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Research on Agriculture Productivity Efficiency Based on Factor Analysis and DEA Model-Taking Beijing-Tianjin-Hebei region of the Belt and Road as an Example

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ABSTRACT

Using the cross-section data from 30 provinces and cities in China, this paper investigates the relative agricultural efficiency of the Beijing-Tianjin-Hebei region of the Belt and Road by the factor analysis and DEA-BCC model. Against the backdrop of 30 provinces and cities of China, the result indicates that the relative agricultural efficiency of the Beijing-Tianjin-Hebei region is not very optimistic. There are some defects in both pure technical efficiency and scale efficiency, which means that the agriculture efficiency of these 3 regions is not in the optimal condition. The agricultural scale in Beijing and Tianjin are too small. Nevertheless, the agricultural scale is excessive in Hebei. The pure technical efficiency in Beijing is optimal, but in Tianjin and Hebei, they did not reach the efficient frontier. To realize the Coordinated Development of the Beijing-Tianjin-Hebei Region and to reach optimal agricultural efficiency, it should optimize the regional division of labor, strengthen agricultural technological innovation, and promote the circulation of regional factors.

Keywords: *DEA-BCC model, Factor analysis, Agricultural productivity efficiency, the Belt and Road.*

1. INTRODUCTION

In 2016, the "Beijing-Tianjin-Hebei Modern Agriculture Coordinated Development Plan (2016-2020)" was issued. The Plan states that, to promote the coordinated development of modern agriculture in the Beijing-Tianjin-Hebei region, China must firmly establish the development concept of innovation, coordination, greenness, openness. China is supposed to place emphasis on coordinating production to ensure supply, interacting, and cooperating to ensure agricultural safety, joint prevention, and control to ensure ecological balance. Meanwhile, improving quality and efficiency are an indispensable part of this plan. Consequently, Howto allocate limited resources efficiently has become an essential problem.

This paper reviews what former scholars have done. Scholars mainly focus on two aspects pertaining to agriculture productivity, which are the construction of indices in the evaluation system and methods to evaluate it. For the indices in the evaluation system, although the views relevant to them are diverse, they more often than not contain some indices including the number of employees in the primary industry, consumption of chemical fertilizers, effective irrigation areas, total power of agricultural machinery, sown area of crops, the gross output value of farming, forestry, animal husbandry and fishery and output of major agricultural products [1-3]. For the methods to appraise the agricultural productivity, Li et al used the DEA-Malmquist model to analyse total-factor energy efficiency in China [4]; Lidia et al evaluated the eco-efficiencyof agricultural practices based on the CF + DEA method[5]; Nan et al assessed the relative efficiency and energy-saving potential in agricultural sectors of 30 provinces in China overall technical efficiency derived from DEA [6]. George et al assessed the agricultural energy and environmental efficiency of EU member state countries using the traditional DEA approach [7].

Whereas many methods are adopted, they often neglected the correlation among variables. According to some scholars, it probably has a huge impact on DEA results, which may be divergent from the actual situation [8-9]. Nevertheless, Factor analysis is a statistical approach based on the principle of data dimensionality reduction, which extracts a few representative common factors from many related variables to reduce the number of indices and eliminate the correlation between them [10]. Additionally, a large amount of concentration has been laid on agricultural productivity in different countries or provinces. There is little research relevant to agricultural productivity around city groups, let alone the Beijing-Tianjin-Hebei region of the Belt and Road Initiatives. Hence, using DEA methods primarily and factor analysis as an auxiliary, this paper will analyse the agricultural productivity in the Beijing-Tianjin-Hebei region.

2. METHOD

Factor analysis is a method that can reduce the dimensionality of data and eliminate the correlation among indicators [11]. Because of the correlation of input indicators, the efficiency of DEA might deviate from the actual results. To evaluate the agricultural productivity more efficiently, this paper will use it to eliminate the correlation among five chosen input indices. The concrete mathematical model is:

$$x_i = a_{ij}\, f_j + e_i, i = 1,2 \ldots ,5\ ; j < 5 \quad (1)$$

Amongthese, x_i is theinput index, f_j is common factor, e_i is specific factor and a_{ij} is factor loading of common factor.

