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MONITORING THE PERFORMANCE OF AGRICULTURAL AND FOOD SECTOR COMPANIES USING DEA

Mohammed Balubaid[1], Waqar Ahmad Gulzar[1], Hani Aburas[1], Osman Taylan[1], Abdulaziz S. Alkabaa[1], Omer A. Bafail[1], Anas A. Makki[2], Ammar Y. Alqahtani[1], Hassan M. Alidrisi[1], Basil Omar Al-Sasi[1], Shoukath Ali Karuvatt[3], Hisham Alidrisi[1*]

[1]Department of Industrial Engineering, Faculty of Engineering, King Abdulaziz University, P.O. Box 80204, Jeddah, 21589 SAUDI ARABIA;*
[2]Department of Industrial Engineering, Faculty of Engineering-Rabigh Branch, King Abdulaziz University, Jeddah 21589, Saudi Arabia;
[3]Sullamussalam Science College, Areacode Ugrapuram Post Malappuram - 673639 Kerala, India;

[*]Corresponding Author Hisham Alidrisi, e-mail: hmalidrisi@kau.edu.sa;

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ABSTRACT

Since the 1970s, Saudi Arabia's Agricultural and Food (A&F) production has grown at an astronomical rate. The Saudi Stock Market (Tadawul) now has several top-ranking agricultural and food processing firms listed, making the country's A&F industry the fourth largest contributor to the local economy. As a result, the A&F sector plays a critical role in maintaining Saudi Arabia's worldwide stock market strength. Any dynamic economy requires long-term sustainability in the A&F industry. To achieve long-term viability, regular evaluations of performance efficiency and comparison are necessary. The study aimed to examine enterprises' financial and operational performance in Saudi Arabia's agriculture and food sectors. Data Envelopment Analysis (DEA) is used in this study to evaluate technological efficacy. A non-parametric analytic approach, the DEA method from one firm, is used to gauge efficiency compared to a productivity unit with the same purpose. According to the findings, the relative efficiency of the examined seven prominent A&F firms significantly varied during the research. According to efficiency-based rankings, financial data may help make more objective decisions. Results of the study indicated potential cost reductions in general administration by 22.63%, owners' equity by 15.15%, and capital expenditures by 10.15%. Implications of this study include providing a reflective understanding of the relative performance of the Saudi A&F companies, which can assist in developing better targeted continuous performance improvement plans and more effective strategies.

Keywords: Data Envelopment Analysis (DEA), Agricultural and Food Sector, Performance Evaluation; Saudi Stock Market.

INTRODUCTION

After almost five decades of establishing the Saudi Arabian Stock Exchange called Tadawul, more than 164 companies are listed under its fifteen market sectors. The contribution of Saudi companies to maintaining the established status of the Saudi share market and moving up the raking is of utmost importance to the country, given its achievements towards industrialization and globalization. Year-to-date (YTD) indices of all the major Tadawul market sectors indicate that the Agriculture and Food (A&F) sector is the eighth major contributor to the Tadawul All Share Index (TASI) of the Saudi stock market (SSM). The average volume traded in the sector during 2013 was 6,505,629, and the market index was 11,192.44, with a 4.31% share out of fifteen major industrial and business sectors (www.gulfbase.com). Furthermore, with the support of the German Agency for International Cooperation (GIZ), the Saudi Government has set plans to beef up organic agricultural production to lead the country to self-sufficiency (Hartmann M. et al., 2012).

Modern farming technology, irrigation networks, warehousing, export facilities, advanced agricultural research, and training institutions steered Saudi Arabia (S.A.) to extraordinary growth in the production of essential foods, resulting in a substantial reduction in food imports. As a result, the country now exports wheat, dates, dairy products, eggs, fish, poultry, vegetables, and flowers to global markets (www.saudiembassy.net). Thus, Saudi Arabia has some of the world's largest and most modern dairy farms. These companies play a vital role in upholding the global rating of the strength of SSM.

Even though the significant domestic companies involved in the organic agriculture sector began operations in 2000, planned organic agriculture did start in Saudi in 2005. Until then, most organic products required were imported from the United States or the European Union.

In 2005, the Saudi Ministry of Agriculture tasked Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ International Services) with assisting the development of organic agriculture in Saudi Arabia, bringing extensive international expertise to the field. GIZ has established a Saudi Organic Farming Association (SOFA) and a Department of Organic Agriculture (DOA) in collaboration with the Ministry of Agriculture (www.giz.de/en/worldwide/). Over the last decade, the Organic Farming Project has established governmental structures and services to improve organic production and promote the growth of this sector. Saudi Arabia introduced its Organic Regulations and Standards to meet high-quality standards in 2010. Consequently, the GIZ Organic Farming Project (OFP) initiated the conversion of ten large farms to organic farming, which became the first organic "pilot farms" on the market (Hartmann M. et al., 2012). According to reports published by the Central Department of Statistics and Information (http://www.cdsi.gov.sa/english/) and the Saudi Ministry of Agriculture (http://moa.gov.sa/organice/), the Kingdom of Saudi Arabia has made significant progress in increasing the arable land for various crops. Table 1 displays the most important economic and agricultural indicators.

Table 1. Main Economic & Agricultural Indicators for Saudi Arabia

Total Area	2,150,000 km2
Population	27,000,000
GDP per Capita	$ 20,000
Total Cultivated Area	835,000 ha
Area of Cereal Crops	329,000 ha
Area of Fodder Crops	160,000 ha
Area of Vegetables – incl. Greenhouses	107,000 ha 9,000 ha
Area of Fruits – incl. Dates	239,000 ha 162,000 ha
Number of Farms	251,000
Labor Force	8,148,000
Employment in Agriculture	4.1%

In Saudi Arabia, fruits and vegetables are essential organic crops. In addition to being grown in the open field, organic vegetables are produced under controlled conditions (for example, in greenhouses and poly-tunnels). Fallow land is either included in agricultural rotations or turned into producing areas for future cultivation. Date palms, vegetables, and fruits combined encompass 6671, 1702, and 2032 hectares of land, respectively. OFP (based on DOA data, www.giz.de/en/worldwide). Their products are sold around the country. In comparison, The fallow land occupies about 5477 hectares.
With the phenomenal growth of Saudi companies in the A&F sector and their contribution to the national economy, monitoring their performance is essential. This was the motivation behind conducting the herein study. Moreover, there is a perceived lack of studies on the quantitative analysis of the operational performance of Saudi A&F sector companies. In response to this gap, this study aimed to examine enterprises' financial and operational performance in Saudi Arabia's agriculture and food sectors. There are sixteen major A&F companies listed in the SSM, out of which seven high-performing companies will be the focus of the herein analysis. The study's objective will be achieved by identifying key performance measures, gathering input and output (I/O) data, analyzing the collected data for comparisons, and finding the relative performance of the A&F companies under study. A non-parametric approach was followed using the Data Envelopment Analysis (DEA) as the performance evaluation method of the A&F companies. Implications of this study include providing a reflective understanding of the relative performance of the Saudi A&F companies. This, in turn, can assist in developing better targeted continuous performance improvement plans and more effective strategies.

