A Dynamic Network Data Envelopment Analysis Model to Calculate the Efficiency of Wheat Farms

Shahin Rajaei Qazlue[1], Ahmad Mehrabian[2*], Kaveh Khalili-Damghani[3], Mohammad Amirkhan[4]

Abstract– Wheat is a strategic crop; the prosperity of production improves any country's economy. In recent years, Iran has faced a significant decrease in wheat production, so it is important to conduct a study in this sector and provide a suitable solution to improve the concerns. A dynamic network model is presented to calculate efficiency for agricultural farmlands over 6 years. This model considers the every-other-year farming method, indirect input part of that is used in one year and the rest in the following years, and the complex relations of wheat production. Finally, to prove the applicability of the presented model, a case study of wheat fields in the northwest of Iran has been selected, and the desired model has been implemented. The results show Zanjanrod performs at the highest efficiency level, followed by Takestan.

Keywords: Performance assessment, Wheat farmlands, Dynamic network data envelopment analysis, Direct and indirect inputs, Every other year cultivation approach

1. Introduction

Data Envelopment Analysis (DEA) is a non-parametric method in operations and economics research that measures production and service organization's performance include factories, transportation, banks, hospitals, libraries, and many more. One of the industries that have been a significant area for the application of DEA models in recent years is the agricultural sector. Since agriculture is an essential part of the economy of any country, it is necessary to pay attention to this sector. DEA is one of the methods that can make significant improvements in this industry. Using this method, the efficiency of the farm and factors that determine the yield can be estimated, as well as the evaluation of operational, environmental, and energy aspects in production.

In recent years, several models have been proposed to study farm performance. However, most of proposed models are based on the classic DEA approach, regardless of their internal structure and relationships. The Classic DEA has led to the inconsistency of the proposed models with the real agriculture conditions. Furthermore, a minority of articles presenting a model with a network structure have ignored the time factor and the unit's performance despite the planning horizon.

In this paper, a dynamic network DEA (DN-DEA) model is presented in that each DMU consists of four stages that are connected sequentially. Each stage shows a two-year time frame, and each year is considered a sub-stage. In the first year, the first land (first sub-stage) is farmed (the second land rests), and in the second year, the second land (second sub-stage) is farmed (the first land

3 rests). Each sub-stage consists of three processes of plowing, planting, and harvesting connected in sequence and have their inputs and outputs. After three specified work processes, the final output is the produced wheat, which part of that is sold and part is stored for next year's planting. *Stored wheat*is an intermediate output that connects the sub-stages to create a long-term planning horizon. In the proposed model, two types of inputs have been defined; the first type is inputs fully consumed at a specific time and not transferred to the following years. The

1 Department of Industrial Engineering, Aliabad Katoul Branch, Islamic Azad University, Aliabad Katoul, Iran. Email: shahinrajaei96@gmail.com

2* Corresponding Author: Department of Industrial Engineering, Aliabad Katoul Branch, Islamic Azad University, Aliabad Katoul, Iran. Email: mehrabian.project@gmail.com

3 Department of Industrial Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran. Email:kaveh.khalili@gmail.com

4 Department of Industrial Engineering, Aliabad Katoul Branch, Islamic Azad University, Aliabad Katoul, Iran. Email: m.amirkhan.ie@gmail.com

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second type of inputs partially consumed in recent years, and a part of it is transferred to following years.

The DN-DEA model, designed to evaluate wheat production processes, seamlessly aligns with the agricultural framework. Its practicality is demonstrated through its application in a real-world case study involving agricultural farms in the northwestern region of Iran. The core objective of this study revolves around a comprehensive assessment of farm efficiency over a long-term planning horizon of six years.

The paper is structured as follows: Section 2 provides an extensive review of DEA application within the agricultural sector, exploring network models, dynamic models, and dynamic network models. Section 3 offers a thorough insight into the DN-DEA model, presenting its intricacies. Moving forward, in Section 4, we showcase the real-world application of the proposed DN-DEA model through a case study involving agricultural farms. Finally, Section 5 encompasses the conclusion, insights into future research possibilities, and suggested directions for further exploration.

2. Literature review

Data envelopment analysis is a technique rooted in mathematical linear programming, utilized to assess the efficiency of comparable decision-makingunits considering multiple inputs and outputs. Charnes et al. [1]pioneered the initial DEA model, referred to as the CCR model, which extended the concepts of production frontier and production possibility set to a non-parametric approach. DEA evaluates each decision-making unit (DMU) independently, identifying those that demonstrate optimal practices and efficiency. In DEA, the focus is on assessing DMUs, considering them efficient if no other DMU can generate higher outputs with the same or fewer inputs.

The conventional DEA models treat a decision-making unit (DMU) like a closed system, where inputs go in, and outputs come out, overlooking the internal workings. Consequently, pinpointing the specific sources of inefficiency within a DMU becomes challenging, denying managers valuable insights into their organization's internal processes, as noted by Hefland and Levine [2]. To solve mentioned issue, the network DEA models presented that can deal with internal structures or intermediate products, which causes to observe more details of the inefficiency of a DMU by Sueyoshi et al. [3]. However, the network DEA models lack the incorporation of time-related factors when assessing DMU performance. Addressing this, dynamic models were introduced, aiming to evaluate DMU performance over a more extended period, as proposed by Cui et al. [4].

