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Technical Efficiency of Tomato Production in Kamyaran County with an Emphasis on Integrated Land Management Strategies

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ABSTRACT

Low production efficiency and land fragmentation are two of the most pressing challenges facing the agricultural sector in Iran. Given the importance of tomato production and Iran's role in this crop, this study evaluates the technical efficiency of tomato farmers in Kamyaran County, Kurdistan Province, with an emphasis on integrated land management. Data were collected from 200 tomato farmers during the 2023–2024 agricultural year using simple random sampling. A Cobb–Douglas stochastic frontier production function was employed to estimate technical efficiency. The results indicate that labor, number of irrigation events, and cultivated area had positive and significant effects, whereas the use of chemical fungicides had a negative and significant effect on tomato production and technical efficiency. The number of cultivated plots, as an indicator of land fragmentation, had a negative and significant effect on tomato production, reflecting higher management costs and reduced input-use efficiency in fragmented farms. Although the effects of cultivated area and number of plots in the technical efficiency function were not statistically significant, their coefficient signs were consistent with theoretical expectations and the production function results. The analysis of technical efficiency distribution shows that average technical efficiency in large-sized farms is considerably higher than in medium and small farms. Farmers' age had a negative effect, while farming experience had a positive and significant impact on technical efficiency. Based on the results, to enhance technical efficiency, optimal input management through targeted training, implementation of land consolidation policies, participatory agriculture, and improvement of farm management structures are recommended.

Keywords: Land consolidation, Land fragmentation, Stochastic frontier analysis, Technical efficiency, Tomato production.

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INTRODUCTION

The agricultural sector as one of the four main sectors of the Iranian economy plays an important role in food security and economic development (Zoghipour et al., 2023). According to World Bank (2024), the value added of the agricultural sector accounts for approximately 10.8 percent of Iran's GDP. This share is particularly significant given that, in 2023, 14.31 percent of the country's labor force was directly engaged in agricultural activities. The importance of this sector becomes more evident when considering that farming is the main activity of 23 percent of the Iranian population living in rural areas (Farajzadeh et al., 2024). However, low levels of production and efficiency are among the main obstacles to development in this sector. The growing population, limited inputs and production resources, and inefficient utilization of production factors have not only challenged production growth, but have also created a significant gap between actual production and optimal production potential (Akinbola et al., 2023). These challenges highlight the critical need to identify and address the factors affecting production and efficiency. One of the key factors influencing production and efficiency, which is also considered as the most significant issues and challenges for agricultural development, are the fragmentation and small size of agricultural land.

Land fragmentation refers to the existence of several non-connected agricultural plots cultivated by a farmer at different geographical distances. This phenomenon, along with the small size of the farm, creates serious structural barriers to mechanization, optimal input management, and achieving economies of scale (Oyebanjo, 2023). In such circumstances, the farmer has to spend more time and labor on moving between plots, which not only leads to labor waste, but also significantly increases production and transportation costs, and consequently, reduces technical efficiency (Wang et al., 2021). This challenge is also very severe in Iran; according to the Food and Agriculture Organization (FAO), the per capita agricultural land area (including arable, orchard, and pasture lands) in Iran has decreased by 80 percent during 1961-2020 (FAOSTAT, 2020). This long-term trend has not only led to the proliferation of smallholdings, but also has been accompanied by the phenomenon of land fragmentation in many areas, especially in mountainous areas such as the rural areas of Kurdistan Province. In such conditions, scalable agriculture and the use of modern technologies face serious structural limitations.

Kurdistan Province, as one of the important agricultural production regions in western Iran, has always faced challenges such as low resource productivity, high production costs, and limited share of producers in the added value of production. According to the agricultural statistics of the Kurdistan agricultural Jihad organization in 2022, the total cultivated area of the province was approximately 853,921 hectares, with 84 percent being rain-fed and 16 percent irrigated. Despite this potential, the agricultural sector in the province has not been able to experience development compared to other more prosperous provinces, which could be due to low total factor productivity, including land, labor, water, and other production inputs. Among these, tomato, as one of the important crops in Kurdistan Province, is highly sensitive to production efficiency due to its intensive requirements for water, labor, and chemical inputs. A significant portion of it is grown in Kamyaran County; According to the agricultural statistics of the Kurdistan agricultural Jihad organization, in 2022, about 704.9 hectares of the total cultivated area in Kamyaran County were dedicated to tomato cultivation, producing 37,552 tons of tomatoes. Like other agricultural products in the province, the problem of land fragmentation and small farm sizes has also affected tomato cultivation. This inappropriate land structure can affect the production and technical efficiency of this product by increasing costs and limiting the adoption of new technologies. Therefore, evaluating the technical efficiency of tomato production in Kamyaran County and identifying the factors affecting it is essential to improve productivity and enhance the performance of the agricultural sector in the region.

