Evaluating technical and scale efficiencies in pangas farming: key influential factors and insights

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Abstract. The technical efficiency of pangas fish (*Pangasianodon hypophthalmus*) producers in Bangladesh was evaluated in this study, and the primary factors that influence technical and scale efficiency were identified. The efficiency scores were determined using data envelopment analysis (DEA) under constant and variable returns to scale (CRS and VRS) on primary data from 200 farms. The socio-economic and environmental factors that influenced efficiency were analyzed using Tobit regression. The results indicated that farmers were only able to operate at 66% and 75% of their potential efficiency under CRS and VRS, respectively, with only 16.82% and 22.02% attaining full efficiency. A distinct underutilization of resources was demonstrated by an average scale efficiency of 0.63. Efficiency was positively impacted by training, experience, and household income sources, while climate impacts had a detrimental effect. This study contributes to the broader advancement of aquaculture research, enhanced food security, and sustainable pangas farming practices by providing actionable recommendations, including capacity building, climate adaptation, and tailored financial programs, through the unique integration of technical and scale efficiency analyses.

Key Words: aquaculture, Bangladesh, efficiency, pangas, productivity.

Introduction. Aquaculture has become an essential component of global food production, contributing significantly to economic development and food security. In 2022, the aquaculture industry produced approximately 131 million metric tonnes of aquatic organisms, which accounted for 59% of the global fish supply (FAO 2024). This rapid expansion has been facilitated by the increasing demand for fish worldwide, technological advancements, and the necessity for more sustainable food supplies. Due to its rapid growth, adaptability, and low production costs, pangas (*Pangasianodon hypophthalmus*), one of the numerous species that are cultivated globally, have gained increased recognition (FAO 2022). Bangladesh and Vietnam are among the primary producers of pangas globally, which has resulted in a rise in pangas production on a global scale (Hossain et al 2022).

The aquaculture industry in Bangladesh, which is one of the fastest-growing sectors of the country, is dependent on pangas. Pangas were a significant contributor to the sector in 2022, accounting for 8% of the nation's total fish production, which amounted to over 4.92 million metric tonnes (DoF 2023). The fishing industry in Bangladesh contributes a considerable amount to the country's GDP, with 2.43% of the GDP derived from the industry and 22.14% from agriculture. Pangas are referred to as the "fish for the poor" due to their affordability, simplicity of cultivation, low initial cost, and rapid profitability. The industry's persistent technical and scale efficiency issues have an impact on the sustainability and productivity of small-scale producers. In order to identify the primary factors that influence these efficiencies, the study will evaluate the technical and scale efficiencies of pangas production in Bangladesh.

There are numerous reasons why it is crucial to understand the technical and scale efficacy of pangas farming. When resources and inputs are utilized efficiently, pangas growers achieve increased productivity and yields. Conversely, inefficiencies can result in increased costs, reduced production, and resource waste, all of which ultimately impede the aquaculture sector's overall prosperity. By evaluating these efficiencies, practitioners and policymakers can acquire a better understanding of areas that require improvement and devise targeted measures to increase productivity. Diverse efficiency levels also significantly influence environmental sustainability, economic growth, and food security in a nation where aquaculture is indispensable.

Numerous studies have examined the technical efficacy of pangas farming, which have also identified critical components. Bangladesh's development prospects are underscored by inefficiencies in cost (54%), allocative (62%), and technical (86%), respectively. Significant factors include the quality of fingerlings, the duration of the culture, the extent of the pond, and the use of pelleted feed (Alam 2011). Transaction costs ultimately lead to a decrease in profits, despite the fact that larger farms benefit from economies of scale (Aktar et al 2018; Tho et al 2021). Efficiency and sustainability are influenced by a variety of factors in Vietnam, including population, farm size, technological advancements, and environmental factors such as saline intrusion (Ngoc 2016; Ngoc et al 2018). Productivity is influenced by a variety of factors in India, where efficient resource use and scale economies are essential (Mugaonkar et al 2019). These factors include fertilizer quality, farm size, and farmer experience. Similarly, improved resource management could eliminate inefficiencies in Chinese farms and increase output by as much as 32% (Zongli et al 2017).