DEA-BCC method is improved by Banker et al based on DEA-CRR method, which relaxes the assumption that returns to scale is constant. Taking into account that returns to scale is mutable, given theinput and output data of DMU(decision-making units), the efficiency results of each decision-makingunit are obtained through linear programming. The original model is as follow:

$$\begin{gathered}\min[\theta_v - \varepsilon(e_1^T SA + e_2^T SB)] \\ s.t \sum_i^n \lambda_i X_i + SA = \theta_v X_0 \\ \sum_i^n \lambda_i Y_i - SB = Y_0 \\ \sum_i^n \lambda_i = 1 \\ \lambda i \geq 0 ; i = 1, 2, \ldots , n ; SA \geq 0 ; SB \geq 0 \quad (2)\end{gathered}$$

This paper will put the common factor extracted into the DEA-BCC model to evaluate the performance of Beijing-Tianjin-Hebei region in context of nationwide agricultural productivity. The specific evaluation model is as follow:

$$\begin{gathered}\mathrm{MAX\ Vp} = \frac{u^T y_{j0}}{v^T x_{j0}} \\ \mathrm{s.\,t.}\ \frac{u^T y_j}{v^T x_j} < 1, j = 1,2, \ldots ,30 \\ v \geq 0, u \geq 0\end{gathered} \quad (3)$$

3. EMPIRICAL WORK

3.1. Data and Variables

Agricultural Input Variables: This paper takes the sown area as the soil input due to the phenomenon of fallow, abandonment, and restoration of cultivated land and the variation of China's arable land is minor. The number of employees in the agriculture, forestry, fishery, and animal husbandry industry is regarded as labor force input. The consumption of chemical fertilizers, effective irrigation areas, total power of agricultural machinery can increase both quantity and quality remarkably, so they are classified as technological input.

Agricultural Output Variables: Taking into consideration that the number of employees in agriculture, forestry, fishery, and animal husbandry is taken as the labor force input, the output which measures economic benefits is the gross output of the primary industry. The fundamental condition to develop an economy is food security that also promotes the stability of society. Accordingly, this paper will use the major agricultural products as social benefits output. The data of this paper is derived from the "China Statistical Yearbook 2018-2019" and statistical yearbook of corresponding provinces and cities. Because the data of Xinjiang is unavailable, it is excluded from this study. Considering the actual situation and convenience, this paper assumes that the time lag between input and output is one year.

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3.2. The Result of Factor Analysis and DEA Model

The KMO and Bartle's tests on the five selected input indices were performed by SPSS 23. 0. From Table 1, it can be concluded that the KMO test value of the input indices is greater than 0. 6. Simultaneously, the $\chi 2$ statistical significance probability of Bartlett's test is p = 0. 000 <0. 05, demonstrating that there is a correlation among input indices.

Table 1 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.807
Bartlett's Test of Sphericity	**Approx. Chi-Square**	188.780
	df	10.000
	Sig.	0.000

The DEA method requests that the indices are as uncorrelated as possible, otherwise the evaluation results will be divergent from the actual situation. Therefore, this paper conduct will conduct a further factor analysis on the input indices. This paper will use principal component analysis to construct the factor variable and perform factor analysis on five input indices by SPSS 23.0. Then extract a common input factor with a characteristic root greater than 1 and a cumulative contribution rate greater than 80%. Finally, calculate the factor score. The DEA method requires that the results of input data and output data are both positive. To ensure the accuracy of the evaluation results, this paper uses the formula $x' = 0.1 + 0.9\frac{x-\min}{\max-\min}$ to standardize the common factor scores extracted in the previously.

Table 2 Results of the Common Factor Extraction after Standardization

Area	Common Factor	Area	Common Factor	Area	Common Factor
Beijing	0. 1	Zhejiang	0. 245853391	Hainan	0. 14571925
Tianjin	0. 118574782	Anhui	0. 643911256	Chongqing	0. 236242795
Hebei	0. 804558405	Fujian	0. 234018384	Sichuan	0. 562052457
Shanxi	0. 279278968	Jiangxi	0. 347591674	Guizhou	0. 29889466
Neimenggu	0. 476833277	Shandong	0. 826004008	Yunan	0. 437019648
Liaoning	0. 322044219	Henan	1	Tibet	0. 116761507
Jilin	0. 395019633	Hubei	0. 530908328	Shanxi	0. 344970386
Heilongjiang	0. 703773102	Hunan	0. 570850288	Gansu	0. 254743905
Shanghai	0. 104294349	Guangdong	0. 39451106	Qinghai	0. 119347147
Jiangsu	0. 550447972	Guangxi	0. 450601388	Ningxia	0. 152057395

