Aquaculture Economics & Management

ISSN: 1365-7305 (Print) 1551-8663 (Online) Journal homepage: http://www.tandfonline.com/loi/uaqm20

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To cite this article: Pham Thi Anh Ngoc, D. Gaitán-Cremaschi, Miranda P. M. Meuwissen, Tru Cong Le, Roel H. Bosma, Johan Verreth & Alfons Oude Lansink (2018) Technical inefficiency of Vietnamese pangasius farming: A data envelopment analysis, Aquaculture Economics & Management, 22:2, 229-243, DOI: 10.1080/13657305.2017.1399296

To link to this article: https://doi.org/10.1080/13657305.2017.1399296

AQUACULTURE ECONOMICS & MANAGEMENT
2018, VOL. 22, NO. 2, 229–243
https://doi.org/10.1080/13657305.2017.1399296

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Technical inefficiency of Vietnamese pangasius farming: A data envelopment analysis

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ABSTRACT

Vietnamese pangasius farming needs to produce efficiently to compete in world markets. This study investigates the input- and output-specific technical inefficiency of Vietnamese pangasius farmers. First, we used a Russell-type (input–output) directional distance function to estimate the input- and output-specific technical inefficiency. Second, we applied a bootstrap truncated regression to analyze the factors influencing these technical inefficiencies. Results show that the main challenges for enhancing the performance of Vietnamese pangasius production are inadequate use of capital assets (inefficiency of 42%) and improper methods to achieve higher fish yield (inefficiency of 30%). Input-specific technical inefficiency (pond area and feed) is negatively associated with the experience and education level of pangasius farmers. Location of the farm in a saltwater intrusion area is positively associated with the inefficiency of producing fish. Outcomes of this study are useful to identify successful strategies to minimize the use of inputs while simultaneously maximizing fish production.

KEYWORDS
Aquaculture; bootstrap truncated regression; data envelopment analysis; inefficiency; pangasius

Introduction

Vietnam is the world's largest producer of pangasius. Total production has increased in recent years, from 37,500 tons in 2001 to more than 1.1 million tons in 2016 (VASEP, 2016). In 2016, pangasius products accounted for 23% of all fish fillet consumption in USA, 18% in China, 15.2% in the European Union, 7.9% in the Association of Southeast Asian Nations (ASEAN), 4% in Brazil, 4.9% in Mexico, and 28% in other countries (VASEP, 2016). Parallel to the fast-growing pangasius production, world markets increasingly require seafood products to be produced in a sustainable way.

At present, most pangasius farmers use surface water in their fish ponds and discharge organic matter and nutrients from ponds, such as nitrogen

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and phosphorus directly into waterways linked to the Mekong River causing eutrophication (Anh, Kroeze, Bush, & Mol, 2010; Bosma, Hanh, Potting, & Dung, 2009). The use of polluted water contributes to diseases in fish and thus to increased use of antibiotics and other chemicals. The resulting water pollution results from many factors, such as excessive use of feed, overuse of antibiotics and other chemicals, and lack of wastewater treatment systems (Anh et al., 2010; James & Francisco, 2015). Thus, potential options to reduce water pollution from pangasius production are to reduce the use of feed and chemicals. According to Anh et al. (2010), redundant feed contributes most to the generation of waste sludge in pangasius production. Moreover, the market for cheap white fish products, such as pangasius, is competitive because many possible substitutes are available (CBI, 2015; Little et al., 2012; Troell et al., 2014). Vietnamese pangasius products have gained a large market share in international markets because of their relatively low price (Bush & Belton, 2011). Reducing the use of inputs and enhancing the competitiveness of the Vietnamese pangasius sector in the world market can lead to reducing the technical inefficiency of pangasius production.

Several studies have estimated technical efficiency in fish farming. For instance, Alam (2011) estimated the average constant returns to scale technical efficiency (CRS TE) of pangasius farmers in Bangladesh to be 0.78, implying that farmers can reduce the use of all inputs by 22% and produce the same output level. Kaliba and Engle (2007) reported the CRS TE of catfish farmers in USA to be 0.57, suggesting that on average, farmers can decrease the use of inputs by 43% and produce the same level of output. Determinants of technical efficiency or inefficiency in aquaculture can be divided into two groups: socio-economic and demographic characteristics of farmers (e.g., age, experience, education, and gender) and farm practices (e.g., pond size, culture length, farm location, and type of feeds) (see Iliyasu et al. (2015) for a review).

