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Assessing Agricultural Malmquist Total Factor Productivity and Environmental Efficiency for Some Arab Countries Via Data Envelope Analysis (A Non Parametric Approach)

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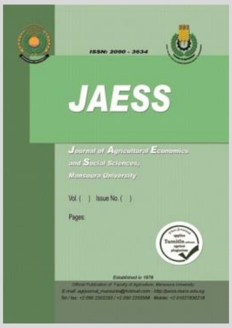

ABSTRACT

The paper aims to assess the relative efficiency of agriculture and agricultural growth change in productivity, as well as, environmental efficiency over the past decade (2007-2017) for ten of the largest Arab agricultural producers. Namely are Egypt, Sudan, Algeria, Syria, Morocco, Yemen, Tunisia, Iraq, Saudi Arabia and United Arab Emirates. The analysis employs data envelope analysis (DEA) a nonparametric approach employing non- radial and non-oriented slacks-based model (SBM) based on the assumption of a constant return to scale with the consideration of agricultural greenhouse gases emissions (CO2-eq) as an undesirable (bad) output. Moreover, it adopts Malmquist technique to estimate TFP index numbers. Technical efficiency results show that excluding agricultural emissions from consideration leads to overestimated scores and thus spurious estimates. TFP results show that average annual growth rate throughout the period 2007-2017 reached -0.12% in general. Efficiency changes attributed by a mere -0.49% while the rest (0.37%) was contributed by technical change. Moreover, the countries with the highest average annual growth in TFP are Syria and Morocco with an impressive 6% each on average, while for Yemen and Algeria about 3.5% (on average), Sudan and Saudi Arabia 0.6% (on average). Whereas, Tunisia achieved the least negative score estimated at -0.3%, Egypt and United Emirates about -2.4% (on average) and Iraq (-15%).

Keywords: *Egypt, Slacks-Based Model (SBM), Total Factor Productivity (TFP) and Environmental Efficiency*

INTRODUCTION

Garibaldi *et al* (2011), argued that agriculture has been and will always continue to play a vital role for humanity, since human well-being depends on the quantity and long term stability of agricultural production, as assessed by crop yield and cultivated area. However, Onjala (2002) suggested that, economic growth could be viewed as a process involving the entire economy's output performance; it mainly depends on the productivity of the country. Productivity, on the other hand, is essentially a microeconomic matter, focusing on how production units hire and use capital, labor, and other resource inputs in their output of goods and services. The direct link between productivity and economic growth is apparent in many ways. The sources of productivity growth over time have nowadays emerged as a central of growth and development.

Basic DEA models have been widely employed to measure technical efficiency; however, agricultural production own undesirable (bad) outputs, such as CO2 emissions, as a result of producing desirable (good) outputs. In other words, neglecting these undesirable outputs in estimating agricultural efficiency does not seem to provide accurate score for benchmarking and comparisons. In this paper, both desirable (good) and undesirable (bad) outputs are considered simultaneously. It is worth mentioning that, cross-country studies for environmental efficiency in the Arab area are very limited. This paper attempts to estimate the relative extent of differences for both technical and environmental performance between selected Arab countries and identifies leading countries with respect to agricultural TFP growth and environmental efficiency. However, production practices, technologies, and policies of the leading country could be used as a benchmark for the other countries in the region

Traditional DEA are only output or input-oriented models that allow constant or variable return to the scale to be measured. Input-oriented models provide a recommendation for inefficient units to achieve efficiency in the form of input reduction, while output-oriented models strive to achieve efficiency increase on the output side.

Productivity growth in several economies has indeed been difficult to attain. For this reason, studies on the sources of growth are an area of great importance for policy makers. However, during the last few decades, productivity growth has attracted much attention, as it is considered to become the key source of development for the agricultural sector, at a rate capable of meeting the demands for food and raw materials resulting from steady population growth (Hayami and Ruttan, 1970; Coelli and Rao, 2003). A country that falls short of achieving growth in agricultural productivity can suffer deterioration, either of its foreign exchange balance or of its internal trade ties with industry, thereby also hindering industrial production. On the other hand, a country which uses its resources best

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within its agricultural sector may enjoy a major comparative advantage in the export markets.

Many studies have focused on this issue, using either the Partial Factor Productivity (PFP) or Total Factor Productivity (TFP) measures. For the first, the most commonly is labor productivity (e.g. Gutierrez, 2000; McErlean and Wu, 2003). While, the latter are generally evaluated using either i) an index number approach, usually the Tornqvist index (e.g. Mukherjee and Kuroda 2003), (ii) a production function approach (e.g. Hayami and Ruttan, 1970; Wiebe *et al*., 2000), or (iii) a Data Envelopment Analysis approach, DEA-based Malmquist index (e.g. Coelli and Rao, 2003; Ludena *et al*., 2005).

Nin and Yu (2008) argued that, for time series data, the least square econometric production function models and total factor productivity indices are usually used assuming that all production units are technically efficient. Whereas, the DEA method can be extended across businesses, plants, regions or countries to compare their relative productivity. While for panel data, DEA and stochastic boundaries can be used to quantify both efficiency improvement and technological progress.

Pioneered by Caves *et al.* (1982), the Malmquist index on distance function has been widely used in productivity calculation and analysis since Fare *et al.* (1994) has shown that the index can be measured using a non-parametric method (Data Envelope Analysis). The nonparametric Malmquist Index (discussed in detail later) has been particularly common because it does not contain assumptions about economic activity (profit maximization or cost minimization). Also, Its ability to break down productivity growth into two components: shifts in technology over time (technical change) and improvements in technological performance over time (catch-up).

Most of these studies have been performed at regional and farm level, such as Reinhard *et al.* (2002) for dairy farms in the Netherlands, Coelli *et al.* (2007) for pig farms in Belgium, Abedullah *et al.* (2010) for rice farms in Pakistan. Thanh Nguyen *et al*. (2012) has also been used in South Korea, Kuo *et al*. (2014) in Taiwan, Marchand and Guo (2014), Li, K *et al.* (2020) modeling technical bias and productivity growth in China and Tu *et al*. (2015) in Vietnam. Other studies performed cross-country analyzes for agricultural TFP and environmental efficiency, such as Hoang and Coelli (2011) and estimates for 30 OECD member countries for the period 1990–2003, and Moreno-Moreno *et al*. (2017) assessed the operating efficiency for 18 Latin American and Caribbean countries for 2012.

This study explores improvements in agricultural productivity and environmental efficiency in the Arab countries where their geographical positions are shown in Figure 1.

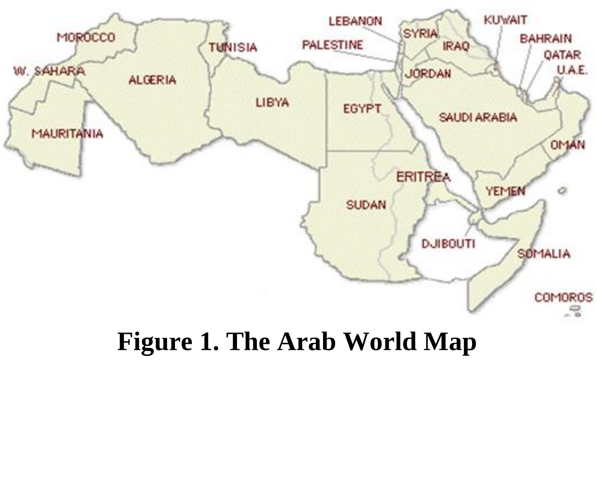


Figure 1. The Arab World Map

Source: Google maps

Figure 2 shows the share of agricultural GDP in Arab countries economies during the period 2007-2017 (on average). It depicts that the agricultural sector plays an important role in Egypt and Sudan that contributes about 20.4% (each on average) to its gross GDP, followed by Algeria (13.0%), Saudi Arabia and Morocco 10.5% (each on average). Next come Syria and Iraq (5.7% each on average), Yemen (3.2%), Tunisia and United Arab Emirates about (2.4% each on average) and Lebanon (1.4%). Whereas, Libya and Jordan accounted about 0.83% (each on average). Meanwhile, Somalia, Mauritania and Oman about (0.64% each on average), Kuwait and Palestine (about 0.32% each on average). Finally, Comoros (0.23%), Qatar (0.14%), Bahrain (0.07%) and Djibouti (0.02%).

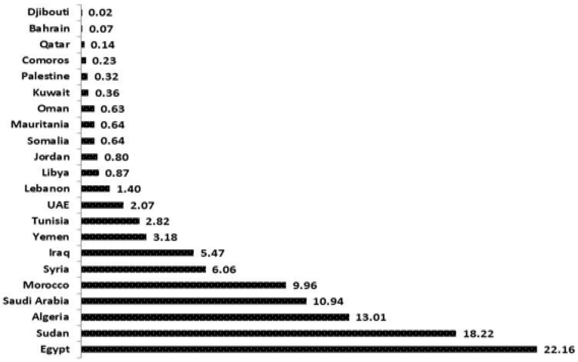


Figure 2. The Share of Agricultural GDP in Country's GDP during the period 2007-2017 (% on average)

Source: Compiled and calculated from Arab Agricultural Statistics Yearbook (several issues)

The analysis dropped from the sample either countries with very small negligible agriculture GDP contribution (such as Qatar, Bahrain, Kuwait and Oman), or countries with missing data (such as Libya, Djibouti, Jordon, Palestine, Lebanon, Mauritania, Comoros and Somalia), in particular the study covers a decade. Indeed, almost the majority of sampled countries of this region continue to be extremely vulnerable to weather and commodity price shocks due to their small economic resource base. They are vulnerable to high volatility in economic activity and it is therefore important to recognize their sources of growth (Belloumi and Matoussi 2009).

Countries considered in this study are Sudan, Syria, Morocco, Yemen, Egypt, Algeria, Tunisia, Iraq, Saudi Arabia and United Arab Emirates. The selected sample is considered the largest growers and importers/exporters of feed grains and food in the Arab world and a major global market for agricultural and food products. For example, Egypt's wheat imports in 2018 accounted $2.2 billion (5.3% of world's wheat imports) implying that Egypt is ranked as the largest wheat importer in the world.

