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I. Introduction

Aquaculture has become the key economic sector of Thua Thien Hue Province in Vietnam. Being richly endowed with 22,000 ha natural water surface of Tam Giang-Cau Hai Lagoon which is considered as one of the largest lagoon systems in Southeast Asia, Thua Thien Hue Province has great potentialsto develop aquaculture activities, especially in the early years of twentieth century. This is because a historical flood that took place in 1999 helped change the water environment in Tam Giang-Cau Hai Lagoon to one that are disease-free, diverse aquatic species, and suitable for aquaculture activities. Hence, since then, shrimp monoculture, which farmers cultivate only a single species (shrimp) in their ponds, has emerged as the prominent model in this lagoon. Within merely a year the total area of aquaculture in the whole lagoon reached 1000 ha by 1999, 1700 ha by mid-2000 and 1850 ha by the end of 2000 (Phap et al., 2002).According to Fishery Department of Thua Thien Hue Province, the corresponding number in 2010 was 5800 ha, which is nearly six times more than that in 1990s - the very early years of aquaculture development (Thua Thien Hue Province People's Committee, 2011). Unfortunately, along with the fact that people have developed aquaculture massively and uncontrollably, in recent years, the productivity of shrimp monoculture productionhasdramatically declineddue to water pollution, the outbreak of shrimp diseases. Along with Vietnam, other countries such as India, Thailand also experienced similar situation of shrimp production (Kutty, 2005).

IMOLA (Integrated Management of Lagoon Activities) project which aims at assisting the Thua Thien Hue Province to promote the livelihoods of local people through the sound and sustainable management of natural resources in the Tam Giang-Cau Hai Lagoon has encouraged farms to apply poly-culture model due to it merits compared to monoculture model (Van, 2010).Therefore, in the current context, shrimp poly-culture has been found as a good solution to deal with risks arisen from shrimp monoculture. Shrimp poly-culture model is the model that farmers feed three kinds of species: shrimp, crab, and fish in their ponds. Accordingly, shrimp, fish and crab together create a good ecosystem in earth pond because fish can eat the algae, dung of shrimp, and uneaten feed. Hence, the water environment can be improved by the poly-culture system itself, there by, lessening the danger of shrimp diseases. Moreover, the initial capital is allocated to three species instead of investing on only shrimp, thus the risk of dead loss, to some extent, could be overcome.

Nevertheless, according to results investigated by Mohan and others, the technical efficiency of freshwater pond poly-culture farms in Vietnam was found to be considerably lower compared to that of China, India, and Thailand (Mohan Dey et al., 2005).The results achieved from poly-culture models in Vietnam so far have not been compatible with the potentials it has. The same story could be found in Tam Giang-Cau Hai Lagoon. Poly-culture techniques are still new to local farms that are used to solely practice shrimp monoculture, henceshrimp poly-culture model is currently characterized as a spontaneous practice performed by the minority farmers in this study area. Even for those who have been applied bravely this new model, the limited knowledge on poly-culture techniques hinders farmers from obtaining the high efficiency and productivity. Therefore, the need for improving efficiency of poly-culture production has become a crucial issue for the improvements of local farms' livelihoods, and

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consequently to achieveaquaculture sustainability developmentin Tam Giang – Cau Hai Lagoon, Thua Thien Hue Province.

Stemming from that reality, this study employs Data Envelopment Analysis (DEA) and Cross Efficiency Method to determine the efficiencies of farmers, segregate efficient farms from inefficient ones, point out the best operating practices for inefficient farms to study, identify the improper uses of inputs of inefficient farmers, and suggest the target input use pattern with respect to shrimp poly-culture production for inefficient farms. Furthermore, scale property of shrimp poly-culture farms is also identified to develop the strategy for these local farms in the long run.

In the current situation of aquaculture activities in Tam Giang – Cau Hai Lagoon when farmers have not accustomed themselves to poly-culture practices yet, the results of this study will be valuable to better farmers 'performance, contributing to improve the efficiency and productivity of their production. Furthermore, to our knowledge, there have not been any studies so far that discusses on the difference in input use pattern between the truly efficient and inefficient farms, nor suggestions made for the optimal combination of inputs in this research site.

The rest of this paper is structured in the following manner. Research method is introduced in section 2, including Data Envelopment Analysis and Cross Efficiency Method. Data sources and variables are mentioned in section 3. Then, section 4 presents the empirical results, which are discussed according to the ideas developed as follows:

- Measuring the efficiency estimates of shrimp poly-culture farms by applying DEA
- Identifying the truly efficient farms by applying Cross Efficiency Method. These results provide the examples of the best operating practices
- Comparing input use pattern between truly efficient farms and inefficient farms in order to identify improper input usage of inefficient farms
- Setting target input levels for inefficient farms individually
- Pinpointing the economic benefits that inefficient farms can achieve if they utilize the target input combination suggested by DEA results
- Orienting the development strategy in the long run for shrimp poly-culture farms based on the property of their returns to scale by applying DEA.

Finally, we conclude the paper with further discussions and policy implications.

II. Methodology

a) *Data Envelopment Analysis*

Two common techniques which are used to measure productive efficiency are parametric and non-parametric. Both of these approaches have their corresponding advantages and disadvantages. The parametric approach assumes a functional relationship between output and inputs, and uses statistical techniques to estimate the parameters of the production function. In contrast, the most advantage of the non-parametric approach is that it does not require specifying the production function. It utilizesmathematical programmingtoconstruct the linear piecewise frontier over a set of empirical observations. Among non-parametric approaches, the most celebrated approach is Data Envelopment Analysis (DEA) proposed by Charnes et al. (1978). It employs linear programming methods to construct a piecewise frontier which floats on the top of a set of decision making units (DMU)[1].

