Factors affecting efficiency of four-eye sleeper poly-culture in Nghia Hung district, Nam Dinh province, Vietnam. A DEA approach to technical efficiency

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Abstract

This research estimated the technical, scale efficiency and its determinants of four-eye sleeper (*Bostrichthys sinensis Lacépède, 1801)* poly-culture in Nghia Hung district, Nam Dinh province, Vietnam. A nonparametric DEA approach were applied to evaluate technical and scale efficiency of farm level using input orientation DEA model. The study was based on the cross sectional primary data collected from 70 four-eye sleeper poly-culture households in Nghia Hung district, Nam Dinh, in 2009. The mean technical efficiency under CRS and VRS as well as scale efficiency were 86.44 percent, 90.24 percent and 95.66 percent, respectively. The difference between TE under CRS and VRS showed that the scale inefficiency existed. Regression analysis was used to investigate relationship between technical super-efficiency as a function of explanatory variables which included age, experience and education level of farm operators, stocking densities of fingerling and tiger shrimp, feed ratio and access into institutions as tranning course and credit. The regression analysis results showed that technical efficiency was influenced positively by experience and the number of year going to school of farmers, the farmer with higher experience and education will be more efficiency performance in aquaculture. Fingerling stocking density was also found positively significant impacted on technical efficiency while feed ratio measured in total feed cost to total four-eye sleeper output influenced negatively significant technical efficiency. Moreover, the empirical results were also found that the number of attendance times in training course of farmer effected positively significant on technical efficiency. The more number of times attending to training course of farmer is, the higher technical efficiency score the farmer will get.

However, the others variables as age of farmer, tiger shrimp density stocking and debt ratio (credit) were not found statistically significant impact on technical efficiency in the sample farms.

Keywords**:** Data envelopment analysis (DEA), technical efficiency, four-eye sleeper poly-culture, Nghia Hung, Vietnam.

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List of Acronym

AE	Allocative efficiency
ANOVA	Analysis of variance
BCC	DEA model proposed by Banker, Charnes and Cooper (1984)
CCR	DEA model proposed by Charnes, Cooper and Rhodes (1978)
CE	Cost Efficiency
CRS	Constant Return to Scale
DEA	Data Envelopment Analysis
DMUs	Decision Making Units
GSO	General Statistics Office
MPSS	Most productive scale size
MT	Metric tons
NDRS	Non Decreasing Return to Scale
NIRS	Non Increasing Return to Scale
RE	Revenue Efficiency
RTS	Return to scale
SE	Scale Efficiency
SPF	Stochastic Production Function
TE	Technical Efficiency
TOPS	Technically optimal productive scale
VND	Vietnam Dong
VRS	Variable Return to Scale

1. Introduction

Nam Dinh is a coastal province with 72 km coastal line and having four large estuaries such as: Ba Lat, Đay, Lach Giang and Ha Lan with large surface of brackish water for cultivating four-eye sleeper[1] (*Bostrichthys sinensis Lacépède, 1801*) locally known as Bong Bop. This is a native species with high economic value and as typical fish. But in fact, this species have only been cultured commonly as exported commercial species in Vietnam especially in Nam Dinh province for some years because in the past, four-eye sleeper fingerling sources was very scarce and mainly depended on natural sources (Dan, 2002).

In recently year, four-eye sleeper cultivation is developing and has contributed to this province high economic value and deriving natural resources advantages. The result has been a sharp increase year by year in the four-eye sleeper cultivation of output quantity. According to Agricultural and Rural development Department of Nam Dinh province, aquaculture quantity of four-eye sleeper cultivation in 2007 was only 500 MT, but up to 2009, there was an significant increase in quantity of four-eye sleeper that quantity of four-eye sleeper output was 715 MT, in 2009. Besides, given abundance of water resources and rising demand for exportation, and its high profitability, four-eye sleeper aquaculture has potential for future expansion if it is given appropriate attention from the local government, authorities. Moreover, production of four-eye sleeper is a relatively new phenomenon in Vietnam. The production may still be considered to be in a developing phase. More than in study of well established aquaculture species, there will be a need to explore this infant aquaculture species before establishing definite criteria for best practice production technologies.

In recent years, a few studies have been conducted to analyze the level and determinants of farm level technical efficiency in aquaculture sector in some regions in Vietnam as Den et al., (2007), Cuong (2009), Hanh (2009) and Au (2009). However, no such studies have been conducted in Nghia Hung district, Nam Dinh province for four-eye sleeper poly-culture.

Studying production efficiency of the four-eye sleeper cultivation is thus necessary for enhancing profit and reducing input waste of producers’ four-eye sleeper cultivation as well as for proposing policy strategies for development of the new commercial species in Nghia Hung district, Nam Dinh province, Vietnam. Besides, investigating some main factors that

[1] Sourced: English name of this species was quoted from http://fish.mongabay.com/data/VietNam.htm, (accessed Jan 10th , 2009).

can influence to the technical efficiency at farm level of four-eye sleeper aquaculture is necessary for not only farmer but also for policymakers to improve productivity of fish poly-culture in Nghia Hung district, Nam Dinh province.

Objectives of the thesis:

- To describe the present overall status of fisheries and aquaculture as well as four-eye sleeper poly-culture in Nam Dinh province, Vietnam.
- To measure the technical and scale efficiency of four-eye sleeper poly-culture at farm level in Nghia Hung district, Nam Dinh province, Viet Nam.
- To investigate the main factors affecting the technical efficiency of four-eye sleeper production in Nghia Hung district, Nam Dinh.
- To propose improvements in production related to four-eye sleeper cultivation based on the technical efficiency study.

Hypothesis:

- The variation in technical efficiency scores between the different pond sizes.
- Personal characteristics of the farmer such as age, experience, education and their ability to access to institutional/public good are significant factors affecting the technical efficiency of four-eye sleeper cultivation.
- Stocking density of four-eye sleeper and tiger shrimp influence to technical efficiency of four-eye sleeper poly-culture.

Methodology procedures:

Two stages DEA model are applied. First stage, a input-orientation of DEA model is applied in order to measure technical and scale efficiency at farm level of four-eye sleeper poly-culture in Nghia Hung district, Nam Dinh province. Second stage is then to apply Ordinary Least Square to explore relationship between technical efficiency score as dependent variable and different exogenous explanatory variables.

Thesis structure:

The remainder of this thesis is organized as follows:

Chapter 2 gives overall information as fisheries, aquaculture and area aquaculture in Nam Dinh province and Nghia Hung district. Chapter 3 mentions several definition of technical efficiency and its measurement after that some empirical researches relating to this issue in aquaculture are summarized. Methodology is presented in chapter 4, while description of data and variables for DEA and OLS stage are provided in chapter 5. In chapter 6, results of estimated technical efficiency score and regression stage are presented in detail. The last ones is chapter 7 in which discussions, conclusions recommendations based on research results are highlighted.

2. General study site information

2.1. Geography and social condition of Nam Dinh

Nam Dinh is located in the South of Red river Delta with 72 km coastal line and having four large estuaries such as: Ba Lat, Đay, Lach Giang, Ha Lan, with large surface of blackish water for aquaculture, its North, East, West and Eastern South is closed to Ha Nam, Thai Binh, Ninh Binh province and Tonkin Gulf, respectively. There are 9 districts and a local city in Nam Dinh and includes 230 communes. Geographically, Nam Dinh can be divided to 3 area as following: Delta area including 6 districts of Vu Ban, Y Yen, My Loc, Nam Truc, Truc Ninh and Xuan Truong. This area is quite suitable for agricultural development, textile industry, processing industry. The second is coastal area including Giao Thuy, Hai Hau and Nghia Hung with 72 km of coastal line. This area is potential natural for aquaculture and fisheries development. And the last ones is industry and service area as local city of Nam Dinh. This city is a centre city of economics and policy for whole province.

To 1st April 2009, the population of Nam Dinh province is 1.825.771 people with density accounted for 1.196 capita per square kilometer. In 2005, the proportion of agriculture, forestry and fisheries was about 41 percentages of GDP of Nam Dinh.[2]

