STOWARZYSZENIE EKONOMISTÓW ROLNICTWA I AGROBIZNESU
Roczniki Naukowe ● tom XVIII ● zeszyt 2

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COMPARISON OF AGRICULTURE EFFICIENCY OF CHINESE PROVINCES

PORÓWNANIE EFEKTYWNOŚCI ROLNICTWA W CHIŃSKICH PROWINCJACH

Key words: efficiency, agriculture, China, DEA method

Słowa kluczowe: efektywność, rolnictwo, Chiny, metoda DEA

JEL codes: R1

Abstract. The article presents the diversification of agriculture efficiency of Chinese provinces in 2013 based on the Data Envelopment Analysis method. The model features the following variables: 1 effect (value of purchased agricultural products) and 5 inputs (area of agricultural land, number of people employed in agriculture, use of fertilizers, number of tractors, livestock). This article presents the use of input-oriented CCR and BCC model, to determine overall technical efficiency, pure technical efficiency and scale efficiency of agriculture in Chinese provinces. The analysis gives the possibility of creating a ranking of provinces. The highest agriculture efficiency during the period was achieved by 7 provinces (in CCR model) and 16 provinces (in BCC model). The results point out reasons for inefficiency and provide directions of improvement for inefficient Decision Making Units.

Introduction

One of the most challenging problems in China's agriculture has always been the lack of arable land. China has less than 9% of the world's arable land, but it has to produce food and other agricultural products for 22% of the world's population [*Agriculture and Chinese*... 2016]. On a per capita land basis, its arable land is just over one mu or 0.0827 hectares (1 mu = 0.067 ha), about one third of the world's average. More than 40% of the world's peasants work on this land area making the farm size per household very small, averaging less that 0.2 ha.

Since China's reform and opening up, China's agriculture as a share of GDP was 28.2% in 1978, the Department of Rural Development Institute at the Chinese Academy of Social Sciences pointed out, in 2014, that the added value of agriculture will fall to 9.8% of the total in the gross domestic product (GDP) [*China's rural*... 2013]. China's current agricultural output value proportion is developed to less than 10%. There is a large amount of rural labor force transfer from countryside to city. Rural farming households and family farms will get more support.

Yu Xinrong, deputy of Agriculture Minister, said, in 2014, that the Chinese national per capita net income of farmers reached 9892 yuan, deducting the price factor, it increased by 9.2% in real terms. The per capita net income of farmers increased faster than the urban per capita disposable income growth in five years, 2.4% higher than in 2013.

The national bureau of statistics pointed out in 2002, that the farming population was 740 million, and that China's agricultural employment has fallen to 50%. From 1979 to 2001, the proportion of Chinese agricultural workers in the total number of the whole society of practitioners fell by more than 20%. China is undergoing the largest ever big labour transfer from agriculture to industry and service.

In the western region of China, such as Gansu, Sinkiang, Shaanxi, Ningxia, Tibet and Inner Mongolia, Guangxi province, and the northeastern region, such as Jilin, Heilongjiang province and other provinces, the population is relatively sparse. Per capita cultivated land resource and agricultural labour force resources are abundant. Per capita arable land area is significantly higher than the national average (0.128 hm^2 per person). Non-agricultural industries' development lags whilst the traditional agricultural production value represents a significant share of GDP [Yunlong et al. 2002, Wanlian 2000]. Grain and cotton are the main crops. In China's eastern coastal areas, such as Jiangsu, Fujian, Guangdong, Zhejiang and Beijing, Tianjin, Shanghai and other provinces and cities, there are obvious geographical, technological and political advantages as well as high agricultural productivity and degree of marketization, but the situation of more people and less land limit the agricultural scale and development of agricultural industrialization. China's southernmost Hainan province, with its characteristic of tropical crops for agriculture, visibly has a comparative advantage, and the agricultural output value accounted for 36.9% of GDP, ranking first in the nation. Henan, Hubei, Hunan, Shandong, and Hebei province and other major agricultural product producing areas, have a relatively higher productivity.