Several international studies have examined the factors affecting technical efficiency in the agricultural sector, mainly focusing on two key dimentions: farm size and land fragmentation. Regarding farm size, there are two opposing views. On the one hand, some studies in South Asia, such as Kumar and Moharaj (2023), have reported an inverse relationship between farm size and productivity in rice cultivation in India, arguing that smallholder farmers are more efficient due to closer supervision and greater use of family labor. Also, In the study by Mwangi et al. (2020) that measured tomato efficiency in Kenya, land size had a significant negative effect on efficiency. In contrast, other studies including Cheruiyot and Sang (2020) in Kenya, Ngango and Hong (2022) in Rwanda, Ji et al., (2023) in the United States and Kusz and Kusz (2024) in the European Union have shown a positive or nonlinear relationship between farm size and efficiency, with medium-sized or larger farms having higher productivity. This discrepancy in findings suggests that the relationship between farm size and efficiency depends on the socio-economic conditions and the specific crop studied.

In contrast, the literature on land fragmentation is more consistent. Wang et al. (2021) in China, Oyebanjo (2023) in Nigeria, Eder (2025) in Austria and Tsaiyu (2025) in Taiwan have independently shown in their studies that land fragmentation leads to increased labor costs, reduced access to mechanization services, and consequently, reduced crop yields and efficiency. However, some studies have reported different findings. A study by Zhou et al., (2024) in southern China showed that the relationship between land fragmentation and agricultural technical efficiency is U-shaped; such that at low levels of fragmentation, increasing the number of plots reduces efficiency due to increased management costs, but at higher levels it leads to improved efficiency through increased crop diversity and reduced production risk. The study by Olarinre and Omonona (2018) also showed that land fragmentation had a positive and significant impact on the productivity of rice farmers in Nigeria. This may be due to differences in the definition of fragmentation or local conditions. However, the literature generally shows that land fragmentation, especially for input-intensive crops such as rice and tomatoes, is a major obstacle to the development of scalable agriculture.

A review of the studies showed that despite the extensive literature, there is a significant research gap; so far, no detailed study has been conducted on the impact of small-scale and fragmented agricultural land on production and technical efficiency across farms of different scales in Iran. Given that Kamyaran County is recognized as a major hub for tomato production in the North West part of Iran with agricultural lands characterized by considerable diversity in size and high levels of fragmentation, this study aims to fill this research gap with an emphasis on land integration management in this region.

MATERIALS AND METHODS

The study area is Kamyaran County, located in Kurdistan province, Iran. Covering an area of 1,852 square kilometers, Kamyaran lies in the southern part of the province at 46°55' E longitude and 34°48' N latitude, with an average elevation of 1,340 meters above sea level. The total population of the county is approximately 102,856 people. Kamyaran County comprises two cities (Kamyaran and Muchesh), two districts (Central and Muchesh), seven rural districts, 144 inhabited villages, and 20 uninhabited villages. The region has a semi-arid climate, with average annual precipitation of about 450 millimeters. The maximum recorded temperature is 36°C, while the minimum can drop to -15°C (Statistical Yearbook of Kurdistan Province, 2022).

The statistical population comprised 300 active tomato farmers in Kamyaran County. To ensure representativeness and minimize selection bias, a simple random sampling approach was employed, providing each farmer with an equal probability of inclusion. The required sample size was calculated using Cochran's (1977) formula for simple random sampling:

$$n = \frac{Nz^2p(1-p)}{d^2(N-1)+z^2p(1-p)}$$

where n denotes the sample size, N is the population size, z represents the critical value of the standard normal distribution, p is the estimated population proportion, and d is the margin of error. Assuming a 95% confidence level (z = 1.96), maximum variability (p = 0.5), and a 5% margin of error, the minimum required sample size was calculated to be 169 farmers. To enhance the reliability and precision of the estimates, a total of 200 farmers were ultimately surveyed.

Empirical Model

In general, there are two distinct approaches for measuring efficiency in a production unit: data envelopment analysis (DEA) and stochastic frontier analysis (SFA). The stochastic frontier model, as a parametric method, enables the separation of technical inefficiency from random shocks and measurement errors. Given the stochastic nature of agricultural activities and the presence of factors beyond the producer's control, the stochastic frontier approach was considered more appropriate for the present study.