MATERIALS AND METHODS

The food and agriculture (A&F) sector plays a vital role in the economic growth of any country globally. A country's economy is highly dependent on the A&F sector especially given that food expenditures typically depend on a nation's ability to produce its own food. Without this, the economic costs of importation would adversely affect its economic growth. The food and Agriculture sector remains an important sector that has contributed immensely to the growth of many nations globally. Few nations have attained high-income status through agriculture following the intense economic transformation that accelerated their overall growth. The United States is one of the nations that greatly benefited from A&F sectors considering the complex production, processing, and delivery of high volumes of food products. However, the US A&F sector does not only end with the farm business. Instead, it also includes a range of several farm-related industries and companies, including food manufacturing, that contributed largely to the country's GDP, for instance, in 2020. The food industries contributed $1.0.55 trillion to the GDP, while the farms contributed $134,7 billion. In fact, the sector's overall contribution to the country's economic growth is estimated to exceed 6% because many sectors related to A&F rely on several inputs for their value (USDA, 2022). This shows how vital the sector is to the country's economy, which calls for the need to apply appropriate analytical techniques to enhance production efficiency.
Agriculture and Food companies usually play an essential role in producing all agricultural commodities by ensuring that the commodities are adequately covered from upstream to downstream. However, to enhance the production efficiency of these commodities in the long term, there is a need to measure the company's performance. Measuring the companies' performances is usually considered a prerequisite for enhancing the decision-making process and other activities, such as governance and developing a healthy competition environment. In this regard, productivity measurement remains a critical tool for application and implementation in A&F companies to measure their efficiency and effectiveness in agricultural commodities production (Sichel, 2019).
The dynamic environment within which A&F industries operate indicates that various measurement techniques must be applied to determine the industry's performance and efficiency. In this regard, it is crucial to consider three types of efficiencies in A &F companies: technical, allocative, and scale. Technical efficiency reflects the entrepreneurial ability to acquire and utilize resources, to produce maximum output within the framework of a company. The allocative efficiency of a firm refers to the best utilization of resources in optimal proportions, intending to minimize costs (Zulfiqar et al., 2021). Under a profit maximization scenario, the scale efficiency of a farm can be defined as the ratio of the optimal output level to the product price with the marginal cost. Scale efficiency reflects the entrepreneurial ability to determine the optimal quantity of resources.
Therefore, in the case of production inefficiency, which relates to technical, allocative, and scale inefficiencies. Technical inefficiency is due to the inefficient use of available tools and techniques. Allocative inefficiency refers to the inefficient allocation of resources within a production process. Scale inefficiency refers to the mismatch between

the size of a production unit and its potential Output (Etuah et al., 2020). In this regard, the measure of technical efficiency remarks a fundamental tool for application in measuring technical efficiency, including both parametric and non-parametric measurements (Aparicio et al., 2021)

The non-parametric approach is used to measure business performance. This approach allows for comparing a group of similar units (e.g., businesses, products) without resorting to parametric assumptions about their distributions (Trinh Doan Tuan, 2020). This makes it more flexible and accurate for measuring business performance across various situations. Thus, the non-parametric approach plays a significant role when analyzing business performances, and the approach does not depend on prior assumptions when studying a business (Asmare & Begashaw, 2018). One key advantage of the non-parametric approach is that it does not require any assumptions about the shape or distribution of the data. This means it can measure performance across various situations, including those that parametric methods must rectify. Another benefit of the non-parametric approach is that it allows for identifying and analyzing patterns in data that are not readily apparent using parametric methods (Ghasemzadeh et al., 2018). This can help identify areas causing a business performance issue and provide insights into how best to improve performance. Generally, the non-parametric approach is an efficient way to measure business performance, especially in banking, supply chain management, transportation, and agriculture (Balcerzak et al., 2017).

Multiple Criteria Decision-Making (MCDM) techniques are critical methods that provide effective quantitative and qualitative means to enhance decision-making when companies are faced with multiple goals that they should measure in various units. The most commonly applied MCDM techniques in comparing companies' performance include statistical techniques that usually help model processes that may present inaccurate data. Different MCDM methods are used to compare companies' performances, such as the Simple Multi-Attribute Rating Technique (SMART), Analytical Hierarchy Process (AHP), and Fuzzy Systematic Approach (Rachmat Partama Adhitya Suryaningkusuma et al. 2018). However, fuzzy MCDM techniques are the most commonly applied techniques comparing companies' performances. Other methods are the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), ELimination and ChoiceExpressingREality (ELECTRE), and Data Envelopment Analysis (DEA). More importantly, the application of these MCDM techniques mainly involves two major stages: criteria-based evaluation of the available alternatives to the companies and eventual accumulation and identification of the top aggregation score to help inform decision-making processes.

Because this study is attempting to compare and benchmark A&F firms in KSA, DEA is most appropriate because DEA is proven to be a "balanced benchmarking" method (Balcerzak et al., 2017). DEA is proven to be effective in analyzing the performance of firms, as it is concerned with efficiency computations involving multiple inputs and outputs. Thus, DEA is one of the most preferred and cited methods of performance measurement reported in the literature (Iyer & Jain, 2019). However, published work on applying DEA in the A&F sector of KSA is not available.

Data Envelopment Analysis

Data Envelopment Analysis (DEA) is a fractional mathematical optimization strategy for determining relative efficiency within a set of businesses that uses a systematic approach. It is a tool used to measure any company's technical, allocative, and scale efficiency. DEA uses linear programming techniques to constrain and determine the operational efficiency of various firms and businesses. Depending on a company's technical efficiency. DEA applies the Constant Return to Scale (CRS) model and the Variable Return to Scale (VRS) model to determine the efficiency score for all the decision-making units. The decision-making units, in this case, can refer to government services, private sector firms, and other non-private organizations. The scores are usually awarded on a zero to 100% scale, whereby the units awarded 100% efficiency scores are considered efficient. In this case, the output will likely increase significantly while the input remains constant or lower. In general, weights are determined within the DEA framework so that the efficiency score of a DMU equals one; otherwise, the DMU is categorized as inefficient. DEA remains a critical tool for estimating the efficient levels of inputs or outputs achieved from either of the orientations or in situations where both the input and output orientation work simultaneously to cause change (Cikovic et al., 2021). In this case, the input orientations aim to estimate the number of inputs a company can reduce during production but still produce the required output. On the other hand, output orientation refers to the percentage by which a company can expand its outputs, provided the available resources for production. Determining these orientations usually helps to measure hyperbolic graph efficiency because the orientations allow both aspects to change equally. In this case, inputs used in production are considered to decrease proportionally as the out increase by the same proportion.

Theoretical understanding of DEA necessitates working experience in economics and mathematics programming, and unlike conventional partial productivity measurements, the conclusions are objective. Farrell (1957) was the first to introduce this concept in his research on the measurement of profitability in the industry. The basic principle behind the method was the distinction between price from technical efficiency. While price measures a firm's success in selecting the optimal inputs, technical efficiency measures its ability to produce maximum outputs out of the chosen inputs. Later in 1978, Charnes et al. (1978) extended Farrell's pioneering work and developed the Charnes, Cooper, and Rhodes (CCR) model (Mehdi T., and Soroosh, S., 2009). They used the efficiency of a single-output to single-input ratio for many inputs and outputs. The initial CCR model proposed that a DMU's efficiency can be calculated as the highest weighted outputs to weighted inputs ratio, with the caveat that the ratio should be below or equal to one for all DMUs. The CCR model assesses both technical and scale efficiencies via the optimal value of the ratio form. As Wen-Chih Chen (2008) explains, the efficiency scores assigned to DEA conform to the economic idea of technical efficiency (T.E.) rather than the more usual partial efficiency (P.E.) of the output-to-input ratio. The DEA framework is built on multi-input, multi-output production functions and is applied across a broad range of industries. DEA creates a function whose shape is determined by the most efficient producers, and firms are benchmarked only against the most efficient producers. This approach contrasts the statistical least squares method, which uses an average to compare producers. DEA establishes a "frontier" against which all utilities in the sample can be compared in terms of their relative performance. The most efficient producers combine to form a 'composite producer,' enabling efficient solution computation at every input-output level.