Nowadays, recent studies have been taken into consideration environmental efficiency analyses. However, agriculture is known to be the main source of GHG emissions that influence climate change. In 2014, FAO indicated that total agricultural emissions increased by about 14 per cent, in other words, it rose from about 4.7 tons to nearly 5.3 billion tons of CO_2-eq during the period

2001-2011. In which developing countries are the key sources of this increase as a result of their agricultural production.

Globally, it is a great challenge to agricultural producers and policymakers to temper GHG emissions while satisfying the escalated food demand via boosting agricultural production. Hence, in-depth and more investigations are also required in order to improve the efficiency of both agricultural production and environment protection.

In 2017, agriculture in the Arab countries accounted for around 2.2% of the world's total agricultural output joined by 1.92 million Gg of CO2-eq, representing about 3.6% of global agricultural GHG emissions. Thus, indicating a lack of considering the environmental aspect in Arab's agricultural production implying the need for more environmental efforts and effective plans to be applied.

This paper is organized as follows. The next section briefly addresses the objective of the study. Data collection is the scope of Part Three. The fourth section is dedicated to provide a background on the DEA and Malmquist TFP index methodology. The paper's estimation process is the key subject of Section 5. The sixth section addresses the estimated results. The conclusion is presented in Section 7 and the last section is devoted to acknowledgment..

1.Aim of the Paper

The objective of this paper is twofold: first, to quantify the effect of agricultural emissions on technical efficiency estimates; second, to provide up-to-date information on total agricultural factor productivity (TFP) growth in the agricultural sector for ten of the largest agricultural producers in the Arab world over the past decade (2007-2017). Moreover, in order to analyze the reasons for the technological change, the article decomposed technological change index into three different indices: the output biased technological change (OBTC), the input biased technological change (IBTC), and the magnitude of technological change (MTC).

2.Data

All data for the study period (2007-2017) are obtained from the World Bank, FAO Statistics Division and Arab Organization for Agricultural Development (AOAD)

3. Methodology (Slacks-Based Measure (SBM) and Malmquist TFP Methodologies)

The nonoriented assumption of the model has the benefit of capturing the ability to boost both inputs and outputs at the same time, while the nonradial assumption depicts movements on the efficiency frontier that are represented through the values of slacks, i.e. nonradial input excess or nonradial output shortfalls. the assumption of CRS is called CCR model (Charnes, Cooper and Rhodes), however, this assumption assumes that units operate under their optimal size (Kocisova and Paleckova, 2017)

For investigating the level and growth pattern in Arab's agricultural productivity the study employs Malmquist total factor productivity approach. As argued by Telleria and Hassan (2011), There are two basic methods to calculating agricultural productivity, which are generally referred to as parametric and non-parametric approaches. The Laspeyres Index (which uses base year prices and current amounts, i.e., base-period weights) was commonly used in the parametric method to calculate agricultural productivity by value added per unit of input in the past. Theil-Tornqvist Index, which employs prices both from base and reference periods, is favored over the Laspeyres Index because it does not require the false assumption that all inputs are ideal substitutes in production. The key issue with the Theil-Tornqvist Index, however, is that it does not meet transitivity requirements, rendering it unrealistic for comparisons involving three or more countries. Index numbers are observed to combine heterogeneous outputs and inputs using local currencies (such as dollars), however such currencies are not modified to account for adjustments in currency value over time, restricting understanding of agricultural productivity patterns. Recently, The Malmquist Index employs the non-parametric approach pioneered as Data Envelopment Analysis (DEA) by Charnes, Cooper, and Rhodes (1978), which builds on Farrell's (1957) individual firm assessments by using linear programming to estimate an empirical production technology frontier for the first time.

However, the next section provides a brief background on the employed techniques.

1. Slacks-Based Measure (SBM)

The study adopts slacks-based measure (SBM) considering undesirable outputs in Linh Le T *et al* (2019), however, Fare *et al* (1994) and Coelli *et al* (1994) define Malmquist index methods (1998, Ch. 10).

The term "technical efficiency" (TE) refers to an aspect of economic efficiency (Farrell, 1957). It is characterized as a company's ability to turn a given set of inputs into the highest possible output based on the available technology (Bravo-Ureta *et al*., 2007). When comparing productivity over time, another cause of potential productivity changes is technological change. It quantifies the degree to which the output frontier, which reflects the state of technology at the moment, moves upwards over time. Such changes reflect technological development.

For the measurement of technical efficiency, various frontier models based on early research of Farrell (1957) have been established. These models could be grouped into parametric and non-parametric frontiers. Since they depend on a particular functional form, the metric frontier is further subdivided into two methods (Aigner *et al*, 1977). These two classes are the deterministic model, which assigns any variance to inefficiency, and the stochastic model, which tolerates statistical noise (Amara, *et al*., 1999). Non-parametric models are usually based on mathematical programming and are also known as data envelopment analysis (DEA) (Banker *et al*, 1984 and Thiam *et al*, 2001). However, DEA only provides relative efficiencies relative to the data being considered. It does not and cannot offer absolute efficiencies.

As cited by (Galanopoulos 2006), DEA models are linear programming (LP) methods for estimating the decision-making units' frontier output function (firms or countries). Those that work on the frontier are technically effective, while the degree of technical inefficiency of the rest is determined based on the Euclidian distance of their input/output ratio from the frontier (Coelli *et al*., 1998)

Tone (2001) developed SBM-DEA model, a nonradial and nonoriented approach is employed where slacks of output and input are employed for efficiency estimate. Then in 2004 he modified this approach to consider the presence of unexpected outputs, in which, The estimated results classify excess inputs and bad outputs that must be minimized if the DMU is to improve its environmental efficiency. However, this model has been widely adopted in a number of empirical studies such as Komleh *et al*. (2020), Linhle *et al*. (2019), Akbar *et al*. (2020), Chen *et al*. (2019), Linh *et al*. (2020), Dong *et al*. (2018), Moreno-Moreno *et al*. (2017), Baležentis and Makutėnienė (2016), Dakpo K. (2015), Nevzat (2014), Song *et al*. (2015), Dakpo *et al*. (2014), Cheng (2014), Song *et al*. (2013), Sueyoshi and Goto (2011), Jahanshahloo *et al* (2005), Suhariyanto and Thirtle (2001) and Färe *et al*. (1996).

Nevzat (2014) argued that DEA models can be divided into three types: radial, non-radial and oriented, and non-radial and non-oriented. The term radial denotes that the primary concern is a proportionate change in input/output values thus; this approach has one general limitation that is slacks ignorance (i.e., input excesses and output shortfalls). In other words, it disregards the presence of slacks as secondary or openly disposable. Non-radial, on the other hand, does not comply to a commensurate with adjustment in input/output and deals with slacks directly. Tone (2001) proposed non-radial slack-based measurements of efficiency (SBM). It is necessary to take slacks into account in this paper as SBM model is characterized by: (1) a scalar model works with the slacks of DMUs that are directly concerned; (2) the model is unit invariant and monotone reducing for the slacks; (3) this measure is determined only by consulting the reference-set of the DMUs, and it is unaffected by statistics encompassing the entire data set; and (4) the new measure is closely related to the other measures proposed so far, e.g., the CCR and (Lo and Lu, 2009).

However, oEnvelope models may also be 'Oriented' (input/output) or 'Nonoriented.' Input oriented models attempt to minimize input quantities as much as possible while maintaining at least the current output levels. Output-oriented models optimize output level while consuming the least amount of input. There is a third option: 'Nonoriented' models, which deal with input limitation and output augmentation simultaneously.

Furthermore, most studies in the previous research adopt the original description of DEA by suggesting that the production technology presents CRS, despite the fact that scale variability is relatively poor in the paper's studied countries.

As explained in Nevzat (2014), Bad Output Model proposed by Tone (2001), It is critical to divide the output matrix Y into desirable output (Y^{d}) and undesirable output (Y^{ud}) matrices. For a DMU (x_0 ,y_0) the decomposition is denoted as (x_0 ,y_0^d,y_0^{ud}). The constant returns to scale of the production possibility set (PPS) can be defined as follows:

$$P = \left\{ \begin{matrix} (x_0, y_0^d, \ y_0^{ud}) | x \geq X\lambda, y^d \leq y^d\lambda \\ y^{ud} \geq Y^{ud}\lambda, L \leq e\lambda \leq U, \lambda \geq 0 \end{matrix} \right\} \quad (1)$$

In equation (1), λ is the intensity vector; U and L are the upper and lower bounds of the intensity vector respectively.

The efficiency status could be defined as follows: a DMU (x_0 ,y_0^d,y_0^{ud}) is efficient in the existence of bad outputs, if there isn't a vector (x, y^d, y^{ud})∈ P such that $x_o \geq 0, y_0^d \leq y^d, y_0^{ud} \geq y^{ud}$ with at least one strict inequality. Tone (2001, 2004) suggested the SBM model with incorporation of bad outputs, specified as follows:

$$\rho^{\rightarrow} = \frac{min\left(1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_{i0}^{-}}{x_{i0}}\right)}{1+\frac{1}{s}\left(\sum_{r=1}^{s_1}\frac{s_r^d}{y_{r0}^d}+\sum_{r=1}^{s_2}\frac{s_r^{ud}}{y_{r0}^{ud}}\right)} \quad (2)$$

Subject to $\boldsymbol{x_0 = X\lambda + S^-}$, $\boldsymbol{y_0^d = Y\lambda - S^d}$, $\boldsymbol{y_0^{ud} = Y\lambda - S^{ud}}$, $\boldsymbol{L \leq e\lambda \leq U}$ **and** $\boldsymbol{S^-, S^d, S^{ud}, \lambda \geq 0}$

In equation (2), where (s–) stands for slacks of inputs, (sg) slack of good outputs, (sb) slacks of bad outputs, and λ denotes weight vector. The vectors S^- and S^{ud} define excesses in inputs and undesirable (bad) outputs, respectively, while S^d shows shortages in desirable outputs. s_1 and s_2 refer to the number of elements in $S^{ud}$and S^d and $S = S_1 + S_2$. If an optimal solution of this program is $([\rho]^{\rightarrow}, S^{-\rightarrow}, S^{d*}, S^{ud*})$, then we can show that the DMU (x_0 ,y_0^d,y_0^{ud}) is efficient in the existence of bad outputs, if only $\rho^{\rightarrow} = 1$ i.e., $S^{-\rightarrow} = 0, S^{d\rightarrow} = 0, S^{ud\rightarrow} = 0$. If the DMU is inefficient, i.e., $\rho^{\rightarrow} < 1$ we can improve and make it efficient by deleting the excesses in inputs and undesirable outputs. In other words, a DMU with score = 1 is considered to be efficient even though there is the presence of undesirable outputs, implying that all S^-, S^d and S^{ud} are equal to zero. Whereas, if the score is less than 1, expressing that the DMU is inefficient, If the DMU wishes to become more environmentally efficient, it must adjust its inputs, desirable (good) outputs, and reduce its bad outputs.