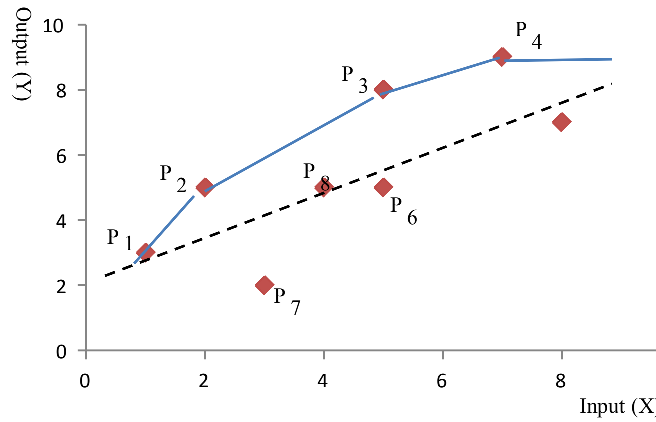

Figure 1: Comparison of DEA and Regression Analysis

Figure 1 visually shows the difference between DEA and one kind of parametric approach- regression analysis. We consider a data set of eight DMUs having single input and single output. In Figure 1, the horizontal and vertical axes depict the quantity of inputs and output, respectively. The dotted line is represented for the linear regression line in the parametric approach, showing the trend in the data points. Regarding DEA, the piecewise frontier over the data set (the solid line) is drawn by joining the boundary points (P_1, P_2, P_3, and P_4) using straight lines. All DMUs lie either on or below the piecewise frontier. For DMUs lying on the piecewise frontier, they are considered as efficient ones (DMU_1, DMU_2, DMU_3, DMU_4), otherwise they are not efficient. As for inefficient DMUs, they will be scaled against to a convex combination of the DMUs, so called their peers in term of DEA terminology, on the piecewise frontier.

Technical Efficiency reflects the ability of a DMU to either obtain the maximum output from a given set of inputs or to produce a given level of output by using the minimum amount of inputs for a given technology (Koopmans, 1951). Two ways for approaching DEA,

[1] "Decision Making Unit" (DMU) is a terminology in DEA. It corresponds to entity to be evaluated as part of a collection that utilizes similar inputs to produce similar outputs. In terms of shrimp poly-culture production, a farmer is considered as a DMU.

thereby, are known as output-orientated and input-orientated models. Farms tend to have more controls over the inputs than over the amount of outputs (Fare et al., 1993). Therefore, applying input-oriented models ismore appropriate than utilizing output-oriented models for evaluating the efficiency of shrimp poly-culture production.

b) Technical Efficiency Estimation using DEA Approach

DEA classifies efficiency into overall technical efficiency, pure technical efficiency, and scale efficiency. Overall technical Efficiency is basically a measure by which DMUs are evaluated for their performance relative to other remaining DMUs in the data set. However, its value also incorporates the effect of the presence of variable returns to scale in the DMUs. In other words, Overall Technical Efficiency estimate is influenced by scale efficiency. Meanwhile, Pure Technical Efficiency is technical efficiency already removed the effect of scale efficiency. The concept of three kinds of efficiencies is graphically depicted in Figure 2.

In Figure 2, the straight line OM passing through the origin and the extreme data points is the frontier with constant returns to scale assumption. The piecewise line joining points (P_1, P_2, P_3, and P_4) is the piecewise frontier with the assumption of variable returns to scale. The DMU lying on line OM and the piecewise line is considered as an efficient DMU in terms of overall technical efficiency and pure technical efficiency, respectively.

We consider DMU_6. It uses AP6 amount of input to produce OA quantity of output. The line AP6 intersects the line OM and the piecewise line at B and C, respectively. Under the constant returns to scale, in order to produce the amount of output OA, DMU_6 only needs AB quantity of input. Meanwhile, if the assumption of variable returns to scale is prevailed, DMU6 is able to use AC instead of AP6 volume of input to produce the same level of output (OA). The horizontal distance between the frontiers under constant returns to scale and under variable returns to scale represents the scale effect, for instance the distance BC in case of DMU6. Therefore, the efficiency measures of DMU6 can be defined as follows:

Overall Technical Efficiency = AB/AP_6
Pure Technical Efficiency = AC/AP_6
Scale Efficiency = AB/AC

Point B and point C are projected horizontally from P6 to frontier under constant returns to scale and under variable returns to scale, respectively. DMUs located at point B and point C are considered as the virtually or hypothetically efficient DMUs of DMU6. The purpose of DEA approach is to determine analytically the position of points B and C.

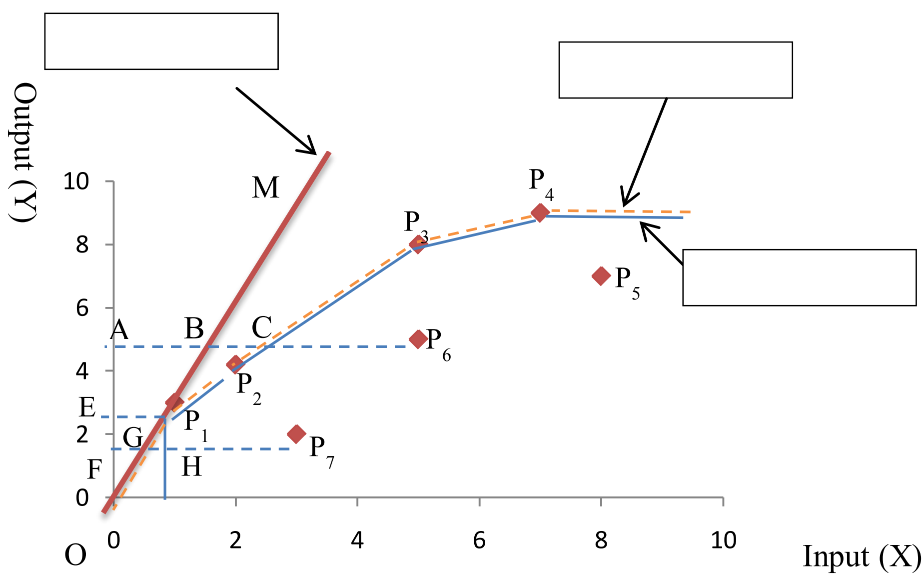

Figure 2 : Technical Efficiency and Scale Effects

In case of DMU_1, it lies on both frontiers. Therefore, its overall technical efficiency is equal to its pure technical efficiency (EP1/EP1 = 1). DMU_1 achieves scale efficiency.