Bafail et al. (2003) comment that DEA distinguishes efficient and inefficient units by considering results in situations specific to the DMUs under consideration. As a result, DEA makes it possible for the best-performing units to be compared and assess their success factors. It may be necessary to include additional variables and weights to a model to reflect management and organizational factors, refine efficiency estimations, or correct inconsistencies. Many alternative models were developed to meet specific application needs. Unfortunately, with a large number of inputs and outputs, the DEA analysis still turned out a large number of DMUs that were 100% efficient. In response to these limitations in the original model, researchers developed more versatile models to accommodate constant returns and variable returns, namely Constant Return to Scale (CRS) and Variable Returns to Scale (VRS). Talluri S. (2000) discusses some methodological extensions of the original DEA model by Charnes A. et al. (1978).

DEA Models

A score of 1 is allocated to a DMU in the DEA model, which was first created by Charnes A. et al. in 1978 when evaluations with other pertinent DMUs failed to show proof of inefficiency for the identical groups of intakes and outcomes. To (relatively) inefficient units, the DEA assigns an efficiency score of less than one. A score smaller than one indicates that other DMUs have been linearly combined. Because DEA is a data-driven program, the model's inputs and outputs (I/O) must be chosen carefully. In most cases, a vast list of available variable combinations is accessible. Morita H. and Avkiran N.K. (2009) proposed an I/O selection method that uses diagonal layout experiments, a statistical approach to find an optimal combination. The DEA method was initially developed by Charnes A. et al. (1978) to assess the overall efficiency of production systems of comparable nature. Later, to suit the applications, other DEA models were developed. In 1984, Banker, Charnes, and Cooper created the (BCC) model to assess the pure technical efficiency of DMUs concerning an efficient frontier. It also determines whether a DMU is in a growing, reducing, or stable returns-to-scale model.CCR standards are a subset of the BCC model. The multiplicative model of Charnes, as well as the additive approaches used to calculate returns to scale, are examined by Charnes, A; et al.; (1985), Sueyoshi T. (1990), Khodabakhshi M. et al. (2010) and many others using the L.P. description below, the BCC input-oriented model analyzes the effectiveness of DMU_0.

$$\text{Maximize} \quad \sum_{r=1}^{s} u_r \, y_{rj} - u_0$$

Subject to:

$$\sum_{i=1}^{m} w_i x_{i0} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} - u_0 - \sum_{i=1}^{m} w_i \, x_{ij} \leq 0, \text{ j} = 1, 2, 3\ldots \text{ n}$$

$$u_0, \text{ free}$$

$$w_i \geq \varepsilon, \quad i = 1, 2, 3, \ldots\ldots, m$$
$$u_r \geq \varepsilon, \quad r = 1, 2, 3, \ldots\ldots, s$$

Where x_{ij} and y_{ij} (all nonnegative) are the inputs and outputs of the j^{th} DMU, w_i, and u_r are the input and output weights (or multipliers), x_{i0} and y_{r0} are the inputs and outputs of DMU_0. ε is the non-Archimedean infinitesimal value for forestalling weights equal to zero.

As previously stated, DEA data show a large number of 100% efficient DMUs. Mehdi T. and Soroosh N. (2009) present a new integrated method for describing the most BCC-efficient DMU by calculating a single set of linear programming equations rather than 'n' sets. DEA simplifies the efficiency calculation by converting multiple inputs and outputs to a scalar value. Each Decision-Making Unit (DMU) is compared to a reference DMU with the same input-output configuration. By awarding the most efficient DMU a score of one and all others a measure of inefficiency compared to it, the DEA model selects the most efficient DMU. Inefficient organizations receive a score between 0 and 1. As a result, DEA is inefficient. Rather than that, it denotes the least efficient organization among all DMUs.

In recent years, DEA has acquired increasing recognition for analyzing and quantifying the relative effectiveness of any system with an input and output, such as corporations, academic institutions, and corporate sectors, given that reliable data are available. Kristiaan K. and Ignace V.W. (2009) argue that DEA and other frontier models must be adapted to deal with negative data. Additionally, they suggested a straightforward modification of Silva et al. (2004) proportional distance function for the directional distance function. R.J. Gholam and P. Malihe (2013) proposed using a semi-oriented radial measure (SORM) model to determine the efficiency of DMUs using negative data. SORM could allocate either negative or positive data but had a flaw with integer data. However, SORM was ineffective at managing DMUs with a large number of integer inputs and outputs. SORM is incapable of resolving all issues and, in addition, complicates and complicates the calculation process. Sergey S., Brysonb K.M.O. (2013) discussed the DEA-centric design of Decision Support Systems (DSS) in productivity-driven organizations that are developed using DEA-monitored performance measures. The DSS was designed in response to a set of system requirements that were highly relevant to an organization's productivity enhancement efforts.

Minh N.K. et al. (2012) propose a novel method for assessing inefficient DMUs that overcomes the drawbacks of infeasibility. The novel approach for categorizing all decision-making units (DMUs) based on slacks-based measures of efficiency (SBM) enables the rating of all inefficient DMUs and overcomes the impossible drawbacks. Additionally, this approach is used to determine the most efficient scores from 2007 to 2010 for 145 agricultural bank branches in Viet Nam.

S.M. Salhieh et al. (2014) offer a method for evaluating and selecting novel product concepts incorporating DEA and Conjoint Analysis (C.A.). The concept development stage of the product development process is crucial. Through the use of C.A., this methodology combines customer impressions of new product concepts in two steps: concept screening and concept selection. This selection technique is comparable to the matrix for deploying quality functions (QFD). In turn, the values are used as metrics in DEA to evaluate the success of the new concepts. A case study demonstrates the proposed methodology's usefulness. The authors argue for the employment of a super-efficiency model to aid with product concept differentiation. The formula for calculating the super efficiency of efficient concepts based on the Super efficiency SBM model is as follows:

$$\text{Minimize } \delta = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}_i}{\bar{y}_{i0}}}{\frac{1}{s}\sum_{r=1}^{s}\frac{\bar{y}_r}{y_{r0}}}$$

Subject to:

$$\bar{x} \geq \sum_{j=1\neq 0}^{n} \lambda j * xj$$

$$\bar{y} \leq \sum_{j=1\neq 0}^{k} \lambda j * xj$$
$$\sum_{j=1}^{n} \lambda j = 1$$

$$j = 1$$
$$j \neq 0$$
$$\bar{y} \geq 0;\ \lambda \geq 0$$
$$\lambda_j \geq 0;\ \lambda \geq 0$$

Where,
δ = the super efficiency scores for the DMU ; $\boldsymbol{\lambda_j}$ = weight given for the DMU_j ;
$\mathbf{x_j}$ = input for a DMUo under evaluation ; $\bar{y}$ = output for a DMUo under evaluation ;
$\mathbf{x_j}$ = amount of input j produced by the DMU_i ; $\mathbf{y_j}$ = amount of output j utilized by the DMU_i ;

The authors claim that the super efficiency scores of the product concepts could be used to recommend the best product concept to develop further.

