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Evaluating contextual factors affecting the technical efficiency of freshwater pond culture systems in Peninsular Malaysia: A two-stage DEA approach

Abdullahi Iliyasu*, Zainal Abidin Mohamed

Department of Agribusiness and Information Systems, Faculty of Agriculture, Universiti Putra Malaysia, 43400 Serdang UPM, Malaysia

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ABSTRACT

The demand for animal protein, especially fish, is growing fast, perhaps due to the rapid expansion of populations, increases in income and changes in eating habits and life styles. Capture fisheries, which supply over 70% of the fish for human consumption in Malaysia, are over-exploited or depleted. Their yields have become stagnant over the last few decades and in some cases have even declined. Nevertheless, aquaculture has the potential to meet these challenges if practised well. This study therefore aims to estimate the technical efficiency of pond culture systems using data envelopment analysis (DEA). In addition, it investigates the determinants of technical efficiency by employing an ordinary least squares (OLS) regression model. The estimated technical efficiency of pond culture was found to be 0.86, which means that the fish farmers in our sample could reach full technical efficiency through reducing their input usage by 14% with the current level of technology to produce the same output levels. The results of the OLS regression indicate that farmers' age, experience, extension training and water management have positive and statistically significant impacts on technical efficiency. Information on water management practices could be passed on by extension agents to inefficient farms to assist them in catching up with the farms demonstrating best practice.

1. Introduction

Pond culture systems have dominated freshwater aquaculture production in Malaysia for the past few decades but still show low productivity, perhaps due to their small scale nature and more often than not their management as extensive or semi-intensive systems. Nevertheless, such systems are still the major contributor to freshwater aquaculture in terms of fish production. Production soared from 2003 to 2009, but declined thereafter (Fig. 1). Despite the decline in production, a recent report from the Department of Fisheries, Malaysia, showed that the estimated production from pond fish farming in 2012 was approximately 78,000 t. This constitutes about 48% of total freshwater aquaculture production in that year. On the other hand, cage and tank culture systems contributed only approximately 12,000 t and 4800 t, respectively (Annual Fisheries Statistics, 2003–2012).

The production of pond culture systems faces many challenges, which continue to hinder the growth of this subsector. High competition for land with other industries leads to greater scarcity and hence higher land prices or rental rates, thereby making it difficult for small-scale fish farmers to expand their farms. Moreover, feed prices have been escalating over time, thus forcing fish farmers to reduce the use of pellet feed and opt for household food waste and animal offal to feed the fish. This will result in lower fish meat quality, subsequently reducing demand for the cultured fish, pulling down the price for the producer and resulting in a low profit margin. To increase farmer's income it is imperative for them to improve the technical efficiency (optimal use of inputs) of their production. This will lead to lower production costs per unit and higher returns to fish farmers. Therefore, measuring technical efficiency and investigating the determinants of inefficiency are of paramount importance for developing sustainable pond fish farming. Based on this background, this study aims to estimate the technical efficiency and determine the contextual factors responsible for inefficiency in pond fish farming using data envelopment analysis (DEA) and ordinary least squares (OLS) regression.

* Corresponding author.
E-mail address: manawaci1@gmail.com (A. Iliyasu).

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Table 1
Description of variables in the DEA model.

Variables	Description	Unit
Output	Total quantity of fish produced	Kg[a]
Stocking density	Fingerlings stocked in the farm	Number
Feed	Total quantity of feed utilized	Kg
Labour	Labour used	Man-day
Other costs	Costs incurred of other inputs	Ringgit[b]

[a] Kilogram.
[b] 4.2 Ringgit (RM) = USD 1.

Many studies have used DEA, developed by Charnes et al. (1978), to estimate technical efficiency in aquaculture in the production frontier literature (Gunaratne and Leung, 1997; Sharma et al., 1999; Cinemre et al., 2006; Kaliba and Engle, 2006; Ferdous Alam and Murshed-e-Jahan, 2008; Chang et al., 2010; Nielsen, 2011; Alam, 2011; Arita and Leung, 2014). Despite this, the application of DEA in estimating the technical efficiency of freshwater pond culture systems in Peninsular Malaysia has not been addressed in the existing literature. In contrast to most previous studies that have focused primarily on examining the impacts of socioeconomic factors on technical efficiency, this study also investigates the influence of farmers' water management skills on performance, water being the most crucial input in any fish farm. This information is of paramount importance in evaluating managerial skills and may provide guidance on the extent to which farmers can catch up with farms demonstrating best practice (i.e. operating on the production frontier) through better water management techniques. In addition, we estimated slacks variables not considered by the majority of previous studies measuring the technical efficiency of aquaculture.

