Performance assessment of peanut production in China

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ABSTRACT
China has developed into the world’s largest producer of peanuts; however, it remains unable to achieve self-sufficiency. We assessed China’s peanut production performance and determined the crucial influential factors to improve the efficiency and productivity of peanut production. In this article, the performance of ten main peanut producing areas was evaluated from 2009 to 2018 through the adoption of a three-stage data envelopment analysis (DEA) approach and the Malmquist index. The results revealed inefficient peanut production in China. First and foremost, the overall efficiency was not located at the production frontier due to the decreasing scale efficiency. In addition, insufficient technological progress led to the relatively low total factor productivity. Last but not least, the managerial inefficiency was the main external environmental factor influencing the peanut production performance in China. Accordingly, we put forward corresponding suggestions, such as enhancing the environmental factors, realising the technological process, and achieving the optimal scale.

Introduction
As an essential agricultural product in China, oilseed is an important raw material for edible vegetable oil and protein feed. However, the gap between the production of and demand for oilseeds has widened, leading to increases in imports and foreign dependence. China has consistently remained the world’s largest importer of edible vegetable oil and the self-sufficiency rate of edible vegetable oil is less than 40% (National Development and Reform Commission 2017). Oilseeds are used in the edible oil refining business, which is among the most significant crops industries. The gap is between area growth and productivity of main oilseed. Therefore, China’s oil production capacity urgently needs to be further improved to maintain a certain level of self-sufficiency.

Among all oilseed categories, peanuts have the greatest potential for production and development. On the one hand, the oil content of peanuts still has room for improvement. At present, the oil content of peanut varieties widely promoted in China can reach 50%, generally 7% higher than that of rapeseed, and a batch of bred varieties with oil contents as high as 55% also exists (National Development and Reform Commission 2017). On the other hand, peanut production has shown a steady growth trend overall. China has developed into the world’s largest producer of peanuts. In 2018, China’s peanut planting area reached more than 50 million hectares, with an output of 17 million tons, accounting for about 40% of the world’s total peanut yield and occupying approximately 50 per cent of all oil crops in China (except soybeans). The output value of the peanut planting industry reached 17.86 billion US dollar, ranking fourth among the country’s crops (after rice, wheat, and corn) (National Bureau of Statistics 2019).

Considering the decreasing agricultural land, the diminishing marginal returns of inputs, and the pressure on the ecological environment, China is facing increasing pressure to improve peanut production performance (Jalilov et al. 2019). To solve this problem, in this study, the ten main peanut-producing areas in China from 2009 to 2018 were used as the research object. A three-stage data envelopment analysis (DEA) approach and the Malmquist index were used to estimate the efficiency, productivity, and the influential factors of China’s peanut production. Data envelopment analysis (DEA) is a nonparametric tool for calculating productivity boundaries in industrial engineering and commerce. It’s being used to quantify the technical capacity of judgement unit’s empirical evidence. As a result, a scalar measurement of each participant unit’s effectiveness is supplied, as well as techniques for quantitatively

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calculating weights for the numerous outcomes and multiple inputs that define such systems using statistical data.

**Literature review**

The link among production rate and input costs is modeled by a Cobb–Douglas production process factors. It is used to compute input–output ratios for an effective model and to forecast technological innovation in manufacturing procedures. According to the Cobb–Douglas (C–D) production function, there are two ways to increase output. One is to locate each decision-making unit (DMU) at the production frontier (Farrell 1957), which is the maximum production that can be achieved by allocating the input combinations effectively under constant techniques. The other way is to improve technological progress and the total factor productivity in order to push the production frontier forward to a higher level. In this chapter, we introduce references related to the measurement methods of efficiency and productivity.

**Measurement of production efficiency**

Generally, two principal approaches used to calculate efficiency: data envelopment analysis (DEA), a linear programming method where parameters are not estimated in advance (Chames et al. 1978), and stochastic production frontier analysis (SFA), a parametric estimation method (Aigner et al. 1977). The pros and cons of the two methods are as follows.

The advantage of the DEA approach is that it can handle multiple input–output variables without specifying the production function or estimating the validity of the regression coefficients. However, the disadvantage of DEA is that it estimates the gaps between each decision-making unit (DMU) and the most efficient DMU using the distance function. Thus, the DEA approach can be used to evaluate the relative efficiency. In addition, DEA cannot determine the influential factors of DMUs. The DEA approach has been widely used in analyzing agricultural efficiency (Karimov 2013; Tian et al. 2016; Frangu et al. 2018; Hosseinzadeh-Bandbafa et al. 2018; Rybaczewska-Błażejowska and Gierulski 2018; Bagchi et al. 2019; Masuda 2019; Tran Nguyen et al. 2020; Li et al. 2020b).