DEA in Food and Agriculture Sector

The application of DEA in the A&F sector is an aspect that has widely been discussed in various literature studies considering the diverse aspects of agricultural inputs and commodities involved in the production process. One of the studies applying the DEA approach in the A&F sector is a study conducted by Gardijan & Lukač (2018), which focuses on the food and drink industry in the E.U. countries. However, from a comparative perspective, Gardijan & Lukač (2018) 's study demonstrates that these industries do not perform as efficiently as other global food and drink companies due to the increasing competitiveness reduction. Therefore, by utilizing the financial data of the industries obtained from the database, Gardijan & Lukač (2018) managed to calculate the company's liquidity, profitability ratios, leverages, and relative efficiency using DEA models. Gardijan & Lukač (2018) 's study revealed the particular food and drinks companies associated with higher efficiency and the areas of inefficiency that other companies should address to enhance their efficiency. Guzmán et al. (2021) is another study that uses DEA in the A&F sector that primarily serves to measure productivity efficiency in dairy industry companies. Guzmán et al. (2021) 's study focuses on Colombian dairy industry companies to establish the particular DMUs that can be used for implementation in other companies across the globe to enhance productivity. The study identified efficient companies through DEA using the VRS model based on companies' inputs and outputs. As a result, Guzmán et al. (2021) 's study identified seven different DMUs considered efficient in utilizing the available inputs to maximize productivity. Another study that applies DEA in the A&F sector is Kapelko & Oude Lansink (2022), which proposes the application of DEA alongside corporate social responsibility to assess the production efficiency of U.S. food and beverage manufacturing companies. The method is considered efficient for the assessment process because it covers all the multi-dimensional aspects of the company's performance. Besides, the model's flexibility is another critical aspect that the study addresses, making it possible to avoid imposing restrictive production assumptions. The input-output data used to perform DEA were obtained from COMPUSTAT Vantage, while CSR data were obtained from KLD databases. Therefore, the researcher computed the dynamic inefficiency measures to estimate the inefficiencies associated with the resulting data. Through the procedure, the study finding demonstrated that the U.S. food and beverage companies are likely to expand their production output by almost 25% while at the same time reducing certain inputs such as labor and other materials by 14% and 10%, respectively.

According to Ait Sidhoum et al. (2020), a study offers insights into the DEA's application in measuring A&F companies. According to the study, DEA is considered an essential measurement approach that helps many A&F farms measure and displays their technical and social performances concerning the prevailing environmental conditions that govern the production of agricultural commodities in the companies. According to Ahmed et al. (2019), the DEA approach identifies the multiple inputs and outputs used within the agricultural sector. The agriculture sector can be analyzed based on the total productivity based on the utilization of water, land, labor, and farm inputs to maximize their output. In such a case, it would be difficult to accurately measure the multiple factors that are at play in determining the efficient utilization of all these points. According to Wang et al. (2017) and Wang et al. (2017), the DEA approach enables the measurement of agricultural productivity and efficiency to consider the heterogeneity of geographic locations and technological gaps across different locations and enable the measurement of temporal and spital aspects that are involved in agricultural production. The DEA approach enables the agricultural sector to measure its effectiveness based on household consumption and cross-regional and cross-country data, all of which do not rely on any prior assumptions about the possible findings. Indeed, non-parametric methodologies typically rely on no assumptions in making decisions on a multi-dimensional approach and Decision-Making Units (DMUs). To this end, the DEA ensures that the A&F sector can effectively improve its technical, allocative, and scale efficiencies from the findings. According to Ahmed et al. (2019), the DEA technique ensures that all technical considerations are made, leading to efficient resource allocation and, ultimately, effective utilization of the available resources to ensure maximum output within the scale of available resources. Several studies have explored the use of DEA in the F&A sector. One is Long et al. (2020) study that used DEA to assess technical efficiency in aquaculture. Long et al. (2020) aimed to use DEA to examine the efficiency level in Vietnamese farms where agricultural practice is carried out on a large scale. Yu and Zhang (2017) used one of the DEA models to measure agricultural performance in one of the provinces in China. Using data from Northern Uganda, Okello et al. (2019) analyzed the allocation efficiency of rice production. Results using DEA showed that rice production is inefficient. Farmer resources could be reallocated to achieve much higher efficiency. By reallocating resources, farmers could increase production by 22% and reduce costs by 41%. Farmers can select input combinations that will produce the greatest yield at the lowest cost. Bournaris et al. (2019) explored DEA's use in determining the efficiency of vegetables produced in glass houses. Bournaris et al. (2019) 's study was necessitated by the fact that glasshouse farming is traditionally one of the most widely used types of production methods for a broad range of agricultural products. Bournaris et al. (2019) 's study recommended using DEA since the methodology has proved to be an efficient alternative for achieving effective land management decision-making. Ogolla (2020) conducted research that complements various studies using DEA in agriculture. Some challenges leading to inefficiencies and low productivity in the agriculture sector include high product costs, farm mismanagement, and sub-optimal production. An additional study complemented Otieno's findings regarding the inefficiencies in the agriculture sector. Streimikis & Saraji (2021) pointed out that measuring efficiency in agriculture and food production is difficult, especially when the measurement is done in the presence of undesirable outcomes. The objective of Streimikis & Saraji (2021) 's study was to evaluate a series of studies where DEA has been applied as a tool for measuring efficiency alongside undesirable outputs. The study was backed by findings from an earlier study by Li et al. (2017) that identified DEA as a more flexible approach that could be approved in diverse scenarios than most models. According to findings demonstrated in each of the above studies, it is important to note that the performance assessment of the A&F sector is a critical aspect that operators must consider and perform to determine the sector's level of sustainability. DEA presents perfect models for utilization in these sectors that can evaluate the efficiency of operations and productivity based on the available input and output variables.

RESULTS

Analysis and results

Various commercial and non-commercial software tools are available now for DEA practitioners and researchers. Barr R.S. (2004) presented a state-of-the-art survey of a few of them, like DEA Solver Pro (Saitech Inc.), Frontier Analyst (Banxia Software Inc.), OnFront (EMQC), Warwick DEA (Warwick University), and DEA Excel Solver (Zhu), and DEAP (Colletti). The incorporation of DEA into decision-support systems (DSS) and benchmarking processes has also been done. The authors chose Frontier Analyst to solve the discussed BCC/CCR and Super Efficiency Models. Various models were tried with different combinations of input/output (I/O) variables. I/O data from seven leading A&F companies were collected from financial reports for the year 2014 published by the Saudi Stock Market on its official websites. Table 2 displays the data after Z-Score normalization, which is a statistical technique used for dealing with inhomogeneity in data structures. Data normalization or standardization removes outliers, brings all of the variables into proportion with one another, displays coefficients to reflect meaningful relative activity between variables, converts non-numeric-qualitative data into numeric-quantitative data, and so on, Sarkis (2002).

Model Scenarios

The data were analyzed to compute standard and super-efficiency scores under several I/O variable combinations. The variables considered were general administration expenses, owners' equity, capital, net profit, earnings per share, gross profit margin, gross profit margin (%), account receivables, and average price. Initially, the first three variables were considered as inputs, and the last five variables as outputs. Because DEA has the inherent disadvantage of yielding wrong results with a large number of input and output variables, care was taken to use an optimal combination of input/output variables. Minimization of inputs and maximization of outputs, in combination with constant rates of returns (CRS) and variable rates of returns (VRS), were used for BCC/CCR models. Three models and their outputs are discussed here.

Table 2. Normalized Values Of Financial Inputs And Outputs From 7 Saudi A&F Companies.

Companies	Inputs			Outputs				
	Gen Admin Expenses	Owners' Equity	Capital	Net profit	EPS	Gross Profit	Gross Profit Margin (%)	Account Receivable
S	2.321	1.718	1.85	1.582	-0.266	2.143	-1.223	2.384
O	-0.366	-0.467	-0.499	-0.443	0.577	-0.511	0.716	-0.184
N	-0.28	-0.38	-0.361	-0.534	-0.811	-0.375	1.53	-0.229
H	-0.44	-0.543	-0.512	-0.396	0.947	-0.601	0.792	-0.79
I	-0.402	-0.532	-0.519	-0.548	-0.153	-0.595	0.721	-0.573
M	0.458	1.503	1.347	1.644	-0.446	1.38	1.344	0.928
A	-0.631	-0.604	-0.643	-0.615	-1.474	-0.677	-1.188	-0.709

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Table 3. Comparison of three Models.