However, augmenting the shortfalls in good outputs by the following projection in equation (3):

$$\begin{aligned} x_0 &\Leftarrow x_0 - S^{-\rightarrow} \\ y_0^d &\Leftarrow y_0^d + S^{d\rightarrow} \\ y_0^{ud} &\Leftarrow y_0^{ud} - S^{ud\rightarrow} \end{aligned} \quad (3)$$

The Charnes–Cooper transformation can be used to transform the above fractional program into an analogous linear program. Taking into consideration the dual side of the linear program, the following dual program in the variables v, u^d, u^{ud} for the CRS case, i.e. $L = 0, U = \infty$ can be shown in equation (4) as follows

Subject to:

$$\max \quad u^d y^d - v x_0 - u^{ud} y_0^{ud} \quad (4)$$

$$u^d Y^d - vX - u^{ud} Y^{ud} \leq 0$$

$$v \geq \frac{1}{m}\left[\frac{1}{x_0}\right]$$

$$u^d \geq \frac{1+u^d y_0^d - v x_0 - u^{ud} y_0^{ud}}{S}\left[\frac{1}{y_0^d}\right]$$

$$u^{ud} \geq \frac{1+u^d y_0^d - v x_0 - u^{ud} y_0^{ud}}{S}\left[\frac{1}{y_0^{ud}}\right]$$

The dual variables v and u^{ud} could be interpreted as the virtual prices (costs) of inputs and bad outputs respectively, while u^d represents desirable outputs price. The dual program's goal is to achieve the optimum virtual costs and prices for the DMU such that the profit $u^d y^d - vx - u^{ud} y^{ud}$ does not exceed zero for every DMU and maximizes the profit $u^d y_0^d - vx_0 - u^{ud} y_0^{ud}$ for the DMU in concern. Obviously, the optimal profit is, at best, zero, indicating that the DMU is efficient. However, for more details is found in Tone (2001) and (2004).

Malmquist TFP Index

Färe *et al*., (1992) developed with the aid of Caves *et al*., (1982) the Malmquist productivity indicators that can be used to track productivity improvements over time. Since then, the Malmquist TFP index has been used in a series of aspects, both in the manufacturing and agricultural sectors. Grifell and Sintas (1995), for example, measured TFP shift in the European textile industry, Färe *et al* (2001) estimated productivity growth in Taiwan's manufacturing industry, and Chen and Ali (2004) analyzed productivity in the computer industry. In the agricultural sector, the Malmquist TFP measure have become extensively used in the measure and analysis of productivity by Bureau *et al*. (1995), Lusigi and Thirtle (1997), Fulginity and Perrin (1997, 1998 and 1999), Rao and Coelli (1998), Arnade (1998), Chavas (2001), Suhariyanto and Thirtle (2001), Suhariyanto *et al*. (2001), Coelli and Rao (2003), Trueblood and Coggins (2003), Nin *et al*. (2003a), Nin *et al*. (2003b) and Ludena *et al*. (2005 and 2007).

As mentioned earlier, DEA may be input oriented or output oriented. In the input oriented case, the DEA approach defines the frontier by attempting to achieve the highest relative decline in input consumption while keeping output levels constant for each province. In the output-oriented case, the DEA method seeks the greatest proportional increase in output production while holding input levels constant. By using constant return to scale (CRS) technology, the two metrics have the same technological efficiency ratings, but they are unequal when using variable return to scale (VRS). It is worth noting that returns to scale properties are critical in TFP calculation. It is advantageous to use CRS in this paper for two reasons. First, it does not appear to be sensible to consider a VRS technology given that it is using aggregate country-level data. Second, the use of a CRS technology is preferable and applicable to both firm-level and aggregate data. a simple example of one-input one-output employed by Grifell-Tatjé and Lovell (1995) to show that when VRS is assumed for the technology, a Malmquist TFP index may not accurately calculate TFP changes. Thus, CRS could be applied on any technology used to measure distance functions for the estimation of Malmquist TFP index. Otherwise, the estimated results can not accurately represent TFP gains or losses incurred by scale effects.

The prevalence of Malmquist TFP indices is largely attributed to a variety of desirable features: (1) It only includes quantity data (inputs and outputs), eliminating the complexity of calculation for fixed factors. (2) It does not involve information on input and output prices as the Tornqvist index does, without which parametric methods cannot be used. Price information is needed for the estimation of costs, profits and other functions for both index numbers and econometric methods. (3) It does not necessitate any hypotheses about the maximizing behavior of business activity (in contrast to traditional index numbers). (4) It does not necessitate econometric estimates and can be applied using the data envelopment methodology. Moreover, Malmquist TFP can be used not only to measure productivity changes over time, but it can also be decomposed into two meaningful elements, one measuring technological change (TNCh) and the other measuring technical efficiency change (TECh). When the sample size is limited, however, this method is vulnerable to data noise effects and degrees of freedom issues.

Bushara *et al* (2009) argued that Total factor productivity increases may occur as a result of either increased technical efficiency (moving closer to the production frontier) or technological advancements (outwards shifts of the production frontier). The Malmquist productivity index allowed researchers to decide how much of a sector's or firm's productivity shift was due to each of these two components Domazlicky and Weber (1997).

Distance functions offered by Malmquist index enable one to explain a multi-input, multi-output production technology without specifying a behavioral goal (such as cost minimization or profit maximization).

Input distance functions and output distance functions can be established. An input distance function portrays production technology by evaluating a minimal proportional contraction of an input vector given an output vector. An output distance function, given an input vector, considers the maximal proportional expansion of the output vector. This article, however, only focuses at an output distance function in depth. Input distance functions, on the other hand, can be defined and used in a similar way.

The output set, P(x), which represents the set of all output vectors, y, that can be generated using the input vector, x, can be $P(x) = \{y: x \text{ can produce } y\}$ used to define a production technology. That is,

It is presumed that the technology meets the axioms outlined by Coelli *et al* (1998, Ch. 3). On the output set, P(x), the output distance function is defined as follows:

$$d_0(x, y) = \min[\delta : (y/\delta) \in P(x)]$$

If the output vector, y, is an element of the feasible production set, P, the distance function, $d_0(x,y)$, will take a value less than or equal to one (x). Moreover, the distance function will return a value of one if y is located on the outer boundary of the feasible production set, and a value greater than one if y is located outside the feasible production set. The distance measurements in this analysis are measured using DEA-like methods.

Owing to Mahadevan (2002), Coelli and Rao (2003), Sufian (2007), Belloumi etal (2009) and Shahabinejad and Akbari (2010), The Malmquist TFP index calculates the ratio of the distances of each data point relative to a standard technology to determine the TFP change between two data points (e.g., that of a specific country in two adjacent time intervals). The Malmquist (output-oriented)

TFP change index between period (s) (the base period) and period (t), as specified by Färe *et al* (1994), is given by:

$$m_0(y_s, x_s, y_t, x_t) = \left[\frac{d_0^s(y_t, x_t)}{d_0^s(y_s, x_s)} \times \frac{d_0^t(y_t, x_t)}{d_0^t(y_s, x_s)}\right]^{1/2} \quad \ldots\ldots\ldots\ldots(1)$$

Where, $d_0^s(x_t, y_t)$ denotes the interval from the time (t) of observation to the period (s) of technology, (y) denotes output, and (x) denotes input. A value greater than one means positive TFP growth over the periods from (s) to (t), while a value less than one indicates negative TFP growth. It should be noted that equation 1 is the geomean of two TFP indices. The first is evaluated in terms of period (s) technology, while the second is evaluated in terms of period (t) technology. This productivity index can also be written as follows:

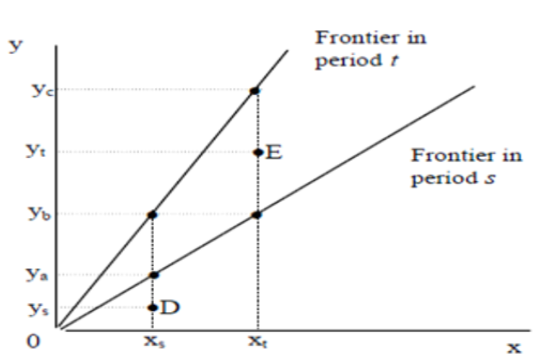
$$m_0(y_s, x_s, y_t, x_t) = \underbrace{\frac{d_0^t(y_t, x_t)}{d_0^s(y_s, x_s)}}_{\textit{Efficiency change}} \underbrace{\left[\frac{d_0^s(y_t, x_t)}{d_0^t(y_t, x_t)} \times \frac{d_0^s(y_s, x_s)}{d_0^t(y_s, x_s)}\right]^{1/2}}_{\textit{Technical Change}} \quad \ldots\ldots\ldots\ldots(2)$$

Where the ratio outside the square brackets measures the shift in the output-oriented measure of Farrell technical efficiency between periods (s) and (t). In other words, the efficiency change is equal to the ratio of the Farrell technical efficiency of period (t) to the technical efficiency in period (s). The efficiency change component defines whether production is keeping up with or declining behind the production frontier, and it is believed that this component catches technical diffusion due to variation in expertise and institutional factors (Rungsuriyawiboon and Lissitsa, 2006). The remainder of the index in equation (2) is a measure of technical change, which is the geometric mean of the technological shift between the two time intervals, as measured at x_t and x_s. however, TFP growth can be rewritten as,

$$\text{TFP Growth} = \underset{\textit{(Catching up effect)}}{\text{Technical Efficiency Change}} \times \underset{\textit{(Frontier effect)}}{\text{Technical Change}} \quad \ldots\ldots\ldots\ldots(3)$$

As cited in Rao *et al*., (2004) the diagram in Figure 3 shows how this decomposition can be explained. Coelli *et al*. (1998) illustrate a CRS technology with a single input and a single output. In periods s and t, the firm produces at points D and E, respectively. The firm operates below the technology for that time in each period.