Contrary to the DEA approach, the SFA model can establish and estimate the production function. While the SFA model is limited by strict constraints, it can evaluate the impacts of managerial inefficiency and random errors due to DMUs. Many researchers choose the SFA model to measure efficiency in agricultural production (Kea et al. 2016; Wang et al. 2019; Liu et al. 2020). The SFA Model is a framework for evaluating and selecting available choices. SFA are acronyms meaning Suitability, Feasibility, and Acceptability. These are the SFA Analysis criterion categories that are used to evaluate and evaluate every method.

Fried et al. suggested that the production performance is influenced by environmental effects, managerial inefficiencies, and statistical noise (Fried et al. 2002). For this reason, they came up with a three-stage DEA approach, which combined the SFA model with the DEA approach. In the three-stage DEA approach, the SFA model is used as the second stage to set the managerial inefficiency apart from both environmental effects and statistical noise. The three-stage DEA method has been widely used in performance assessment in numerous domains, for instance, culture (Zeng et al. 2016), air transportation (Song et al. 2020), banking (Novickyte and Drozdz 2018), and semiconductors (Li et al. 2019). DEA has also been applied to calculate carbon emissions in agricultural production (Li et al. 2020a) and water-usage efficiency (Cao et al. 2020), and scholars have used it to analyze urbanisation (Jia et al. 2017).

**Measurement of total factor productivity (TFP)**

The methods mentioned above evaluate the efficiency statically. We also analyzed the change in productivity dynamically by using TFP. The efficiency of all resources is referred to as total factor productivity (TFP). TFP is a measurement of a sectors or economy overall production in relation to the total size of its major factor input. TFP denotes any effect on total output that isn’t captured by inputs. We noticed that the change in productivity led to the movement of the production frontier, i.e. the higher the productivity, the further the production frontier, and the higher the potential yield. There are two common ways to measure TFP, one is the gain of TFP, e.g. through Solow residuals, and the other is the change in TFP, which is represented by the TFP index, for example, the Malmquist index and Luenberger–Hicks–Mooresteen (LHM) TFP indicator. Previous articles evaluated the agricultural productivity growth (Pang et al. 2016; Anik et al. 2017; Li et al. 2017; Reza Anik et al. 2020).

From the previous articles, we found that the research on the performance of agricultural production focused either on the static efficiency or on a dynamic TFP change. However, few papers fully researched the performance of agricultural production and the environmental impact, particularly with respect to China’s peanut production. To bridge the gaps in the previous
literature, the three-stage DEA was used in this article to solve two problems: (1) the decisive factors related to China’s peanut performance and (2) the paths through which the external environmental factors affected the DMU efficiency.

The remainder of the article includes four sections: In Chapter 3, we introduce the methodology, including the three-stage DEA approach and Malmquist index. In Chapter 4, we describe the variable selection and data sources. In Chapter 5, we present the empirical results. Finally, the conclusions and corresponding suggestions are given in Chapter 6.

**Methods**

**Three-stage DEA approach**

In this part, the three-stage DEA approach is introduced step by step.

**The first stage: the original DEA model**

Data envelopment analysis (DEA) was first presented by Charnes, Cooper, and Rhodes in 1978 and has been widely applied in evaluating the relative efficiency among departments. The basic principle of the DEA approach is determining the production frontier and measuring the distance between the decision-making unit (the combination of inputs and outputs) and the production frontier. Thus, understanding the concept of the production frontier is critical in the DEA approach. The production frontier is constructed from all the decision-making units (DMUs). A DMU located at the production frontier means the current allocation of inputs has achieved the maximum output. However, not all the DMUs are located at the production frontier, but rather, beneath it or close to it. In addition, each DMU’s distance to the production frontier reflects the relative efficiency; the closer the distance, the higher the relative efficiency score.

