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Assessing technical efficiency of tomato farms in ALjabal Alakhdar, Libya: An input orientation model approach

Masauda A. Abuarosha*

Faculty of Agriculture, Omer Almokhtar University, Albida, Libya

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Abstract

Tomato cultivation holds significant importance in the Al Jabal Al Akhdar region, yet the varied input utilization among farmers has led to discrepancies in technical efficiency. This study addresses the need to assess the efficiency of tomato farming in the region, aiming to identify input limitations and facilitate improvement processes to minimize resource consumption. Utilizing primary data collected in 2023 via a closed questionnaire distributed among 100 randomly selected farmers, the study employs Data Envelopment Analysis (DEA) in its input-oriented form, utilizing win4DEAP software. The results reveal that while pure technical efficiency surpasses technical efficiency, there's a notable discrepancy between the flexible frontier of the Variable Returns to Scale (VRS) model and the Constant Returns to Scale (CRS) model. Specifically, the VRS model indicates a slightly lower input reduction of 11.3%, emphasizing the importance of considering both models in decision-making processes. Farm-specific projections clarify that some are well-managed and serve as benchmarks, while others require improvement to achieve 100% efficiency scores. Key observations highlight the potential for cost reduction through input streamlining, with DEA proving to be an effective and user-friendly method for farm management enhancement. Its accessibility benefits both researchers and farmers, enabling informed decision-making to optimize profits while maintaining performance standards. The estimation results underscore the necessity for input reduction among tomato farms in Libya, particularly regarding variable capital costs, emphasizing the importance of tighter control over cultivation expenses.

* **Corresponding Author:** Masauda A. Abuarosha ✉ masauda.abuarosha@omu.edu.ly

Introduction

Al Jabal Al Akhtar locates in Cyrenaica Region of Libya, this enchanting is distinguished by its generous rainfall, where fertile lands need to be tilled and nurtured by the hands of skilled farmers. These fertile soils yield an abundance of crops, where tomatoes crops are one of the most important yields in ALjabal Alakhdar region, and although its production is one of the most important crops; the use of its inputs among farmers completely different, which resulted in a difference in the efficiency of its use, so it was necessary to identify its strengths and weaknesses. The 1990s witnessed a recognized expansion in Al Jabal Al Akhdar as the cultivation of tomatoes began to flourish. This burgeoning farming was propelled by the adoption of drip irrigation technology, and with the provision of fertilizers and pesticides at the minimum cost; farmers found them empowered to expand their tomato cultivation endeavors (Elbeydi, 2011).

However, amidst the promising growth of tomatoes production, several challenges and constraints have emerged, casting shadows over the success story. The uncontrolled expansion of cultivation areas has led to unforeseen consequences, exacerbating issues such as water scarcity, limited access to fertilizers and pesticides, shortage of skilled labor, and inadequate availability of electrical energy to power irrigation pumps. In the face of these obstacles, farmers struggle with the delicate balance between ambition and constraint, striving to navigate a fruitful landscape with challenges (Shaloof, 2010). Yet, despite the hurdles, their resilience and determination continue to fuel the hope of overcoming these limitations and fostering sustainable agricultural practices in Al Jabal Al Akhdar.

The concept of efficiency, crucial in assessing the performance of production units, involves comparing their actual input and output values with their optimal counterparts. Efficiency analysis serves as a valuable tool for managers striving to maximize profits and minimize costs, potentially fostering positive developments at both microeconomic and macroeconomic levels. The literature identifies several types of efficiency, including technical, allocative, economic, scale, and eco-efficiency (Fumbwe *et al.*, 2021). While these types share similarities, they differ in the parameters used for estimation, as evidenced by various studies (Ng'ombe and Kalinda, 2015). In agriculture, technical efficiency reigns supreme, reflecting a farm's ability to achieve a given level of output using minimal inputs or to maximize output with a fixed input level (Bournaris *et al.*, 2019). This efficiency type addresses fundamental questions of production theory, emphasizing the prudent management of resources. Among methodological approaches, Data Envelopment Analysis (DEA) stands out as widely accepted. However, despite its prevalence, relevant estimations for farms in Al Jabal Al Akhdar, appear lacking. Motivated by this gap and a desire to demonstrate DEA's operational mechanics, the author undertook this study, aiming to enrich both the literature and local agriculture by offering insights into effective input management for farmers. Consequently, this study seeks to address two primary questions:

1. What is the technical efficiency level of tomato farms in the Al Jabal Al Akhdar region?
2. How can the results of DEA be interpreted to suggest effective input management strategies for farmers?