Within the framework of the stochastic frontier production model, the frontier function represents the highest attainable output corresponding to a specific combination of inputs. Any decision-making unit at this maximum level is considered to be technically perfect, and other units will have levels of technical inefficiency depending on how far they are from this production frontier. The stochastic frontier production model is typically expressed by the following functional equation:

$$y_i = f(X_i, \beta)\exp(\varepsilon_i) \quad i=1,2,\ldots,N \tag{1}$$

In this specification, y_i indicates the output level for the ith farm, X_i denotes the input vector associated with ith farm, β represents the parameter vector to be estimated, and ε_i refers to the composite error term comprising two distinct components.

$$\varepsilon_i = V_i + U_i \tag{2}$$

V_i represents a symmetric random error, which is assumed to be normally distributed with a mean of zero and a constant variance. Ui is a non-negative error term to calculate the inefficiency of farm ith (Workneh and Kumar, 2023). To determine the technical efficiency, the parameter γ is defined as follows:

$$\gamma = \frac{\sigma_u^2}{(\sigma_v^2 + \sigma_u^2)} \tag{3}$$

In this context, γ is defined as the ratio of the variance of the inefficiency component to the total variance, and its numerical value lies between zero and one. If γ = 0, it implies that technical inefficiency can be attributed to a set of explanatory variables which are hypothetically associated with managerial factors, and as a result, the estimation of technical efficiency becomes unfeasible. Under this condition, the ordinary least squares method is considered more appropriate than the maximum likelihood estimation (MLE) approach. Conversely, when $\gamma > 0$, it indicates the presence of inefficiency, and the model parameters should then be estimated using the maximum likelihood method (Ji et al., 2023; Zhou et al., 2024). In the current study, the stochastic frontier production function was estimated, with its empirical specification presented as follows:

$$\ln(Y) = \beta_0 + \beta_M \ln(M) + \beta_L \ln(L) + \beta_F \ln(F) + \beta_H \ln(H) + \beta_P \ln(P) + \beta_C \ln(C) + + \beta_A \ln(A) + \beta_G \ln(G) + V_{it} + U_{it} \tag{4}$$

Here, Y represents the production of tomato (in kilograms). The explanatory variables M, L, F, H, P, C, A and G respectively denote: machinery input (in hours), labor input (in person-days), chemical fertilizers (including phosphate, potash, and urea) (in kilograms), organic fertilizer (in tons), liquid pesticides (including herbicides and insecticides) (in liters), fungicides (in kilograms), cultivated area (in thousand square meters), and the number of tomato cultivation plots.

The term V_i captures random variation in output arising from factors beyond the control of the producer, while U_i is included in the model to represent technical inefficiency. In this study, the effect of age, agricultural work experience, and education on inefficiency has been investigated. Following the estimation of the stochastic frontier production function and the calculation of technical efficiency, farms were classified based on land size using Dalenius and Hodges (1959) stratification method to analyze efficiency across different farm size categories (Zimmer et al., 2013).

This study is applied in nature with respect to its objectives and employs a field-based data collection approach.Cross-section Data were collected for the agricultural year 2023-24 via structured interviews and questionnaire administration. The collected data were subsequently analyzed using STATA MP17, SPSS 16, and Excel 2016 softwares.

RESULTS AND DISCUSSION

According to the descriptive statistics related to the general characteristics of farmers, the average age of the respondents was 45.8 years. The average number of years engaged in agricultural activities particularly tomato cultivation was 21.5 years. These findings suggest that farmers possess a relatively high level of experience and skill in agriculture and specifically in tomato cultivation. The majority of respondents (77 percent) had an educational level equivalent to diploma or lower. Furthermore, the results indicated that, 48.5 percent of farmers cultivated tomatoes on a single plot, while 51.5 percent cultivated on multiple plots. This showed the fragmented nature of landholdings under tomato cultivation in the studied region.

Based on the Dalenius and Hodges (1959) stratification method, farms were categorized into 3 groups according to land size: small, medium, and large holdings. Among the surveyed farmers, 120 individuals (60 percent) cultivated tomatoes on small-scale plots (5,000 square meters or less), 43 farmers (21.5 percent) operated on medium-sized plots (between 5,000 and 10,000 square meters), and 37 farmers (18.5 percent) cultivated on large plots (greater than 10,000 square meters). The results indicate that the majority of tomato farms in the study area are small and fragmented in scale (see Table 1).