2. Methodology

2.1. Sampling procedure

Two states (Perak and Selangor) out of eleven states in Peninsular Malaysia were purposively selected for this study for two reasons. First, they have the highest concentration of active pond fish farmers. Second, they produce a large share of fish in terms of freshwater pond aquaculture (41%). These states are further subdivided into clusters/districts using a cluster sampling method. Three and two districts were selected from Perak and Selangor, respectively. The selection of districts was based on the large number of active fish farmers pertaining to pond culture systems present in these localities and their volume of production. Finally, a total of 100 sample respondents (pond fish farmers only) from the population of 539 farmers were then selected using simple random sampling.

Data were collected from these sample respondents using well-structured questionnaires and oral interviews. Information was collected on the inputs used in production processes and the outputs produced. In addition, relevant information on socioeconomic features and water management practices were also collected. The data were analysed using MaxDEA and SPSS version 20 software.

2.2. Data description

Table 1 shows the input and output variables used in this study. The output represents the total quantity of fish produced and is measured in kilogrammes (kg). The optimal measure of output for polyculture would have been the geometric mean or quantity index based on revenue share or the prices of different species of fish. However, data on the prices of different species were not available and thus we used total fish production as a proxy for output (Iinuma et al., 1999). Similarly, Vassdal and Holst (2011) and Asche et al. (2013) used total weight of fish produced as the measured of output in their study of productivity growth of Norwegian Salmon aquaculture.

Stocking density, feed, labour and other costs were used as the inputs. The number of fingerling stock in the fish farms was used to measure stocking density. Feed is one of the most expensive inputs in any fish farm and is estimated in kg. Farmers were questioned on the quantity of feed used throughout the production cycle in terms of the number of bags and this was then also converted into kg. The labour variable was estimated by the number of hours spent (family and hired workers) working on the farms using man-days as the unit. The rule of thumb is that one day (eight working hours) is equivalent to 1 man-day, 0.75 man-day and 0.50 man-day for a single adult male, adult female and child of less than 18 years, respectively (Battese et al., 1996; Coelli and Battese, 1996; Onumah and Acquah, 2010). Children are prohibited from working in Malaysia and therefore child man-days were omitted from the study. The price of some relevant inputs, such as farm rent, the maintenance and repair of machinery, equipment and ponds, electricity and medicines, are termed "other costs" and measured in Malaysian Ringgit (USD 1 = RM 4.2).

Our measures are in line with other studies in the literature. Asche and Roll (2013) in their study of the determinants of inefficiency in Norwegian salmon aquaculture, used total fish production as the output measured in kg, with feed, labour and capital as the inputs. In addition, Iinuma et al. (1999) estimated the technical efficiency of carp pond culture in Peninsular Malaysia using total production (output) and feed, stocking density and labour, as well as other costs (inputs).

Table 2 shows the contextual factors used in the OLS regression models to investigate the determinants of inefficiency in pond culture. Age and experience are incorporated in the model to investigate whether they have any influence on technical inefficiency. Older farmers are expected to have gained more experience over time and hence demonstrate more technical efficiency. On the other hand, age may be related to conservatism, older farmers being less willing to adopt new and improved technology. However, the newer farms are likely to adopt new and improved technology, thereby being more technically efficient. The household size is also expected to have a positive influence on technical efficiency. Farmers with large families may have helping hands to perform some of the farms' operations, especially in developing countries. As a result, they are expected to use resources efficiently. The variable education is expected to have a positive impact on technical efficiency. That is to say, the higher the educational level the lower the technical inefficiency.

Farm status is a dummy variable that indicates whether the farmer is the owner of the farm or rents it. Ownership is expected to have a positive impact on technical efficiency. Job status is also a dummy variable measured in terms of whether farmers are full time or part time. Full-time farmers are expected to be more efficient in using their inputs due to the ample time they spend managing their farms. Farms close to input suppliers, especially feed, have better opportunities to obtain supplies on time and at cheaper rates due to low transportation cost and are thus expected to be more efficient. The coefficient signs of both extension services and workshops attended are also expected to be positive. Farmers who have extension services or have attended workshops are more likely to adopt new technology and hence be more technically efficient.