Based on that the importance of this study lies in knowing the efficiency of tomato cultivation in Al Jabal Al Akhdar region, and identifying its limitations from inputs, through an improvement process that reduces highly consumed inputs.

Technical efficiency analysis using data envelopment

The non-parametric approach, grounded in linear programming principles, has long been a cornerstone of DEA. Farrell, in 1957, laid the groundwork by defining efficiency measures and methods for estimating efficiency scores within a non-parametric framework. Specifically, Farrell's work focused on scenarios where the frontier exhibits constant returns to scale (CRS) (Førsund *et al.*, 2007). This model was with one input and one output, then Charnes *et al.*, 1978 developed the model to accommodate several inputs and several outputs. It is a mathematical programming model applied to data that provides a way to construct production limits as well as to calculate efficiency scores closest to those constructed limits (Cooper *et al.*, 2007, 2011). DEA in addition to its ease of use, it diagnoses deficiencies (inefficiency) while proposing appropriate solutions in a scientific manner. Thoughtful, far from random, because it takes into account the principle of dynamic variables and the relationship between causes and results, which accurately leads to reaching precise solutions while providing clear information about the performance efficiency of each farm and how to direct it to improve its performance. The DEA method relies primarily on Pareto Optimality, which states that any decision-making unit is inefficient if another unit or a combination of units is able to produce the same amount of outputs with a less amount of inputs or without an increase in resources (Coelli, 2008).

DEA is based on the possibility of choosing between constant returns to scale (CRS) and variable returns to scale (VRS), which allows the estimation of technical efficiency (TE) and scale efficiency (SE) of the production units. Efficiency and its components can be calculated either using the input map (input-oriented efficiency) or the output map (output-oriented efficiency).

Materials and methods

The study relies on primary data collected in 2023 through closed - questionnaire which is distributed to a random sample of 100 farmers in the ALjabal Alakhdar region. The study relies the DEA in its typical form, and according to the input map (input-oriented efficiency) uses **w**in4DEAP software.

Data envelopment analysis model in the case of constant returns to scale (CRS)

To find the efficiency index for unit (i) using the input oriented, assuming constant returns to scale and providing statistical data on (K) of inputs, (M) of outputs, and (N) of time periods, and the vector (Xi) represents a symbol for the inputs and the vector (Yi) is a symbol for output, as (i) symbolizes the production unit, (X) represents the input matrix K*N, and (Y) represents the output matrix M*N. Using the duality method in linear programming, the efficiency index can be found by solving the linear programming problem. The following:

$\text{Min}_{\mathbf{Q}}: \lambda^{\wedge \theta \mathbf{CRS}}$ ....(1)

Subject to:

$$-Y_i + Y\lambda \geq 0$$
$$\theta X_i - X\lambda \geq$$
$$\lambda \geq 0$$

Whereas:

λ = vector N*I represents standard weights

θ = the vector of the technical efficiency index for production unit i, and takes the values 1 ≥ 0.

The value of one means that the performance point of the production unit falls on the curve of the maximum limits and thus indicates the efficiency of the production unit from a technical standpoint. Whereas if the value of the indicator is less than one, it indicates that the performance of the production unit falls below the boundary curve and that it is technically inefficient (Ajilbefunt *et al.*, 1994; 58). The explanation for this is that the linear programming problem seeks to reduce the input vector (Xi) for the unit. Productivity I to the lowest possible extent while maintaining the possibility of achieving the output level at Yi and on the optimal production frontier curve.

Data envelopment analysis model in the case of variable returns to scale (VRS)

The DEA model, in the event that returns to scale are assumed to be constant, is based on the constant return to scale property of production, meaning that a change in the quantity of inputs used by the production unit has a constant effect on the quantity of output (production). This property is considered appropriate only when all the production units "being compared" are working at their optimum size level. However, imperfect competition, government laws, restrictions on financing, and others actually prevent production units from achieving their optimal sizes. The assumption of constant returns to scale is used in the (DEA) model when not all production units are operating at their optimal size level, and these results in Technical Efficiency indicators overlapping with Scale Efficiency indicators. To separate the effect of technology and the effect of scale in measuring efficiency, the VRS model is used (Fraser and Cordina, 1999).