Based on the concept of three kinds of efficiencies presented above, we consider how DEA using linear programming problems to measure Overall Technical Efficiency, Pure Technical Efficiency, and Scale Efficiency.

c) Overall Technical Efficiency

Assume there is a set of n DMUs, in which $x_{ip}(i=1,2,\ldots,m)$ and $y_{rp}(r=1,2,\ldots,s)$ are the quantity of i-thinput and the amount of the r-th output of $DMU_p(p=1,2,\ldots,n)$. The ratio of weighted sum of outputs to weighted sum of inputs used to measure the efficiency of DMU_p is expressed as follows:

$$Max \frac{\sum_{r=1}^{s} u_r y_{rp}}{\sum_{i=1}^{m} v_i x_{ip}}$$

$$s.t.$$

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{s} v_i x_{ij}} \le 1 \qquad (1)$$

$$j = 1, 2, \ldots, n$$

$$u_r, v_i \ge 0 \forall r, i$$

Where v_i and u_r are the associated input and output weights. This linear programming problem aims to maximize efficiency of DMU under evaluation - DMUp. It is constrained that all efficiencies measures must be less than or equal to 1, and the input and output weights must be more than or equal to 0.

The work of DEA is to calculate an optimal set of weights (v_i*, u_r*) for the DMU under the evaluation. However, the model (1) yields an infinite number of solutions, that is if (v_i*, u_r*) is a solution, then (αv_i*, αu_r*) is another solution (α>0). To avoid this situation, a linear programming problem is introduced by Charnes et al. (1978) and known as the multiplier model:

$$Max \sum_{r=1}^{s} u_r y_{rp}$$

$$s.t.$$

$$\sum_{i=1}^{m} v_i x_{ip} = 1 \qquad (2)$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0$$

$$j = 1, 2, \ldots, n$$

$$v_i, u_r \ge 0 \forall r, i$$

Model (2) deals with the problem of model (1) by adding the constraint that is sum of weighted inputs of DMU under the consideration is unity. Using the duality in linear programming, we can derive an equivalent form of above linear programming problem as follows:

$$\text{Min}_{\theta,\lambda}\ \theta$$

s.t.

$$\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{rp}$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{ip}$$

$$\lambda_j \ge 0, \forall j$$

Whereλ denotes an Nx1 vector of constant weights which defines the linear combination of the peers of pth farm. The value of λ is used to find the location of the virtually or theoretically DMU of DMU under the evaluation. For instance, model (3) generates the location of the virtually efficient DMU at point B of inefficient DMU_6 in Figure 2 is equal λ times the location of the efficient DMU1from the origin.θ is a scalar and the solution of linear programming problem of model (3), which is named the CCR model - the initial model of DEA approach with the assumption of constant returns to scale (Charnes et al.1978). θ derived from the CCR model is Overall Technical Efficiency score of DMU.

d) Pure Technical Efficiency

The CCR model can be modified to become model (4), which assumes variable returns to scale by adding the convexity constraint $\sum_{j=1}^{n} \lambda$^nλj =1(Banker et al., 1984). Model (4) is so-called the BCC model. θ derived from the BCC model is Pure Technical Efficiency.

Min θ,λ θ

s.t.

$$\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{rp}$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{ip}$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \ge 0, \forall j$$

Taking DMU_6 in Figure 2as an example, Model (4) will yield the location of C by determining λ, which is the convex combination of two efficient farms DMU_2 and DMU_3. In this case, DMU_2 and DMU_3 are called as the peers of DMU_6.

Both linear programming problem (3) and (4) will be solved N times in order to get θ for each DMU.θ ranges from 0 to 1. The DMU is considered to be efficient if θ is equal to 1, otherwise it is inefficient.

e) Scale Efficiency

Scale efficiency is calculated by using equation (5)(Cooper et al., 2006) as follows:

$$\text{Scale Efficiency} = \frac{Overall\ Technical\ Efficiency}{Pure\ Technical\ Efficiency} \qquad (5)$$

If scale efficiency score is equal to 1, DMU has scale efficiency. Otherwise, it has scale inefficiency. In other words, if overall technical efficiency derived from model (3) is equal to pure technical efficiency derived from model (4), DMU operates at constant returns to scale (CRS). Otherwise, there is existence of scale inefficiency, which is on account of either increasing returns to scale (IRS) or decreasing returns to scale (DRS).A DMU operates at constant returns to scale, increasing returns to scale, and decreasing returns to scale if a given proportional increase in all inputs used in the long run results in the same, greater than, or less than the proportional increase in outputs.

However, the drawback of scale efficiency is that the value is unable to point out whether DMU is operating at increasing returns to scale or decreasing returns to scale. This problem can be solved by running an additional DEA problem with non-increasing returns to scale (NIRS) condition imposed. This is done by replacing the $\sum_{j=1}^{n} \lambda_j = 1$ restriction in model (4) with $\sum_{j=1}^{n} \lambda_j \leq 1$.

The NIRS frontier (dotted line) is plotted in Figure 2 together with the CRS and VRS frontiers (solid lines). The nature of the scale inefficiencies due to increasing returns to scale or decreasing returns to scale for a particular DMU can be determined by comparing the NIRS technical efficiency and pure technical efficiency derived. If they are equal, DMU has the decreasing returns to scale. Otherwise, the increasing returns to scale exist for the DMU (Coelli, 1996). For instance, in Figure 2, DMU_6 operates at decreasing returns to scale, while DMU_7 operates at increasing returns to scale.

f) Cross Efficiency Method

Model (2) allows for the unrestricted factor weights (v_i and u_r) to measure the relative efficiency score. Because of the unrestricted weight flexibility problem in DEA, some DMUs can obtain high relative scores by being involved in a reasonable weight scheme (Dyson & Thannassoulis, 1988; Wong & Beasley, 1990). Consequently, among efficient DMUs, some DMUs perform better than the others. Traditional DEA models do not allow for ranking DMUs, particularly the rank of efficient DMUs(Talluri, 2000), the need to discriminate truly efficient DMUs from other efficient ones with the aim of seeking the best operating practices, however, is still a big concern.