Table 1. The classification of tomato cultivated area in the study sample using the Dalenius and Hodges stratification method

Description	Range (thousand square meters)	Absolute Frequency	Relative Frequency (percent)
small-scale plots	$X \le 5$	120	60
medium-sized plots	$5 < X \le 10$	43	21.5
Large-sized plots	$X > 10$	37	18.5

In order to estimate the tomato production function, four functional forms transcendental, translog, Cobb–Douglas, and generalized quadratic were evaluated using various criteria and statistical tests.

Table 2. Statistics from the estimation of production functions.

Description	Transcendental	Translog	Cobb-Douglas	Generalized quadratic
Percentage of significance	31.8	32.5	50	34.2
R^2	0.926	0.937	0.926	0.986
Adjusted R^2	0.923	0.932	0.926	0.985
F	397.87 (0.000)	210.077 (0.000)	312.435 (0.000)	1007.529 (0.000)
Breusch-Pagan	-1.299 (0.99)	-1.139 (0.98)	-0.904 (0.99)	0.406 (0.99)
DW	1.943	2.008	2.043	2.008
Kolmogorov-Smirnov	0.053 (0.200)	0.065 (0.400)	0.046 (0.200)	0.192 (0.000)
VIF	22.884	780.023	3.205	742.187

According to the results reported in Table 2, the Cobb–Douglas functional form was selected as the preferred specification. This choice was based on the statistical significance of 7 out of the 14 estimated coefficients, a coefficient of determination exceeding 90 percent, a statistically significant F-statistic, and the absence of violations of the classical regression assumptions. Accordingly, the Cobb–Douglas production function was also employed in estimating the stochastic frontier production function.

Table 3. Results of estimating the stochastic frontier production function.

Variable	Variable symbol	Coefficient	Std. Error	Prob.
Cons	Cons	8.778	0.277	0.000
Machinery	Ln(M)	0.049	0.057	0.389
Labor	Ln(L)	0.239	0.071	0.001
Organic fertilizer	Ln(H)	-0.005	-0.006	0.408
Chemical fertilizer	Ln(F)	-0.028	0.051	0.577
Liquid pesticides	Ln(P)	-0.015	0.010	0.160
Fungicide	Ln(C)	-0.025	0.013	0.052
Cultivated area	Ln(A)	0.832	0.071	0.000
Number of plots	Ln(G)	-0.092	0.053	0.083
Age	Ln(O)	2.669	0.945	0.005
Agricultural work experience	Ln(E)	-1.219	0.312	0.000
Education level	Ln(K)	-0.791	0.445	0.075
	Log Likelihood	-19.192		
	$\sigma^2 v$	0.0163		
	$\sigma^2 u$	0.168		
	$\sigma^2= \sigma^2 v+ \sigma^2 u$	0.184		0.000
	Γ	0.911		0.000
	Likelihood Ratio Test (LRT)	23.58		0.000
	Average technical efficiency: 0.722	Maximum efficiency: 1	Minimum efficiency:0.104	

Source: Research findings

According to the results in Table 3, labor has a positive and significant effect on production at the 99 percent confidence level. In fact, with a 1 percent increase in labor use, production increased by 0.239 percent. Labor contributes to improved management across different stages of production, which can enhance productivity, reduce losses, and improve the quality of the product. This result is consistent with the findings of Ayen et al. (2025), Lestari et al. (2024), Younas et al. (2024), and Oladele et al. (2024).

According to the estimated coefficients, a 1% increase in fungicide application is associated with a 0.025% decrease in tomato production. Field data indicated that Ridomil fungicide, as the most commonly used fungicide in the region, was applied by the majority of farmers. The observed average application rate (1.98 kg/ha) falls within the internationally recommended range for this fungicide in tomato cultivation (approximately 2–2.5 kg/ha). The observed negative effect may be attributed to factors such as application of the fungicide at inappropriate times, mismatch between the fungicide type and the causal pathogen, or inefficient management of input use.Among the inputs, cultivated area had the most positive and significant impact on tomato production, so that for every 1 percent increase in cultivated area, tomato production increased by 0.832 percent. Although this elasticity is less than one, indicating diminishing marginal returns to land; larger farms benefit from better access to machinery, technology, and specialized labor, which enhance management capacity. These findings support policies promoting land consolidation not for increasing yield per hectare, but for enabling more efficient resource use and adoption of modern practices, consistent with Akbar et al. (2024), Bendjouad (2023), Shafiwu et al. (2022), Ngango and Hong (2022), and Alizadeh et al. (2019).

