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Application of Data Envelopment Analysis to Evaluate Efficiency of Commercial Greenhouse Strawberry

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Abstract: Investigation of strawberry greenhouses showed a big variation of data and high mean benefit to cost ratio (1.74), so the proper potential was seen for improvement of economic efficiency and management in strawberry greenhouses and detailed study was seriously required. In this study, Data Envelopment Analysis (DEA) technique was applied to investigate the degree of technical and scale efficiency of greenhouse strawberries of Iran, also to compare and optimize the performance of each greenhouse. Based on the amount of four important inputs: human labor (h/ha), fertilizers (kg/ha), capital ($/ha) and other expenses ($/ha), and gross return of strawberry ($/ha) as output. Mean technical efficiency was 0.73, indicating that there is ample potential for more efficient and sustainable input utilization in production and 27% of overall resources could be saved. The majority of the scale-inefficient greenhouses are operating under increasing returns to scale; efficiency analysis theory suggests that they are obviously small greenhouses that need to increase their sizes in order to achieve cost savings. Ranking of productive efficiencies based on the four mentioned inputs is also shown to differ significantly from that based on a single resource (labor).

Key words: Benchmarking, gross return, human labor, return to scale

INTRODUCTION

Strawberry belongs to the family *Rosaceae*, genus *Fragaria*, and is among the most widely consumed fruits throughout the world. Currently, United State of America, Spain, Turkey, Russian Federation, and Republic of Korea are the main strawberry producer countries (FAO, 2007). For many years in Iran, conventional strawberry growers have routinely used to cultivate in open field. Today's demand for locally and off-season produce of fresh fruits and viable crop exhorts the production to spread greenhouses. Cultivating strawberry varieties for commercial production (Fragaria×Ananassa) has recently started in greenhouses (Hancock, 1999).

Growers can use various methods of "forced cultivation" in greenhouses to produce off-season strawberries to take advantage of the high market prices during winter and spring months (Anonymous, 1995).The greenhouse business is very capital intensive with the basic structure erected depending on major options. Choosing the best treatment program for a greenhouse operation is required for providing economical and effective results. In greenhouse production, management practices can be defined as a set of alternative production techniques such as structure, nutrient injection system, heating and ventilation systems, labors, cultivating programs and etc.

The level of global agricultural competition is expected to increase. The greenhouse production sector will unavoidably be affected as well, leading to a more market-orientated sector characterized by increased competition and imports, reduced statutory subsidies, export supplements and intervention measures. With the increasing consciousness about excess production and the induced burden on the Common Agricultural Policy (CAP) budget, the main point of concern for the industry, as well as for officials and the academics, has shifted from output growth to efficient greenhouse management. Within this context, producers need to adapt to these changes if they are going to remain profitable. The reduction of input wastes and costs may prove the most effective means of enhancing the viability of greenhouses; given that greenhouses have more control over inputs.

In recent years, Data Envelopment Analysis (DEA) has become a central technique in productivity and efficiency analysis applied in different aspects of economics and management sciences. Although within this context, several researchers have focused on determining efficiency in agricultural units and various products ranging from cultivation and horticulture to aquaculture and animal husbandry (Shafiq and Rehman 2000; Sharma *et al*. 1999; Iraizoz *et al*. 2003; Galanopoulos *et al*., 2006; Singh *et al*., 2004; Chauhan *et al*., 2006; Banaeian *et al*., 2010b). A

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further comparative review of frontier studies on agricultural products can be found in Thiam *et al*. (2001). Applications in assessing the efficiency of greenhouses are growing (Omid *et al*., 2010; Banaeian *et al*., 2010a) but none of them focused on commercial points. This study was conducted in the Alborz province of Iran in January 2010. According to annual statistics of Agricultural Jihad Ministry, Alborz province is the main greenhouse production area of Iran (MAJ, 2010). DEA technique is subjected to data of twenty five commercial greenhouse strawberry producers in this area. The selection of greenhouses was based on random sampling method (Mohammadi and Omid, 2010; Zangeneh *et al*., 2010).

Over the last few years, performance analysis of decision entities has been given considerable attention, based on the realization that comparable firms, operating under similar constraints and circumstances and producing similar outputs, exhibit wide variations in their competence. Basically, the DEA methodology is centered in determining the most efficient producers of the sample to be used as a reference, with which the efficiency of the rest of the producers is compared. The most efficient greenhouses are those for which there is no other greenhouse or linear combination of greenhouses that produce more of a product (given the inputs) or use less of each input (given the gross return). Economic theory asserts that the goal for efficient management is the optimal utilization of inputs to produce outputs in such a manner that maximizes economic returns.

The methodology presented in this paper demonstrates how greenhouse producers may benefit from applying operational management tools to assess their performance. It focuses on the application of DEA to benchmark and rank the technical efficiency of strawberry growers based on the amount of four important inputs (human labor, fertilizers, capital and other expenses) use, and gross return of strawberry as output.