To overcome the above problem, cross-efficiency methodwhich is initially introduced by Sexton et al. (1986) is employed. Cross-efficiency method evaluates the performance of a DMU with respect to the optimal input and output weights (v_i*, u_r*) of other DMUs. This method could effectively rank DMUs and identify good overall performers.

For each DMU_p (p=1,..,n) under the evaluation of model (2), we can obtain a set of optimal weights (v_{ip}*, u_{rp}*). Then, using this set, the cross-efficiency of any DMUj (j=1,…,n) evaluated by the optimal weights of DMU_p is calculated as follows:

$$z_{pj} = \frac{\sum_{r=1}^{s} u_{rp}^{*} y_{rj}}{\sum_{i=1}^{m} v_{ip}^{*} x_{ij}} \qquad (6)$$

$$p, j = 1, 2, ..., n$$

All cross-efficiency scores will be aggregated in a Cross Efficiency Matrix (n x n). In this matrix, the element z_{pj} in the p-th row and j-th column represents the efficiency score of each DMU_j computed using the optimal weights of DMU_p.

$$\begin{bmatrix} z_{11} & z_{12} & .. & z_{1n} \\ z_{21} & z_{22} & .. & z_{2n} \\ .. & .. & .. & .. \\ z_{n1} & z_{n2} & .. & z_{nn} \end{bmatrix}$$

For DMU_j (j=1,…,n), the average cross-efficiency score of DMU_j, , is calculated by averaging the j-th column of cross-efficiency matrix.

$$\bar{z}_j = \frac{\sum_{p=1}^{n} z_{pj}}{n} \qquad (7)$$

$$j = 1, 2, ..., n$$

The efficient farms could be ranked based on their average cross-efficiency score. The higher the average cross-efficiency score the DMU achieves, the higher ranking it has (Zerafat et al., 2012).

Based on the literature review, in recent years, DEA has been started applying extensively in the field of aquaculture such as the study of Sharma et al. (1999), Cinemre et al. (2006), Kaliba et al. (2006), Ferdous Alam et al. (2008). Literature review proves that DEA is an extremely useful tool to evaluate the efficiency of farm production. In case of shrimp poly-culture production, DEA is the most appropriate method because it is considered the only technique available to employ multiple inputs, multiple outputs situation without resort to the aggregation (Charnes et al., 1978).Unlike many previous studies measured the efficiency of aquaculture production by solely applying DEA approach, we utilize Cross Efficiency Method in conjunction with DEA method to overcome the shortcomings of DEA in this study. It is expected to yield more convincing results in segregating the truly efficient and inefficient farms.Cross Efficiency Method has been already applied in some studies ofother fields such as in the study of Chauhan et al. (2006), Zhang et al. (2009), Mohammadi et al. (2011).

III. Data and Variables

The cross-sectional data was caught through questionnaire interview. 70 shrimp poly-culture farms in Tam Giang-Cau Hai Lagoon were randomly selected and face to face interviewed in order to get detailed information on various aspects of shrimp poly-culture production. Five inputs to produce three kinds of output were identified. Farm size represents the cultured area of farm, measured in m2. Labor denotes the number of person-days per m^2. Shrimp seed, Crab seed, Fish seed respectively indicate the amount of shrimp, crab, and fish fingerlings released per m^2. Feed is expressed as the volume of feed used per 10,000 fingerlings. Chemicals represent the quantity of lime and antibiotics used to deal with diseases and water pollution, measured in kilograms per m^2.

Table 1 : Summary Statistics of the Inputs and Outputs of Shrimp Poly-Culture Farms

Variable	Unit	Mean	Std.Dev	Min	Max
Inputs					
Farm size	m^2	5882.800	2551.100	1500.000	12000.000
Labor	person- day/ m^2	0.054	0.032	0.009	0.015
Shrimp seed	fingerlings/ m^2	19.700	9.296	5.000	40.000
Crab seed	fingerlings/ m^2	1.283	1.044	0.125	6.000
Fish seed	fingerlings/ m^2	3.958	3.485	0.625	17.500
Feed	kg/10,000 fingerlings	162.840	67.766	14.268	305.049
Chemicals	kg/ m^2	0.035	0.010	0.010	0.060
Outputs					
Shrimp	kg/ m^2	0.129	0.080	0.003	0.344
Crab	kg/ m^2	0.115	0.009	0.001	0.050
Fish	kg/ m^2	0.082	0.268	0.002	1.805

Table 1 presents the summary statistics of inputs and outputs of shrimp poly-culture farms. The most striking feature, as can be seen, is the large variability of outputs and inputs among farms. These considerable variations reveal that there exist inefficiencies on inputs usage among farms, indicating the need for managerial efficiency.

IV. Empirical Results and Discussion

a) Measuring the efficiency estimates

The software DEAP version 2.1 (Coelli, 1996) was utilized to estimate three kinds of efficiency measures. As can be seen in Figure 3, 25 farms out of total 70 poly-culture farms are recognized as overall technical efficient farms, occupying 35.72% (=25/70*100). Meanwhile, the corresponding number of pure technically efficient farms is 32, accounting for 45.72% (=32/70*100).Therefore, it can be inferred that there are only 25 farms obtaining the scale efficiency of unity. The rest of 7 efficient farms are solely pure technical efficiency owing to their disadvantageous conditions of scale size.