Fish farmers were asked to respond to eight items, measured on a five-point Likert scale, pertaining to their water quality maintenance and monitoring as a proxy for measuring water management. Water management is expected to have a positive influence on technical efficiency as fish rely on high-quality water to survive. Other variables, such as adaptation of technology, farm size, climatic changes and credit availability, may well be of importance in determining technical inefficiency, but the survey information collected lacked data on these factors.

2.3. Specification of models

The tools used in this study were data envelopment analysis (DEA) and ordinary least squares (OLS) regression. The DEA technique was employed to estimate the technical efficiency scores of the sample fish farmers. In addition, the determinants of technical inefficiency were also investigated using the OLS regression model.

2.3.1. Data envelopment analysis (DEA) model

Since their inception in 1978, DEA models have widely been employed in real world applications in the top five industries: banking, hospitals, agriculture, transportation and education (Liu et al., 2013a,b; Emrouznejad et al., 2008). DEA models are of two common types, radial and non-radial. The major setback of the radial approach, otherwise called the CRR (Charnes–Cooper–Rhodes) model, is that it does not take slacks into consideration when measuring efficiency. This led Charnes et al. (1985) to develop the additive DEA model, which deals with slacks variables directly. Although this approach uses slacks to discriminate between the efficiency and inefficiency of a decision-making unit (DMU), it fails to provide an efficiency estimate that can help to determine the DMU's performance. This motivated Tone (2001) to propose a non-radial model, popularly known as the slacks-based measure of technical efficiency (SBMTE), for DEA that deals directly with slacks (excess inputs and output shortages) in efficiency estimation. The merit of SBMTE lies in its ability to estimate efficiency scores that are unit invariant, monotone (Torgersen et al., 1996) and reference-set dependent (Banker et al., 1984), which implies no influence from outliers (extreme values). Thus, SBMTE was adopted for this study, expressed as follows:

$$\begin{aligned}
&\min\rho = \frac{1-\left(1/m\right)\sum_{i=1}^{m} s_i^-/x_{ik}}{1+\left(1/s\right)\sum_{r=1}^{s} s_r^+/y_{rk}} \\
&st: x_{rk} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^-, i = 1, \ldots\ldots\ldots, m \\
&y_{rk} = \sum_{j=1}^{n} y_{rj}\lambda_j + s_r^+, r = 1, \ldots\ldots\ldots\ldots, s \\
&\lambda_j \geq 0, j = 1, \ldots\ldots\ldots\ldots\ldots, n \\
&s_i^- \geq 0, i = 1, \ldots\ldots\ldots\ldots\ldots, m \\
&s_r^+ \geq 0, r = 1, \ldots\ldots\ldots\ldots\ldots, s
\end{aligned} \tag{1}$$

where ρ denotes the SBMTE of n DMUs associated with m input set x_{ij} (m = stocking density, feed, labour, costs of other relevant inputs) and s output set y_{rj} (s = different types of fish products); λ_j is a nonnegative vector that allows the construction of a production possibility set for j DMU; n is the number of DMUs ($j = 1\ldots n$); m is the number of inputs ($I = 1\ldots m$); s is the number of outputs ($r = 1\ldots s$);. s_i^- is defined as input excess and s_r^+ denotes output shortfalls, respectively. DMU is SBM-efficient if $\rho = 1$, implying no input excess ($s_i^{-*} = 0$) or output shortfall ($s_r^{+*} = 0$) for all i and r.

2.3.2. Ordinary least squares (OLS) regression model

Although most previous studies used the Tobit regression model (TRM) in investigating the determinants of technical inefficiency in aquaculture (Alam, 2011; Cinemre et al., 2006; Kaliba and Engle, 2006), McDonald (2009) argued that the use of TRM is inappropriate in this situation. Technical efficiency scores are fraction data and not generated by a censoring process. He further suggested the use of OLS regression modelling as the most appropriate technique. This argument was supported by Banker and Natarajan (2008). They reported that the use of OLS regression analysis in the second stage of DEA gives a better result than using TRM. In addition, it does significantly better than both single- and double-stage stochastic frontier analysis (SFA). Therefore, the two-stage DEA method was employed to investigate the determinants of technical efficiency among the sample pond fish farmers. Following Banker and Natarajan (2008), the model can be expressed as follows:

$$\text{SBMTE} = \beta_0 = \sum_{i=1}^{n} \beta_i z_i + \delta \tag{2}$$

where SBMTE denotes the slack-based measure of technical efficiency and β_s denote unknown parameters to be estimated. Z_s are the contextual or socioeconomic variables defined in Table 2, while δ is the error term.