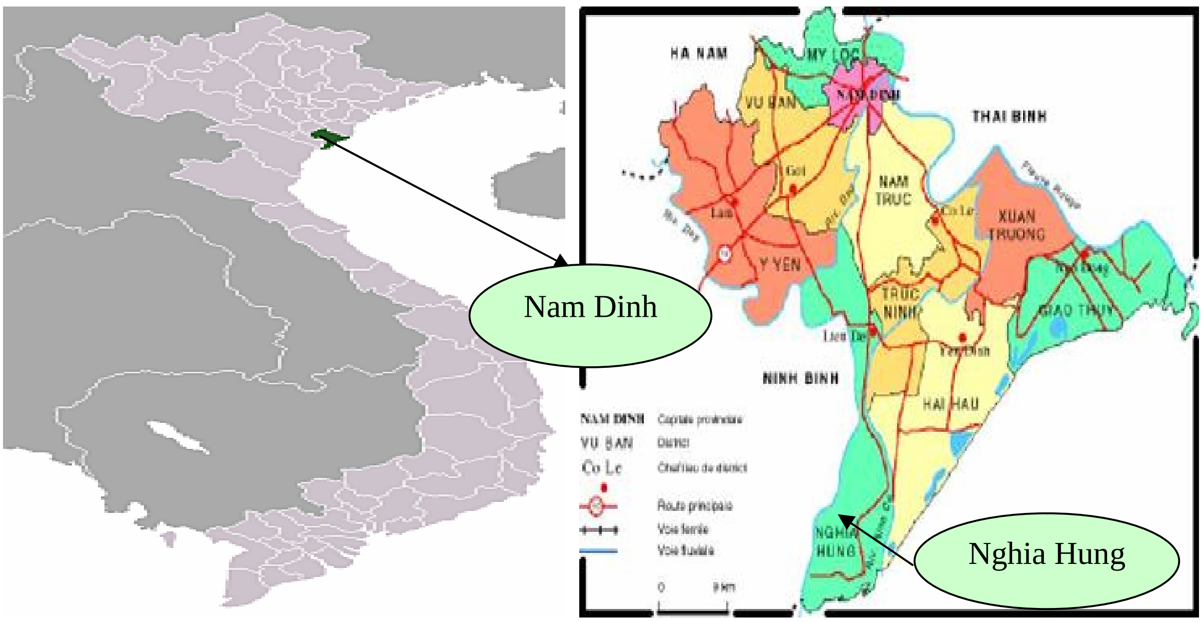

Figure 2.1: Map[3] of Viet Nam and Nam Dinh province respectively

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[2] Source: http://vi.wikipedia.org/wiki/Nam_%C4%90%E1%BB%8Bnh, (accessed 7th May, 2010).

[3] Source: vinhbacviet.tripod.com/chuong3a.htm; http://vi.wikipedia.org/wiki/Nam_%C4%90%E1%BB%8Bnh, (accessed 7th May, 2010).

2.2. Status of fisheries and aquaculture in Nam Dinh

Located in the central Northwest of Tonkin Gulf with high biodiversity and biomass of marine species, Nam Dinh is favored natural conditions with 72 km coastline, four big estuaries of Ba Lat, Lach Giang, Day, Ha Lan and large sea surface, edge of sea and interior field that give facility to the development of aquaculture. The Fisheries sector of Nam Dinh province has achieved effective improvement on fishing, aquaculture and processing. This is considered basic steps to make fisheries economy become one of the key important economic part in agriculture and rural area structure reform in Nam Dinh.

Implementing programmes on offshore fishing over the past few years, the fishing fleet in Nam Dinh had increased in terms of both quantity and quality. In 2000, total offshore vessel of Nam Dinh was 50 vessels with total capacity of 16.6 thousand of CV[4] but up to 2008, this number was up to 111 offshore vessels with 23.4 thousand of CV in total (Appendix 2.1). Moreover, thanks to the concentrated investment and sound utilization, the ability for offshore fishing and fishing logistic services significantly increased during 1995 to 2008. Hence, the volume of high-quality aquatic products, such as tuna, codfish, cuttlefish, etc. increased rapidly (Tai, 2004).

In addition, the offshore fishing was focused, the coastal fishing also maintained and consolidated. Result in, total quantity of harvest had increased significantly from 9 thousand of tons in 1995 to 36 thousand of tons in 2008, it was four times greater comparing to year of 1995 in shortly period time. This information number are presented in Figure 2.2 more detail. Beside harvesting sector, aquaculture can be seen essential and important sector of Nam Dinh's economic development. Thank to potential, plentiful and advantages of natural resources, as well as right polices, direction, supporting and guidance from local government and Vietnamese government, the aquaculture sector of Nam Dinh has got great achievements and it can be said that aquaculture movement has been widely conducted with the increase in area, productivity, volume and effectiveness (Tai, 2004).

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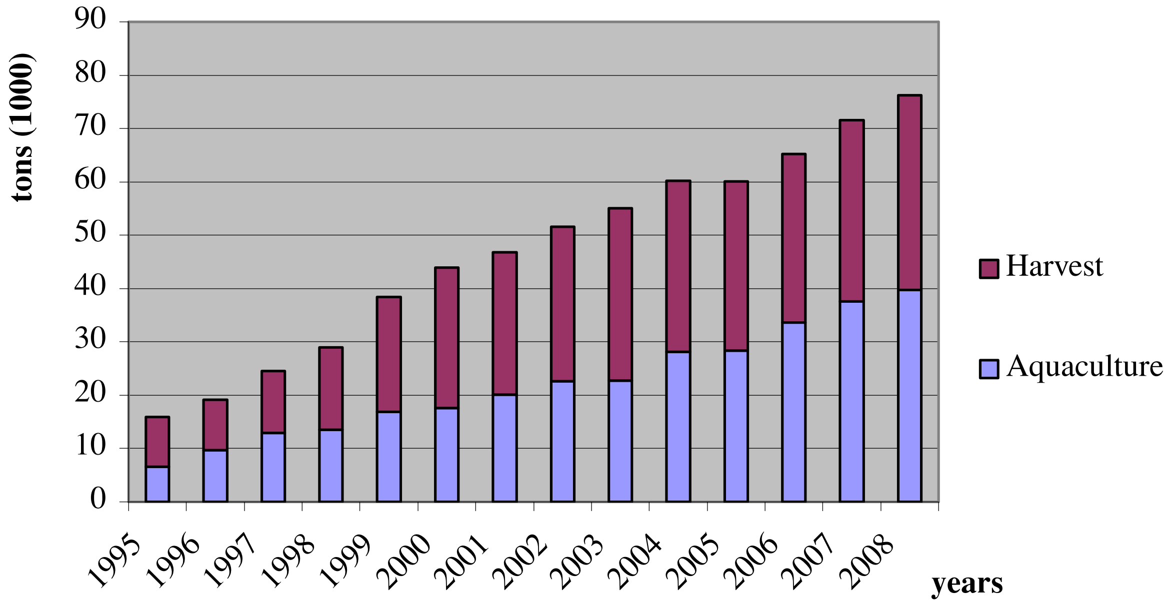
[4] CV stands for Chevaux Vapeur, a unit to measure engine capacity.

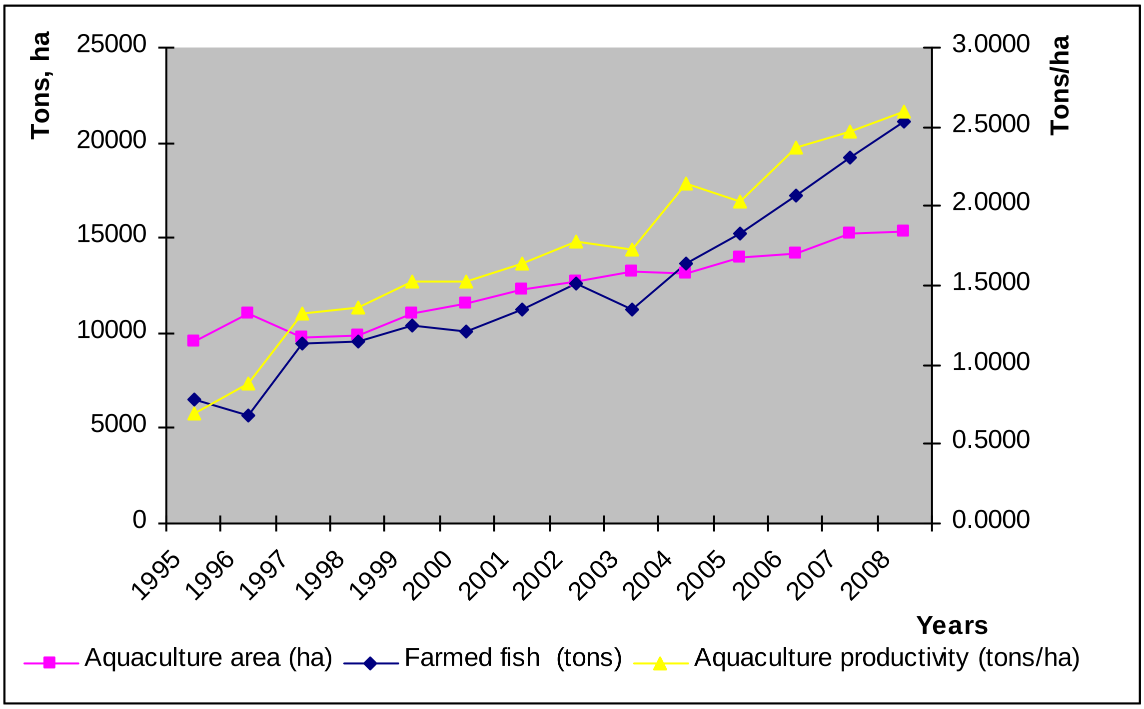


Source: General Statistic Office.

Figure 2.2: Aquaculture and harvest quantity in Nam Dinh

In 1995, total quantity of aquaculture was only 6,500 tons with total aquaculture area of 9,500 ha, but up to 2008, it was 6 times more than those in 1995 in term of total quantity meanwhile it was 1.5 times more than its area. This implies that productivity and effectiveness of aquaculture was improved and innovated.

Figure 2.3 below presents detail about total aquaculture area, aquaculture productivity and farmed fish quantity corresponding to three different color lines in the Figure.



