Iran Agricultural Research (2022) 41(1) 49-60

**Research Article**

Shiraz University

# Ranking production units by integrating data envelopment analysis and multi-criteria decision-making: The case of potato-producing provinces in Iran

**S. M. J. Esfahani*, E. Barikani**

Agricultural Planning, Economic and Rural Development Research Institute (APERDRI), Tehran, I. R. Iran.

* jesfahani@gmail.com
DOI: 10.22099/IAR.2022.42629.1473

**ARTICLE INFO**
***Article history:***
Received **28 December 2021**
Accepted **02 August 2022**
Available online **09 November 2022**
***Keywords:***

Data Envelopment Analysis
Efficiency
Potato
TOPSIS

**ABSTRACT** - Efficiency is the first step towards accomplishing sustainable agriculture. To provide a comprehensive image of the status of potato-producing provinces in Iran, this research was conducted to rank potato-producing provinces in Iran using the DEA ranking models, including cross-efficiency, super efficiency, best and worst relative efficiency, and distance to the ideal hyperplane. Then to provide a more comprehensive image of their status, the results were integrated using the TOPSIS technique for 2018. In this regard, the research considered yield and gross profit as indicators of production and profitability. The results showed that considering yield as an output shows higher efficiency than when profit is considered. Higher yield efficiency than profit efficiency means that producers care more about increasing production as an objective output than increasing profitability. The rankings of the provinces revealed that different ranking models do not provide similar results, so they need to be integrated to give a more precise assessment. The integration of these indicators by the TOPSIS method shows that the provinces of Mazandaran, Kerman and West Azerbaijan, which have good ranks in yield and profit efficiency, can be good patterns for other provinces. Furthermore, profit and yield efficiency are negatively related to seed, K-fertilizer, and pesticide, so the management of biofertilizers, as well as biological control and integrated pest management, are recommended for the improvement of the efficiency of potato-producing provinces.

## INTRODUCTION

The potato has an essential role in food security and poverty alleviation, especially in developing countries (Wijesinha-Bettoni & Mouillé, 2019). The potato, rice, wheat, and corn constitute the four crops that supply 50% of the global food energy demand (Durst & Bayasgalanbat, 2014). The year 2008 was declared the International Year of Potato by the UN General Assembly to formally recognize the role of this crop as the most important non-cereal staple food in ensuring food security and eradicating poverty (UN, 2006). Potato has the adaptation and extensive geographical distribution, further, farmers have the chance to produce it to grasp the added value of potato markets, which will contribute to economic development and livelihood protection (Haverkort et al., 2013). So, this crop is a major food whose potential for meeting food security should be taken seriously. The development of the cultivation and production of this crop has, therefore, drawn the attention of policymakers in most developing countries (Devaux et al., 2020).

The Sixth Development Action Plan in Iran has required the government to increase potato production as an important staple food by up to 5,596,000 tons. A look at the trend of potato production during the years of this action plan shows that this goal has not been accomplished. In 2018, 142,904 ha of arable land in Iran was allocated to potato cultivation, and a total of 523,733 tons of potato was harvested (Ministry of Agriculture-Jahad of Iran, 2020). Potato production has even declined in recent years due to the decline in its cultivation area from 2016 to 2020 (FAO, 2020).

In the agricultural sector, indicators such as production and yield are commonly used to explain position and prioritization, which is the basis for decision- making in most cases. Since less attention is paid to the production inputs in calculating these indicators, the use of these indicators has always been criticized (Shahnavazi, 2017a). Decisions in agriculture, especially in the cultivation of crops, are issues in the real world that require attention to many factors such as available land, natural resources, manpower, technology, etc. (Kazemi et al., 2017). Therefore, other indicators have been used to prioritize production areas in addition to production and yield(Esfahani,2022a).

It has been shown that improving resource use efficiency is an important prerequisite for establishing a link between development and environmental impacts (Wood et al., 2018). In addition to increasing income and food access, efficiency has been reported to be the first step toward sustainable agriculture (Naderi Mahdei et al., 2015). Today, all these should be considered.

In this respect, since the Iranian government is obliged to increase production to improve food availability and enhance efficiency in the five-year development action plans, it is crucial to consider improving efficiency and optimally using production inputs and resources. Recognizing the status of different regions in terms of efficiency and determining the production-apt regions that use production resources more optimally are important steps for guiding the policymaking process towards production and efficiency improvement. The data envelopment analysis (DEA) technique is one of the most well-known techniques for estimating the efficiency of production units. Despite its extensive application, DEA cannot distinguish efficient units, so researchers have been motivated to improve it and present new techniques (Bian & Xu, 2013; Peykani et al., 2021). Along with their advantages, all ranking methods have limitations, so their application as the only decision-making criterion may not yield rational and correct results.

The DEA was used by Amadeh et al. (2011) to measure the technical efficiency Of the Industrial Sector of Iranian provinces from 1996-2004. Then, the efficient units were ranked with the Anderson-Peterson method. Results indicated that Boohsher, Kerman, Khuzestan and Hormozgan provinces have the greatest value of technical efficiencies.

Sargazi et al. (2014) used the integrated DEA approach and analytic hierarchy process (AHP) for ranking farm units in the Sistan region. Their study indicated that the farm units could not be appropriately ranked in the DEA method identifying only the ranks of efficient and inefficient groups. Therefore, they showed that a complete ranking requires a measurement of the relative productivity and comparing units in terms of some applied aspects such as AHP, controlling the inputs and outputs again to ensure their accuracy.

An integrated AHP/DEA- Assurance Region (AR) technique (AHP/DEA-AR technique) was used as a multi- criteria decision-making method to evaluate the efficiency performance of 24 major international airports and analyze using the empirical analysis method (Lai et al, 2015). Their results indicated that discriminatory power in the proposed AHP/DEA-AR model is greater than in the basic DEA model when measuring the efficiency of airports.

Lo Storto (2016) combined DEA Cross-Efficiency and Shannon’s Entropy Method to compute the ecological efficiency of a sample of 116 Italian provincial capital cities. Their results showed that the proposed index has a good discrimination power and performs better than the ranking provided by the Sole24Ore method, which is generally used in Italy.

Through a astudy, 25 onion-producing provinces of Iran were ranked using DEA. The evaluation of average efficiency rankings showed that the provinces of Ilam, South Khorasan, Golestan, Sistan, and Baluchestan had the best ranks (Shahnavazi.,2017a).

Lee & Chang (2018) applied Multi-criteria decision-making (MCDM) methods to rank renewable energy sources (RESs) for electricity generation in Taiwan. The ranking results showed that hydro RES is the best alternative in Taiwan, followed by solar, wind, biomass and geothermal RESs.

The integrated DEA-TOPSIS Model has been used to measure the efficiency and ranking of 25 Indian companies known for best practices for controlling their carbon footprints. The model has helped compute the efficiency score of all DMUs and provide a unique rank to each efficient unit identified with the help of the DEA technique (Mehta et al.,2019).

DEA has been used to analyze the performances of different sugarcane production systems of Thailand from an efficiency perspective. The efficiency analysis indicates a huge potential for improving efficiency through a reduction in the current pattern of farm inputs in the lower north, upper central and upper northeastern regions (Ullah et al., 2019).

Najafi et al. (2020) used Estimation Efficiency and Ranking of Iranian Sugar Beet Producers as the DEA approach. Their results show that West Azarbaijan, Kermanshah and Khorasan Razavi provinces have the highest and Semnan, South Khorasan, and Ilam have the lowest rank.

Window Data Envelopment Analysis (DEA) has been used to assess the input use efficiency of agricultural sectors of EU countries for the 2005–2019 period. Results indicate that Estonia (1.000), the Netherlands (0.999) and Slovenia (0.999) are the most efficient countries in terms of input use efficiency. At the same time, Finland, the UK, and Hungary (0.670, 0.755 and 0.771) score the least(Kyrgiakos et al., 2021).