FIGURE 3: MALMQUIST PRODUCTIVITY INDICES



Source: Rao *et al* (2004)

Thus, technological inefficiency appears in both periods. We can get the following results from equations 1 and 2:

$$\text{Efficiency Change} = \frac{y_t / y_c}{y_s / y_a} \quad \& \quad \text{Technical change} = \left[\frac{y_t / y_b}{y_t / y_c} \times \frac{y_s / y_a}{y_s / y_b}\right]^{1/2}$$

Owing to Grifell-Tatje and Lovell (1995), (CRS) technology should be adopted to estimate the above distance functions in order to measure a Malmquist TFP index accurately. Fare *et al.* (1994) decomposed the catching up effect into 'pure' technical efficiency efficiency change and scale efficiency change. The impact of new technology on a firm's ability to be more competitive is depicted by pure efficiency (Färe *et al*., 1994). That,

$$\text{Technical Efficiency Change Index} = \text{Pure Technical Efficiency Change Index} \times \text{Scale Efficiency Change Index} \quad \ldots\ldots(4)$$

Following Färe *et al.* (1994), and assuming that suitable panel data are employed, we can use the DEA linear program to determine the required distance measures for the Malmquist TFP index. To calculate the TFP change between two times, s and t, we must calculate four distance functions for the i-th country. This necessitates the resolution of four linear-programming (LP) problems. Färe *et al.* (1994) base their research on a constant returns-to-scale (CRS) technology. The appropriate LPs are as follows:

$$\begin{aligned} &\left[d_0^t(y_t, x_t)\right]^{-1} = \max_{\phi,\lambda} \phi \quad \textit{Subject to} \\ &-\phi y_{it} + Y_t\lambda \geq 0, \\ &x_{it} - X_t\lambda \geq 0, \\ &\lambda \geq 0 \quad \ldots\ldots\ldots\ldots\ldots\ldots(5) \end{aligned}$$

$$\begin{aligned} &\left[d_0^s(y_s, x_s)\right]^{-1} = \max_{\phi,\lambda} \phi \quad \textit{Subject to} \\ &-\phi y_{is} + Y_s\lambda \geq 0, \\ &x_{is} - X_s\lambda \geq 0, \\ &\lambda \geq 0 \quad \ldots\ldots\ldots\ldots\ldots\ldots(6) \end{aligned}$$

$$\begin{aligned} &\left[d_0^t(y_s, x_s)\right]^{-1} = \max_{\phi,\lambda} \phi \quad \textit{Subject to} \\ &-\phi y_{is} + Y_t\lambda \geq 0, \\ &x_{is} - X_t\lambda \geq 0, \\ &\lambda \geq 0 \quad \ldots\ldots\ldots\ldots\ldots\ldots(7) \end{aligned}$$

and

$$\begin{aligned} &\left[d_0^s(y_t, x_t)\right]^{-1} = \max_{\phi,\lambda} \phi \quad \textit{Subject to} \\ &-\phi y_{it} + Y_s\lambda \geq 0, \\ &x_{it} - X_s\lambda \geq 0, \\ &\lambda \geq 0 \quad \ldots\ldots\ldots\ldots\ldots\ldots(8) \end{aligned}$$

y_{it} is a M×1 vector of output quantities for the i-th country in the t-th period;
x_{it} is a K×1 vector of input quantities for the i-th country in the t-th period;
Y_t is a N×M matrix of output quantities for all N countries in the t-th period;
X_t is a N×K matrix of input quantities for all N countries in the t-th period;14
λ is a N×1 vector of weights; and
ϕ is a scalar with $1 \leq \phi \leq \infty$, $\phi - 1$ is the proportional increase in outputs that could be achieved by the i-th unit, with input quantities held constant (Nkamleu, 2004).

It is worth noting that in LPs (7) and (8), where production are compared with technologies from different periods of time, the φ parameter does not have to be more than or equal to one (as it must be when calculating standard output-orientated technical efficiencies). The data point may be located above the production frontier. This is most likely to happen in LP (8), where a production point from time t is compared to technology from a previous period, s. If there has been technological advancement, a value of φ<1 is conceivable. It is also possible that it could occur in LP (7) if technical regress happened, but this is less expected. More comprehensive analyses of DEA methods can be found in Seiford and Thrall (1990), Lovell (1993), Ali and Seiford (1993). Lovell (1994), Charnes etal (1995) and Seiford (1996)

However, TFP is defined as ratio of total output (crop and livestock products) to total production inputs (land, labor, capital, and materials). A rise in TFP indicates that more output is being achieved with the same amount of resources used in the production processes.

TFP is the primary driver of agricultural growth in the long run, and it can be influenced by policies and investments. Since they are simple to estimate, partial factor productivity (PFP) indicators such as labor and land productivity are frequently used to assess agricultural-production output. These productivity indicators generally show exaggerated rates of growth than TFP because growth in land and labor productivity may result from more intensive use of inputs, such as fertilizer and machinery, rather than an increase in TFP. TFP is the only source of growth if productivity rises without the addition of more inputs.

One of the strengths of MaxDEA is the splitting of technical change into three components; (1) the bias of technological change caused by output change from period t-1 to period t. (2) the bias of technological change caused by input change from periods t-1 to t. (3) the magnitude of technological change from periods t-1 to t, a value > 1 implies an increase of technical efficiency.

After gathering the suitable panel data for outputs and inputs variables and assuming constant returns to scale (CRS) as mentioned earlier, then, using DEA-like linear programs, the desired distance measurements for the Malmquist TFP index could be computed. However, a number of N (3T-2) LP's would be solved. In this study N= 10 countries and T = 10 periods (2007-2017), this requires the solving of [10 (3 ×10 – 2)] =280 LP's.

4.Estimation Process

The article employs MaxDea software to estimate SBM-DEA model with undesirable (bad) output to estimate both the agricultural sector's environmental efficiency and the Malmquist indexes of efficiency (total factor productivity). In line with Coelli and Rao (2003), Balloumi and Matoussi (2009), Shahabinejad and Akbari (2010), Le etal., (2019) and other studies, the study employed two outputs (good and bad) and six inputs (land, capital, labor, fertilizer, animal livestock, irrigation water and manure). Table 1 displays the average values of these variables and the definitions are outlined as follows.

Table 1. average outputs and inputs by country throughout the period 2007-2017

country	Egypt	Sudan	Algeria	Saudi Arabia	Morocco	Syria	Iraq	Yemen	Tunisia	Emirates
Good Output	30,411	22,538	15,853	14,582	13,060	9,842	7,885	3,350	3,763	2,451
Bad Output	30,224	64,101	10,393	5,570	13,206	6,982	7,176	7,219	4,470	1,633
Land	3,678	78,510	41,374	173,505	30,149	13,914	8,796	23,480	9,863	417
Capital	173	97	117	109	105	65	122	97	97	137
Labor	7,955	4,416	1,239	530	4,597	818	1,664	1,695	638	250
Fertilizer	1,681	120	139	267	485	162	177	20	160	35
Livestock	9,258	30,073	5,871	3,553	7,175	3,130	3,261	4,273	2,476	940
Water	61.30	25.90	5.60	18.60	9.20	14.50	44.40	3.20	3.10	2.80
Manure	30,232	101,034	22,700	19,909	33,182	5,942	13,981	10,759	14,631	2,512

Source: author calculation

Output Series

The analysis was based on two outputs, one desirable (good) and one undesirable (bad).

Desirable (good) Output

Agricultural output for crops and livestock is described as is the total value of agricultural production in million US dollar at the constant prices of 2010.

Undesirable (bad) Output

As adopted in Le (2019), this variable expresses agricultural emissions in gigagrams of CO2-equivalent. This figure reflects the cumulative GHG emissions from agricultural activities. In many previous studies, the variable of GHG emissions was used as a bad output for evaluating environmental efficiency.

Input Series

As previously mentioned, the analysis takes into account seven input variables. The following variables are defined in detail as follows

Land

This variable includes arable and permanent cropland expressed in 1000 hectare.

Capital

This variable is calculated as the value of gross fixed capital formation of agriculture, forestry and fishing. In other words, this is the country's physical investment in agriculture, expressed in millions of US dollars at 2010 constant prices.

Labor

The total economically active agricultural population in thousand people is used to calculate this variable.

Fertilizer

This article uses consumption of Nitrogen (N), Potassium (P_2O_2), and Phosphate (K_2O) in thousand metric tons, in line with other studies that used DEA, such as Hayami and Ruttan (1970), Fulginiti and Perrin (1997), and Shahabinejad and Akbari (2010).

Livestock

This variable is calculated by the animal-equivalent in livestock thousand unit.

Water Withdrawal

The study employs water withdrawal associated with farmlands irrigation as a crucial agricultural input measured in billion M^3.

Manure

This variable is measured as manure applied to soil (N content) in ton

RESULTS AND DISCUSSION

Results

Traditional CCR vs Slacks Based Measure (SBM) Results

Table (2) shows that, in general, the average efficiency for conventional DEA (excluding agricultural emissions) throughout the study period 2007-2017 is relatively higher than employing SBM approach for all selected Arab countries, where it reached about 0.87 for the first compared to 0.66 for the latter, indicating a misleading and spurious efficiency scores if bad output (agricultural emissions) is not considered. Thus, the study would rely on SBM results for their creditability. However, the average non-oriented and non-radial SBM efficiency during the period 2007-2017 depicts that the Arabian agricultural sector has to improve its efficiency by 34% (on average). Moreover, SBM results show that Saudi Arabia is ranked the first (95%), followed by Syria, Algeria, Egypt and Emirates about 91% (on average). Then comes Sudan 75%, Morocco 44%, Iraq 55%, Yemen 39% and finally Tunisia 33%.