	Model 1 BCC/CCR (Minimize Inputs, Constant Rate of Returns)		Model 2 BCC / CCR (Minimize Inputs, Constant Rate of Returns)		Model 3 BCC / CCR (Minimize Inputs, Constant Rate of Returns)	
Companies	Standard Eff	Super Eff	Standard Eff	Super Eff.	Standard Eff	Super Eff.
A	100.00%	189.10%	100.00%	189.10%	100.00%	298.40%
H	100.00%	218.40%	100.00%	182.10%	100.00%	179.20%
M	100.00%	106.70%	100.00%	106.70%	100.00%	125.30%
O	78.50%	78.50%	70.40%	70.40%	100.00%	147.50%
I	58.30%	58.30%	48.80%	48.80%	79.50%	79.50%
S	54.40%	54.40%	54.40%	54.40%	100.00%	119.70%
N	28.80%	28.80%	28.80%	28.80%	52.10%	52.10%
Inputs	Gen Admin Expenses, Owners Equity, Capital		Gen Admin Expenses, Owners Equity, Capital		Gen Admin Expenses, Owners Equity, Capital, Avg. Price	

Model 1. Model 1 used general administrative expenses, owner's equity, and capital as inputs and net profit and earnings per share (EPS) as outputs. BCC/CCR model with an objective function to minimize inputs with constant returns were considered. Standard efficiency scores were computed for all seven companies (Table 3). It can be seen that there are three companies with efficiency scores of 100%. As discussed before, super efficiencies were calculated to distinguish between the best-performing companies. It is found that a clear distinction is made among the three top-scoring companies, all of which were scoring 100% standard efficiency. When super efficiencies are considered, they score 218.4%, 189.10%, and 106.7%. Figure 1 shows the standard and super-efficiency scores of the highest-performing companies. Super efficiency values are distinct from each other, whereas the three highest-performing companies score 100% as far as standard efficiency scores are considered. Thus, it is found that there is an advantage to computing super-efficiencies.

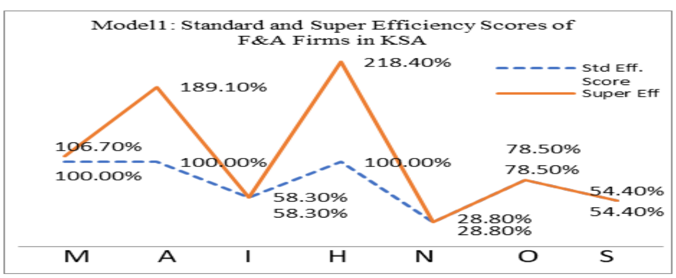

Figure 1. Standard and Super Efficiency Scores of F&A firms in KSA.

Model 2. Model 2 was developed with three inputs and one output, as shown in Table 3. The highest-performing companies in Model1 were also found to be the same in Model2. However, the ranking of the top-performing three companies differs from the Model1 output. This is because EPS was removed from the list of outputs. Model2 used general administrative expenses, owner's equity, and capital as inputs and net profit as output. BCC/CCR model was considered with an objective function to minimize inputs with constant returns (Figure2).

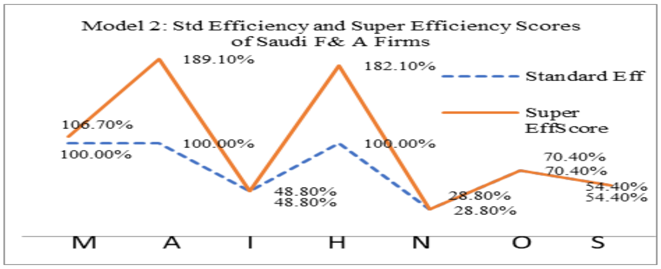

Figure 2. Model 2 Standard and Super Efficiency Scores of F&A firms in KSA.

Model 3. Model 3 was based on four inputs and two outputs, as shown in Table 3. The top-ranking companies are found to be the same as in the previous two models. Four companies are found to be exhibiting 100% standard efficiency while, as far as super efficiency scores are concerned, they are distinctly wide apart (Figure 3).

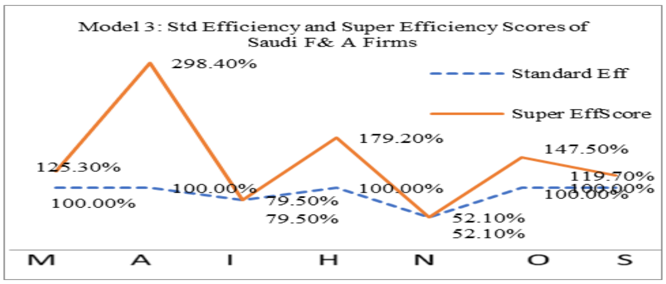

Figure 3. Model 3 Standard and Super Efficiency Scores of F&A firms in KSA.

It is quite logical that companies differ in performance when the criteria are changed. Company A was found to be the best performing one, followed by Company H and Company M. All three companies performed more or less equally well under varying I/O combinations. Such a result would not have been obtained if a large number of inputs and outputs were considered for building the models. This is so because inputs and outputs unrelated to companies' financial performance could alter the entire picture. In this study, key financial performance indicators (KPIs), like owners' equity, capital, net profit, etc., were considered in all models after consultation with subject experts.

Distribution of Efficiency Scores

Figure 4 presents the distribution of standard or technical efficiency values among the seven companies considered for the study. The distribution pattern gives an idea about the spread of the performance level of companies.

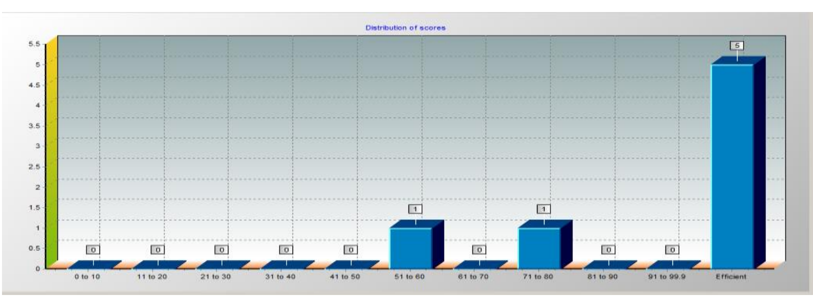

Figure 4. Distribution of Standard Efficiency Scores for Model 1

A graphical display of the varying ranges of efficient and inefficient firms is obtained from the Figure. This also warns whether groups of companies are doing well or can't improve, or perhaps that input/output variables will discriminate between them better. In Model 1, three companies share 100% efficiency scores. There is only one company in the 71% to 80% efficiency scores band, two companies in the 51% to 60% efficiency scores band, and one in the 21% to 30% efficiency scores band. Figure 5 gives the scores distribution pattern for Model 2. Only three companies are coming in at a 100% score level. The remaining four companies are way behind in 61-70%, 51-60%, 41-50%, and 21-30% Efficiency scores bands. Probably this is the worst case of all scenarios.