Khare et al. (2021) used the superefficiency DEA method to ranking transit-oriented development (TOD) areas in Bhopal city, India.

The literature shows that although in the industry and services sectors, DEA combined with different multi-criteria decision making has been used to rank different regions, units, or technologies, in the agricultural sector, this method has not been used. . Given the importance of efficient use of resources in reducing economic and environmental costs in the agricultural sector, determining the position of each province in terms of efficiency can help better planning and policymaking along with other factors influencing decision-making .

This research first estimates the rank of potato-producing provinces using different ranking methods in DEA. Then, TOPSIS is employed to integrate different criteria to provide a general image of the status of each province in the production of this strategic crop. The results can provide policymakers and planners of the agricultural sector with useful information to help the process of planning and policymaking for increasing crop production by enhancing efficiency and using resources optimally.

## MATERIALS AND METHODS

Data envelopment analysis (DEA)

Data envelopment analysis (DEA) is one of the most important techniques to evaluate the relative efficiency of decision-making units (DMUs) that produce similar products in different quantities by consuming different amounts of similar inputs (Podinovski & Bouzdine-Chameeva, 2021). This method includes two different models known as BCC and CCR. CCR model was named after Charnes, Cooper, and Rhodes to measure technical efficiency (TE). BCC was proposed by Banker, Charnes, and Cooper who first introduced it. The CCR model assumes constant returns to scale (CRS) so that all observed production combinations can be scaled up or down proportionally (Cullinane et al. 2004). BCC is based on the variable return to scale (VRS) model further divides TE into pure technical efficiency (PTE) and scale efficiency (SE) (Esfahani, 2022b). The overall form of DEA CCR is shown by Eq. (1), (Zahedi-Seresht et al., 2021).

$$\begin{aligned} &\text{Max}=\frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \\ &\&\text{st:} \\ &\frac{\sum_{r-1}^{s} u_{rj} y_{rj}}{\sum_{i=1}^{m} v_{ij} x_{ij}} \leq 1 \\ &u_r \geq 0, v_r \geq 0 \end{aligned} \tag{1}$$

in which $y_{rj}$ represents the $r$th output of the $j$th DMU, $x_{ij}$ represents the $i$th input of the $j$th DMU, and $u$ and $v$ represent the weight equivalent of the outputs and inputs, respectively.

The BCC model, or Pure Technical Efficiency (PTE), developed by Banker et al. (1984), divides TE into PTE and SE. It is represented by Eq. (2) (Zheng & Park, 2016):

$$\begin{aligned} &\text{Max } Z_0=\sum_{r=1}^{s} u_r y_{ro}+W \\ &\& \text{ St:} \\ &\sum_{i=1}^{s} v_i x_{io}=1 \\ &\sum_{r=1}^{s} u_r y_{rj}-\sum_{i=1}^{m} v_i x_{ij}+w \leq 0 \quad j=1,\cdots,n, \end{aligned} \tag{2}$$

in which $W$ is a sign-free variable representing the return to scale of the $j$th unit. If $W = 0$, the unit is working within the optimal scale; if $W > 0$, the unit has a decreasing return to scale; and if $W < 0$, the unit has an increasing return to scale.

SE is defined by TE and PTE as follows (Bolandnazar et al., 2014):

$$\text{SE}=\frac{\text{TE}}{\text{PTE}} \tag{3}$$

It has been reported that efficiency assessment models in DEA cannot distinguish efficient DMUs (Zamani et al., 2017). It has been shown that they only divide DMUs into efficient and inefficient groups (Bian & Xu, 2013). The lack of diagnosis in DEA is related to the fact that DMUs are highly flexible in their weight selection (Jahanshahloo et al., 2009). Researchers have gradually presented new methods for the full ranking of DMUs. Sexton et al. (1986) presented a cross-efficiency matrix. They suggested using the set of weights of other DMUs for determining the efficiency score instead of weight assignment based on the information of the DMUs themselves. The cross-efficiency of each $\text{DMU}_j$ can be calculated by the optimal weights of $\text{DMU}_d$, i.e., $E_{dj}$, as Eq. (4) (Aparicio & Zofio, 2020).

$$\text{Edj}=\frac{\sum_{r}^{s} u_{rd}\, y_{rj}}{\sum_{i}^{m} v_{id}\, x_{ij}} \tag{4}$$

The cross-efficiency of the $j$th DMU can be calculated by Eq. (5) (Tavana et al., 2021).

$$E_j=\frac{1}{n}\sum_{d=1}^{n} E_{dj} \tag{5}$$

Cross-efficiency may not be capable of ranking all efficient units due to the likelihood of giving multiple optimal solutions (Najafi et al., 2020).

Anderson and Peterson (1993) introduced the super-efficiency model for ranking DMUs. The super-efficiency model refers to a modified DEA in which enterprises can have efficiency scores greater than one (Aydin et al., 2020). They excluded the DMU under assessment from the production set and executed the model for the remaining DMUs. The general form of Anderson and Peterson's (AP) model is as follows (Tran et al., 2019):

$$\begin{aligned} &\min \theta_o \\ &\text{st:} \\ &\sum_{j=1,j=o}^{n} v_j x_{ij} \leq \theta_o x_{io} \qquad i=1,2,\ldots,m \\ &\sum u_j y_{rj} \geq y_{ro} \quad r=1,2,\ldots,s \\ &v_j \geq 0 \quad j=1,2,\ldots,n\ ,\ j \neq o \end{aligned} \tag{6}$$

in which if $\theta_O \geq 1$, the DMU (O) is efficient; otherwise, it is inefficient (Tone, 2001). The AP model may not be feasible for DMUs whose input is zero. In addition, it may not be able to precisely assess the DMUs whose data are close to zero (Aghayi et al., 2018).

In the subsequent efforts to modify DEA, ideal and anti-ideal virtual DMUs were introduced. An ideal DMU is a virtual unit with maximum production and minimum inputs. On the contrary, an anti-ideal DMU is a unit that exhibits minimum production with maximum inputs (Hatami et al., 2010). In this case, the efficiency of the ideal DMUwas expressed by Eq. (7) (Wang & Luo, 2006):

$$\theta_{\text{IDMU}}=\frac{\sum_{r=1}^{s} u_r y_r^{\max}}{\sum_{i=1}^{m} v_i x_i^{\min}} \tag{7}$$

An ideal DMU should be able to gain the best relative efficiency. Thus, the relative efficiency score of an ideal DMU can be calculated by Eq. (8) (Wang & Luo, 2006).

$$\begin{aligned} &Maximize\ \theta_{j_0}=\sum_{r=1}^{s} u_r y_{rj_0} \\ &subject\ to\ \sum_{i=1}^{m} v_i x_{ij_0}=1, \\ &\qquad \sum_{r=1}^{s} u_r y_j^{max}-\sum_{i=1}^{m} v_i\left(\theta_{IDMU^*} x_i^{min}\right)=0, \\ &\qquad \sum_{r=1}^{s} u_r y_{rj}-\sum_{i=1}^{m} v_i x_{ij} \leq 0, j=1,\ldots,n, \\ &\qquad u_r, v_i \geqslant \varepsilon, \forall r, i. \end{aligned} \tag{8}$$

After solving the above model, the best relative efficiency of the $j$th unit is obtained by Eq. (9).

$$\begin{aligned} &\text{Maximize } \theta_{j_0}=\sum_{r=1}^{s} u_r y_{rj_0} \\ &\text{subject to } \sum_{i=1}^{m} v_i x_{ij_0}=1, \\ &\qquad \sum_{r=1}^{s} u_r y_j^{max}-\sum_{i=1}^{m} v_i\left(\theta_{\text{IDMU}^*} x_i^{min}\right)=0, \\ &\qquad \sum_{r=1}^{s} u_r y_{rj}-\sum_{i=1}^{m} v_i x_{ij} \leq 0, j=1,\ldots,n, \\ &\qquad u_r, v_i \geqslant \varepsilon, \forall r, i. \end{aligned} \tag{9}$$

