Efficiency analysis of sugar beet farms in Turkey: case of Kahramanmaraş

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Abstract

The purpose of the study is to measure the technical efficiency of sugar beet farms and to identify the relationship between social and environmental factors with technical efficiency in sugar beet production. Data were obtained from 95 sugar beet farms in the Afşin district of Kahramanmaraş of Turkey in 2018. Data Envelopment Analysis and Tobit regression were used in the analyzes. The efficiency scores of the sugar beet farms were 0.86 (CRS) and 0.91 (VRS). This result shows that farmers can reduce their inputs by 14% and 9% to achieve the same level of output. Further, higher education, sugar beet area located far from the thermal power plant, using certified hybrid seed, and benefiting from Environment-Friendly Agricultural Land Protection (EFALP) subsidy increase the technical efficiency of the sugar beet farms. Policymakers should provide better extension services for strengthening farmers' knowledge and administrative skills for the improvement of technical efficiency. Besides, increasing the amount of environmental subsidies and monitoring the steps taken by thermal power plants to reduce environmental pollution will play a crucial role to improve sugar beet farms' efficiency and sustainability.

Keywords: Sugar beet. Technical efficiency. Data envelopment analysis

1. Introduction

Sugar beet is the second most important raw material required for all industrial raw and refined crystal sugar. The world's sugar production was approximately 166.7 million tons and 76.24% was obtained from sugar cane and 23.76% from sugar beet in 2019/20 production period (Turkseker, 2020). Sugar beet is an important product for human and livestock nutrition and industrial needs (Erdal et al., 2007). In addition to sugar production, sugar beet is an important source to produce ethanol, biogas, molasses and pulp (Reineke et al., 2013; Zicari et al., 2019). Due to its economic contribution to sugar industries, benefits for farmers' welfare, and a crucial role in human and animal nutrition, its importance and production increase in many countries day by day (Cagatay & Teoman, 2006; Asgharipour et al., 2012; Baran & Gokdogan, 2016).

Tukey's sugar production mainly depends on sugar beet production. In 2019, Turkey produced approximately 18.9 million tons of sugar beet from a total area of 310100 ha which makes up 6.49% of total world production. Considering the quantity, Turkey is the fifth major sugar beet producer after Russia, France, Germany, and the United States of America in the world and third place in Europe (FAO, 2019). In Turkey, the sugar regime is regulated by Sugar Law since 2001. A total of 33 companies (15 public, 12 private and 6 sugar beet cooperatives) operate within the sugar industry and the production is controlled by Turkish Sugar Factories with a quota system (Turkseker, 2020). Sugar production is done under contracts between farmers and sugar factories depending on the sugar quotas. Sugar beet, one of the basic products in Turkey's agricultural production, is also important in terms of its contributions to the agricultural industry, animal husbandry and Turkey's economy through income and employment. Further, sugar beet production is an important source of livelihood for farmers in rural areas. Approximately 350 thousand families are growing sugar beet (Erdal et al., 2007).

As in all other sectors, the main purpose of the farms in the agricultural sector is to maintain the business' financial success by maximizing the output using the lowest amounts of inputs (Rashidghalam, 2018). Considering the competitive market conditions, farmers must use the inputs in production effectively and efficiently to survive in the market. Also, policymakers are making great efforts to improve farm efficiency and quality for combatting high input costs and waste of scarce resources. With efficiency analyzes resource efficiency of the efficient and inefficient farms can be determined and compared (Parlakay & Alemdar, 2011). In this context, studying and analyzing the farms' efficiency and its determinants will provide useful information for better productivity in the agricultural sector as in all economic sectors. Given that the increasing demand and inadequate resources, more efficient use of resources through innovative ways have a crucial role in the future (Lampach et al., 2018). Also, considering the importance of sugar beet production for country economies, productive and efficient use of resources is very important for the future of the sugar beet industry (Wu et al., 2003).