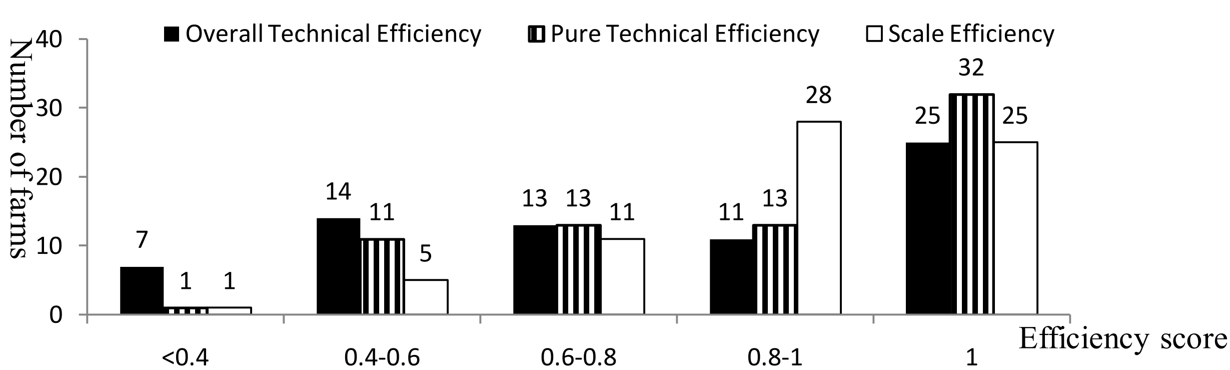

Figure 3 : Efficiency score distribution of shrimp poly-culture farms

The summary statistics of efficiency scores are reported in Table 2. The results reveal that the average values of overall technical, pure technical and scale efficiency were 0.76, 0.84 and 0.88, respectively. The results are quite similar to the study of Ferdous et al. (2008), who found that the overall technical efficiency, pure technical efficiency, scale efficiency of the prawn-carp farmers in Bangladesh were 0.5, 0.85 and 0.88, respectively. By eliminating inefficiency, shrimp poly-culture farms could reduce inputs by 24% (=(1-0.76)*100) with unalterable output. Furthermore, the results imply that there is a 12% (=(1-0.88)*100) potential yield increment earned by achieving the optimal scale.

Table 2 : Average Efficiencies of Shrimp Poly-Culture Farms

	Average	Minimum	Maximum	Std. Dev
Overall Technical Efficiency	0.76	0.13	1.00	0.26
Pure Technical Efficiency	0.84	0.34	1.00	0.20
Scale Efficiency	0.88	0.38	1.00	0.17

The existence of substantial room for efficiency improvement presses the need of seeking and disseminating the efficient operating practices. Therefore, the next section aims to identify truly efficient farmerswho have the best operating practices among 70 poly-culture farmers by employing Cross Efficiency Method.

b) Identifying Truly Efficient Farms

Table 3 presents the average and standard deviation of cross efficiency scores for 10 truly efficient farms.The results indicate that farmers having serial numbers 45, 66 and 37 are identified as those who have the best performance in shrimp poly-culture practices, with the highest average cross efficiency scores of 0.741, 0.73 and 0.729, respectively.

Table 3 : Average Cross Efficiency Score for Truly 10 Most Efficient Farms

Farmer Number	Average Cross Efficiency	Std. Dev
45	0.741	1.703
66	0.730	1.789
37	0.729	2.074
53	0.674	1.664
1	0.646	1.231
41	0.612	1.056
54	0.573	1.053
67	0.572	0.948
40	0.570	0.971
63	0.563	0.938

The information concerning to the production of the truly efficient farms (Appendix 1) should be disseminated to other farms in order to help not only inefficient farms but also other relatively efficient farms to upgrade their efficiency. This is because inefficient farms could be better off their efficiency production by learning from examples of good operating practice in their local area.

With respect to extension service, this information could be used as an effective source for the diffusion of the best practices in term of farm management throughout aquaculture farms. The dissemination of these practices could be conducted by various ways such as broadcasting media of local area, group activities, farm visits or field trips on truly efficient farms, thus farmers can easily catch the information of the best operating practices. In this respect, DEA as well as Cross efficiency method assert themselves as extremely useful tools for extension service.

c) Comparing Input Combination between Truly Efficient and Inefficient Farms

Jaforullah & Whiteman (1999) mentioned that in the absence of environmental differences and errors in measurement of inputs and outputs, technical inefficiency could be derived from the best practice farm management. Adopting the best practice of efficient farms, thus, is the crucial way to eliminate inefficiency. Therefore, it is worthwhile to distinguish the input use pattern between the 10 truly efficient farms and inefficient ones in an attempt to detect the sources of inefficiency.

Table 4 : Amount of Physical Inputs and Output for 10 Truly Efficient Farms and Inefficient Farms

Variable	Unit	10 truly most efficient farms (n=10) (A)	Inefficient farms (n=38) (B)	Difference (%) (B-A)*100/B
Inputs				
Farm size	m^2	3690.000	6184.200	40.33
Labor	person-days/m^2	0.067	0.056	-19.64
Shrimp seed	fingerlings/m^2	11.700	21.763	46.24
Crab seed	fingerlings/m^2	1.801	1.210	-48.84
Fish seed	fingerlings/m^2	3.844	3.170	-21.26
Feed	kg/10,000 fingerlings	138.927	183.200	24.17
Lime	kg/m^2	0.028	0.039	28.21
Outputs				
Shrimp	kg/ m^2	0.238	0.094	-153.19
Crab	kg/ m^2	0.022	0.009	-144.44
Fish	kg/ m^2	0.153	0.016	-89.54

Table 4 exhibits the physical inputs and outputs for truly efficient and inefficient farms. In general, the shrimp, crab, and fish production yield of efficient farms are found to be 153.19%, 144.44%, and 89.54% higher than that of inefficient farms, respectively. The considerable differences in output level are attributed to the difference in the composition of inputs among farms. The results reveal that inefficient farms tend to operate at farm size bigger than that of the truly efficient farms. Meanwhile, the person-days used to take care and oversee shrimp poly-culture practices of inefficient farms are less than that of efficient farms by approximately 19.64%. In spite of the shortage of labor force, the inefficient farms still implement their aquaculture practices with large farm size. This contradiction between farm size and the labor force makes inefficient farms perform poorly. The results reveal that in short run, farms should reduce their farm size to be commensurate with their current labor force, helping farms to better their management ability.

In addition, the results find that inefficient farms over-stock shrimp seed per m^2, releasing the quantity of shrimp fingerlings more than efficient farms do by nearly 46.24%. In contrast, they under-stock crab and fish. Relative to the truly efficient farms, inefficient farms release the number of crab and fish seed less than 48.84% and 21.26%, respectively. In other words, farms tend to densely release shrimp per m^2, while the stocking density of two others species is not as high as it should be. This results stems from the fact that despite of transforming from monoculture into poly-culture techniques, most of farms do not dare to make a big change in the combination of 3 species. This is because local farms have a long history attaching to shrimp monoculture, while just accustomed to poly-culture techniques for a short time. Shrimp, thus, is still the main species, accounting for a high stocking density relative to other species. In terms of technical efficiency, DEA results suggest farms to apply the more efficient the stocking density, decreasing the stocking density of shrimp and increasing that of crab and fish.