The existing studies on technical efficiency in fish production measured technical efficiency for all inputs simultaneously, assuming that all inputs can be reduced by the same magnitude. In practice, some specific inputs, or inputs and outputs, are more controllable than others. Thus, inefficient farmers have better opportunities to reduce certain inputs or increase the production of some outputs. The identification of input- and output-specific technical inefficiency would help farmers to improve the performance of their farms by providing information to better prioritize their efforts to reduce the use of inputs and expand outputs. In an input- and output-specific approach, technical inefficiency is measured for each input and output separately as the maximum feasible reduction in input use and expansion of outputs.

The objective of this study was to measure the input- and output-specific technical and scale inefficiency of Vietnamese pangasius farmers and to assess the impact of farmer demographics and farm characteristics on these technical inefficiency. Insight into the determinants of technical inefficiencies is expected to provide useful information for policymakers, which can be used to design policies and measures to help farmers improve their farm management.

The remainder of the paper is organized as follows. "Materials and methods" section presents the methods, data collection, and the selection of variables. This is followed by the presentation of results and discussion in the third section. Last section provides conclusion and policy implications.

Materials and methods

Data envelopment analysis and bootstrap truncated models

This paper used a two-stage approach to measure and explain the technical inefficiency of Vietnamese pangasius farmers. At the first stage, data envelopment analysis (DEA) was used to measure the input- and output-specific technical, while at the second stage, bootstrap truncated regression was used to estimate the impact of farmer and farm characteristics on these technical. DEA is a nonparametric technique that is frequently used to measure technical inefficiency in the presence of multiple inputs and outputs (Charnes, Cooper, & Rhodes, 1978; Dey et al., 2005; Farrell, 1957; Iliyasu et al., 2015; Singbo & Oude Lansink, 2010).

Russell-type (input–output) directional distance function

At the first stage, the Russell-type (input–output) directional distance function was used to compute the input- and output-specific technical inefficiency (Gaitán-Cremaschi, van Evert, Meuwissen, and Oude Lansink (2015), Mahlberg and Sahoo (2011), and Wang, Zhou, and Zhou (2013)). The Russell-type (input–output) directional distance function accounts for the inefficiency due to the slacks in inputs and outputs. Consider that there are k = 1, …, K pangasius farms using a vector x of N inputs and producing a vector y of M outputs. The input- and output-specific technical inefficiency of farm k relative to the production frontier, assuming variable returns to scale (VRS), is computed using the following linear programming problem:

$$\vec{D}(x, y; g|\text{VRS}) = \max\left[\frac{1}{2}\left(\frac{1}{N}\sum_{n=1}^{N}\mu_n + \frac{1}{M}\sum_{m=1}^{M}\beta_m\right)\right] \quad (1)$$

s.t.

$$\sum_{k=1}^{K}\alpha_k x_{kn} \le x_n - \mu_n g_{xn}, \quad n = 1, \ldots, N, \quad \text{(i)}$$

$$\sum_{k=1}^{K}\alpha_k y_{km} \ge y_m + \beta_m g_{ym}, \quad m = 1, \ldots, M, \quad \text{(ii)}$$

$$\sum_{k=1}^{K} \alpha_k = 1, \tag{iii}$$

$$\mu_n \geq 0(\forall n), \beta_m \geq 0(\forall m). \tag{iv}$$

The objective function in Eq. (1) represents the weighted average technical inefficiency of inputs and outputs. Each estimated μ_n or β_m provides the nth input-specific or mth output-specific technical inefficiency score of a fish farm, which is weighted, respectively, by the total number of N inputs and M outputs. In this case, the inputs and outputs each contribute half to the weighted technical inefficiency score. An estimated technical inefficiency of zero represents a fully efficient farmer, who is located on the production frontier. An estimated technical inefficiency greater than zero indicates the presence of technical inefficiency; the farmer is located below the production frontier. The directional vectors (g_x, g_y) used in this study are the observed quantities of inputs and outputs. Hence, the technical inefficiency is interpreted as the percentage by which input use can be reduced and output can be increased (Färe & Grosskopf, 2010).