For an anti-ideal DMU, too, the relative efficiency shows the worst efficiency among the DMUs, which is expressed as Eq. (10).

$$\text{Min } \varphi_{\text{ADMU}} = \frac{\sum_{r=1}^{s} u_r y_r^{min}}{\sum_{i=1}^{m} v_i x_i^{max}}$$
$$\text{subject to } \theta_j = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \geq 1, j = 1, \dots, n, \quad (10)$$
$$u_r, v_i \geqslant \varepsilon, \forall r, i,$$

Eq. (11) is used to determine the worst relative efficiency of each DMU (Wang & Luo, 2006):

$$\text{Minimize } \varphi_{j_0} = \sum_{r=1}^{s} u_r y_{rj_0}$$
$$\text{subject to } \sum_{i=1}^{m} v_i x_{ij_0} = 1,$$
$$\sum_{r=1}^{s} u_r y_j^{min} - \sum_{i=1}^{m} v_i (\varphi_{\text{IDMU}^*} x_i^{max}) = 0, \quad (11)$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \geqslant 0, j = 1, \dots, n,$$
$$u_r, v_i \geqslant \varepsilon, \forall r, i.$$

If $\varphi_{jo}$ or $\theta_{jo}$ is equal to 1, the *o*th DMU will be inefficient and efficient, respectively. Indeed, $\varphi_{jo}$ and $\theta_{jo}$ provide us with two distinctive assessments of the performance of the *o*th DMU and may lead to different conclusions. It is, therefore, necessary to consider these two efficiency scores together. So, the multiple attribute decision making (MADM) method can combine these two indices to form a comprehensive index called relative closeness (RC).

$$\text{RC}_{j_0} = \frac{\varphi_{j_0}^* - \varphi_{\text{ADMU}}^*}{(\varphi_{j_0}^* - \varphi_{\text{ADMU}}^*) + (\theta_{\text{IDMU}}^* - \theta_{j_0}^*)} \quad (12)$$

The index RC, represented by Eq. (12), gives us a general assessment of each DMU. The greater difference between $\varphi_{\text{ADMU}}^*$ and $\varphi_{j_0}^*$ and the lower difference between $\theta_{j_0}^*$ and $\theta_{\text{IDMU}}^*$ imply the better performance of the *o*th DMU.

Aghayi et al. (2018) presented a ranking method based on the distance to an ideal hyperplane. In this case, the minimum distance of the DMU from the ideal hyperplane obtained from Eq. (13) will be the basis of ranking (Aghayi et al., 2018).

$$Min \quad \sum_{j=1}^{n} s_j$$
$$\text{s.t.} \quad \sum_{r=1}^{s} u_r y_{vj} - \sum_{i=1}^{m} v_i x_{ij} + s_j = 0, j = 1, \dots, n,$$
$$\sum_{r=1}^{s} u_r y_r^* - \sum_{i=1}^{m} v_i x_i^* = 0, \quad (13)$$
$$u_r \geq \varepsilon, \quad r = 1, \dots, s,$$
$$v_i \geq \varepsilon, \quad i = 1, \dots, m.$$

in which $S_j$ is the distance of the *j*th unit from the ideal hyperplane. The lower the distance is, the higher the rank of the DMU will be (Aghayi et al., 2018).

## TOPSIS Technique

Given the limitations of the DEA-based ranking models, it is preferred to use an ensemble of models to rank DMUs. In other words, using multi-criteria techniques can provide a more precise and comprehensive assessment of DMUs. Indeed, a more comprehensive image of each unit's status can be obtained by applying multi-criteria assessment techniques as they integrate the results of different ranking techniques. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a multi-criteria decision-making technique that many researchers have integrated with DEA to rank production units in different economic sectors (Bian & Xu, 2013; Lotfi et al., 2011; Rakhshan, 2017; Varatharajulu et al., 2021; Venkata Subbaiah et al., 2014). The TOPSIS technique was introduced by Hwang and Yoon (1981) for assessing the *j*th alternative with *n* indices. In this method, the selected alternative should have the lowest distance from the positive ideal and the highest distance from the negative ideal (Jozi & Majd, 2014).

In this method, the decision matrix, composed of *m* DMUs and *n* criteria, is first converted to a normalized dimensionless matrix using the Euclidean norm and Eq. (14) (Singaravel & Selvaraj, 2015). $x_{ij}$ show the rank of $\text{DMU}_\text{i}$ using DEA model j.

$$N_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} j = 1,2, \dots, n \quad (14)$$

Then, the weight of each index is calculated. The weight of each index ($W_j$) can be obtained by the entropy method using Eq. (15)-(18) (Dehdasht Id et al., 2020; Zheng et al., 2018).

$$P_{ij} = \frac{x_{ij}}{\sum_j x_{ij}} \quad (15)$$
$$E_j = -k \sum P_{ij} \text{Ln}(P_{ij}) \quad (16)$$
$$d_j = 1 - E_j \quad (17)$$
$$W_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \quad (18)$$

After calculating the weight of each index and building the weighted matrix $[V_{ij}]$, the hypothetical positive ideal and negative ideal alternatives are calculated by Eq. (19) and (20), in which $J^+$ represents the optimal criterion, so its higher values are more optimal. In contrast, $J^-$ represents the non-optimal criterion so that its smaller values show more optimality (Chen, 2021).

$$\text{A}^+ = \{\text{Max V}_{\text{ij}} \mid (\text{J}\varepsilon\text{J}^+), (\text{MinV}_{\text{ij}} \mid \text{J}\varepsilon\text{J}^-)\} = (V_1^+, V_2^+, \dots\dots. V_\alpha^+) \quad (19)$$
$$\text{A}^- = \{\text{MinV}_{\text{ij}} \mid (\text{J}\varepsilon\text{J}^+), (\text{MaxV}_{\text{ij}} \mid \text{J}\varepsilon\text{J}^-)\} = (V_1^-, V_2^-, \dots\dots. V_\alpha^-) \quad (20)$$

The distance of each alternative to the positive and negative ideal alternatives is obtained from Eq. (21) and (22) (Behzadian et al., 2012).

$$d^+ = [\sum (A^+ - A_{ij})^2]^{0.5} \quad (21)$$
$$d^- = [\sum (A^- - A_{ij})^2]^{0.5} \quad (22)$$

The closeness coefficient (CC) of each alternative is calculated by Eq. 23, where the ratio of the ideal solution to the ideal alternative is obtained. (Yoon & Kim, 2017).

$$CC_\text{i} = \frac{\text{d}_\text{i}^-}{\text{d}_\text{i}^- + \text{d}_\text{i}^+} \quad (23)$$

The rank of alternatives will be obtained according to the $\text{CC}_\text{i}$ in descending order, allowing relatively better performances to be compared. According to the value $\text{CC}_\text{i}$, the higher the value of the closeness coefficient, the higher the ranking order and hence the better the performance of the alternatives (Rejab et al., 2021).

This study was conducted for different potato-producing provinces of Iran. In this study, the ranks of each DMU using different models of DEA were considered as criteria and integrated by TOPSIS. The data requirement of the research on the amount of input use (water, nitrogen fertilizer, phosphate fertilizer, potash fertilizer, manure, and pesticides) and yields in the 2018-2019 crop year was supplied from the production cost system. Data on the cultivation areas were collected from the agricultural statistics books of the Ministry of Agriculture Jahad. They were analyzed in MATLAB and MS-Excel software packages.

## RESULT AND DISCUSSION

Table 1 presents the amounts of production, gross profit, and consumption rate of the inputs. The mean production per ha of the potato farms is about 34 tons with a standard deviation of about 7863 kg. The maximum value is 50 t/ha and the minimum is 20 t/ha.