In this context, this study aims to measure the technical efficiencies of the sugar beet farms and to identify the social and environmental factors affecting the economic performance of sugar beet farms in Kahramanmaraş province of Turkey. Moreover, this study will reveal the relationship between the technical efficiency of sugar beet farms and thermal power plants, Environment-Friendly Agricultural Land Protection (EFALP) subsidy, using certified seed. The results can provide useful information for the policymakers for developing and implementing new policy instruments to increase the farm productivity and encouraging farmers to allocate their resources more properly. By determining the inefficiency sources, more efficient production will be provided, costs can be minimized and profits can be maximized as stated by Gunduz et al., (2011).

2. Literature Review

Efficiency measurement has received an extensive attention from researchers in agricultural production. Several studies have been conducted on efficiency measurement for different products. They have primarily concentrated on plant production (Abate et al., 2019; Ahmad et al., 2002; Aye & Mungatana, 2010; Bozoğlu & Ceyhan, 2007; Mohdidris et al., 2014; Mugera & Langemeier, 2011; Odeck, 2007; Parichatnon et al., 2018; Tipi et al., 2009). There are also studies in dairy farming (Ahmad & Bravo-Ureta, 1996; Ahmed et al., 2020; Mayen et al., 2010), goat and sheep farming (Gül et al., 2016; Qushim et al., 2016) and trout farming (Cinemre et al., 2006).

Considering the studies on sugar beet production have been generally focused on energy use efficiency. However, there have been a limited number of studies measuring the technical efficiency of sugar beet farms. For example, Wu et al., (2003) computed the technical, scale and congestion efficiency of sugar beet farms in Idaho by using non-parametric procedures. Also, they employed the Tobit model to examine the inefficiency of farms. They calculated the average efficiency score as 0.88 with 45% of farms being efficient.

Tzilivakis et al., (2005) evaluated the environmental impact and economic performance of different sugar beet production systems in the UK. They used 13 sugar beet production scenarios. They found that a significant proportion of the UK crop is being grown economically efficient while minimizing environmental damage.

Erdal et al., (2007) determined the energy consumption of input and output and cost analysis of sugar beet production in Tokat, Turkey. They have found that total energy consumption was 39 685.51MJha^{-1}, and accounted for 49.33% of fertilizer energy, and 24.16% of diesel energy. Further they estimated that 82.4% total energy input was in non-renewable energy form, and only 12.82% was in renewable form. Also, they calculate the profit-cost ratio as 1.17.

In Iran, Asgharipour et al., (2012) evaluated the energy consumption of inputs and outputs used in sugar beet production. Also, they determined the relationship between energy inputs and sugar beet yield. Another study in Iran, Zamani et al., (2019) compared the economic performance of the cooperative and non-cooperative sugar beet farms. They used super efficiency data envelopment analysis. They found that the average efficiency scores of cooperative farms were significantly higher than non-cooperative farms.

In a study conducted in Kırklareli province of Turkey, Baran & Gokdogan, (2016) aimed to perform an energy analysis of sugar beet production. The data were collected by face-to-face questionnaires with 48 sugar beet farms. According to the results, the energy input and output were calculated as 34201.75 MJ ha^{-1} and 285.600 MJ ha^{-1}. Energy usage efficiency, energy productivity, specific energy and net energy in sugar beet production were calculated as 8.35, 1.98 kg MJ^{-1}, 0.50 MJ kg^{-1} and 251398.25 MJ ha^{-1}, respectively.

In Germany, Reineke et al., (2013) calculated the energy balances for sugar beet cultivation in commercial farms. They determined the total energy input 17.3 GJ ha^{-1}, energy output 261.7 GJ ha^{-1}, energy gain 244.6 GJ ha^{-1}, output-input ratio 15.4 and energy intensity 87.4 MJ GE^{-1}. Mansour & Eldeep, (2014) estimated the technical and economic efficiencies of sugar beet farms in Egypt. The data of the study were collected from 250 sugar beet farmers that were divided into three categories. The results showed that under the constant returns to scale the average technical efficiency for the whole sample was %83.