MATERIALS AND METHODS

Data Envelopment Analysis (DEA) technique is used for estimation of resource use efficiency and ranking production units on the basis of their performances. Production units are termed decision-making units (DMUs) in DEA terminology. The DEA model has been described in detail by several authors (Banker *et al*., 1984; Charnes *et al*., 1978, 1985).

According to Farrell (1957), Technical Efficiency (TE) represents the ability of a DMU to produce maximum output given a set of inputs and technology (output-oriented) or, alternatively, to achieve maximum feasible reductions in input quantities given input prices and output (input-oriented). The choice between input- and output-oriented measures is a matter of concern, and selection may vary according to the unique characteristics of the set of DMUs under study. Greenhouse production relies on finite and scarce resources. Producer has more control over inputs rather than output levels, which may often be exogenously bounded (e.g., CAP provisions). In addition, the inelastic demand of most agricultural products renders cost reduction a better means of increasing profitability than output growth, notwithstanding that in many cases the choice of orientation has only minor influences upon the scores obtained (Coelli, 1996).Therefore the use of input-oriented DEA models are more appropriate to reduce inputs consumed in the production process (Malana and Malano, 2006; Chauhan *et al*., 2006).

Assuming Constant Returns to Scale (CRS), TE for a unit that produces *k* outputs using *m* different inputs is obtained by solving the following model:

$$\begin{aligned} &\text{Min } \theta, \lambda \\ \text{Subject to:} \quad &Y_i \le Y\lambda, \\ &\theta x_i \ge Y\lambda \\ &\lambda \ge 0 \end{aligned} \tag{1}$$

where Y_i is the (k × 1) vector of the value of outputs produced and is the (m × 1) vector of the value of inputs used for unit *i*. Y is the (k × n) vector of outputs and *X* is the (m × n) vector of inputs of all n units included in the sample. k is a (n × 1) vector of weights and θ is a scalar with boundaries of one and zero that determines the efficiency score of each DMU, i.e., θ = 1 shows a technically efficient DMU; θ < 1 shows a technically inefficient DMU. In order to obtain efficiency scores for each greenhouse, Eq. (1) has to be solved n times, once for each greenhouse. The efficiency score (θ) in the presence of multiple- input and -output factor is defined as (Nassiri and Singh 2009):

$$\text{Efficiency} = \frac{\text{Weighted sum of outputs}}{\text{Weighted sum of inputs}} = \frac{u_1 y_1^{j*} + u_2 y_2^{j*} + \ldots + u_N y_N^{j*}}{v_1 x_1^{j*} + v_2 x_2^{j*} + \ldots + v_M x_M^{j*}} \tag{2}$$

where, u_1,u_2 are the weight given to output n (n = 1,2,. . . ,N); $y_1^{j*}, y_2^{j*}, \ldots, y_N^{j*}$ are the amount of output n (n = 1,2 ,. . . , N) of DMU *j** ; v_1, v_2 are the weight given to input m (m = 1, 2 ,. . . , M); $x_1^{j*}, x_2^{j*}, \ldots, x_M^{j*}$ are the amount of input m (m = 1, 2 ,. . . , M) to DMU *j** and *j** is the DMU under consideration. The efficiency is usually constrained to be between zero and one.

Banker *et al*. (1984) developed a Variable Returns to Scale (VRS) frontier by which technical efficiency scores are obtained from a reformulation of Eq. (1) with a convexity constraint N'λ = 1 (where *N* is an n × 1 vector of ones) included. By imposing the convexity constraint

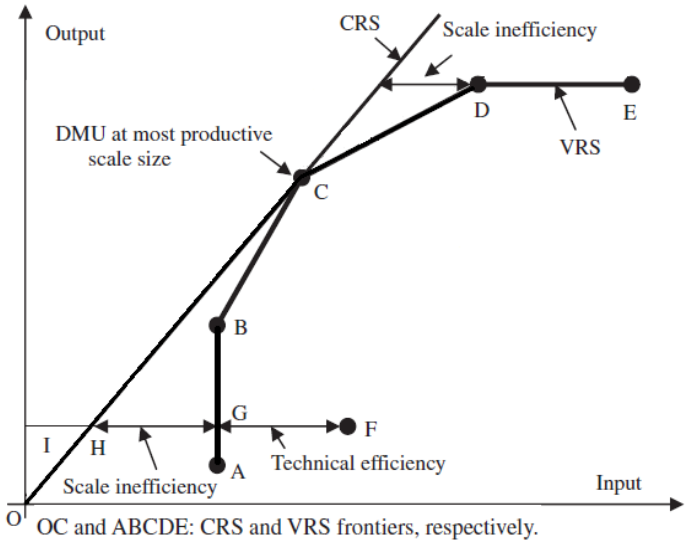

Fig.1: Constant and variable return to scale

the data points are enveloped more tightly so that the projected ''greenhouse'' for a technically inefficient unit are only efficient units of a similar size. Correspondingly, Because the VRS is more flexible and envelops the data in a tighter way than the CRS, the score or pure TE (θ_{VRS}) is equal to or greater than the CRS or overall TE score (θ_{CRS}).