The first two constraints reflect strong disposability of inputs (i) and outputs (ii), where finite inputs can only produce finite outputs (Färe, Grosskopf, & Pasurka, 2007). Constraint (iii) imposes VRS; the model in (1) can be transformed into a model assuming constant returns to scale (CRS) by replacing restriction $\sum_{k=1}^{K} \alpha_k \geq 0$. Constraint (iv) restricts the technical inefficiency scores to non-negative values.

Scale inefficiency, which reflects the ability of a farmer to employ each input and output at an optimal scale, can be computed as the difference between the technical inefficiency under CRS and VRS. All linear programming problems consistent with Eq. (1) were solved using General Algebraic Modeling Systems (GAMS).

Bootstrap truncated regression model

At the second stage, the bootstrap truncated regression procedure proposed by Simar and Wilson (2007) was used to assess the impact of farmer demographics and farm characteristics on input- and output-specific technical inefficiency. Simar and Wilson (2007) noted that traditionally used approaches such as censored regression and truncated regression are invalid due to serial correlation of nonparametrically derived inefficiency estimates. The bootstrap approach developed by Simar and Wilson (2007) corrects for this serial correlation. This technique has been used to study the determinants of specific technical inefficiency in other farming systems (Singbo and Oude Lansink 2010; Singbo, Oude Lansink, and Emvalomatis 2014). The model in this study was specified as:

$$\mathrm{TE}_k = \beta_0 + \beta_1 \mathrm{AGE} + \beta_2 \exp + \beta_3 \mathrm{EDU} + \beta_4 \mathrm{GEN} + \beta_5 \mathrm{LOT} + \varepsilon_k \tag{2}$$

where TE_k are the input- or output-specific technical inefficiency scores of farm k obtained from the DEA model; AGE is the age of the farmer measured in years; EXP is the pangasius production experience of the farmer measured as the inverse of the number of years; EDU is the level of education of the farmer measured in years; GEN is the gender of the farmer dummy (1 if female, 0 if male); and LOT is the farm location dummy (1 if saltwater intrusion region, 0 if freshwater region). The random error terms, ε_k, are assumed to be normally distributed and represent unobservable variables, measurement errors, and specification errors. For the input- and output-specific scale inefficiency, bootstrap ordinary least squares (OLS) was used because the input- and output-specific scale inefficiency are both positive and negative. Eq. (2) was estimated using STATA version 8.

The variable EXP was measured as the inverse of the number of years of experience with fish farming (one divided by the number of years of experience). The inverse was used because a scatter diagram showed a convex nonlinear relationship between the number of years of experience in fish farming and technical inefficiency. This means that the marginal impact on technical inefficiency declines with the number of years. The inverse of the number of years can capture this relationship. The marginal effect of an additional year of experience in fish farming was computed at the sample mean of the number of years of experience and is given by the partial derivative of Eq. (2) with respect to the number of years as:

$$\frac{\partial Y_k}{\partial \#\,\text{years experience}} = \gamma * \left(- \frac{1}{\#\text{years experience}^2} \right) \tag{3}$$

Data collection and selection of variables

Data collection

Data for this study were gathered in January 2013 through a questionnaire survey of 82 farmers (Ngoc, Meuwissen, Le, Verreth, et al. 2016). The farmers participating in the survey mainly represented small and medium pangasius farms (less than 3 ha). A workshop was organized in December 2013 to increase the number of observations for large farms (equal to or greater than 3 ha). During the workshop, 14 farmers with large-scale farms were invited to complete the same questionnaire as in the survey. Respondents for the survey and workshop were randomly selected from the lists of pangasius farmers maintained by the Aquaculture Department; aquaculture officers from this department assisted with the selection process.

For the survey, the selected pangasius farmers were from An Giang, Can Tho, and Soc Trang provinces. Participants in the workshop also came from the Dong Thap, Vinh Long, and Tra Vinh provinces. Respondents covered the two main production regions in Vietnam, i.e., pangasius farmers from Soc Trang and Tra Vinh mainly operate newly developed farms in the saltwater intrusion region. Pangasius farmers in the other provinces come from the traditional pangasius production areas in the freshwater region.