The model of (CRS) is modified to the (VRS) model in the linear programming by adding scale constraint NI' λ= 1, whereas: N1 refers to the unit vector N*I, and it takes the following formula:

Min θ, λ θ VRS ....(2)

Subject to:

$-Yi + Y\lambda \geq 0$

$\theta Xi - X\lambda \geq 0$

$I = 1, 2.............N$

$NI'\lambda = 1$

$\lambda \geq 0$

Results and discussion

The analysis in the current carried out using the (*win4DEAP*) software. There are a number of conditions associated with the use of (*win4DEAP*) software that are fulfilled in the current study: 1) the production units are categorically required to be of the same economic activity (Tomato farms). 2) The relationship between inputs and outputs must be direct. However, in order to estimate the technical efficiency on the input oriented side, it is important to specify the model variables as presented in Table (1).

Table 1. Varibles of the DEA model

	Model variables		
	Type	Measurement	Mean
Tomato production	Out put	Ton	318.6
araes	In put	Hectare	5.5
Number of seedlings	In put	Unit	56750
Quantity of fertilizer	In put	Ton	43.25
Working Hours	In put	Hour	78.71

Table 2 presents the findings of the technical efficiency analysis, showcasing average efficiency scores across various scenarios. Under constant returns to scale (CRSTE), the average efficiency score stands at 84.7%. This indicates that, on average, farms could potentially reduce their inputs by 15.3% while still maintaining the same level of tomato production output. Moving to variable returns to scale (VRSTE), the average efficiency score improves to 88.7%. In this scenario, farms could enhance their input management practices to achieve a reduction of 11.3% in inputs while maintaining output levels. Scale efficiency (SE) yields the highest average efficiency score of 95.7%. Farms, by adjusting their scale, could potentially reduce inputs by 4.3%. However, despite these positive results, it is notable that most farms fall short of achieving perfect efficiency, indicated by a score of 100%.

Furthermore, Table 2 provides insights into the nature of returns to scale, denoted by IRS, DRS, or a dash. Farms associated with increasing returns to scale (IRS) experience economies of scale, while those linked with decreasing returns to scale (DRS) encounter diseconomies of scale. Farms denoted by a dash (-) operate at a scale where they achieve constant returns, reflecting an optimal operational scale.

From Table 3, it is evident that 8% of the sample farms reached 100% efficiency under the constant returns to scale (CRSTE) scenario, while 18% achieved the same under the variable returns to scale (VRSTE) scenario. Additionally, approximately 15% of the total sample reached 100% efficiency under the scale efficiency (SE) scenario. Interestingly, the majority of farms in the study sample demonstrated efficiency levels ranging between less than 100% and greater than 80%. It is noteworthy that all sampled farms achieved efficiency levels exceeding 60%.

Indeed, while the results indicate a generally positive performance in terms of efficiency, it's essential to acknowledge that achieving less than 100% efficiency suggests room for improvement and elements of inefficiency within the farms' operations. Identifying and addressing the inefficiencies can lead to improved resource utilization, cost reduction, and ultimately, greater profitability for the farms. Therefore, while the findings are promising, they also highlight the importance of ongoing efforts to refine operational processes and maximize efficiency in agricultural practices. In this context, it is also important to point out that the win4DEAP program can identify inefficient farms and determine the factors of inefficiency, propose solutions to them by identifying possible improvements and reference farms fort the inefficient farms to use as a guide. If inefficient farms want to improve their performance, they have to look at the best practices developed by their respective peers. However, it is important to mention that in an input orientation model, DEA minimizes input for a given level of output; in other words, it indicates how much a farm can decrease its input for a given level of output.

