Drivers of milkfish pond productivity gaps in coastal Sidoarjo, Indonesia

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Abstract. Milkfish (*Chanos chanos*) pond farming in coastal Sidoarjo, Indonesia, shows unequal productivity among smallholder farms operating within the same brackishwater production region. This study quantified farm-level productivity gaps and identified measured technical, economic, environmental and operational variables associated with productivity variation. Field data were collected from 30 active milkfish farmers. Productivity was calculated as harvest output per pond area per production cycle and evaluated against the best-observed productivity benchmark of 4.72 ton ha^{-1} $cycle^{-1}$. The analyzed variables were feed conversion ratio, feed cost, operational cost, dissolved oxygen, salinity, ammonia and labor involvement. Average productivity was 3.39 ton ha^{-1} $cycle^{-1}$, leaving a mean productivity gap of 1.33 ton ha^{-1} $cycle^{-1}$ and an average achievement ratio of 71.92%. Cost per harvested output showed the strongest empirical signal, with a significant negative association with productivity (Spearman correlation coefficient (ρ) = -0.564; p = 0.001). Ammonia and feed conversion ratio showed technically consistent negative directions, although their statistical support was limited. The results indicate that low-productivity farms mainly require better cost-output conversion, improved feed-use efficiency and stronger waste-pressure control rather than simple input expansion.

Keywords: *Chanos chanos*, cost-output efficiency, feed conversion ratio, pond productivity, water quality.

Introduction. Milkfish (*Chanos chanos*) pond farming is a major brackishwater aquaculture activity in coastal Sidoarjo, East Java, Indonesia. The production system is dominated by smallholder earthen ponds that depend on feed allocation, tidal or managed water exchange, operating capital and repeated labor-based control during one production cycle. Milkfish is widely cultivated in brackishwater pond systems because of its salinity tolerance, established pond-culture history and suitability for coastal smallholder production (Bagarinao, 1994). In this setting, harvest output is not determined only by pond area or stocking activity. Productivity reflects the efficiency of the pond-production process, where feed must be converted into biomass, production cost must remain within farmer operating capacity, water quality must support growth and survival, and labor must maintain routine pond operations until harvest.

Aquaculture has become an important component of aquatic food production, rural livelihood support and coastal food systems, but its expansion must be evaluated through productivity, resource efficiency and environmental performance rather than output growth alone (Golden et al., 2021; Naylor et al., 2021; FAO, 2022).

The main problem in coastal Sidoarjo is a persistent productivity gap. Field observations show that milkfish pond productivity differs substantially among farms operating within the same coastal production region. This variation indicates that some farms convert pond area, feed, cost, water condition and labor into harvest output more efficiently than others under comparable local production conditions. This gap represents a farm-level input-output conversion loss rather than a simple shortage of production input. In production-engineering terms, low productivity should be diagnosed from measurable process variables that regulate conversion efficiency and production feasibility. Feed conversion ratio (FCR), feed cost, operational cost, dissolved oxygen (DO), salinity, ammonia and labor involvement are relevant because they represent technical efficiency, economic burden, environmental operating condition and observable operational capacity at pond level.

Such a gap is consistent with the broader concept of performance differences among farms, where farms operating under comparable production conditions may show unequal technical and economic efficiency because of differences in input use, management routines and environmental control (Kumar & Engle, 2016; Gephart et al., 2021). FCR is the main technical indicator of feed-to-biomass conversion. A lower FCR indicates that less feed is needed to produce the same biomass, while a higher FCR indicates feed-use loss. Inefficient conversion increases feed requirement, raises feed cost and increases the probability of uneaten feed entering the pond environment. Feed is widely recognized as the largest cost component in aquaculture and a critical determinant of production efficiency (Tacon & Metian, 2015; Glencross et al., 2020). Poor feed utilization also connects technical inefficiency with environmental pressure because residual feed and metabolic waste increase ammonia concentration and oxygen demand (Dauda et al., 2019; Yu et al., 2023). Increasing feed input is therefore not automatically a productivity solution. The more precise engineering question is whether feed input is converted efficiently into harvestable biomass.

Economic variables define the financial boundary of productivity improvement. Feed cost represents the direct burden of feed allocation, while operational cost represents the broader expenditure required for pond preparation, labor, water management and harvest activities. Smallholder farmers operate with limited cash capacity, so input expansion is feasible only when additional output exceeds additional cost. Aquaculture economics emphasizes that production intensification must be evaluated through cost efficiency and profitability, not output increase alone (Anderson et al., 2019; Jolly & Clonts, 2020). In milkfish ponds, higher productivity may be technically possible but financially weak when feed cost and operational cost rise faster than harvest gain. Cost burden can therefore help explain why the best-observed productivity level is not consistently approached across farms.

Water quality defines the environmental operating condition of the pond. DO supports metabolism, feed intake and biomass retention, while ammonia indicates waste pressure that can reduce pond suitability for fish growth. Salinity affects osmotic balance in brackishwater ponds and can modify growth performance when it moves outside a suitable operating range. Low DO reduces growth efficiency and increases mortality risk, while ammonia accumulation reflects organic loading from feed and metabolic waste (Liu et al., 2019; Boyd et al., 2020). Although milkfish tolerates salinity fluctuation, tolerance does not imply equal productivity across all salinity conditions. In ponds with limited water exchange, unstable water quality reduces the ability of the production system to retain biomass until harvest.

Labor involvement represents observable operational capacity for pond management. Feeding, water observation, pond maintenance, response to declining oxygen and harvest preparation require repeated actions during one production cycle. In smallholder aquaculture, technical recommendations often fail when farmers cannot implement them consistently at pond level (Bush et al., 2019; Joffre et al., 2020; Kumaran et al., 2021). Labor involvement does not capture all dimensions of management quality, but it reflects the minimum labor availability required for routine pond operations. More labor does not automatically increase productivity, but insufficient labor may reduce feeding precision, delay water-quality response and increase production losses.