2.1 Efficiency analysis in agriculture

The agricultural sector is the essential industry supporting the construction and development of a national economy. Therefore, the existence of a tool that can measure the growth and efficiency of this sector is vital. DEA is one of the powerful tools for measuring the agricultural sector's efficiency. In recent years much research has been conducted to calculate the efficiency of different farm regions.

Sueyoshi and team [5] introduced a novel application of Data Envelopment Analysis to compare the performance of Japan Agricultureco-operatives. Their model for performance assessment encompasses three key indices: comparative production index, comparative cost index, and comparative cost reduction ratio. In a different context, Frija et al. [6] proposed a DEA-based approach to evaluate the impact of rising water prices on agricultural farms in Tunisia. Their study emphasized the critical role of farmers' technical efficiency in influencing water demand elasticity, revealing that water pricing significantly affects less efficient farms. Furthermore, Toma et al. [7] utilized the DEA methodology to measure the efficiency of agricultural farms, categorizing them into three distinct types based on geographical features: plain, hill, and mountain areas. Results showed that only 14 out of 37 counties achieved a complete efficiency score. The other counties need to change their input combination to achieve higher efficiency by decreasing the working hours or increasing the output levels (production value) through better-fixed capital and higher yields. Angulo-meza et al. [8]introduced a multi-objective Data Envelopment Analysis model aimed at assessing the eco-efficiency of blueberry orchards. The study also identified alternative objectives for units that were found to be inefficient. In their proposed model, life cycle assessment and DEA approaches are joined to give a powerful tool for assessing the eco-efficiency of producers and determining best practices (benchmarks) and targets for the inefficient producers.

Li et al. [9]applied Data Envelopment Analysis to gauge the efficiency and energy conservation within China's agricultural sector. They used the energy theory and classified nine input types into chemical energy, heat energy, mechanical energy, and biological energy. Results showed: 1-energy demand and saving during 2015-2020 is more stable than before, 2-there is a relationship between the geographical region and efficiency of agricultural sectors, 3-overall technical efficiency of the agricultural sector in China is 0.792. Chen et al. [10]utilized a three-stage slack-based DEA model to evaluate the actual total factor productivity pertaining to agricultural green practices within the diverse provinces of China from 2000 to 2017. [11] adopts DEA method and Tobit model to computes the agricultural energy conservation and emission reduction efficiency, and threshold regression model to study the connection between internet advancement and the China's agricultural energy conservation and emission reduction efficiency. [12] Applied a comprehensive methodology employing slack-based measure, Meta frontier Analysis, and the Malmquist productivity index. This approach was utilized to evaluate agricultural water usage efficiency, agricultural production technology heterogeneity, and changes in total factor productivity in the context of pre- and post-implementation of agriculture water policies in 2012 across diverse regions in China.

2.2 Network DEA models

Specialized models known as network DEA have emerged to evaluate the efficiency of decision-making units considering their internal structures. These structures can vary from a straightforward two-stage process to intricate systems interconnecting multiple divisions using intermediate measures. Broadly speaking, network DEA models can be categorized into two main types: series and parallel systems, as outlined by Chen and colleagues [13].

Fare and Grosskopf [14] introduced a two-stage DEA approach tailored for assessing organizational performance and its components in the realm of health economics. This approach offers a comprehensive evaluation of institutes. In a distinct domain, Yang [15] developed a two-stage model that seamlessly integrates the production and investment performance of insurance companies. This integration allows for a holistic evaluation of overall performance, optimizing management strategies. Another application was observed in the railway industry, as highlighted by Yu and Lin [16]. Their innovative two-stage DEA model estimates technical efficiency for both passenger and freight services, providing valuable insights for this sector. Shifting focus to urban transit, Yu and Fan [17] presented a two-stage DEA model involving parallel sub-processes with shared inputs to evaluate the efficiency of bus transit systems. This model offers a robust assessment of transit operations. Furthermore, Yang et al. [18] innovated a two-stage DEA model to calculate technical efficiency within the steel sector. Additionally, they conducted a comparative analysis between traditional DEA and network DEA methods, illustrating the advantages of employing the network DEA approach.

Khalili-Damghani and Shahmir[19] developed a network DEA model to calculate the efficiency of agility in supply chains. The proposed model contains three serially connected sub-DMU associated with sourcing, making, and delivery in the supply chain. The proposed model was applied in a real case study involving 40 dairy supply chains. In examining the effectiveness of OPEC member countries in utilizing their oil wealth to enhance social prosperity, Keskin [20] proposed an innovative slacks-based Network DEA model. This model offers a method to gauge the efficiency levels of social prosperity within these nations, providing valuable insights into the impact of oil wealth management on societal well-being.[21] to evaluate the low carbon efficiency of multimodal transport, proposed a cross efficiency DEA method for complex network structures from the perspective of fairness, and takes China's rail-water intermodal transport as an example for research.[22]a DEA approach along with cross-efficiency assessments, the comprehensive total factor productivity for various industries across 30 provinces in China was computed. This evaluation encompassed both overall productivity and productivity within the dual stages of power generation and pollutant treatment. In addition, the study employed the Tobit regression method to identify influential factors that drive changes in total factor productivity.