On the basis of two different returns to scale assumptions, the DEA can be divided into two models: one is the DEA-CCR (Charnes et al. 1978) model, based on the assumption of constant returns to scale. The CCR ratio approach estimates the unit’s total efficiency by combining its basic efficiency levels and allocative efficiency into some kind of single number. Because effectiveness has always been measured according to the area, it is never perfect. The other is the DEA-BCC (Banker et al. 1984) model, based on the assumption of variable returns to scale (Banker et al. 1984). The DEA-BCC model was adopted in this article, as in agricultural production, it is unrealistic and impossible to maintain a constant cultivation scale. The BCC DEA system is based upon VRS technological assumptions and assesses purely productivity growth, or input-to-output conversions. The CCR model calculates general efficiency levels (OTE), whereas the BCC model calculates pure efficiency levels (PTE) irrespective of scale economies. Pure technical efficiency is produced directly by management inefficiencies in organising the resources, whereas technical efficiency is the efficiency at which a particular set of numbers is employed to produce a result. The DEA-BCC model can be written as follows:

The number of DMUs is \( n \), the input vector of DMU \( j \) is \( X_j = (X_{1j}, X_{2j}, \ldots, X_{mj}) \), the output vector is \( Y_j = (Y_{1j}, Y_{2j}, \ldots, Y_{nj}) \), and the set of production possibilities is \( T = \{ (X, Y) \mid \sum_{i=1}^{m} x_{ij} \lambda_i - s_i^+ = X, \sum_{j=1}^{n} y_{rj} \lambda_j - s_r^- = Y, \lambda_i \geq 0, j = 1, 2, \ldots, n \} \). Under the assumptions of cone, invalidity, minimum, and convexity, the DEA-BCC model can be written as follows:

\[
\begin{align*}
\text{Min} & \quad \theta = \epsilon \left( \sum_{r=1}^{s} s_r^- + \sum_{i=1}^{m} s_i^+ \right) \\
\text{s.t.} & \quad \sum_{j=1}^{n} x_{ij} \lambda_i + s_i^+ = \theta x_{ir}, i \in (1, 2, \ldots, m) \\
& \quad \sum_{j=1}^{n} y_{rj} \lambda_j + s_r^- = y_{ro}, r \in (1, 2, \ldots, s) \\
& \quad \sum_{j=1}^{n} \lambda_j = 1 \\
& \quad \theta, \lambda_i, s_i^+, s_r^- \geq 0, j = 1, 2, \ldots, n
\end{align*}
\]

where \( \theta \) represents the relative efficiency, \( \lambda_j \) represents the weight of the DMU reference set, \( s_i^+ \) represents the redundancy of the \( r \)-th output, and \( s_r^- \) represents the lack of the \( i \)-th input. If there exists a \( \lambda_j \) that makes \( \sum_{j=1}^{n} \lambda_j = 1 \), the return to scale remains unchanged; but if there exists no \( \lambda_j \) that makes \( \sum_{j=1}^{n} \lambda_j = 1 \), when \( \sum_{j=1}^{n} \lambda_j \leq 1 \), there is an increasing return to scale; otherwise, when \( \sum_{j=1}^{n} \lambda_j \geq 1 \), there is a decreasing return to scale. In the DEA-BCC model, the comprehensive technical efficiency (CTE) of the DMU can be decomposed into the pure technical efficiency (PTE) and scale efficiency (SE), that is, \( CTE = PTE \times SE \).

**The second stage: the simulated SFA regression**

In the first stage, each DMU input slack value was calculated as being equal to the differences between the actual input and the target input. However, according to Fried et al. (2002), a DMU’s efficiency is affected by...
the external environment, including the managerial inefficiency, environmental factors, and statistical noise. Thus, Fried et al. attempted to eliminate the external environmental influences using a Tobit model in 1999 (Fried et al. 1999) and an SFA model in 2002 (Luo et al. 2019). Fried et al. found that the SFA method was better than the Tobit regression since the SFA model could effectively isolate the environmental factors that were implicit in the statistical noise. SFA (stochastic frontier analysis) is an economics modelling technique. Likewise, it has its origins in stochastic frontier production boundary models. SFA is a parametric approach in which the information is used to empirically update the model of an objective function employing the whole set of DMUs. The Tobit model, also known as a restricted linear regression, is used to evaluate linear correlations between variables whenever the response variable has either left- or correct.