The number of plots under tomato cultivation had a negative effect on production, so that a 1 percent increase in this variable led to a 0.092 percent decrease in production. In fact, as the number of plots under cultivation increases, production costs increase and farm management becomes more difficult, so land fragmentation can act as a structural barrier to increased production. This result is in line with the results of Wang et al (2021), Ashrit (2022), and Lu et al. (2018) who demonstrated that land fragmentation increases production costs and reduces production. However, the coefficient of machinery, was not statistically significant; In several stochastic frontier analyses, machinery inputs have similarly exhibited positive but statistically insignificant coefficients. For instance, Bai et al. (2019) and Ifegwu and Ajetomobi (2018) reported non-significant positive effects of machinery on agricultural output, reflecting limited marginal returns under prevailing smallholder farming conditions which consistent with the findings of this study. Also, the coefficients for organic fertilizer, chemical fertilizer, and liquid pesticides were negative but statistically insignificant, a pattern observed in several efficiency studies (Ji et al., 2023; Kerorsa, 2025; Hardiyanti et al., 2022). As Mohamed and Bakr (2025) note, such results often reflect excessive or misaligned agrochemical use, which can harm soil health and reduce yields despite theoretical expectations.

The gamma (γ) parameter, which represents the share of technical inefficiency in the total variance, is estimated at 0.911 and is statistically significant at the 1% level. This value indicates that approximately 91.1% of the total variation in the composite error term is attributable to technical inefficiency, while only a small proportion is due to random shocks and factors beyond the control of producers. Therefore, differences in output levels across farms are largely explained by variations in their technical efficiency.

Furthermore, the likelihood ratio test (LRT = 23.58) is statistically significant at the 1% level, leading to the rejection of the null hypothesis of no technical inefficiency. This finding confirms that the stochastic frontier model is more appropriate than the conventional ordinary least squares (OLS) regression model. According to the results of the stochastic frontier Cobb-Douglas production function, age has a positive effect on technical inefficiency among tomato producers at the 99 percent confidence level. In other words, as age increases, technical inefficiency tends to rise. This may be attributed to older farmers being less inclined to adopt modern technologies or to alter traditional farming practices. Education has a negative effect on technical inefficiency among tomato producers at the 90 percent confidence level, meaning that higher levels of education are associated with lower inefficiency. Farmers with higher educational attainment are likely to possess better analytical skills, greater capacity to adopt modern technologies, and enhanced ability to optimize agricultural processes, all of which contribute to improved efficiency and reduced technical inefficiency. This result is in line with the results of Tanursaz et al., (2021) and Ghasemi et al., (2025). Farming experience also has a negative effect on technical inefficiency among tomato producers, indicating that increased experience leads to a reduction in technical inefficiency. This result is consistent with the findings reported by Tanursaz et al., (2021) and Kazmi Shabanzade Aflaki et al., (2025).

As the results demonstrate, the average technical efficiency of tomato production in the studied sample is 72.2 percent, indicating a relatively satisfactory performance among the tomato farmers. This means that farmers can reduce their input usage by approximately 28 percent without any loss in production. Sadozai et al. (2025) reported a technical efficiency level of 78 percent for tomato production in the Bajaur District of Khyber Pakhtunkhwa. In another study by Hassan shahi (2019), 81 percent of producers in Arsanjan county had technical efficiency levels ranging between 80 percent and 100 percent. In contrast, Mwangi et al. (2020) reported a much lower average technical efficiency of 39.55 percent in Kirinyaga county. Given that the maximum observed technical efficiency among tomato producers was 1 and the minimum was 0.104, there is a substantial variation (0.9) in efficiency across the surveyed units. Following the estimation of technical efficiency and classification of farms using the Dalenius Hodges method, the average technical efficiency across different farm sizes was examined. The results revealed a significant positive relationship between farm size and technical efficiency. Specifically, tomato producers operating on larger plots exhibited higher average technical efficiency compared to those farming on medium- and small-sized plots. These results align with the findings reported by Begum et al. (2023), Anang et al. (2016), and Kenari et al. (2020), but contrast with the study by Mwangi et al. (2020), which reported an inverse relationship between farm size and efficiency.

Table 4. Technical efficiency of tomato farmers in different sized fields.

	Amount of technical efficiency		
Description	Large-sized land	Medium-sized land	Small-sized land
Average	0.808	0.745	0.687
Maximum	1	0.889	0.952
Minimum	0.584	0.411	0.104

Source: Research findings.