2.3 Dynamic DEA models

Classic and network DEA models generally serve to calculate the efficiency of DMUs in a specific time and ignore considering the efficiency of DMUs over time. Dynamic DEA models are supposed to fill this gap; the primary purpose of these models is to consider the efficiency of DMUs in the long-term planning horizon. The main difference and specificity of the structure of dynamic models with previously proposed approaches is the inclusion of transition elements between subsequent observations of activities, which establish the interdependence between periods.

Tone and Tsutsui [23]presented a slacks-based model for calculating the efficiency of units. In their model, non-radial SBM is adopted to deal with inputs and outputs individually and carry-over activities categorized into four types; desirable, undesirable, discretionary, and non-discretionary (fixed) to cope with the demands of researchers and practitioners correctly.

Khalili-Damghani et al. [24] devised a dynamic DEA model to assess energy consumption efficiency in cotton production, applied in a case study on the Iranian cotton industry. In another context, Chen and Wang [25] examined the low-carbon city pilot scheme's direct and indirect effects, utilizing a range-directional DEA-based green efficiency model and calculating the global Malmquist-Luenberger Index for the cities involved. Furthermore, Wang and colleagues [26] developed and compared two DEA models to simulate joint and separate trading systems, offering insights into their economic and environmental effects. [27] In order to accurately foresee and assess shifts in safety management effectiveness within coal companies using big data technology, an integration of model-based DEA methodology and data-centric BP neural network approach was employed. This amalgamation resulted in a novel DEA-BP neural network hybrid model, specifically designed to evaluate and forecast safety management efficiency within coal enterprises. Empirical investigation was conducted using data spanning from 2015 to 2020, encompassing a sample of 20 coal firms to facilitate this research.[28] Introduces four metrics to evaluate node significance, considering both static and dynamic viewpoints. Employing data envelopment analysis (DEA) technology, it conducts a thorough evaluation of power grid node importance, followed by the identification of crucial nodes within the system. A practical case study is executed to validate the proposed approach.

2.4 Dynamic network DEA

Unlike the dynamic DEA which every period is considered a black box, in the dynamic network DEA, each time is formed of a network structure to view the details of every period. When network and dynamic dimensions are brought together, a more comprehensive analysis is enabled where divisional and between-period interactions are reflected in efficiency estimates.

Tone and Tsutsui [29]presented a slack-based model to evaluate the efficiency of U.S. electric utilities. They proposed a network SBM model and a dynamic SBM model separately, combined these two models, and developed a new model. The new model can calculate the efficiency score of the entire period, each period, and every sub-DMU. Kao et al. [30]presented three approaches (dynamic black box DEA, static network DEA and dynamic network DEA) by considering the internal process of the cloud service industry to evaluate its efficiency in a different situation. Designed models were formulated by using multi-objective programming techniques. An empirical study is conducted to demonstrate the proposed models' applicability. Tavana et al. [31]proposed dynamic DEA for calculating of oil refineries' efficiency. Within their framework, they consider factors like the quality of raw oil inputs and CO_2 emissions, leading to an enhanced evaluation outcome. In the proposed model, there is no connection between periods and DMUs do not interact. The efficiency of DMUs is calculated based on two features: The performance of DMUs in each timeframe and the comparative efficiency of the DMU being evaluated over various intervals are analyzed. Yu et al. [32]introduced a dynamic network model to calculate the high-tech firm's efficiency. In the presented approach, each DMU is composed of two stages: research and development stage and commercialization stage. In their proposed model, capital stock and patent stock are carry-over links and connect the multi-period innovation processes over time. They calculated the performance of the R&D process, the commercialization process, and the overall innovation process.

In their work, Gazori-Nishabori et al. [33] introduced a Nash Bargaining game approach designed to gauge the efficiency of DMUs operating within dynamic network structures. The model's practicality was demonstrated by assessing efficiency within Industrial Management Companies. Shifting focus, Luo and team [28] devised a stochastic non-parametric approach aimed at assessing green development efficiency. Their findings emphasized the notable enhancement of GDE brought about by the digital economy. [34] investigated urban metabolism's role in environmental degradation due to economic activities. They developed a model combining emerge analysis and dynamic network DEA for assessing industrial efficiency. Applying the model to 18 Chinese cities (2016-2020), they found inefficiencies in all cities, suggesting a need for sustainable improvements. The study provides a framework to address specific inefficiencies and enhance urban economic sustainability. [35] evaluated bus transit benefits using a novel approach, combining data analysis methods. They applied this to bus systems in 33 Chinese cities (2016-2019), finding inefficiencies in most cities. Service improvement was highlighted over production efficiency, with better results in small cities and regional variations. These findings offer valuable insights for managing and improving public transit services.

2.5 Research Gap

In this research, for the first time, the method of planting every other year, which is a conventional method of agriculture, has been implemented in the presented model. On the other hand, the indirect input, which shows the impact of input not only in the used year but also in the following years, is also proposed in the developed model. The existence of such input by considering the dynamic and network model marks a pioneering feature within the proposed model. On the other hand, in this model, complex relations between periods in the wheat production process are considered, which does not exist in any of the previous studies.

3. Proposed dynamic network DEA

Proposed dynamic network model which is depicted in Fig 1 shows the real process of wheat production in agricultural farms in the northwest region of Iran over a period of 6 years.

