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Research Article

Performance of cold-water fish farms (rainbow trout) in Sistan, Iran: Applying the super-efficiency envelopment analysis approach

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Abstract

This study examined the performance of rainbow trout (*Oncorhynchus mykiss*) farms in the Sistan region of Iran during 2023-2024, using the super-efficiency envelopment analysis technique. Data were collected through structured questionnaires, and technical efficiency was evaluated using the basic Data Envelopment Analysis (DEA) approach. The findings were then compared with the super-efficiency DEA model. The average technical efficiency was 63.50% (ranging from 0.21 to 1) under the constant return to scale model and 79.35% (ranging from 0.54 to 1) under the variable return to scale model. Additionally, average scale efficiency was 76.1% (ranging from 0.38 to 1). Only 20% of the farms achieved full efficiency, exhibiting significant variations in technical efficiency. The results demonstrated that discrepancies in input consumption management were the primary factor contributing to technical inefficiency. Therefore, optimizing input management is critical for enhancing efficiency in these aquaculture systems.

Introduction

Marine fish stocks are a vital part of the global food system. However, overfishing is on the rise, raising widespread concerns about the depletion of fish stocks in most parts of the world (Hilborn *et al*., 2020). According to the Food and Agriculture Organization (FAO) report in 2025, 35.5% of global marine fish stocks are currently being exploited at levels beyond their biological sustainability capacity, meaning these stocks are at risk. This situation is particularly difficult in certain regions, especially in the southeastern Pacific Ocean and the Mediterranean and Black Seas, where only 46 to 47.4% of stocks are sustainably harvested. Furthermore, reports indicate that in some areas, fish stocks have decreased to less than 10% of their original levels, which is referred to as “approaching extinction” or “severe depletion” (FAO, 2025). Today, the aquaculture industry holds a significant place in the global economy, particularly in food security, trade, job creation, and rural poverty reduction. Aquaculture, which is projected to reach 106 million tons by 2030 (FAO, 2022), is expected to play a crucial role in bridging the gap between fish supply and the growing global demand (Lubchenco *et al*., 2020). Research has shown that compared to other agricultural sectors, aquaculture produces fewer environmental wastes and damages, and focusing on it could significantly contribute to economic development and food security. Additionally, food security has always been of great importance in developing countries. In line with food security and governments' efforts to preserve public health, increasing the share of aquatic products in people's diets is crucial (Farashi *et al*., 2019). However, the growth of this industry faces a wide range of environmental concerns (Naylor *et al*., 2000; Hall *et al*., 2011) stemming from the ecological impacts of its inputs and resources (Waite *et al*., 2014; Ahmed and Thompson, 2019). These challenges include water pollution, increased consumption of natural resources for fish feed, habitat destruction, and the transmission of diseases and parasites, which can negatively affect aquatic ecosystems. Therefore, ensuring the sustainability of aquaculture is essential, as it can improve environmental productivity, environmental compatibility, profitability, and the social benefits of this industry (Sun *et al*., 2020).

Cold-water aquaculture is a fundamental and expanding sector of the aquaculture industry, which has captured the attention of countries and global organizations responsible for improving nutrition and alleviating national poverty (Mohammaditabar *et al*., 2019). Among cold-water fish, rainbow trout (*Oncorhynchus mykiss)* is considered a protein-rich source (Fry *et al*., 2018). In 2018, global rainbow trout production in domestic and freshwater settings reached 664,854 tons, with Iran accounting for 26 percent of this figure. Iran has over 50 years of experience in aquaculture, particularly in freshwater fish production. In 2018, it ranked second in the Middle East and 19th globally in aquaculture. Total seafood production was approximately 72,000 tons in 1978/79, including nearly 4,935 tons from aquaculture. However, this amount significantly rose to 1,282,475 tons in

2019/20, comprising 527,747 tons from aquaculture and 559,095 tons from fishing. The high potential for aquaculture across all provinces, combined with the attractiveness of investment in this sector, alongside efforts to promote seafood consumption and raise public awareness about this valuable protein source, can drive the growth and development of this industry (Abdolhay and Asgari, 2020).