Returns to Scale

Table 5 presents the estimated returns to scale, reflecting the proportional change in output resulting from a simultaneous proportional change in all production inputs. Within the Cobb–Douglas production framework, the scale elasticity is obtained by summing the estimated output elasticities of all inputs. The estimated returns to scale coefficient (0.954) suggests that production operates close to constant returns to scale. This finding indicates that increasing all inputs simultaneously leads to an almost proportional increase in output. Therefore, while expansion of cultivated area contributes positively to production, the overall production structure appears to be operating near its optimal scale.

Table5. Returns to Scale.

	Coefficient	**Std. err.**	**Prob.**
Returns to Scale	0.954	0.049	0.000

Source: Research findings.

Based on the theoretical framework and review of the literature, the effects of production inputs, socio-economic characteristics of farmers, cultivated area, and the number of cultivated plots on the technical efficiency of tomato producers were examined using 3 functional forms linear, semi-logarithmic, and Cobb-Douglas along with various evaluation criteria and statistical tests.

Table 6. Statistics from estimating different functional forms.

Description	Linear	semi-logarithmic	Cobb-Douglas
Percentage of significance	42.85	42.85	42.85
R^2	0.161	0.191	0.159
Adjusted R^2	0.135	0.166	0.132
F	6.149 (0.000)	7.546 (0.000)	6.032 (0.000)
Breusch-Pagan	-1.593 (0.99)	-0.365 (0.99)	-0.019 (0.99)
DW	2.134	2.013	2.060
Kolmogorov-Smirnov	0.041 (0.200)	0.46 (0.200)	0.48 (0.200)
VIF	7.213	5.419	4.189

Source: Research findings.

According to the results presented in Table 6, none of the 3 estimated functional forms violated the classical assumptions. In all 3 models linear, semi-logarithmic, and Cobb-Douglas, 42.85 percent of the coefficients were statistically significant at the 5 percent level. The coefficient of determination (R^2) and the adjusted R^2 were approximately 19 percent for the semi-logarithmic model, and around 16 percent for both the linear and Cobb-Douglas models. In all 3 models, the F-statistic confirmed the overall statistical significance of the regression. Based on the evaluation criteria and statistical assumptions, the semi-logarithmic functional form was identified as the most appropriate specification.

Table 7. Results of estimating the semi-logarithmic technical efficiency function.

Variable	Variable symbol	Coefficient	Std. Error	Prob.
Machinery	Ln(M)	0.027	0.036	0.453
Labor	Ln(L)	0.047	0.013	0.000
Organic fertilizer	Ln(H)	-0.001	0.004	0.838
Chemical fertilizer	Ln(F)	-0.004	0.029	0.891
Liquid pesticides	Ln(P)	-0.001	0.006	0.920
Fungicide	Ln(C)	-0.022	0.008	0.006
Cultivated area	Ln(A)	0.029	0.039	0.467
Number of irrigation events	Ln(I)	0.230	0.079	0.004
Number of plots	Ln(G)	-0.003	0.033	0.928
Age	Ln(O)	-0.216	0.071	0.003
Agricultural work experience	Ln(E)	0.061	0.028	0.027
Education level	Ln(K)	0.026	0.036	0.408
Seed type	S	0.069	0.026	0.008
Cons	Cons	0.417	0.454	0.360
	F=7.546(000)	R^2=0.191	DW=2.013	

Source: Research findings.

As indicated by the results presented in Table 7, the F-statistic confirms the overall significance of the model. The coefficient of determination for the technical efficiency model is 0.19. Although this value appears relatively low, such magnitudes are common in cross-sectional farm-level studies, where efficiency is influenced by multiple unobserved factors. Variables such as climatic variability, access to extension services, and farmers' managerial capabilities, which were not directly observable in the available data, may explain part of the unexplained variation. These findings are consistent with the results reported by Hassan Shahi (2019).

Based on the results, the coefficient of labor was 0.047 and was significant at the 1% level, indicating that farmers who use more labor have higher technical efficiency. In tomato production, which is a labor-intensive, time-sensitive crop that requires precise operations in the planting, maintenance, and harvesting stages, labor plays a key role in timely implementation of agricultural operations, better farm management, and optimal use of inputs such as fertilizer, pesticides, and water. Therefore, increasing the efficient labor force enhances input coordination and improves the technical efficiency of production units. This finding is consistent with the results of the study by Workneh et al. (2023) who stated that labor has a positive effect on farmers' efficiency.