Table 2. Technical efficiency of tomato farmers

Farm	(CRSTE)	(VRSTE)	(SE)	(RTS)	Farm	(CRSTE)	(VRSTE)	(SE)	(RTS)
1	0.889	0.925	0.960	DRS	51	0.889	0.912	0.975	DRS
2	0.910	0.910	1.000	-	52	0.935	0.937	0.998	DRS
3	1.000	1.000	1.000	-	53	0.775	0.778	0.997	DRS
4	0.948	1.000	0.948	DRS	54	0.945	0.948	0.997	DRS
5	0.889	0.896	0.992	DRS	55	0.747	0.771	0.969	IRS
6	1.000	1.000	1.000	-	56	0.808	0.839	0.963	DRS
7	0.900	0.903	0.997	DRS	57	0.847	0.930	0.910	DRS
8	0.991	1.000	0.991	IRS	58	0.847	1.000	0.847	DRS
9	0.741	0.752	0.984	DRS	59	0.795	0.811	0.981	DRS
10	0.847	0.866	0.978	DRS	60	0.741	0.758	0.977	IRS
11	0.963	0.971	0.992	DRS	61	0.774	0.787	0.984	DRS
12	0.741	0.748	0.990	DRS	62	1.000	1.000	1.000	-
13	0.763	0.775	0.985	DRS	63	0.769	0.799	0.963	DRS
14	0.952	0.973	0.979	DRS	64	0.704	0.722	0.975	DRS
15	0.671	0.697	0.963	DRS	65	0.782	0.826	0.947	DRS
16	0.742	0.748	0.992	IRS	66	0.601	0.615	0.976	DRS
17	0.833	0.834	1.000	-	67	1.000	1.000	1.000	-
18	0.815	0.843	0.967	DRS	68	0.837	0.857	0.977	DRS
19	1.000	1.000	1.000	-	69	0.833	0.839	0.994	DRS
20	0.741	0.954	0.777	IRS	70	0.845	0.856	0.988	DRS
21	1.000	1.000	1.000	-	71	0.949	0.966	0.983	DRS
22	0.892	1.000	0.892	DRS	72	0.914	0.921	0.992	IRS
23	0.889	0.889	1.000	-	73	0.919	0.926	0.992	DRS
24	0.944	0.944	1.000	-	74	0.690	0.698	0.988	DRS
25	0.778	0.798	0.975	DRS	75	0.759	0.762	0.995	IRS
26	0.667	0.672	0.992	IRS	76	0.711	0.720	0.987	IRS
27	0.889	0.984	0.904	IRS	77	0.766	0.782	0.980	DRS
28	0.741	0.891	0.832	IRS	78	0.891	0.891	1.000	-
29	0.934	0.963	0.969	DRS	79	0.859	1.000	0.859	IRS
30	0.896	0.908	0.987	DRS	80	0.852	0.867	0.982	IRS
31	0.669	0.670	0.999	-	81	0.859	0.889	0.967	DRS
32	1.000	1.000	1.000	-	82	0.777	0.783	0.992	DRS
33	0.889	0.889	1.000	-	83	0.889	0.984	0.904	IRS
34	0.741	0.741	1.000	-	84	0.685	0.703	0.975	DRS
35	0.811	0.827	0.981	IRS	85	0.961	1.000	0.961	DRS
36	0.741	0.777	0.953	IRS	86	0.939	0.974	0.964	DRS
37	0.815	0.993	0.821	IRS	87	0.945	1.000	0.945	IRS
38	0.946	0.972	0.973	IRS	88	0.890	0.978	0.910	DRS
39	0.799	0.800	0.999	DRS	89	0.890	0.930	0.956	DRS
40	0.676	0.728	0.927	IRS	90	0.757	0.771	0.982	IRS
41	0.800	0.885	0.904	IRS	91	0.897	0.926	0.968	IRS
42	0.914	0.921	0.992	IRS	92	0.904	0.907	0.997	IRS
43	0.661	0.775	0.853	IRS	93	0.919	0.928	0.990	DRS
44	0.858	0.923	0.929	IRS	94	0.993	1.000	0.993	IRS
45	0.825	0.940	0.878	IRS	95	0.895	0.928	0.964	DRS
46	0.849	0.854	0.995	DRS	96	1.000	1.000	1.000	-
47	0.698	0.709	0.984	DRS	97	0.949	1.000	0.949	DRS
48	0.711	0.924	0.769	IRS	98	0.978	0.999	0.978	IRS
49	0.720	1.000	0.720	IRS	99	0.833	0.855	0.974	DRS
50	0.910	0.915	0.994	DRS	100	0.988	0.990	0.997	IRS

Source: win4DEAP Program Outputs

Table 3. Distribution of technical efficiency levels of tomato farmer

TE	(CRSTE)		(VRSTE)		(SE)	
	Number of Farm	Percentage from total	Number of Farm	Percentage from total	Number of Farm	Percentage from total
100	8	%8	18	%18	15	%15
100 < 80 ≥	58	%58	55	%55	80	%80
80 < 60 ≥	34	%34	27	%27	5	%5
60 < 40 ≥	0	%0	0	%0	0	%0
40 <	0	%0	0	%0	0	%0
Total	100	%100	100	%100	100	%100

Source: based on Table 2

1. Reference units (Peers) for inefficient farms according to VRS with input-oriented efficiency

Fig. 1 shows the outputs of the (win4Deap) program for the peers and their weights for the farms in the study sample, as each farm is compared to other farms that operate under the same conditions, whether competitive or productive. As a result, every inefficient farm has a group of efficient reference farms to compare to in order to identify weaknesses. In other words, these reference farms operate in the same competitive conditions and were able to achieve better efficiency.