For each DMU, there exists a distinct structure comprising four interconnected stages denoted as *Dt (Dt = 1,2,…, DT)*. Each stage spans a two-year period, amounting to four identical stages performing similar processes. Within a stage, two sub-stages (t = 1,2) are connected in sequence. The initial sub-stage characterizes the production process in the first farm, while the subsequent one delineates the production process in the second farm. Within each sub-stage, a series of three processes—plowing, planting, and harvesting—are executed in a sequential manner. The plowing phase transforms I inputs x_{itDtj} *(i=1,2,..,I)* into P intermediate measures z_{ptDtj}*(p=1,2,..,P)*, These intermediates are then transferred from the plowing phase to the planting phase. In the planting phase, P intermediate measures z_{ptDtj}*(p=1,2,..,P)*, F additional first-type inputs w_{ftDtj} *(f=1,2,..,F)*, and an extra second-type input w'_{tDtj} are utilized to generate A intermediate measures z'_{atDtj} *(a=1,2,..,A)*. These intermediate measures are then conveyed to the harvesting phase. Notably, during the planting phase, a fraction % *(1-ß)*of the extra second-type input is forwarded to the subsequent stage. In the harvesting phase, A intermediate measures z'_{atDtj}*(a=1,2,..,A)* and Ḟ additional inputs $w''_{f'tDtj}$ (f' =1,2,…,*Ḟ*) are employed to produce R outputs y_{rtDtj}*(r=1,2,..,R)*. Interestingly, a portion of output R is channeled back to the subsequent planting phase, augmenting it as an extra input. For a comprehensive overview of sets, parameters, and decision variables used in this model, Table 1 is provided.

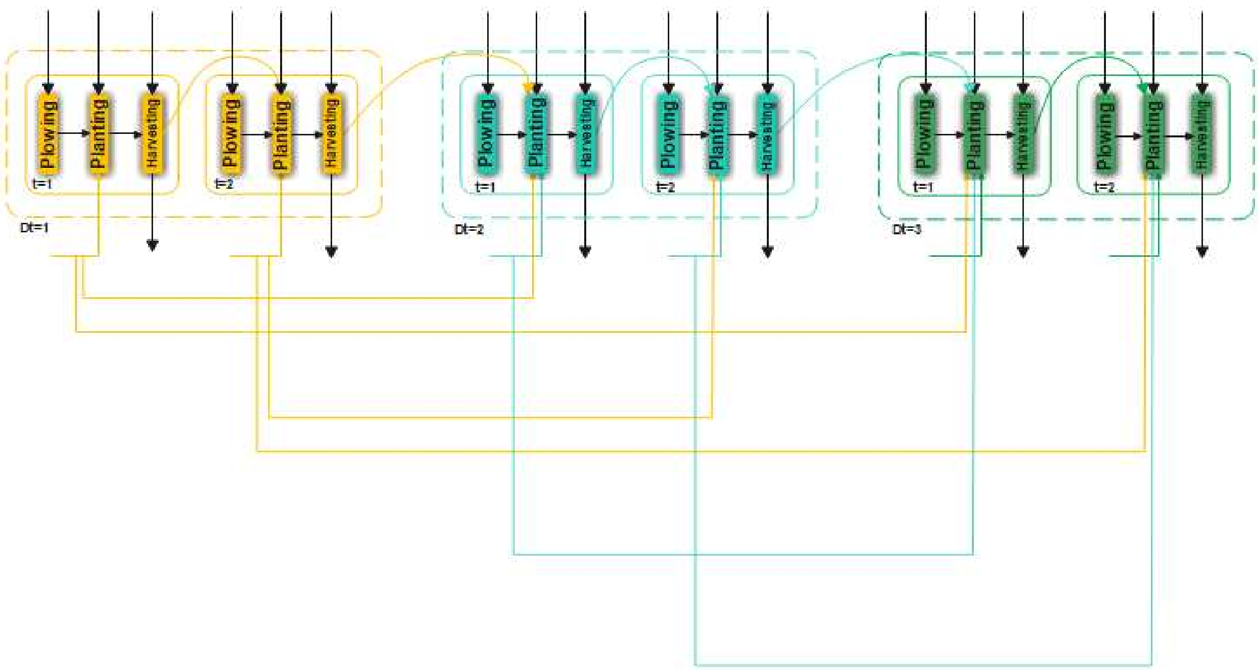

Fig. 1: *Dynamic Network Mode*

Table 1:*parameters, and variables*

j	DMU $j=1,2,\dots,n$
Dt	2 year planning
t	1 year planning
i	Plowing instance
p	Planting instance
f	Extra planting input instance
a	Planting output in; harvesting input instance
f'	Harvesting extra input
r	Harvesting output instance
x_{itDtj}	i^{th} plowing input of DMU j in the t^{th} sub-stage fromDt^{th} stage
z_{ptDtj}	p^{th} plowing output of DMU j in the t^{th} sub-stage fromDt^{th} stage
w_{ftDtj}	f^{th} planting additional direct input of DMU j in the t^{th} sub-stage fromDt^{th} stage
w'_{tDtj}	planting extra indirect input of DMU j in the t^{th} sub-stage fromDt^{th} stage
z'_{atDtj}	a^{th} planting output of DMU j in the t^{th} sub-stage fromDt^{th} stage;
$w''_{f'tDtj}$	f'^{th} harvesting extra input of DMU j in the t^{th} sub-stage fromDt^{th} stage
y_{rtDtj}	r^{th} harvesting output of DMU j in the t^{th} sub-stage fromDt^{th} stage
z	*DMU j*efficiency amount
v_{itDt}	Weight of i^{th} plowing input in t^{th} sub-stage fromDt^{th} stage
s_{ftDt}	Weight of f^{th} planting extra direct input in t^{th} sub-stage fromDt^{th} stage
s'_{tDt}	Weight of planting extra indirect input in t^{th} sub-stage fromDt^{th} stage
$s''_{f'tDt}$	Weight of f'^{th} harvesting additional input in t^{th} sub-stage fromDt^{th} stage
u_{rtDt}	Weight of r^{th} harvesting output in t^{th} sub-stage fromDt^{th} stage
(1-ß)	Fraction of extra second-type planting input forwarded to the next stage.