Given the limitations of food production resources and the increasing food demands of human communities, developing countries can explore and reduce the gap among producers under similar conditions by assessing farmers' efficiency. Moreover, the scarcity of production factors forms the basis of economic science. The availability of production inputs, both human and non-human, is limited under any circumstances at any time. Consequently, evaluating farmers' efficiency can play a key role in analyzing agricultural policies (Tozer, 2010). Efficiency is an essential factor in enhancing the productivity of production inputs in developing countries. These countries face resource shortages and limited opportunities for the development and adoption of better technologies on one hand, while failing to efficiently utilize existing technologies on the other.

The first research on estimating efficiency in the aquaculture sector was conducted by Gunaratne and Leung over two consecutive years, 1996 and 1997 (Gutiérrez *et al*., 2020). In subsequent years, numerous studies focused on assessing technical, allocative, and economic efficiency in this sector (Hassanpour *et al*., 2010; Alam, 2011; Nielsen, 2011). Additionally, some researchers employed the super-efficiency method to evaluate the performance and productivity of various sectors, including agriculture and aquaculture. A selection of these studies is reviewed below.

Pham (2010) conducted a thesis on the technical efficiency of improved extensive shrimp farms in Ca Mau province, Vietnam, estimating the mean technical super-efficiency of these farms. Using the cost minimization method with variable returns to scale through DEA, the study revealed that wetland area, farmers' experience, and their technical knowledge were the most significant factors positively influencing productivity and improving efficiency in non-centralized farms. Wang *et al*. (2024) employed three-stage DEA and SBM models to evaluate the technical and environmental efficiency of inland aquaculture. The results indicated that the average efficiencies were below the optimal level, suggesting a considerable potential for improvement. Le *et al*. (2022) employed the Cobb–Douglas stochastic production frontier model to examine the determinants of inefficiency in intensive and extensive shrimp aquaculture systems in Vietnam. The results showed that climatic conditions, education, and management practices play significant roles in determining efficiency levels. Moreover, the length of the culture period affects efficiency differently across systems, while disease occurrence and farm location are key factors contributing to efficiency reduction. Long *et al*. (2022) applied a two-stage bootstrap DEA model to assess cost efficiency in intensive white-leg shrimp farms. The results showed that allocative inefficiency was the main source of cost inefficiency, and adjusting input levels—especially feed, chemicals, and fingerlings—could improve efficiency. Yang and Wang (2024) utilized the non-expected outcome super-efficiency slacks-based measure (SBM) and global Malmquist–Luenberger index models for the static evaluation of green development efficiency and its dynamic analysis in the marine aquaculture industry across nine coastal provinces in China from 2012 to 2021. They reported that the mean static efficiency of green production in the marine aquaculture industry was 0.705 over this period. The southern marine economic zone demonstrated the highest green development static efficiency, with a stepped distribution pattern descending in the order of "south-north-east." Input-output redundancy analysis identified redundant inputs and carbon emissions as the main factors contributing to the decline in the static efficiency of the marine aquaculture industry in China. Huang *et al*. (2021) assessed the efficiency of water and other resource usage for cultivation, forestry, animal farming, and fishing across various regions of China using the super-efficiency SBM analysis method. The findings showed that the overall productivity of agricultural water usage exhibited a fluctuating downward trend, with notable regional disparities. Lu *et al*. (2021) employed the super-DEA method to evaluate agricultural water use efficiency in 52 cities in northwest China between 2000 and 2018. According to the results, the overall efficiency displayed a steady upward trend in the studied region; however, by 2018, only a limited number of cities had successfully achieved efficient agricultural water usage. Clear differences in efficiency were observed among the cities.

The literature review indicates that various efficiency methods have been utilized to evaluate the performance of fish farms. Since the present research aimed to rank cold-water fish producers, it employed the super-efficiency DEA method, derived from the basic non-parametric method, through a linear programming model. Aquaculture thrived in the Sistan region due to the inability to fish from the International Hamoun Wetland following prolonged droughts in the 1990s. According to the General Fishing Department of Sistan, The Sistan region, which hosts over 3,000 aquaculture units, serves as a fish-production hub in the southeast of Iran. There were 99 rainbow trout farms in this region in 2022/23, producing 146.266 tons of rainbow trout. However, in 2023/24, the number of farms decreased to 90 units, producing 162.336 tons of trout.This decline is primarily linked to the prolonged droughts and the significant reduction in water levels of the Hamoun Wetland, which directly impacted the availability of water for aquaculture. The depletion of the Hamoun Wetland, which has been a crucial water resource in the region, forced many farms to shut down or reduce production, contributing to the overall decrease in the number of farms in the area. The study population included all aquaculture units in the region, from which 20 farms were selected by simple randomization to complete the research questionnaire.