Dimitrijević et al., (2020) evaluated the energy and economic efficiency of sugar beet and wheat production in Serbia. The results of this study showed that energy input of sugar beet was 0.93 $MJ.kg^{-1}$. They found that wheat production was a low profitable production in comparison with sugar beet production.

3. Material and Method

The study was conducted in the Afşin district of Kahramanmaraş Province located in the eastern Mediterranean of Turkey. The Afşin district is 1230 meters above sea level, has a continental climate, and has rich lignite deposits. Turkey's largest thermal power plant complex has located in the district. Afşin and Elbistan ‘A’ power plant has a power of 1355 MW and it is the 2nd largest lignite power plant in Turkey. On the other hand, Afşin and Elbistan ‘B’ thermal power plant has a power of 1440 MW which is the largest lignite power plant in Turkey. Consequently, 2.7 million tons of ash was released from the chimneys and spread to the environment, as a result of the burning of coal extracted from thermal power plants (Akbay & Bilgiç, 2020).

In this study, 12 villages were chosen as the study area and a face-to-face questionnaire was conducted in 2018. The sample size was calculated 95 using the

Proportional Sampling Method at 95% confidence interval and 10% error margin (Newbold, 1995). Sample size was calculated by using the formula below:

$$n = \frac{N * p * q}{(N-1) * \sigma_p^2 + p * q}$$

where n is sample size, N: total number of sugar beet farms, p: The ratio of sugar beet farms in the population (0.05 was taken for maximum sample) and σ_p^2: variance calculated as 0.00260.

The efficiency scores of sugar beet farms were measured by DEA (Data Envelopment Analysis) and the effective factors on the farm efficiency were evaluated by Tobit regression.

DEA, a non-parametric mathematical technique is used to measure the relative efficiency of decision-making units (Tipi et al., 2009). It was first used by Charnes et al. (1978). Two basic assumptions, one is Constant Returns to Scale (CRSTE) (Charnes et al., 1978), and the other is Variable Returns to Scale (VRSTE) (Banker et al., 1984) are used in DEA. DEA can be categorized into input-oriented or output-oriented. The input-oriented model minimizes input for a given level of output while in the output-oriented model it maximizes output for a given level of input.

An input-oriented DEA was utilized for estimating the efficiency scores in this study considering that farmers have more control on inputs than outputs. Assume that there are data on M outputs and K inputs for each of N farms. Input-oriented DEA model is obtained by solving the following linear programming problem (Coelli et al., 2005);

$$\begin{aligned} &\mathrm{Min}_{\theta,\lambda}\ \theta, \\ &\theta \text{ Subject to} \quad -y_i + Y\lambda \geq 0, \qquad (1) \\ &\theta x_i - X\lambda \geq 0 \\ &\lambda \geq 0, \end{aligned}$$

where θ is the TE score for ith farm and λ is a vector of constants, Y and X are the output and input matrix. y_i (M*1) and x_i (K*1) represents the vector of output and input weights of the i-th farm. θ is a score lies between zero and one, and a value of 1 indicates a point on the frontier and the farm is technically efficient (Farrell, 1957). θ<1 indicates the technical inefficiency of each farm. Therefore, the CRS model extended to VRS by adding a convexity constraint (N1′λ = 1) to previous linear programming (Banker et al., 1984). By adding a convexity constraint, TE scores obtained from TE_{CRS} (also called total efficiency) decomposed into pure technical efficiency (TE_{VRS}) and scale efficiency (SE). If there is a difference between TE_{CRS} and TE_{VRS} scores indicating that a farm is scale-inefficient (Coelli et al., 2005). SE is equal to TE_{CRS} / TE_{VRS} scores. While SE=1 indicates that the farm is scale efficient, SE<1 indicates scale inefficiency.