The efficiency of pangas farming can be enhanced by optimizing farm size, input quality, and management techniques. After attaining the highest level of economic efficiency, larger farms experience a decline in returns (Tho et al 2021). Regional conditions, such as saline intrusion, also affect productivity (Ngoc 2016). Innovations in nutrition systems, best management practices, and focused environmental interventions are essential for enhancing sustainability and efficiency (Lota et al 2011; Alam et al 2019). Policy recommendations prioritize enhanced accessibility to financing, training, and extension services, in addition to region-specific strategies for managing environmental and agglomeration externalities (Rahman et al 2019; Mitra et al 2020). The significance of land tenure systems and the necessity for policies that promote productive farming methods and increase resource accessibility are illustrated by the fact that tenant farms typically outperform self-owned farms (Mitra et al 2022). Despite the fact that numerous studies have examined the technical efficiency of aquaculture, none of the studies have examined the relationship between technical and scale efficiencies in pangas farming, particularly in Bangladesh, to the best of the authors' knowledge. In order to enhance the competitive positioning and operational performance of pangas farming, which will result in more sustainable and profitable methods, both must be addressed.

Therefore, the aim of this research is to evaluate the technical and scale efficiencies of pangas producers in Bangladesh and identify the primary determinants of these efficiencies. This research provides policymakers and relevant stakeholders with valuable insights by combining the examination of efficiency with the consideration of critical factors such as climate, financial resources, farm size, and education. The study delivers a comprehensive analysis of efficiency levels across a variety of farm sizes and production techniques by employing Tobit regression and data envelopment analysis (DEA). This method contributes to the existing corpus of knowledge by addressing the comparatively understudied interplay between technical and scale efficiency in the context of pangas farming. The results will provide practical recommendations for enhancing the efficacy of pangas production, in addition to enhancing the sustainability and productivity of aquaculture in Bangladesh.

Material and Method

Data collection. Bangladesh's fish market is based on both wild-caught and farmed fish, with pangas being an important species in aquaculture (E-Jahan et al 2010; Fitzsimmons et al 2011). Bangladesh is recognized as an ideal place for pangas farming due to its advantageous geographical location and plenty of resources, notably in the Barishal division, such as ponds, canals, rice paddies, and low-cost labor. Following the literature review, a data collection questionnaire was developed, with an initial trial with 25 farmers, followed by focus group talks and pilot tests in all of Bangladesh's Barishal districts. Participants were questioned about the pangas farming method and other aspects of pangas production. They were also requested to provide feedback on the factors that influence pangas growers' technical efficiency.

Before the field survey began, the enumerators were thoroughly trained. They were thoroughly briefed on the study's aims and objectives, as well as how to properly communicate with clients during data collection. To recruit people, a random sampling method was adopted, ensuring easy access and willing participation. Using this approach, we were able to interview 199 people from six districts in Bangladesh's Barishal division.

Random sampling was used to acquire representative and unbiased data from pangas producers in the districts of Barisal, Bhola, Barguna, Jhalokati, Patuakhali, Pirojpur, and Borguna. By selecting participants at random, the study aimed to ensure that the sample accurately reflected the diversity and features of the larger community. This approach ensures that the researchers' tastes do not influence the results and that the findings may be applied to a larger community of pangas producers, reducing selection bias. Furthermore, random sampling improves the study's statistical validity, allowing for more exact identification of the elements influencing technical efficiency via robust inferential analysis. It also ensures that the sample will include all potential variances within the population, allowing for a full understanding of the various factors that determine pangas aquaculture productivity. Finally, this methodology contributes to the development of informed policy suggestions and actions aimed at increasing the profitability and productivity of pangas aquaculture in the region.

The study collected data through in-person interviews, with the goal of achieving a high response rate while also resolving any linguistic barriers or unclear scenarios that may have emerged. The questionnaire was divided into three sections: the first section gave an overview of the study, including the title, concept, and purpose; the second section focused on the participants' sociodemographic information; and the final section asked survey questions about the primary research variables, such as years of experience, farming training, and years of education. The survey questionnaire was first created in English and then rigorously translated into Bangla using a randomized translation-back-translation procedure to assure accuracy.