Previous aquaculture studies have established the importance of feed efficiency, economic feasibility, water quality and farm management in production performance (Belton et al., 2020; Gephart et al., 2021; Troell et al., 2023). The remaining limitation is that these variables are often discussed separately or translated into broad recommendations. For smallholder milkfish ponds, the more specific gap lies in the limited farm-level quantitative diagnosis that measures productivity loss against a local best-observed productivity benchmark and evaluates FCR, cost burden, DO, salinity, ammonia and labor involvement within one empirical framework. Without this diagnosis, intervention remains imprecise: farms with high FCR, high cost burden, low DO, high ammonia or limited labor capacity may receive the same recommendation even though their dominant constraints differ.

This study analyzes measured variables associated with milkfish pond productivity gaps in coastal Sidoarjo, Indonesia. Productivity is treated as the main output, while FCR, feed cost, operational cost, DO, salinity, ammonia and labor involvement are evaluated as farm-level explanatory variables. The objectives are to quantify the productivity gap against the best-observed productivity benchmark and to identify the technical, economic, environmental and operational variables associated with productivity variation among farms. The study provides a farm-level quantitative basis for locating productivity loss and defining where improvement should begin under smallholder milkfish pond conditions.

Material and Method

***Study area and farm data*.** The study was conducted in coastal Sidoarjo, East Java, Indonesia, where milkfish pond farming is commonly practiced in smallholder brackishwater ponds. The observed farms represented farmer-level earthen pond production units operated under local coastal conditions. Production decisions in these farms depend on feed allocation, operating cost, pond water condition, and routine labor involvement during one production cycle. The unit of analysis was one active milkfish pond farming unit.

Primary data were collected from 30 active milkfish farmers through structured interviews and field observation. Field data were collected from February 2025 to March 2026. Respondents were selected purposively because the study required farms with complete information on harvest output, pond area, feed use, feed cost, operational cost, water-quality variables, and labor involvement. The sample was used for farm-level productivity-gap diagnosis and process-variable screening. It was not intended to statistically represent all milkfish farmers in East Java.

The collected variables consisted of harvest output, pond area, feed use, feed cost, operational cost, DO, salinity, ammonia, and labor involvement. Harvest output was recorded in ton cycle^{-1} and pond area in ha. Feed use was recorded in ton cycle^{-1} and used to calculate FCR. Feed cost and operational cost were recorded in Indonesian Rupiah cycle^{-1}. DO was recorded in mg L^{-1}, salinity in ppt, and ammonia in mg L^{-1}. Labor involvement was recorded as the number of persons involved in routine pond operations during the observed production cycle.

Water-quality variables were obtained from farmer records and field confirmation during observation. Therefore, DO, salinity and ammonia were interpreted as farm-level screening indicators rather than continuous water-quality measurements.

***Variable definition and engineering role*.** Productivity was treated as the main output variable because it represents the ability of the pond system to convert pond area, feed input, cost, water condition, and labor involvement into harvestable biomass. The explanatory variables were grouped into four process dimensions. FCR represented technical conversion efficiency. Feed cost and operational cost represented economic burden. DO, salinity, and ammonia represented environmental operating conditions. Labor involvement represented observable operational capacity.

This classification follows a farm-level production-engineering logic. Low productivity was not treated as a single biological problem, but as a measurable input-output conversion loss that may be associated with feed-use inefficiency, cost pressure, water-quality limitation, and limited routine management capacity. The variables, symbols, units, engineering roles, and expected directions used in the diagnosis are summarized in Table 1.

Table 1

Variables used in the productivity-gap diagnosis of milkfish pond farming in coastal Sidoarjo

Variable	*Symbol*	*Unit*	*Engineering role*	*Expected direction*
Productivity	P	ton ha^{-1} $cycle^{-1}$	Main output	Higher is better
Productivity gap	PG	ton ha^{-1} $cycle^{-1}$	Output loss from best-observed benchmark	Lower is better
Productivity achievement ratio	PAR	%	Relative achievement against best-observed benchmark	Higher is better
Feed use	FU	ton $cycle^{-1}$	Feed input for biomass formation	Efficient use is better
Feed conversion ratio	FCR	ratio	Feed-to-biomass conversion efficiency	Lower is better
Feed-efficiency gap	FEG	ratio	Feed-use loss from best observed FCR	Lower is better
Feed cost	FC	IDR $cycle^{-1}$	Direct feed-cost burden	Lower burden is better
Operational cost	OC	IDR $cycle^{-1}$	Non-feed operating burden	Lower burden is better
Total production cost	TC	IDR $cycle^{-1}$	Total recorded cost burden	Lower burden is better
Cost intensity	CI	IDR ha^{-1} $cycle^{-1}$	Production cost per pond area	Lower is better
Cost per output	CPO	IDR ton^{-1}	Production cost per harvested output	Lower is better
Dissolved oxygen	DO	mg L^{-1}	Oxygen support for growth and survival	Higher within suitable range is better
Salinity	SAL	ppt	Brackishwater suitability condition	Suitable range is better
Ammonia	NH_3	mg L^{-1}	Waste-pressure indicator	Lower is better
Labor involvement	LAB	persons	Observable operational capacity	Adequate level is better

Productivity and best-observed productivity gap calculation. Milkfish pond productivity was calculated as harvest output per pond area per production cycle. Productivity was expressed in ton ha^{-1} $cycle^{-1}$ to allow comparison among farms with different pond sizes. Productivity of each farm was calculated using Equation 1:

$$P_i = H_i / A_i \qquad (1)$$

where P_i is productivity of farm i in ton ha^{-1} $cycle^{-1}$, H_i is harvest output of farm i in ton $cycle^{-1}$, and A_i is pond area of farm i in ha.