This paper calculates the agricultural productivity of 30 provinces in China in 2018 by DEAP2.1. The result is showed in Table 2. The technical efficiency represents the overall agricultural production efficiency. From Table 2, it can be seen that the technical efficiency of Liaoning, Heilongjiang, Fujian are 1, which means they are in the efficient frontier. Pure technical efficiency reflects the agricultural productivity efficiency on the assumption that returns to scale is optimal [12]. In addition to the 3 provinces mentioned above, the pure technical efficiency of Beijing, Jilin, Shanghai, Jiangsu, Shandong, Henan, Guangdong, and Sichuan reach *1*. It indicates that there is no misallocation of resources in those provinces and cities. Their management is relatively better than the rest of the cities or provinces. The scale efficiency reflects the gap between the actual scale and optimal production scale. Apart from Liaoning, Heilongjiang, and Fujian, the rest provinces and cities are not on an efficient scale. Hebei, Jiangsu, Anhui, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Sichuan, and Yunnan exhibit decreasing returns to scale, which means these provinces should not expand the scale of agriculture blindly. The oversized scale has increased the managed cost and made management in agriculture become inefficient. The remained provinces and cities are supposed to increase the agricultural scale so that the scale efficiency can be in the efficient frontier.

Table 3 The agricultural productivity efficiency in 30 provinces and cities in China

Area	Crste	Vrste	Scale	Returns to scale	Rank for Crste	Rank for Vrste	Rank for scale
Beijing	0.142	1	0.142	irs	29	1	29
Tianjin	0.254	0.969	0.263	irs	26	13	26
Hebei	0.584	0.6	0.974	drs	22	30	8
Shanxi	0.533	0.753	0.708	irs	24	25	23
Neimenggu	0.742	0.818	0.906	irs	14	21	17
Liaoning	1	1	1	-	1	1	1
Jilin	0.921	1	0.921	irs	7	1	15
Heilongjiang	1	1	1	-	1	1	1
Shanghai	0.17	1	0.17	irs	28	1	28
Jiangsu	0.961	1	0.961	drs	5	1	11
Zhejiang	0.738	0.838	0.881	irs	15	19	18
Anhui	0.707	0.712	0.994	drs	17	27	5
Fujian	1	1	1	-	1	1	1
Jiangxi	0.779	0.837	0.93	irs	10	20	14
Shandong	0.862	1	0.862	drs	8	1	19
Henan	0.753	1	0.753	drs	13	1	21
Hubei	0.831	0.855	0.972	drs	9	17	9
Hunan	0.774	0.796	0.972	drs	11	23	9
Guangdong	0.98	1	0.98	drs	4	1	7
Guangxi	0.702	0.708	0.991	drs	18	28	6
Hainan	0.585	0.984	0.595	irs	21	12	24
Chongqing	0.68	0.863	0.789	irs	19	16	20
Sichuan	0.953	1	0.953	drs	6	1	12
Guizhou	0.767	0.81	0.946	irs	12	22	13
Yunan	0.729	0.732	0.996	drs	16	26	4
XiZang	0.128	0.899	0.142	irs	30	15	29
Shanxi	0.646	0.702	0.92	irs	20	29	16
Gansu	0.574	0.786	0.731	irs	23	24	22
Qinghai	0.217	0.906	0.239	irs	27	14	27
Ningxia	0.303	0.839	0.362	irs	25	18	25

Note: Crste, Vrste and Scale stand for technical efficiency, pure technical efficiency and scale efficiency respectively

4. CONCLUSION

This paper uses factor analysis and the DEA-BCC model to evaluate the agricultural productivity efficiency in the Beijing-Tianjin-Hebei region. The result demonstrates that it is not in the efficient frontier, and it is far below the average in China. So the Beijing-Tianjin-Hebei region must respond to the national call, which needs it to increase agricultural productivity to achieve agriculture modernization. Based on what has been analyzed above, this paper proposes some improvements.

First, optimize the regional division of labor. The differentiated labor division of agricultural production processes can effectively exert comparative advantages and rationally allocate agricultural resources, thereby promoting the efficient use of modern production factors, enhancing the quantity and quality of agricultural products, and extending the agricultural industry chain. Beijing-Tianjin-Hebei region can deepen the division of labor in the agricultural production processes and then extend the value chain to achieve mutual benefits in agricultural production.

Second, strengthen agricultural technological innovation. Agricultural technological innovation is a driving force for the transformation of traditional agriculture to modern agriculture. It improves agricultural production efficiency and optimizes the structure of the agricultural industry through the development and replacement of new production factors. On one hand, agricultural science and technology innovation projects are non-competitive and non-exclusive. On the other hand, agricultural science and technology innovation subjects have diverse and synergic characteristics. Therefore, each region in the Beijing-Tianjin-Hebei region should be clear that the government ought to occupy a leading role in strengthening the institutional guarantee of the agricultural science, technology innovation system, actively integrating the innovative forces of multiple parties, and vigorously promoting the transformation and application of scientific research results. Beijing, which has strong scientific and technological resources, should focus on the frontier development of agricultural production technology and the transformation of results, while Tianjin and Hebei need to concentrate on the promotion of agricultural production technology and the construction of agricultural clusters to attract more modern production factors such as talents and equipment.