Analytical tools. This study used the DEA paradigm to assess the technical efficiency (TE) and scale efficiency (SE) of pangas producers in Bangladesh. DEA, a non-parametric method, evaluated the performance of decision-making units (DMUs) in this case, pangas farms, by examining their input-output relationships. A second-stage Tobit regression was also used to investigate the effect of socio-demographic parameters on the efficiency scores produced by DEA. The DEA analysis relied on two models: constant returns to scale (CRS) and variable returns to scale (VRS). The CRS model assumes farms run at ideal scale, but the VRS model takes into consideration scale inefficiencies, allowing for changes in farm size, technology, and management. Both models took an input-oriented strategy, attempting to lower inputs while preserving output levels, which aligned with resource optimization goals.

The DEA study used feed, fingerlings, labor, fertilizer, and capital expenses as inputs, with total pangas production as the output. Each farm's efficiency was measured by comparing it to a production frontier, which represents the most efficient farms. Efficiency scores range from 0 to 1, with a score of 1 indicating complete efficiency and scores below 1 indicating inefficiency.

Let K represent the observed number of units, where $k = 1, \dots, K$, x_j^k is the amount of input i $(i = 1, \dots, m)$ consumed by unit k to produce each of n outputs y_j^k $(j = 1, \dots, n),$), and (x^0, y^0) represents the unit under analysis, and VRS and CRS model can be expressed as:

VRS input-oriented model:

$$\boldsymbol{Eff(x^0, y^0) = \theta^{0^*} = Min\,\theta}$$

Subject to:

$$\sum_{k=1}^{K} \lambda^k x_i^k \leq \theta x_i^0, i = 1, \dots, m$$
$$\sum_{k=1}^{K} \lambda^k y_j^k \geq y_j^0, j = 1, \dots, n$$
$$\sum_{k=1}^{K} \lambda^k = 1$$
$$\lambda^k \geq 0, k = 1, \dots, K$$

CRS input-oriented model:

$$\boldsymbol{Eff(x^0, y^0) = \theta^{0^*} = Min\,\theta}$$

Subject to:

$$\sum_{k=1}^{K} \lambda^k x_i^k \leq \theta x_i^0, i = 1, \dots, m$$
$$\sum_{k=1}^{K} \lambda^k y_j^k \geq y_j^0, j = 1, \dots, n$$
$$\lambda^k \geq 0, k = 1, \dots, K$$

The SE of pangas farms was determined by comparing the TE scores from the CRS and VRS models. The ratio of CRS TE to VRS TE reveals if a farm is working at its ideal scale. The operational effectiveness of the scale is defined by the ratio between the constant return and variable return scale models (Charnes et al 1978; Banker 1984):

$$SE = \frac{TE_{i,CRS}}{TE_{i,VRS}}$$

A scale efficiency score of 1 indicates that a farm is running at its optimal scale, whereas scores less than 1 indicate inefficiencies owing to suboptimal scale (Altaie 2022).

Decision-makers can increase efficiency by controlling regulated inputs such as fingerlings, labor, feed, and capital, which are closely related to the input-output correlations studied in DEA. However, contextual variables such as farming training, years of education, and climate effect factors outside farmers' immediate control influence production outcomes (Da Silva et al 2019). To investigate the impact of these socio-demographic factors on pangas producers' technical efficiencies (TEs), this study used a second-stage DEA analysis. In this stage, the technical efficiency scores from the CRS and VRS models were compared to socioeconomic characteristics.

Second-stage analysis, a widely acknowledged approach, helps policymakers and regulators understand how socio-demographic characteristics influence DEA efficiency scores (Hoff 2007; Simar & Wilson 2007). Tobit regression and ordinary least squares are the two most used methods for assessing the link between socio-demographic variables and DEA efficiency scores. Tobit regression was chosen for this investigation because the efficiency ratings can be both discrete and continuous (Tobin 1958; Wooldridge 2012).