Figure 5. Distribution of Standard Efficiency Scores for Model 2

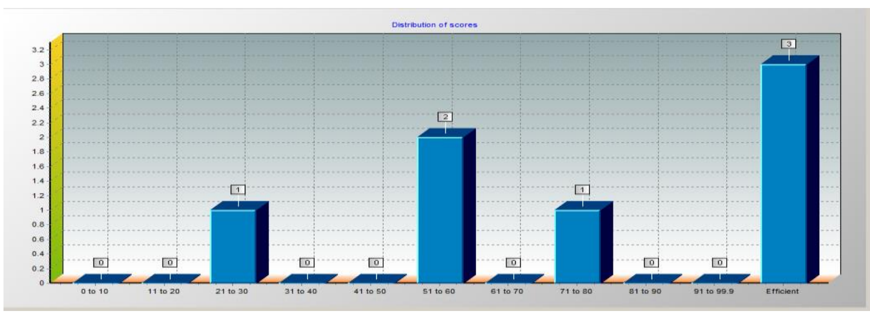

Figure 6. Distribution of Standard Efficiency Scores for Model 3

Similarly, in Model 3, five companies share the 100% efficiency score. Out of the remaining two companies, one comes under the 71% to 80% efficiency scores band, and the other comes under the 51% to 60% efficiency scores band. A brief examination of the distribution of the technical efficiency scores in all three models reveals that, in Model 3, overall company performances are better. Comparing the I/O configurations in the three models, when only the 'Net Profit' was considered, the performance of the companies lowered significantly. When earning per share (EPS) was added in Model 1 and Model 3, the efficiency scores improved.

Table 4. Normalized Values Additive Model: Minimize Inputs, Varying Returns

Company	Avg. Price	Gen Admin Expenses	Owners' Equity	Capital	Net Profit	EPS	Efficiency Score
S	-0.036	2.407	1.789	1.919	1.646	1.262	100.00%
O	0.386	-0.379	-0.486	-0.518	-0.461	2.105	100.00%
N	-0.274	-0.29	-0.396	-0.375	-0.556	0.717	42.90%
H	2.121	-0.456	-0.566	-0.531	-0.412	2.474	100.00%
I	0.322	-0.417	-0.554	-0.538	-0.571	1.374	72.50%
M	0.283	0.475	1.565	1.397	1.711	1.082	100.00%
A	-1.521	-0.654	-0.629	-0.666	-0.64	0.054	100.00%

Prospective Improvements

The results of the DEA analysis can be used best as a reference by companies who wish to go for improvements after benchmarking. After examining the results, one can assess in which direction the improvements need to be followed up. Table 4 displays the DEA results of the companies which wish to minimize inputs and maximize efficiency for variable returns (VRS). The negative signs indicate the possibility of reducing the financial variable to improve. Logically, the efficiency of any company can be enhanced by reducing average prices and general administration expenses (Cooper, W. et al. 2002).

The relative percentages of potential improvement for each input/output are computed by adding up the potential improvements for each unit – without applying weightings. The total potential improvements calculated in percentages are average price (0%), general admin expenses (-22.63%), owners' equity (-15.15%), capital (-24.1%), net profit (14.29%), earning per share (23.83%).

Discussion

Taking into account recent events in Saudi Arabia's A&F industry, the conclusions of this research should be viewed with caution. According to official predictions, the Saudi agriculture and food industry is expected to rise by 55.3% to reach SRs 262.5 billion each year. Agricultural imports are predicted to rise by up to 76% by 2016, accounting for SRs 65.5 billion (15%) of overall imports. Agriculture is expected to grow at a pace of 18.5% each year, driven by rising populations and strong consumer spending due to its growth and positive economic effect. It is also encouraging more cooperation between the public and private sectors to promote food security in the nation, which is the Middle East's biggest individual food importer and the region's largest agri-food commodities and technology market. It imports $14.2 billion in food and drinks per year to meet its consumption needs, accounting for 74.1% of the GCC's total production (www.arabnews.com). These observations show that businesses in Saudi Arabia are under substantial strain due to a multitude of interrelated issues, such as increasing incomes, expanding populations, and a booming domestic economy. As of this year, the Saudi government has committed almost $15 billion in A&F projects and efforts to satisfy demand. These facts provide context for the study's relevance. Firms must improve their financial performance to meet the increasing demand for more products. Using benchmarking to determine which firm is performing the best financially or operationally is a terrific method to learn from others. Competition is high, as seen by the outcomes. Table 5 summarizes the data and ranks the companies according to their extraordinary efficiency.

Table 5. Overall Ranking of A&F Companies Compared

	Authors' Ranking			MacroPolis Rankings	
Decision-Making Unit	Based on Overall Efficiency		Excluding Company A & Company H	Based on Market Value	Based on Revenue
A	225.53%		-	-	-
H	193.23%	II	-	-	-
M	112.90%	III	I	II	I
O	98.80%	IV	II	III	III
S	90.77%	V	III	III	III
I	62.20%	VI	-	-	-
N	36.57%	VII	-	I	II

The findings from the investigation were compared to the Metropolis rankings by the authors (www.macropolis.net). MacroPolis eliminated Company A, a Kuwait-based firm, and Company H, which has a wide range of products, from its rankings. The authors' ranks and those of Companies M, O, and S are generally in agreement.

The firm's performance may be different at different points in time. Periodic benchmarking efforts compel continuous development and long-term expansion. To achieve the aforementioned goals, it is recommended that the models produced be used to assess the relative performance of the A&F sector enterprises year after year. In order to keep an eye on the performance of businesses and identify the ones that are most important to national progress, it is necessary to conduct such an analysis. Window analysis is a technique that may allow each firm to enhance its share market contributions and, as a result, improve KSA's position in the global stock market rankings.

With the use of the most recent software technologies, businesses are able to assess how efficiently they function. They may be purchased independently or as part of a DSS or ERP system. In the long run, all of these phrases concentrate on bringing prospective future improvements into reality via benchmarking, performance measurement, and sustainability.

CONCLUSIONS

Saudi Arabia's agriculture economy was inefficient from an economic standpoint (total revenues were less than total costs), while the food manufacturing industry was productive (earnings achieved). For more than 40 years already, Saudi Arabian agriculture and food production have made amazing growth. The Saudi Stock Exchange currently has more than 16 top-ranking agricultural and food processing companies listed, making the A&F business the fourth biggest contributor to the Saudi Stock Exchange. In addition, Saudi Arabia's stock market strength rating is dependent on the A&F sector. In every dynamic economy, the A&F industry must be sustainable. For long-term success, regular performance reviews and benchmarking are essential. The research aimed to examine the operational and financial situations of agricultural and food firms in Saudi Arabia. Data Envelopment Analysis (DEA) was utilized in this research to evaluate technological efficiency (DEA). Non-parametric analytic methods, such as the DEA methodology used by one organization, are used to measure efficiency in relation to other productivity units. According to the data, relative efficiency in A&F enterprises has fluctuated dramatically over time. Efficiency-based rankings paralleled actual performance, suggesting that financial indicators may assist us in making more unbiased choices. Owners' equity (15.15%) and capital expenditures (22.63%) all have significant room for improvement, the study finds (24.1%).