Based on the data of Table 2, the highest potato cultivation areas are related to the Hamedan, Ardabil, and Isfahan provinces, respectively. 11.21 percent of the Hamedan irrigated farms are allocated to potato production, which ranks first in the country. In this respect, followed by Kurdistan and Ardabil provinces are in the next rank, respectively (Table 2).

For in-depth analysis and achievement of interpretable results, the models presented in the previous section were run in two distinctive cases considering yield and gross profit as the indices of production and profitability, respectively.

The mean TE, PTE, and SE are lower when gross profit is considered the output than when yield is considered the output (Table 3). In this respect, it should be remembered that a yield increase will not necessarily lead to more profitability, and it is necessary to consider production costs in addition to revenue and increase production up to the maximum point of producers' profitability by considering input prices.

According to the ranking of the potato-producing provinces using different models of DEA, including the Cross-Efficiency (CE), Anderson-Peterson method (AP), Relative Efficiency (RE), and Distance to Ideal Hyperplane (DIH), it was observed that different techniques do not provide similar rankings (Tables 4 and 5).

Najafi et al., (2020) ranked Provinces producing sugar beet in Iran by different DEA models, and their results were not the same. The use of different DEA models by Shahnavazi (2017b) to rank the irrigated crops in the Iranian agricultural sector did not yield the same results. So it is necessary to integrate the results by a multi-criteria technique to have a clearer image of the ranking of the provinces. Accordingly, the TOPSIS technique was employed to assess and rank the provinces in this study (Table 6).

Based on the closeness coefficient (CC), when yield is considered the output, the provinces of Mazandaran, Qazvin, Kerman, West Azerbaijan, Markazi, and East Azerbaijan are ranked first to fifth, respectively. Based on gross profit, the TOPSIS technique shows that the provinces of Mazandaran, Kerman, West Azerbaijan, Qazvin, Chaharmahal and Bakhtiari are ranked first to fifth, respectively (Table 6).

This study showed that the important potato-producing provinces were not in a good position in terms of efficiency. Similar results have been reported in other studies. Amadeh et al. (2011) showed that important industrial provinces did not gain a good rank of provinces in terms of industry efficiency. Shahnavazi (2017a) showed that the important onion-producing provinces were not in a favorable position in the efficiency ranking. Based on the results of this study and studies that have been done in the past, it seems that although there is an emphasis on increasing efficiency in the upstream laws, in the implementation phase, increasing production has a higher priority than increasing efficiency.

**Table 1.** The descriptive statistics on yield and input consumption of potato farms in Iran

| | Mean | Max | Min | Sd |
|---|---|---|---|---|
| Yield (kg /ha) | 34110.35 | 50000.00 | 20000.00 | 7863.84 |
| Gross profit (1000IRR/ha) | 29494.77 | 112305.19 | 375.33 | 23617.20 |
| Water price (1000IRR/ha) | 3356.98 | 7365.38 | 721.15 | 1790.54 |
| Seed (kg/ha) | 3976.07 | 6845.10 | 1533.30 | 1031.05 |
| Phosphate (kg/ha) | 166.56 | 278.80 | 50.00 | 59.86 |
| Nitrogen (kg/ha) | 298.00 | 750.00 | 42.50 | 148.98 |
| Potash (kg/ha) | 98.56 | 233.30 | 0.00 | 64.99 |
| Labour (day/ha) | 28.51 | 71.40 | 5.80 | 15.27 |
| Pesticides (kg/ha) | 3.30 | 5.43 | 0.00 | 1.74 |
| Land rent (1000IRR/ha) | 6495.13 | 11013.38 | 1033.33 | 2623.50 |
| Manure (ton/ha) | 4.68 | 18.40 | 0.00 | 5.43 |

**Table 2**. The descriptive statistics of potato cultivation areas in different provinces of Iran

| Province | Cultivation area | Rank in area | Proportion of irrigated lands | Rank in Proportion of irrigated lands |
|---|---|---|---|---|
| Ardabil | 21174 | 2 | 9.709% | 3 |
| Chaharmahal and Bakhtiari | 5400 | 12 | 7.294% | 5 |
| East Azerbaijan | 7709 | 7 | 3.776% | 9 |
| Fars | 9539 | 5 | 1.542% | 14 |
| Golestan | 6760 | 10 | 1.878% | 12 |
| Hamedan | 21236 | 1 | 11.208% | 1 |
| Isfahan | 16247 | 3 | 6.233% | 7 |
| Kerman | 3800 | 15 | 3.073% | 11 |
| Kermanshah | 6631 | 11 | 3.219% | 10 |
| Khuzestan | 4495 | 13 | 0.463% | 19 |
| Kurdistan | 9410 | 6 | 9.895% | 2 |
| Lorestan | 6787 | 9 | 4.866% | 8 |
| Markazi | 2586 | 16 | 1.616% | 13 |
| Mazandaran | 1000 | 18 | 0.295% | 20 |
| Qazvin | 380 | 21 | 0.259% | 21 |
| Razavi Khorasan | 4476 | 14 | 1.098% | 16 |
| Semnan | 867 | 20 | 1.314% | 15 |
| South Kerman | 11873 | 4 | 7.431% | 4 |
| Tehran | 890 | 19 | 0.641% | 17 |
| West Azerbaijan | 1646 | 17 | 0.514% | 18 |
| Zanjan | 7475 | 8 | 7.035% | 6 |

**Table 3**. Technical Efficiency (TE), Pure Technical Efficiency (PTE) and Scale Efficiency (SE) of the potato-producing provinces in Iran

| Province | Considering yield as the output | | | Considering Gross profit as the output | | |
|---|---|---|---|---|---|---|
| | TE | PTE | SE | TE | PTE | SE |
| Ardabil | 1 | 1 | 1 | 1 | 1 | 1 |
| Chaharmahal and Bakhtiari | 1 | 1 | 1 | 0.048 | 1 | 0.048 |
| East Azerbaijan | 1 | 1 | 1 | 0.64 | 1 | 0.64 |
| Fars | 0.832 | 0.837 | 0.994 | 0.7 | 0.886 | 0.79 |
| Golestan | 0.851 | 0.879 | 0.968 | 0.196 | 0.873 | 0.224 |
| Hamedan | 0.848 | 0.861 | 0.985 | 0.706 | 0.876 | 0.806 |
| Hormozgan | 1 | 1 | 1 | 1 | 1 | 1 |
| Isfahan | 0.771 | 0.953 | 0.81 | 0.555 | 0.953 | 0.583 |
| Kerman | 1 | 1 | 1 | 1 | 1 | 1 |
| Kermanshah | 0.956 | 1 | 0.956 | 0.527 | 1 | 0.527 |
| Khuzestan | 1 | 1 | 1 | 0.871 | 1 | 0.871 |
| Kurdistan | 1 | 1 | 1 | 1 | 1 | 1 |
| Lorestan | 1 | 1 | 1 | 0.279 | 1 | 0.279 |
| Markazi | 1 | 1 | 1 | 0.356 | 0.958 | 0.372 |
| North Khorasan | 0.98 | 1 | 0.98 | 0.45 | 0.805 | 0.559 |
| Razavi Khorasan | 1 | 1 | 1 | 1 | 1 | 1 |
| Semnan | 0.93 | 0.933 | 0.997 | 0.395 | 0.848 | 0.465 |
| South Kerman | 1 | 1 | 1 | 0.747 | 1 | 0.747 |
| Tehran | 1 | 1 | 1 | 0.515 | 1 | 0.515 |
| West Azerbaijan | 0.809 | 1 | 0.809 | 0.622 | 1 | 0.622 |
| Zanjan | 1 | 1 | 1 | 1 | 1 | 1 |
| Average | 0.951 | 0.974 | 0.976 | 0.648 | 0.962 | 0.669 |

TE, PTE and SE represent Technical Efficiency, Pure echnical Efficiency and Scale Efficiency, respectively.