Therefore, the purpose of this article is to compare agricultural efficiency in Chinese provinces based on the Data Envelopment Analysis method. Data Envelopment Analysis method was already used in the study of Chinese agriculture by Dong Hongqing and Li Si [2010] and Wang Xuhui and Liu Yong [2008].

Material and methods

The study used data on agriculture in a particular Chinese province published in the Statistical Yearbook of Agriculture and data from the reports on the activities of the Ministry of Agriculture. Based on the sample, efficiency of agriculture was evaluated using Data Envelopment Analysis (DEA) methods. DEA is the non-parametric approach to the analysis of the technical and scale efficiency relied on linear programming methods. The DEA model may be presented mathematically in the following manner [Cooper et al., 2007]:

$$\max \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}}$$

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1$$

$$u_r, v_i \ge 0$$

whereby:

s – quantity of outputs, m – quantity of inputs, u_r – weights denoting the significance of respective outputs, v_i – weights denoting the significance of respective outputs, y_{rj} – amount of output of r^{th} type (r =1,…,R) in j^{th} object, x_{ij} – amount of input of i^{th} type (n = 1,…, N) in j^{th} object, (j =1,…, J).

In the DEA model m of inputs and s of diverse outputs come down to single figures of "synthetic" input and "synthetic" output, which are subsequently used for calculating the object efficiency index [Rusielik 1999]. The quotient of synthetic output and synthetic input is an objective function, which is solved in linear programming. Optimized variables include μ_r and v_i coefficients which represent weights of input and output amounts, and the output and input amounts are empirical data [Cooper et al. 2007].

By solving the objective function using linear programming it is possible to determine the efficiency curve also called the production frontier, which covers all most efficient units of the focus group. Objects are believed to be technically efficient if they are located on the efficiency curve (their efficiency index equals 1). However, if they are beyond the efficiency curve, they are technically inefficient (their efficiency index is below 1). The efficiency of the object is measured against other objects from the focus group and is assigned values from the range (0, 1). In the DEA method Decision Making Units (DMU) represent objects of analysis [Charnes et al. 1978].

The DEA models may be categorized based on two criteria: model orientation and type of returns to scale. Depending on the model orientation a calculation is made of technical efficiency focused on the input minimization or of technical efficiency focused on output maximization. But taking into account the type of returns to scale the following models are distinguished: the CCR model providing constant returns to scale and the BCC model providing changing return to scale. The CCR model is used to calculate the overall technical efficiency – TE (Technical Efficiency), the BCC model is used to calculate pure technical efficiency – PTE (Pure Technical Efficiency) [Coelli et al. 2005].

With the overall technical efficiency and pure technical efficiency calculated, it is possible to determine the object scale efficiency (Scale Efficiency – SE) according to the formula: SE = TE/PTE [Coelli et al. 2005].

Results

The CCR and BCC models were used to determine the relative efficiency of Chinese agriculture. Models aimed at minimizing inputs (*input - oriented*) were chosen, which were based on strong pressure from farmers to reduce costs.

At the first stage of the study, a set of variables for the models of Data Envelopment Analysis models was defined. According to the literature, total production is normally measured by its volume, i.e. a set of manufactured products expressed either in physical units or in fixed prices [W. Welfe, A. Welfe 1996]. In this study total production was measured by value of purchased agricultural goods. Production factors are variables explaining the production volume. In the theory of economics a distinction is made of three major production factors, i.e.: human labour, objectified labour (capital) and land. In agriculture, the land element plays a vital role, and that is why it is used in this article. Moreover, raw material and material factor in this study was defined to be measured as NPK and CaO fertilization consumption. The human labour factor is often measured in the literature as manhours or the number of workers [Keat, Young 2003]. Given the data availability, the measure of the labour factor was defined in the study as the number of people employed in agriculture. According to the literature, capital represents the most diversified production factor. The factor involves own funds, acquired loans or unpaid liabilities, as well as elements represented in the form of resources (machinery, production lines, equipment, transportation means, buildings and building structures etc.) [Mercik, Szmigiel 2007]. Given the above, capital, in this study, was defined to be measured as the number of big tractors and livestock.