The productivity gap was calculated using a best-observed productivity benchmark. The benchmark was defined as the highest productivity recorded among the sampled farms. This approach was used to avoid relying on an assumed external productivity reference and to ensure that the comparison was based on a productivity level empirically achieved under farmer-level pond conditions in coastal Sidoarjo. In this study, the best-observed productivity was 4.72 ton ha^{-1} $cycle^{-1}$. The productivity gap was calculated using Equation 2:

$$PG_i = P_{\_best} - P_i \qquad (2)$$

where PG_i is the productivity gap of farm i in ton ha^{-1} $cycle^{-1}$, $P_{\_best}$ is the best-observed productivity among the sampled farms, and P_i is the observed productivity of farm i. A higher PG_i value indicates a larger productivity loss relative to the best-performing farm, while a value of zero indicates that the farm reached the best-observed productivity level.

The productivity achievement ratio was calculated using Equation 3:

$$PAR_i = P_i / P_{\_best} \times 100 \quad (3)$$

where PAR_i is the productivity achievement ratio of farm i in percent. This ratio indicates how close each farm is to the best-observed productivity level achieved under the same regional production.

Technical and economic indicators. FCR was calculated from feed use and harvest output using Equation 4:

$$FCR_i = Fu_i / H_i \quad (4)$$

where FCR_i is the feed conversion ratio of farm i, FU_i is feed use in ton cycle^{-1}, and H_i is harvest output in ton cycle^{-1}. A lower FCR indicates better feed-to-biomass conversion, while a higher FCR indicates feed-use loss.

The feed-efficiency gap was calculated by comparing each farm's FCR with the best observed FCR in the sample using Equation 5:

$$FEG_i = FCR_i - FCR_{\_min} \quad (5)$$

where FEG_i is the feed-efficiency gap of farm i, FCR_i is the feed conversion ratio of farm i, and $FCR_{\_min}$ is the lowest observed FCR among the sampled farms. A higher FEG value indicates a larger feed-efficiency loss relative to the best observed feed conversion performance.

Economic burden was evaluated using feed cost, operational cost, total production cost, cost intensity, and cost per harvested output. Total recorded production cost was calculated using Equation 6:

$$TC_i = FC_i + OC_i \quad (6)$$

where TC_i is total recorded production cost of farm i, FC_i is feed cost, and OC_i is operational cost.

Cost intensity per pond area was calculated using Equation 7:

$$CI_i = TC_i / A_i \quad (7)$$

where CI_i is cost intensity of farm i in IDR ha^{-1} cycle^{-1}.

Cost per harvested output was calculated using Equation 8:

$$CPO_i = TCi / H_i \quad (8)$$

where CPO_i is production cost per harvested output of farm i in IDR ton^{-1}. These indicators were used to evaluate whether higher productivity was achieved through efficient cost conversion or through excessive cost burden.

Environmental and operational variables. DO, salinity, and ammonia were analyzed as individual environmental operating variables. DO indicated oxygen availability for metabolism, feeding activity, and biomass retention. Salinity represented brackishwater suitability, while ammonia represented waste pressure from uneaten feed, metabolic waste, and organic loading. These variables were not combined into a composite environmental index because the objective of the study was to identify which individual measured variables were associated with productivity gaps.

Labor involvement was used as an observable proxy for routine operational capacity. It represented the number of persons involved in feeding, pond observation, water management, pond maintenance, and harvest preparation. This variable was not interpreted as a complete measure of management quality. It was used only as a measurable indicator of minimum labor availability for repeated pond operations.

Data analysis. The analysis was conducted in five stages. First, descriptive statistics were calculated for all variables, including mean, minimum, maximum, standard deviation, and coefficient of variation. The coefficient of variation was used to describe heterogeneity among farms and not as direct evidence of productivity influence.

Second, productivity-gap analysis was performed by calculating productivity, productivity gap, and productivity achievement ratio for each farm. Farms were then evaluated according to their position relative to the best-observed productivity benchmark. This step identified the magnitude and distribution of productivity loss across the sampled farms.

Third, bivariate association analysis was used to screen the relationship between productivity and each explanatory variable. Normality was examined using the Shapiro-Wilk test. Pearson correlation was used for normally distributed variables, while Spearman rank correlation was used for non-normal or strongly skewed variables. Correlation analysis was treated as the main screening tool for identifying measured variables associated with productivity variation.

Fourth, regression analysis was used as diagnostic support, not as a standalone predictive model. Because the sample consisted of 30 farms, a full model containing all explanatory variables was not used as the main basis of interpretation. A parsimonious regression model was developed by including variables that showed technical relevance and sufficient bivariate association with productivity. The general form of the diagnostic regression model was expressed as Equation 9:

$$P_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + ... + \beta_k X_{ki} + \varepsilon_i \quad (9)$$

where P_i is productivity of farm i, X_{1i} to X_{ki} are selected explanatory variables, β_0 is the intercept, β_1 to β_k are regression coefficients, and ε_i is the error term. The number of explanatory variables was kept limited to reduce overfitting. The signs of the coefficients were interpreted according to the engineering role of each variable. Negative coefficients for FCR, cost indicators, or ammonia indicated that feed-use loss, cost burden, or waste pressure was associated with lower productivity. Positive coefficients for DO or labor involvement indicated that better operating condition or stronger routine operational capacity was associated with higher productivity.

Multicollinearity was examined using variance inflation factor. Variables with strong collinearity were not interpreted simultaneously as independent explanatory variables. When collinearity occurred among cost variables, interpretation emphasized the broader economic-burden mechanism rather than mechanically separating feed cost, operational cost, cost intensity, and cost per output.

Fifth, productivity-gap driver screening was developed by combining four criteria: direction of association, correlation strength, regression support, and consistency with pond-production logic. A variable was prioritized when it showed a clear association with productivity, had an interpretable direction, was supported by the diagnostic regression, and was technically consistent with aquaculture production processes. The screening result was used to indicate whether improvement should prioritize feed conversion, cost control, water-quality stabilization, or operational labor capacity.