**Table 4**. Ranking of potato-producing provinces considering yield as the output in Iran

| Province | RE | Rank | DIH | Rank | AP | Rank | CE | Rank |
|---|---|---|---|---|---|---|---|---|
| East Azerbaijan | 0.044 | 10 | 828.98 | 5 | 0.747 | 6 | 0.605 | 6 |
| West Azerbaijan | 0.082 | 1 | 859.27 | 6 | 0.608 | 4 | 0.644 | 4 |
| Ardabil | 0.052 | 6 | 878.50 | 7 | 1.236 | 17 | 0.457 | 14 |
| Isfahan | 0.050 | 8 | 1032.40 | 13 | 1.047 | 13 | 0.520 | 9 |
| Tehran | 0.046 | 9 | 817.99 | 4 | 1.298 | 18 | 0.362 | 20 |
| South Kerman | 0.030 | 19 | 1900.31 | 21 | 1.202 | 15 | 0.396 | 16 |
| Chaharmahal and Bakhtiari | 0.022 | 21 | 1243.93 | 19 | 0.767 | 7 | 0.569 | 7 |
| Razavi Khorasan | 0.026 | 20 | 1026.09 | 12 | 1.421 | 20 | 0.347 | 21 |
| Khuzestan | 0.055 | 3 | 1065.72 | 14 | 0.784 | 9 | 0.533 | 8 |
| Zanjan | 0.042 | 11 | 1127.98 | 16 | 1.228 | 16 | 0.435 | 15 |
| Semnan | 0.034 | 15 | 1212.59 | 17 | 1.437 | 21 | 0.388 | 17 |
| Fars | 0.039 | 13 | 1487.61 | 20 | 0.802 | 10 | 0.382 | 18 |
| Qazvin | 0.051 | 7 | 950.10 | 11 | 0.280 | 2 | 0.735 | 2 |
| Kurdistan | 0.038 | 14 | 1086.01 | 15 | 1.075 | 14 | 0.491 | 12 |
| Kerman | 0.042 | 12 | 887.65 | 8 | 0.342 | 3 | 0.470 | 13 |
| Kermanshah | 0.032 | 18 | 806.79 | 3 | 0.861 | 11 | 0.502 | 11 |
| Golestan | 0.034 | 17 | 1238.22 | 18 | 1.325 | 19 | 0.374 | 19 |
| Lorestan | 0.054 | 4 | 918.25 | 10 | 0.778 | 8 | 0.611 | 5 |
| Mazandaran | 0.053 | 5 | 304.52 | 1 | 0.000 | 1 | 0.766 | 1 |
| Markazi | 0.065 | 2 | 503.75 | 2 | 0.716 | 5 | 0.680 | 3 |
| Hamedan | 0.034 | 16 | 889.69 | 9 | 1.020 | 12 | 0.519 | 10 |

RE, DIH, AP and CE represent Relative efficiency, Distance to an ideal hyperplate, Super-efficiency and Cross-efficiency respectively.

**Table 5**. Ranking of potato-producing provinces considering gross profit as the output in Iran

| Province | RE | Rank | DIH | Rank | AP | Rank | CE | Rank |
|---|---|---|---|---|---|---|---|---|
| East Azerbaijan | 0.002 | 5 | 2617.13 | 11 | 2.808 | 18 | 0.174 | 17 |
| West Azerbaijan | 0.002 | 3 | 2550.06 | 8 | 1.562 | 10 | 0.347 | 12 |
| Ardabil | 0.001 | 7 | 2286.09 | 5 | 1.609 | 12 | 0.417 | 10 |
| Isfahan | 0.001 | 12 | 2724.65 | 15 | 1.899 | 13 | 0.375 | 11 |
| Tehran | 0.001 | 16 | 1926.93 | 3 | 1.203 | 6 | 0.528 | 5 |
| South Kerman | 0.001 | 21 | 4652.80 | 21 | 1.429 | 9 | 0.440 | 8 |
| Chaharmahal and Bakhtiari | 0.001 | 18 | 2644.81 | 13 | 0.355 | 4 | 0.858 | 1 |
| Razavi Khorasan | 0.001 | 17 | 2571.31 | 10 | 2.357 | 16 | 0.268 | 14 |
| Khuzestan | 0.001 | 10 | 2663.00 | 14 | 1.564 | 11 | 0.445 | 7 |
| Zanjan | 0.001 | 13 | 3017.60 | 17 | 1.417 | 8 | 0.418 | 9 |
| Semnan | 0.001 | 6 | 3353.07 | 19 | 20.871 | 21 | 0.028 | 21 |
| Fars | 0.002 | 2 | 3885.14 | 20 | 3.730 | 19 | 0.111 | 19 |
| Qazvin | 0.001 | 20 | 2380.07 | 7 | 0.216 | 3 | 0.775 | 2 |
| Kurdistan | 0.001 | 11 | 3014.40 | 16 | 2.533 | 17 | 0.257 | 15 |
| Kerman | 0.001 | 9 | 2178.11 | 4 | 0.005 | 2 | 0.661 | 4 |
| Kermanshah | 0.001 | 15 | 2376.58 | 6 | 1.961 | 14 | 0.245 | 16 |
| Golestan | 0.002 | 4 | 3335.55 | 18 | 5.104 | 20 | 0.103 | 20 |
| Lorestan | 0.001 | 8 | 2626.66 | 12 | 1.339 | 7 | 0.461 | 6 |
| Mazandaran | 0.007 | 1 | 1123.82 | 1 | 0.000 | 1 | 0.113 | 18 |
| Markazi | 0.001 | 19 | 1420.11 | 2 | 0.804 | 5 | 0.685 | 3 |
| Hamedan | 0.001 | 14 | 2562.75 | 9 | 2.224 | 15 | 0.314 | 13 |

RE, DIH, AP and CE represent Relative efficiency, Distance to an ideal hyperplate, Super-efficiency and Cross-efficiency, respectively

When the provinces are ranked based on gross profit versus yield, the results show that the provinces of East Azerbaijan, Fars, Kermanshah and Hamedan need more improvement than the other provinces. Farmers in these provinces seem to care more about increasing production than profit. These results imply a better orientation of their policies and programs toward increasing production in these regions.

Also, Ardabil, South Kerman, Tehran and Zanjan provinces had the highest improvement in terms of gross profit relative to yield efficiency. This shows that cost management in these provinces is better than in other provinces.

The Spearman correlation (Winter et al., 2016) was used in the current study to analyze the relation between potato-producing provinces' rank in terms of gross profit and yield efficiency. The analysis showed that the yield and gross profit efficiency ranks negatively related to seed, K-fertilizer, and pesticide (Table 7). So management of conception of these inputs is necessary for increasing the efficiency rank. For this purpose, the use of biofertilizers, as well as biological control and integrated pest management, are recommended.