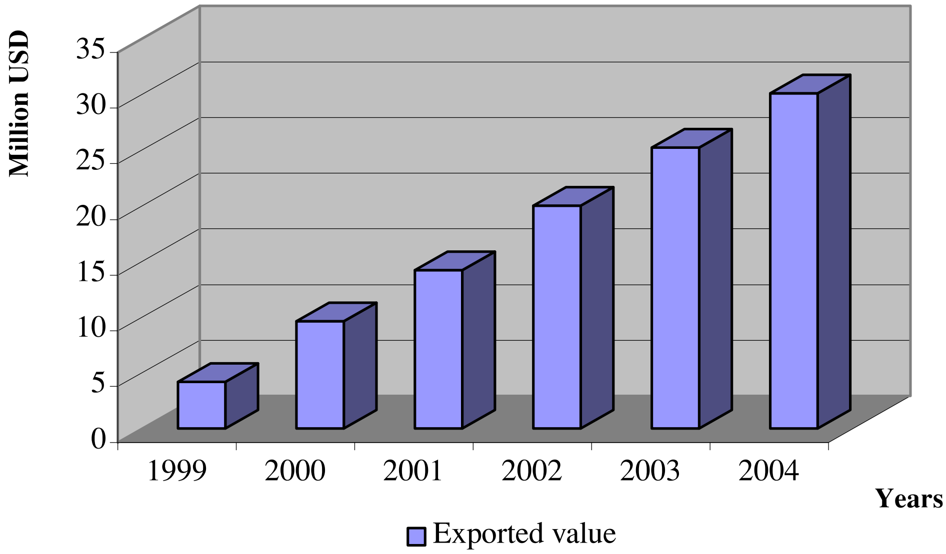
Source: General Statistic Office (GSO).

Figure 2.3: Aquaculture area, aquaculture productivity and farmed fish quantity in Nam Dinh

Figure 2.3 shows that although the total aquaculture area increased slightly over past more than 10 years, the total aquaculture quantity went up sharply from 1995 to 2008. In 1995, total area for aquaculture was only 9,533 hectares but in 2008 this area was up to 15,300 hectares. At the same time, the amount of farmed fish increased significantly from 6,488 tons to above 21 thousand of tons in which for four-eye sleeper also increased from 500 tons in 2007 to 715 of tons in 2009 (Appendix 2.1).

From the Figure 2.3 above, it can be seen that there were a considerable increasing not only in aquaculture area and farmed fish but also in aquaculture productivity. The productivity of aquaculture measured in tons per hectare increased rapidly in period time of 1995 and 2008. In 1995 this number was only 0.6883 tons per hectare but in 2008, this number had been changed significantly with productivity per hectares of 2.5936 that was four times higher than its in 1995.

While concentrating producing in order to meet demand of its habitant and domestic, Nam Dinh's fisheries and aquaculture sectors were also focused on high value species production for exported orientation. In fact, over past some years, this sector had benefited for Nam Dinh by contributing to GDP, job creation, poverty reduce. There was a steadily increase in exported value of fisheries of Nam Dinh province. In 1999, total exported value accounted for 4.2 millions USD but to 2004, this amount was more than just above of 30 millions USD.[5]



Source: Fisheries Department of Nam Dinh.

Figure 2.4: Exported fisheries of Nam Dinh

2.3. General information about Nghia Hung District

Nghia Hung district is located in the South of Nam Dinh province in which its East is closed to Hai Hau and Truc Ninh district, respectively, in the West its boundary is Ninh Binh province. Its North is near to Nam Truc and Y Yen district. In the South, it is closed to South China Sea with 12 km costal line (Figure 2.1). There are 22 communes and 3 wards as Lieu De, Rang Dong and Quy Nhat in the district. It comprises 250.47 square kilometers of land with its population accounted for 202,281 persons in 2007[(6)] and its density is about 807 persons per square kilometers.

[5]Source: http://www.namdinh.gov.vn/Quangba/tiengviet/300.html, (accessed 27th April 2010).

[6]Source: http://vi.wikipedia.org/wiki/Ngh%C4%A9a_H%C6%B0ng, (accessed 7th May, 2010).

3. Literature review

3.1. Technical efficiency concept

Koopmans (1951) stated a formal definition of technical efficiency: A producer is called as technically efficient if an increase in any output requires a reduction in at least one other output or an increase in at least one input, and if a reduction in any input requires an increase in at least one other input or a reduction in at least one output. In contrast, a technically inefficiency producer could produce the same output with less of at least one input or could use the same inputs to produce more of at least one output (Lovell, 1993).

According to Farrell (1957), the efficiency of a firm consist of two parts: technical and allocative or price efficiency in which technical efficiency refers to the ability of a firm can get maximal output from a given set of inputs, and allocative efficiency implies the ability of a firm to use the input in optimal proportions, given their respective prices and the production technology. These two components are combined to form total economic efficiency[7], (Coelli et al., 2005).

In 1957, the new aspect of Farrell was to offer a decomposition into technical efficiency, price (or allocative) efficiency and overall efficiency at micro level of a firm or production unit, the radial contraction/expansion connecting inefficiency observed points with reference points on the production frontier as the basic for the measure is the hallmark (Førsund and Sarafoglow, 2002).

Production is an act of transforming inputs into outputs. Because the objective of production is to create value through transformation, outputs are, in general, desirable outcomes. Meanwhile, inputs are valuable resources with alternative uses. The two objectives of efficient resource utilization by a firm are (1) to produce as much output as possible from a specific quantity of input and, at the same time, (2) to produce a specific quantity of output using as little input as possible. Two concepts commonly used to characterize a firm’s resource utilization performance are (1) productivity, and (2) efficiency. These two concepts are often seen as equivalent in the sense that if firm A is more productive than firm B, then it is generally believed that firm A must also be more efficient. This is not always true, although closely related, they are fundamentally different concepts. For one thing, productivity is a

[7] Farrell used the term price efficiency instead of allocative efficiency and the term overall efficiency instead of economic efficiency.

descriptive measure of performance. Efficiency, on the other hand, is a normative measure (Ray, 2004).

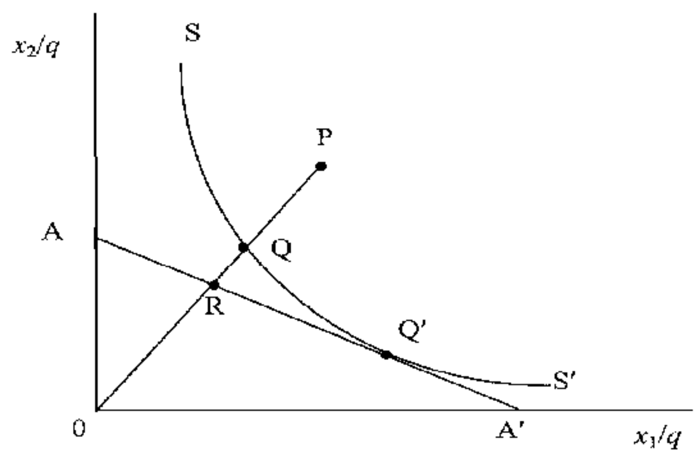
Efficiency and productivity are core concepts of economics in which productivity of a firm is measured by the ratio of the output produced to the input used. We do not always need to know the production technology in order to measure productivity. Meanwhile, efficiency, compares the actual output from a given input with the maximally producible quantity of output.

The concept of technical efficiency implies the producer's ability to avoid wasting resources by producing as much output as used input allows, or by using as little input as output production allows or generally technical efficiency means that there is no waste of resources in production. Thus, the concept of technical efficiency can have naturally an output orientation or an input conserving orientation: In which, input-orientated efficiency finds out a projected point maximizing the proportional reduction in inputs or produces a given level of output from an optimal combination of inputs. Meanwhile output-orientated efficiency seeks a projected point such that maximizes the proportional augmentation in outputs or produces the optimal output from a given set of inputs. Two these concepts will be illustrated following sections.

3.1.1. Input orientation measures

Input orientation technical efficiency can be understood that how much can input quantities reduce while keep unchanged the output produced or an other ways, the producer try to reduce input used as much as possible while keep output produced unchanging.

In his paper, Farrell illustrated his ideas using a simple model involving firms that use two input x_1 and x_2 to produce a single output q under the assumption of constant return to scale.



Sources: Coelli et al., 2005.

Figure 3.1: Technical and allocative efficiencies

From Figure 3.1, knowledge of the unit iso-quant of fully efficiency firms represented by SS' and allows the measurement of technical efficiency. Hence, any firms lay on the curve SS' are considered fully technical efficiency. In contrast, if any firms are not on the curve of SS' then are considered inefficiency firms. In here, Q and Q' are two point efficiency for any firm at these points and P is inefficiency point. So if a firm at point P uses quantities of input to produce a unit of output, the technical inefficiency of this firm could be represented by the gap between point Q and point P (or distance of QP) which is the total quantity of input that could be reduced proportionally without a reduction in output or in other words the distance PQ is the amount of input that the firm at point P could save meanwhile keep unchanging of output produced. The ratio QP/OQ represents the percentage by which all inputs need to be reduced to obtain technical efficiency production. The technical efficiency (TE) of a firm at point P is most commonly measured by the ratio:

$$\mathbf{TE_I = OQ/OP}$$ [8]

which is equal to one minus QP/0P. A firm can be seen perfectly efficiency if they move from point P to point Q and then their technical efficiency is equally to unity. Because, maximal reduction of input used is only QP, thus technical efficiency value is between from zero and unity.