Of the 96 questionnaires, 8 were excluded from the analysis due to incomplete information. Another eight questionnaires were excluded due to the presence of outliers. Outliers were defined as values beyond two standard deviations from the median. According to Fried, Lovell, and Schmidt (2008), outliers could influence the position of the production frontier far from the inefficient farmers.

Variables for the inefficiency computation

Inputs for pangasius production consisted of three variable inputs representing the operational costs, i.e., *feed, labor,* and *others* (all expenses of pond preparation, fingerling, energy, sludge discharge, and veterinary services), and two fixed inputs, i.e., *pond area* and *capital*. Table 1 presents the descriptive statistics of the input and output variables. The output is *fish yield* and is expressed in tons. Operational costs and *capital* are expressed as annual costs in USD (applied exchange rate: 1 USD equals 20,000 VND). Pond area is expressed in ha.

Feed is the main cost of pangasius farms, accounting for 84–86% of operational costs (Ngoc, Meuwissen, Le, Verreth, et al. 2016). *Labor* consists of family labor and hired labor. Cost of hired labor was measured as the salary paid to hired labor. To quantify the cost of family labor, the monthly salary for hired labor in the aquaculture sector was used and this value was multiplied by the number of family members working full-time on the farm. The category *Other*s includes the expenses associated with pond preparation, fingerling, energy, sludge discharge, and veterinary services. Variable input costs differed among farms, with an average of 139,500 USD for capital, 779,700 USD for feed, 16,300 USD for labor, and 116,100 USD for other costs.

Table 1. Descriptive statistics of inputs and outputs (for the most recent production cycle in 2012–2013).

Item	Mean	Standard deviation	Minimum	Maximum
Inputs				
Pond area (ha)	1.6	1.5	0.2	8.5
Capital (1,000 USD)	139.5	146.5	5.7	744.1
Feed (1,000 USD)	779.7	725.0	30.9	3,531.1
Labor (1,000 USD)	16.3	14.9	1.6	72.3
Others[a](1,000 USD)	116.1	114.5	4.4	562.9
Output				
Fish yield (tons)	879.2	788.8	44	3,666

[a]Others include all expenses of pond preparation, fingerling, energy, sludge discharge, and veterinary services.

Pond area represents the total water surface area used for pangasius production. *Pond area* ranged from 0.2 to 8.5 ha, with an average of 1.6 ha. *Capital* cost includes the annual depreciation of capital invested in pond construction, sluice gates, waste water treatment (if any), storage houses, and equipment. The *capital* cost differed across farms, ranging between 5,700 USD and 744,100 USD, with an average of 139,500 USD. Similarly, the output variable *fish yield* also varied greatly, from 44 to 3,666 tons with an average of 879 tons.

Variables for the bootstrap truncated regression model

The following variables were used in the bootstrap truncated regression model: *age* of farmers (measured in years), *experience* (measured as the inverse of the number of years), the level of *education* (number of years), *gender* (1 if female, 0 if male), and farm *location* (1 if saltwater intrusion region, 0 if freshwater region).

These variables were chosen based on the literature on technical inefficiency in the aquaculture sector. The literature shows negative associations between age and technical inefficiency, while experience, gender, and education all have positive relationships with technical inefficiency. For instance, Iliyasu et al. (2015) concluded, in an extensive review of technical inefficiency studies in aquaculture, that younger farmers may be less technically inefficient than their counterparts, presumably because of their higher willingness to adopt technological innovations. Regarding *experience,* more experienced farmers may make better managerial decisions and may therefore be less inefficient (Engle, 2010; Iliyasu et al., 2015). Likewise, more educated farmers are generally less technically inefficient, possibly due to their open minds toward new technological information as well as better capability to access and process such information (Dey et al., 2005; Iliyasu et al., 2015). In addition, female fish farmers were found to be more technically inefficient than their male counterparts, likely attributed to the domestic responsibility of women

Table 2. Descriptive statistics of farmer demographics and farm characteristics ($n = 80$).