Table 4 reports that the amount of feed used by efficient farms is less than that of inefficient farms by 24.17%. Investigating the shrimp poly-culture practices, we recognize that due to being bursting to grow up the stock rapidly as well as the lack of poly-culture techniques knowledge, farmers just have simple thinking in rearing their stock that the more feed is provided, the big size and weight of their stock could be achieved. However, this perception brings the completely opposite results to what farms expect. According to Tuan et al. (2009), one of the main reasons deteriorate the water environment into pollution, is feed redundant from aquaculture activities. In fact, over-feeding the stock leads to much redundant feed and then, the accumulation of these uneaten feed at the bottom of the pond will create sediment. This leads to water pollution. Hence, low efficiency is inevitable consequence of improper feeding.

Similarly, the results also reveal that inefficient farms tend to abuse chemicals for improving the environment of pond at the beginning of crop, and treating shrimp diseases. It appears that the inefficient farms apply the higher quantity of chemicals compared to efficient farms. The different percentage in chemical usage is around 28.21%. It seems that farmers do not fully perceive the deep consequences of side-effects from using improper chemicals. By doing so, the efficiency of shrimp poly-culture farm is further reduced. The results accelerate farmers to make changes of their incorrect awareness of chemicals usage. In case of making good this shortcoming, shrimp poly-culture production could be prevented from not only the increase of input costs but also the harmful effects on environment.

d) Setting Target Input Use Pattern for Inefficient Farms and Economic Benefits Achieved from Applying the Target Input Use Pattern

i. *Setting Target Input Use for Inefficient Farms*

There are two options for inefficient farms to upgrade their efficiency level. The first option is that inefficient farms adopt the best efficient practices. Accordingly, inefficient farms will follow the input use pattern of truly efficient farms, changing both their level inputs used and outputs achieved. The second option is that inefficient farms can minimize the amount of inputs used while still maintain their current production levels by applying the target input use recommended from their peers. In other words, we can set the targets for every inefficient farmindividually and guide them to improved performanceby collating their current performance with the performance of their peers from DEA results (Boussofine et al., 1991). The precise and concrete solutionshown in Appendix 2 will provide farms individually with the feasible target input use associated with their current situations.

ii. *Economic Benefits Achieved from Applying the Target Input Use Pattern*

Table 5 reports the perspective of economic indices of inefficient farms if they all utilize the optimal input combination recommended by DEA results from Appendix 2. By minimizing the quantity of inputs, on average, the total cost is found to be 66,404.53 thousand VND, indicating 141.85% reductions compared to that of the current situation. Figure 4 shows that the highest potential savings within input costs was feed cost, followed by labor cost and pond preparation cost. In fact, the optimization of the quantity of feed can substantially reduce the cost by the highest percentage of 66.11%. The results emphasize the important role of using feed properly.

Table 5 : Economic Analysis of Shrimp Poly-Culture Production In the Optimum Level of Inputs Used

Cost and returns components	Unit	Actual (A)	Optimum (B)	Difference (%) (B-A)*100/B
Gross value of production	1,000 VND	120,740.50	120,740.50	-
Production cost	1,000 VND	160,599.30	66,404.53	-141.85
Net return	1,000 VND	-39,858.80	54,335.97	173.36
Benefit to cost ratio		0.75	1.82	58.79

Note: Number of observation n=38inefficient farms

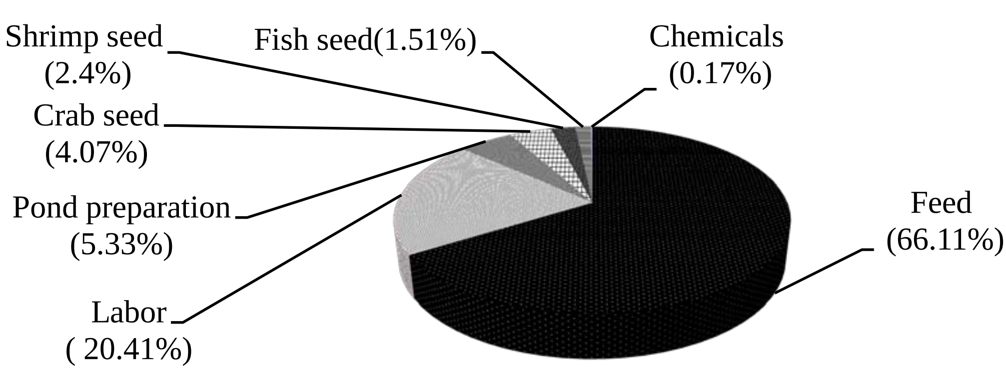

Figure 4 : Potential Reduction of Input Cost of Inefficient Farms

The gross value of production earned from 3 kinds of products: shrimp, crab, and fish is 120,740.5 thousand VND. However, the current input combination leads inefficient farms get loss approximately 39,858.8 thousand VND per crop. If these inefficient farms can apply the target input use, they will get the net return of 54,335.97 thousand VND. Moreover, the benefit to cost ratio of sample farms is computed at 1.82, indicating 58.79% improvement compared to the current benefit to cost ratio index. The high potential for improving the economic indices of shrimp poly-culture production reflected in Table 5 will have powerful motivation towards farms to change their current practices into more efficient ways, which are recommended by the results presented above. It highlights the importance of the rational utilization and proper allocation of inputs in shrimp poly-culture production.

e) Scale Properties of Shrimp Poly-Culture Farms and the Development Strategy in the Long Run

It should bear in mind that the achievement of Pure Technical Efficiency might be a short-run concern. However, in the long-run, farms not only need to obtain pure technical efficiency but also to accomplish scale efficiency. Hence, it is interesting to investigate the sources of inefficiency that farm might have, answering the question whether efficiencies are caused by the inefficient operation of farm itself or by disadvantageous conditions under which farm is operating (Cooper et al., 2005). The advantage of DEA approach is that it is capable of pointing out the returns to scale of farms (Figure 5). It is evident that the dominant scale property of shrimp poly-culture farms is increasing returns to scale, exhibiting that the small scale production seems to be one of critical obstacles of farms. In fact, 52.86% of total sample farms are operating at increasing returns to scale (IRS), followed by 35.71%, and 11.43% for constant returns to scale (CRS) and decreasing returns to scale (DRS), respectively.