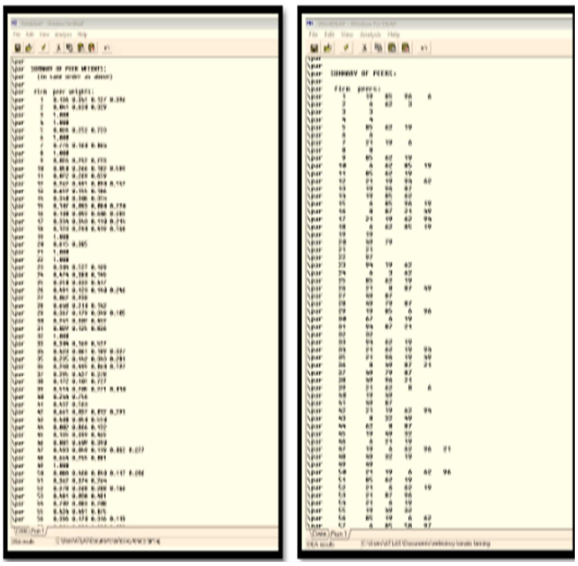

Fig. 1. Outputs of the win4Deap program for the farms peers and their weights in the study sample

Source: win4Deap program outputs

The listing of peers is mentioned in Table 4. Each peer is identified by a number and has an associated weight ('lambda weight') representing the relative importance of the peer. By going through Table 4 for example; farm No. (1), which is inefficient, is matched by a number of farms (19-96-85-6) that have achieved higher efficiency while operating under the same conditions; this can also be recognized in other farms such as farm (2), farm (4), farm (5) and so on. When we follow the Table 4, we find that the efficient farms correspond to themselves, as in farm No. (3), farm No. (6) and so on.

2. *Identifying surplus and deficit inputs according to input orientation model (Radials & Slacks movements*

Through the win4Deap program and in accordance to the input orientation model adopted in this study, it is possible to estimate whether there are deficient or surplus inputs that have affected the technical efficiency of the farm, and the slack outputs can also be estimated. In fact, the ability to estimate these matters contributes greatly to increasing farm efficiency. Fig. 2 shows the outputs of the win4Deap program for the farm by farm results; the first column of the matrix recalls the original values of the variables' inputs and output.. The second column of the matrix represents the movement an inefficient farm has to take in order to be located on the frontier ('radial movement'). The third column of the matrix is the additional movement a DMU located on a segment of the frontier running parallel to the axis has to take in order to become efficient ('slack movement'). The fourth column of the matrix lists the values of the variables which enable the farms to be efficient ('projected value'); these projected values take into account both the radial and the slack movements.

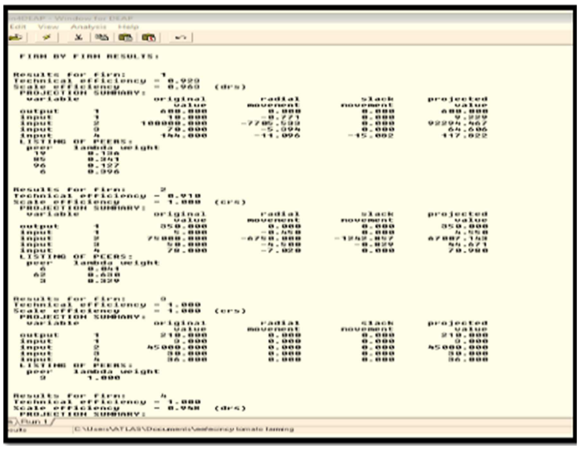

Fig. 2. Outputs of the win4Deap program for the farms

Source: win4Deap program outputs

The lines below show the listing of peers. Coelli (2008) explained that; each PEER is identified by a number and has an associated weight ('lambda weight') representing the relative importance of the peer. SLACK MOVEMENT shows the discrepancy in the constant or proportional change of input and output variables. It also represents the amount of value of improvement in both input and output. RADIAL MOVEMENT shows the adjusted proportionality of input and output variables.

According to the Win4DEAP program Outputs, the results show the projection summary for each farm separately. Therefore, in order to explain how inefficient farms can improve their efficiency, the results for the first ten farms will be summarized in Table 5 below, while the remaining results will be included in the appendix. From Table 5 farms (3, 4, 6 and 8) have a 'perfect' efficiency score of 100% and a scale efficiency scores of (100%, 94.8%, 100% and 99.1%) respectively. These farms are well managed. So the original values of the farm's variables are equal to the projected ones ('perfect' efficiency = 100%) because the farms are perfectly efficient, they act as their own peers.