Furthermore, the coefficient of number of irrigation events is 0.230 and statistically significant at the 1% level, indicating that this factor has the greatest effect on the technical efficiency of tomato production among all inputs. Since tomato is a crop sensitive to moisture stress and water supply timing, appropriately increasing and scheduling irrigation events improves plant growth and yield, more efficient use of other inputs, and ultimately increases technical efficiency. This result is consistent with the empirical evidence of studies by Morais et al., (2021), Chand and Kishore (2021) and Kalli et al. (2024), which show that access to irrigation and its effective management increase the efficiency of production units.

The coefficient of the variable of fungicide use is -0.022 and is significant at the 1% level, indicating that higher consumption of this input is associated with a decrease in the technical efficiency of tomato production. dummy variable for seedling type (assigned 0 for farmers who used seeds and 1 for those who used transplants) exhibited a positive and statistically significant effect on technical efficiency. Farmers who used seedlings (transplants) demonstrated 0.069 units' higher technical efficiency compared to those who used seeds.

Among the socio-economic variables, the age of the farmer had a significant negative effect on the technical efficiency with a coefficient of -0.216. This negative effect could be due to the lower willingness of older farmers to adopt new technologies and optimal farm management practices; this finding is consistent with the results of the study by Seok et al., (2018) and Liu et al., (2019). In contrast, the agricultural work experience variable with a coefficient of 0.061 and a significance level of 5% led to an increase in the production efficiency, which could be due to the farmer's higher ability to manage resources and carry out agricultural operations. This finding is also in line with the results reported by Debebe et al., (2015), which found that increasing experience leads to an increase in the level of technical efficiency of farmers.

Other variables, including machinery, chemical and organic fertilizers, liquid pesticides, marital status, education, cultivated area, and number of plots under cultivation were not statistically significant; therefore, based on the results of this model, the significant effect of these variables on the technical efficiency of tomato farmers in Kamyaran County cannot be confirmed. The lack of statistical significance for these variables indicates that within the sample data and by controlling for other factors, their variations did not directly lead to a significant difference in technical efficiency. However, the signs of the coefficients for cultivated area and number of plots under cultivation are consistent with the theoretical foundations and the results obtained from the stochastic frontier production function; so that increasing the cultivated area has a positive effect and increasing the number of plots has a negative effect on technical efficiency.

CONCLUSIONS

In recent years, due to the increased demand for agricultural products and limited resources, improving technical efficiency in the production of strategic crops has become essential. Understanding the precise factors affecting production quantity and efficiency can pave the way for enhancing productivity and optimizing the use of inputs. In this regard, the present study investigates the economic evaluation of technical efficiency among tomato farmers in Kamyaran County, with an emphasis on the role of farm size and integrated land management. To assess the technical efficiency of tomato farmers, a stochastic frontier production function with a Cobb-Douglas specification was utilized. Additionally, to investigate the factors affecting technical efficiency, 3 functional forms linear, semi-logarithmic, and Cobb-Douglas were examined. Based on various criteria and statistical tests, the semi-logarithmic form was selected as the appropriate model. The findings of the stochastic frontier production function showed that the cultivated area has the strongest positive effect on production. Also, the number of plots under cultivation, as an indicator of land fragmentation, showed a negative and significant effect on production, reflecting higher managerial costs and reduced efficiency in input utilization on fragmented farms. Among the inputs, labor had a positive and significant effect on production, while fungicides had a negative effect. These results indicate that inappropriate land structure and improper management of inputs can act as significant constraints to enhancing agricultural productivity.

The results also showed that the technical efficiency of tomato production in Kamyaran County is significantly affected by both production inputs and socio-economic characteristics of farmers. Specifically, labor, number of irrigation events, seed type, and agricultural work experience had a positive and significant effect on technical efficiency, while fungicide use and farmer age had a negative effect on technical efficiency. Although the effects of cultivated area and number of plots in the technical efficiency model were not statistically significant, the signs of their coefficients are consistent with the theoretical foundations and results of the stochastic frontier production function. In addition, descriptive analysis of technical efficiency based on farm size showed that the average technical efficiency in large farms (0.808) is higher than that of medium farms (0.745) and small farms (0.687). This finding confirms that farm size indirectly affects the improvement of technical efficiency by reducing management constraints and facilitating the use of technology and inputs.

Based on the findings, agricultural policies should focus on improving the technical efficiency of tomato production through effective input management and optimization of farm operations.