Statistical significance was evaluated at $p < 0.05$. Results with $p < 0.10$ were interpreted cautiously as weak evidence because of the limited sample size. The interpretation emphasized effect direction, engineering consistency, and practical relevance, not statistical significance alone.

Analytical control and interpretation limits. The study used observational farm-level data; therefore, the analysis identified measured variables associated with productivity gaps and did not claim experimental causality. Analytical control was maintained through three steps. First, all variables were measured at the same farm-production unit and within the same production-cycle. Second, productivity was standardized as ton ha^{-1} $cycle^{-1}$ to avoid pond-size bias. Third, explanatory variables were interpreted according to their technical, economic, environmental, and operational roles in pond production.

The analytical framework was considered acceptable when the identified variables were statistically interpretable, consistent with aquaculture production logic, and useful for defining farm-level improvement priorities. This approach allowed productivity loss to be diagnosed as a measurable input-output conversion problem under smallholder pond conditions in coastal Sidoarjo.

Results. Farm-level productivity gap against the best-observed benchmark. Milkfish pond productivity varied among the 30 sampled farms in coastal Sidoarjo. Observed productivity ranged from 2.22 to 4.72 ton ha^{-1} $cycle^{-1}$, with an average of 3.39 ton ha^{-1} $cycle^{-1}$ and a standard deviation of 0.82 ton ha^{-1} $cycle^{-1}$. The coefficient of variation reached 24.17%, indicating substantial productivity heterogeneity among farms operating within the same coastal production region.

The highest observed productivity was 4.72 ton ha^{-1} $cycle^{-1}$. This value was used as the best-observed productivity benchmark because it represented the maximum productivity empirically achieved under farmer-level pond conditions in coastal Sidoarjo. Based on this benchmark, the average productivity gap was 1.33 ton ha^{-1} $cycle^{-1}$. The lowest-performing farm produced 2.22 ton ha^{-1} $cycle^{-1}$, leaving a gap of 2.50 ton ha^{-1} $cycle^{-1}$ from the best-observed benchmark. The average productivity achievement ratio was 71.92%, meaning that the sampled farms reached, on average, less than three-quarters of the best observed local productivity level.

This result shows that the productivity problem in coastal Sidoarjo is not the absence of productive farms. A productivity level of 4.72 ton ha^{-1} $cycle^{-1}$ was already achieved under local farmer-level conditions. The main issue is the unequal ability of farms to convert pond area, feed, cost, water condition, and labor into harvestable biomass. The descriptive productivity-gap indicators are summarized in Table 2.

Table 2

Farm-level productivity gap against the best-observed benchmark

Indicator	*Mean*	*Minimum*	*Maximum*	*SD*	*CV (%)*
Productivity, ton ha^{-1} $cycle^{-1}$	3.39	2.22	4.72	0.82	24.17
Productivity gap, ton ha^{-1} $cycle^{-1}$	1.33	0.00	2.50	0.82	61.91
Productivity achievement ratio, %	71.92	47.03	100.00	17.38	24.17

Productivity achievement groups*.* Based on the productivity achievement ratio, the sampled farms were grouped into three achievement classes. Eleven farms reached at least 80% of the best-observed benchmark, ten farms reached 60–<80%, and nine farms remained below 60%. The high-achievement group produced an average productivity of 4.32 ton ha^{-1} $cycle^{-1}$, while the medium- and low-achievement groups produced 3.21 and 2.47 ton ha^{-1} $cycle^{-1}$, respectively. The achievement-group results are presented in Table 3.

Table 3

Productivity achievement groups based on the best-observed benchmark

Group	*Number of farms*	*Mean productivity, ton ha^{-1} $cycle^{-1}$*	*Mean productivity gap, ton ha^{-1} $cycle^{-1}$*	*Mean achievement ratio, %*
High, ≥ 80% of benchmark	11	4.32	0.40	91.47
Medium, 60 - < 80% of benchmark	10	3.21	1.51	68.05
Low, < 60% of benchmark	9	2.47	2.25	52.33

The mean productivity gap increased from 0.40 ton ha^{-1} $cycle^{-1}$ in the high-achievement group to 1.51 ton ha^{-1} $cycle^{-1}$ in the medium group and 2.25 ton ha^{-1} $cycle^{-1}$ in the low group. The low-achievement group reached only 52.33% of the best-observed benchmark. This shows that productivity loss was concentrated in farms with weak input-output conversion performance.

Technical and economic performance. FCR ranged from 1.50 to 2.20, with an average of 1.86. The lowest FCR, 1.50, represented the best observed feed-to-biomass conversion in the sample. The average feed-efficiency gap was 0.36, indicating that the average farm operated above the best observed FCR by 0.36 ratio points. The high-achievement group had a slightly lower average FCR than the low-achievement group, indicating a technically consistent but weak feed-efficiency pattern.

Feed cost ranged from IDR 9.02 to 15.64 million cycle^{-1}, with an average of IDR 12.42 million cycle^{-1}. Operational cost ranged from IDR 3.41 to 7.29 million cycle^{-1}, with an average of IDR 5.23 million cycle^{-1}. Total recorded production cost averaged IDR 17.65 million cycle^{-1}. Cost intensity per pond area ranged from IDR 4.51 to 25.83 million ha^{-1} cycle^{-1}, while cost per harvested output ranged from IDR 1.32 to 9.22 million ton^{-1}.

The clearest economic signal appeared in cost per harvested output. The high-achievement group had an average cost per output of IDR 2.51 million ton^{-1}, while the medium- and low-achievement groups reached IDR 3.02 million ton^{-1} and IDR 5.06 million ton^{-1}, respectively. This means that low-achievement farms spent about twice as much per harvested ton as high-achievement farms. The result indicates that productivity gaps were strongly reflected in cost-output conversion inefficiency. The complete technical and economic indicators are summarized in Table 4.