With respect to technical efficiency (in CRS model), technical efficiency of VRS model, which is called Pure Technical Efficiency (PTE), could separate both technical and scale efficiencies.

The relationship among these forms of efficiency is given in follow:

$$\text{Scale efficiency} = \frac{\text{Technical efficiency}}{\text{Pure technical efficiency}} = \frac{\text{CRSScore}}{\text{VRSScore}}$$

DEA models can evaluate the relative technical efficiency of each unit, thereby allowing a distinction to be made between efficient and inefficient DMUs. Those identified as ''best practice units'' (i.e., those determining the frontier) are given a rating of one, whereas the degree of technical inefficiency of the rest is calculated on the basis of the Euclidian distance of their input–output ratio from the frontier (Coelli, 1998). For each inefficient DMU, target input and output levels have to be prescribed. These targets are the results of respective slack values added to outputs (Thanassoulis, 2001). To calculate the target values for inputs (x^A $i0$) , the input value (x_{i0}) is multiplied with an optimal efficiency score (θ), and then slack amounts (s^-) are subtracted from this amount, viz (Onut and Soner, 2006; Omid *et al*., 2010):

$$x_{i0}^A = \theta * x_{i0} - S_i^- \qquad i = 1,2,....,m \tag{4}$$

Similarly, in an input-oriented model, efficient output targets are calculated as:

$$y_{r0}^A = y_{r0} + S_r^+ \qquad i = 1,2,..., S \tag{5}$$

In Fig. 1, points A, B, C, D and E are efficient DMUs lying on the efficient frontier while point F represents an inefficient DMU (Chauhan *et al*., 2006). The point C represents the maximum productivity for a given mix of inputs and outputs and is called the Most Productive Scale Size (MPSS). The MPSS was defined as the scale where constant returns to scale prevail and the slope of outputs to inputs is one. Increasing returns to scale exist if the slope exceeds one and decreasing returns to scale occur when slope of the line is less than one. Increasing returns to scale indicate that an increase in the input resources produces more than proportionate increase in outputs. Similarly, decreasing returns to scale suggest a less than proportionate increase in the outputs in response to an increase in inputs. The information on whether a greenhouse operates at increasing, constant or decreasing returns to scale is particularly helpful in indicating the potential redistribution of resources among the greenhouse and, thus, enables grower to attain higher gross return.

The technical efficiency of point F is represented by the ratio MG/MF. This ratio measures efficiency of unit F relative to point G at the same scale size. The ratio MH/MG measures the divergence of actual scale size (G) from the most productive scale size (C). The overall efficiency is the ratio MH/MF which is also equal to the

product of technical and scale efficiency (MG/MF× MH/MG).

Thomas and Tauer (1994) showed that the use of value-aggregated inputs may result in failure to distinguish between technical and allocative effects and also that the ranking of the DMUs can change with different aggregation levels. The multi-stage DEA method that is applied in this paper is invariant to units of measurement (Coelli, 1998), thereby ensuring that the ranking of the DMUs will be consistent regardless of aggregation levels.

Economic analysis was done (Banaeian *et al*., 2010) for achieving important factors in commercial greenhouse strawberry. DEA model in economical aspect was applied to identify efficient and inefficient greenhouses and the sources of inefficiency. The current study consists of one output (gross returns of strawberry greenhouse) and four inputs. Gross returns include revenues from strawberry production only. Inputs are including labor, capital, fertilizer expenses and all other expenses per hectare in year 2010. Capital includes interest costs (short and long-term debt), depreciation, maintenance, insurance and other annual expenses of fixed assets (i.e., construction, irrigation, ventilation and machinery equipments). Labor includes family and hired labor and is measured in hours. Since the hydroponic cultivation method is used in strawberry greenhouses, fertilizer expenses represent the annual quantity for plant nutrition and measured in kilogram; while other expenses are the summation of all trifle other variable costs (water for irrigation, chemicals, transportation, electricity, taxes and etc.).

The data analysis was carried out with the help of the Excel 2007 spreadsheet, SPSS 16.0 software and DEA-Solver professional Release 6. The DEA-solver software was used to calculate constant and variable returns to scale with radial distances to the efficient frontier and to rank DMUs using the benchmark method.