Materials and methods

The method for calculating efficiency using Data Envelopment Analysis (DEA) was first conceptualized by Farrell (1957) and formally developed by Charnes *et al*. (1978) (Banker *et al.,* 1984). This approach estimates the boundary production function using linear programming; hence, it is also referred to as a linear programming method. Being non-parametric, this method does not require the determination of the production function's form, thereby reducing the risk of model specification error. These models can be either output-oriented or input-oriented. In this method, rather than explicitly determining the boundary production function, the performance of enterprises with the highest output/input ratio is considered the efficiency boundary. Subsequently, all observed units are positioned on or below this boundary. In this way, the efficiency of each production unit is assessed relative to the efficiency of all production units. Efficiency is computed as follows:

Assume that there are N inputs and M outputs for each sample unit. The vectors x_i and q_i represent the input and output quantities for the ith unit, respectively. (X)N×I is the input matrix, and (Q)M×I is the output matrix for all units. The ratio of total outputs to total inputs can then be calculated, representing the overall productivity level:

$$T = U_{qi} / V_{xi} \qquad (1$$

So that the vector U represents the weights of the outputs, and the vector V represents the weights of the inputs. A decision-making unit (DMU) can set maximizing the above value as its objective. Thus, we have:

$$\begin{aligned} & Max \quad U'q_i / V'x_i \\ & St: \quad U'q_j / V'x_j \le 1 \ ; \quad j = 1,2,\ldots,I \qquad (2 \\ & U,V \ge 0 \end{aligned}$$

The data envelopment level may exhibit either constant or variable returns to scale.

Constant return to scale (CRS) model

CRS is an input-oriented model proposed by Charnes *et al*. (1978), where the CRS pattern is expressed as follows:

$$\begin{aligned} & Min \quad \theta \\ & St: \quad -q_j + Q\lambda \ge 0 \qquad (3 \\ & \qquad \theta Xi - X\lambda \ge 0 \\ & \qquad \lambda \ge 0 \end{aligned}$$

Where, θ represents the efficiency of each unit, with values ≤1. The vectors x_i and q_i denote the input and output quantities for the ith unit, respectively. The model can also be represented as follows:

$$\begin{aligned} & Min\ \acute{\varepsilon} - \theta\left[\Sigma_i{}^m S_i{}^- + \Sigma_r{}^s S_r{}^+\right] = D_{ot}\left(x_{ot}, y_{ot}\right) \\ & St: \qquad (4 \\ & \Sigma_j{}^n \lambda_j y_{rj} - S_r{}^+ = y_{rp} \quad ; \quad r = 1,\ldots,S \\ & \Sigma_j{}^n \lambda_j x_{ij} + S_i{}^- = \theta X_{ip} \quad ; \quad i = 1,\ldots,m \\ & \lambda_j \ge 0 \quad ; \quad j = 1,\ldots,n \\ & S_i{}^-, S_r{}^+ \ge 0 \quad ; \ r = 1,\ldots,s \ ; \ i = 1,\ldots,m \end{aligned}$$

Where, $D_{ot}(x_{ot}, y_{ot})$ serves as the distance function (measuring the distance between the unit and the efficiency boundary), S^- is the input shortage variable, and S^+ is the output shortage variable. These variables are incorporated into the model to transform unequal constraints into equal constraints. Additionally, λ represents constants, which reflect the weights of the reference set. To address the issue of zero weights, the non-Archimedean number ε is introduced as a lower bound to prevent the input and output weights from becoming zero.