Item	Mean	Frequency (%)	Standard deviation	Minimum	Maximum
Farmer demographics					
Age (years)	43		7.03	23	60
Experience (years)	8		2.23	5	20
Education (years)	11		2.12	6	16
Gender (1 if female, 0 if male)					
Female		8			
Male		92			
Farm characteristics					
Location[a] (1 if saltwater intrusion region, 0 if freshwater region)					
Saltwater intrusion region		14			
Freshwater region		86			

[a]Saltwater intrusion region consists of Soc Trang and Tra Vinh provinces; freshwater region consists of An Giang, Dong Thap, Can Tho, and Vinh Long provinces.

in most developing countries (Onumah, Brümmer, & Hörstgen-Schwark, 2010). Farm characteristics such as *location* are also expected to have a negative effect on technical inefficiency. For instance, Anh et al. (2015) found that Vietnamese farms located in the saltwater intrusion region are less technically inefficient than those in the freshwater region.

Table 2 provides the descriptive statistics of the variables used in the bootstrap truncated regression. Table 2 shows that the respondents had a relatively low average age, i.e., 43 years old, with about 8 years of experience (as reflected by the average inverse ratio of 0.12) and up to 11 years of education. Within the sample, 92% of respondents was male and 86% of respondents originated from the main pangasius freshwater production region.

Results and discussion

Technical and scale inefficiency results

Table 3 shows the technical and scale inefficiency scores of Vietnamese pangasius farmers. The weighted average score of technical inefficiency relative to the frontier was 0.25 assuming VRS and 0.31 assuming CRS. The difference between the technical inefficiency under the CRS and VRS assumptions indicates the presence of scale inefficiency in pangasius production. The scale inefficiency was quite low, with a weighted average of 0.06, indicating that the majority of pangasius ponds are operating close to their optimal size.

The results for the weighted average technical inefficiency scores suggest a substantial scope for improving performance by reducing the use of inputs and increasing output. The weighted average scores, however, conceal the variation in inefficiency across inputs and output. For instance, Vietnamese pangasius farmers could reduce the use of *capital* by 42%, *labor* by 23%, *pond area* by 16%, *others* by 10%, and the use of *feed* by 3%, while simultaneously increasing the *fish yield* by 30% relative to the VRS frontier. These results reveal that the technical inefficiency of pangasius farmers is mainly driven by the high inefficiency in the use of capital and the relatively low fish yield.

Table 3. Input- and output-specific technical and scale inefficiency.

	Technical inefficiency under VRS		Technical inefficiency under CRS		Scale inefficiency	
Item	Mean	Frequency (%)	Mean	Frequency (%)	Mean	Frequency (%)
Weighted average	0.25	84	0.31	90	0.06	88
Input-specific						
Pond area	0.16	60	0.21	75	0.05	79
Capital	0.42	74	0.49	81	0.07	81
Feed	0.03	21	0.02	15	−0.01	20
Labor	0.23	69	0.29	73	0.06	76
Others	0.10	49	0.13	64	0.03	68
Output-specific						
Fish yield	0.30	80	0.39	88	0.09	86

The input- and output-specific scale inefficiency scores ranged from −0.01 to 0.09. It should be noted though that no farm in the sample presented a negative weighted average scale inefficiency over both inputs and outputs. Hence, the method itself can produce negative values for input-specific and output-specific scale inefficiency. The technical inefficiency scores of *capital, pond area,* and *labor* are relatively low, which is explained by their quasi-fixed nature, i.e., their levels are not easily adjusted from one year to another. In practice, it is costly to upscale or downscale the investments in machinery, equipment, or pond area. Similarly, labor is not easily adjusted from year to year, due to the large share of family labor in total labor costs. The low *feed* technical inefficiency might be explained by careful fish feeding as feed costs are the main cost of pangasius production.

Results in Table 3 also show that farmers are more technically inefficient in producing fish yield than in utilizing inputs. Within the sample, 21–74% of the farms were inefficient in the use of inputs, whereas 80% of the farms were inefficient in the production of fish yield.

Determinants of input- and output-specific technical inefficiency

Table 4 presents the estimated parameters of the bootstrap truncated regression model. The discussion in this section is mainly restricted to the variables that had a statistically significant effect on input- and output-specific technical inefficiency. Most of the signs of the estimated parameters for the determinants of technical and scale inefficiency were in line with a priori expectations.