Given the positive and significant impact of number of irrigation events on efficiency, designing extension programs to educate farmers on optimal irrigation timing and appropriate water application rates can increase water productivity and the efficiency of other inputs. Additionally, educating farmers on the appropriate timing of pesticide application, improving input management, and using expert supervision can help reduce the negative effects of these inputs on technical efficiency. Furthermore, promoting the use of seedlings (compared to conventional seeds) among farmers, which had a positive and significant impact on efficiency in this study, is recommended.

Considering the negative effect of age and the positive effect of agricultural work experience on the level of technical efficiency, it is suggested that while taking advantage of the experience of experienced farmers, policies should encourage the active participation of young people in agriculture and employ them in extension and training programs, production cooperatives, and farm-based activities. On the other hand, considering the negative effect of land fragmentation on production and the higher technical efficiency observed on large farms, gradual and voluntary implementation of land consolidation plans is recommended as a structural strategy in the study area. Such initiatives should be carried out by building mutual understanding, gaining the trust of local communities, and engaging local leaders. This can be accomplished by clearly communicating the benefits of consolidation through educational workshops and organizing field visits to successful projects in which the integration plan has been implemented. Also, in order to solve the problem of smallholdings and fragmentation of farms, solutions such as designing and drafting new legal laws to prevent land fragmentation, creating technically and economically suitable plots, voluntary exchange of plots, cooperative farming, and land consolidation management are suggested.

LIMITATIONS

It should be noted that our analysis captures only the structural dimension of integrated land management. Broader ecological, institutional, and participatory aspects of ILM such as soil conservation practices, water governance, or community-based land use planning are not measured in this study due to data limitations. Also, a potential limitation of the two-stage approach is the possible presence of generated regressor bias, as the technical efficiency scores used in the second-stage regression are estimated rather than observed variables. This may affect the standard errors and statistical inference in the efficiency determinants model. While this method is widely applied in empirical studies for its flexibility, the results of the second-stage analysis should be interpreted with caution.

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کارایی فنی تولید گوجه فرنگی در شهرستان کامیاران با تأکید بر استراتژی مدیریت یکپارچه زمین

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چکیده

کارایی پایین تولید و پراکندگی زمین دو چالش اساسی پیش‌روی بخش کشاورزی در ایران هستند.با توجه به اهمیت گوجه‌فرنگی و جایگاه ایران در تولید آن، این مطالعه کارایی فنی کشاورزان گوجه‌فرنگی در شهرستان کامیاران، استان کردستان، با تأکید بر مدیریت یکپارچه زمین را ارزیابی می‌کند. داده‌ها از ۲۰۰ کشاورز گوجه‌فرنگی‌کار در سال زراعی ۲۰۲۳–۲۰۲۴ از طریق نمونه‌گیری تصادفی ساده جمع‌آوری شده است. برای برآورد کارایی فنی، از تحلیل مرزی تصادفی مبتنی بر فرم کاب–داگلاس استفاده شده است. نتایج نشان داد که نیروی کار، تعداد دفعات آبیاری و سطح زیرکشت اثر مثبت و معنادار، و مصرف سموم شیمیایی اثر منفی و معناداری بر تولید و کارایی فنی داشته است. تعداد قطعات زیرکشت به‌عنوان شاخصی از پراکندگی اراضی، اثر منفی و معنی‌داری بر میزان تولید گوجه‌فرنگی داشت که بیانگر افزایش هزینه‌های مدیریتی و کاهش کارایی استفاده از نهاده‌ها در مزارع پراکنده است. اگرچه اثر سطح زیرکشت و تعداد قطعات در تابع کارایی فنی از نظر آماری معنی‌دار نبود، اما جهت ضرایب آن‌ها با مبانی نظری و نتایج تابع تولید سازگار بوده و تحلیل توزیع کارایی فنی حاکی از آن است که میانگین کارایی فنی در مزارع با اندازه بزرگ به‌طور قابل‌ملاحظه‌ای بالاتر از مزارع متوسط و خرد است. سن کشاورزان اثر منفی و تجربه کاری اثر مثبت و معناداری بر کارایی فنی داشته است. بر اساس نتایج، به منظور ارتقای کارایی فنی، مدیریت بهینه مصرف نهاده‌ها از طریق آموزش‌های هدفمند، اجرای سیاست‌های یکپارچه‌سازی و کشاورزی مشارکتی و بهبود ساختار مدیریت مزارع توصیه می‌شود.