Variable return to scale (VRS) model

The CRS model is applicable when all enterprises operate optimally. However, factors such as imperfect competition and financial constraints hinder enterprises from reaching optimal performance. To address this limitation, Banker *et al.* (1984) extended the CCR model by introducing the VRS assumption, resulting in what is commonly known as the BCC model. This was achieved by adding the convexity constraint $\Sigma_j^n \lambda_j = 1$ (Charnes *et al*., 1978). The VRS model is expressed as follows:

$$
\begin{aligned}
&Min\ \acute{\varepsilon} - \theta \left[\Sigma_i^{\,m} S_i^{-} + \Sigma_r^{\,s} S_r^{+} \right] \\
&S\,t \\
&\Sigma_j^{\,n} \lambda_j y_{rj} - S_r^{+} = y_{rp} \quad ; \quad r = 1, \ldots, S \qquad (5 \\
&\Sigma_j^{\,n} \lambda_j x_{ij} + S_i^{-} = \theta X_{ip} \quad ; \quad i = 1, \ldots, m \\
&\Sigma_j^{\,n} \lambda_j = 1 \\
&\lambda_j \geq 0 \quad ; \quad j = 1, \ldots, n \\
&S_i^{-}, S_r^{+} \geq 0 \ ; \ r = 1, \ldots, s \ ; \ i = 1, \ldots, m
\end{aligned}
$$

These two models categorize DMUs into efficient and inefficient groups and can rank inefficient DMUs. Nonetheless, all DMUs located on the boundary have an efficiency score of one, making it impossible to differentiate among them. To overcome this limitation, Andersen and Petersen (1993) introduced the super-efficiency method, which identifies the most efficient DMU and assesses the extent to which an efficient DMU can increase (or decrease) its inputs (or outputs) while maintaining its efficiency.

Non-parametric super-efficiency method

This method ranks inefficient DMUs like the base method. However, efficient DMUs can achieve efficiency levels greater than one, allowing for their ranking as well. The arithmetic model for super-efficiency is as follows:

$$
\begin{aligned}
&Min\ \theta - \varepsilon \left[\Sigma_i^{\,m} S_i^{-} + \Sigma_r^{\,s} S_r^{+} \right] \\
&S\,t: \\
&\Sigma^{n} \lambda_j y_{rj} - S_r^{+} = y_{rp} \quad ; \quad r = 1, \ldots, S \qquad (6 \\
&j = 1, \neq p \\
&\Sigma^{n} \lambda_j x_{ij} + S_i^{-} = \theta X_{ip} \quad ; \quad i = 1, \ldots, m \\
&j = 1, \neq p \\
&\Sigma_j^{\,n} \lambda_j = 1 \\
&\lambda_j \geq 0 \quad ; \quad j = 1, \ldots, n \\
&S_i^{-}, S_r^{+} \geq 0 \ ; \ r = 1, \ldots, s \ ; \ i = 1, \ldots, m
\end{aligned}
$$

Where, x_{ij} and y_{rj} represent the ith input and rth output of the jth DMU, respectively. $S-$ denotes the input-related shortage, and $S+$ represents the output-related shortage. The non-Archimedean number ε is again employed as a lower bound to prevent the weights of inputs and outputs from becoming zero. For further details, readers are referred to Chen (2005), which explains the performance of the super-efficiency model with a VRS assumption using a straightforward example.

As shown in Figure 1, adapted from Chen (2005), five DMUs (A, B, C, D, and H), each with one input and one output, are evaluated. According to the super-efficiency model under the VRS framework, DMU D is unable to increase its input usage as expected. Despite being an efficient unit under VRS, it cannot retain any inputs beyond the input level H' (which corresponds to the usage level of input H). Since H demonstrates the highest level of input utilization, it must be evaluated in comparison to D. Conversely, DMU B can increase its input utilization and reach point B' (the projection of point B on the convex combination of A and C). This expected and feasible increase in input utilization compared to other DMUs enhances the efficiency of DMU B, classifying it as a super-efficient unit.