Thirdly, promote the circulation of regional factors. All regions should actively promote the reform development of the provinces, regional coordination and cooperation, and the flow of movable elements in agricultural scientific research and production. Firstly, all regions should break down administrative barriers and set up organizations and coordination agencies to provide a new platform for regional cooperation. Secondly, all regions should strengthen the construction of rural circulation service industries, urge the circulation of resource elements, and inject new impetus into regional cooperation. Last but not least, the coordinated development and integrated construction among regions are a pivotal process of marketization. The Beijing-Tianjin-Hebei region should rely on its ecologically abundant resource advantages and location advantages to expand open corridors, link up with the "Belt and Road" initiative and actively expand demand for agricultural products, then dig the potential for international trade of characteristic agricultural products.

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REFERENCES

[1] Gang-Ping L, Zhi-Yong Z. Study of Agricultural Production Efficiency in Chongqing Based on DEA Method[J]. Journal of Chongqing University of Posts & Telecommunications, 2009, 21(01): 104-110.

[2] Wen-zhong Y, Yu-xi L. Agricultural Productivity and Influential Factors in the Yangtze River Economic Belt[J]. East China Economic Management, 2018, 32(03): 83-88. “in Chinese”. DOI:10.19629/j.cnki.34-1014/f.170517021.

[3] Znenping L. Analysis on Regional Difference of Agricultural Efficiency Using DEA Model in Six Provinces of Central China[J]. Anhui Agricultural Science Bulletin, 2007(03): 21-22+140. DOI:10.16377/j.cnki.issn1007-7731. 2007.03.011.

[4] Li N, Jiang Y, Yu Z, Shang L. Analysis of Agriculture Total-Factor Energy Efficiency in China Based on DEA and Malmquist indices[J]. Energy Procedia, 2017, (142): 2397-2402. DOI: https://doi.org/10.1016/j.egypro.2017.12.173.

[5] Lidia Angulo-Meza a,Marcela González-Araya b,Alfredo Iriarte b,Ricardo Rebolledo-Leiva c,Joo Carlos Soares de Mello a. A Multiobjective DEA Model to Assess the Eco-efficiency of Agricultural Practices within the CF+DEA Method[J]. Computers and Electronics in Agriculture, 2019, 161: 151-161. DOI: https://doi.org/ 10.1016/j.compag.2018.05.037.

[6] Nan Li, Yuqing Jiang, Hailin Mu, Zhixin Yu. Empirical Study on the Regional Agricultural Energy Efficiency Convergence Across Provinces in China[J]. Energy Procedia, 2017, 142: 2391-2396. DOI: https://doi.org/10.1016/j.energy.2018.08.150.

[7] George Vlontzos, Spyros Niavis, Basil Manos. A DEA Approach for Estimating the Agricultural Energy and Environmental Efficiency of EU Countries[J]. Renewable and Sustainable Energy Reviews, 2014. DOI: https://doi.org/ 10.1016/j.rser.2014.07.153.

[8] Guangmou W. The Relation between Effectiveness of DEA and Speciality Index Systems[J]. Journal of Southeast University (Natural ence Edition), 1992(05): 124-127.

[9]Dongxiao Z. Impact of Correlation between Variables on DEA Evaluation[J]. Statal Thinktank, 2009(06): 40-44.

[10] Jia-Fen Wu. Reproducing an Alternative Model of Intercultural Sensitivity for Undergraduates from Taiwan and Hainan[J]. International Journal of Modern Education and Computer Science, 2016, 1(8): 1-7. DOI: 10.5815/ijmecs.2016.01.01.

[11] Olabiyisi S.O.,Adetunji A.B.,Oyeyinka F.I. An Evaluation of the Critical Factors Affecting the Efficiency of Some Sorting Techniques[J].

International Journal of Modern Education and Computer Science, 2013, 2(4): 25-33, DOI: 10.5815/ijmecs.2013.02.04.

[12] Gbadamosi Babatunde, Adeniyi Abidemi Emmanuel, Ogundokun Roseline Oluwaseun, Oladosu Bukola Bunmi, Anyaiwe Ehiedu Precious. Impact of Climatic Change on Agricultural Product Yield Using K-Means and Multiple Linear Regressions[J]. International Journal of Education and Management Engineering, 2019, 5(8): 16-26, DOI: 10.5815/ ijeme.2019.03.02.