In the second stage, the SFA model was used to regress the obtained input slack values based on the environmental variables as dependent variables. According to Fried et al. (2002), the input-oriented (minimising the inputs to achieve the potential yield) SFA regression function is constructed as follows:

$$S_i = f(Z_i; \beta_i) + v_i + \mu_i; \ i = 1, 2, \cdots, l; \ n = 1, 2, \cdots, N$$

where $S_i$ is the $n$-th input slack value of the $i$-th DMU; $Z_i$ is the environmental variable, and $\beta_i$ is the regression coefficient of the environmental variable; $v_i \sim N(0, \sigma_v^2)$ is the random error, which represents the effect of statistical noise on the input slack values; and $\mu_i \sim N(0, \sigma_\mu^2)$ is the management inefficiency, which represents the effect of management factors on the input slack values. Use of the SFA regression aims to eliminate the influences of the environmental effects and statistical noise on the DMU efficiency. The adjustment formula is as follows:

$$X_{ni} = X_{ni} - [\max (f(Z_i; \hat{\beta})) - f(Z_i; \hat{\beta})] + [\max (v_m)]$$

where $X_{ni}^a$ and $X_{ni}$ represent the input after and before the adjustment, respectively. $[\max (f(Z_i; \hat{\beta})) - f(Z_i; \hat{\beta})]$ is the adjustment to the same external environment, and $[\max (v_m) - v_m]$ is the placement of all DMUs facing the same operating environment with the same luck. We can decompose the external environmental influence using the following formula:

$$E(\mu|\sigma) = \frac{\sigma_\mu\sigma_v}{\sqrt{\sigma_\mu^2 + \sigma_v^2}} \left[ \frac{\phi\left(\frac{\sigma_\mu}{\sigma}\right)}{\Phi\left(\frac{\sigma_\mu}{\sigma}\right)} + \frac{\lambda\sigma_v}{\sigma} \right], \lambda = \frac{\sigma_\mu}{\sigma_v}$$

$$\gamma = \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_v^2}$$

The closer $\lambda$ is to 1, the greater the impact of the management coefficient; otherwise, the greater the impact of the statistical noise.

**The third stage: the adjusted DEA model**

The adjusted input variables and original output variables were used as input–output variables, and the DEA model was used again to measure the efficiency of each DMU.

**Malmquist index**

Sten Malmquist initially suggested the Malmquist index in 1953. Subsequently, Caves constructed the Malmquist productivity index by using the distance function and successfully applied it to productivity analysis in 1982 (Caves et al. 1982).

Assuming that $X_t$ and $Y_t$ are the respective input and output indicators in period $t$, $D_0^t(X_t^0, Y_t^0)$ and $D_0^t(X_t^{t+1}, Y_t^{t+1})$ represent, under the technology condition in period $t$, the output-oriented distance function in periods $t$ and $t+1$, respectively. The Malmquist productivity index in period $t$ based on the output can be obtained as follows:

$$M_t^o(X_t^0, Y_t^0, X_t^{t+1}, Y_t^{t+1}) = \frac{D_0^t(X_t^{t+1}, Y_t^{t+1})}{D_0^t(X_t^0, Y_t^0)}$$

In the same way, the Malmquist productivity index in period $t+1$ based on the output can be described with the following formula:

$$M_t^{o+1}(X_t^0, Y_t^0, X_t^{t+1}, Y_t^{t+1}) = \frac{D_0^{o+1}(X_t^{t+1}, Y_t^{t+1})}{D_0^{o+1}(X_t^0, Y_t^0)}$$

Farell et al. defined the geometric mean of the above two indicators as the Malmquist productivity change index: $M_o(X_t^0, Y_t^0, X_t^{t+1}, Y_t^{t+1}) = \frac{D_0^{o+1}(X_t^{t+1}, Y_t^{t+1})}{D_0^o(X_t^0, Y_t^0)} \times D_0^{o+1}(X_t^{t+1}, Y_t^{t+1})$. To eliminate the errors caused by the arbitrariness of the base period selection, the formula can be further rewritten as follows:

$$M_o(X_t^0, Y_t^0, X_t^{t+1}, Y_t^{t+1}) = \frac{D_0^{o+1}(X_t^{t+1}, Y_t^{t+1})}{D_0^o(X_t^0, Y_t^0)} \times \left[ \frac{D_0^{o+1}(X_t^{t+1}, Y_t^{t+1})}{D_0^{o+1}(X_t^0, Y_t^0)} \times \frac{D_0^o(X_t^0, Y_t^0)}{D_0^{o+1}(X_t^0, Y_t^0)} \right]^2$$

**SOIL & PLANT SCIENCE**
variables and data

In agricultural production, labour, land, and capital are the three most important factors of production. Out of the three aspects that go into agricultural output, labour is among the most crucial. Simultaneously, increased agricultural productivity growth shifts agriculture labour away from food supply and toward other products and services. In this paper, we selected the labour and the material and service costs invested in peanut production as the input variables and the total yield of the peanut main product as the output variable. According to the data sources (Compilation of the Cost–Benefit Data of Agricultural Products for 2010–2019), the input and output variables were statistically analyzed by unit area (per 667 square meters), and the input of the land was set as a constant. Therefore, the land area was not selected as an input in this article (Liang et al. 2019). The description of the variables is shown in Table 1, including the unit, source, and detailed description of variables.