The input and output variables that are used to measure technical efficiency vary due to the aim of the study and data availability. Mostly, yield and production value used as output variables while land, labor, fertilizer, seed, herbicide, irrigation, fuel were commonly used as input variables (Wu et al., 2003; Yazdani & Rahimi, 2013; Atici & Podinovski, 2015; Rashidghalam, 2018; Todorović et al., 2020; Wimmer & Sauer, 2020). Following the literature, as summarized in Table 1, one output and three inputs were involved to calculate efficiency scores in the model. The output variable is Gross Production Value and it was calculated by the sum of the market value of sugar beet and its pulp value. The labor cost of the farmers and their family members on the farm has been estimated by taking into account the current wages paid to the hired labor force. Fertilizer, seed, herbicide, fuel, and irrigation costs were calculated by multiplying the amount and market prices declared by farmers. All variables were measured in Turkish Liras per decare. DEA analysis was performed by using Deap 2.1 software (Coelli, 1996).

In this study, the relationship between social and environmental factors and TE was analyzed by the Tobit regression (Wu et al., 2003; Coelli et al., 2005; Bozoğlu & Ceyhan, 2007). The variables in the Tobit model have been considered by the literature (Wu et al., 2003; Odeck, 2007; Balcombe et al., 2008; Nguyen et al., 2019). Farm's region, type of seed, and benefitting from Environment-Friendly Agricultural Land Protection (EFALP) subsidy were added as determinants that were related to the external environment. EALP is one of the most comprehensive environmental protection programs in Turkey (Boz, 2016). It has implemented since 2006 for the protection of soil and water quality, prevention of erosion, and mitigation of agriculture-derived negative impacts, executed by the Ministry of Agriculture and Forestry. Within the scope of the EFALP program, payments are made for three years to applications specified in different three categories. In the study area, the third category was employed which includes the use of fertilizers and plant protection products in the general principles of integrated crop management with appropriate pressurized irrigation systems. Also, the program includes the implementation of organic or good agricultural practices and underground drainage systems (Hasdemir & Hasdemir, 2016).

The Tobit model is expressed as follows:

$$Y = \alpha + \beta x_i + \ldots . + X_n + u \qquad (2)$$

While dependent variable Y is TE_{VRS} score obtained from DEA model, X_{i-n} is explanatory variables and β is the coefficient parameter of X_i variable. Table 1 presents descriptive statistics and descriptions of the variables used in the analyzes.

Table 1: Descriptive statistics of the variables used in the analyzes

	Description	Mean	Std. Deviation	VIF
Output variable in DEA				
Gross production value	TL/decare	2280.19	227.08	N/A
Input variables in DEA				
Labour cost (family and hired)	TL/decare	319.82	97.28	N/A
Fertilizer cost	TL/decare	268.57	50.37	N/A
Other costs (seed, chemicals, fuel and irrigation)	TL/decare	336.82	58.50	N/A
Tobit variables				
Education	years	8.94	2.49	1.46
Experience in farming	years	26.64	11.13	1.43
Sugar beet production area	decare	54.19	50.38	1.31
Region	1: if a farm is located near the thermal power plant, 0:otherwise	0.53	0.50	1.55
Extension contact	Frequency of interaction with extension services (times/month)	1.94	1.21	1.25
Seed	1:if farmers use certified hybrid seed, 0:otherwise	0.88	0.32	1.25
Subsidy	1: if farmer benefits from EFALP subsidy, 0:otherwise	0.57	0.49	1.49

4. Results and Discussion

The frequency distributions of TE_{CRS}, TE_{VRS} and SE scores of sugar beet farms are given in Table 2. Eight farms were fully efficient under the CRS while 14 farms under VRS and 10 farms under SE. It was also found that approximately 65% of farms had an efficiency score above 80%, implying that the farms can enhance their production by 20%.