TABLE 2. conventional and sbm efficiency scores during the period 2007-2017

Country	Conventional TE Score	SBM TE Scores
Saudi Arabia	0.99	0.95
Syria	0.98	0.93
Algeria	0.98	0.92
Egypt	0.97	0.92
Emirates	0.97	0.89
Sudan	0.94	0.75
Morocco	0.82	0.44
Iraq	0.78	0.55
Yemen	0.74	0.39
Tunisia	0.60	0.33

Source: Appendix 1

It is worth mentioning that, the lower the difference between SBM technical efficiency score compared to conventional score may be presumably due to either lower levels of bad output (GHG emissions) or successful environmental plans achievements, for example, the first case could be seen for Saudi Arabia while the second for Egypt. Moreover, the higher the difference indicates a lot needed to be done by environmental policy advisors.

Figure (4) shows the disaggregation of SBM inefficiency into input and output inefficiencies. In general, the results show that input inefficacy is higher than output inefficiency for all countries with different levels.

Malmquist Results

Conceptually, a country can increase its agricultural productivity by two different ways. One approach is to increase efficiency change by increasing the diffusion of technology, while the other is to encourage technical change through the importation and adoption of innovative technology. A combination of the two approaches boosts agricultural production.

There is massive computer output on efficiency scores for each country in each year to illustrate. The outcomes include technical efficiency change, technical change, and TFP change for each country in each pair of adjacent years (see Appendixes 2). However, the paper would be selective in what results to present.

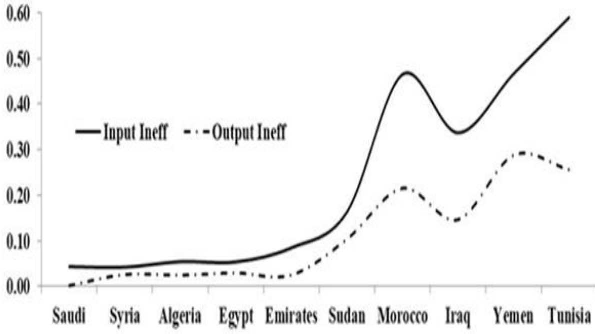


Figure 4. Input and Output Inefficiency during the period 2007-2017

Source: Appendix 2

An output oriented technical efficiency level depicts the ratio of each country's actual output to what is feasible (given the available technology in that period). The DEA technique identifies technology in each period as a piece-wise linear envelopment of all observed points in the multi output and multi-input Euclidean space. The countries that define the technological frontier are referred to as "peers," or the best-performing countries. Peer countries have a technical efficiency score of one, and each year there are normally multiple peers.

The results show that the annual average TFP index of the studied countries during the period 2007-2017 is 0.9988, that is, their TFP grows at an average annual rate of -0.12%. The decomposition results show that increase in TFP is mainly driven by a technological regression of 0.37%, whereas the efficiency change produced a negative effect of -0.49% on TFP.

According to Table 3, the annual average growth rate of TFP for Syria, Morocco, Yemen and Algeria are 6.28%, 5.65%, 4.31% and 2.79% respectively. Then come, Sudan and Saud Arabia accounting 0.56% and 0.47% respectively. On the contrary, Iraq, Egypt, United Arab Emirates and Tunisia achieved a negative TFP annual growth accounted about -14.55%, -2.37%, -2.3% and -0.32% respectively. Except for Egypt and United Arab Emirates, technological change the key motivator the growth of TFP in the studied countries. It worth mentioning that Iraq showed a negative annual growth rate in both technological change and efficiency change estimated at -10.90% and -4.09% respectively. Although the technological change in Syria has an average annual increase of 6.28%, higher than all other studied countries, its efficiency change has not changed. The above results indicate that the ineffective management or the unreasonable resource allocation mainly restrict their TFP growth.

As cited in Le etal., (2018), Suhariyanto and Thirtle (2001) clarified that variations in agricultural productivity levels between countries and over time were caused by the financial resources, circumstances, and level of economic development of each country. However, Coelli and Rao

(2005) stated that the increase in agricultural productivity in Asia from 1980 to 2000 was primarily due to improved efficiency. The main explanation for this disparity can be seen in a shift in agricultural goals over time. In the past, most countries used to seek agricultural production increment, but recently, more and more advanced technologies have been introduced in agriculture, and the target is to produce efficiently while not jeopardizing societal well-being.

Table 3. TFP, EC and TC Results

	MI TFP	EC	TC	OBTC	IBTC	MATC
Iraq	0.8545	0.9591	0.8910	1.0000	1.2796	0.6963
Egypt	0.9763	1.0000	0.9763	1.0000	1.1462	0.8518
Emirates	0.9769	1.0000	0.9769	1.0000	1.1327	0.8624
Tunisia	0.9968	0.9793	1.0179	1.0000	1.0929	0.9193
Saudi	1.0047	1.0000	1.0047	1.0000	0.9997	1.0182
Sudan	1.0056	1.0000	1.0056	1.0000	1.1755	0.8555
Algeria	1.0279	1.0000	1.0279	1.0000	1.1281	0.9112
Yemen	1.0431	0.9848	1.0592	1.0000	1.1837	0.8948
Morocco	1.0565	1.0295	1.0262	1.0000	1.0011	1.0251
Syria	1.0628	1.0000	1.0628	1.0000	1.2618	0.8422
Overall Geomean	0.9988	0.9951	1.0037	1.0000	1.1366	0.8830

Source: author calculations Appendices 3A and 3B

As a matter of completeness, for output biased technical change, the results show that all studied countries have scored unity, meaning no technological progress in output production. On the contrary, for the index of input bias, all studied countries have scored more than unity meaning technological progress in the use of inputs with various levels. So, for the magnitude of technological change, only Morocco and Saudi Arabia experienced magnitude technological progress greater than one. However, more research is needed to study this issue in depth to determine the progress happened in which input/inputs in particular. However, that could be a new topic for further studies.

CONCLUSION

The main perspective for this study is to assess the impacts of agricultural emissions on efficiency and estimate agricultural total factor productivity for major Arab countries. This paper employed maxDEA software, Tone (2001) suggested the Bad Output model, which is nonradial and nonoriented, and explicitly uses input and output slacks in generating efficiency measures under CRS. However, the bad output model, handles both good and undesirable (bad) outputs separately.

The annual average TFP, efficiency change and technical change for the time period 2007–2017 show that Syria, Morocco, Yemen, Algeria and Sudan were found to have had positive changes in TFP. In other words, implying that the equivalent average growth in agricultural TFP was about 6% for each Syria and Morocco, 4% for Yemen, 3% for Algeria and 1% for Sudan. Moreover, all these productivity improvements resulted from growth in technical changes while the efficiency changes were sustained. On the other hand, Emirates, Egypt and Iraq showed TFP levels less than one, indicating fall in their agricultural productivity. In contrast, Saudi Arabia and Tunisia were shown to have stable TFP throughout the studied period.

Decomposing TFP index into its components technical change (TC) and efficiency change (EC), the results show that efficiency change results for Iraq, Egypt and Emirates is higher than technical change. Whereas, Morocco and Saudi Arabia are the only two Arab countries, where, their TFP growth is attributed equally to both efficiency change and technical change, meaning that there was no change in efficiency. On the other hand, technical change attributes to TFP in Syria, Yemen, Algeria, Tunisia and Sudan than efficiency change.

It is worth mentioning that in all of the countries surveyed, the overall contribution of technical change to overall productivity improvements is higher than efficiency change. Even with current technologies, this means a significant potential increase in production. It is critical to reverse the efficiency recession that is evident in the majority of countries and attain a rapid and more widespread diffusion of technical innovations across regions.

In line with Telleria and Hassan (2011), the fact that technical change has been the primary driver behind TPF suggests that investing in agricultural research is the primary lever for increasing productivity. However, it should be noted that low efficiency change values typically mean that there are long time lags between agricultural research investments and productivity response. This implies that agricultural research investment must be followed by agricultural extension programs that contribute not only to expanding the use of modern technologies, but also to agricultural capital formation.

Finally, the government should take the serious proceedings to improve crop productivity and supply growers with comprehensive and coordinated services and support in order to make crop growing more effective.

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REFERENCES

(AOAD), Arab Organization for Agricultural Development, on line statistics, www.aoad.org

Aigner, D., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. Journal of Econometrics, 6(1), 21-37. doi: 10.1016/0304-4076(77)90052-5

Akbar, U., Popp, J., Khan, H., Khan, M.A., Oláh, J. (2020) "Energy Efficiency in Transportation along with the Belt and Road Countries". Energies, 13, 2607.

Ali, A.I. and L.M. Seiford (1993). "The Mathematical Programming Approach to Efficiency Analysis" in The Measurement of Productive Efficiency: Techniques and Applications", (Eds) H. O. Fried, C. A. K. Lovell and S. S. Schmidt, Oxford University Press, New York, 120-159.

Amara, N., Traoré, N., Landry, R., & Remain, R. (1999). Technical Efficiency and Farmers' Attitudes toward Technological Innovation: The Case of the Potato Farmers in Quebec. Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie, 47(1), 31-43. doi: 10.1111/j.1744-7976.1999.tb00214.x

Arnade, C. (1998). “Using a programming approach to measure international agricultural efficiency and productivity”. Journal of Agricultural Economics 49: 67–84.

Baležentis., T and Makutėnienė., D (2016) “Energy-related carbon dioxide emissions and environmental efficiency in the European union agriculture: comparison of different benchmarking techniques management theory and studies for rural business and infrastructure Development”. Vol. 38. No. 3: 192–206ISSN 1822-6760, ISSN 2345-0355. DOI: 10.15544/mts.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. Management Science, 30(9), 1078-1092.

Belloumi, M and Matoussi, M S., (2009). “Measuring agricultural productivity growth in MENA countries”. Journal of Development and Agricultural Economics Vol. 1(4), pp. 103-113.

Bravo-Ureta, B., Solís, D., Moreira López, V., Maripani, J., Thiam, A., & Rivas, T. (2007). “Technical efficiency in farming: a meta-regression analysis”. Journal of Productivity Analysis, 27(1), 57-72. doi: 10.1007/s11123-006-0025-3

Bureau, C., R. Färe, and S. Grosskopf. (1995). “A comparison of three nonparametric measures of productivity growth in European and United States Agriculture”. Journal of Agricultural Economics 45: 309–26.