3.1. Efficiency rate of DMU

The aggregate outputs for the DMU comprise the outputs from last stage, and the complete inputs for the DMU are constituted by the inputs for the initial stage.As indicated earlier, within the planting process, we distinguish two types of inputs. One type is utilized partially during the current planning period, with a certain percentage carried forward to the subsequent stage. In our model, the fertilizer input utilized during planting exemplifies this second type of input. Following its use in the planting phase, a portion of the fertilizer remains in the soil. This residual amount continues to be effective in the wheat production process, particularly when the farm undergoes re-cultivation.

The evaluation of efficiency for the dynamic network structure in Fig 1 is carried out using the measurement model outlined by equations (1) through (8).

Equation (1) in the objective function evaluates the efficiency of the DMU over a six-year period, as illustrated in Figure 1. Specifically, it considers the outputs from the final stage as the DMU's outputs and regards the inputs from the initial stage as the comprehensive inputs for the DMU. Equation in (2) ensure that the efficiency scores for each stage of the DMUs are maintained at or below one. Equation (2) involves the term $\left[\sum_{s=1}^{Dt}(1-\beta)^{s-1} w'_{t(Dt-s+1)j}\right]$ denoting inputs accumulating over years at a predetermined transfer rate of*(1-β)*. Ensuring efficiency scores below or equal to one for all DMUs. Equation set (3) is designed to uphold efficiency scores at or below one for all DMUs, while Equation (4)-(8) outline specific restrictions on the decision variables.

Equation from 1 to 8 is a fractional model, its optimized answer is difficult to find; so, the equation (1)-(8) converts to the subsequent linear programming model (9)-(17).

Solving Model (9)-(17) results in the DMUs' efficiency.

$$Max\ z = \frac{\sum_{r=1}^{R}\sum_{t=1}^{T} u_{rtDT}\, y_{rtDTo}}{\sum_{i=1}^{I}\sum_{t=1}^{T} v_{it1} x_{it1o} + \sum_{f=1}^{F}\sum_{t=1}^{T} s_{ft1} w_{ft1o} + \sum_{t=1}^{T} s'_{t1} w'_{t1o} + \sum_{f'=1}^{F'}\sum_{t=1}^{T} s''_{f't1} w''_{f't1o}} \tag{1}$$

s.t.

$$\frac{\sum_{r=1}^{R}\sum_{t=1}^{T} u_{rDt}\, y_{rDtj}}{\sum_{i=1}^{I}\sum_{t=1}^{T} v_{itDt} x_{itDtj} + \sum_{f=1}^{F}\sum_{t=1}^{T} s_{ftDt} w_{ftDtj} + \sum_{t=1}^{T} s'_{tDt}\left[\sum_{s=1}^{Dt}(1-\beta)^{s-1} w'_{t(Dt-s+1)j}\right] + \sum_{f'=1}^{F'}\sum_{t=1}^{T} s''_{f'tDt} w''_{f'tDtj}} \le 1, \forall Dt, \forall j \tag{2}$$

$$\frac{\sum_{r=1}^{R}\sum_{t=1}^{T} u_{rtDT}\, y_{rtDTj}}{\sum_{i=1}^{I}\sum_{t=1}^{T} v_{it1} x_{it1j} + \sum_{f=1}^{F}\sum_{t=1}^{T} s_{ft1} w_{ft1j} + \sum_{t=1}^{T} s'_{t1} w'_{t1j} + \sum_{f'=1}^{F'}\sum_{t=1}^{T} s''_{f't1} w''_{f't1j}} \le 1, \forall j \tag{3}$$

$$u_{rtDt} \ge 0, \forall \mathrm{r}, \forall \mathrm{t}, \forall Dt \tag{4}$$

$$v_{itDt} \ge 0, \forall i, \forall \mathrm{t}, \forall Dt \tag{5}$$

$$s_{ftDt} \ge 0, \forall f, \forall \mathrm{t}, \forall Dt \tag{6}$$

$$s'_{tDt} \ge 0, \forall \mathrm{t}, \forall Dt \tag{7}$$

$$s''_{f'tDt} \ge 0, \forall f', \forall \mathrm{t}, \forall Dt \tag{8}$$

$$Max\ z = \sum_{r=1}^{R}\sum_{t=1}^{2} u_{rtDT}\, y_{rtDTo} \tag{9}$$

s.t.