RESULTS AND DISCUSSION

Economic analysis: Economic analysis of strawberry greenhouses is shown in Table 1 and investigated by Banaeian *et al*. (2011). About 76% of the total expenditure was variable costs, whereas 24% was fixed. The benefit to cost ratio of strawberry (1.74) indicate that strawberry production is a high profitable agricultural operation and net return was +151907.91 $/ha, in year of 2009. Productivity expressed by kg/$ that means each dollars expending in strawberry production how much product is produced, calculated in this study 0.59 kg/$.

Inputs and output of DEA model: Total cost of production include four section of fertilizer, labor, capital (fixed cost) and other costs (water, diesel, electricity and etc.), share of each section can be seen in Fig. 2. It is feasible that 51% of total cost of production related to fertilizer and human labor inputs which are the most cost consuming inputs in greenhouse strawberry production. In this study these four sections of total cost of production selected as inputs and gross return as output of DEA model.

Table 1: Economic analysis of greenhouse strawberry production

Cost and return components	Unit	Strawberry
Yield	kg/ha	64153.33
Sale price	$/kg	4.05
Gross value of production	$/ha	259821
Variable cost of production	$/ha	82344.91
Fixed cost of production	$/ha	25568.18
Total cost of production	$/ha	107913.09
Total cost of production	$/kg	1.68
Gross return	$/ha	177476.09
Net return	$/ha	151907.91
Benefit to cost ratio	-	1.74
Productivity	kg/$	0.59

Table 2 presents descriptive statistics of variables used in the analysis. A wide variation in both input use and output is noticeable. In some cases output and inputs obtained is more than ten times larger than that achieved by other greenhouses. Such a variation in input levels certainly suggests that certain levels represent poor resource management by producers. Considering this variation and high benefit to cost ratio, the proper potential for improvement of economic efficiency in strawberry greenhouses was seen and detailed study was seriously required.

Efficiency review:

Technical, pure technical and scale efficiency of greenhouses: Results obtained by application of the input-orientated DEA are illustrated in Table 3. The mean radial technical efficiencies of the samples under CRS and VRS assumptions are 0.73 and 0.96, respectively. This implies first, that on average, greenhouses could reduce their inputs by 27% (4%) and still maintains the same output level, and second, that there is considerable variation in the performance of greenhouses.

Increasing the technical efficiency of a greenhouse actually means less input usage, lower production costs and, ultimately, higher profits, which is the driving force for producers motivation to adopt new techniques.

Return to scale: The analysis shows that only two DMUs numbered 3 and 6 have best practice and actually are operating at the most productive scale size where CRS apply and scale efficiency equals one. The return to scale (RTS) indicated that all efficient units (based on technical efficiency) were operating at CRS, whereas all inefficient ones were at Increasing Return to Scale (IRS), which indicates that for considerable changes in yield,

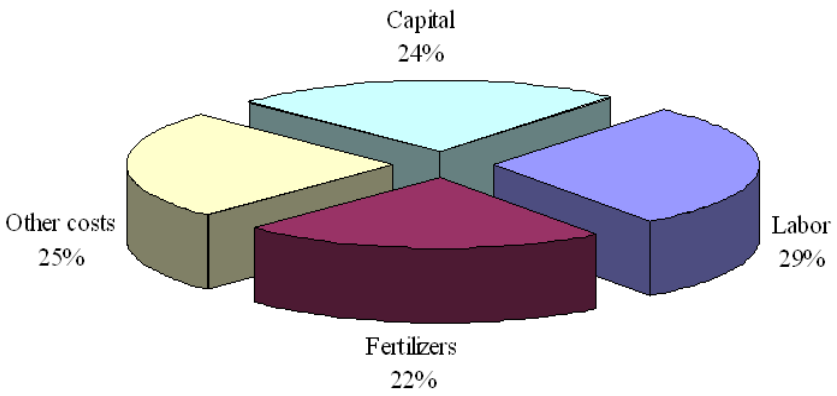

Fig. 2: Share of four section of total cost of production (Inputs used in DEA model)

Table 2: Descriptive statistics of the variables used in the DEA model

	Labor (h/ha)	Fertilizer (kg/ha)	Capital ($/ha)	Other costs ($/ha)	Gross return ($/ha)
Max	33600	18330	53396	83622	584589
Min	6832	1800	16047	11554	32508
Average	15364	5104	25568	33257	177476
SD[a]	5379	3713	6982	15580	109530