In the presence of input price information, it would be possible to measure the cost efficiency of the firm under consideration. The AA' curve is expressed iso-cost line, thus, R and Q' have the same total cost. But, Q' can be seen as technical efficient as well as allocative efficient. And the cost efficiency (CE) can be valued by the ratio:

$$\mathbf{CE_I = OR/OP}$$

If the input price ratio, represented by the slope of the iso-cost line AA' is also known, then allocative efficiency (AE) and technical efficiency measures can be calculated of the firm operating at P using the iso-cost line. The allocative efficiency can be measured as ratio:

$$\mathbf{AE_I = OR/OQ}$$

And the distance RQ represents the reduction in production costs that would occur if production were to occur at the allocatively (and technically) efficient point Q', instead of at the technically efficient, but allocatively inefficient, point Q.

And the technical efficiency can be defined as ratio:

$$\mathbf{TE_I = OQ/OP}$$

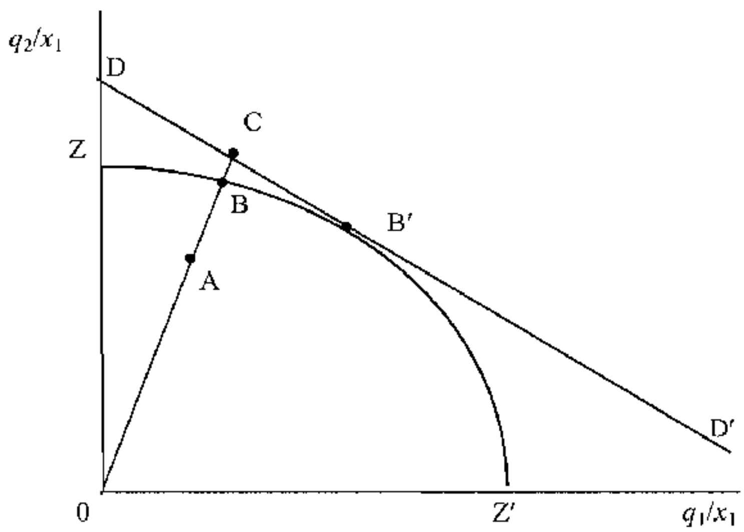
[8] The subscript "I" is used on the TE measure to implies that it is an input-orientated measure

From these equation, the total cost efficiency (CE_I) can be represented as a product of technical and allocative efficiency measure:

$$TE_I * AE_I = (OQ/OP) * (OR/OQ) = OR/OP = CE_I$$ [9]

3.1.2. Output orientation measures

In contrast, output orientation technical efficiency can be seen as how much can output quantities be proportionally expanded without altering the input quantities used. Output oriented measure refers to the firms' ability to produce output as much as possible while keep unchanging input used.



Source: Coelli et al., 2005.

Figure 3.2: Technical and allocative efficiencies from an output orientation

Figure 3.2 illustrates the output orientation measure by considering the case where production involves two outputs q_1 and q_2 and a single input x. The curve ZZ' is the unit production possibility curve and this curve also represents the upper bound of the production possibilities. Thus, any firms are on beneath of ZZ' curve are called inefficiency firms for instance, a firm at point A. The distance AB represents technical inefficiency, which is the amount by which outputs could be increased without requiring extra input. Hence, a measure of output orientated technical efficiency is the ratio:

$$\mathbf{TE_O = OA/OB}$$ [10]

Similar to the input-oriented case, if we have prices information then we can draw the iso-revenue line DD' line. Hence, the point of B' that is a tangent between ZZ' technical

[9] Note that all of CE_I, AE_I value measure are bounded zero and unity (Coelli et al., 2005, p 54)

[10] The subscript "O" is used on the TE measure to implies that it is an input-orientated measure

efficiency curve and the iso-revenue line is said to be revenue efficient. And the revenue efficiency (RE) can be measured as the ratio:

$$\mathbf{RE_O = OA/OC}$$

The allocative efficiency of a firm at point A is as the ratio:

$$\mathbf{AE_O = OB/OC}$$

From the technical efficiency (TE_O) and allocative efficiency (AE_O), the overall revenue efficiency can be formed as the product of these two measures

$$\mathbf{RE_O = OA/OC = (OA/OB) * (OB/OC) = TE*AE}$$

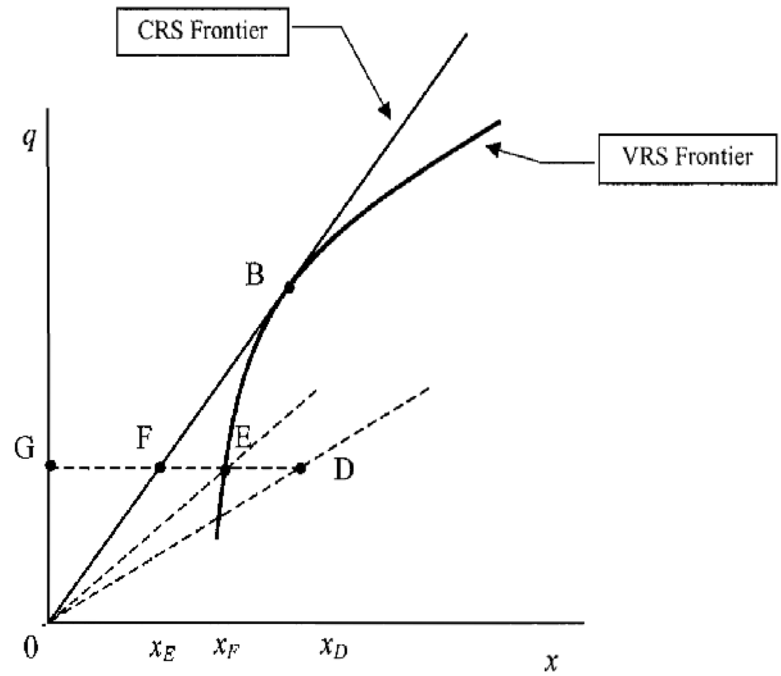
It should be noted that all TE, AE, RE and CE under input orientation and output orientation are measured along a ray from the origin to the observed production point or can be called radial efficiency measurement. An other ways, all of them are measured along a ray from the origin to the observed production point. Hence they hold the relative proportions of inputs or outputs constant.

In summary, the level of technical efficiency of a firm can be defined as the relationship between observed production point and the projected production point or best practice production point. A firm is technical efficient if its production point is on the frontier curve. In contrast, it is technical inefficient if the production point of that firm is on beneath frontier curve. Efficiency can be considered in terms of an input-orientation in which how much can inputs be proportionally reduced without changing the output quantities produced? or an output-orientation in which how much can outputs be proportionally increased without changing the inputs quantities used? (Farrell, 1957).

3.1.3. Scale efficiency

One of the limitations of Farrell's (1957) approach was an assumption of Constant Returns to Scale (CRS hereafter) which itself is very restrictive. This assumption refers that the scale of production does not affect efficiency. If the technology of the production process exhibits Variable Returns to Scale (VRS hereafter), it is clear that some of the existing inefficiency could be due to in-optimal scale (Roland and Vassdal, 2003).

To illustrate scale efficiency, one input and one output VRS production technology and in case of output orientation is depicted in Figure 3.3 as below:



Source: Coelli et al., 2005.

Figure 3.3: Scale efficiency

The firm operating at points E and B are both technical efficiency because they are operating on production frontier. However, their productive result are different because the productivity of these firms is equal to ratio of their observed output and input quantities and this expression is equivalent to the slope of a ray drawn from the origin through the data point. Thus, their productivity is different, this apparent inconsistency is due to the effect of scale. Based on this, the productivity of a firm at point B is maximal because its maximum slope in comparison to other firms at point E and D.

From this Figure 3.3, it is obviously that the productivity of firm D could be improved by moving from point D to point E on the VRS frontier (removing technical inefficiency) or in other word, firm D can reduce input used of x meanwhile keep unchanged the output produced of q, and it could be further improvement from the point E to the point B (removing scale efficiency). Hence, the distance of DE is technical inefficiency and the distance EF is scale inefficiency.

A scale efficiency measure can be used to indicate the amount by which productivity can be increased by moving to the point of technically most productive scale size (MPSS) or equivalently at the technically optimal productive scale (TOPS) (Coelli et al., 2005).

The technical efficiency of firm D relates to the distance the observed data point to the VRS technology and equals to the ratio:

$$\mathbf{TE_{VRS} = GE/GD}$$

The scale efficiency of firm D can be calculated be the distance from technically efficiency data point to the CRS technology and is equal to the ratio:

$$\mathbf{SE = GF/GE}$$

The technical efficiency of firm D in term of CRS is equal to the ratio as:

$$\mathbf{TE_{CRS} = GF/GD}$$

From the TE_{VRS} and TE_{CRS}, SE can be estimated by combination of two these measurement

$$\mathbf{SE = GF/GE = TE_{CRS}/TE_{VRS} = (GF/GD)/(GE/GD)}$$

3.2. Efficiency measurement

Efficiency measurement is typically implemented by either an econometric or mathematical programming approach. In which, the former approach involves the estimation of a stochastic frontier production function (SPF) that independently proposed by Aigner, Lovell and Schmidt (1977), and Meeusen and Van den Broeck (1977). This approach in which output is a function of a set of inputs, inefficiency, and random errors. The stochastic frontier production function, thus, has two error terms; one to account for random effects (e.g., measurement errors in the output variable, weather conditions, diseases, etc. and the combined effects of unobserved/uncontrollable inputs on production) and another to account for technical inefficiency in production (Dey et al., 2000).