$$\sum_{i=1}^{I}\sum_{t=1}^{T} v_{it1} x_{it1o} + \sum_{f=1}^{F}\sum_{t=1}^{T} s_{ft1} w_{ft1o} + \sum_{t=1}^{T} s'_{t1} w'_{t1o} + \sum_{f'=1}^{F'}\sum_{t=1}^{T} s''_{f't1} w''_{f't1o} = 1 \tag{10}$$

$$\sum_{r=1}^{R}\sum_{t=1}^{T}u_{rDt}\,y_{rDtj}-\sum_{i=1}^{I}\sum_{t=1}^{T}v_{itDt}\,x_{itDtj}-\sum_{f=1}^{F}\sum_{t=1}^{T}s_{ftDt}w_{ftDtj}-\sum_{t=1}^{T}s'_{tDt}\left[\sum_{s=1}^{Dt}(1-\beta)^{s-1}w'_{t(Dt-s+1)j}\right]$$
$$-\sum_{f'=1}^{F'}\sum_{t=1}^{T}s''_{f'tDt}w''_{f'tDtj}\leq 0,\forall Dt,\forall j \tag{11}$$

$$\sum_{r=1}^{R}\sum_{t=1}^{T}u_{rDT}\,y_{rDTj}-\sum_{i=1}^{I}\sum_{t=1}^{T}v_{it1}x_{it1j}-\sum_{f=1}^{F}\sum_{t=1}^{T}s_{ft1}w_{ft1j}-\sum_{t=1}^{T}s'_{t1}w'_{t1j}-\sum_{f'=1}^{F'}\sum_{t=1}^{T}s''_{f't1}w''_{f't1j}\leq 0,\forall j \tag{12}$$

$$u_{rtDt}\geq 0,\forall \mathrm{r},\forall \mathrm{t},\forall Dt \tag{13}$$

$$v_{itDt}\geq 0,\forall i,\forall \mathrm{t},\forall Dt \tag{14}$$

$$s_{ftDt}\geq 0,\forall f,\forall \mathrm{t},\forall Dt \tag{15}$$

$$s'_{tDt}\geq 0,\forall \mathrm{t},\forall Dt \tag{16}$$

$$s''_{f'tDt}\geq 0,\forall f',\forall \mathrm{t},\forall Dt \tag{17}$$

4. Case study and results

In the northwestern areas of Iran, farmers follow a unique agricultural approach, where they rotate their land usage each year. For instance, if a farmer owns ten hectares land, they may plant five hectares in one year and another five hectares in the next year. This practice is guided by the specific soil characteristics of this region, which require a period of rest to restore soil vigor for subsequent planting. Given the strategic importance of this region as a major wheat producer in Iran, assessing farm performance can be instrumental in optimizing their operations.

This section illustrates the proposed model's application for calculating the total efficiency of eleven farms for six-year period. The areas involving Takestan and Abiek in Ghazvin district. Zanjanrod, Abhar and Khoramdare in Zanjan district. Hashtrod and qazlue in East Azerbaijan district.Parsabad and Meshkenshahr in Ardebil district. Khoy and Bokan in Urmiya district.

The wheat production process comprises three fundamental phases: plowing phase, planting phase, and harvesting phase. In the plowing phase, the inputs involve the land prepared for plowing and the workforce engaged in plowing operations. The outcome of this phase is land suitable for planting. However, it's important to acknowledge that not all plowed part is viable for cultivation due to natural factors like heavy rains leading to floods or damage by local wildlife such as boars. Consequently, the usable land output at this stage is less than the initially plowed area. Moreover, as previously mentioned, the planting involves two types of inputs. The first type involves inputs consumed within a single period and not carried over to next periods. These include stored wheat from the prior year for this year, water for irrigating the wheat, and the plan table land obtained from the plowing phase. The second type comprises inputs used within one period, with a certain percentage transferred to the subsequent period. Specifically, this pertains to the fertilizer utilized during planting. This fertilizer remains in the soil, proving effective upon farm re-cultivation in the wheat production process. The extent of this transfer is dictated by a coefficient denoted by ß, which, in our case, is set at 0.9 for a year. This implies that 0.9 of this input is utilized in the current year, and 0.1 is carried forward to the following year. The result of the planting process is the land area with fully grown wheat ready for harvest, which may be less due to natural factors like hail and boar disturbances, resulting in a reduced harvestable land compared to the initially planted area. The harvesting process involves utilizing labor as input to gather mature wheat. The outcome of this process is the harvested wheat, which is then divided. Some of it is stored for the next year's planting, while the rest is sent to silos for sale. The following year, the cycle is repeated, but with a rotation of cultivated and resting land. These elements are summarized in Table 2, outlining the inputs, outputs, and intermediates for the case study.

Data pertaining to inputs, intermediaries, and outputs for the model can be found in Table 3, presenting summary statistics for ease of reference, omitting specific details for conciseness.

Table 2: *Inputs, Intermediates and, Outputs*

Criteria	Name	Explanation
Input	Workforce (plowing phase)	Total workforce hours spent on plowing phase within a year
	Land for plowing	The extent of land utilized during the plowing phasewithin a year
	Water	Quantity of water utilized during the planting phase within a year
	Fertilizer	Volume of fertilizer applied during the planting phase within a year
	Workforce (harvesting phase)	Total workforce hours allocated for the harvesting phase within a year
output	Harvested wheat (sold)	Quantity of wheat obtained from the harvesting phase within a year
Intermediate	Plant-able land	Extent of land prepared for the planting phase
	Stored wheat	Reserved harvested wheat for the next year's use
	Harvestable land	Land with mature wheat prepared for the harvest