Table 4. Distribution of reference units (peers) of tomato farmers and required improvements according to the peers' weights (PW)

Farm	Peers				Farm	Peers				Farm	Peers				Farm	Peers			
1	19	85	96	6	26	21	8	87	49	51	85	62	19		76	21	94	87	
PW	0.14	0.34	0.13	0.39	PW	0.49	0.12	0.14	0.24	PW	0.36	0.37	0.26		PW	0.24	0.01	0.74	
2	6	62	3		27	49	87			52	21	6	62	19	77	19	6	62	85
PW	0.05	0.63	0.32		PW	0.06	0.93			PW	0.27	0.26	0.28	0.16	PW	0.15	0.15	0.61	0.08
3	3				28	49	79	87		53	21	87	96		78	6	62	96	21
PW	1.00				PW	0.64	0.21	0.14		PW	0.48	0.03	0.48		PW	0.01	0.18	0.02	0.76
4	4				29	19	85	6	96	54	21	6	19		79	79			
PW	1.00				PW	0.36	0.17	0.34	0.11	PW	0.71	0.08	0.21		PW	1.00			
5	85	62	19		30	67	6	19		55	19	49	32		80	21	87	94	
PW	0.03	0.25	0.72		PW	0.24	0.31	0.45		PW	0.43	0.49	0.07		PW	0.25	0.49	0.24	
6	6				31	94	87	21		56	85	19	6	62	81	85	62	19	
PW	1.00				PW	0.39	0.12	0.83		PW	0.39	0.17	0.31	0.11	PW	0.54	0.44	0.01	
7	21	19	6		32	32				57	6	85	58	97	82	49	21	96	
PW	0.77	0.17	0.06		PW	1.00				PW	0.31	0.39	0.22	0.08	PW	0.03	0.58	0.39	
8	8				33	94	62	19		58	58				83	49	87		
PW	1.00				PW	0.31	0.16	0.53		PW	1.00				PW	0.06	0.94		
9	85	62	19		34	21	62	19	94	59	6	96	62	19	84	85	19	62	
PW	0.02	0.25	0.73		PW	0.42	0.06	0.18	0.32	PW	0.09	0.08	0.15	0.67	PW	0.16	0.54	0.30	
10	6	62	85	19	35	21	96	19	49	60	21	49	87	8	85	85			
PW	0.05	0.26	0.18	0.51	PW	0.23	0.14	0.34	0.28	PW	0.26	0.15	0.52	0.07	PW	1.00			
11	85	62	19		36	8	49	87	21	61	96	6	19	62	86	85	6	96	19
PW	0.08	0.26	0.65		PW	0.25	0.49	0.07	0.19	PW	0.06	0.15	0.45	0.33	PW	0.09	0.22	0.58	0.11
12	21	19	94	62	37	49	79	87		62	62				87	87			
PW	0.26	0.49	0.09	0.15	PW	0.29	0.43	0.28		PW	1.00				PW	1.00			
13	19	96	87		38	49	96	21		63	19	6	96		88	6	85	58	97
PW	0.65	0.15	0.19		PW	0.17	0.11	0.72		PW	0.44	0.17	0.39		PW	0.33	0.35	0.29	0.02
14	19	85	62		39	21	62	8	6	64	85	62	19		89	85	96	6	19
PW	0.34	0.31	0.35		PW	0.51	0.21	0.27	0.11	PW	0.18	0.31	0.51		PW	0.19	0.56	0.21	0.04
15	6	85	96	19	40	19	49			65	85	62	97		90	96	8	49	87
PW	0.11	0.09	0.08	0.72	PW	0.24	0.76			PW	0.51	0.01	0.48		PW	0.03	0.29	0.19	0.49
16	8	87	21	49	41	49	87			66	32	19	49		91	94	62	87	8
PW	0.11	0.09	0.61	0.21	PW	0.44	0.56			PW	0.26	0.71	0.03		PW	0.01	0.03	0.23	0.74