The efficiency scores produced from the DEA models (both VRS and CRS) in the first stage were regressed on farm-level and farmer-specific socioeconomic factors using Tobit regression in the second stage. Zongli et al (2017), for example, used this strategy. The regression equations are as follows:

$$TE_{VRS} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \Phi \text{.........}(1)$$
$$TE_{CRS} = \rho_0 + \rho_1 X_1 + \rho_2 X_2 + \rho_3 X_3 + \rho_4 X_4 + \rho_5 X_5 + \rho_6 X_6 + \rho_7 X_7 + \Psi \text{.........}(2)$$

Here, TE_{VRS} and TE_{CRS}, respectively indicate the technical efficiency score obtained from the VRS and CRS DEA models. $X_1 - X_7$ indicate socio-economic factors where, $X_1 =$ farming training, $X_2 =$ years of education, $X_3 =$ years of experience, $X_4 =$ age, $X_5 =$ family size, $X_6 =$ credit access, and $X_7 =$ climate impact. Tobit equations 1 and 2 determine how the farmer's contextual variables affect TE_{VRS} and TE_{CRS}, respectively. Φ and Ψ are the models' error terms.

The study employs Tobit analysis to quantify technical efficiency in pangas farming and the factors that influence this efficiency, as well as a variety of output and input variables (Table 1). The primary output variable is the annual total income from pangas cultivation per hectare, which is expressed in US dollars. This variable (Y) serves as an exhaustive indicator of agricultural output. The five cost components considered on the input side are feed cost (X_a), fingerling cost (X_b), labor cost (X_c), fixed cost (X_d), and other input cost (X_e). This includes both conventional and commercial feed. Each of these parameters represents the distribution of resources and costs associated with pangas production, as measured in US dollars per hectare annually.

Table 1

Measurement of output and input variables of technical efficiency in the data envelopment analysis and Tobit analysis

	Variables description	*Unit*
	Variables used in measuring technical efficiency	
Y	Total revenue of pangas farming during the year of the sample farms per hectare (ha)	US$
X_a	Amount of feed cost (traditional and commercial) applied per hectare per year	US$
X_b	Amount of fingerlings cost for the production per hectare per year	US$
X_c	Amount of labor cost employed per hectare per year	US$
X_d	Amount of fixed cost per hectare per year	US$
X_e	Amount of others input cost incurred per hectare per year	US$
	Variables used in Tobit analysis	
X_1	Taking pangas farming-related training (1= taken, 0 = otherwise)	1, 0
X_2	Education of the farmers	Years
X_3	Farming experience of the farmers	Years
X_4	Age of the farmers	Years
X_5	Number of earnings members of the farmers	Number
X_6	Farmers are included to access affordable financial services to meet their financial needs (1 = included 0 = otherwise)	1, 0
X_7	Impact of climate change on pangas farming (1 = adverse impact, 0 = otherwise)	1, 0

The Tobit analysis examines the influence of several explanatory variables on technical efficacy. A binary variable known as "training participation" (X_1) denotes whether or not farmers have received pangas farming-related training (1 indicates that they have received training, 0 indicates that they have not). The formal education of farmers is determined in years by education (X_2), which serves as a proxy for human capital and knowledge. The cumulative practical skill of a farmer is represented by farming experience (X_3), which is the number of years the farmer has been immersed in pangas farming. The demographics of the producers are indicated by age (X_4), which is also expressed over the years. The number of earning individuals in a farmer's household (X_5) can be used to determine the quantity of financial assistance that is available, which may affect resource allocation and investment. Financial inclusion (X_6) is an additional binary variable that assesses the extent to which farmers have access to financial services that are reasonably priced (1 indicates inclusion, 0 indicates exclusion). Finally, a binary indicator (X_7) is employed to assess the impact of climate change on pangas farming, with 1 indicating a negative influence and 0 indicating no discernible impact. Together, these variables offer a comprehensive comprehension of the factors that influence technical efficiency and provide valuable information for the development of interventions that would enhance sector output.