The main application of the stochastic frontier production function has been in estimating and calculating TE of various production processes. The advantage of this approach is that can take into account for noise and also can be used to conduct conventional test of hypotheses. However, this approach require to specify a distributional form for inefficiency term and specify a functional form for production function (Coelli et al., 2005).

Meanwhile, the latter approach commonly referred to as Data Envelopment Analysis (DEA), first was proposed by Charnes, Cooper and Rhodes (CCR) in 1978, is a non-parametric method that does not assume an explicit mathematical form of the production function. This approach involves the use of linear programming methods to construct a piecewise linear surface or frontier over the data. Efficiency measures are then calculated relative to this surface. Also random effects are interpreted as part of inefficiency. The major advantage of DEA approach is that DEA can be employed in multi input and multi output situation. Moreover, Data envelopment analysis (DEA) constructs the efficient frontier based on extreme values of the observed data and also uses the linear programming techniques to measure the efficiency. Therefore, it is unnecessary to assume in advance any specific functional form or any assumption on distributions of error or no restrictions on the functional form of the production relationships between inputs and outputs. Besides, DEA can also identify amounts of inefficiency in each input and each output for each production unit, and identify the benchmark members of the efficient set.

General speaking, these two approaches have proved extremely useful in measurement of technical efficiency of production units (Tsionas, 2002).

3.3. The DEA approach to efficiency measurement

The terminology “Data Envelopment analysis” (DEA), was first proposed by Charnes, Cooper and Rhodes (CCR) in 1978, is a non-parametric method that assumes the production function is unknown. These authors introduced both input orientation and output orientation models under assumption of constants return to scale (CRS) based on Farrell (1957) that was ignored until CCR was published (Førsund & Sarafoglow, 2002).

DEA involves the use of linear programming methods to construct a non-parametric piece-wise surface or frontier over the data so as to be able to calculate efficiencies relative to this surface. The piece-wise linear convex hull approach to frontier estimation, proposed by Farrell (1957), was considered by only a few authors in the two decades following Farrell’s paper. This DEA method identifies the most efficiency production unit within a sample and calibrates the level of efficiency of each unit by constructing an efficiency frontier, which provides a yardstick for all unit in the sample. The efficiency of each unit is calculated by comparing output and input use with points on the efficiency frontier or best observed practice. If the production unit is on the frontier it will be assigned an efficiency score of unity, and a unit that does not locate on the frontier will be assigned an efficiency score smaller than unity. These production units are often called as Decision Making Units (DMUs). A DMU will be defined either efficient or inefficient. In the latter case, the DMU will be assigned an index reflecting how far it is from the frontier in terms of potential reduction (increase) in its input (output) use in case of input orientation and output orientation, respectively. Fare and Lovell (1978) showed that, when there is presence of constant return to scale (CRS) in production, the input and output orientation technical measures will provide equal measures of efficiency. Otherwise, they are unequal.

One of the most notable characteristic of DEA is that it generates a single output/input index to characterize efficiency of a firm producing one or multiple outputs from a set of inputs according to Charnes, Cooper and Rhodes (1978). Moreover, this approach does not require a distributional form for the inefficiency term and not need also to specify a functional form for the production function as mentioned above. Therefore, to my comprehension, non parametric of DEA approach was used in this study rather than parametric method of stochastic production function since some advantages as mentioned above and most notable is that it can solve case of multiple output of poly-culture farming pattern.

3.4. Technical efficiency analysis in Aquaculture

Two main approach of stochastic production function (SPF) and Data Envelopment Analysis (DEA) have become an accepted approach for assessing efficiency in a wide range of case.

A significant variety of applications of DEA have been employed in many researches to investigate technical, allocative, cost and scale efficiency, ranking of DMUs by applying input and output oriented models in many different contexts in many different countries. The field where application of DEA can be mentioned as hospitals, universities, cities, business firms, banks, agricultures and including the performance of countries, regions, etc. Meanwhile, stochastic production function is more commonly applied for assessing technical efficiency of DMUs related to production than other sector such as services and non-profit DMUs.

Recently, the application of production frontier techniques to aquaculture have been regarded and to illustrate for this application, some empirical technical efficiency researches in aquaculture are summarized as followings and its outline are also noted in Appendix 3.1.

Sharma, K. R. and P. S. Leung (1998) examined technical efficiency and its determinants for a sample of fish farms in Nepal by using a stochastic production frontier involving a model for technical inefficiency effects. Cobb-Douglas form was chosen for analysis based on 286 farms (213 intensive farms and 73 extensive farms), in which output variable was the total amount of fish production and inputs variables were seed, seed ratio, labor, fertilizers, fertilizer dummy, feed, feed dummy and other cost, other cost dummy. Moreover, a number of relevant farm-specific variables were also included in the analysis to determine important factors influencing technical efficiency in carp production such as intensive production dummy, farmer's experience, owner operator dummy, pond area, fish management index, water management index, central region dummy, western region dummy, Mid and Far Western region dummy. The estimated mean technical efficiency was 77%, with intensive farms being more efficient than extensive farms. And the empirical results revealed that the adoption of regular fish, water, and feed management activities had a strong positive effect on technical efficiency.

Sharma et al., (1999) measured the economic efficiency of fish poly-culture in China using output-based data envelopment analysis (DEA) approach. Then the optimum stocking densities for those farms were suggested. Cross-sectional data of 115 fish poly-culture farms from eight provinces in China were used. The analysis was based on four output categories of fish including black carp, grass carp, silver carp and common carp and the combination of inputs as seed, feed, and labor. The main results showed that the sample average technical, allocative, and economic efficiencies were 0.83, 0.87, and 0.74, respectively. Moreover, this research indicated that the technical and economic efficiency had negative relationship with farm size (Sharma et al., 1999).

Sharma (1999) estimated technical efficiency of carp production in Pakistan. A stochastic production frontier involving the model for technical inefficiency effects was applied separately to the samples of semi-intensive/intensive and extensive carp producers based on the cross sectional data of 778 carp farms. In which, the analysis was based on the Cobb Douglas production frontier involving one output was quantity of fish production while input of production including seed, labor, chemical fertilizer, organic manure, feed, other input, fertilizer dummy, manure dummy, feed dummy, other input dummy and farm-specific variables were used in inefficiency model as: primary activity, farmer's experience, pond area, fish management index, water management index, Punjab dummy, sindih dummy. The results showed that mean technical efficiency for semi-intensive/intensive and extensive farms were 0.673 and 0.561, respectively. Moreover, the results also indicated that semi-intensive/intensive farms were more technically efficient compared to extensive farms and seed, labour, and organic manure determinants were found significant influencing technical efficiency.

Iinuma et al., (1999) measured the technical efficiency of carp pond culture in Peninsula Malaysia by using stochastic production frontier (SPF) approach. The database of 94 farms, comprising 52 intensive/semi-intensive farms and 42 extensive farms were used for analysis. The analysis was based on the production frontier, which was in Cobb Douglas functional form, involving output of total quantity of fish harvested in 1994 and six input variables including seed, seed ratio, feed, feed ratio, labor and other inputs. And technical inefficiency model that included farm-specific variables such as intensive culture, ownership, primary activity, pond area, and pond age. The main results explored that mean technical efficiency was 42%. In which, intensive/semi-intensive system was more technically efficient than extensive one, those TE were 57% and 24% on average, respectively. Moreover, age and ownership were found to have positive effects on technical inefficiency. Meanwhile, there was a negative relationship between intensive culture and technical inefficiency (Iinuma, Sharma et al. 1999).

Dey et al., (2000) investigated technical efficiency of tilapia growout pond operations in the Philippines. A stochastic production frontier with technical inefficiency model was specified and estimated. The analysis was based on translog production frontier involving 4 inputs as stocking density (number of fish/ha), feeding rate in terms of crude protein (g/fish/ha), fertilization rate expressed as nitrogen (g/fish/ha), and pre-harvest labor use (family and hired person-days/ha) and one output of observed farm output (kg/ha). Then, technical inefficiency model including four variables as total farm areas, education of the operator, age of operator, and minimum water level of pond. The estimated mean technical efficiency of the 78 farmers in the sample was 83%. These authors showed that total farm area, education and age of the farmers were some factors affecting technical efficiency. The farmers with a larger farm area, higher age and a higher educational level attained higher technical efficiency (Dey et al., 2000).