17	21	19	62	94	42	21	19	62	94	67	67				92	62	94	21	19
PW	0.33	0.34	0.11	0.21	PW	0.66	0.04	0.01	0.29	PW	1.00				PW	0.05	0.53	0.26	0.16
18	6	62	85	19	43	8	32	49		68	19	21	6		93	85	6	62	19
PW	0.12	0.29	0.41	0.16	PW	0.40	0.05	0.55		PW	0.72	0.08	0.19		PW	0.03	0.03	0.23	0.72
19	19				44	62	8	87		69	21	19	96	62	94	94			
PW	1.00				PW	0.01	0.87	0.12		PW	0.22	0.39	0.26	0.13	PW	1.00			
20	49	79			45	19	49	32		70	85	6	62	19	95	85	96	6	19
PW	0.61	0.34			PW	0.14	0.39	0.47		PW	0.01	0.15	0.12	0.72	PW	0.27	0.28	0.32	0.13
21	21				46	6	21	19		71	62	19	6	85	96	96			
PW	1.00				PW	0.01	0.61	0.38		PW	0.07	0.53	0.26	0.14	PW	1.00			
22	21				47	19	6	62	96	72	21	19	62	94	97	97			
PW	1.00				PW	0.49	0.04	0.12	0.35	PW	0.66	0.04	0.01	0.29	PW	1.00			
23	94	19	62		48	49	32	19		73	62	85	19		98	94	21	87	
PW	0.31	0.52	0.16		PW	0.66	0.26	0.08		PW	0.26	0.04	0.69		PW	0.46	0.27	0.27	
24	6	3	62		49	49				74	62	21	19	94	99	19	6	62	85
PW	0.47	0.38	0.14		PW	1.00				PW	0.44	0.17	0.33	0.06	PW	0.36	0.04	0.31	0.29
25	85	62	19		50	21	19	6	62	75	8	62	87	94	100	94	19	62	
PW	0.25	0.33	0.42		PW	0.08	0.47	0.15	0.29	PW	0.46	0.11	0.02	0.41	PW	0.57	0.33	0.10	

Source: win4Deap program outputs

Table 5. Result of projection summary for the first 10 farms

Farm DMU	output	Input1		Input2		Input 3		Input 4	
		Projected values	% of reduction	Projected values	% of reduction	Projected values	% of reduction	Projected values	% of reduction
Farm 1	600.000	9.229	7.71%	92294.467	7.70 %	64.606	7.70%	117.822	18.17 %
Farm 2	350.000	4.550	9.00%	67007.143	10.65%	44.671	10.60%	70.980	9.00%
Farm3	210.000	3.000	0.00%	45000.000	0.00%	30.000	0.00%	36.000	0.00%
Farm 4	1150.000	18.000	0.00%	180000.000	0.00%	150.000	0.00%	240.000	0.00%
Farm 5	300.000	4.456	10.88%	44557.823	10.00%	31.250	21.87%	60.371	13.75%
Farm 6	700.000	10.000	0.00%	120000.000	0.00%	80.000	0.00%	120.000	0.00%
Farm 7	240.000	3.608	9.80%	36080.000	9.00%	24.320	39.20%	43.296	9.88%
Farm 8	140.000	2.000	0.00%	24000.000	0.00%	15.000	0.00%	28.000	0.00%
Farm 9	300.000	4.456	25.70%	44557.823	26.00%	31.250	37.50%	60.371	31.40%
Farm 10	400.000	6.026	13.90%	60255.366	13.20%	43.436	27.60%	81.775	13.49%

Source: based on the win4Deap program outputs (see the appendices)

Table 6. Result of farm 1 for input orientation model

FARM 1				
Technical efficiency	0.923			
Scale efficiency	0.963 (DRS)			
Variable	Original value	Radial movement	Slack movement	Projected value
output	600.000	0.000	0.000	600.000
input 1	10.000	-0.771	0.000	9.229
input 2	100000.000	-7705.533	0.000	92294.467
input 3	70.000	-5.394	0.000	64.606
input 4	144.000	-11.096	-15.082	117.822
Listing of peers:	Peer	Lambda weight		
	19	0.136		
	85	0.341		
	96	0.127		
	6	0.396		

Source: win4DEAP Program Outputs

While the farms (1, 2,5,7,9 and 10) have efficiency scores less than 100%, so these farms are insufficient and require improvement in their inputs values to achieve efficiency scores of 100%. For example, Table 6 shows the results of the improvements that should be made for the 4 inputs of farm (1): Input 1 (Area) should be reduced by 7.71 % to achieve efficiency. Input 2 (Number of seedlings) should be reduced by 7.70 % to achieve efficiency. While for input 3 (Quantity of fertilizers) the reduction should be made by 7.70%, and input 4 (Working Hours) should be reduced by 18.17 % to achieve efficiency. Table 7 shows the results of the improvements that should be made for the 4 inputs of farm (9): Input 1 (Area) should be reduced by 25.7 % to achieve efficiency. Input 2 (Number of seedlings) should be reduced by 26 % to achieve efficiency. While for input 3 (Quantity of fertilizers) the reduction should be made by 37.5%, and input 4 (Working Hours) should be reduced by 31.4 % to achieve efficiency.