The following variables were set for DEA models:

- effect y_1 – value of agricultural production (billion Yuan),
- input x_1 – agricultural land area (thousands of hectares),
- input x_2 – number of people employed in agriculture (ten thousand person),
- input x_3 – NPK and CaO fertilization (ten thousand t),
- input x_4 – number of big tractors (pcs),
- input x_5 – livestock (thousands).

As a result of the study, a ranking of Chinese provinces was created according to the efficiency index for agriculture (see Tab. 1). The average technical efficiency of the agriculture sector in China in 2013 achieved a fairly high level. The DEA efficiency indicator in the CCR model was 0.73 and 0.83 in the BCC model. It was found that among the 31 studied provinces, 7 provinces (CCR model) and 16 provinces (BCC model) had an agriculture sector efficient, i.e. the efficiency ratio stood at 1. The group of efficient DMUs in both models included the following provinces: Chongqing, Beijing, Shandong, Fujian, Zhejiang, Jiangsu, Shanghai. The higher efficiency agricultural districts are mainly located in more experienced agricultural province, and economic developed areas, such a: Beijing, Shanghai, Jiangsu, Zhejiang, Fujian, and Shandong. Among inefficient provinces the lowest rate of technical efficiency in agriculture was seen, both in the CCR and BCC model, in: Jilin and Anhui provinces (Tab. 1).

Taking into account economies of scale, it has been found that the agriculture sector deemed efficient in 12 provinces is characterized by constant economies of scale, in 6 provinces agriculture sector sees increasing economies of scale, while the agriculture sector in the remaining 13 provinces is characterized by decreasing economies of scale.

Based on the DEA method, benchmarks have been defined for provinces with an inefficient agriculture. On the basis of these benchmarks for inefficient sectors (DMU), it is possible to determine a combination of technologies that allows the same results to be achieved with less input. Calculations were made based on the values of coefficients of the linear combination of common technology. Based on these coefficients, it is possible to construct an optimal technology modelled on agriculture from regions defining benchmarks for them. Table 2 shows potential changes that should be made within the scope of inputs in inefficient agriculture in individual provinces. The results suggest how much smaller the use of inputs should be in inefficient agriculture sectors in order to achieve the current value of effects (value of agricultural production).

Table 1. The technical efficiency, scale efficiency and returns to scale of agriculture in China in 2013
Tabela 1. Efektywność techniczna, efektywność skali i charakter korzyści skali rolnictwa w poszczególnych prowincjach Chin