The variables in the DEA input-output model are closely related to the principal operations at pangas farms. Aquaculture research generally acknowledges that feed, fingerlings, labor, fertilizer, and capital are the major elements influencing farm productivity and efficiency. These parameters ensure that the study covers the critical inputs that determine production outcomes. According to standard productivity analysis methods, total production per hectare was chosen as the output variable, offering a clear and quantifiable indicator of farm success. The study also employed socioeconomic and environmental variables in the second stage of Tobit regression, in addition to input-output variables, to acquire a better knowledge of the larger context in which Pangas farmers work.

Results and Discussion

Summary statistics of the variables. Table 2 presents a statistical summary of the factors used in the pangas agricultural experiment. The farm sizes range from 0.95 to 3.09 hectares (standard deviation = 2.27), with an average of 1.85 hectares. Feed costs thousands of dollars per hectare every year, with an average of 21, a minimum of 14, and a maximum of 34. Fingerlings cost between 2.70 and 4.90 thousand USD per hectare (SD = 6.20), with a mean price of 3.80 thousand USD per hectare. Labor costs vary from 3.90 to 6.30 (SD = 9.40), with an average of 5.20 thousand USD per hectare. The average cost of capital expenditure per hectare is $42,000 USD, ranging from $24 to $57,000 (SD = 129). Other expenses, which include diverse inputs, range between 2.60 and 5.90 (SD = 18.40) per hectare, with an average of 4.30 thousand USD. Agricultural income varies significantly, as indicated by revenue earned per hectare, which averages 498.6 USD with a low of 229.6 and a high of 564.8 (SD = 1279.70). Farmers have an average formal education of 3.37 years, ranging from 1 to 6 years (SD = 1.28). The majority of farmers have extensive knowledge of pangas production, as evidenced by their average farming experience of 15 years, with a minimum of 7 years and a maximum of 28 years (SD = 7.52). The farmers' ages range from 26 to 67 years (SD = 16.20), with an average of 42. The average number of members of a family earned is 2.24, with a minimum of one and a maximum of four (SD = 3.21).

Table 2

Summary statistics of the variables

Name of the variables	*Mean*	*Max*	*Min*	*SD*
Farm size ($^{a}ha^{-1}$)	1.85	3.09	0.95	2.27
Feed (^{b}USD’000 ha^{-1})	21	34	14	57
Fingerlings (USD’000 ha^{-1})	3.80	4.90	2.70	6.20
Labor (USD’000 ha^{-1})	5.20	6.30	3.90	9.40
Capital (USD’000 ha^{-1})	42	57	24	129
Other costs (USD’000 ha^{-1})	4.30	5.90	2.60	18.40
Revenue (USD ha^{-1})	498.6	564.8	229.6	1279.70
Education (years)	3.37	6.00	1.00	1.28
Experience (years)	15.00	28.00	7.00	7.52
Age (years)	42.00	67.00	26.00	16.20
Earnings member (no.)	2.24	4.00	1.00	3.21

$^{a}ha^{-1}$ = per hectare; ^{b}USD 1 equaled approx. Bangladesh Taka 119 in the year 2024; SD = standard deviation.

These data show the great diversity in farm sizes, expenses, and incomes among pangas farmers, as well as differences in household financial support, education, and experience. Variability in income and input costs indicates potential inefficiencies and areas for targeted intervention to boost pangas farming productivity and profitability.

Data envelopment analysis (DEA). The distribution of SE and TE for pangas production is illustrated in Table 3 under constant and variable returns to scale (CRS and VRS). According to the data, the efficacy scores on the three criteria present a significant degree of diversity. A greater proportion of producers achieved full efficiency (TE = 1.00) under CRS (16.82%) than under VRS (22.02%), indicating that scale changes enhanced efficiency for a greater number of farmers. However, only 10.70% of producers were able to achieve full SE, suggesting that scale utilization was not optimal in numerous instances.

Under the CRS and VRS frameworks, 5.81% and 10.09% of producers, respectively, fall within the TE range of 0.90 to less than 1.00, while an equivalent SE is achieved by 6.73%. For producers with TE scores between 0.80 and 0.90, 10.40% are classified under CRS, 11.01% under VRS, and 11.31% for SE. CRS, VRS, and SE comprise 8.56%, 14.37%, and 13.46% of producers in the 0.70 to 0.80 range, respectively. This pattern suggests that efficiency ratings are generally higher when variable returns are considered, which is likely due to the ability to adjust scale effects.