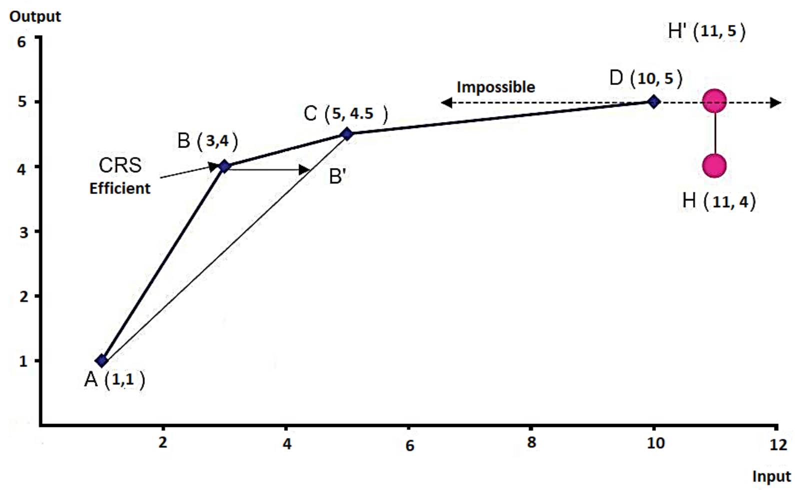

Figure 1: The super-efficiency with a variable return to scale (VRS) assumption (Chen, 2005).

In this study, the performance of cold-water fish producers was initially assessed using the efficiency index and fundamental DEA models, including those based on CRS and VRS assumptions. Subsequently, scale efficiency was calculated separately, followed by the application of super-efficiency DEA. All these models were approached in an input-oriented manner, meaning the farms' technical efficiency was measured assuming a fixed level of fish production alongside a proportional reduction in input utilization. The data were further analyzed using IRS and DRS models. The return-to-scale type for each farm was identified by comparing the efficiency levels derived from the variable-return model with those obtained from the two recent models. Additionally, the actual (mean) consumption of inputs and their optimal consumption levels were compared to determine the percentage of inefficiency in input utilization. To compute the optimal level of input use (mean optimal use) required for achieving the current production and efficiency levels of the producers, the software-generated consumption level for each input was subtracted from its mean actual consumption level (Ören and Alemdar, 2006).

The variables analyzed in this study include one output variable (the product) and seven input variables. The input variables utilized across all models in this research were the production area (fish farm area) in m² *(X1)*, labor in person-days *(X2)*, the initial count of eyed eggs *(X3)*, feed consumption rate in grams *(X4)*, and medication consumption rate in grams *(X5)*. The output variable represented fish production *(Y)*. Data analysis and modeling were performed using MATLAB.

Results

Table 1 provides the statistical estimates for the dependent and independent variables associated with cold-water fish production.

According to the results, fish production ranged from 700 to 3,500 kg, with a mean of 1,452.23 kg and a standard deviation (SD) of 963.25. The relatively high SD indicates substantial variations among the farms. Farm areas ranged from 80 to 11,800 m² (mean: 6,589.21 m²; SD: 1,258.92).

Table 1: The descriptive statistics for the variables used in the process of cold-water fish production.

Variables	Standard deviation	Mean	Maximum	Minimum	CV%	Median	IQR
Fish production in kg (Y)	963.25	1452.23	3500	700	66.3	1776.12	1299.82
Production farm area in m^2 (X_1)	1258.92	6589.21	11800	80	19	6264.60	1690.13
Labor in person-days (X_2)	2.25	9.80	12	3	23	8.65	3.04
Initial count of eyed eggs (X_3)	8569.2	26987.9	35800	4500	32	23568.95	11658.77
Feed consumption rate in g (X_4)	2850	7560.21	29865	3900	37	122.2135	3776.32
Medication consumption rate in g (X_5)	4.23	3.2	22	2	132	7.60	5.70

The variation in size suggests the presence of both very small and relatively large farms. Labor input varied from 3 to 12 person-days (mean: 9.80; SD: 2.25), showing considerable differences among the farms, as reflected by a coefficient of variation (CV) of about 23%. The count of eyed eggs ranged from 4,500 to 35,800, with a mean of 26,987.9 and an SD of 8,569.2. This wide dispersion suggests that while some farms operate on a small scale, others are significantly larger. Feed consumption rates ranged from 3,900 to 29,865 g (mean: 7,560.21 g; SD: 2,850). The variation in feed use indicates differences in farm size, productivity, and management strategies. Medication use ranged from 2 to 22 g, with a mean of 3.2 g and an SD of 4.23. This finding shows that medication is used at very low levels in some farms and at much higher levels in others, potentially reflecting differences in hygiene and disease management practices. Table 2 provides an overview of the technical efficiency levels of the aforementioned models.