Chiang et al., (2004) estimated the technical efficiency of milkfish in Taiwan using stochastic frontier production function (SPF) approach. This study specified a stochastic production frontier function to estimate potential milkfish farms by using data from 1997 to 1999 in year from a survey of 433 aquaculture milkfish farms. Both Translog and Cobb–Douglas frontier production models were estimated using the maximum likelihood estimation. The production frontier based on the output of milkfish production quantity and five inputs as pond area, fry cost, feed cost, water and electricity as well as oil cost, and other miscellaneous costs. And inefficiency factors included the data collecting time (dummy), monoculture farm (dummy), fresh water (dummy), location (dummy), pond scale (dummy), education (dummy), experience, labor. The empirical results showed that the mean technical efficiency was 84% in the Translog model, and that milkfish farming in Taiwan diminished return to scale. Furthermore, the results revealed that geographic location, type of water, operator's education, farmer's experience, and number of employee were the major positively determinants of efficiency. Meanwhile, collected data in 1998, monoculture farm, reading ability of the farmer had negatively effects on technical inefficiency (Chiang et al., 2004).

Cinemre et al., (2006) investigated the cost efficiency of trout farms in the Black Sea Region, Turkey using (DEA) approach. In this paper, two stages approach of DEA was applied basing on cross section data of 73 trout farms in the Black Sea Region, Turkey. In the first stage, input based DEA model was used to estimate efficiency measures of sample farms based on two inputs of feed (tons/year) and labor (thousands of hours /year), and a single output of trout. The second stage was Tobit regression model of inefficiency on potential determinants as personal characteristics: education level and experience of the operators; farm characteristics: pond size and off-farm income; and accessing to institutions/public goods: credit and extension services. The results showed that the mean technical, allocative and cost efficiencies were 0.82, 0.83 and 0.68, respectively. Furthermore, the research results also suggested that there were positive relationships between cost efficiency and pond tenure, farm ownership, experience of the operators, education level of the operators, contact with extension services, off-farm income and credit availability. While feeding intensity, pond size, and capital intensity had negative effects on cost efficiency (Cinemre et al., 2006).

Kaliba et al., (2006) estimated technical, allocative and cost efficiencies of a sample 32 of small-sized and medium-sized catfish farms in Chicot County, Arkansas in 2001, with cross sectional data. The first stage, DEA model was applied for efficiency analysis with five inputs of labor, energy, quantity of fingerlings/stockers, quantity of feed and other costs, and the quantity of fish marketed in 2001 was used as output measure. The second stage, then regressed cost efficiency score in Tobit model on operator characteristics, farm practices, and institutional support services to determine whether these factors lead to a higher level of efficiency. An notable finding of this research was that these authors found that higher cost efficiency of catfish farm efficiency in Chicot County, Arkansas, could be achieved by adjusting inputs used in production to optimal levels rather than by adjusting the scale of operation (Kaliba et al., 2006).

Alam and Murshed-e-Jahan, (2008) estimated resource allocation efficiency of prawn-carp poly-culture systems in Bangladesh using data envelopment analysis (DEA) approach. This paper evaluated resource allocation efficiency of prawn-carp poly-culture systems by making use of the cross sectional data of 105 farmers in Bangladesh. The efficiency estimation was based on two outputs of prawn and carp (whitefish) and five inputs as labor, fingerlings, inorganic fertilizers, organic fertilizer and feed. Mean technical efficiency, allocative efficiency and cost efficiency were 85%, 58%, and 49%, respectively. Moreover, the research found that there were positively relationship among pond size and technical and cost efficiency. And there was a negative relationship between feed application and technical, allocative and cost efficiency (Alam & Murshed-e-Jahan, 2008).

Poulomi, (2008) investigated traditional vs. scientific shrimp farming in West Bengal, India. In this study, Stochastic frontier production with Cobb- Douglas functional form approach was used to estimate technical efficiency of traditional and scientific shrimp farming in West Bengal based on dataset of 108 traditional and 100 scientific shrimp farmers for the study in 2004-2005. The mean technical efficiency of the traditional and scientific shrimp farmers was were 49% and 61%, respectively (Poulomi, 2008).

Singh et al., (2009) assessed the level of technical efficiency and its determinants of small-scale fish production in the West Tripura district of the state of Tripura, India. The study was based on the cross-sectional primary data collected from 101 fish farmers. The paper employed stochastic production frontier approach, and followed both one-stage and two-stage procedures to analyze the determinants of technical efficiency. In stochastic production frontier (SPF) function was specified which related the fish production as a function of inputs used. The output of freshwater was fish production (kg) variable and the input variables included pond area, lime, cow dung, chemical fertilizers, rice bran, oil cake, health care, fingerlings stocked, and labor used. The inefficiency model was specified of farm characteristic variables as marketed surplus, family non-farm income, family farm income, source of fingerlings, experience of the operator, training in fisheries and education level of the farmer. The results of empirical results revealed that mean TE was 0.66 and one-stage procedure with technical inefficiency model gave reliable estimates of coefficients of stochastic frontier production function than that of two-stage procedure. The study has revealed the Cobb-Douglas form of stochastic frontier production function was more dependable than that of translog form under the farming conditions in the West Tripura district of Tripura state. Besides, experience of the operators was found positively significant effect on technical inefficiency and seed quality has been found as an important determinant of technical efficiency (Singh et al., 2009).

Den et al., (2007) measured the technical efficiency of prawn farms in the Mekong Delta in Vietnam using stochastic production frontier (SPF) approach. Cross sectional data in 2004 of 193 prawn farms decomposing 163 extensive farms and 30 intensive farms were used for analyzing. A Cobb Douglas production function was applied in which dependent variable of output measured in kilogram prawn per hectare per year and seven input explanatory variables such as fingerlings, feed, chemical inputs, fuel, hired labor, type of farms (dummy) were used. The farm specific technical inefficiency was explained by four variables farm area, and experience, age and education of the operators. The main results showed that the mean technical efficiency was quite low of 46 percent. In which, extensive farms were technically more efficient than intensive farms with 48% and 35%, respectively. In addition, there was a positive relationship between experience and technical efficiency. However, it was found that the negatively relationship between age of operator and technical efficiency of farm, the older the operators were, the less technically efficient the farms were (Den et al., 2007).

Au (2009) estimated technical efficiency of prawn poly-culture in Tam Giang lagoon, Vietnam using two stages DEA model. The cross sectional data of 44 planned and unplanned farms in 2008 was used for analyzing. Outputs were used in estimating technical efficiency score in the first stage were the quantity of three kind of aquatic products including prawn (*Peneaus monodon*), rabbit-fish (*Siganus oramin*), and crab (*Scylla serrata*) and inputs including seed, labor and feed. And then a Cobb Douglas model was used to identify the relationship between super efficiency and some inputs variables such as education level, experience of shrimp poly-culture farmers, their ability to access extension service, the aquatic stocking density and the production environment. The results showed that mean technical efficiency of DMUs was 91% and the mean value of technical efficiency score under VRS was higher in planned farms than in unplanned ones with 95% and 89%, respectively. Moreover, the research investigated that in general, experience of the farmers, ability to access extension services, and production environment had statistically significant positive effects on technical super-efficiency of all shrimp poly-culture farms. However, shrimp density had significantly negative relationship with technical super-efficiency (Au, 2009).

Cuong (2009) explored technical and scale efficiency of the intensive tiger shrimp cultivation farms in Binh Dai district, Ben Tre province, Viet Nam using DEA approach. Cross sectional data of 28 shrimp farms were selected to analyze with only single output of quantity of shrimp production and seven inputs of culture area, seed, feed, fuel, labor, chemical and furniture. The empirical finding showed that overall technical efficiency, scale and pure technical efficiency were 0.911, 0.923 and 0.984, respectively. However, in this paper, the author found that there was no influence of shrimp farm size to technical efficiency of shrimp farm level. Besides, super-efficiency model that proposed by Andersen and Petersen (1993) was applied to rank shrimp farm in study area (Cuong, 2009).

Hanh (2009) explored impact of financial variables on the production efficiency of Pangasius farms in An Giang province, Vietnam using two stage DEA approach with cross sectional primary data of 61 Pangasius farms. In the first stage of the analysis, the technical efficiency and scale efficiency of individual farms was assessed by input orientation data envelopment (DEA) super-efficiency approach with output of Pangasius production and six inputs as labor, seed, feed, fuel, chemical and electricity. Then tranlog model was employed in the second stage to evaluate the influence of selected farm-specific factors including financial variables on estimated technical efficiency scores. In which, super efficiency score of first step was explained by some variable as farm investment, age of the household head, schoolings of the household head, experience of the household head, debt-to-asset ratio, bank debt-to-asset ratio, debt-to-equity ratio. The empirical results showed that mean technical efficiencies under assumption of CRS and VRS and scale efficiency were 0.595, 1.058 and 0.58, respectively. Moreover, technical efficiency was found to be influenced positively by debt-to-asset ratio and debt-to-equity ratio, while the variable bank debt-to-asset ratio was not statistically significant to impacted on technical efficiency. Besides, this paper showed that technical efficiency was positively influenced by farm investment, and experience of household head (Hanh, 2009).

In summary, in order to measure technical efficiency and identify exogenous variable impacting on technical efficiency or inefficiency both data envelopment analysis (DEA) and stochastic production frontier approaches had been used in commonly of the above researches. In which, stochastic production frontier measures the efficiency by using econometric techniques. Thus, the need for imposing a particular parametric form for the underlying technology is, perhaps, the main weakness of the stochastic frontier technique. While data envelopment analysis measures the efficiency by using the linear programming techniques. Therefore, some constraints as stochastic production frontier are unnecessary requirement in this method. Moreover, the main advantage of DEA is that it eliminates the need for the parametric assumption of the underlying technology. However, since DEA is deterministic and it attributes all deviations from the frontier to inefficiencies, a frontier estimated by this technique is likely to be sensitive to stochastic noise in the data.