Peanut production efficiency is not only due to controlling inputs but also the external environment. The selected environmental variables must influence the DMU efficiency; however, this cannot be controlled by the DMUs. Considering both the previous literature (He and Liu 2015; Liu and Wang 2015; Yi and Luo 2015) and the scientific data, we selected environmental variables that included seven aspects, covering almost the entire production process associated with economics, policy, society, and nature, such as rural economic development, agricultural policy, planting structure, human resources, agricultural infrastructure, agricultural mechanism, and natural disasters, as shown in Table 1.

variable selection and data source

The selection of decision-making units (DMUs)

Peanut is a traditional economic crop that has a long history of cultivation and application in China. Peanuts are widely planted in China, mainly in East China, South China, North China, and Central China, and Henan and Shandong are the two largest peanut growing provinces. Considering the samples, as well as the continuity and availability of data, in this article, we selected ten regions as DMUs: Hebei (North China), Liaoning (Northeast China), Anhui, Fujian, and Shandong (East China), Henan (Central China), Guangdong and Guangxi (South China), Chongqing and Sichuan (Southwest China), covering all areas except Northwest China. As shown in Figure 1, across these ten regions, the total sown area and the total yield were 35,266,000 hectares (76.34% of the whole country) and 1394.07 tons (80.43% of the whole country), respectively.

results and discussion

In this section, ten main peanut production areas were used as the DMUs. Based on the methods proposed, we analyzed the efficiency and productivity of DMUs from the static and dynamic aspects. We initially calculated the efficiency sources and the influential factors of each DMU, adopting the three-stage DEA approach. Then, we used the Malmquist index to assess the total factor productivity (TFP) change and technological progress change.

Efficency scores of peanut production

Efficiency analysis before adjustment

In the first stage, we calculated the annual comprehensive efficiency, pure technical efficiency, and scale efficiency of each DMUs from 2009 to 2018, applying the input-oriented DEA-BCC approach. Table 2, Figures 2 and 3 represent the results.
Figure 2 illustrates the nationwide trend of annual efficiency and its decomposed indexes during the studied period. We found that (1) The DMU’s capacity to transform inputs into outputs is referred to as comprehensive technical efficiency. The comprehensive technical efficiency (CTE) had a slightly downward trend, and there was no year that achieved DEA efficiency (in other words, located at the production frontier), and the maximum efficiency score was 0.887; (2) All inefficiencies are caused directly by management inefficiencies in structuring the inputs, according to a pure efficiency scores rating that ignores nonlinearities, the pure technical efficiency (PTE) showed a continuous decreasing trend; and (3) the scale efficiency (SE) exhibited a stable fluctuation around its average score, and the trend of SE was consistent with that of CTE. A unit is scale effective when its operational size is ideal, and any changes to its size will make it a little less effective. The findings indicated that the overall CTE tendency was the combined result of PTE and SE. SE determined the trend of CTE, and PTE was the decisive factor for the decrease in CTE.

Environmental impact analysis

In the first stage, we calculated the gaps between the actual and the optimal input, that is, the input slack values of each DMU. However, as mentioned previously (Chapter 3), the external environment still affects the DMU efficiency via the managerial inefficiency, environmental factors, and statistical noise. Thus, in this section, taking the seven environmental variables as the dependent variable, we regressed the input slack values using the SFA regression in order to solve two problems: one was to determine how the external environment influences the DMU efficiency, and the other was to eliminate the three kinds of influences of the external environment on DMU efficiency, ensuring that all studied regions were under the same operating environment and the same luck.

The results of the SFA regression were obtained, as shown in Table 3. The one-sided likelihood ratio test value was higher than the mixed chi-square distribution critical value (equal to 1.65); that is, the regression function passed the test. The gamma values were close to 1. This finding demonstrated that it is reasonable to
construct an SFA model and that managerial inefficiency was the decisive influential factor.