[a]Standard Deviation

Table 3: Technical and scale efficiencies and returns to scale

DMU	TE score	PTE score	SE score	Return to scale
GH1[b]	0.79	1.00	0.79	Increasing
GH2	0.63	0.84	0.75	Increasing
GH3	1.00	1.00	1.00	Constant
GH4	0.75	0.93	0.80	Increasing
GH5	0.88	1.00	0.88	Increasing
GH6	1.00	1.00	1.00	Constant
GH7	0.45	1.00	0.45	Increasing
GH8	0.63	1.00	0.63	Increasing
GH9	0.74	0.84	0.87	Increasing
GH10	0.81	0.98	0.82	Increasing
GH11	0.82	1.00	0.82	Increasing
GH12	0.81	1.00	0.81	Increasing
GH13	0.66	0.90	0.73	Increasing
GH14	0.80	0.95	0.84	Increasing
GH15	0.79	0.94	0.84	Increasing
GH16	0.68	1.00	0.68	Increasing
GH17	0.79	0.95	0.82	Increasing
GH18	0.82	1.00	0.82	Increasing
GH19	0.70	0.92	0.75	Increasing
GH20	0.40	1.00	0.40	Increasing
GH21	0.50	1.00	0.50	Increasing
GH22	0.78	0.94	0.83	Increasing
GH23	0.63	1.00	0.63	Increasing
GH24	0.72	1.00	0.72	Increasing
GH25	0.75	0.98	0.76	Increasing
Average	0.73	0.96	0.76	
SD[a]	0.14	0.04	0.14	

[a]: Standard deviation; [b]: Green House number 1

technological change is required. Increasing returns to scale indicates that an increase in the input resources produces more than proportionate increase in outputs. The average SE score of greenhouses is far from the optimal size (0.76), which indicates that if inefficient producers utilize their inputs efficiently, some savings in the different sources is possible without any change in technological practices. By contrast, Omid *et al*. (2010)

Table 4: Actual and efficient input use level of GH1

Items	Inputs			
	Labor (h/ha)	Fertilizer (kg/ha)	Capital ($/ha)	Other expenditure ($/ha)
Actual values	23520	3600	27803	26083
Radial movement	-8558	-619	-5818	-4140
Projected point	14962	2981	21985	21943
Slack adjustment	4792	43	4214	0

reported a higher (0.9) scale efficiency for cucumber greenhouses in Tehran province. An additional 24% productivity gain would be feasible - assuming no other constraining factors - provided they adjusted their greenhouse operation to an optimal scale. In the present dataset, no producer was found to operate at Decreasing Return to Scale (DRS).

Actual and target inputs of inefficient GH1: TE score for GH1 is 0.79, implying that the greenhouse could become technically efficient (under the Farrell definition) provided it reduces all its inputs proportionally by 21%. Hence, the analysis suggests that input use could be reduced to those shown in the third row of Table 4 while maintaining current production levels, assuming no other constraining factors. However, this greenhouse would not be Pareto-efficient, as it would be operating on the vertical section of the production frontier. In order to project a Pareto-efficient point, a further slack adjustment is necessary. Ultimately, GH1 has to reduce all inputs by 21% and labor, fertilizer and capital expense by another 20, 2 and 15%, respectively, in order to be operating at a fully technically efficient point (last row of Table 4). It can be seen that labor is the most inefficient source in GH1, so the greenhouse holder should make more attention to management of human labor hours.

For a sample of DMUs, DEA separates the efficient units from the inefficient ones and computes the efficient input levels for inefficient units in terms of linear combinations of input and output levels of efficient units. Optimal use of fertilizer, labors and etc not only is a way of improving the fruit quality characteristics, but also may have a crucial impact on the performance of greenhouse from an economic point of view as well.

Benchmarking:

Benchmarking of inefficient greenhouses: With the help of DEA method, the performance assessment can be carried out by comparing a particular system with key competitors having best performance within the same group or another group performing similar functions (Malana and Malano, 2006). This process is called benchmarking. Table 5 shows the results of pure technical efficiency analysis for the inefficient greenhouse unit (DMUs). Efficient DMUs can be selected by inefficient DMUs as best practice DMUs, making them a composite DMU instead of using a single DMU as a benchmark. A composite DMU is formed by multiplying the lambda value λ (intensity vector) by the inputs and outputs of the respective efficient DMUs.

Table 5: Results of pure technical efficiency analysis

DMU	PTE score	Benchmark
GH02	0.84	3(0.04) 24(0.96)
GH04	0.93	3(0.07) 12(0.14) 24(0.79)
GH09	0.84	1(0.66) 3(0.16) 6(0.18)
GH10	0.98	3(0.01) 11(0.74) 12(0.10) 18(0.15)
GH13	0.90	1(0.6) 3(0.02) 5(0.38)
GH14	0.95	3(0.06) 6(0.02) 11(0.4) 18(0.52)
GH15	0.94	3(0.05) 11(0.2) 12(0.13) 18(0.61)
GH17	0.95	3(0.01) 6(0.03) 11(0.66) 18(0.3)
GH19	0.92	1(0.34) 12(0.05) 16(0.41) 18(0.15) 24(0.05)
GH22	0.94	1(0.11) 3(0.04) 6(0.07) 18(0.78)
GH25	0.98	3(0.04) 12(0.02) 24(0.94)

Detailed benchmarking of inefficient GH14: Detailed benchmarking of inefficient GH14 is shown in Table 6, the composite DMU that represents the best practice or reference composite benchmark DMU is formed by the combination of GH3, GH6, GH11 and GH18. The summation of all lambda values in a benchmark DMU must equal 1. The lambda values are weights to be used as multipliers for the input levels of a reference greenhouse to indicate the input targets that an inefficient greenhouse should aim at in order to achieve efficiency. Based on the lambda values obtained by solving Eq. (1), the higher value calculated for GH18 (=0.52). It is clear that GH18 is the most influential benchmark and its level of inputs and output is closer to GH10 compared to the other four DMUs.