4. Methodology

This section presents methodology of two stages DEA approach in which in the first stage of the analysis, the technical efficiency and scale efficiency of individual farms is computed by the data envelopment (DEA) approach. The second stage, regression analysis is employed to assess the influence of various factors upon estimated technical efficiency scores at farm level.

4.1. Data envelopment analysis stage

The term Data envelopment analysis (DEA) was first used in 1978 by Charnes, Cooper and Rhodes (CCR). These authors proposed both input orientation and output orientation models under assumption of constant return to scale (CRS).The DEA technique uses the linear programming methods to construct a non-parametric piece-wise surface or frontier envelopment for all sample observations, which provides a yardstick for all DMUs in a sample. This surface is determined by those units that are on it and then are treated as efficient DMUs. Efficiency measures are then calculated relative to this surface. A unit on the efficient frontier is given a score of unity and called best practice DMUs or efficiency DMUs. In contrast, units that do not lie on that surface can be considered as inefficient and an individual inefficiency score will be calculated for each one of them, given a score between zero and unity. DEA is a nonparametric production frontier approach that can measure the efficiency of a firm relative to the production possibility. Under the output oriented approach, performance is judged by the ability to produce the maximum outputs achievable from a given set of inputs. Oppositely, under the input oriented approach, performance is measured in terms of maximum feasible reductions in input quantities.

This paper was applied input oriented approach since in aquaculture farmers have more control over their inputs than their output (Coelli, 2005; Kaliba and Engle, 2006; Alam and Jahan, 2008), and in four-eye sleeper poly-culture the input variables such as working hours, seed, feed as well as chemical appear to be the primary decision variables. Moreover, because of existence of some things like limited good quality seed, scarce feed, constraints on finance of farmer and infrastructure in the research area, the use of input-oriented approach is more appropriate than opposed output-oriented approach.

Assuming that there are *n* farms as DMUs $(DMU_j = 1,2,3,\ldots, n)$ to be evaluated, each DMU produces s outputs y_j $(y_{1j}, y_{2j},\ldots y_{sj})$ by using m inputs x_j $(x_{1j}, x_{2j},\ldots x_{mj})$. An input-oriented model developed by Charnes, Cooper and Rhodes (CCR-1978) can be written as:

$$Min\theta_o$$
$$\text{Subject to}:$$

$$\theta_o x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0 \quad i = 1,...,m \tag{4.1}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - y_{ro} \geq 0 \quad r = 1,...,s$$

$$\lambda_j \geq 0 \qquad\qquad j = 1,...,n$$

where, x_{io} and y_{ro} are the i^{th} input and r^{th} output, respectively for a DMU_o under evaluation. A scalar factor of θ_o represents the efficiency measure of DMU_o under evaluation, while λ_j is considered as an intensity variable which defines the linear combination of the peers of the j^{th} DMU that the DMU_o is compared with. The magnitude of θ_o is greater or equal to zero and less than or equal to unity. If θ_o equal to unity, then the current input levels cannot be reduced proportionally, indicating that DMU_o is on the frontier and can be regarded as full efficiency DMU. Otherwise, if θ_o is less than unity, then DMU_o is dominated by the frontier and can be seen as inefficiency DMU.

According to Coelli et al. (2005), the CRS DEA model is only appropriate when the farm is operating at an optimal scale. Factors such as imperfect competition, constraints on finance, etc. may cause the farm to not operate at an optimal level in practice. Since CCR (1978) model stands for constant returns-to-scale (CRS) technology. This means that all farms are operating at optimal scale or if all inputs are increased proportionally by a certain amount then the outputs will also increase proportionally by the same. The results of technical efficiency measurement by solving CCR model does not account into effect of scale thus this may be inappropriate for all of the farms in the sample. Therefore, the BCC model, developed by Banker, Charnes and Cooper (BCC-1984) and called the input-oriented BCC model, allows for variations in the returns to scale is considered.

This model based on input orientation under variable return to scale (VRS) and developed basing on CCR model by adding a convexity constraint $\sum_{1}^{n} \lambda_j = 1$ in to CCR model (4.1) and then it can be written as:

$$Min\theta_o$$
Subject to:

$$\theta_o x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0 \quad i = 1,\dots,m \tag{4.2}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - y_{ro} \geq 0 \quad r = 1,\dots,s$$

$$\sum_{1}^{n} \lambda_j = 1 \qquad j = 1,\dots,n$$

The scores estimated from BCC model after imposing the restriction are therefore pure technical efficiency for the selected farm. This is because scale-inefficiency effects are eliminated from the analysis. Therefore, some authors call technical efficiency score in this model pure technical efficiency and decomposing overall technical efficiency into pure technical efficiency and scale efficiency (SE). If there is a difference technical efficiency in the CRS and VRS scores for a specific farm, then this indicates that the farm has scale inefficiency.

The use of the VRS specification when not all farms are operating at the optimal scale permit to calculate scale efficiency (SE). The scale efficiency measures is calculated as the ratio of the measure of technical efficiency calculated under the assumption of CRS to the measure of technical efficiency calculated under the assumption of VRS.

Operationally, scale efficiency (SE) has been defined from the following ratio

$$SE = \frac{TE_{CRS}}{TE_{VRS}} = \frac{\theta_{CRS}}{\theta_{VRS}}$$

In general, $0 \leq SE \leq 1$, if SE=1 implies scale efficiency and if SE<1 implies that the production are not scale efficient. The model with VRS creates the frontier as a convex hull of intersecting planes in contrast to the model with CRS, which forms a conical hull. Thus, the VRS model envelops the data more tightly, and it provides efficiency scores that are equal or greater than those of the CRS model.

One shortcoming of this measure of scale efficiency is that the value does not indicate whether the farm is operating in an area of increasing or decreasing returns to scale. This issue can be determined by running an additional DEA problem with non-increasing returns to scale

(NIRS) or non-decreasing returns to scale (NDRS) imposed. This is done by substituting the $\sum_{j=1}^{n}\lambda_j = 1$ by $\sum_{j=1}^{n}\lambda_j \leq 1$ or $\sum_{j=1}^{n}\lambda_j \geq 1$ restrictions into model (4.2), respectively (Coelli et al., 2005).

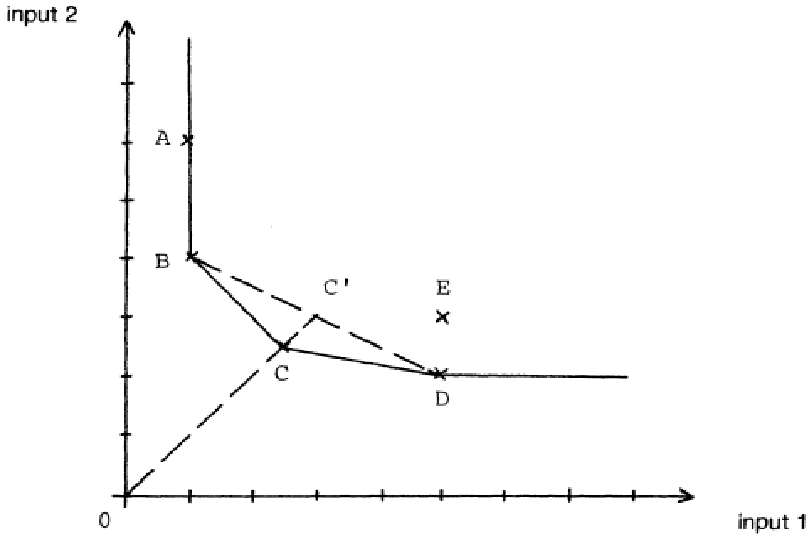
The nature of the scale inefficiencies for a particular farm can be determined by seeing whether the NIRS technical efficiency score is equal to the VRS technical efficiency score. If NIRS and VRS technical efficiency scores are unequal then increasing returns to scale exist for that farm. If they are equal then decreasing returns to scale apply (Coelli et al., 2005).

4.2. Supper-efficiency

This research was applied two stage DEA methodology as mention in which the first stage is to measure technical efficiency score of four-eye sleeper poly-culture and the second is to identify exogenous factors influencing farm technical efficiency. To identify the exogenous factor influencing to farm technical efficiency, ordinary least square (OLS) regression method was used. However, the result of technical efficiency in BCC (1984) model as dependent variable in the second stage is censored between zero and unity. Therefore, instead of using Tobit model, result of super-efficiency model that allow technical efficiency score greater than unity was used as dependent variable in the regression analysis stage.

The super-efficiency ranking techniques which was initially developed by Andersen and Petersen (1993). The methodology enables an extreme efficient DMU to achieve an efficiency score greater than one because each DMUs under evaluation is not included in the reference sets of original DEA model, which allows efficiency DMUs to become super-efficiency and to have different super-efficiency score above unity. Besides, this method also provide a ranking system that can help discriminate between efficiency DMUs with criteria such a DMU with higher super-efficiency score is better than one with lower score (Coelli et al., 2005; Mei Xue and Harker, 2002).