3. Results and discussion

3.1. Technical efficiency scores

The minimum and maximum technical efficiency scores were estimated as 0.68 and 1.00, respectively. On average, the technical efficiency score of the sample fish farmers in the study area was estimated at 0.86, relatively similar to the findings of Kareem et al. (2008) and Alam et al. (2012), but higher compared to Awoyemi et al.'s (2003) value of 0.24 and Amos's (2007) of 0.67. The results indicate that the pond fish farmers could reduce their level of input use by approximately 14% to achieve full technical efficiency given the current level of technology. Fig. 2 illustrates the frequency distributions of technical efficiency in pond culture and shows that the greater part of the fish farmers falls within technical efficiency scores in the ranges 80–84.99 (22.73%) and 95–100 (21.21%). However, less than 5% of the fish farmers have technical efficiency scores lower than 0.70. This implies that most of the pond fish farmers in the sample are operating close to the production frontier. However, for those inefficient farmers to catch up with the farms demonstrating best practice, information on input slacks or slacks variables is

Table 2
Description of inefficiency determinants.

Variables	Description	Unit
Age (Z_1)	Represents age of fish farmer/manager	Year
Experience (Z_2)	Years spent in fish farming	Year
Educational level (Z_3)	Level of education of fish farmer/manager	Level
Farm status (Z_4)	Dummy (1 = owner, and 0 = otherwise)	Dummy
Job status (Z_5)	Dummy (1 = full-time, and 0 = otherwise)	Dummy
Extension services (Z_6)	Dummy (1 = yes; 0 = otherwise)	Dummy
Workshop attended (Z_7)	Dummy (1 = yes; 0 = otherwise)	Dummy
Distance feed supplier (Z_8)	Distance from the nearest feed supplier	Kilometers
Household size (Z_9)	Number of the fish farmer family	Number
Water management (Z_{10})	Water management practiced used	Likert-scale

of paramount importance. Thus, the following section deals with the analysis of slacks variables.

3.2. Slacks analysis

Fish farmers perhaps face a dilemma when it comes to the selection of the most appropriate input levels for production. They sometimes find it difficult to decide on the right quantity of inputs to be used on their farms. However, as all fish farms are assumed to operate in a similar environment, using the technical efficiency of the fish farms with the best practices as a benchmark for comparison is a realistic approach. This simply implies that it is appropriate to set input targets for inefficient DMUs to enable them to achieve full technical efficiency in comparison with the most technically efficient DMUs. Input targets refer to the total amount of input adjustment required for inefficient DMU to operate on the production frontier. Therefore, an input target is always less than the actual input for an inefficient DMU. The differences between actual and target inputs are referred to as input slacks (Ramanathan, 2003).

Stocking density is one of the main determinants of successful fish farming. More often than not, fish farmers assume that an increase in their stocking rate will lead to higher outputs and thus more income. However, overstocking will reduce the available space and create stress for the fish, which will eventually lead to a high mortality rate. Hence, to avoid this scenario, information on the appropriate stocking rate is of paramount importance. The slack in the stocking density of pond culture systems was found to be 13.36%. Based on this result, the stocking rate needs to be reduced by 13.36% to reach full efficiency. Any increase in the stock-

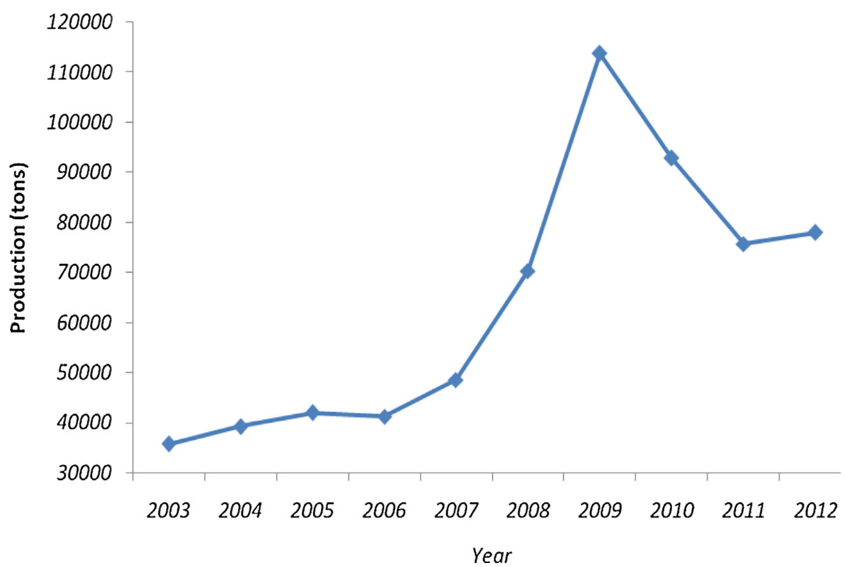

Fig. 1. Pond culture productions (2003–2012).