Farms 1, 4, 7, and 11 achieved a score of 1 across all indicators, indicating that they utilized their resources most optimally and operated at an optimal scale. The results also revealed that most farms experienced increasing returns to scale (IRS). In other words, an increase in input use in these farms would lead to a disproportionately higher increase in production, suggesting that they can enhance their efficiency by scaling up their production. For instance, Farm 2 had a scale efficiency of 0.88, while its technical efficiency was 0.75 under CRS and 0.85 under VRS, implying potential for further efficiency improvements through expansion. Farm 15 was nearly ideal, with an efficiency of 0.95 under CRS, 0.99 under VRS, and 0.89 in scale.

The results regarding the type of return to scale indicate the production stage of a farm and the policies that could help it move closer to an optimal state. If a farm has IRS (e.g., Farm 2), it can reach the minimum point on the long-term cost function by increasing its size. Farms 20, 17, 14, 19, and 13 showed the lowest efficiency levels. For instance, Farm 20 had a technical efficiency of 0.21 under CRS, 0.54 under VRS, and 0.38 in scale efficiency. This indicates that it uses its resources inefficiently and does not optimize its production scale. To improve, these farms need to adjust their management practices or operate on a larger scale.

Table 2: The efficiency calculated by the data envelopment analysis method with an input-oriented assumption.

Farm	Scale efficiency	Technical efficiency (VRS)	Technical efficiency (CRS)	Return-to-scale type
1	1	1	1	-
2	0.88	0.85	0.75	IRS
3	0.61	0.68	0.42	IRS
4	1	1	1	-
5	0.93	0.91	0.85	IRS
6	0.73	0.71	0.52	-
7	1	1	1	-
8	0.93	0.74	0.69	IRS
9	0.72	0.85	0.62	IRS
10	0.90	0.92	0.83	IRS
11	1	1	1	-
12	0.78	0.61	0.48	IRS
13	0.63	0.61	0.39	IRS
14	0.51	0.60	0.31	IRS
15	0.89	0.99	0.95	IRS
16	0.73	0.71	0.52	IRS
17	0.44	0.63	0.28	IRS
18	0.66	0.84	0.56	IRS
19	0.49	0.67	0.33	IRS
20	0.38	0.54	0.21	IRS

The results indicated that only four farms (1, 4, 7, and 11) exhibited CRS, while the majority (16 out of 20 farms) showed IRS. These farms operated at an optimal production level, meaning that increasing or decreasing inputs would result in a proportional change in production. They demonstrated higher performance than other farms and could serve as a model for others. These farms should focus on optimizing input usage and enhancing quality to improve profitability. However, over 80% of fish producers in the region exhibited IRS, where a simultaneous 1% increase in all inputs would result in more than a 1% increase in production. These farms were in a phase where increasing inputs, such as labor, feed, and farm area, would lead to a disproportionately greater production increase. These findings suggest that most trout farms did not operate optimally and could boost productivity by expanding their production capacity. Such farms should aim to increase their production levels, as doing so would reduce average costs and improve efficiency through scaling up. No farms exhibited decreasing returns to scale (DRS). In other words, no farms were in a state where increasing inputs would lead to reduced production, so their expansion would result in inefficiency and wastage.

Table 3 compares the actual input consumption rates with their optimal levels and highlights the inefficiencies in input usage. The results of Table 4 show that farm area, with an inefficiency of 0.75%, is almost at the optimal level and requires no major adjustment. In contrast, labor, with an inefficiency of 12.14%, is among the inputs with considerable deviation from the optimal level, suggesting that insufficient utilization of labor is a limiting factor in production. The initial count of eyed eggs, with an inefficiency of only 0.78%, is the closest input to the optimal level, reflecting proper management in this area. For feed consumption, an inefficiency of 20.13% was observed, which is relatively high. This highlights the importance of better feed management, as inadequate or untimely feeding could adversely affect the growth and productivity of the farms. Finally, medication consumption, with an inefficiency of 28.12%, showed the largest deviation from the optimal level. This indicates that medication use is significantly below the optimal requirement, which may expose farms to higher risks of diseases. Therefore, improving medication management is essential to prevent losses and enhance overall farm productivity. It should be noted that the inefficiency values were computed using the Slack-Based Measure (SBM) model within the DEA framework, which accounts for both radial and non-radial slacks in input usage.

Table 3: The comparison of means for input consumption rates and their optimal levels for cold-water fish production.