A substantial majority of producers is observed in the lower efficiency levels. In particular, the percentage of producers with TE scores below 0.50 dropped from 39.14% under CRS to 13.76% and 26.30% under VRS and SE, respectively. The mean TE ratings of 0.66 under CRS and 0.75 under VRS indicate that producers are generally operating at 66% and 75% of their potential efficiency, respectively. The mean SE of 0.63 suggests that scale inefficiencies are consistent across the sample.

The lowest TE scores, indicating severe inefficiencies among the least efficient producers, are 0.44 under CRS, 0.53 under VRS, and 0.52 under SE. These findings emphasize the importance of focused efforts to increase TE and SE. The findings highlight the importance of resource management approaches and scale optimization in improving overall production efficiency in pangas farming.

Table 3

Distribution of TE and SE in pangas production

TE range	*TE (CRS)*		*TE (VRS)*		*SE*	
	Frequency	*%*	*Frequency*	*%*	*Frequency*	*%*
1.00	55	16.82	72	22.02	35	10.70
0.90 > 1.00	19	5.81	33	10.09	22	6.73
0.80 > 0.90	34	10.40	36	11.01	37	11.31
0.70 > 0.8	28	8.56	47	14.37	44	13.46
0.60 > 0.70	30	9.17	51	15.60	49	14.98
0.60 > 0.50	33	10.09	43	13.15	54	16.51
< 0.50	128	39.14	45	13.76	86	26.30
Mean	0.66		0.75		0.63	
Maximum	1		1.00		1.00	
Minimum	0.44		0.53		0.52	

These findings suggest that specific policy interventions are required to improve TE and SE among pangas growers. TE could be significantly boosted by enhancing access to resources, training, and technology that optimize resource utilization. Furthermore, improving SE necessitates recommendations on the optimal farm size. Helping farmers optimize their operations, whether by scaling up or down, can boost productivity and resource usage. The study's findings also highlight the urgent need for comprehensive programs to improve pangas production's technological and scale efficiencies. Policymakers should prioritize initiatives that promote good farm management approaches to improve the sector's overall sustainability and productivity. Stakeholders can significantly boost pangas farming's contribution to food security and economic growth by creating an environment conducive to efficient operations.

Tobit analysis. Table 4 displays the results of a Tobit regression study that examined the variables influencing farmers' technical efficiency under constant returns to scale (CRS) and variable returns to scale (VRS). The substantial log-likelihood values of 57.80 for VRS and 69.81 for CRS indicate that both models match well. The Wald χ² values of 26.17 for CRS and 23.12 for VRS are statistically significant ($p < 0.01$), indicating that the explanatory factors have a considerable impact on technical efficiency when taken together. The models appear to account for a substantial degree of variance in technical efficiency, as seen by pseudo R^2 values of 0.573 for CRS and 0.526 for VRS.

Table 4

Factors affecting the farmer’s technical efficiency (Tobit analysis)

No.	*Factors*	*CRS*		*VRS*	
		Coefficient value	*Standard error*	*Coefficient value*	*Standard error*
1	Training (number of days)	0.038*	0.020	0.021**	0.015
2	Education (years)	0.048	0.022	0.042	0.020
3	Experience (years)	0.007**	0.004	0.012*	0.010
4	Age (years)	0.003	0.003	0.002	0.001
5	Earning members (numbers)	0.017*	0.010	0.015*	0.008
6	Financial inclusion (included = 1, excluded = 0)	0.134*	0.028	-0.126**	0.022
7	Climate impact	-0.056*	0.044	-0.047*	0.040
		Log likelihood = 69.81 Prob > chi^2 0.002 Wald^{x2} = 26.17 PSEUDO R^2 = 0.573		Log likelihood = 57.80 Prob > chi^2 0.003 Wald^{x2} = 23.12 PSEUDO R^2 = 0.526	

Note: ** and * represent the significance levels of the coefficients at 5% and 10%, respectively.