Table 4

Technical and economic indicators of milkfish pond farming

Indicator	*Mean*	*Minimum*	*Maximum*	*SD*	*CV (%)*
FCR	1.86	1.50	2.20	0.23	12.40
Feed-efficiency gap	0.36	0.00	0.70	0.23	64.53
Feed cost, IDR cycle^{-1}	12.42 million	9.02 million	15.64 million	2.14 million	17.22
Operational cost, IDR cycle^{-1}	5.23 million	3.41 million	7.29 million	1.17 million	22.33
Total production cost, IDR cycle^{-1}	17.65 million	13.52 million	21.46 million	2.33 million	13.23
Cost intensity, IDR ha^{-1} cycle^{-1}	10.95 million	4.51 million	25.83 million	5.00 million	45.69
Cost per output, IDR ton^{-1}	3.45 million	1.32 million	9.22 million	1.87 million	54.11

Environmental and operational conditions. DO ranged from 4.94 to 7.40 mg L^{-1}, with an average of 6.38 mg L^{-1}. The minimum DO value was close to oxygen-limited operating conditions for pond aquaculture, indicating that some farms operated near a lower oxygen boundary during the observed production cycle. Salinity ranged from 16.10 to 28.00 ppt, with an average of 21.36 ppt, reflecting the brackishwater character of coastal Sidoarjo ponds. Ammonia ranged from 0.07 to 0.32 mg L^{-1}, with an average of 0.18 mg L^{-1} and a coefficient of variation of 41.66%. The high-achievement group had lower average ammonia than the medium- and low-achievement groups. This pattern is technically meaningful because ammonia represents waste pressure in pond water. Although the difference does not prove causality, the direction supports the interpretation that lower waste pressure is associated with better productivity achievement.

Labor involvement ranged from 2 to 8 persons, with an average of 5.27 persons. The coefficient of variation reached 43.16%, indicating strong heterogeneity in observable operational capacity. However, labor quantity alone did not clearly separate high- and low-achievement farms. This result confirms that labor involvement should be interpreted as an observable operational-capacity variable, not as a complete measure of management quality. The environmental and operational indicators are summarized in Table 5.

Table 5

Environmental and operational indicators of milkfish pond farming

Indicator	*Mean*	*Minimum*	*Maximum*	*SD*	*CV (%)*
Dissolved oxygen, mg L^{-1}	6.38	4.94	7.40	0.76	11.95
Salinity, ppt	21.36	16.10	28.00	3.66	17.12
Ammonia, mg L^{-1}	0.18	0.07	0.32	0.08	41.66
Labor involvement, persons	5.27	2.00	8.00	2.27	43.16

Bivariate association screening. Shapiro-Wilk testing indicated that productivity did not meet the normality assumption at $p < 0.05$. Therefore, Spearman rank correlation was used as the primary association screening tool. The strongest association with productivity was found for cost per harvested output, with a negative and statistically significant correlation ($\rho = -0.564$; $p = 0.001$). This result shows that higher productivity was associated with lower production cost per harvested ton.

Among the measured process variables, none showed a statistically significant association with productivity at $p < 0.05$. However, several variables had directions consistent with pond-production logic. FCR had a negative association with productivity ($\rho = -0.126$; $p = 0.508$), indicating that higher feed conversion loss tended to accompany lower productivity. Ammonia also showed a negative association ($\rho = -0.196$; $p = 0.299$), indicating that higher waste pressure tended to accompany lower productivity. DO had a weak positive association ($\rho = 0.097$; $p = 0.611$). Labor involvement was nearly neutral ($\rho = 0.009$; $p = 0.964$), confirming that worker number alone did not explain productivity variation.

Cost per output was not interpreted as an independent causal driver because it was derived from total cost and harvested output. It was interpreted as an economic efficiency indicator that reflects productivity performance. In contrast, FCR, ammonia, DO, cost variables, and labor involvement were treated as measured process variables. The correlation results indicate that productivity gaps were not controlled by a single dominant independent variable, but were reflected most clearly in cost-output conversion efficiency. The bivariate association results are presented in Table 6.

Table 6

Spearman correlation between productivity and explanatory variables

Variable	*Spearman ρ*	*p-value*	*Direction of association*	*Interpretation*
FCR	-0.126	0.508	Negative	Higher FCR tended to accompany lower productivity, but not significant.
Feed cost	0.082	0.667	Positive	No clear productivity association.
Operational cost	0.220	0.244	Positive	Higher operating expenditure tended to accompany higher productivity, but not significant.
Total production cost	0.161	0.395	Positive	No clear productivity association.
Cost intensity	-0.127	0.504	Negative	Higher cost per hectare tended to accompany lower productivity, but not significant.
Cost per output	-0.564	0.001	Negative	Strong cost-output efficiency signal.
Dissolved oxygen	0.097	0.611	Positive	Better oxygen condition tended to accompany higher productivity, but not significant.
Salinity	0.047	0.807	Positive	No clear productivity association.
Ammonia	-0.196	0.299	Negative	Higher waste pressure tended to accompany lower productivity, but not significant.
Labor involvement	0.009	0.964	Positive	Worker number alone did not explain productivity.

Diagnostic regression support. A parsimonious diagnostic regression was performed using FCR, ammonia, and operational cost as selected explanatory variables. These variables were selected because they represented technical conversion efficiency, environmental waste pressure, and economic operating burden. The model explained 12.42% of productivity variation ($R^2 = 0.124$; adjusted $R^2 = 0.023$), but the model was not statistically significant ($p = 0.319$). Therefore, the regression was interpreted as diagnostic support rather than as a predictive model.

The standardized coefficient for ammonia was negative ($\beta = -0.236$; $p = 0.216$), while FCR also showed a negative coefficient ($\beta = -0.092$; $p = 0.631$). Operational cost showed a positive coefficient ($\beta = 0.266$; $p = 0.171$), indicating that farms spending more on operational activities tended to have higher productivity, although the evidence was weak. This result should not be interpreted as a recommendation to increase operating cost. It indicates that some operational expenditure may support pond control only when it is converted efficiently into output.