DMU	CCR-model	BCC-model	SE	RTS
Agriculture in Chinese provinces/*Rolnictwo w chińskich prowincjach*	Technical efficiency/ *Całkowita efektywność techniczna*	Pure technical efficiency/*Czysta efektywność techniczna*	Scale Efficiency/ *Efektywnosć skali*	Return to Scale/ *Charakter korzyści skali*
Beijing	1.00	1.00	1.00	constant/*stałe*
Shanghai	1.00	1.00	1.00	constant/*stałe*
Jiangsu	1.00	1.00	1.00	constant/*stałe*
Zhejiang	1.00	1.00	1.00	constant/*stałe*
Fujian	1.00	1.00	1.00	constant/*stałe*
Shandong	1.00	1.00	1.00	constant/*stałe*
Chongqing	1.00	1.00	1.00	constant/*stałe*
Guangdong	0.88	1.00	0.88	decreasing/*malejące*
Qinghai	0.88	1.00	0.88	increasing/*rosnące*
Sichuan	0.79	1.00	0.79	decreasing/*malejące*
Tianjin	0.78	1.00	0.78	increasing/*rosnące*
Hunan	0.76	1.00	0.76	decreasing/*malejące*
Heilongjiang	0.73	1.00	0.73	decreasing/*malejące*
Hebei	0.72	1.00	0.72	decreasing/*malejące*
Xizang	0.64	1.00	0.64	increasing/*rosnące*
Henan	0.51	1.00	0.51	decreasing/*malejące*
Hainan	0.90	0.92	0.98	constant/*stałe*
Liaoning	0.74	0.85	0.88	decreasing/*malejące*
Gansu	0.77	0.80	0.96	constant/*stałe*
Shanxi	0.69	0.75	0.92	decreasing/*malejące*
Hubei	0.56	0.73	0.77	decreasing/*malejące*
Xinjiang	0.61	0.71	0.86	decreasing/*malejące*
Guizhou	0.70	0.70	1.00	constant/*stałe*
Guangxi	0.52	0.64	0.82	decreasing/*malejące*
Jiangxi	0.59	0.61	0.97	increasing/*rosnące*
Yunnan	0.51	0.56	0.90	decreasing/*malejące*
Shanxi	0.53	0.53	1.00	constant/*stałe*
Ningxia	0.44	0.51	0.87	increasing/*rosnące*
Anhui	0.41	0.51	0.79	decreasing/*malejące*
Neimenggu	0.41	0.45	0.91	constant/*stałe*
Jilin	0.40	0.40	1.00	increasing/*rosnące*

Source: own calculation
Źródło: obliczenia własne

Table 2. Recommendations regarding reduction of input in agriculture in provinces in order to achieve efficiency
Tabela 2. Zalecenia dotyczące obniżenia poziomu nakładów w rolnictwie w poszczególnych prowincjach w celu poprawy ich efektywności

Agriculture in Chinese provinces/ *Rolnictwo w chińskich prowincjach*	Agricultural land area [thous. ha]/ *Powierzchnia użytków rolnych [tys. ha]*	Number of people employed in agriculture [ten thous. person]/ *Liczba pracujących w rolnictwie [10 tys.osób]*	NPK and CaO fertilization [10 thous. t]/ *Zużycie nawozów [10 tys. t]*	Number of big tractors/ *Liczba ciągników*	Livestock [thous.]/ *Inwentarz żywy [tys.]*
	%				
Tianjin	-22	-22	-31	-92	-78
Hebei	-30	-28	-28	-84	-90
Shanxi	-56	-47	-47	-90	-89
Neimenggu	-60	-59	-59	-92	-94
Liaoning	-26	-81	-26	-86	-94
Jilin	-60	-93	-60	-97	-97
Heilongjiang	-49	-73	-27	-87	-82
Anhui	-61	-59	-59	-88	-82
Jiangxi	-67	-64	-41	-41	-89
Henan	-49	-49	-58	-90	-94
Hubei	-44	-44	-44	-85	-80
Hunan	-45	-24	-24	-77	-92
Guangdong	-12	-12	-19	-51	-63
Guangxi	-48	-65	-48	-48	-92
Hainan	-10	-10	-15	-83	-55
Sichuan	-47	-21	-21	-75	-96
Guizhou	-67	-30	-30	-74	-97
Yunnan	-58	-49	-49	-91	-97
Xizang	-49	-45	-36	-97	-100
Shanxi	-31	-31	-49	-87	-79
Gansu	-49	-23	-23	-81	-96
Qinghai	-46	-25	-12	-52	-99
Ningxia	-59	-56	-56	-87	-95
Xinjiang	-39	-96	-39	-95	-95

Source: own calculation
Źródło: obliczenia własne

Conclusions

The paper presents the application of the DEA methodology to the evaluation of efficiency of agriculture in China. From the methodological point of view the proposed approach for ranking and benchmarking DMU has a universal character and can be applied in different industries and sectors. It allows comparing relative efficiency of DMU by determining the efficient DMUs as benchmarks and by measuring the inefficiencies in input combinations in other units relative to the benchmark.