Given that the constructed SFA model is based on a cost function, when the regression coefficient of an environmental variable related to the input slack values was positive, an increase in the environmental variable could result in an increase of the input redundancy or output loss (Xiong et al., 2017). Based on the above, the impact of each environmental variable on the two input slack variables was analyzed as follows.

Initially, as we expected, agricultural mechanisation had a positive impact on the labour and capital inputs, as its regression coefficients were all negative. This finding indicates that there were benefits from the increasing and more skilled usage of agricultural machinery and equipment, that the technology improved, and that the inputs were allocated effectively.

Contrary to the expectations, the influences of agricultural policy, planting structure, and agricultural infrastructure on inputs were negative. This result suggests that increasing fiscal expenditures, expanding the planting scale, and improving agricultural infrastructure will not improve the DMU efficiency, but instead, will cause input redundancy. This phenomenon might be caused by the fact that as an important agricultural country, China consistently invests in agriculture; however, due to the marginal decreasing effect, improper agricultural investments have proven unsuitable for the current peanut production situation.

Natural disasters had a positive effect on all inputs, which was inconsistent with the expectation. The reason is that frequently occurring natural disasters encouraged the government and farmers to establish systems for disaster prevention and mitigation, such as cultivating disaster-resistant peanut varieties and building drought-resistant irrigation systems, thereby enhancing the overall disaster resistance and promoting the DMU efficiency.

Finally, although the regression coefficient values of rural economic development and human resources with respect to input slack values were not significant, they could be used to indicate the influential direction on the DMU efficiency. The impact of rural economic development on labour input was negative, but positive on capital input, indicating that the increase in rural household income reduced the waste of capital input but led to a waste of labour input. This phenomenon was primarily due to the attitude of farmers who were unwilling to leave their hometown. With more income, they were more willing to engage in agricultural production, which led to a surplus of labour input. In addition, the increase in income encouraged farmers to choose high-productivity seeds, fertilisers, and other production materials, thereby improving the DMU efficiency.

The impact of human resources on labour input was positive, but negative on capital, which was possibly due to the fact that, with the improvement of education, farmers’ production technology improved; thus, peanut production gradually changed from labour-intensive to capital-intensive, which was conducive to reducing labour redundancy, but might lead to excessive capital investment.
Efficiency analysis after adjustment
In the second stage, we constructed a simulated SFA regression to analyze and strip away the influences of the external environmental variables on the input variables. In this section, the DEA approach was again used to analyze the input variables after adjustment as well as the original output variable. The actual peanut production efficiency of China from 2009 to 2018 was obtained, shown in Figures 4 and 5.

A comparison of the annual comprehensive technical efficiency and its decomposed indexes of the first to the third stages showed they were apparently different (Figure 4). The differences included the following aspects: (1) After adjustment, the comprehensive technical efficiency (CTE) and the pure efficiency (PTE) increased by 8.91% and 11.32%, respectively, but the scale efficiency (SE) decreased by 3.1%. (2) Compared with the first stage, the CTE after adjustment had a decreasing trend with less fluctuation, mainly due to the downward trend and decreasing fluctuation of SE. (3) PTE and SE exhibited opposite directions of fluctuation. (4) The adjusted PTE was maintained at a higher level, with a fluctuation interval of [0.922, 0.946].

These findings showed that after the adjustment, SE was still the main driving force that affected the CTE. However, the decrease in CTE was due to the decrease of SE, as opposed to the PTE. The increasing PTE effectively overcame the decline of SE, while making a great contribution to the CTE. Therefore, it is necessary to pay attention to the economics of the proper scale while maintaining a relatively high level of allocation and management.

Figure 5 demonstrates the differences of the efficiency scores before and after adjustment, from the points of the cross-regions. Differing from the other regions, Liaoning, Fujian, Guangdong, and Guangxi changed significantly after adjustment, indicating that the peanut production efficiency in these four regions was considerably affected by the external environment. Among them, thanks to the increase of the pure technical efficiency (PTE), the comprehensive technical efficiency (CTE) of Fujian, Guangdong, and Guangxi increased markedly, indicating that, compared with other regions, the external environment of peanut production in these regions was unfavourable. On the contrary, Liaoning’s CTE dramatically decreased as

Table 2. The comprehensive technical efficiency of each region from 2009 to 2018 before adjustment.