Multicollinearity was low in the diagnostic regression, with variance inflation factor values close to 1. This indicates that the selected explanatory variables did not overlap strongly. However, the small sample size and weak statistical significance limit causal interpretation. The parsimonious regression results are summarized in Table 7.

Table 7

Parsimonious diagnostic regression for productivity variation

Variable	*Standardized coefficient*	*p-value*	*VIF*	*Interpretation*
FCR	-0.092	0.631	1.06	Direction consistent with feed-use loss, but weak evidence.
Ammonia	-0.236	0.216	1.03	Strongest negative process signal, but not significant.
Operational cost	0.266	0.171	1.06	Weak positive operating-support signal.
Model R^2	0.124	-	-	Low explanatory power.
Adjusted R^2	0.023	-	-	Very limited predictive strength.
Model p-value	0.319	-	-	Not statistically significant.

Productivity-gap driver screening. The productivity-gap driver screening combined descriptive patterns, correlation direction, regression support, and consistency with pond-production logic. Cost per harvested output showed the strongest empirical signal because it was significantly and negatively associated with productivity. However, because this variable was derived from total cost and harvested output, it was classified as an economic efficiency signal, not as an independent production driver. The resulting evidence-based driver screening is presented in Table 8.

Among the measured process variables, ammonia provided the clearest negative technical-environmental signal, followed by FCR. Operational cost showed a weak positive signal, suggesting that some farms may benefit from higher operational expenditure when it supports pond control. DO had the expected positive direction but weak statistical support. Labor involvement showed no meaningful association with productivity, indicating that worker quantity alone was insufficient to explain productivity differences.

Overall, the results show that milkfish pond productivity gaps in coastal Sidoarjo were real and measurable, but they were not explained by one dominant independent process variable. The clearest measurable signal was cost-output conversion inefficiency, shown by the significant negative association between productivity and cost per harvested output. The most relevant process variables were ammonia and FCR because both showed directions consistent with aquaculture production logic, although their statistical support was limited. Therefore, productivity improvement should not be framed as increasing feed, labor, or operating expenditure alone. The more defensible interpretation is that low-productivity farms need to improve cost-output conversion, reduce feed-use loss, and control waste pressure in pond water.

Table 8

Productivity-gap driver screening based on statistical and engineering evidence

Rank	*Variable*	*Evidence strength*	*Main signal*	*Interpretation*
1	Cost per output	Strong as efficiency indicator	Significant negative association	Productivity gaps were most clearly reflected in cost-output inefficiency.
2	Ammonia	Moderate technical signal	Negative direction in correlation and regression	Waste pressure may contribute to productivity loss.
3	FCR	Moderate technical signal	Negative direction in correlation and regression	Feed-use loss remains technically relevant.
4	Operational cost	Weak operating-support signal	Positive but not significant	Cost may support productivity only when converted into effective pond control.
5	Dissolved oxygen	Weak environmental signal	Positive direction only	Oxygen condition is relevant, but not a dominant statistical signal in this sample.
6	Labor involvement	Weakest signal	Near-zero association	Labor quantity alone did not explain productivity variation.

Discussion. The present study shows that productivity variation in coastal Sidoarjo milkfish ponds is better interpreted as a farm-level conversion-efficiency problem than as a simple shortage of production input. The best-observed farm reached 4.72 ton ha^{-1} cycle^{-1}, whereas the lowest-performing farm produced only 2.22 ton ha^{-1} cycle^{-1}. This difference generated a maximum productivity gap of 2.50 ton ha^{-1} cycle^{-1} and an average gap of 1.33 ton ha^{-1} cycle^{-1}. The benchmark used in this study was not an assumed technical target, but the highest productivity empirically recorded among the sampled farms. This makes the productivity gap more defensible because the comparison is anchored to a performance level actually achieved under local farmer-level pond conditions.

The use of a best-observed benchmark changes the interpretation of productivity loss. The result does not claim that every farm can immediately reach 4.72 ton ha^{-1} cycle^{-1}, because farms differ in pond condition, management routines, cost capacity and environmental exposure. It does show, however, that the local production system already contains farms capable of higher output conversion. The problem is therefore not the biological impossibility of achieving higher milkfish productivity in coastal Sidoarjo. The main issue is the uneven ability of farms to convert pond area, feed input, operating expenditure, water condition and labor involvement into harvestable biomass. This interpretation is consistent with current aquaculture-performance literature, which emphasizes that productivity improvement should focus on closing performance gaps through targeted technical, economic and environmental interventions rather than relying only on production expansion (Boyd et al., 2020; Gephart et al., 2021; Troell et al., 2023). The productivity achievement grouping strengthens this interpretation. Farms in the high-achievement group reached 91.47% of the best-observed benchmark, while farms in the low-achievement group reached only 52.33%. This gap is too large to be treated as random output fluctuation. It indicates that farms operating in the same coastal region experienced different levels of input-output conversion performance. In agricultural industrial engineering terms, low-achievement farms represent inefficient production units because similar types of inputs and operating conditions generated substantially lower harvest output. The relevant improvement question is not merely how to increase input volume, but how to reduce conversion loss between input use and harvested biomass.

The strongest empirical signal was cost per harvested output. Productivity was significantly and negatively associated with cost per output, and the difference among achievement groups was large. High-achievement farms spent an average of IDR 2.51

million ton^{-1}, whereas low-achievement farms spent IDR 5.06 million ton^{-1}. Low-achievement farms therefore spent about twice as much per harvested ton as high-achievement farms. This finding is important because it shows that low productivity is not only a biological or technical issue; it is also an economic-efficiency problem. A farm may allocate feed, labor and operating expenditure, but those costs become inefficient when they do not produce proportional harvest biomass. Aquaculture economics has long emphasized that production growth must be evaluated through cost efficiency, profitability and input productivity, not through output increase alone (Anderson et al., 2019; Jolly & Clonts, 2020; Engle & van Senten, 2022).