Regarding the technical inefficiency relative to the VRS frontier, the variable *experience* (years) had a significantly negative effect on *pond area* and *feed* technical inefficiency, indicating that an additional year of experience is associated with a better management of the pond by 1.6% and the use of feed by 4%. Experienced fish farmers may make better managerial decisions on farms and be more efficient in utilizing the pond and feed to their full potential. This is in line with Kaliba and Engle (2007), who found that experienced farmers may make better decisions regarding the feed brand, feed ingredients, and feed practices. In contrast, *experience* was found to have a positive and significant relation with the technical inefficiency of *fish yield*. This might be because experienced farmers are more conservative and find it difficult to adjust and adopt new technologies, as suggested by Onumah et al. (2010).

We also found that *education* had a negative effect on the technical inefficiency of *pond area, feed, others,* and *fish yield,* implying that, *ceteris paribus,* an additional year of education decreases inefficiency in the use of these inputs and increases fish yield by 3–4%. This result is consistent with our prior expectation that more educated farmers are generally more likely to adopt technological innovations due to their open minds toward new

Table 4. Results of the regression of the input- and output-specific technical inefficiency scores on farmer demographics and farm characteristics.

	Technical inefficiency under VRS						Technical inefficiency under CRS					
Variable	Pond area	Capital	Feed	Labor	Others	Fish yields	Pond area	Capital	Feed	Labor	Others	Fish yields
Constant	−0.229	0.529	0.418	0.232	0.343	0.197	0.299	0.430	**1.250**	0.505	**0.443**	0.672
Age	0.010	0.005	−0.008	−0.003	−0.001	0.002	−0.002	0.001	**−0.013**	−0.005	−0.004	0.000
1/experience[a]	**−0.016**	0.013	**−0.040**	0.005	0.009	**0.003**	0.009	0.011	−0.003	0.006	0.013	−0.120
Education	**−0.027**	−0.009	**−0.031**	0.020	**−0.043**	**−0.025**	0.015	0.022	**−0.046**	0.024	−0.008	**−0.045**
Gender	−0.020	0.084	−0.041	0.083	0.031	−0.021	0.035	0.007	0.014	−0.081	0.040	0.118
Location	0.040	**−0.333**	−0.035	0.011	0.161	**0.285**	0.125	−0.163	−0.003	0.020	**−0.088**	**0.311**

[a]For 1/experience, the coefficient represents the marginal effect of an additional year of experience calculated at the sample mean. The statistically significant variables at 5% level are in bold.

technologies and because they have a better capability to access and process information (Dey et al. 2005; Ngoc, Meuwissen, Le, Bosma, et al. 2016). Therefore, more educated farmers are better in managing the pond, feeding fish, and using other variable inputs to increase fish yield.

The *location* of farms in the saltwater intrusion region was negatively associated with the technical inefficiency of *capital* and *fish yield*. The negative relationship between *location* and *capital* technical inefficiency suggests that farmers farming in the saltwater intrusion region are, *ceteris paribus,* 33% better in managing their capital assets than those in the freshwater region. Farmers with farms located in the saltwater intrusion region might be more careful in investing in and operating their capital assets because they have to cope with salinity intrusion, as suggested by Anh et al. (2015). However, these farmers also adapt to the salinity intrusion by limiting their stocking frequency, i.e., only once a year, and thus appear more inefficient (29%) in producing *fish yield* than farmers in the freshwater region, in line with our prior expectation.

The results of regression of technical inefficiency relative to the CRS frontier were not always consistent with the results of the regression relative to the VRS frontier, given the scale component in the former. For instance, *age* of farmers was negatively and significantly associated with the technical inefficiency of *fish yield,* implying that each additional year decreases, *ceteris paribus,* the technical inefficiency of fish feeding by 1%. This result contradicts our prior expectation and suggests that farmers gain experience in using resources effectively over time, as suggested by Amos (2007).

Furthermore, there was a negative and significant relationship between *location* of farms and the technical inefficiency of *other* inputs, suggesting that farmers with farms located in the saltwater intrusion region are, *ceteris paribus,* 9% less technically inefficient in the use of other variable inputs than those in the freshwater region. In the long run, the unpredictable level of salinity intrusion can be controlled by investing in technological innovations and learning from others. This might give farmers farming in the saltwater intrusion region better opportunities to also monitor the use of other variable inputs.