Input	Consumption rate (mean actual level)	Input slacks	Optimal consumption rate (mean optimal level)	Inefficiency (%)	paired t-tests
Production farm area in m^2 (X_1)	6589.21	50.02	6639.23	0.75	0.38
Labor in person-days (X_2)	9.80	1.11	10.99	12.14	1.12
Initial count of eyed eggs (X_3)	26987.9	213.11	27200.11	0.78	0.95
Feed consumption rate in g (X_4)	7560.21	1521.89	9082.1	20.13	2.57
Medication consumption rate in g (X_5)	3.2	0.91	4.11	28.12	2.25

Table 4 indicates the efficient farms (boundary enterprises) that inefficient farms should refer to in order to enhance their performance. In DEA, boundary farms serve as efficiency models for other farms. According to the results, Farm 7 received the highest number of referrals among the efficient farms, with 11 referrals. Although all efficient farms achieve efficiency scores of 1 in the basic DEA model, they differ in the number of referrals from inefficient farms. This indicates that some efficient farms are more efficient than others, despite having the same score. Specifically, Farm 7 received the highest number of referrals, signifying that it is the best-performing unit. In other words, it closely aligns with the efficiency boundary and serves as a more suitable reference for other inefficient farms. To enhance their performance, inefficient farms should use efficient farms as models. For example, Farm 2, which is inefficient, needs to compare its performance with that of Farms 3, 12, 6, 8, and 9 to improve its efficiency. Inefficient farms can approach the performance level of boundary farms by adopting better management practices, optimizing input usage, and increasing productivity.

The super-efficiency model can be used to rank boundary DMUs. The findings indicated that the efficiency levels of inefficient farms remained consistent with those in the previous model, leaving their ranking unchanged. In this model, efficiency levels ranged from 0.52 to 4.25, highlighting substantial disparities among the fish farms studied. Table 5 presents the rankings of several farms in the region, derived using the input-oriented super-efficiency approach.

Table 4: Referral of efficient enterprises to the composition of boundary enterprises in the basic input-oriented data envelopment analysis model (a part of farms).

DMUs	Reference DMUs	Repetition	DMUs	Reference DMUs	Repetition
Farm 1	Farms 9, 20, 11, 8, 3	0	Farm 6	Farm 6	5
Farm 2	Farms 3, 12, 6, 8, 9	0	Farm 7	Farm 7	11
Farm 3	Farms 20, 10, 5, 7, 8	0	Farm 8	Farm 8	3
Farm 4	Farm 4	0	Farm 9	Farm 9	1
Farm 5	Farms 6, 7, 4, 8, 10	0	Farm 10	Farm 10	0

Table 5: The ranking of some fish farms in the region using the input-oriented super-efficiency approach.

Farm	Rank	Super-efficiency	Farm	Rank	Super-efficiency
11	1	4.25	12	5	0.68
7	2	3.63	15	6	0.63
4	3	3.10	9	7	0.58
1	4	2.58	20	8	0.52

In DEA, all efficient farms have efficiency scores of 1. However, the super-efficiency model addresses this issue by enabling the ranking of efficient farms. Farm 11, with a score of 4.25, demonstrated the highest super-efficiency and was therefore ranked first. In other words, it achieved the best performance among all the farms. The second and third ranks were assigned to Farms 8 and 4, with super-efficiency scores of 3.63 and 3.10, respectively. Farms with scores below 1 (e.g., Farm 20, which scored 0.52) exhibited lower efficiency than other efficient farms. While all these farms had an efficiency score of 1 in the initial DEA model, the super-efficiency model highlighted performance differences among them. Farms with higher super-efficiency scores (e.g., Farms 11 and 8) served as better benchmarks for inefficient farms, whereas farms with lower super-efficiency scores (e.g., Farm 20) were still efficient but demonstrated lower productivity than the top-performing farms.