| Region  | 2009  | 2010  | 2011  | 2012  | 2013  | 2014  | 2015  | 2016  | 2017  | 2018  | Annual average | Rank |
|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|----------------|------|
| Hebei   | 0.849 | 0.936 | 0.779 | 0.764 | 0.737 | 0.877 | 0.906 | 0.869 | 0.794 | 0.943 | 0.845          | 7    |
| Liaoning| 1.000 | 1.000 | 0.827 | 1.000 | 1.000 | 1.000 | 0.969 | 1.000 | 1.000 | 1.000 | 0.952          | 2    |
| Anhui   | 1.000 | 1.000 | 0.824 | 0.931 | 0.834 | 1.000 | 0.972 | 0.878 | 1.000 | 1.000 | 0.944          | 3    |
| Fujian  | 0.661 | 0.639 | 0.643 | 0.665 | 0.508 | 0.535 | 0.564 | 0.618 | 0.616 | 0.506 | 0.596          | 10   |
| Shandong| 0.930 | 1.000 | 0.852 | 0.900 | 0.837 | 0.994 | 0.878 | 0.832 | 0.791 | 0.948 | 0.896          | 4    |
| Henan   | 1.000 | 0.981 | 1.000 | 0.922 | 0.929 | 0.996 | 1.000 | 1.000 | 0.885 | 0.948 | 0.966          | 1    |
| Guangdong| 0.598| 0.706 | 0.683 | 0.644 | 0.560 | 0.654 | 0.677 | 0.613 | 0.582 | 0.587 | 0.630          | 8    |
| Guangxi | 0.704 | 0.679 | 0.727 | 0.733 | 0.552 | 0.559 | 0.564 | 0.566 | 0.503 | 0.55  | 0.614          | 9    |
| Chongqing| 0.851| 0.928 | 0.874 | 0.955 | 0.865 | 0.954 | 0.816 | 0.893 | 0.818 | 0.786 | 0.874          | 5    |
| Sichuan | 0.810 | 1.000 | 1.000 | 0.879 | 0.761 | 0.758 | 0.889 | 0.936 | 0.801 | 0.839 | 0.867          | 6    |
| Average | 0.840 | 0.887 | 0.821 | 0.839 | 0.758 | 0.833 | 0.796 | 0.821 | 0.779 | 0.811 | 0.819          |      |

Figure 2. The annual comprehensive technical efficiency (CTE) and its decomposed indexes before adjustment.
determined by the both reduction of the PTE and scale efficiency (SE), which meant that Liaoning had a better external environment for peanut production, which promoted the DMU efficiency.

**Malmquist indexes of peanut production**

Compared to static efficiency scores (moving along the production frontier), the productivity measures the technological progress (shifting to a higher frontier) from the dynamic aspect. In order to investigate how the total factor productivity and technological progress changed, the Malmquist and its decomposition indexes in ten studied regions from 2009 to 2018 were calculated, adopting DEAP 2.1 software. Data envelopment analysis was performed using Deap (Version 2.1) (DEA). Several different approaches can be utilised to achieve operational efficiency measurements with this application. Since the computation of the Malmquist index requires data for two consecutive years, based on 2009, the index for each area was generated from 2010 to 2018.

From Table 4, the adjusted total factor productivity (TFP) changes of peanut production in China fluctuated between 0.952 and 1.098. Compared to the indexes in the first stage, the mean value increased from 0.996 to 1.002; however, the standard deviation and the coefficient of variation (C.V.) values decreased to 0.047 and 0.047 from 0.061 and 0.062, respectively, indicating that the actual TFP of peanut production in China maintained a more steady growth at the annual average rate of 0.2% (Wang 2020).

As viewed from all studied regions, we observed that, compared to the first stage, the adjusted average change of the TFP, technological progress (Tech), technical efficiency (Effch), and pure technical efficiency (Pech) increased by 0.6%, 0.3%, 0.3%, and 0.7%, respectively. However, the change of scale efficiency (Sech) decreased by 0.5%. This finding showed that the dominating factor in the improvement of China’s peanut production TFP was Tech, while Effch changes relied on Sech changes. Thus, it is important to achieve the optimal scale and continue to encourage and support technical innovation.

As shown in Table 5, from the regional perspective, the ratios of the decline in TFP, Effch, Tech, and Sech in all studied regions were 30%, 40%, 40%, and 50% respectively, while Pech remained basically the same, except in

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**Figure 3.** The three categories of the comprehensive technical efficiency across regions before adjustment.