**Table 6**. The closeness coefficient (CC) and ranking of each potato-producing provincesin Iran

| Province | Considering yield as the output | | Considering Gross profit as the output | |
|---|---|---|---|---|
| | CC | Rank | CC | Rank |
| East Azerbaijan | 0.502 | 6 | 0.745 | 15 |
| West Azerbaijan | 0.621 | 4 | 0.787 | 3 |
| Ardabil | 0.293 | 15 | 0.769 | 7 |
| Isfahan | 0.342 | 13 | 0.755 | 12 |
| Tehran | 0.275 | 16 | 0.764 | 10 |
| South Kerman | 0.144 | 21 | 0.753 | 13 |
| Chaharmahal and Bakhtiari | 0.422 | 10 | 0.774 | 5 |
| Razavi Khorasan | 0.194 | 18 | 0.736 | 19 |
| Khuzestan | 0.473 | 8 | 0.766 | 9 |
| Zanjan | 0.242 | 17 | 0.762 | 11 |
| Semnan | 0.165 | 20 | 0.034 | 21 |
| Fars | 0.396 | 11 | 0.736 | 18 |
| Qazvin | 0.728 | 2 | 0.774 | 4 |
| Kurdistan | 0.304 | 14 | 0.740 | 17 |
| Kerman | 0.682 | 3 | 0.791 | 2 |
| Kermanshah | 0.429 | 9 | 0.746 | 14 |
| Golestan | 0.179 | 19 | 0.679 | 20 |
| Lorestan | 0.493 | 7 | 0.774 | 6 |
| Mazandaran | 0.868 | 1 | 0.909 | 1 |
| Markazi | 0.578 | 5 | 0.768 | 8 |
| Hamedan | 0.350 | 12 | 0.742 | 16 |

CC : Closeness Coefficient, The higher value of the CC, the higher ranking

**Table 7.** The correlation between inputs and efficiency in terms of yield and gross profit in potato-producing provinces of Iran

| Input | Water | Seed | P-fertilizer | N-fertilizer | K-fertilizer | Labor | Pesticide | Land rent | Manure |
|---|---|---|---|---|---|---|---|---|---|
| Yield efficiency | -0.186 (0.420) | -0.544 (0.011)* | -0.194 (0.401) | -0.277 (0.225) | -0.521 (0.015)* | -0.329 (0.146) | -0.522 (0.015)* | -0.186 (0.420) | -0.093 (0.690) |
| Profit efficiency | -0.132 (0.568) | -0.501 (0.02)* | -0.308 (0. 174) | -0.280 (0. 218) | -0.483 (0. 026)* | -0.254 (0. 27) | -0.659 (0. 001)** | 0.021 (0. 926) | 0.009 (0. 968) |

** and *. Significant in statistic level of 1% ($P < 1\%$) and 5% ($P < 5\%$).

## CONCLUSIONS

Policymakers have always considered increasing potato production, especially in developing countries, due to its significance in households' food baskets and its role in creating employment and alleviating poverty. The Sixth Development Action Plan of Iran has required the government to increase potato production to at least 5596 thousand tons. Any plan and policy for production increase should consider efficiency enhancement and optimal use of resources. Accordingly, the knowledge of the status of different potato-producing regions can provide policymakers with useful information. Given the limitation of DEA in ranking producing units, various models have been suggested to improve it, each with its limitations. So far, no consensus has happened in authentic scientific resources for introducing a certain model as the best method of DMU ranking. Therefore, it seems more appropriate to use an ensemble of methods and integrate their results to provide a general assessment of DMU rankings.

This research integrated the results of different DEA ranking models using the TOPSIS technique. To gain more practical results and better interpretation, gross profit was also considered in efficiency estimation and yield. The results of ranking potato-producing provinces reveal that the provinces of Hamedan, Ardabil, Isfahan, South Kerman, Fars, and Kurdistan, which account for over half of the potato production in Iran, are not ranked high in efficiency. Hamedan is ranked 12th, Ardabil 15th, Isfahan 13th, South Kerman 21th , Fars 11th and Kurdistan 14st. Based on the results, higher production levels and yield will not necessarily lead to higher efficiency. This is consistent with similar studies (Graubner & Ostapchuk, 2018; Malana & Malano, 2006; Shahnavazi, 2017a; Shahnavazi, 2020). On the other hand, the lower ranks of the main potato-producing provinces show that there is a high potential for increasing potato production by enhancing production efficiency.

South Kerman, Fars, Ardabil, and Zanjan provinces, which are in a good rank in terms of area under cultivation, exhibited the highest improvement in their ranks when they were ranked by yield than when they were ranked by gross profit. One important factor underpinning production increase is to make crop cultivation attractive by increasing its profitability, which will increase cultivation area and production in the long run. Among potato-producing provinces, Mazandaran, Kerman and West Azerbaijan were ranked higher in efficiency regardless of whether the yield was the output or gross profit. This means that inputs in this province have been optimally applied to increase yield and profitability considering production costs. Furthermore, higher mean TE of yield than the mean TE of profit means that producers care more about increasing production as an objective output. The experience of These provinces in optimally using production inputs and simultaneously considering both yield and profitability can be used by other provinces. Accordingly, it can be noted that the increase in yield is regarded as an increase in profit in most parts of Iran. In contrast, gross profit is the yield of revenue minus costs, while the increase in yield will only increase revenue. However, to achieve the maximum profit, sound management of costs is as important as yield increment.

According to the correlation between efficiency and seed, P-fertilizer, and pesticide, the use of biofertilizers, as well as biological control and integrated pest management, are recommended for improvement of efficiency of potato producing provinces.

## REFRENCES


Aghayi, N., Hosseinzadeh Lotfi, F., Gholami, K., & Ghelej Beigi, Z. (2018). Ranking and sensitivity analysis for ranks of DMUs based on the ideal hyperplan. *Journal of Operational Research and Its Applications*, 15(2), 125-133. In persian.

Amadeh, H., Emami Meibodi, A., & Azadinezhad, A. (2011). Ranking the Iranian provinces by technical efficiency of industrial sector by applying DEA method. *Monetary & Financial Economics*, 16(29), 162-180.In persian. https://doi.org/10.22067/pm.v16i29.27199

Anderson, P., & Peterson, N. C. (1993). A procedure for ranking efficient units in data envelopment analysis. *Management Science* 10, 1261-1264.

Aparicio, J., & Zofío, J. (2020). Economic cross-efficiency. *Omega,* 100, 1-16. https://doi.org/10.1016/j.omega.2020.102374

Aydın, U., Karadayi, M. A., & Ülengin, F. (2020). How efficient airways act as role models and in what dimensions? A superefficiency DEA model enhanced by social network analysis. *Journal of Air Transport Management*, 82, 101725. https://doi.org/https://doi.org/10.1016/j.jairtraman.2019.101725.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30(9), 1078-1092 .

Behzadian, M., Khanmohammadi Otaghsara, S., Yazdani, M., & Ignatius, J. (2012). A state-of the-art survey of TOPSIS applications. *Expert Systems with Applications*, 39(17), 13051-13069. https://doi.org/https://doi.org/10.1016/j.eswa.2012.05.056

Bian, Y., & Xu, H. (2013). DEA ranking method based upon virtual envelopment frontier and TOPSIS. *System Engineering Theory and Practice*, 33(2), 482-488 .

Bolandnazar, E., Keyhani, A., & Omid, M. (2014). Determination of efficient and inefficient greenhouse cucumber producers using data envelopment analysis approach, a case study: Jiroft city in Iran. *Journal of Cleaner Production*, 79, 108-115.

Chen, P. (2021). Effects of the entropy weight on TOPSIS. *Expert Systems with Applications*, 168, 114186. https://doi.org/https://doi.org/10.1016/j.eswa.2020.114186

Cullinane, K., Song, D. W., Ji, P., & Wang, T. F. (2004). An application of DEA windows analysis to container port production efficiency. Review of network Economics, 3(2), 184-205.

Dehdasht Id, G., Salim, M., Id, F., Zin, R. M., & Abidinid, N. Z. (2020). A hybrid approach using entropy and TOPSIS to select key drivers for a successful and sustainable lean construction implementation, *PLoS One,* 15(2),1-32. https://doi.org/10.1371/journal.pone.0228746.

Devaux, A., Goffart, J. P., Petsakos, A., Kromann, P., Gatto, M., Okello, J., Suarez, V., & Hareau, G. (2020). Global food security, contributions from sustainable potato agri-food systems, In H. Campos & O. Ortiz (Eds.), *The Potato Crop: Its Agricultural, Nutritional and Social Contribution to Humankind* (pp. 3-35). Springer International Publishing. https://doi.org/10.1007/978-3-030-28683-5_1

Durst, P., & Bayasgalanbat, N. (2014). Promotion of underutilized indigenous food resources for food security and nutrition in Asia and the Pacific. Food and Agriculture Organization of the United Nations regional office for Asia and the Pacific Bangkok, 2014. Retrived from: http://www.fao.org/3/a-i3685e.pdf

Esfahani, S.M.J (2022a). Ranking wheat-producing provinces of Iran based on eco-efficiency. Environmental Resources Research, 10(1), 81-92. doi: 10.22069/ijerr.2022.6033.