Input targets are shown in the last column and compares the actual input mix against those of its peers. It can be seen that the inefficiency of GH14 is attributed to the excessive use of inputs, especially regarding labor and fertilizer expenses. Because GH14 has more than one peer, it is essential to identify how much each peer influences the projected efficient production point.

The preceding analysis provides useful information to a greenhouse manager in determining excessive use of inputs and assessing alternative production strategies. The identification of the greenhouses that should be used in terms of benchmarking allows the establishing of the most appropriate best-practice management relative to the particular characteristics of each individual greenhouse.

Table 6: Input use levels of GH14 and of its peers

		Input use level of peers				
	GH14	GH3	GH6	GH11	GH18	Input target
Lambda		0.06	0.02	0.40	0.52	
Input						
Labor (h/ha)	13580	15866	24528	9520	14746	12918
Fertilizer (kg/ha)	5553	2400	18330	3000	3600	3582
Capital ($/ha)	26919	53396	16047	25656	22815	25650
Other expense ($/ha)	37651	83622	63262	32364	32122	35931
Output						
Gross return ($/ha)	212280	584589	348883	187547	184559	212280

Table 7: Ranking of DMUs on the basis of multi-input and single-input technical efficiency

DMU	PTE Score	Frequency in reference set	Benchmark ranking	Ranking based on human labor consumption (h/ha)	Gross return ($/ha)
GH3	1	9	1	1	584589.2
GH18	1	5	2	10	184559.1
GH12	1	4	3	3	155078.4
GH6	1	3	4	9	348883.3
GH11	1	3	5	4	187547.3
GH1	1	3	6	17	151208.1
GH24	1	3	7	20	101247.6
GH5	1	0	8	2	283340.1
GH16	1	0	9	14	119276.1
GH23	1	0	10	22	87222.8
GH8	1	0	11	16	86731.2
GH7	1	0	12	21	76580.5
GH20	1	0	13	25	32508.5
GH21	1	0	14	24	51195.6
GH10	0.988	_	15	5	183800.4
GH25	0.981	_	16	18	122507.9
GH17	0.956	_	17	6	193668.7
GH14	0.951	_	18	7	212280.9
GH22	0.946	_	19	11	207922.1
GH15	0.943	_	20	8	200652.5
GH4	0.937	_	21	13	142252.8
GH19	0.929	_	22	15	140787.3
GH13	0.909	_	23	12	211976.3
GH9	0.844	_	24	19	254911.9
GH2	0.841	_	25	23	116173.6

Benchmark ranking (multi and single input models): The benchmark ranking method is used to rank DMUs in this study. In this method, efficient DMUs are ranked according to their importance for inefficient units which do not lie on the frontier. Adler *et al*. (2002) described a simple two-stage technique to rank DMUs using the benchmark method. Firstly, an efficient DMU is ranked on the basis of counting the number of times it appears in a referent set. Each set is formed by the efficient DMUs that are similar to the input and output levels of inefficient DMUs. For instance, in this analysis GHs numbered 1,3, 6, 11, 12, 18 and 24 appear 3, 9, 3, 3, 4, 5 and 3 times in the reference set, respectively (Table 7). Those efficient DMUs that appear more frequently in the reference set of inefficient DMUs are considered superior because they are not only efficient but are also close to input–output levels of inefficient DMUs in the group. It follows those DMUs that are efficient but do not appear as reference for inefficient DMUs (GHs: 5, 7, 8, 16, 20, 21 and 23), will obtain a lower ranking. Inefficient DMUs (GHs: 2, 4, 9, 10, 13, 14, 15, 17, 19, 22 and 25) are considered more adequate to become efficient by following the best practices of the efficiency DMUs. In the second stage, inefficient units are ranked on the basis of their efficiency scores. The only drawback with this method is that an explicit and consecutive ranking is sometimes not possible as it is possible that more than one DMU may have the same score (Omid *et al*., 2010). Table 7 presents the performance ranking of the DMUs using this approach. GH3 appeared in the benchmark referent set of all inefficient DMUs and is given the top ranking. In this way, the benchmark ranking assigns more importance to the GH3 as an efficient DMU that is considered useful by the inefficient DMUs as a reference benchmark. The analysis also identified potential for improvements in technical efficiency of strawberry.