**Table 3.** The regression results of the stochastic production frontier analysis (SFA).

| Environmental variables | Labour input | Capital input |
|--------------------------|--------------|---------------|
| Constant                 | -3.6793 **  | -92.9354 ***  |
| Rural economic development | 0.0002      | 0.0004        |
| Agricultural policy      | 0.4677 **   | 8.6736 **     |
| Planting structure       | 0.0304 **   | 1.0892 **     |
| Human resources          | -0.0127     | 1.5653        |
| Agricultural infrastructure | 0.0767 *   | 2.4861 **     |
| Agricultural mechanism   | -0.0004     | -0.0132 **    |
| Natural disaster         | -0.2284     | -8.0761       |
| Sigma-squared            | 0.2335      | 125.5673      |
| Gamma                    | 1.0000      | 1.0000        |
| Log likelihood function  | 0.1862      | -31.2074      |
| LR one-sided test        | 6.8145 **   | 5.0093 *      |

Notes: *, **, and *** related to the regression coefficient represent the significance of the t-test at the confidence levels of 10%, 5%, and 1%, respectively; * and ** related to the one-sided likelihood ratio test represent the significance of the mixed chi-square value at the confidence levels of 10% and 5%, respectively.
Hebei. Across the entire region, Liaoning’s TFP fell the most, reaching 4.63%, due to both the Effch and Tech decreasing dramatically. To find out why Liaoning differed so greatly, we made a detailed analysis of Liaoning’s Malmquist and its decomposed indexes (Figure 6).

By comparing the efficiency score and Malmquist index of the first and third stages in Liaoning, we found the following: (1) Benefiting from the favourable external environment, Liaoning’s peanut production efficiency and productivity appeared strong, which was far from the actual operations. (2) The trend of Effch was in accordance with that of TFP, and the technological progress remained stable at a relatively high level (the average value was equal to 1.011). (3) The fluctuation range of Sech was slightly larger than that of Pech. These findings implied that Sech played a key role in improving the TFP of Liaoning peanut production, while, unexpectedly, Tech contributed little.

Therefore, Liaoning should focus on adjusting the peanut cultivation scale to be optimal and economic, improving the management and allocation of resources, and renewing the technology, such as with improved varieties, cultivation techniques, and machinery and equipment, instead of increasing the inputs extensively.

**Conclusions and suggestions**

As the largest peanut production country, analyzing the efficiency and productivity of China’s peanut production is important. In this article, we aimed to assess the performance of peanut production in China and to identify the external environmental factors of this efficiency. Adopting a three-stage DEA approach and the Malmquist index, we analyzed the performance of peanut production in China from 2009 to 2018, from both static and dynamic aspects. The research results are as follows.
First, the SFA regression illustrated that the managerial inefficiency was the main factor influencing the peanut production performance in China, and the agricultural policy had the greatest influence. Agricultural mechanisation and natural disasters may promote peanut production performance; however, the agricultural policy, planting structure, and agricultural infrastructure did not have a positive impact, which is not consistent with previous articles.

Second, the analysis regarding the efficiency after adjustment showed that peanut production did not demonstrate efficient performance, which was caused by the decreasing scale efficiency (SE). However, the pure technical efficiency (PTE) was sustained as stable at a higher level, close to one. From the regional aspect, each region’s efficiency varied significantly, especially that of Liaoning, which operated at the lowest level, very different from the first stage.
finding implied that Liaoning’s peanut production was positively and significantly affected by the external environment.

Third, the analysis of the total factor productivity (TFP) after adjustment showed that the TFP of peanut production in China was lower than 1, and the root cause was the insufficient technological progress (Tech) of peanut production. In addition, the change in technical efficiency depended more on the change in scale efficiency.

Based on the analysis conclusions, we propose the following. The first proposal is to enhance the environmental factors, improve the management efficiency, and allocate the inputs rationally. The second proposal is to make a great effort to realise technological progress, such as breeding new varieties and promoting new agricultural machinery. The last proposal is to achieve the optimal scale to improve the operational efficiency.

In this research, there remain problems to be solved, which provides the prospect of future study. First, for the sake of overcoming the limitations of the data availability and sample size, we could attempt to adopt a bootstrap DEA to correct the deviation and evaluate the overall efficiency. Second, peanut production not only generates revenue but also causes environmental effects; thus, the DEA-SBM model could be used to evaluate the peanut production performance considering the unexpected output.

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