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REFERENCES

1. Ahmed, S., Hasan, M. Z., Laokri, S., Jannat, Z., Ahmed, M. W., Dorin, F., Vargas, V., & Khan, J. A. M. (2019). Technical efficiency of public district hospitals in Bangladesh: a data envelopment analysis. Cost Effectiveness and Resource Allocation, 17(1), 1–10;
2. Ait Sidhoum, A., Serra, T., & Latruffe, L. (2020). Measuring sustainability efficiency at farm level: A data envelopment analysis approach. European Review of Agricultural Economics, 47(1), 200–225;
3. Aparicio, J., Monge, J. F., & Ramón, N. (2021). A new measure of technical efficiency in data envelopment analysis based on the maximization of hypervolumes: Benchmarking, properties and computational aspects. European Journal of Operational Research, 293(1), 263–275;
4. Asmare, E., & Begashaw, A. (2018). Review on parametric and non-parametric methods of efficiency analysis. Biostatistics and Bioinformatics, 2(2), 1–7;
5. Bafail Abdulla Omar, Abdel Aal Reda M.S., Shoukath Ali Karuvat (2002). A DEA approach for measuring relative performance of Saudi banks. Proceedings DEA2002, Moscow, 2002;
6. Bafail Abdulla Omar, Abdel Ala Reda M.S., Shoukath Ali Karuvat (2003). DEA as an Integrated Approach for measuring Efficiency of a Dynamic Economy - A case study. Computational Engineering in Systems Applications (CESA'2003);
7. Balcerzak, A. P., Kliestik, T., Streimikiene, D., & Smrcka, L. (2017). Non-parametric approach to measuring the efficiency of banking sectors in European Union Countries. Acta Polytechnica Hungarica, 14(7), 51–70;
8. Banker, R.D., Charnes, A., and Cooper, W.W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science, Vol. 30, pp. 1078-1092;
9. Barr Richard S. (2004). DEA Software Tools and Technology: A State-of-the-Art Survey. Handbook on Data Envelopment Analysis, Vol. 71, International Series in Operations Research & Management Science. Pp. 539-566. DOI: 10.1007/1-4020-7798-X_18;
10. Barros Carlos Pestana (2006). Efficiency measurement among hypermarkets and supermarkets and the identification of the efficiency drivers: A case study International Journal of Retail & Distribution

Management. Emerald Group Publishing Limited. Vol. 34 No. 2., pp. 135-154. DOI 10.1108/09590550610649795;
11. Berger Allen N., Humphrey David B. (1992). Measurement and Efficiency Issues in Commercial Banking. Proceedings of conference on Output Measurement in the Service Sectors, University of Chicago, 1990.Pp. 245 – 300 http://www.nber.org/books/gril92-1;
12. Bournaris, T., Vlontzos, G., & Moulogianni, C. (2019). Efficiency of vegetables produced in glasshouses: The impact of Data Envelopment Analysis (DEA) in land management decision making. Land, 8(1), 17;
13. Cikovic, K. F., Martincevic, I., & Smoljic, M. (2021). Data Envelopment Analysis (DEA) Application in Supply Chain Management. 72nd International Scientific Conference on Economic and Social Development. https://doi.org/10.4324/9780203004937;
14. Cooper,W., Seiford,L., Tone,K.,(2002). Data Envelopment Analysis: A comprehensive text with Models applications references. 3rd Edition. Kluwer Academic publishers;
15. Charnes, A; Cooper W., and Rhodes, E., (1978). Measuring efficiency of decision-making units. European Journal of Operational Research, Vol. 2/6, pp. 428-449;
16. Charnes, A; Cooper W., and Rhodes, E., (1982). A multiplicative model for efficiency analysis. Socio-Economic Planning Sciences, Vol.16/5, pp. 223-224;
17. Charnes, A., Cooper, W.W., Golany B.L., Seiford, and Stutz, J. (1985). Foundations of data envelopment analysis for pareto koopmans efficient empirical production functions. Journal of Econometrics, Vol.30/1, pp. 91-107;
18. Dimara Efthalia, Skuras Dimitris, Tsekouras Kostas, Tzelepis Dimitris (2008). Productive efficiency and firm exit in the food sector. Food Policy 33 (2008) 185–196. www.elsevier.com/locate/foodpol;
19. Doyle, J.R., and Green, R.H., (1993). Data Envelopment Analysis and Multiple Criteria Decision Making. OMEGA, Vol. 21, 1993;
20. Etuah, S., Ohene-Yankyera, K., Liu, Z., Mensah, J. O., & Lan, J. (2020). Determinants of cost inefficiency in poultry production: Evidence from small-scale broiler farms in the Ashanti region of Ghana. Tropical Animal Health and Production, 52(3), 1149–1159;
21. Fried Harold O., Lovell C. A. Knox, & Schmidt Shelton S., Editors, (2008). The Measurement of Productive Efficiency and Productivity Growth. Oxford University Press Inc., New York. ISBN 978-0-19-518352-8 www.oup.com;
22. Gardijan, M., & Lukač, Z. (2018). Measuring the relative efficiency of the food and drink industry in the chosen E.U. countries using the data envelopment analysis with missing data. Central European Journal of Operations Research, 26(3), 695–713;
23. Ghasemzadeh, A., Hammit, B. E., Ahmed, M. M., & Young, R. K. (2018). Parametric ordinal logistic regression and non-parametric decision tree approaches for assessing the impact of weather conditions on driver speed selection using naturalistic driving data. Transportation Research Record, 2672(12), 137–147;
24. Gholam Reza Jahanshahloo1, Malihe Piri1 (2013). Data Envelopment Analysis (DEA) with integer and negative inputs and outputs. Journal of Data Envelopment Analysis and Decision Science 2013 (2013) 1-15. Intl Scientific Publications and Consulting Services (ISPCS). DOI:10.5899/2013/dea-00007;
25. Guzmán, B. V. R., Lozano, G. I. R., & Domínguez, O. F. C. (2021). Measuring productivity of dairy industry companies: an approach with data envelopment analysis. Journal of Agribusiness in Developing and Emerging Economies;
26. Hartmann M., Khalil S., Bernet T., Ruhland F., Al Ghamdi A. (2012). Organic Agriculture in Saudi Arabia - Sector Study 2012. Deutsche Gesellschaft für Internationale Zusammenarbeit GIZ (GmbH), Saudi Organic Farming Association (SOFA), Research Institute of Organic Agriculture (FiBL) & Ministry of Agriculture of Saudi Arabia (MoA), Riyadh, KSA 2012. P.13;
27. http://www.tadawul.com.sa/wps/portal/!ut/p/c1/04_SB8K8xLLM9MSSzPy8xBz9CP0os3g_A-ewIE8TIwP3gDBTA08Tn2Cj4AAvY_dQA_3g1Dz9gmxHRQCHg5RU/;
28. http://www.saudiembassy.net/about/country-information/agriculture_water/Agricultural_Achievements.aspx; retrieved on 12-10-2013;
29. http://www.arabnews.com; Arab News, 29 November 2014 | 6 Safar 1436 AH; retrieved on 30-11-14;
30. http://www.gulfbase.com/saudi-stock-exchange-indices-1#10/07/2014 Accessed 11-10-2014;
31. http://www.giz.de/en/worldwide/18343.html. Introducing Organic Farming in the Kingdom of Saudi Arabia;