Training improves technical efficiency in both models significantly, as evidenced by the number of training days. More training increases production (correlation coefficient = 0.038, $p < 0.05$) under CRS. Under VRS, the effect is more obvious, with a coefficient of 0.021 ($p < 0.01$), highlighting the role of training to enhance efficiency when scale effects are taken into consideration. Experienced farmers are more efficient, with coefficients of 0.007 ($p < 0.01$) under CRS and 0.012 ($p < 0.05$) under VRS, indicating improved resource utilization.

The characteristics of the household are also essential. Efficiency is considerably influenced by the number of members earning, with values of 0.017 ($p < 0.05$) under CRS and 0.015 ($p < 0.05$) under VRS. This finding implies that having numerous sources of income allows households to better manage their resources. It's worth noting that financial inclusion produces conflicting consequences. It has a significant negative impact under VRS (coefficient = -0.126, $p < 0.01$), but a positive impact under CRS (coefficient = 0.134, $p < 0.05$), demonstrating that the advantages of financial inclusion may change depending on the amount of activities.

The investigation reveals the detrimental impact of climate change, which significantly reduces technical efficiency in both models. The coefficients for CRS and VRS are -0.056 ($p < 0.05$) and -0.047 ($p < 0.05$), indicating the importance of climate resilience strategies in agriculture. Despite having positive coefficients, age and education had no statistically significant effects in either model, implying that their influence on efficiency in this sample may be limited. Overall, the findings emphasize the importance of targeted interventions to improve agricultural technical efficiency, such as financial inclusion plans, training initiatives, and climate adaptation strategies. These findings provide valuable information to stakeholders and governments seeking to improve the sustainability and productivity of agricultural systems.

Discussion. Pangas farming's effectiveness is a crucial feature of sustainable aquaculture, particularly in locations where resource limitations and environmental challenges persist. In addition to enhancing farm profitability, knowing the factors that determine technical and scale efficiency in this industry promotes rural development and food security. Along with a thorough assessment of the socioeconomic and environmental factors influencing

Pangas farmers' TE and SE, this study provides new insights into these efficiencies. The findings have significant implications for increasing resource efficiency and closing productivity gaps in the sector.

The average TE scores for pangas farmers under CRS and VRS are 0.66 and 0.75, respectively, suggesting that TE and SE scores vary significantly. These findings are consistent with previous studies highlighting how differences in farm management approaches and resource access contribute to aquaculture inefficiencies (Alam et al 2019; Rahman et al 2019). The mean SE score of 0.63 indicates suboptimal use of production capacity due to scale inefficiencies. This complements previous research on the problems of achieving optimal size in aquaculture systems (Coelli et al 2005; Sumon et al 2025).

The Tobit regression analysis identifies additional key TE predictors in the CRS and VRS frameworks. Training proves to be a very useful component, supporting research by Hossain et al (2022) that emphasizes the relevance of capacity building in increasing farm productivity. Farming experience also has a favorable impact on TE, which is similar with the findings of Coelli & Battese (1996), who emphasized experiential learning as a crucial efficiency driver. The benefits of financial services may vary with size, as indicated by the dual impact of financial inclusion, which has a positive effect on TE under CRS but a negative effect on TE under VRS (Sumon et al 2022). This complex relationship is consistent with the theoretical reasons for the contextual impacts of financial access proposed by Banerjee & Duflo (2011). Furthermore, it has been proven that climatic impacts significantly reduce TE, consistent with the larger body of research on the negative effects of environmental pressures on agricultural output (IPCC 2019).

The results are backed by theoretical frameworks such as economic theories of production efficiency and the resource-based view (RBV). According to the RBV, efficiency and competitive advantage are driven by a unique combination of farm-level resources, including financial resources, human capital, and environmental adaptation (Barney 1991). This validates the study's findings that experience, and training significantly increase TE by maximizing the use of available resources. The study supports the concept of production efficiency, which highlights the necessity of input optimization in achieving maximum output levels economically (Farrell 1957). The discrepancies in efficiency ratings between the CRS and VRS models lend support to the economic theory of scale economies, which states that changes in scale can have an impact on productivity outcomes.