From a practical point of view, the results of this analysis can be summarized as follows:

1. The CCR model proved to be more restrictive than the BCC model. However, the same seven Chinese provinces had the highest scores in both the CCR and BCC models.
2. The provinces with the most efficient agriculture are Beijing, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Chongqing.
3. Detailed analysis of efficient DMUs as a benchmark for other evaluated units point out the reasons of inefficiency and provide directions for improvement of inefficient DMUs.

Given that efficiency is a complex economic phenomenon and individual methods used for its analysis have their advantages and limitations, it is difficult to clearly state the superiority of the presented non-parametric approach. According to the authors, assessments of efficiency of agriculture should be performed by means of an integrated approach – based on different methods that complement each other, as well as help to achieve a better understanding and explain the situation of assessed sectors, and formulate reliable conclusions.

Bibliography

Agriculture and Chinese peasants, http://www.panap.net/en/fs/post/food-sovereignty/76, dostęp marzec 2016.
Charnes Abraham, William W. Cooper, Edwardo Rhodes. 1978. "Measuring the Efficiency of Decision Making Units". *European Journal of Operational Research* 2 (6): 429-444.
China's Rural Economic Situation Analysis and Prediction (2013-2014). 2013. Report of Department of Rural Development Institute at the Chinese Academy of Social Sciences.
Coelli Timothy J., Rao D.S. Prasada, Christopher J. O'Donnell, George E. Battese. 2005. *An Introduction to Efficiency and Productivity Analysis*. New York: Springer.
Cooper William W., Lawrence M. Seiford, Tone Kaoru. 2007. *Data Envelopment Analysis. A Comprehensive Text with Models, Applications, References and DEA-Solver Software*. New York: Kluwer Academic Publisheres.
Dong Hongqing, Li Si. 2010. „The empirical research about agricultural production efficiency in China based on DEA model". *Forwad Position* 17 (17): 60-69.
Keat Paul, Philip K. Young. 2003. *Managerial Economics*. Prentice Hall, Upper Saddle River.
Mercik Jacek, Czesław Szmigiel. 2007. *Ekonometria*. Wrocław: Oficyna Wydawnicza Politechniki Wrocławskiej.
Rusielik Robert. 1999. DEA – Zastosowanie w badaniach efektywności spółek AWRSP. [W] *Strategiczne modele funkcjonowania spółek handlowych Agencji Własności Rolnej Skarbu Państwa,* 113-176. Szczecin: AWRSP.
Yunlong Cai, Zeqiang Fu, Erfu Dai. 2002. "The minimum area per capita of cultivated land and its implication for the optimization of land resource allocation". *Acta Geographica Sinca* 57 (2): 127-134.
Wang Xuhui, Liu Yong. 2008. Over all appraisal of agricultural production efficiency in China based on DEA model. *Journal of Hebei University of Economics and Trade* 29 (1): 53-59.
Wanlian Lan. 2000. "Agricultural comparative advantage and analysis of relative proportion in China". *Agricultural Technology Economy* 2: 1-5.
Welfe Władysław, Aleksander Welfe. 1996. *Ekonometria stosowana*. Warszawa: PWE.

Streszczenie

Dokonano oceny efektywności rolnictwa w poszczególnych prowincjach Chin w 2013 roku, bazując na metodzie nieparametrycznej. Wykorzystano metodę programowania liniowego DEA (Data Envelopment Analysis). Zastosowano modele CCR i BCC ukierunkowane na minimalizację nakładów. Do modelu jako zmienne przyjęto: 1 efekt (wartość skupu produktów rolnych) oraz 5 nakładów (powierzchnia UR, liczba pracujących w rolnictwie, zużycie nawozów, liczba ciągników, inwentarz żywy). Efektywnym rolnictwem charakteryzowało się 7 prowincji w modelu CCR, a 16 w modelu BCC. Dla pozostałych (nieefektywnych) prowincji zgodnie z ideą benchmarkingu zaproponowano zmiany w poziomie nakładów, które mogłyby przyczynić się do poprawy ich efektywności.

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