Table 2: Distributions of technical efficiency scores

Efficiency scores	TE_{CRS}	%	TE_{VRS}	%	SE	%
0.600-0.700	2	2.11	0	0.00	1	1.05
0.701-0.800	23	24.21	3	3.16	4	4.21
0.801-0.900	38	40.00	38	40.00	9	9.47
0.901-0.999	24	25.26	40	42.11	71	74.74
1.000	8	8.42	14	14.74	10	10.53
Total	95	100.00	95	100.00	95	100.00

Table 3 presents the average input-oriented technical efficiency scores of sugar beet farms. Under the CRS assumption, the TE score ranges from 0.63 to 1 with an average of 0.86. Under the VRS assumption, the minimum TE score is 0.76 with an average of 0.91.

These results imply that by reducing their input use %14 and 9%, sugar beet farms still achieve the same level of output.

Table 3: Efficiency scores obtained from DEA

Effectiveness	Min.	Max.	Mean	Std. Deviation	Efficient Farms	Efficient Farms (%)
TE_{CRS}	0.63	1	0.86	0.08	8	8.40
TE_{VRS}	0.76	1	0.91	0.07	14	14.70
SE	0.68	1	0.94	0.06	10	10.50

The mean of TE indicates that if the sugar beet farms operated at full efficiency they would increase their output 14% and %9 using the existing sources and level of technology. Moreover, technically inefficient farms could improve their efficiency by %14 and %9 by exploiting inputs optimally to achieve TE levels of efficient farms. In a study conducted by Wu et al. (2003), TE ranged between 0.46 to 1 with 45% of the sugar beet farms exhibiting full efficiency. In Iran, Yazdani & Rahimi (2013) measured the technical efficiency of the sugar beet farms to be 0.89 and 0.70 under the CRS and VRS assumptions, respectively. Another study in Iran, Rashidghalam (2018) reported that technical efficiency scores vary between 0.67-0.94 with respect to different non-parametric models.

Generally, the cause of inefficiency is due to inappropriate scale or misallocation of resources. Inappropriate scale means that the farm is not taking advantage of economies of scale, while misallocation of resources refers to inefficient input combinations (Ören & Alemdar, 2006). From the results in Table 3, SE ranges between 0.68 and 1 with an average of 0.94. The average SE of the sugar beet farms suggests that farms are relatively efficient in their choice of scale. Therefore, the causes of inefficiency may be due to the use of improper input combinations, lack of technical knowledge, and inappropriate management practices.

The descriptive statistics of return to scale of sugar beet farms were given in Table 4. According to the Table, 7.36% of farms operated under DRS. This indicates that the proportional increase in inputs results in a smaller proportional increase in output. Besides, the inputs are overuse which results in a capacity underutilization. Moreover, 82.12% of farms are operating under IRS which means the increase of output is higher than the increase in inputs. To increase their output, farms operate under DRS should reduce input consumption while farms under IRS should increase the use of their inputs. In addition, the CRS rate in the study area is 10.52%. This means that a 1% increase in inputs leads to the same proportional increase in output (Table 4).

Table 4: Characteristics of sugar beet farms concerning returns to scale

	Farm number	%	Sugar beet area	Yield (kg/da)	Gross production value (TL/da)
CRS	10	10.52	42.20	9300.00	2462.50
DRS	7	7.36	87.86	9928.57	2571.50
IRS	78	82.12	52.71	8688.46	2230.68

1$=4.82 TL in 2018.

After measuring the TE of farms it is important to identify the determinants of TE. Seven variables were analyzed in the Tobit regression model (Table 5). According to the results, four out of seven variables have been found a statistically significant effect on the level of TE in sugar beet production. These variables are the education of farmers, region, use of certified hybrid seed and EFALP subsidy.

The educational status of the farmers has been found statistically significant ($p<0.10$). This result revealed that as the education level of farmers increases, the TE of sugar beet farms increases. This is due to the fact that higher education increases the possibility to adopt and utilize new technologies and innovation in the production process. This finding was in line with rice farms in Bangladesh (Balcombe et al., 2008), Vietnam (Nguyen et al., 2019), red pepper farms in Ethiopia (Abate et al., 2019) and trout farms in Turkey (Cinemre et al., 2006).