A more granular examination of the results reveals that the average technical efficiency among farms utilizing the VRS model surpasses the average technical efficiency among farms using the CRS model, indicating a notable distinction between the flexible frontier of the Variable Returns to Scale (VRS) model compared to the Constant Returns to Scale (CRS) model. Specifically, the VRS model demonstrates a greater level of efficiency. According to the CRS model, a 15.3% reduction in inputs is advised for the farms to enhance operational efficiency. However, the VRS model suggests a slightly lower input reduction of 11.3%, underscoring the importance of considering both models in decision-making processes.

Significantly, the analysis highlights that farms with lower efficiency levels exhibit the highest variations in input reduction, emphasizing the pivotal role of effective input management in influencing technical efficiency levels. The preference for the VRS model over CRS is justified by the complexity of the agricultural sector, where assumptions of perfect competition and unrestricted resource access are impractical. This rationale holds implications for similar studies in the future.

Table 7. Result of farm 9 for input orientation model

FARM 9				
Technical efficiency	0.743			
Scale efficiency	0.997 (DRS)			
Variable	Original value	Radial movement	Slack movement	Projected value
output	300.000	0.000	0.000	300.000
input 1	6.000	-1.544	0.000	4.456
input 2	60000.000	-15442.177	0.000	44557.823
input 3	50.000	-12.868	-5.882	31.250
input 4	88.000	-22.649	-4.981	60.371
Listing of peers:	peer	lambda weight		
	85	0.026		
	62	0.252		
	19	0.723		

Furthermore, the study unveils that technical efficiency of (100%) does not fully exist for the total of the examined farms, necessitating reasonable input reductions across a subset of farms to optimize operations. Notably, a high level of scale efficiency (SE) is observed among the examined farms, suggesting that they may already be operating at an optimal size. Analysis of returns to scale indicates that a majority of farms experience decreasing returns to scale (51% of the total sample), implying that these farms could enhance technical efficiency by reducing their size. In essence, these findings underscore the nuanced dynamics within the agricultural sector and emphasize the importance of tailored strategies informed by sophisticated analytical frameworks like DEA. By shedding light on the inefficiencies and opportunities for improvement, this study contributes to the discourse surrounding agricultural productivity enhancement and resource optimization in ALjabal Alakhdar.

Conclusion

Efficiency serves as a vital instrument across various domains including economics, agriculture, literature, and research. Technical efficiency, in particular, stands as a crucial tool for managers striving to maximize profits while minimizing costs. Within the agriculture sector, Data Envelopment Analysis (DEA) emerges as a widely accepted methodology for estimating technical efficiency. With the objective of extracting actionable insights into effective input management among farmers, this study focused on implementing DEA across 100 farms in Libya. An input-oriented DEA model was employed to estimate technical efficiency under constant returns to scale (CRS) and variable returns to scale (VRS).

The findings of this study unveiled several significant observations. Firstly, it became evident that the farms under consideration possess the potential to streamline their inputs, thereby reducing costs. Secondly, DEA demonstrated its efficacy as a functional and user-friendly method, capable of providing valuable conclusions for enhancing farm management. Notably, its accessibility makes it equally beneficial for both researchers and farmers, fostering informed decision-making to optimize profits without compromising performance. Specifically, the estimation results underscored the imperative for input reduction among tomato farms in Libya, particularly concerning variable capital costs. This highlights the necessity for farmers to exercise tighter control over cultivation expenses. Consequently, the study advocates for the provision of specialized advisory services to empower farmers in optimizing their input usage, with support from local authorities and governmental policies promoting rational input utilization.

In terms of originality, this study stands out for its innovative approach in employing the DEA method to evaluate the technical efficiency of agricultural farms. Furthermore, it sets a precedent by offering not only results but also a comprehensive tutorial on data collection and analysis methodologies. By democratizing the use of DEA, this study equips researchers and farmers alike with a practical tool to enhance agricultural productivity.

The implications of this study extend beyond the agricultural domain. By guiding farmers towards income augmentation, cost reduction, and sustainability practices, it contributes to societal welfare and economic growth within the regional unit. Additionally, at the macroeconomic level, it strengthens the competitiveness of the agricultural sector, thereby fostering overall economic development. Looking ahead, there exists potential for further research exploring different facets of efficiency, such as allocative or eco-efficiency, utilizing alternative methodologies like stochastic frontier analysis (SFA). By delving deeper into these dimensions, future studies can enrich our understanding of the agricultural sector in Libya, building upon the foundations laid by this investigation.

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