Single-input benchmarking analysis is commonly used in agriculture to rank productive performance in relation to various inputs including land, personnel, fuel consumption, fertilizer usage, water for irrigation, etc. The level of agricultural inputs used by producers is often related to input costs, and within certain limits, inputs can be substituted for one another in the production process. This is not reflected in single-input benchmarking

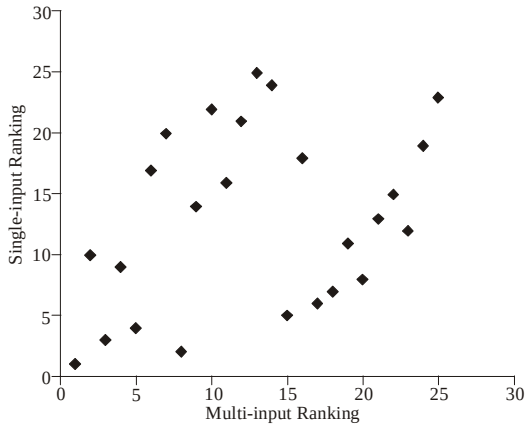

Fig. 3: Relation between multiple-input and single-input benchmarking of greenhouses

analysis (Malana and Malano, 2006; Omid *et al*., 2010). Figure 3 shows the correlation (R^2 = 0.11) between performance ranking on the basis of multi-input and single-input (labor) technical efficiency (Table 7), as the most cost consuming inputs for strawberry production in the different greenhouses investigated were labor. The low level of correlation between the two benchmark ranking approaches indicates that the remaining inputs (fertilizer costs, capital and other expenses) play important roles in determining the level of DMUs productive performance. Conversely, a high correlation would have indicated that the selected input is more important in determining the level of gross return. Based on the technical efficiency analysis, a ranking based only on labor would mask the effect of input substitution with capital input. As indicated above, we cannot expect greater gross return of some other inputs such as fertilizers and other expense given that their slack values are negligible in the greenhouse unit analysis of technical efficiency.

These results suggest that a degree of caution must be exercised in the number and selection of variables included in the benchmarking analysis. The selection of variables must be closely related to the objectives of the study and the output yield being evaluated.

The present analysis considered only four inputs and a single output. However, strawberry management inputs were not quantified in this analysis. DEA assumes all DMUs to have the same quality of inputs regardless of differences in environment, climate and cultural practices. However, depending on the availability of data, this type of information could also be included in the analysis as variables.

CONCLUSION

Since result showed that greenhouse strawberry production is a high profitable agricultural operation with large variation of data, a detailed study for improvement of economical efficiency in greenhouses was required. This study described an in-depth application of input-oriented DEA model to investigate the degree of technical and scale efficiency of 25 commercial strawberry greenhouses in the Alborz province of Iran. This procedure allows the determination of GH 3 and 6 as the best practice greenhouses that can be providing useful insights for other greenhouse management.

The practices followed by the truly efficient greenhouses form a set of recommendations in terms of efficient operating practices for the inefficient ones. By using these greenhouses as benchmark, inefficient greenhouses can determine which changes in resource use are necessary in order to increase their overall performance and, ultimately, their profitability. If producers can reach a higher level of technical efficiency, this would bring about an increase in gross return or a reduction in the consumption of inputs. On average; a potential 27% reduction in input use could be achieved provided that all strawberry greenhouses operated efficiently, assuming no other constraints on this adjustment. This would cut down the average cost of production and improve the competitiveness of greenhouse.

RTS indicated that all efficient units (based on technical efficiency) were operating at CRS, whereas all inefficient ones were at IRS, which indicates that for considerable changes in yield, technological change is required.

Differences between multi-input and single-input (labor as the most cost consuming inputs) ranking indicates that the remaining inputs (fertilizer costs, capital and other expenses) play important roles in determining the level of DMUs productive performance. Undoubtedly, additional research is required to generalize the evidence provided in this study, in particular regarding the explanation of the underlying differences in efficiencies in the use of a particular input and the assessment of the constraints to changes in operational practices that would improve efficiency.

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REFERENCES

Adler, N., L. Friedman and Z. Sinuany-Stern, 2002. Review of ranking methods in the data envelopment analysis context. Eur. J. Oper. Res., 140: 249-265.

Anonymous, 1995. Monthly wholesale prices for fresh strawberries in New York (1980-1993). US Department of Agriculture Mktg Serv.

Banaeian, N., M. Omid and H. Ahmadi, 2011. Energy and economic analysis of greenhouse strawberry production in Tehran province of Iran. Energ. Convers. Manage., 52(2): 1020-1025.