Bushara, M and Mohayidin M. G., (2009). “Catching-up and Technological Change in Malaysian Oil and Fat Industry: A Nonparametric Frontier Analysis”. University Of Gezira, Sudan, Gezira Journal of Engineering and Applied Sciences. Vol.2 (2).

Caves, D.W., Christensen, L.R., Diewert, W.E. (1982). The economic theory of index numbers and the measurement of input, output and productivity. Econometric, 50(6), 1414- 1939.

Charnes, A., Cooper, W., & Rhodes, E. (1978). Measuring efficiency of decision-making units. European Journal of Operation Research, 6, 429–444.

Charnes, Al, W.W. Cooper, A.Y. Lewin and L.M. Seiford (1995). “Data Envelope Analysis: Theory, Methodology and Applications”, Kluwer

Chavas, J. P. (2001). An international analysis of agricultural productivity. In Agricultural investment and productivity in developing countries, edited by L. Zepeda. Rome: Food and Agriculture Organization.

Chen, Y., Ali, A.I. (2004). “DEA Malmquist productivity measure: New insights with an application to computer industry”. European Journal of Operational Research , 159 (1), 239- 249

Chen., H, Liu., J, Li., Y, Chiu., Y and Lin., T (2019) “Two-stage Dynamic Undesirable Data Envelopment Analysis Model Focused on Media Reports and the Impact on Energy and Health Efficiency” International Journal of Environmental Research and Public Health, 16, 1535. doi:10.3390/ijerph16091535

Cheng, G. (2014). “Data Envelopment Analysis: Methods and MaxDEA Software” [in Chinese].Beijing: Intellectual Property Publishing House Co., Ltd.

Coelli, T. J., and Rao , D.S (2003). “Total factor productivity growth in agriculture: a Malmquist index analysis of 193 countries. Centre for Efficiency and Productivity Analysis”. School of Economics. University of Queensland. St Lucia. Australia. Working paper 02/2003. 30 pages

Coelli, T.J., D.S. Prasada Rao and G.E. Battese (1998). “An Introduction to Efficiency and Productivity Analysis”, Kluwer Academic Publishers, Boston.

Dakpo, Hervé K & Jeanneaux, Philippe & Latruffe, Laure, 2014. "Inclusion of undesirable outputs in production technology modeling: The case of greenhouse gas emissions in French meat sheep farming. Working Paper SMART – LERECO N°14-08

Dakpo., KH (2015) “Non-parametric modelling of pollution-generating technologies: theoretical and methodological considerations, with an application to the case of greenhouse gas emissions in suckler breeding systems in French grassland areas”. Economics and Finance, Université d’Auvergne - Clermont-Ferrand I. NNT: 2015CLF10474.

Domazlicky, B. R., William L. Weber. (1997). “Total Factor Productivity in the Contiguous United States, 1977 – 1986”. Journal of Regional Science 37 (2): 213-233.

Dong ., G, Wang., Z, Mao., X (2018) “Production efficiency and GHG emissions reduction potential evaluation in the crop production system based on emergy synthesis and nonseparable undesirable output DEA: A case study in Zhejiang Province, China”. PLoS ONE 13(11): e0206680. https://doi.org/10.1371/journal.pone.0206680

El-Kholei, A., Abo-Zeid, A., and Abo-Saad, H. “Further Evidence on Agricultural Output and Rural-Urban Migration Linkages in Egypt: Drives and Policy Implications”. Alexandria Journal of Agricultural Research, 2008, 53(2), pp. 13-21.

FAO, Food and Agriculture Organization, online statistics.

Färe, R., Grosskopf, S., Lee, W. (2001). Productivity and technical change: The case of Taiwan. Applied Economics, vol. 33, 1911- 1925.

Färe, R., Grosskopf, S., Lindgren B., Roos P. (1992). Productivity change in Swedish pharmacies 1980-1989: A non- parametric Malmquist approach. Journal of Productivity Analysis, 3, 85- 102.

Färe, R., Grosskopf, S., Norris, M. and Zhang, Z., (1994). “Productivity growth, technical progress and efficiency change in Indus trialized countries.” American Economic Review 84, 66--83.

Färe, R., S. Grosskof, and C. A. K. Lovell (1994). “Production Frontiers”, Cambridge University Press.

Farrel, M., 1957. “The Measurement of Productive Efficiency” Journal of the Royal Statistical Society. Series A, general, 120(3): 253-281.

Fulginiti, L., and Perrin, R.K. (1999). “Have price policies damaged LDC agricultural productivity?” Contemporary Economic Policy 17: 469–75.

Fulginiti, L., and Perrin, R.K. (1998). “Agricultural productivity in developing countries”. Agricultural Economics , 19 (1- 2), 45- 51 .

Fulginiti, L.E., Perrin, R.K. (1997). “LDC Agriculture: Nonparametric Malmquist Productivity Index”. Journal of Development Economics , 53, 373- 390.

Galanopoulos, K., Lindberg, E., Surry, Y., and Mattas, K., (2006). Agricultural situation in the Mediterranean and Tests of Convergence Among Countries. Paper prepared for presentation at the 98th EAAE Seminar 'Marketing Dynamics within the Global Trading System: New Perspectives', Chania, Crete, Greece as in: 29 June – 2 July.

Garibaldi, L. A., Aizen, M. A., Klein, A. M., Cunningham, S. A., & Harder, L. D. (2011). "Global growth and stability of agricultural yield decrease with pollinator dependence". Proceedings of the National Academy of Sciences, 108(14), 5909-5914. doi: 10.1073/pnas.1012431108

Grifell, E. and J. López Sintas (1995). Total Factor productivity: technical efficiency, bias and technical change in the European textile- clothing industry, 1980- 1989. Management Report series No 210. Erasmus University. Rotterdam School of Management. Rotterdam. March 1995.

Grifell-Tatj'e, E. and Lovell, C. A. K, (1995). "A Note on the Malmquist Productivity Index". Economics Letters 47, 169-175.

Gutierrez, L. (2000). "Convergence in US and EU agriculture". European Review of Agricultural Economics, 27(2), 187- 206.

Hayami, Y., Ruttan, V.W. (1970). Agricultural Productivity Differences Y among Countries. American Economic Review, vol. 60(5), 895- 911.

Jahanshahloo., G , Lotfi., F , Shoja., N , Tohidi., G and Razavyan., S (2005) "Undesirable inputs and outputs in DEA models". Applied Mathematics and Computation 169, 917–925

Komleh S., Zylowski T., Rozakis S and Kozyra J. (2020). "Efficiency under different methods for incorporating undesirable outputs in an LCA+DEA framework: A case study of winter wheat production in Poland". Journal of Environmental Management 260, pp 110-138.

Li, K., Qu, J., Wei, P., Ai, H. and Jia, P. (2020) "Modelling technological bias and productivity growth: a case study of China's three urban agglomerations", Technological and Economic Development of Economy, 26(1), pp. 135-164. doi: 10.3846/tede.2020.11329.

Linh Le T., Lee P., Chung Peng K., H. Chung R. (2019) "Evaluation of total factor productivity and environmental efficiency of agriculture in nine East Asian countries. " Agric. Econ. – Czech, 65: 249-258.

Linh Le., T, Hailuu., T, Huynh., N and Chung., R (2020) "Environmental efficiency of rice production in Vietnam: An application of SBM-DEA with undesirable output". Biodiversitas, Volume 21, Number 6, pp. 2710-2715, ISSN: 1412-033X, E-ISSN: 2085-4722, DOI:10.13057/biodiv/d210645

Lovell, C A K. (1993). "Production frontiers and productive efficiency", in The Measurement of Productive Efficiency: Techniques and Applications", (Eds) H. O. Fried, C. A. K. Lovell and S. S. Schmidt, Oxford University Press, Oxford, UK.

Lovell, C A K. (1994). "Linear Programming Approaches to The Measurement and Analysis of Productive Efficiency" Top, 2, 175-248

Ludena, C. E., Hertel, T. W., Preckel, P. V., Foster, K., Nin- Pratt, A. (2005). "Technological change and convergence in crops and livestock production" Contributed paper presented for the 8th Annual Conference on Global Economic Analysis, Lübeck, Germany, June 9- 11, 2005.

Ludena, C. E., T. W. Hertel, P. V. Preckel, K. Foster, and A. Nin. (2007). "Productivity growth and convergence in crop, ruminant, and non-ruminant production: Measurement and forecasts". Agricultural Economics 37 (1): 1–17

Lusigi, A., and C. Thirtle. (1997). "Total factor productivity and the effects of R&D in African agriculture". Journal of International Development 9: 529–38.

Mahadevan, R., (2002). "A DEA Approach to Understanding the Productivity Growth of Malaysia's Manufacturing Industries" Asia Pacific Journal of Management, 19(4), pp. 587–600

McErlean, S., Wu, Z. (2003). "Regional agricultural labour productivity convergence in China". Food Policy, 28, 237- 252.

Moreno-Moreno, J., Sanz Díaz, M.T., Velasco Morente, F. y Ludena, C. E. (2017). A DEA-based Evaluation of Latin America and the Caribbean Agricultural Environmental Performance under the Assumption of Natural and Managerial Efficiency. Revista de economía mundial, 47, 157-178.

Mukherjee, A.N., Kuroda, Y. (2003). "Productivity growth in Indian agriculture: Is there evidence of convergence across states?" Agricultural Economics, 29, 43- 53.

Nevzat Simsek (2014). "Energy Efficiency with Undesirable Output at the Economy-Wide Level: Cross Country Comparison in OECD Sample". American Journal of Energy Research. 2(1):9-17. doi: 10.12691/ajer-2-1-2

Nin, A., B. Yu, and S. Fan, 2008. "Developing Countries and Total Factor Productivity Growth in Agriculture: New Evidence Using a Malmquist Index with Constrained Implicit Shadow Prices" Paper presented at Presented at the 11th Annual Conference on Global Economic Analysis, Helsinki, Finland

Nin, A., C. Arndt, and P. Preckel. (2003a). "Is agricultural productivity in developing countries really shrinking? New evidence using a modified non-parametric approach". Journal of Development Economics 71: 395–415.