Table 2:Data Regarding Inputs*

	Input																			
	Workforce (plowing phase)				Land for plowing				Water ($\times 10^3$)				Workforce (harvesting phase)				Fertilizer			
Area	SD	Ave.	Max	Min	SD	Ave.	Max	Min	SD	Ave.	Max	Min	SD	Ave	Max	Min	SD	Ave.	Max	Min
Zanjanrod	1.3	6.3	8.1	5.2	0	5	5	5	0	22	22	22	1.9	8.7	9.1	7.6	31.4	255	290	200
Abhar	11.1	8.2	9.1	6.8	0	4	4	4	5.4	19	37	17	2.8	9	11.4	7.6	25.1	385	390	380
Khoramdare	0	8.4	8.5	8.1	0	5	5	5	0	18	18	18	3.5	9.4	10.3	9.1	47.5	555	595	505
Hashtrod	1.1	10.9	11.1	10.7	0	7	7	7	0	28	28	28	3.1	14.2	15.9	12.5	69.5	640	695	610
qazlue	1.4	16.1	17.4	15	0	10	10	10	2.1	41	42	37	1.1	21.4	21.8	20.9	68.1	855	890	830
Parsabad	1.3	8.4	9	7.5	0	5	5	5	0.6	19.3	21	19	5.2	11.8	16.1	10.6	42.6	435	440	430
Meshkenshahr	0.6	9.1	9.7	8.9	0	6	6	6	0	22	22	22	3.3	12	11.8	8.7	54.3	680	690	670
Khoy	1.4	5.9	6	5.6	0	4	4	4	0	23	23	23	4.1	8.1	8.2	8	22.5	288	290	280
Bokan	1.9	11.7	12.2	10.1	0	8	8	8	1.6	31	33	30	3.1	16.7	18.6	15.7	71.3	895	950	850
Takestan	1.5	8	8.1	7.7	0	5	5	5	1.1	20.6	21	18	1.9	10	10	10	30.7	380	400	360
Abiek	1.3	8.3	9.2	6.1	0	5	5	5	1.6	19.3	20	19	4.6	14.2	10.9	7.7	14.3	500	500	500

Table 3: *Data Regarding Intermediates*

	Intermediate											
	Plantable land				Stored wheat				Harvestable land			
Areas	SD	Ave	Max	Min	SD	Ave.	Max	Min	SD	Ave	Max	Min
Zanjanrod	0.3	4.7	4.9	4.1	0.4	2.5	4.9	1.7	0.2	4.7	4.8	4.1
Abhar	0.5	3.9	4	3.70	0.3	1.9	2.6	1.5	0.1	3.9	4	3.7
Khoramdare	0.2	4.8	5	4.3	0.1	1.5	1.6	1.5	0.2	4.7	4.9	4.1
Hashtrod	0.1	6.9	7	6.8	0.4	2.6	2.9	2.3	0	6.9	6.9	6.9
qazlue	0.3	9.9	10	9.8	0.1	3.3	3.4	3.2	0.3	9.9	10	9.9
Parsabad	0.3	4.9	5	4.9	0	1.7	1.7	1.7	0.2	4.9	5	4.9
Meshkenshahr	0	6	6	6	0.4	2.2	2.6	1.8	0	6	6	6
Khoy	0.3	3.9	4	3.7	0.3	1.2	1.2	1.1	0.2	3.8	4	3.8
Bokan	0.2	7.9	8	7.8	0.5	2.3	2.4	2.2	0.1	7.9	8	7.8
Takestan	0	5	5	5	0	1	1	1	0	5	5	5
Abiek	0	5	5	5	0	2	2	2	0	5	5	5

	Output			
	Harvested wheat(sold)			
Areas	SD	Ave.	Max	Min
Zanjanrod	15.3	61	75	42
Abhar	13.8	20.2	22.9	18.6
Khoramdare	19.1	41.3	43.4	37.7
Hashtrod	8.5	48.7	50.6	44.3
qazlue	17.9	46	49	44
Parsabad	12.6	38	43	34
Meshkenshahr	14.3	32	33	27
Khoy	11.6	20	27	18
Bokan	10.9	48.5	52.5	44.5
Takestan	16.6	35	48	20.5
Abiek	13.3	40	42	39

4.1 Result

Efficiency for 11 studied regions were computed and ranked over a span of six years, determining their relative efficiency within the specified timeframe. These results are illustrated in Table 4.

In the proposed model, it is possible to evaluate the efficiency score of each DMU over a one-year period. However, considering that half of the farm will be cultivated in one year and the other half in the next year, it was decided to evaluate the efficiency score in two-year intervals. Considering the efficiency of each DMU over time can allow managers to evaluate their organization by impacting of time. Time is an important factor which most of the time is ignored. Dynamic process gives managers an alignment to analyze their organization productivity over time in order to identify the weakness and strength points in different years to improve the efficiency process.

By observing Tables 4, we can notice that the efficiency score is not necessarily the same in neighboring regions. For example, the two regions of Zanjanrood and Abhar, which are both are located in the same province and the distance between these two regions is very small, it is expected that they will have close efficiency scores. However, according to table 4, Zanjanrod region is ranked first and Abhar region is ranked tenth. There are many similarities in the case study. This shows that the environmental conditions do not have a significant effect on the efficiency of the regions. Field studies show that factors such as the method of cultivation, raw materials (type of used wheat and fertilizer) and irrigation times are the most influential factors in increasing the efficiency of farms.