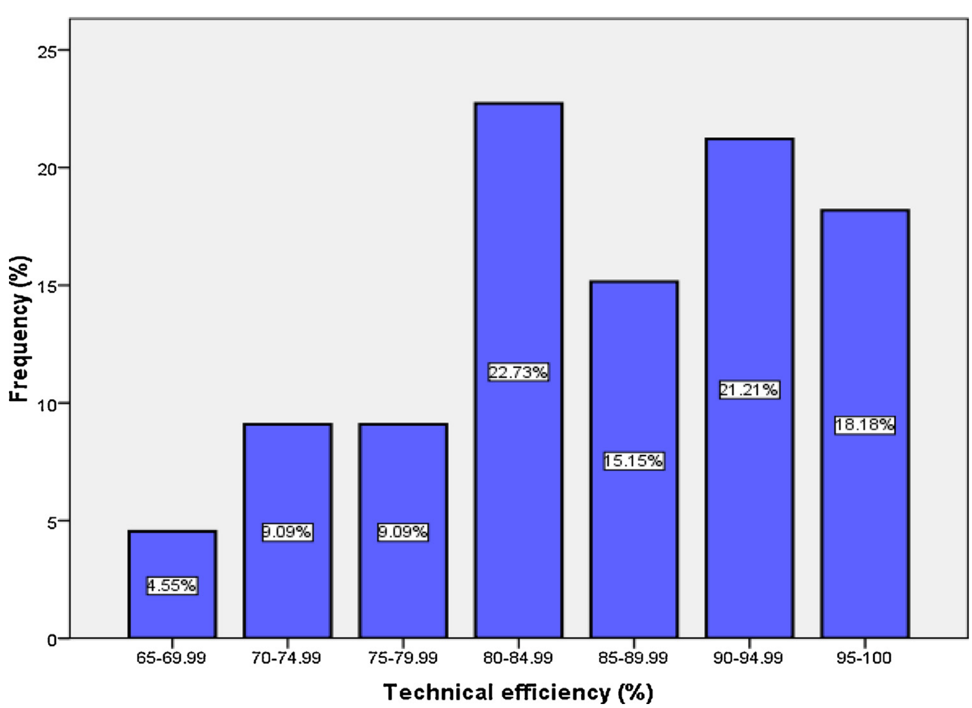

Fig. 2. Frequency distribution of technical efficiency in ponds culture systems.

ing rate beyond the recommended level will have adverse effects on fish growth.

Feed is one of the most significant components of successful fish farming and constitutes the highest percentage of production costs in many fish farms (Irz and Mckenzie, 2003; Alam, 2011; Alam et al., 2012; Vassdal and Holst, 2011). The majority of fish farms in the sample employed no standard measurement of the quantity of feed required for the fish. More often than not, fish farmers depend on their past farming experiences to nourish the fish, leading to inefficient use of this important resource. The implications of overfeeding by fish farmers are twofold. First, it increases the production costs, leading to low profits for fish farmers. Second, the excess feed may pollute the fish habitat, thereby reducing the oxygen contained in the water and resulting in a high mortality rate. The estimated feed slack for pond fish farmers was found to be 24.61%. This percentage is indeed high considering the quantity of feed required and the escalating price of feed. For instance, for every 50 kg of feed, approximately 12.5 kg is lost or wasted, which is equivalent to wastage of approximately RM 25 (USD 6).

The requirement for labour is usually low in small-scale fish farming when compared to large fish farms because the latter need more employees to perform various production activities. Most of the fish farmers in this study were operating on a small-scale level. They largely depended on family labour and only occasionally hired one or two casual workers during harvesting or pond preparation. Consequently, the estimated labour slack was found to be low (less than 10%). This implies that labour is used relatively efficiently in pond culture systems, at least for small-scale farmers.