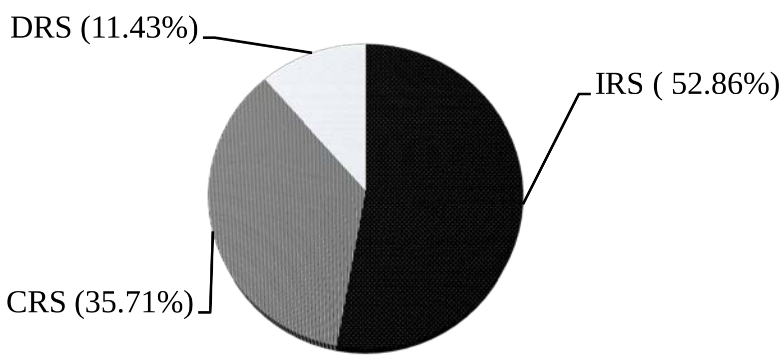

Figure 5 : The scale properties of shrimp poly-culture farms

Regarding constant returns to scale farms, nothing is needed to be adjusted. It would be appear that the largest increase in technical efficiency could be achieved by addressing the problem of increasing returns to scale. Removing increasing returns to scale would contribute to raise the overall technical efficiency by an average of 14.7% from 61% to 75.7%. Furthermore, an improvement of overall technical efficiency that farms could accomplish by removing decreasing returns to scale is around 5.9% from 66.4% to 72.3% (Table 6). From an aquaculture policy view point, the trend of supporting farms to expand the production scale is likely to be better than discouraging this trend. Unfortunately, most of farms in Tam Giang-Cau Hai Lagoon are intrinsically poor people, thus it is difficult for them to have enough capital to make change of their scale production in long run. This obstacle could be settled only if the local government creates more opportunities for farms to approach loans with lower interest rate to fully exploit their potentials to achieve higher efficiency level.

Table 6 : Mean of Technical Efficiency of Shrimp Poly-Culture Farms Classified by Scale Property

	CRS	IRS	DRS
Overall Technical Efficiency	1.000	0.610	0.664
Pure Technical Efficiency	1.000	0.757	0.723

V. Conclusion and Policy Implication

This paper takes advantages of DEA method under the input-orientated approach in conjunction with Cross Efficiency Method to help shrimp poly-culture farms evaluate and improve technical efficiency. Cross efficiency method is applied to identify thetruly efficient farms in order to offer the valuable information sources for aquaculture extension service, and clarify the difference of the input usage between truly efficient and inefficient farms. The optimization of input pattern for inefficient farmsis discovered with the aim of improving technical efficiency and increasing income of local farmers, whose livelihoods are mainly dependent on aquaculture activities. Moreover, this study also utilizes DEA to figure out the returns to scale of shrimp poly-culture farms, which can be used to develop the long-run strategy for their production.

There is the considerable room for enhancing efficiency and productivity of shrimp poly-culture production. In order to help farms improve their efficiency, this study pinpoints the top ten farmers among 70 farmers who have the best operating practices. Accordingly, other farms can learn from these typical practices to better their performances. In term of farm management, the results prove that the composition of inputs used by truly efficient and inefficient farms is at substantially different levels. It is found that operating at large farm size beyond the available labor force results in the poor supervision of shrimp poly-culture practices. The DEA results also suggest that instead of releasing high shrimp stocking density, farms should spend that capital on raising the density of crab and fish per m^2. By doing so, farm could reduce the risk of shrimp diseases and diversify their outputs in order to meet the high market demand of crab and fish. The findings also emphasize that using the proper amount of feed and chemicals is imperative to not only lowering production cost and, improving farm efficiency but also to reducing negative effects to water environment.

Moreover, by taking advantages of DEA results, this study can provide farms with the target input use pattern individually, by which farms can obtain the same current level of outputs with the minimum of input cost. The proper use of inputs shows the considerable improvement on the net return and benefit to cost ratio of farms. It is predicted that the net return and benefit to cost ratio increases by 173.36%, and 58.79%, respectively. In other words, by following the above recommendations, this research reveals the promising future, in which shrimp poly-culture farms could reach higher efficiency levels given their existing sources and production technology.

The scale properties of shrimp poly-culture farms derived from the DEA results indicate that the expansion of production scale is the tendency needed to be encouraged in the long run. Therefore, the financial support from local government to local farms is needed.

Lastly, although this study offers valuable information, it still has certain limitations. It has not pinpointed the allocative and economic efficiency level of shrimp poly-culture farms yet. Therefore, the extension of investigating allocative and economic efficiency of shrimp poly-culture farms is being researched by the author. It is expected to provide farms and local government with a comprehensive picture of the efficiency of shrimp poly-culture production in Tam Giang – Cau Hai Lagoon.

Appendix

Appendix 1 : The Input Use Pattern of Truly Efficient Farms

Farmer number	Farm size (m2)	Labor (person-days/m2)	Shrimp seed per m2	Crab seed per m2	Fish seed per m2	Feed (kg/10,000 fingerlings)	Chemicals per m2 (kg)
1	3000	0.084	13.000	3.333	10.000	126.364	0.010
37	3500	0.034	10.000	1.171	2.457	144.714	0.030
40	5000	0.096	18.000	0.760	1.840	115.880	0.030
41	4900	0.051	11.000	1.020	1.490	183.806	0.030
45	3500	0.065	10.000	0.543	1.829	153.720	0.020
53	4000	0.053	10.000	1.450	1.500	143.981	0.020
54	4000	0.044	24.000	2.500	12.500	150.048	0.020
63	1500	0.133	5.000	1.800	2.400	95.280	0.040
66	3500	0.060	6.000	3.429	1.429	78.725	0.040
67	4000	0.050	10.000	2.000	3.000	196.747	0.040

