heterogeneity of agricultural development among regions should be fully considered when formulating agricultural development policies. The government should continuously formulate differentiated agricultural development strategies and explore agricultural development paths with regional characteristics, as different regions require different improvement paths. For example, Lianyungang should focus on improving the production efficiency of land and pesticides, whereas Nantong should focus more on fertilizers. In addition, Jiangsu province should pay more attention to promoting the improvement of agricultural production efficiency through institutional innovation. Furthermore, the government of Jiangsu province should consider the establishment of an inter-regional coordination and cooperation mechanism to guide each region regarding rational investment, and to complement the use of agricultural production resources, thus improving the spatial allocation efficiency of the resources and promoting the continuous improvement of the overall production capacity of agriculture.

Third, the government should strengthen the construction of agricultural infra-structure and formulate relevant policies to better cope with climate change to increase the marginal contribution of agricultural inputs. Agricultural production is greatly affected by climate change and how to respond accurately to climate changes is crucial for agricultural production. Furthermore, climate change is uncontrollable; therefore, it is particularly important to formulate reasonable and accurate policies in order to deal with it. The government should provide input subsidies and implement policies to improve the marginal products of inputs in agricultural production. In addition, owing to the differences in the natural environment, location, economic foundation, and other conditions, when formulating policies to deal climate change, measures should be adapted to local conditions, and implemented according to the differences in primary conditions.

The current study has the following limitations. First, we only used data from 2001 to 2018. Hence, future studies should extend the time span. Second, this study mainly investigates the reasons for changes in the marginal products of agricultural inputs at the prefectural level. Thus, future research should explore the reasons for such changes at higher administrative levels.

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