Other costs involve operational costs, such as rent, transportation, maintenance of machinery, consultancy, fuel, electricity, Internet, telephone calls and miscellaneous expenses. Accordingly, these operational costs are not applicable to all fish farms in the sample as some of them are operating on a small scale and thus have no machinery, trucks or large buildings. The slack in other costs was estimated and found to be relatively low (14.10%) for the sample fish farms. In conclusion, the slacks analysis indicates that fish farmers are not using their inputs efficiently. The question that needs to be answered is what factors are responsible for this. This necessitates evaluation of the main determinants of technical efficiency, addressed in the following section.

3.3. *Determinants of technical efficiency*

The data was tested for normality distribution before the OLS regression analysis in which the dummy variables where excluded. However, both Kolmogorov–Smirnov (p-value = 0.20) and Shapiro–Wilk (p-value = 0.24) tests shows that the residuals are approximately normally distributed. In addition, result from the Breusch–Pagan (p-value = 0.10) and White tests (p-value = 0.18) proved absence of heteroscedasticity. Finally, no multicollinearity was detected among the variables using variance inflator factors (VIFs) and tolerance (1/VIF) test. In conclusion, the data are well fitted for OLS regression analysis.

Table 3 shows the results of OLS regression analysis. The important determinants of technical efficiency in freshwater pond cultures are farmers' age, experience, extension services and water management practices. Contrary to expectations, the coefficient of the age variable is estimated to have a negative and statistically significant impact on technical efficiency. The possible explanation for this is the conservative nature of older fish farmers, making them less willing to adopt new or improved technology and resulting in low technical efficiency in production. This finding is consistent with the results reported by Onumah et al. (2010) and Arjumanara et al. (2004). The coefficient of farmers' experience in the OLS regression model was estimated to be positive and highly statistically significant. This implies that those fish farmers in the sample with greater experience in farming are more technically efficient. This finding agrees with the works of Irz and Mckenzie (2003), Cinemre et al. (2006) and Kareem et al. (2009). Experienced farmers have probably acquired skills over time due to frequent contact with extension workers or by attending workshops, thereby making them more efficient. This finding is supported by the coefficient of extension services in the regression results, which has a positive sign and is statistically significant. Fish farmers who had received extension training were also found to be more efficient, perhaps because they had learned about new or improved production technology.

Water management is a proxy used to capture the impact of good management practices in aquaculture (GMPA) on technical efficiency. This factor is found to have a positive and statistically significant impact on technical efficiency. Therefore, those fish farmers who adopted GMPA on their farms exhibited less technical inefficiency (i.e. were more efficient) than those who did not practise it. Other factors, such as family size, education, farm status and workshop attendance, show positive impacts on technical efficiency but are statistically insignificant.

Table 3
Determinants of technical efficiency in ponds culture.

Variables	Coefficients	Standard error	*t*-value	*p*-value
Age	−0.029	0.013	−2.17	0.034
Family size	1.685	1.251	1.35	0.183
Experience	1.689	0.624	2.71	0.009
Education	0.172	0.132	1.31	0.196
Extension services	2.277	0.734	3.1	0.003
Workshop attended	0.181	0.448	0.4	0.687
Distance feed supplier	−0.011	0.009	−1.39	0.170
Farm status	0.14	0.379	0.37	0.712
Job status	0.44	0.445	0.99	0.326
Water management	0.04	0.022	1.92	0.057
Constant	-0.553	1.463	-0.38	0.707

4. Conclusion

On average, the pond fish farmers in the sample are operating below the production frontier, which indicates room for improvement. Fish farmers have greater control over their inputs than outputs because they are able to adjust them. All the inputs contain slacks and need to be reduced accordingly. Feed being the main input in fish production and constituting over half of the production costs is over utilized. Thus, fish farmers need carefully to regulate their fish-feeding practices to reduce production costs and increase turnover. In addition, government should collaborate with research institutes to formulate affordable feed and design a good feeding formula for fish depending on species types, culture system and stage of growth. The Department of Fisheries should ensure that extension personnel pass information on input slacks to farmers with relatively low technical efficiency to aid them in catching up with farms engaged in best practice. Fish farmers should be motivated by the government to improve their efficiency through incentives, such as the provision of water quality testing equipment at a discounted price to ensure good water quality is maintained, hence enhancing productivity.

Most of the variables in the inefficiency model have expected sign but statistically insignificant. Despite this limitation, the research has contributed to existing literature on studies of technical efficiency in aquaculture. However, future research should consider using different method such as fraction regression model in the second-stage of DEA in an attempt to find better findings.

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