Appendix 2 : The actual and target input use for inefficient farms (based on BCC model)

Farmer number	Actual input used							Target (optimal) input used						
	Farm size (m2)	Labor (person-days/m2)	Shrimp seed per m2	Crab seed per m2	Fish seed per m2	Feed (kg/10,000 fingerlings)	Chemicals per m2 (kg)	Farm size (m2)	Labor (person-days/m2)	Shrimp seed per m2	Crab seed per m2	Fish seed per m2	Feed (kg/10,000 fingerlings)	Chemicals per m2 (kg)
2	5000	0.080	12.000	0.600	3.400	258.563	0.020	3692.304	0.054	11.714	0.674	2.917	141.496	0.023
3	4500	0.047	15.000	1.111	1.111	95.786	0.040	3121.694	0.062	12.749	1.486	1.486	140.283	0.040
4	6000	0.064	29.000	1.667	3.333	294.469	0.030	2988.139	0.053	9.548	1.667	3.333	133.680	0.029
5	4000	0.038	25.000	1.750	7.500	161.715	0.040	3824.106	0.038	17.081	1.255	7.500	112.946	0.028
6	12000	0.021	36.000	4.167	4.167	284.211	0.040	4000	0.021	26.000	0.900	3.550	14.268	0.040
7	10000	0.018	40.000	1.500	2.500	201.525	0.040	4601.734	0.037	18.334	1.193	5.276	140.289	0.033
8	5000	0.088	18.000	1.000	4.100	123.194	0.040	2362.495	0.088	9.113	0.999	4.102	117.457	0.027
9	9000	0.022	37.000	0.778	2.778	77.404	0.040	4423.119	0.022	23.746	0.737	2.779	49.813	0.039
10	4000	0.033	20.000	0.750	7.000	102.436	0.040	3917.734	0.032	18.557	0.750	4.296	75.496	0.035
11	8500	0.069	31.000	0.706	2.059	205.530	0.040	4406.851	0.065	15.183	0.865	2.521	127.172	0.030
12	10000	0.035	40.000	0.700	1.900	241.352	0.040	4983.054	0.038	19.307	0.751	2.039	203.558	0.027
13	10000	0.025	26.000	0.450	2.900	228.136	0.050	5339.254	0.025	26.084	0.451	2.909	145.581	0.032
14	7500	0.024	35.000	1.133	1.333	151.177	0.050	4736.402	0.028	20.891	0.473	1.556	110.054	0.040
15	7800	0.032	28.000	1.282	2.179	124.472	0.050	3824.895	0.032	12.191	0.993	2.180	147.715	0.032
16	5000	0.050	12.000	0.640	1.800	255.956	0.050	2884.707	0.062	14.917	0.797	2.239	133.405	0.039
17	9000	0.028	22.000	0.222	1.944	281.916	0.050	6672.305	0.036	27.003	0.288	2.519	201.314	0.027
18	7500	0.060	25.000	0.560	3.587	121.806	0.050	3588.796	0.060	11.561	0.560	3.586	139.040	0.023
19	12000	0.039	31.000	0.550	3.083	223.370	0.060	5079.892	0.039	21.182	0.549	3.083	190.941	0.025
20	5000	0.080	14.000	1.600	6.900	129.970	0.040	2749.52	0.077	10.729	1.029	6.899	109.916	0.022
21	7000	0.043	24.000	1.114	3.571	179.061	0.040	3181.799	0.043	13.257	1.116	3.454	91.114	0.033
22	4000	0.064	10.000	1.250	3.250	150.820	0.040	2828.598	0.055	9.524	1.252	3.249	136.371	0.033
23	5000	0.064	16.000	2.000	5.200	111.284	0.040	3295.34	0.064	11.841	2.000	5.201	135.584	0.029
25	6000	0.041	30.000	0.833	1.667	305.049	0.040	3662.948	0.041	15.026	0.762	1.665	141.305	0.037
26	3200	0.133	8.000	1.250	1.563	138.935	0.040	1506.954	0.133	5.103	1.805	2.455	95.224	0.040
31	5000	0.040	16.000	0.800	1.360	193.754	0.040	3820.8	0.042	16.667	0.623	1.416	142.109	0.039
32	4000	0.048	11.000	1.750	2.000	204.846	0.040	3057.008	0.049	11.452	1.079	2.084	143.505	0.034
33	5000	0.150	10.000	3.400	6.000	78.403	0.040	2796.216	0.078	7.721	3.151	3.877	103.130	0.032
34	6000	0.020	29.000	0.417	4.100	116.443	0.040	5173.834	0.021	22.185	0.445	3.879	83.068	0.037
35	4000	0.125	9.000	0.925	5.000	149.101	0.030	2417.946	0.086	9.413	0.968	5.232	110.629	0.026
38	7000	0.036	15.000	0.471	1.857	272.671	0.030	4713.853	0.034	15.870	0.509	2.009	152.411	0.032
39	3500	0.126	9.000	1.543	2.257	174.003	0.030	2274.274	0.083	9.106	1.579	2.308	145.263	0.031
47	4000	0.094	20.000	1.250	2.500	122.536	0.020	2631.274	0.069	10.128	1.714	3.428	143.044	0.027
52	4000	0.070	8.000	1.075	2.325	129.144	0.020	2319.34	0.086	8.576	1.509	3.268	129.843	0.028
59	5000	0.028	35.000	0.640	5.400	214.375	0.040	4259.908	0.028	22.134	0.641	5.399	55.871	0.036
62	4000	0.050	20.000	1.375	2.250	128.455	0.040	3740.412	0.050	10.472	1.374	2.251	161.421	0.031
64	5000	0.041	14.000	1.380	1.500	201.399	0.040	3915.422	0.048	16.719	1.093	1.790	181.010	0.030
68	5000	0.042	19.000	1.800	2.000	287.292	0.040	4170.624	0.045	20.282	1.043	2.134	194.350	0.034
70	6500	0.050	28.000	1.538	3.077	241.098	0.040	4242.226	0.052	11.098	1.605	3.213	170.744	0.032

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