The region variable has a negative and significant effect on the farms' technical efficiency ($p<0.01$). The farms which operated near the thermal power plant are less technically efficient compared to the farms far from. This could be due to fact that the dust and ash released from thermal plant's chimneys pollute natural resources and the environment. Thus, in the area, the farmers use more inputs to have a higher yield. According to a study in the region that investigates the effects of the thermal power plant on the environment and human health, it was stated that the pollution maybe 10 km away depending on the prevailing wind direction (Akbay & Bilgic, 2020). The authors also stated that not having filters and necessary technology, there was a negative effect on agricultural production due to the environmental pollution created by power plants. The third explanatory variable is the hybrid seed. It was found that using certified hybrid seed has a positive and significant effect on-farm efficiency ($p<0.01$). In the study area, various options are offered by the sugar factory on what type of seed to use for farmers. Farmers mainly preferred local or imported seed. The result shows that the farms that using imported hybrid seed has higher technical efficiency than those using local hybrid seed.

Finally, farmers who benefit from the EFALP subsidy had higher technical efficiency levels than their most efficient counterparts. A possible explanation for this might be that the EFALP ensures optimal input usage by encouraging farmers to implement pressurized irrigation systems, controlled use of pesticides and fertilizers, organic production and good agricultural practices. In a study conducted in Kırşehir, Boz (2016) stated that the EFALP program increased the local environmental quality and income level of the farmers. On the contrary, Yıldırım et al. (2018) found that non-participating farms in EFALP were more efficient than the participants of EFALP.

Table 5: Tobit regression results

Parameters	Coefficients	Std. Err.	t-value	P-value
Constant	0.8161***	0.0400	20.39	0.000
Education	0.0053*	0.0028	1.87	0.065
Experience in farming	0.0003	0.0006	0.53	0.595
Sugar beet area	0.0001	0.0001	1.26	0.210
Region	-0.0873***	0.0156	-5.59	0.000
Extension contact	0.0007	0.0057	0.12	0.901
Seed	0.0704***	0.0208	3.37	0.001
Subsidy	0.0375**	0.0153	2.44	0.017

LR X^2 =51.34; p-value= 0.000, ***p<0.01, **p<0.05, *p<0.10

5. Conclusion

This study aims to investigate the technical efficiency and its determinants of sugar beet farms in Kahramanmaraş province of Turkey in 2018. An input-oriented DEA was employed to estimate TE scores under CRS and VRS assumptions and Tobit regression was applied to determine the factors affecting TE.

According to the results, there is room to enhance the efficiency of sampled farms, given the same level of output and current technology. TE scores were 0.86 and 0.91, implying that the inefficient farms could have reduced the inputs by 14% and 9% without output loss. Results also indicate that 65% of farms obtained have TE scores above 80%. Moreover, SE and pure technical efficiency (TE_{VRS}) evaluated together, the main cause of inefficiency primarily occurs from improper input combinations. In other words, there is excessive use of inputs in the production process. Second, Tobit regression results showed that higher education, having sugar beet area far from the thermal power plant, using certified hybrid seed, and benefiting from EFALP subsidy, are all associated with technical efficiency.

This study has several policy implications regarding the results of DEA and its determinants. Generally, policymakers need to focus on strengthening farmer' knowledge and administrative skills by creating an environment for better extension services to contribute to the improvement of technical efficiency. Considering the positive effect of education, sugar factories will play a crucial role in providing technical information to improve farm productivity. Also, given the positive effect of certified hybrid seed on TE, policymakers should continue to support the use of certified hybrid seed. Applying price premiums may encourage farmers to use certified seed that was offered by sugar factories. Besides, the EFALP program may be considered as a central strategy to achieve improved productivity and reduce the negative impacts of thermal power plants. Furthermore, policymakers should monitor the steps taken to prevent environmental pollution by thermal power plants for sugar beet farms' sustainability.

6. References

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