Esfahani, S. M. J. (2022b). Management of energy consumption and greenhouse gas emissions using the optimal farm scale: Evidence from wheat production in South Khorasan Province. Iran Agricultural Research, 40(2), 71-83. doi: 10.22099/iar.2022.41569.1461

FAO. (2020). FAOSTAT, crop statistics. Retrived from: http://www.fao.org/faostat/en/#data/QC

Graubner, M., & Ostapchuk, I. (2018). Efficiency and profitability of Ukrainian crop production. Agricultural Policy Report, Institute for Economic Research and Policy Consulting, Reytarska, Kyiv, Ukraine. Retrieved from: https://www.apd-ukraine.de/images/Efficiency_and_Profitability_of_Ukrainian_Crop_Production.pdf

Hatami, A., Marbini Saati, S., & Makui, A. (2010). Ideal and anti-ideal decision making units: A fuzzy DEA approach. *Journal of Industrial Engineering International*, 6(10), 31-34.

Haverkort, A. J., de Ruijter, F. J., van Evert, F. K., Conijn, J. G., & Rutgers, B. (2013). Worldwide sustainability hotspots in potato cultivation. 1. Identification and mapping. *Potato Research*, 56(4), 343-353. https://doi.org/10.1007/s11540-013-9247-8

Hwang, C. L., Yoon, K. (1981). Methods for multiple attribute decision making. In: *Multiple attribute decision making. Lecture notes in economics and mathematical systems*. (pp.58-191). Berlin, Heidelberg, Springer. https://doi.org/10.1007/978-3-642-48318-9_3

Jahanshahloo, G. R., Junior, H. V., Hosseinzadeh Lotfi, F., & Akbarian, D. (2007). A new DEA ranking system based on changing the reference set. *European Journal of Operational Research*, 181(1), 331-337.

Jozi, S. A., & Majd, N. M. (2014). Health, safety, and environmental risk assessment of steel production complex in central Iran using TOPSIS. *Environmental Monitoring and Assessment*, 186(10), 6969-6983. https://doi.org/10.1007/s10661-014-3903-6

Kazemi, J., Dehghan Sanch, K., & Khalilzadeh, M. (2017). Ranking of agricultural production using decision making approach Fuzzy multi-attribute : Case study of West Azarbayjan. *Agricultural Economics Research*, 9(35), 145-162. In persian. http://jae.marvdasht.iau.ir/article_2519.html

Khare, R., Villuri, V. G. K., & Chaurasia, D. (2021). Urban sustainability assessment: The evaluation of coordinated relationship between BRTS and land use in transit-oriented development mode using DEA model. *Ain Shams Engineering Journal*, 12(1), 107-117. https://doi.org/https://doi.org/10.1016/j.asej.2020.08.012.

Kyrgiakos, L. S., Vlontzos, G., & Pardalos, P. M. (2021). Ranking EU agricultural sectors under the prism of alternative widths on window DEA. *Energies*, 14(4). 1021. https://doi.org/10.3390/en14041021

Lai, P. L., Potter, A., Beynon, M., & Beresford, A. (2015). Evaluating the efficiency performance of airports using an integrated AHP/DEA-AR technique. *Transport Policy*, 42, 75-85. https://doi.org/https://doi.org/10.1016/j.tranpol.2015.04.008

Lee, H. C., & Chang, C. T. (2018). Comparative analysis of MCDM methods for ranking renewable energy sources in Taiwan. *Renewable and Sustainable Energy Reviews*, 92, 883-896. https://doi.org/https://doi.org/10.1016/j.rser.2018.05.007

Lo Storto, C. (2016). Ecological efficiency based ranking of cities: A combined DEA cross-efficiency and Shannon's Entropy Method. *Sustainability*, 8(2), 124-137. https://doi.org/10.3390/su8020124

Lotfi, F. H., Fallahnejad, R., & Navidi, N. (2011). Ranking efficient units in DEA by using TOPSIS method. *Applied Mathematical Sciences*, 5(17), 805-815 .

Malana, N. M., & Malano, H. M. (2006). Benchmarking productive efficiency of selected wheat areas in Pakistan and India using data envelopment analysis. *Irrigation and Drainage*, 55(4), 383-394. https://doi.org/10.1002/ird.264

Mehta, K., Sharma, R., & Vyas, V. (2019). Efficiency and ranking of sustainability index of India using DEA-TOPSIS. *Journal of Indian Business Research*, 11(2), 179-199. https://doi.org/10.1108/JIBR-02-2018-0057

Ministry of Agriculture-Jahad of Iran (2020). Statistics of crop production. Retrived from: https://maj.ir/page-amar/FA/65/form/pId28830

Naderi Mahdei, K., Fotros, M. H., & Esfahani, S. M. J. (2015). Investigation relationship between social capital and efficiency (case study: Saffron producers of Ferdows county). *Journal of Research and Rural Planning*, 4(2), 21-34. In persian. https://doi.org/10.22067/jrrp.v4i2.33954

Najafi, P., Fehresti- Sani, M., Nazari, M. R., & Neshat, A. (2020). Efficiency estimation and ranking of Iranian sugar beet producers. *Agricultural Economics and Development*, 28(111), 125-145. In persian. https://doi.org/10.30490/aead.2020.252671.0

Peykani, P., Rahmani, D., Gheidar-Kheljani, J., Jabbarzadeh, A., & Gavareshki, M. (2021). A novel ranking method based on Uncertain DEA Model. . 2nd International Conference on Challenges and New Solutions in Industrial Engineering and Management and Accounting, Damghan, Iran, 2021, Iranian Operations Research Society.

Podinovski, V., & Bouzdine-Chameeva, T. (2021). Optimal solutions of multiplier DEA models. *Journal of Productivity Analysis*, 56. 45-68. https://doi.org/10.1007/s11123-021-00610-3

Rakhshan, S. A. (2017). Efficiency ranking of decision making units in data envelopment analysis by using TOPSIS-DEA method. *Journal of the Operational Research Society*, 68(8), 906-918 .

Rejab, E. N., Haridan, N. A., Nizam, N. E. N. S., & Rodzi, Z. M. (2021). The TOPSIS of different ideal solution and distance formula of fuzzy soft set in Multi-Criteria Decision Making. *International Journal of Academic Research in Economics and Managment and Sciences*, 10(2), 87-91. https://doi.org/10.6007/IJAREMS/v10-i2/10063

Sargazi, A. R., Sabouhi, M., & Nader, H. (2014). Ranking of farm units using data envelopment analysis (DEA) approach and analytic hierarchy process (AHP): A case study of Sistan region. *Agricultural Economics and Development*, 22(1), 107-128. In persian.

Sexton, T. R., Silkman, R. H., & Hogan, A. J. (1986). Data envelopment analysis: Critique and extensions. *New Directions for Program Evaluation*, 1986(32), 73-105.

Shahnavazi, A. (2017a). Determining the efficiency of Iran's provinces in onion production: Application of data envelopment analysis. *Agricultural Economics Research*, 9(33), 145-164. In persian http://jae.miau.ac.ir/article_2185_2aaf47a086c3552586f01df1bde1be66.pdf

Shahnavazi, A. (2017b). Determining the efficiency rank of irrigated crops in Iranian agricultural sector. *Iranian Journal of Agricultural Economics and Development Research*, 48(2), 227-240. In persisn. https://doi.org/10.22059/ijaedr.2017.62742

Shahnavazi, A. (2020). Evaluation of efficiency and profitability of potato cultivation in Iran. *Agricultural Economics Research*, 12(47), 151-188. In persisn. http://jae.miau.ac.ir/article_4203.html

Singaravel, B., & Selvaraj, T. (2015). Optimization of machining parameters in turning operation using combined TOPSIS and AHP method. *Tehnicki Vjesnik*, 22(6), 1475-1480 .