This result also explains why feed cost and operational cost did not show a simple negative association with productivity. In aquaculture production, higher expenditure is not automatically inefficient. Feed cost may support biomass formation when feed is properly converted, and operational cost may support water control, pond maintenance, harvest preparation and routine production management. The weak positive direction of operational cost in the diagnostic regression suggests that some operating expenditure may support productivity when it is converted into effective pond control. However, this result should not be read as a recommendation to increase cost. The more precise interpretation is that cost must be evaluated through its conversion into output. Cost reduction that removes necessary pond operations can damage productivity, while cost increase without output gain will worsen production efficiency. The managerial target is therefore cost-output optimization, not cost minimization or cost expansion alone.

FCR remains a central technical variable even though its statistical association with productivity was weak in this dataset. The average FCR was 1.86, while the best observed FCR was 1.50, producing an average feed-efficiency gap of 0.36 ratio points. This means that average farms required more feed per unit biomass than the most feed-efficient farm in the sample. The direction of the relationship was consistent with aquaculture production logic: higher FCR tended to accompany lower productivity. Feed is one of the most important cost and resource components in fed aquaculture, and feed efficiency strongly affects economic performance, nutrient discharge and environmental pressure (Tacon & Metian, 2015; Cottrell et al., 2020; Glencross et al., 2020). In milkfish pond farming, FCR is not only a feeding indicator. It connects technical efficiency, feed cost, uneaten feed, organic loading and water-quality pressure.

The weak statistical strength of FCR should be interpreted carefully. It does not mean that feed conversion is irrelevant. Rather, it indicates that FCR alone did not dominate productivity variation among the 30 farms. Pond productivity is affected by the combined result of feed use, survival, water condition, stocking condition, pond maintenance and farmer response during the cycle. A farm with moderate FCR can still perform well when survival and water quality are stable. Conversely, a farm with acceptable feed input can underperform when ammonia rises, DO declines or pond operations are inconsistent. This explains why the regression model had limited explanatory power. The result is not methodologically weak; it reflects the multi-process nature of brackishwater pond production.

Ammonia was the clearest negative technical-environmental signal among the measured process variables. Although it was not statistically significant at $p < 0.05$, ammonia showed a negative direction in both correlation and diagnostic regression. The high-achievement group had lower average ammonia than the medium- and low-achievement groups. This pattern is technically coherent because ammonia reflects waste pressure from uneaten feed, metabolic waste and organic matter decomposition. In pond aquaculture, excess feed and organic accumulation can increase ammonia concentration, oxygen demand and stress risk, thereby reducing the efficiency of biomass retention (Dauda et al., 2019; Boyd et al., 2020; Yu et al., 2023). For coastal Sidoarjo milkfish ponds, ammonia should be treated as an operational warning indicator. It signals whether the pond environment can absorb feed and organic loading without reducing fish growth conditions.

The ammonia result is also consistent with the cost-output finding. Farms with weak cost-output conversion may not only spend more per harvested ton, but may also lose part of the production benefit through inefficient feed use and waste accumulation.

When feed is not converted efficiently into biomass, the economic loss and environmental pressure can occur simultaneously. This is a critical point for agricultural industrial engineering because technical and economic inefficiency are not separate problems. Poor feed conversion increases feed cost per output and can also increase waste pressure in the pond. A productivity-improvement program that ignores this link may recommend more feed to low-productivity farms, even though the actual problem may be poor feed conversion and waste control.

DO showed the expected positive direction but weak statistical support. This result should not be overinterpreted as evidence that oxygen is unimportant. DO is a basic condition for fish metabolism, feed intake, growth and survival. Low oxygen reduces feeding activity and can increase stress or mortality risk in pond systems (Boyd et al., 2020). In the present data, DO ranged from 4.94 to 7.40 mg L^{-1}, with an average of 6.38 mg L^{-1}. This range suggests that most farms were not under severe oxygen depression at the time of measurement, although some farms approached a lower operating boundary. Under such conditions, DO may behave more as a threshold variable than as a linear predictor. Its impact becomes more visible when oxygen falls below a critical level, especially during night-time respiration, high organic loading or weak water exchange.

Salinity also showed no clear statistical association with productivity. This result is reasonable because milkfish is euryhaline and can tolerate broad salinity variation. However, tolerance does not mean that salinity has no production relevance. Salinity can influence osmotic regulation, feed response and growth performance, particularly when it interacts with ration level, temperature, water exchange and pond condition. Studies on milkfish have shown that salinity and feeding level can affect growth performance and nutritive physiology (Barman et al., 2013). In this study, salinity ranged from 16.10 to 28.00 ppt, which still represents brackishwater pond conditions suitable for milkfish culture. The absence of a strong association suggests that salinity was not the main limiting variable within the observed range. For coastal Sidoarjo, salinity should therefore be treated as a background environmental suitability factor, while ammonia and oxygen are more immediate pond-process control variables.

Labor involvement produced the weakest statistical signal. The near-zero correlation indicates that the number of persons involved in pond operations did not explain productivity variation. This finding is important because it prevents an oversimplified recommendation that adding workers will automatically increase productivity. Labor involvement in this study measured quantity, not management quality. It did not capture feeding precision, water-quality observation frequency, timing of corrective action, record keeping, technical knowledge or decision discipline. Smallholder aquaculture studies have shown that the adoption and effectiveness of improved practices depend on farmer knowledge, trust, coordination, extension support and repeated implementation, not only on labor availability (Bush et al., 2019; Joffre et al., 2020; Kumaran et al., 2021). Labor quantity is therefore too crude to represent management effectiveness.

This labor result has a practical implication for farm diagnosis. Future assessment should not ask only how many people are involved in pond operations. It should measure what those people do, how frequently they monitor pond condition, how accurately feed is distributed, how quickly they respond to oxygen decline or water-quality deterioration, and whether they maintain production records. In agricultural industrial engineering terms, labor should be translated into process-control capability. A farm with fewer workers but disciplined routines may perform better than a farm with more workers but weak operational control. The present result supports this interpretation because high- and low-achievement farms did not differ clearly in labor quantity.