32. http://www.cdsi.gov.sa/english/ (2014) Latest Statistical Reports, Center Department of Statistics and Information. Retrieved on 22-10-2014;
33. http://moa.gov.sa/organice/ (2014). A Glance on Agricultural Development in Saudi Arabia, Ministry of Agriculture (MoA). Retrieved on 22-10-2014;
34. http://www.macropolis.net/largest-agriculture-companies-in-saudi-arabia.htm. Accessed 12-9-2015;
35. Iyer, K. C., & Jain, S. (2019). Performance measurement of airports using data envelopment analysis: A review of methods and findings. Journal of Air Transport Management, 81 (August), https://doi.org/10.1016/j.jairtraman.2019.10170;
36. Kapelko, M., & Oude Lansink, A. (2022). Measuring firms' dynamic inefficiency accounting for corporate social responsibility in the U.S. food and beverage manufacturing industry. Applied Economic Perspectives and Policy;
37. Khodabakhshi M., Gholami Y., Kheirollahi H. (2010). An additive model approach for estimating returns to scale in imprecise data envelopment analysis. Applied Mathematical Modelling 34 (2010) 1247–1257. www.elsevier.com/locate/apm. doi:10.1016/j.apm.2009.08.011;
38. Khouja, M., (1995). The Use of Data Envelopment Analysis for Technology Selection. Computers and Industrial Engineering, Vol. 28, 1995;
39. Kristiaan Kerstens, Ignace Van de Woestyne (2009). Negative Data in DEA: A Simple Proportional Distance Function Approach. IÉSEG School of Management, CNRS-LEM (UMR 8179). Hogeschool Universiteit Brussel, Belgium;
40. Li, N., Jiang, Y., Yu, Z., & Shang, L. (2017). Analysis of agriculture total-factor energy efficiency in China based on DEA and Malmquist indices. Energy Procedia, 142, 2397–2402;
41. Liu John S. http://www.sciencedirect.com/science/article/pii/S0305048312002186 - aff1, Louis Y.Y. Lu, Wen-Min Lu, Bruce J.Y. Lin (2013) A survey of DEA Applications. Omega, Volume 41, Issue 5, October 2013, Pages 893–902;
42. Mehdi Toloo, Soroosh Nalchigar (2009). A new integrated DEA model for finding most BCC-efficient DMU. Applied Mathematical Modeling 33 (2009) 597–604;
43. Minh Nguyen Khac, Van Khanh Pham, Anh Tuan Pham (2012). A New Approach for Ranking Efficient Units in Data Envelopment Analysis and Application to a Sample of Vietnamese Agricultural Bank Branches. American Journal of Operations Research, 2012, 2, 126-136 http://dx.doi.org/10.4236/ajor.2012.21015;
44. Morita Hiroshi and Avkiran Necmi K. (2009). Selecting Inputs And Outputs In Data Envelopment Analysis By Designing Statistical Experiments. Journal of the Operations Research Society of Japan. 2009, Vol. 52, No. 2, 163-173;
45. Farrell, M.J. (1957) "The Measurement of Productive Efficiency," Journal of the Royal Statistical Society vol. 120, pp. 253–281;
46. Ogolla, M. O. (2020). An Empirical Assessment Of Technical Efficiency In The Kenya Sugar Industry: Data Envelopment Analysis (Dea) Approach. University of Nairobi;
47. Okello, D. M., Bonabana-Wabbi, J., & Mugonola, B. (2019). Farm level allocative efficiency of rice production in Gulu and Amuru districts, Northern Uganda. Agricultural and Food Economics, 7(1), 1–19;
48. Perrigota Rozenn, Barros Carlos Pestana, (2008). Technical efficiency of French retailers. Journal of Retailing and Consumer Services. Vol. 15 (2008) p.296–305. DOI:10.1016/j.jretconser.2007.06.003;
49. Rahman Sanzidur (2003). Profit efficiency among Bangladeshi rice Farmers. Food Policy 28 (2003) 487–503. http://www.elsevier.com/locate/foodpol. Accessed 24-12-2014;
50. Rachmat Partama Adhitya Suryaningkusuma, S., Subyantoro, A. S., & Sabihaini, S. (2018). Combining Analytical Hierarchy Process and Simple Multi-Attribute Rating Technique for designing a Sustainable Balanced Scorecard as Strategic Performance Measurement System. International Journal of Computer Science and Network, 7(4), 279–288;
51. Rostam Pour Shahram (2012). An empirical method to measure the relative efficiency of dairy producers using deterministic frontier analysis. Management Science Letters 2 (2012) 229–234. DOI: 10.5267/j.msl.2011.09.001;
52. Salhieh Sa'Ed M., Al-Harris Mira Y. (2014). New product concept selection: an integrated approach using data envelopment analysis (DEA) and conjoint analysis (C.A.). International Journal of Engineering & Technology, 3 (1) (2014) 44-55. ©Science Publishing Corporation *www.sciencepubco.com/index.php/IJET*; DOI: 10.14419/ijet.v3i1.1635;

53. Sarkis, Joseph, (2000). A Comparative Analysis of DEA as a discrete alternative multiple criteria decision tool. European Journal of Operational Research, Vol. 123, pp. 543-557, 2000;
54. Sarkis Joseph, (2002). Preparing Your Data for DEA Productivity Analysis in the Service Sector with Data Envelopment Analysis, 2nd Edition, Ch 4 - Necmi Avkiran;
55. Sherman, H.D., and Zhu, J., (2013). Analyzing performance in service organizations, Sloan Management Review, Vol. 54, No. 4 (Summer 2013), 37-42;
56. Sichel, D. E. (2019). Productivity measurement: racing to keep up. Annual Review of Economics, 11, 591–614;
57. Silva Portela, M., E. Thanassoulis, and G. Simpson (2004): Negative Data in DEA: A Directional Distance Approach Applied to Bank Branches," Journal of the Operational Research Society, 55(10), 1111{1121;
58. Stewart, T.J., (1996). Relationship between Data Envelopment Analysis and Multi-Criterion Decision Analysis. European Journal of Operational Research, Vol. 47;
59. Sergey Samoilenkoa,, Kweku-Muata Osei-Brysonb(2013). Using Data Envelopment Analysis (DEA) for monitoring efficiency - based performance of productivity-driven organizations: Design and implementation of a decision support system. Omega 41 (2013) 131–142. Elsevier. doi:10.1016/j.omega.2011.02.010;
60. Streimikis, J., & Saraji, M. K. (2021). Green productivity and undesirable outputs in agriculture: a systematic review of DEA approach and policy recommendations. Economic Research-Ekonomska Istraživanja, 1–35;
61. Sueyoshi Toshiyuki (1990). A Special Algorithm for an Additive Model in Data Envelopment Analysis. The Journal of the Operational Research Society Palgrave Macmillan Vol. 41, No. 3. Pp. 249-257, http://www.jstor.org/stable/2583820;
62. Talluri Srinivas, (2000). Data Envelopment Analysis: Models and Extensions. Production and Operations Management, Decision Line, 31(3)., May2000. p8-11;
63. Thanassoulis, Emmanuel, (1993). Comparison of regression analysis and data envelopment analysis as alternative methods for performance assessments. JORS, Vol.4. No. 11. 1129-1144;
64. Trinh Doan Tuan, L. (2020). Non-Parametric approach to measuring the efficiency of banking sectors crediting agribusiness in ASEAN countries. E3S Web of Conferences, 175(7), 51–70. https://doi.org/10.1051/e3sconf/202017513031;
65. USDA. (2022). Ag and Food Sectors and the Economy. US Department of Agriculture. https://www.ers.usda.gov/data-products/ag-and-food-statistics-charting-the-essentials/ag-and-food-sectors-and-the-economy/;
66. Wang, Y., Shi, L., Zhang, H., & Sun, S. (2017). A data envelopment analysis of agricultural technical efficiency of Northwest Arid Areas in China. Frontiers of Agricultural Science and Engineering, 4(2), 195–207;
67. Wen-Chih Chen (2008). Integrating Approaches to Efficiency and Productivity Measurement. PhD Dissertation, Georgia Institute of Technology, tp://hdl.handle.net/1853/25422;
68. Yu Wantao and Ramanathan Ramakrishnan (2008). An assessment of operational efficiencies in the U.K. retail sector. International Journal of Retail & Distribution Management. Vol. 36 No. 11, 2008. pp. 861-882. Emerald Group Publishing Limited. DOI:10.1108/09590550810911656;
69. Zulfiqar, F., Shang, J., Nasrullah, M., & Rizwanullah, M. (2021). Allocative efficiency analysis of wheat and cotton in district Khanewal, Punjab, Pakistan. GeoJournal, 86(6), 2777–2786. https://doi.org/10.1007/s10708-020-10228-x;