Table4. Area's efficiency score

Region	*Efficiency*	*Ranking*
Zanianrod	1	1
Takestan	0.84	2
Bokan	0.69	3
Hashtrod	0.64	4
Parsabad	0.6	5
Abiek	0.59	6
Khoramdare	0.58	7
quzlue	0.5	8
Meshkinshahr	0.48	9
Abhar	0.39	10
Khoy	0.29	11

4.2 Discussion of results

A fundamental aspect of the presented model is its capacity to assess DMUs' efficiency using every other year cultivation approach, commonly practiced in Iran, thus allowing for an evaluation of efficiency trends over time. Note that long-term farm performance review can be very effective for strategic decision makers. Examining the production process of farms in the long term by considering the relationship between several years makes the farmers identify how their farming method was compared to other farms. By using the obtained results, farmers can find out the efficiency or inefficiency of their cultivation method in the long term and, if necessary, to improve the yield, model the cultivation methods of areas with higher efficiency or if it is not possible to model completely, make the necessary corrections in some vital factors such as the amount and method of irrigation, fertilization time, seed type and other cases.

Examining a DMU dynamically allows the relationship between years to be considered, making it possible to consider the efficiency of the desired DMU in a macro way and consider several years. In examining the efficiency of DMU on a one-year basis, it is impossible to draw a correct conclusion about its efficiency. Because the DMU may have high efficiency in the year under review, but the efficiency level is low in the previous years. Therefore, the result is unreliable and cannot be a suitable criterion for strategic decisions. However, checking performance dynamically by considering multiple years causes all years to be calculated; Therefore, when the efficiency of a DMU is high, this result is reliable and can be used for macro-decisions and modeling for other farms.

5. Managerial Application

By using the obtained efficiency scores, it is possible to achieve points that will guide managers to improve the production process at the macro level. The existence of ranking tools makes managers obtain the factors that increase production in farms by examining high-ranked farms and using them to use low-ranked farms and improve their production process. On the other hand, examining low-ranked farms also causes managers to identify weak points and turn them into strong points. In this section, according to the obtained efficiency score, the studies conducted on these scores, and the cultivation method, we found some points that can help managers improve the production process.

Zanjanrod region stands out among the examined regions, showcasing the highest efficiency score of 1.considering that the study was conducted for the past 6 years and is reliable, it can be modeled on the cultivation method and used in other regions that have a low-efficiency score. Some methods can be used even if the necessary resources are unavailable for similar implementation for other farms. Field surveys of high-efficiency areas, especially in Zanjanrod and Takestan regions, show that several important factors have a significant impact on increasing the productivity of farms.

- **Time**

One of these factors is the time of wheat cultivation. Surveys show that the closer the planting time is to the start of autumn, the greater the amount of harvested wheat. The three regions of Zanjanrod, Takestan, and Bokan, which rank first, second, and third in terms of efficiency, have done their cultivation at the start of October. On the other hand, regions such as Khoramdare, Meshkenshahr, and Khoy, ranked seventh, ninth, and eleventh respectively, have cultivated in the middle of December. This factor clearly shows that the cultivation time significantly affects efficiency, and the closer it is to the early of autumn, the better the results will be.

- **Wheat Type**

The next factor that significantly increases farm efficiency is the type of wheat used, which is highly sensitive due to the cold weather conditions in the studied regions. The important point is that the farmers of the investigated regions do not show sensitivity in choosing the type of wheat, and they believe that the type of wheat used does not have much effect on increasing the productivity of their fields, but the surveys show the opposite opinion. Field investigations show that wheat used in Zanjanrod and Takestan regions is Sardari type. This type of wheat is the most suitable wheat available in Iran for cold regions, and it is better to use this type of wheat for cultivation in other regions. Currently, the regions use different types of wheat, such as Azar, Kalanpa, and Yaldan. Studies show that none of these varieties have the quality of Sardari wheat for cold regions. Therefore, it is suggested that these regions' farmers use this wheat type to cultivate their fields to increase productivity.

Field studies show that the two investigated points have the greatest effect on the efficiency and productivity of lands, but there are other factors, such as the amount and frequency of irrigation, and the amount and type of fertilizer used, which are effective in this matter. However, their effectiveness is not as important as the previous two factors.

6. Conclusion remarks and future research directions

Wheat is a strategic product, and increasing its production per capita will lead to economic prosperity. Iran is one of the countries that has seen a significant decline in wheat production in recent years compared to previous years. Considering that the northwestern regions of this country are responsible for more than 35% of the annual production, studying how to cultivate these regions and identifying the weak points, and improving them significantly impact increasing production per capita. In this study, a model (DN-DEA) is presented by considering the planting conditions every other year and indirect inputs to evaluate the efficiency of agricultural fields and identify their strengths and weaknesses.

The most important features of the presented model are as follows: 1- Every other year cultivation method was considered. 2- Fertilizer that affects the soil indirectly in the following years has been determined as an indirect input. 3- Time, an important factor in strategic decisions, is considered in the studied model. 4- The model incorporates a network framework encompassing plowing, planting, and harvesting phases, illustrating the wheat production procedure.

Here are the study's limitations: 1) The current model considers only one practical input for subsequent periods. Future research could explore the inclusion of multiple inputs. 2) Future studies could focus on devising strategies to enhance the efficiency of inefficient DMUs and further increase their overall efficiency

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