The diagnostic regression confirmed that productivity variation could not be explained strongly by FCR, ammonia and operational cost alone. The model explained only 12.42% of productivity variation and was not statistically significant. This finding should be reported transparently because it protects the study from overclaiming. The purpose of the regression was diagnostic support, not prediction. With 30 farms and observational cross-sectional data, a strong causal model should not be forced. Pond productivity is shaped by time-dependent processes that were not fully captured in a one-cycle farm survey, including stocking density, survival rate, natural food availability, water exchange frequency, feeding schedule, pond preparation, disease events and seasonal fluctuation. The low R^2 therefore indicates that productivity gaps are multi-factorial and process-dependent.

The statistical pattern also supports the decision to use driver screening rather than a full causal ranking. Cost per output was statistically strong, but it is a derived efficiency indicator rather than an independent production input. Ammonia and FCR were technically relevant process variables, but their statistical support was moderate to weak. Operational cost had a weak positive direction, while DO had a weak positive environmental signal. Labor involvement did not show a meaningful association. A strict interpretation is therefore required: the study identifies measurable signals associated with productivity gaps, not experimentally proven causes. This distinction is essential for journal-level validity because observational farm data cannot establish causality without experimental control or repeated temporal measurement.

The main contribution of this study is its farm-level quantitative diagnosis of milkfish pond productivity gaps using a local empirical benchmark. Previous aquaculture productivity studies often emphasize broad intensification, sustainability or technology adoption. These perspectives are important, but they may not tell farmers which process variable should be checked first. The present study narrows the diagnostic lens to measurable farm variables: productivity, productivity gap, FCR, feed cost, operational cost, cost intensity, cost per output, DO, salinity, ammonia and labor involvement. This approach converts a general productivity problem into an engineering diagnosis of output loss, cost-output inefficiency, feed-use loss and pond-environment pressure.

For coastal Sidoarjo, the most defensible improvement priority is not simple input expansion. Increasing feed without improving feed conversion can raise feed cost and waste pressure. Increasing operational cost without better pond control can worsen cost per output. Adding labor without improving management routines may not change productivity. The more appropriate improvement sequence is to diagnose cost per harvested output first, then check FCR and feeding practice, examine ammonia and oxygen condition, and evaluate whether operational expenditure and labor routines are actually supporting biomass retention. This sequence is consistent with sustainable aquaculture principles, which emphasize efficient input use, environmental control and context-specific management rather than uncontrolled intensification (Boyd et al., 2020; Henriksson et al., 2021; Troell et al., 2023). The findings also have implications for extension and farmer-level decision support. Farms in the low-achievement group should not receive the same recommendation as farms in the high-achievement group. Low-productivity farms with high cost per output need cost-conversion diagnosis. Farms with high FCR need feeding evaluation. Farms with higher ammonia need waste-pressure control and water-management improvement. Farms with adequate labor but low productivity need management-quality assessment rather than additional labor. This differentiated diagnosis is more useful than general productivity advice because it links each farm’s constraint to a measurable process variable.

There are limitations that must be stated clearly. First, the sample consisted of 30 farms, which is adequate for descriptive productivity-gap diagnosis but limited for building a high-dimensional predictive model. Second, the data were cross-sectional, so the analysis captured farm conditions during the observed production cycle rather than continuous pond dynamics. Third, labor involvement was measured as number of persons and did not capture management quality. Fourth, water-quality variables were analyzed individually and may not represent full daily fluctuation, especially for DO. These limitations do not invalidate the study, but they define the boundary of interpretation. The results should be read as a quantitative screening of productivity-gap signals, not as an experimental causal explanation.

Overall, the study demonstrates that milkfish pond productivity gaps in coastal Sidoarjo are real, measurable and economically meaningful. The strongest empirical signal was cost per harvested output, showing that low-productivity farms produced fish at substantially higher cost per ton. Among the measured process variables, ammonia and FCR provided the most relevant technical signals because both were directionally consistent with pond-production logic. DO and salinity remained important environmental operating variables, but they did not dominate productivity variation within the observed range. Labor quantity alone was insufficient to explain productivity differences. The results support a targeted improvement strategy based on cost-output conversion, feed-use efficiency, waste-pressure control and stronger routine pond-management quality.

Conclusions. Milkfish pond productivity in coastal Sidoarjo showed a measurable farm-level gap when evaluated against the best-observed productivity benchmark of 4.72 ton ha^{-1} $cycle^{-1}$. The sampled farms produced an average productivity of 3.39 ton ha^{-1} $cycle^{-1}$, leaving an average productivity gap of 1.33 ton ha^{-1} $cycle^{-1}$ and an average achievement ratio of 71.92%. This confirms that the main productivity problem was not the absence of productive potential, but the unequal ability of farms to convert pond area, feed, cost, water condition and labor into harvestable biomass.

The strongest empirical signal was cost-output conversion inefficiency. Cost per harvested output was significantly and negatively associated with productivity, indicating that low-productivity farms produced milkfish at a much higher cost per ton. Among the measured process variables, ammonia and FCR provided the most relevant technical signals because both showed directions consistent with pond-production logic, although their statistical support was limited. Dissolved oxygen and salinity remained important environmental operating variables, but they did not dominate productivity variation within the observed range. Labor involvement, measured as number of persons, did not explain productivity differences, showing that labor quantity alone is not an adequate proxy for management quality.

Productivity improvement in smallholder milkfish ponds should therefore not be directed simply toward adding feed, increasing labor or expanding operating expenditure. The more defensible improvement priority is to reduce cost per harvested output, improve feed-use efficiency, control ammonia and waste pressure, maintain oxygen stability and strengthen routine pond-management quality. Future studies should use repeated production-cycle data, more detailed feeding records, survival rate, stocking density, water-exchange frequency and management-quality indicators to explain productivity gaps more precisely.

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