Tavana, M., Toloo, M., Aghayi, N., & Arabmaldar, A. (2021). A robust cross-efficiency data envelopment analysis model with undesirable outputs. *Expert Systems with Applications*, 167, 114117. https://doi.org/https://doi.org/10.1016/j.eswa.2020.114117

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, 130(3), 498-509. https://doi.org/10.1016/S0377-2217(99)00407-5

Tran, T. H., Mao, Y., Nathanail, P., Siebers, P. O., & Robinson, D. (2019). Integrating slacks-based measure of efficiency and super-efficiency in data envelopment analysis. *Omega*, 85, 156-165. https://doi.org/10.1016/j.omega.2018.06.008

Ullah, A., Silalertruksa, T., Pongpat, P., & Gheewala, S. H. (2019). Efficiency analysis of sugarcane production systems in Thailand using data envelopment analysis. *Journal of Cleaner Production*, 238, 117877. https://doi.org/https://doi.org/10.1016/j.jclepro.2019.117877

UN. (2006). General assembly. sixtieth session Agenda item 52. Resolution adopted by the general assembly on 22 December 2005. Retrived from: https://undocs.org/en/A/RES/60/191

Varatharajulu, M., Duraiselvam, M., Kumar, M. B., Jayaprakash, G., & Baskar, N. (2021). Multi criteria decision making through TOPSIS and COPRAS on drilling parameters of magnesium AZ91. *Journal of Magnesium and Alloys*. In Press, Corrected Proof. https://doi.org/https://doi.org/10.1016/j.jma.2021.05.006.

Venkata Subbaiah, K., Chandra Shekhar, N., & Kandukuri, N. (2014). Integrated DEA/TOPSIS approach for the evaluation and ranking of engineering education institutions–a case study. *International Journal of Management Science and Engineering Management*, 9(4), 249-264.

Wang, Y. M., & Luo, Y. (2006). DEA efficiency assessment using ideal and anti- ideal decision making units. *Applied Mathematics and Computation*, 173(2), 902-915. https://doi.org/https://doi.org/10.1016/j.amc.2005.04.023

Wijesinha-Bettoni, R., & Mouillé, B. (2019). The contribution of potatoes to global food security, nutrition and healthy diets. *American Journal of Potato Research*, 96, 1-19. https://doi.org/10.1007/s12230-018-09697-1

Winter, J. C. F., Gosling, S. D., & Potter, J. (2016). Comparing the Pearson and Spearman correlation coefficients across distributions and sample sizes: A tutorial using simulations and empirical data. *Psychological Methods*, 21(3), 273-290. https://doi.org/10.1037/met0000079

Wood, R., Stadler, K., Simas, M., Bulavskaya, T., Giljum, S., Lutter, S., & Tukker, A. (2018). Growth in environmental footprints and environmental impacts embodied in trade: Resource efficiency indicators from EXIOBASE3. *Journal of Industrial Ecology*, 22(3), 553-564. https://doi.org/https://doi.org/10.1111/jiec.12735

Yoon, K. P., & Kim, W. K. (2017). The behavioral TOPSIS expert systems with applications, 89, 266-272. https://doi.org/https://doi.org/10.1016/j.eswa.2017.07.045

Zahedi- Seresht, M., Khosravi, S., Jablonsky, J., & Zykova, P. (2021). A data envelopment analysis model for performance evaluation and ranking of DMUs with alternative scenarios. *Computers & Industrial Engineering*, 152, 107002. https://www.sciencedirect.com/science/article/abs/pii/S0360835220306720

Zamani, P. (2017). Sensitivity in ranking for perturbations of data in DEA. *International Journal of Data Envelopment Analysis*, 5(1), 1183-1192.

Zheng, H., Si, D., Wang, W., & Wang, R. (2018). Quantitative entropy weight TOPSIS evaluation of sustainable Chinese wind power developments. *Mathematical Problems in Engineering*, 2018, 6965432- 6965439. https://doi.org/10.1155/2018/6965439.

Zheng, X. B., & Park, N. K. (2016). A Study on the efficiency of container terminals in Korea and China. *The Asian Journal of Shipping and Logistics*, 32(4), 213-220. https://doi.org/https://doi.org/10.1016/j.ajsl.2016.12.004

تحقیقات کشاورزی ایران (۱۴۰۱) ۴۱(۱) ۶۰-۴۹

# رتبه بندی واحدهای تولیدی بر مبنای تلفیق تحلیل فراگیر داده‌ها و تصمیم‌گیری چندمعیاره (مطالعه موردی: استان‌های تولید کننده سیب‌زمینی در ایران)

**سید محمد جعفر اصفهانی، الهام باریکانی**

مؤسسه پژوهش‌های برنامه‌ریزی، اقتصاد کشاورزی و توسعه روستایی. تهران، ج.ا. ایران

*نویسنده مسئول

اطلاعات مقاله

تاریخچه مقاله:
تاریخ دریافت: ۱۴۰۰/۱۰/۰۷
تاریخ پذیرش: ۱۴۰۱/۰۵/۱۱
تاریخ دسترسی: ۱۴۰۱/۰۸/۱۸

**واژه‌های کلیدی:**
تاپسیس
تحلیل فراگیر داده‌ها
سیب‌زمینی
کارایی

**چکیده** - ارتقا کارایی گام اول درحرکت به سمت کشاورزی پایدار است. در این مطالعه باهدف ارائه یک تصویر جامع از جایگاه استان‌های تولیدکننده محصول سیب‌زمینی، رتبه‌بندی استان‌ها با استفاده از مدل‌های کارایی متقاطع، ابر کارایی، فاصله نسبی با واحد ایده‌آل و آنتی ایده‌آل و فاصله تا ابر صفحه ایده‌آل انجام شد.سپس برای ارائه تصویری جامع تر از وضعیت آنها، نتایج به‌دست‌آمده برای سال ۱۳۹۷ با استفاده از تکنیک تاپسیس تلفیق شدند. در این پژوهش میزان عملکرد و سود ناخالص به‌عنوان شاخصی برای تولید و سودآوری در نظر گرفته شد. نتایج مطالعه نشان داد میانگین کارایی تولیدکنندگان با در نظر گرفتن عملکرد به‌عنوان ستاده بالاتر از زمانی است که سود به‌عنوان ستاده در نظر گرفته شود. بالاتر بودن کارایی عملکرد از کارایی سود نشان‌دهنده توجه بیشتر به افزایش تولید نسبت به سودآوری است. نتایج رتبه‌بندی استان‌های تولیدکننده نشان داد که مدل‌های مختلف رتبه-بندی نتایج یکسانی ارائه نمی‌کنند و لازم است به‌منظور ارزیابی دقیق‌تر این نتایج با یکدیگر تلفیق شوند. تلفیق این شاخص ها به روش تاپسیس نشان داد استان‌هایی مانند مازندران، کرمان و آذربایجان غربی که هم از نظر کارایی عملکرد و هم از نظر کارایی سود در موقعیت مطلوبی قرار داشتند میتواند الگوی‌های مناسبی برای سایر استانهای در زمینه تولید این محصول باشند. همچنین با توجه به رابطه منفی نهاده‌های بذر، کودپتاسه و سموم شیمیایی با رتبه استان‌های تولید کننده، مدیریت در استفاده از کودهای زیستی، همچنین کنترل بیولوژیکی و مدیریت تلفیقی آفات برای بهبود کارایی استانهای تولید کننده سیب‌زمینی توصیه می‌شود.