Nin, A., C. Arndt, T. Hertel, and P. Preckel. (2003b). "Bridging the gap between partial and total factor productivity measures using directional distance functions". American Journal of Agricultural Economics 85 (4): 937–51.

Nkamleu GB (2004). Productivity Growth, Technical Progress and Efficiency Change in African Agriculture. Afr Dev. Rev. 16: 203-222.Rao, P., and Alauddin M (2004). "Agricultural productivity growth, employment and poverty in developing countries, 1970-2000". Centre for Efficiency and Productivity Analysis (CEPA), Employment Strategy Paper no. 9/2004, School of Economics, University of Queensland, Brisbane, Australia.

Rao, P., and T. J. Coelli. (1998). "Catch-up and convergence in global agricultural productivity, 1980–1995". CEPA Working Papers, No. 4/98, Department of Econometrics, University of New England, Armidale, p. 25.

Rungsuriyawiboon, S and Lissitsa A (2006) "Agricultural Productivity Growth in The European union and Transition Countries". Leibniz Institute of Agricultural Development in Central and Eastern Europe. Discussion Paper No.94

Seiford, L M and Thrall R M. (1990). "Recent Development in DEA: The Mathematical Programming Approach to Frontier Analysis". Journal of Econometrics

Seiford, L.M. (1996). "Data Envelope Analysis: The Evolution of the State of the Art (1978-1995)". Journal of Productivity Analysis, 7, pp 99-138

Shahabinejad, V and Akbari, A (2010). "Measuringagricultural productivity growth in Developing Eight" Journal of Development and Agricultural Economics Vol. 2(9), pp. 326-332.

Song M., Wang S and Liu Q. (2013). "Environmental efficiency evaluation considering the maximization of desirable outputs and its application Mathematical and Computer Modelling" 58, pp 1110–1116

Sueyoshi T, Goto M, (2011) "DEA approach for unified efficiency measurement: Assessment of Japanese fossil fuel power generation", Energy Economics, Volume 33, Issue 2, , Pages 292-303, ISSN 0140-9883, https: // doi.org /10.1016 /j.eneco. 2010.07.008 .(http : //www .sciencedirect. com /science /article/pii/S0140988310001179)

Sufian, F., (2007). "The efficiency of Islamic banking industry in Malaysia: Foreign vs domestic banks" Humanomics, Vol. 23(3), pp.174 - 192

Suhariyanto, K., A. Lusigi, and C. Thirtle. (2001). "Productivity growth and convergence in Asian and African agriculture". In Asia and Africa in comparative economic perspective, edited by P. Lawrence and C. Thirtle, 258–74. London: Palgrave.

Suhariyanto, K., and C. Thirtle. (2001). "Asian agricultural productivity and convergence". Journal of Agricultural Economics 52: 96–110.

Telleria, R and Hassan, A (2011), "Agricultural Productivity in the WANA Region", the Journal of Comparative Asian Development, Vol. 10(1)

Thiam, A., Bravo-Ureta, B. E., & Rivas, T. E. (2001). "Technical efficiency in developing country agriculture: a meta-analysis". Agricultural Economics, 25(2-3), 235-243. doi: 10.1111/j.1574-0862.2001.tb00204.x

Tone K. (2004), Dealing with Undesirable Outputs in DEA: A Slacks-Based Measure (SBM) Approach. National Graduate Institute for Policy Studies, Tokyo, Japan.

Tone, K. (2001), 'A slacks-based measure of efficiency in data envelopment analysis, European Journal of Operational Research, Vol. 130, pp.498-509.

Trueblood, M. A., and J. Coggins. (2003). "Intercountry agricultural efficiency and productivity: A Malmquist index approach". Mimeo. World Bank, Washington, D.C.

Wiebe, K., Soule, M., Narrod, C., Breneman, V. (2000). "Resource quality and agricultural productivity: a multi - country comparison". Selected paper for presentation at the annual meeting of the American Association of Agricultural Economists. Tampa, Florida, July 31 2000.

World Bank, World Development Indicators, online statistics

APPENDIXES

Appendix 1.

SBM Efficiency Results during 2008-2017

	Algeria	Egypt	Emirates	Iraq	Morocco	Saudi	Sudan	Syria	Tunisia	Yemen
2007	1.00	0.82	1.00	1.00	0.33	1.00	0.52	1.00	0.31	0.26
2008	1.00	0.76	0.77	0.71	0.36	1.00	0.59	1.00	0.28	0.34
2009	1.00	1.00	1.00	0.31	0.58	0.89	1.00	1.00	0.34	0.25
2010	0.72	1.00	1.00	1.00	0.47	0.93	0.66	1.00	0.34	0.54
2011	0.74	0.97	0.75	0.40	0.42	1.00	0.68	1.00	0.27	0.34
2012	1.00	1.00	0.85	0.43	0.44	1.00	0.73	1.00	0.33	0.74
2013	1.00	0.87	1.00	0.37	0.40	1.00	0.84	0.73	0.34	0.50
2014	0.87	0.92	0.81	0.56	0.49	0.91	1.00	0.82	0.33	0.30
2015	0.86	0.93	1.00	1.00	0.47	1.00	0.91	0.83	0.34	0.29
2016	1.00	0.89	0.79	0.45	0.48	0.87	0.76	0.93	0.38	1.00
2017	1.00	0.97	0.88	0.38	0.43	0.89	0.75	1.00	0.37	0.23

SOURCE: MAXDEA SOFTWARE RESULTS

CCR Efficiency Results during 2008-2017

	Algeria	Egypt	Emirates	Iraq	Morocco	Saudi	Sudan	Syria	Tunisia	Yemen
2007	1.00	0.98	1.00	1.00	0.73	1.00	0.81	1.00	0.62	0.59
2008	1.00	0.89	0.90	0.87	0.72	1.00	0.87	1.00	0.56	0.76
2009	1.00	1.00	1.00	0.54	1.00	0.97	1.00	1.00	0.63	0.58
2010	0.93	1.00	1.00	1.00	0.84	0.99	0.96	1.00	0.61	0.89
2011	0.93	1.00	0.94	0.77	0.78	1.00	0.95	1.00	0.55	0.74
2012	1.00	1.00	0.96	0.76	0.79	1.00	0.95	1.00	0.60	0.97
2013	1.00	0.96	1.00	0.60	0.76	1.00	0.94	0.88	0.64	0.90
2014	0.95	0.96	0.95	0.84	0.88	0.97	1.00	0.90	0.55	0.67
2015	0.92	0.97	1.00	1.00	0.86	0.98	0.98	0.95	0.60	0.68
2016	1.00	0.95	0.95	0.75	0.88	0.97	0.95	1.00	0.66	1.00
2017	1.00	0.98	0.97	0.66	0.79	0.97	0.94	1.00	0.62	0.55

Source: MaxDEA Software Results

Appendix 2

Input Inefficiency SBM model

	Algeria	Egypt	Emirates	Iraq	Morocco	Saudi	Sudan	Syria	Tunisia	Yemen
2007	0.00	0.11	0.00	0.00	0.58	0.00	0.34	0.00	0.60	0.64
2008	0.00	0.15	0.17	0.20	0.55	0.00	0.29	0.00	0.64	0.54
2009	0.00	0.00	0.00	0.62	0.33	0.11	0.00	0.00	0.58	0.65
2010	0.21	0.00	0.00	0.00	0.43	0.06	0.28	0.00	0.58	0.33
2011	0.19	0.02	0.19	0.50	0.49	0.00	0.27	0.00	0.65	0.55
2012	0.00	0.00	0.13	0.47	0.47	0.00	0.21	0.00	0.59	0.17
2013	0.00	0.08	0.00	0.55	0.50	0.00	0.08	0.17	0.58	0.37
2014	0.10	0.06	0.18	0.36	0.42	0.07	0.00	0.12	0.59	0.59
2015	0.10	0.05	0.00	0.00	0.44	0.00	0.06	0.14	0.58	0.60
2016	0.00	0.09	0.17	0.47	0.43	0.13	0.13	0.04	0.54	0.00
2017	0.00	0.03	0.10	0.54	0.48	0.11	0.14	0.00	0.55	0.68

Source: MaxDEA Software Results

Output Inefficiency SBM model

	Algeria	Egypt	Emirates	Iraq	Morocco	Saudi	Sudan	Syria	Tunisia	Yemen
2007	0.00	0.09	0.00	0.00	0.30	0.00	0.28	0.00	0.29	0.37
2008	0.00	0.12	0.08	0.12	0.26	0.00	0.20	0.00	0.28	0.34
2009	0.00	0.00	0.00	0.23	0.16	0.00	0.00	0.00	0.24	0.40
2010	0.09	0.00	0.00	0.00	0.19	0.01	0.09	0.00	0.27	0.23
2011	0.10	0.01	0.08	0.25	0.22	0.00	0.08	0.00	0.30	0.34
2012	0.00	0.00	0.02	0.22	0.21	0.00	0.08	0.00	0.26	0.12
2013	0.00	0.05	0.00	0.23	0.23	0.00	0.09	0.14	0.25	0.26
2014	0.03	0.02	0.01	0.15	0.18	0.01	0.00	0.08	0.25	0.34
2015	0.05	0.02	0.00	0.00	0.20	0.00	0.03	0.04	0.26	0.36
2016	0.00	0.02	0.05	0.18	0.20	0.00	0.14	0.03	0.22	0.00
2017	0.00	0.00	0.02	0.22	0.22	0.00	0.16	0.00	0.22	0.40

Source: MaxDEA Software Results

Appendix 3.