Discussion

This study assessed the performance of cold-water fish producers in rainbow trout (*O. mykiss*) farms in the Sistan region, calculating their technical efficiency using the DEA model under the assumptions of CRS and VRS. Additionally, the scale efficiency and return-to-scale type of the farms were identified. The super-efficiency DEA model was employed to rank the superior farms. Subsequently, the performance of the fish producers based on the basic DEA method was compared with the results of the super-efficiency DEA. The efficient farms (Farms 1, 4, 7, and 11) can serve as models for other farms. Most farms demonstrated increasing returns to scale, indicating that they can enhance their efficiency by expanding their production scale. Farms with lower efficiency require serious revision, as they fail to utilize their resources effectively and need to improve their managerial and technical strategies. Farms that scored higher in the VRS model compared to CRS clearly operate at a non-optimal scale and may be smaller than their optimal size. This analysis provides valuable insights for policymakers and farm owners to make better decisions aimed at boosting productivity and increasing production levels. Therefore, farms operating at a non-optimal scale should prioritize increasing their production levels, either through collective input procurement through cooperatives, which can reduce feed and medication costs without requiring mergers, or by adopting participatory investment strategies to reach their economically optimal scale. Based on the scale efficiency results, most farms demonstrated increasing returns to scale, meaning that they could lower their costs by increasing farm size. Among the fish farms with increasing returns to scale (constituting 80% of the sample farms), a simultaneous 1% increase in the use of production inputs could result in more than a 1% increase in production levels, positively impacting their efficiency. These findings align with those reported by Sardar Shahraki and Esfandiari (2019). Both studies observed that input values were within the economic zone, while production was in the second zone. The findings are also consistent with the results of Tveterås and Asche (1999), Long *et al*. (2022), and Ogundari and Akinbogun (2010).

Based on the results, the average technical efficiency of the cold-water fish producers in the CRS model was 0.63 with a standard deviation of 0.271. Only 20% of the farms were operating at the efficiency frontier. Similarly, in the VRS model, the average technical efficiency was 0.793 with a standard deviation of 0.160, and again, only 20% of the farms were fully efficient. The results showed that the greatest inefficiencies stemmed from medication consumption (28.12%) and feed consumption (20.13%), indicating that they are below optimal levels and need to be optimized. Low medication consumption can lead to an increased risk of diseases and health problems for the fish. Therefore, increasing medication use to prevent diseases and improve fish health is necessary. The farm area and the initial count of eyed eggs were nearly optimal and had minimal inefficiency. However, labor usage had an inefficiency of 12.14%, indicating that human resources are not being utilized effectively. These findings are consistent with those of Naghshinefard *et al*. (2011) and Yousefi *et al*. (2014).

Finally, the super-efficiency model was estimated, revealing significant disparities in technical efficiency among the farms. The results highlighted substantial differences in performance among the efficient farms. It is essential to use this model for a more accurate ranking of the farms. Farms with higher super-efficiency (such as Farms 11, 7, and 4) should be identified as superior models for inefficient farms to emulate. These farms can serve as educational and consulting centers for others. To increase productivity, farms with lower super-efficiency (such as Farm 20) should adopt strategies for optimizing input consumption, improving resource management, and expanding production scale. Effective feed and medication management, better control of farm conditions, and the integration of modern technology can also contribute to boosting productivity. Ultimately, this study emphasized that the DEA model alone is insufficient for assessing efficiency and highlighted the importance of the super-efficiency technique for more accurate rankings. However, this study is also subject to limitations. The findings reflect the specific conditions of the Sistan region, and generalizing these results to other regions requires further research and investigation.

Conclusions

Using Data Envelopment Analysis, this study demonstrated that there is a considerable space for efficiency improvement in the rainbow trout aquaculture sector in the Sistan region. It was revealed that only a small number of farms operated on the efficiency frontier, while the majority can significantly enhance their performance through better input management, technical improvements, and movement toward an economically optimal production scale. The dominance of increasing returns to scale among the farms further indicated that expanding production capacity particularly through cooperative input procurement or joint investment strategies, can serve as an effective approach for improving efficiency.

Overall, the results highlight that optimizing feed and medication use, improving managerial capabilities, and adopting scale-adjustment strategies constitute the most critical pathways for increasing productivity in this sector. Moreover, the super-efficiency model underscores the importance of identifying and utilizing the experience of top-performing farms to support the improvement of less efficient units.

In summary, the study emphasizes that enhancing technical, managerial, and scale-related factors can play a pivotal role in reducing production costs, increasing output, strengthening food security, and improving rural livelihoods in the region. Consequently, developing targeted policies that promote better management practices, optimizing input consumption, and supporting the formation of cooperative structures are essential for ensuring the long-term sustainability and growth of the cold-water aquaculture industry in Sistan.

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Conflicts of Interest

The authors report no conflicts of interest.

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