Banaeian, N., M. Omid and H. Ahmadi, 2010a. Energy use pattern and benchmarking of greenhouse strawberry by Data Envelopment Analysis. In: 8th International conference of Data Envelopment Analysis (DEA 2010), 10 -12 June, Beirut, Lebnon, pp: 39.

Banaeian, N., M. Zangeneh and M. Omid, 2010b. Energy use efficiency for walnut producers using Data Envelopment Analysis (DEA). Aust. J. Crop Sci., 4(5): 359-362.

Banker, R.D., A. Charnes and W.W. Cooper, 1984. Some models for estimating technical and scale inefficiencies in Data Envelopment Analysis (DEA). Manage. Sci., 30: 1078-1092.

Charnes, A., WW. Cooper, B. Golany, L. Seiford and J. Stutz, 1985. Foundations of Data Envelopment Analysis for Pareto-Koopmans efficient empirical production functions. J. Econom., 30: 91-107.

Charnes, A., WW. Cooper and E. Rhodes, 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res., 2: 429-444.

Coelli, T., 1996. A Guide to DEAP Version 2.1: A Data Envelopment Analysis (Computer) Program. CEPA Working Papers, Department of Econometrics, University of New England, Australia.

Coelli, T., 1998. A multi-stage methodology for the solution of orientated DEA models. Oper. Res. Lett., 23: 143-149.

Chauhan, N.S., P.K.J. Mohapatra and K.P. Pandey, 2006. Improving energy productivity in paddy production through benchmarking - an application of data envelopment analysis. Energ. Convers. Manage., 47: 1063-1085.

FAO (Food and Agriculture Organization), 2007. Agricultural Statistics. Retrieved from: http:// www.fao.org.

Farrell, M.J., 1957. The measurement of productive efficiency. J. Royal Stat. Soc. Ser. A, 120: 253-281.

Galanopoulos, K., S. Aggelopoulos, I. Kamenidou and K. Mattas, 2006. Assessing the effects of managerial and production practices on the efficiency of commercial pig farming. Agric. Sys., 88: 125-141.

Hancock, J.F., 1999. Strawberries. CAB International, Wallingford, pp: 237.

Iraizoz, B., M. Rapun and I. Zabaleta, 2003. Assessing the technical efficiency of horticultural production in Navarra, Spain. Agric. Sys., 78: 387-403.

MAJ (The Ministry of Agriculture of Jihad), 2010. Annual Agricultural Statistics. Ministry of Jihad-e-Agriculture of Iran. Retrieved from: http://www. maj.ir/english/main/default.asp.

Malana, N.M. and HM. Malano, 2006. Benchmarking productive efficiency of selected wheat areas in Pakistan and India - data envelopment analysis. Irrig. Drain., 55: 383-394.

Mohammadi, A. and M. Omid, 2010. Economical analysis and relation between energy inputs and yield of greenhouse cucumber production in Iran. Appl. Energ., 87: 191-196.

Nassiri, M.S. and S. Singh, 2009. Study on energy use efficiency for paddy crop using data envelopment analysis (DEA) technique. Appl. Energ., 86: 1320-1325.

Omid, M., F. Ghojabeig, M. Delshad and H. Ahmadi, 2010. Energy use pattern and benchmarking of selected greenhouses in Iran using data envelopment analysis. Energ. Convers. Manage., doi:10.1016/ j.enconman.2010.06.054.

Onut, S. and S. Soner, 2006. Analysis of energy use and efficiency in Turkish manufacturing sector SMEs. Energ. Convers. Manage., 48: 384-394.

Shafiq, M. and M. Rehman, 2000. The extent of resource use inefficiencies in cotton production in Pakistan'S Punjab: An application of Data Envelopment Analysis. Agric. Econ., 22: 321-330.

Sharma, K.R., P.S. Leung and H.M. Zaleski, 1999. Technical, allocative and economic efficiencies in swine production in Hawaii: A comparison of parametric and nonparametric approaches. Agric. Econ., 20: 23-35.

Singh, G., S. Singh and J. Singh, 2004. Optimization of energy inputs for wheat crop in Punjab. Energ. Convers. Manage., 45: 453-465.

Thanassoulis, E., 2001. Introduction to the Theory and Application of Data Envelopment Analysis. Kluwer Academic Publishers, Norwell.

Thiam, A., B.E. Bravo-Ureta and T.E. Rivas, 2001. Technical efficiency in developing country agriculture: A meta-analysis. Agric. Econ., 25: 235-243.

Thomas, A.C., L., Tauer, 1994. Linear input aggregation bias in nonparametric technical efficiency measurement. Can. J. Agric. Econ., 42: 77-86.

Zangeneh, M., M. Omid and A. Akram, 2010. A comparative study on energy use and cost analysis of potato production under different farming technologies in Hamadan province of Iran. Energy, 35: 2927-2933.