The findings emphasize the need for producers investing in training and implementing best management practices to boost production. Farmers' technical abilities can be considerably enhanced by regionally tailored training programs that maximize input use while minimizing inefficiencies. A more regular supply of high-quality pangas may benefit retailers and other value chain participants since enhanced agricultural productivity leads to higher product availability and quality. These findings highlight for policymakers the importance of comprehensive methods that address technical and size inefficiencies. A more sustainable and productive aquaculture business is dependent on policies that promote training access, financial inclusion, and climate resilience. Supporting research and development in cutting-edge agricultural technologies can boost production, ensuring pangas farming's long-term viability and role in fostering economic growth and food security.

Even when there are potential efficiency benefits, it is critical to consider larger financial constraints. Market instability, regulatory changes, and economic downturns can all influence pangas pricing and customer behavior. For example, abrupt changes in market demand or supply chain might have an impact on pricing stability and return on investment. Changes in regulations or subsidy programs may have an influence on operating expenses and resource availability. Financial troubles may grow during economic downturns if farmers are unable to invest in productivity-boosting strategies. The long-term stability and expansion of the pangas aquaculture sector are dependent on stakeholders' ability to adapt and respond to changing economic conditions.

Conclusions. Bangladesh's pangas fish population is growing as a result of both favorable climatic conditions and altering consumer tastes. To improve their technical efficacy, pangas producers must identify the primary elements driving productivity. The study's goal was to analyze the technical proficiency of pangas farmers in Bangladesh, identify the primary factors influencing productivity, and provide meaningful recommendations for increasing output. Data envelopment analysis (DEA) was used to assess the efficiency scores of sampling farms under both constant and variable returns to scale. To further study the factors influencing technical efficiency, a Tobit regression model was used. The findings provide a complete understanding of the efficiency levels and factors that influence production changes in pangas farming.

The results indicate that producers are operating at 66% and 75% of their potential efficiency levels, respectively, with average technical efficiency scores of 0.66 under CRS and 0.75 under VRS. This implies that there is a significant amount of potential for growth. Furthermore, the average scale efficiency score was 0.63, which suggests that the farm resources were not utilized to their full potential. Only 16.82% of farmers attained 100% efficiency under CRS, and 22.02% under VRS, suggesting a substantial percentage of inefficiencies. These results underscore the importance of implementing measures to enhance technical and scale efficiencies.

The Tobit study identified a number of critical factors for technical efficacy. As a consequence of training, efficiency increased, underscoring the critical role that capacity-building initiatives play. Efficiency was also enhanced by the number of earning members and expertise, indicating that financially secure households and seasoned producers are better prepared to optimize resource utilization. It is remarkable that financial inclusion had two distinct effects: under CRS, it increased efficiency, while under VRS, it had the opposite effect. This implies that financial assistance systems should be appropriately configured to operate at varying dimensions. The efficiency of pangas farming was compromised as a result of climate impacts, which underscored its vulnerability to climatic fluctuations.

The results have substantial implications for stakeholders. Focused training and resource optimization strategies are indispensable for producers to enhance their technical efficiency. Assisting producers in implementing optimal procedures could result in more dependable supply chains for retailers. Policymakers play a critical role in the establishment of an enabling environment by implementing programs such as access to contemporary technologies, climate-resilient farming practices, and financial inclusion measures that are tailored to the scale of enterprises. The study underscores the significance of establishing integrated policy frameworks that enhance technological and scale efficiency to facilitate the more overarching objectives of economic development and food security.

Despite its contributions, this study has its limitations. The results are not applicable to other aquaculture environments due to the region-specific nature of the sample. Additionally, the cross-sectional structure of the data restricts the ability to gain insights into efficiency trends over time. Future research should investigate the impact of market dynamics and new technologies on Pangas farming, as well as longitudinal data to document changes in efficacy over time. Furthermore, a more comprehensive understanding of sustainable aquaculture would be achieved by expanding the focus to include the social and environmental aspects of efficacy. By addressing these areas, future research can further develop the existing findings and offer a more comprehensive understanding of how to optimize aquaculture methods in Bangladesh and other regions.

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