Regarding scale inefficiency as presented in Table 5, none of the variables were found to have a significant relation with input-specific scale inefficiency, whereas *experience* and *location* were found to influence the scale inefficiency of *fish yield*. The negative coefficient of *experience* indicates that experienced farmers are better in adjusting the scale of their operation as measured by the size of output, resulting in an improvement of fish yields by 2%. Better scale adjustment was also found for farmers farming in the freshwater region, with a 13% improvement in fish yield compared to farmers in the saltwater intrusion region. This confirms the findings of Anh et al. (2015) that farmers limit the stocking frequency and thus reduce the annual yield of the farm to cope with salinity problems.

Table 5. Results of the regression of the input- and output-specific scale inefficiency scores on farmer demographics and farm characteristics.

	Scale inefficiency					
Variable	Pond area	Capital	Feed	Labor	Others	Fish yields
Constant	0.205	0.323	0.062	0.299	0.301	−0.023
Age	−0.002	−0.003	−0.000	−0.002	−0.002	0.002
1/experience[a]	0.006	0.006	0.001	0.005	0.008	**−0.021**
Education	0.006	0.007	−0.000	0.007	−0.000	−0.007
Gender	−0.017	−0.059	−0.003	−0.021	0.003	0.003
Location	0.036	0.060	−0.006	0.006	−0.031	**0.125**

[a]For 1/experience, the coefficient represents the marginal effect of an additional year of experience calculated at the sample mean. The statistically significant variables at 5% level are in bold.

The nonsignificant effect of *gender* on both technical and scale inefficiency implies that the technical and scale inefficiency of farms operated by men are, *ceteris paribus,* the same as the technical and scale inefficiency of farms operated by women. This result contrasts with the findings of Onumah et al. (2010) for Ghana and Ekunwe and Emokaro (2009) for Nigeria; both these studies found that male fish farmers operate less inefficiently than their female counterparts.

Conclusions and policy implications

The main objective of this paper was to measure the input- and output-specific technical and scale inefficiency of Vietnamese pangasius production to identify potential areas for improvement and to assess the effect of farmer and farm characteristics on these technical and scale inefficiencies. The results provide information that is useful in designing measures to help farmers improve their farm management.

We found that the main challenges for enhancing the performance of Vietnamese pangasius production are inadequate management skills in using capital assets, as indicated by a capital technical inefficiency of 42%, and improper methods for producing fish, as indicated by fish yield technical inefficiency of 30%. Furthermore, farmers with a higher education level and more years of experience are generally better in managing the pond area, using fish feed, and producing fish yield. Farming in areas with saltwater intrusion is associated with a lower technical inefficiency in the use of capital assets and other variable inputs but also with a higher technical inefficiency in the production of fish yield.

Results provide useful information for farmers and policymakers who aim to improve the performance of Vietnamese pangasius farms. The recommendations for pangasius farmers are targeted toward those inputs and outputs with relatively high inefficiency. For instance, pangasius farmers can improve their capital management skills by better estimating the amount of required capital and the timing of capital asset replacement, and by monitoring the use of capital assets. Furthermore, the introduction of technological innovations that enable higher stocking densities and improve the quality of pond water, such as recirculating aquaculture systems (RAS) (see also the discussion in Ngoc, Meuwissen, Le, Bosma, et al. 2016; Ngoc, Meuwissen, Le, Verreth, et al. 2016), could potentially increase pangasius yields. Policymakers can assist farmers to improve their farm management by targeting farmers with lower education levels, fewer years of experience, and farms located in saltwater intrusion areas.

Funding

This research was financed under the SUPA project (improving waste management for pangasius culture in the Mekong Delta of Vietnam), funded by the bilateral Vietnamese-Netherlands Public Private Partnership between the Vietnamese Ministry of Agriculture and Rural Development (MARD), the Ministry of Economic Affairs from the Netherlands, and several European and Vietnamese private companies. The authors wish to acknowledge NUFFIC (Netherlands Organization for International Cooperation in Higher Education) for awarding a partial fellowship, which has made it possible to perform this study. We are grateful to the aquaculture officers in An Giang, Can Tho, Dong Thap, Tra Vinh, Vinh Long, and Soc Trang provinces for inviting farmers to the survey and workshop. Farmers and experts who participated in the survey and workshop are gratefully acknowledged.

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