3A: TFP Results during 2008-2017

Malmquist Index[i]		Algeria	Egypt	Emirates	Iraq	Morocco	Saudi Arabia	Sudan	Syria	Tunisia	Yemen
	MI	1.10	0.91	0.80	0.50	1.09	1.21	1.04	0.97	0.87	1.47
2008	EC	1.00	1.00	1.00	1.00	1.19	1.00	1.00	1.00	0.97	1.06
	TC	1.10	0.91	0.80	0.50	0.91	1.21	1.04	0.97	0.89	1.40
	MI	1.00	1.14	1.11	1.82	1.26	1.03	0.80	1.14	1.10	1.21
2009	EC	1.00	1.00	1.00	1.00	1.09	1.00	1.00	1.00	0.97	1.03
	TC	1.00	1.14	1.11	1.82	1.15	1.03	0.80	1.14	1.13	1.18
	MI	1.03	0.97	0.86	0.37	0.93	1.07	0.94	1.00	0.90	0.71
2010	EC	1.00	1.00	1.00	0.86	0.95	1.00	1.00	1.00	0.90	1.00
	TC	1.03	0.97	0.86	0.43	0.97	1.07	0.94	1.00	1.00	0.71
	MI	1.12	1.05	1.02	0.98	1.08	0.97	1.12	0.90	1.10	1.51
2011	EC	1.00	1.00	1.00	1.09	1.02	1.00	1.00	1.00	1.00	1.00
	TC	1.12	1.05	1.02	0.90	1.06	0.97	1.12	0.90	1.10	1.51
	MI	0.97	0.72	0.97	0.81	0.92	0.99	1.44	0.93	1.07	0.91
2012	EC	1.00	1.00	1.00	0.85	0.88	1.00	1.00	1.00	1.10	1.00
	TC	0.97	0.72	0.97	0.95	1.04	0.99	1.44	0.93	0.97	0.91
	MI	0.96	1.06	0.89	1.25	1.21	0.90	1.18	1.11	0.85	0.78
2013	EC	1.00	1.00	1.00	1.25	1.19	1.00	1.00	1.00	0.84	0.81
	TC	0.96	1.06	0.89	1.00	1.02	0.90	1.18	1.11	1.01	0.97
	MI	1.01	0.97	1.14	1.19	0.99	0.94	0.80	1.21	1.07	1.00
2014	EC	1.00	1.00	1.00	1.00	0.98	1.00	1.00	1.00	1.05	1.08
	TC	1.01	0.97	1.14	1.19	1.00	0.94	0.80	1.21	1.01	0.93
	MI	1.09	0.84	0.97	0.73	1.01	0.91	0.91	1.13	1.11	2.75
2015	EC	1.00	1.00	1.00	0.96	0.96	1.00	1.00	1.00	1.06	1.15
	TC	1.09	0.84	0.97	0.76	1.05	0.91	0.91	1.13	1.05	2.39
	MI	1.05	1.16	1.03	0.89	0.91	1.08	0.91	1.10	0.94	0.35
2016	EC	1.00	1.00	1.00	0.88	0.89	1.00	1.00	1.00	0.92	0.74
	TC	1.05	1.16	1.03	1.01	1.03	1.08	0.91	1.10	1.03	0.47
	MI	0.96	1.02	1.04	0.81	1.26	0.99	1.08	1.20	1.01	1.14
2017	EC	1.00	1.00	1.00	0.78	1.20	1.00	1.00	1.00	0.99	1.06
	TC	0.96	1.02	1.04	1.04	1.04	0.99	1.08	1.20	1.02	1.07

Source: MaxDEA Software Results

3B: OBTC, IBTC AND MATC RESULTS DURING 2008-2017

Technical Change[ii]		Algeria	Egypt	Emirates	Iraq	Morocco	Saudi	Sudan	Syria	Tunisia	Yemen
	OBTC	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2008	IBTC	1.35	1.16	1.13	1.78	1.01	1.24	1.04	1.09	1.00	0.96
	MATC	0.81	0.79	0.71	0.28	0.90	0.97	1.00	0.89	0.89	1.46
	OBTC	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2009	IBTC	1.28	1.15	1.24	1.89	1.00	1.06	1.48	1.20	1.00	1.06
	MATC	0.78	0.99	0.89	0.97	1.15	0.97	0.54	0.95	1.13	1.11
	OBTC	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2010	IBTC	1.08	1.09	1.14	2.72	1.00	1.06	1.08	1.45	1.00	1.19
	MATC	0.95	0.89	0.75	0.16	0.97	1.01	0.87	0.69	1.00	0.60
	OBTC	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2011	IBTC	1.05	1.07	1.05	1.02	1.00	1.06	1.13	1.21	1.00	1.20
	MATC	1.07	0.99	0.97	0.89	1.06	0.91	0.99	0.74	1.10	1.27
	OBTC	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2012	IBTC	1.14	1.44	1.35	0.97	1.00	1.05	1.47	1.20	1.00	1.02
	MATC	0.85	0.50	0.72	0.98	1.03	0.94	0.98	0.77	0.97	0.90
	OBTC	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2013	IBTC	1.14	1.10	1.14	1.01	1.01	1.12	1.12	1.34	0.99	1.02
	MATC	0.84	0.96	0.78	0.98	1.01	0.80	1.05	0.83	1.02	0.95
	OBTC	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2014	IBTC	1.09	1.06	1.20	1.21	0.98	1.13	1.25	1.41	1.00	1.00
	MATC	0.93	0.92	0.95	0.98	1.02	0.83	0.64	0.86	1.01	0.93
	OBTC	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2015	IBTC	1.04	1.29	1.08	1.08	1.00	1.10	1.11	1.11	1.00	2.06
	MATC	1.05	0.65	0.90	0.70	1.05	0.83	0.82	1.02	1.05	1.16
	OBTC	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2016	IBTC	1.07	1.13	1.02	1.00	1.00	1.10	1.15	1.22	1.00	1.73
	MATC	0.99	1.03	1.01	1.01	1.03	0.98	0.79	0.90	1.02	0.27
	OBTC	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2017	IBTC	1.07	1.02	1.02	0.99	1.00	1.01	1.03	1.45	1.00	1.01
	MATC	0.89	1.01	1.02	1.05	1.04	0.98	1.05	0.83	1.02	1.06

Source: MaxDEA Software Results

تقدير مؤشر مالمكويست للإنتاجية الكلية للعوامل الزراعية و الكفاءة البيئية لبعض الدول العربية مستخدماً طريقة مغلف البيانات: المنهج الا معلمى

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قسم الاقتصاد الزراعى-كلية الزراعة-جامعة طنطا

يهدف البحث الى تقييم آثار الانبعاثات الزراعية وانعكاسها على الكفاءة التكنولوجية الزراعية والانتاجية الكلية لعوامل الانتاج الزراعي لبعض الدول العربية. وقد استخدم هذا البحث رقم أو مؤشر مالمكويست لقياس وتحليل الإنتاجية باستخدام المدخل اللابرامترى (DEA), كما طبق البحث نموذج المخرجات الضارة الذي اقترحه (Tone, 2001) باستخدام برنامج maxDEA. ويستند النموذج المطبق على الفوائض الغير المستغلة (راكده) سواء فى المدخلات و/أو مخرجات الانتاج سواء كانت مخرجات نافعة (المرغوبة) السلع الزراعية المنتجة أو المخرجات غير المرغوبة "الضارة" المتمثلة فى الانبعاثات الغاذية المصاحبة للإنتاج الزراعي والتي لها تأثيرات سلبية على البيئة وذلك في ظل افتراض ثبات العائد للسعة. ويضم البحث أهم الدول العربية سواء وفقا لنسبة مساهمة كل منها فى الناتج الزراعي العربي و/أو نسبة مساهمة الناتج الزراعى فى إجمالي الناتج المحلى, وتتضمن الدول المختارة السودان وسوريا والمغرب واليمن ومصر والجزائر وتونس والعراق والمملكة العربية السعودية والإمارات العربية المتحدة. ويتبين من النتائج المقدرة أن متوسط الكفاءة الفنية المقدرة بالطريقة التقليدية (باستبعاد أثر الانبعاثات الزراعية) خلال فترة الدراسة 2007-2017 كان أعلى نسبيًا من استخدام منهج SBM (يأخذ الانبعاثات الزراعية فى الاعتبار) لجميع الدول العربية المختارة، حيث بلغ المتوسط الهندسي العام حوالي 0.87 للأولى مقارنة بـ 0.66 للأخيرة على الترتيب، مما يشير إلى الحصول على تقديرات مضللة وزائفة للكفاءة الفنية إذا لم يؤخذ في الاعتبار المخرجات الضارة (الانبعاثات الزراعية). وهو ما يشير الى أنه يتعين على القطاع الزراعي العربي تحسين كفاءته بنسبة 34٪ في المتوسط. علاوة على ذلك ، تظهر نتائج SBM أن المملكة العربية السعودية احتلت المرتبة الأولى (95٪) ، تليها سوريا والجزائر ومصر والإمارات بنحو 91٪ (في المتوسط) ثم السودان 75٪ ، المغرب 44٪ ، العراق 55٪ ، اليمن 39٪ وأخيراً تونس 33٪. ويتبين أيضا من نتائج البحث أن التغير التقني بصفة عامة يساهم بنسبة أكبر من نسبة مساهمة تغير الكفاءة في التغيرات في الإنتاجية الكلية لعوامل الانتاج الزراعية في جميع البلدان التي شملتها الدراسة، وهذا يعني امكانية زيادة كبيرة في الإنتاج الزراعى في ظل التكنولوجيا المتاحة وذلك برفع كفاءة استخدامها . كما تشير أيضا الى أهمية العمل على تبنى ونشر تطبيق الابتكارات التقنية الحديثة. وتوصى الدراسة بأهمية الاستثمار في البحوث الزراعية، والاهتمام ببرامج الإرشاد الزراعي ليس فقط في تبنى ونشر تطبيق الابتكارات التقنية الحديثة بل وأيضا رفع كفاءة استخدام التكنولوجيا المتاحة. كما يجب على الحكومات اتخاذ بعض الخطوات الضرورية للتركيز على تحسين إنتاجية المحاصيل سواء بتقديم خدمات ودعم واسع النطاق للمزارعين في الوقت المناسب ورفع الوعى البيئي بحيث يمكن جعل زراعة المحاصيل أكثر كفاءة.

الكلمات الدالة: نموذج مغلف البيانات ، نموذج اس بي أم، مالمكويسيت ، الانتاجية الكلية للعوامل الزراعية

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[i] **Malmquist Index = Efficiency Change × Technical Change**

[ii] **Technical Change = Output Biased Technical Change (OBTC) × Input Biased Technical Change (IBTC) × Magnitude Technical Change (MATC)**