To illustrate this technique, Figure 4.1 is used for more detail.



Source: Andersen et al., 1993

Figure 4.1: Super efficiency

An illustration of this technique is provided in Figure 4.1 where five farms A, B, C, D, and E use two inputs to produce a particular output. If the standard DEA model is applied then A, B, C and D are on frontier as technical efficiency score of unity. However, if super-efficiency DEA model is applied then the new frontier is bounded by A, B and D farms so considering in case of farm C, it is no longer a part form of the frontier. Therefore, farms C has its projected point of C’ and the super-efficiency score of farm C will be ratio as OC’/OC. This indicate that this farms could increase input usage by distance of CC’ and still be within the technology defined by the other firms in the sample. In addition, A and E are inefficient farms in case of applying standard DEA method and their original technical efficiency scores do not change when the super efficiency method is applied (Coelli et al., 2005).

However, Adler et al., (2002) showed that there are three problematic areas with this methodology: infeasible occurrence, giving specialized DMUs an excessively high ranking and authors refer to the DEA objective function value as a rank score for all units, despite each unit is evaluated according different weights. Despite these drawbacks, possibly because of the simplicity of the concept, many published papers have used this approach. For example, Hashimoto (1997) developed a DEA super-efficient model with assurance regions in order to rank the DMUs completely, Sueyoshi (1999) introduced specific bounds on the weights in a super-efficient ranking model , and Mehrabian et al. (1999) suggested a modification to the dual formulation in order to ensure feasibility.

From BCC (1984) model above, all the frontier DMUs or efficient DMUs have technical efficiency score equal to unity. In order to discriminate the performance of efficient DMUs, the VRS super-efficiency DEA model in case of input-oriented is applied. The VRS super-efficiency model related to BCC (1984) model is discussed below:

$$
\begin{aligned}
& Min\theta_o^{\text{VRS-super}} \\
& \text{Subject to:} \\
& \theta_o^{\text{VRS-super}} x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0 \qquad i = 1,....,m \\
& \sum_{\substack{j=1 \\ j \neq 0}}^{n} \lambda_j y_{rj} - y_{ro} \geq 0 \qquad r = 1,....,s \\
& \sum_{\substack{j=1 \\ j \neq 0}}^{n} \lambda_j = 1 \qquad j \neq 0 \\
& \theta_o^{\text{VRS-super}} \geq 0 \\
& \lambda_j \geq 0,\ j \neq 0
\end{aligned}
\qquad (4.3)
$$

where the DMU_o under evaluation is excluded from the reference set. If we drop $\sum_{\substack{j=1 \\ j \neq 0}}^{n} \lambda_j = 1$ from model (4.3), we obtain a super-efficiency DEA model under CRS. Although one of its drawbacks is infeasible results of some samples, it is commonly used in sensitivity testing, identifying the outliers, and as a method of circumventing the bounded-range problem in a second stage regression method so that standard ordinary least squares regression methods can be used instead of Tobit regression (Coelli et al., 2005). However, Zhu (1996) indicated that the input-orientation CRS super-efficiency DEA model is always feasible unless certain pattern of zero data entries are present in the inputs and infeasible can not also arise in an output orientation CCR super-efficiency model. Similarly, Thrall pointed out that the model developed by Anderson and Petersen may result in infeasibility and instability when some inputs are close to zero (Li et al., 2007).

In addition, Yao Chen (2003) noted that the possible infeasible of super-efficiency DEA model may occur as a result, in his research, the author used both input and output orientated super-efficiency models to fully characterize the super-efficiency.

Mei Xue and Harker (2002) indicated that the problems becoming infeasible in a VRS super-efficiency DEA model is unavoidable unless in the input-oriented VRS super-efficiency DEA model existing at least two DMUs in the observation set having the same two maximal output. But, in practice, it is rare to have a data set that happens to meet the above requirement.

Moreover, these authors showed that in the input- oriented VRS Super-efficiency DEA model, a DMU with an infeasible is a DMU that can proportionately increase its input to positive infinity while remaining efficient, which results in its efficiency score going to positive infinity. Therefore, theoretically, the efficiency scores for such DMUs are higher than the other DMUs, and consequently they should have the highest efficiency ranking.

Besides, Lovell and Rouse (2003) implied that infeasibility arises in either orientation whenever there is no referent DMU for the excluded DMU. And they also point out that as quoted below (Lovell and Rouse, 2003, pp. 102):

> *"A necessary and sufficient condition for infeasibility is that the excluded DMU be super-efficient in the sense that (a) in an input-oriented model it has at least one output strictly larger than a convex combination of that output among all DMUs in the reference set, or (b) in an output-oriented model it has at least one input strictly smaller than a convex combination of that input among all DMUs in the reference set"*

Hence, to avoid infeasible occurrence, results of CRS super-efficiency DEA model was used as dependent variable for second stage in this study and it can be seen as a limitation of this research.

4.3. Model specification of regression stage

The two-stages approach include the traditional inputs and outputs in the linear programming formulation used to compute radial technical efficiency as mentioned above, which is then used as the dependent variable in a second stage regression. An advantage of the two-stage approach is that the influence of the external variables on the production process can be tested in terms of both sign and significance (Fried et al., 1999 and Coelli et al., 2005). This method also accommodates both continuous and categorical variables (Coelli et al., 2005).

In this research, in order to determine factor influencing in technical efficiency in the first stage, OLS was applied. Measured farm technical efficiency score obtained from step one is used in regression analysis to estimate the relationship between the technical efficiency and characteristic of farm operator, stocking densities and institution access, credit access. Since maximal technical efficiency score of BCC (1984) model equals to unity and they are always bounded between zero and one or censored. Hence, the result of super-efficiency score is used in this stage as dependent variable.

The following regression model is estimated as:

$$TE_{Super} = \beta_0 + \beta_1 AGE + \beta_2 EDU + \beta_3 EXP + \beta_4 DENF + \beta_5 DENS + \beta_6 FEED + \beta_7 TRAIN + \beta_8 DEBT + \varepsilon \quad (4.4)$$

Where:

TE_{Super} is the estimated supper-efficiency index resulting from super efficiency DEA model.

AGE is age of farm operator, measured in year.

EDU is the number schooling year of farm operator, measured in year.

EXP is the number of experience year of farm operator in aquaculture activities, measured in year.

DENF is stocking density of fish per square meter measured in the number of fingerling four-eye sleeper per square meter (individual/m^2).

DENS is stocking density of seed tiger shrimp per square meter, measured in the number of post-larva of tiger shrimp per square meter (individual/m^2).

FEED is ratio between total feed cost and total four-eye sleeper output, it is measured in thousand VND per kilogram of four-eye sleeper (1000VND/kg). This ratio indicates that how much money spending on feed cost in order to get one kilogram output of four-eye sleeper, it can be seen this feed ratio as part of production cost. Thus, feed ratio is expected to influence negatively to technical efficiency.

TRAIN is the number of attendance training course times of farm operator, this institutional services is commonly distributed by Fisheries Department of Nam Dinh Province. Normally, Fisheries Department of Nam Dinh Province support aquaculture training course freely for farmer every year. Therefore, how many times a farmer have attended aquaculture training course is regarded as this term. It is measured in attendance times (times).

DEBT is ratio between total debt that farmer borrow from bank to total expense for farming of crop in 2009 year only, in which total expense here include total feed cost, total seed cost and total other costs as chemical, limestone and fuel expenses. Since four-eye sleeper poly-culture production requires quite huge investment for feed and seed cost that are two main expenses components in total expenses for four-eye sleeper poly-culture. Therefore, most of farmers usually borrow capital from bank to operate their production.

And **ε** is error term.

5. Data and variable description

5.1. Data collection

This study is based on the secondary data and cross-sectional primary data colleted from Nghia Hung district, Nam Dinh province, Vietnam in which secondary data was collected from some different sources such as Agriculture and Rural development Department of Nam Dinh province, General Statistic Office (GSO), journals and books with relevant issue on fisheries, aquaculture in Nam Dinh, Vietnam. While, primary data was implemented in Nghia Hung district, Nam Dinh province. The cross-sectional primary data was employed in this research with the results of the crop in year 2009. The household survey was carried out during months from January to February, 2010 in coastal Nghia Hung district, Nam Dinh province where four-eye sleeper is cultured commonly.

The cross-sectional primary data was caught through questionnaire interview. The design structured questionnaire was based on necessary indicators that meet the objectives of this study was used. In order to fulfill the questionnaire, a pilot interview by using this structured questionnaire was done for some households (six households for pilot survey) to help correct mistakes, have revision, evaluate and select relevant questions, information as well as adding or eliminating necessary and unnecessary information. This survey also helped make the questionnaire in accordance with identified indicators and gave the basis for revision of the questionnaire and refining the indicators. Then the final completed version of questionnaire was used for interviewing.

The questionnaire was designed to catch some necessary output and input information of four-eye sleeper production in Nghia Hung district such as: household characteristics, farm characteristics, labor, seed, feed, quantity of harvested four-eye sleeper and tiger shrimp as well as available price of output and input. Besides, some socioeconomic and environmental factors can influence in the technical efficiency of four-eye sleeper poly-culture production also were addressed. Before implementing the survey, some relevant local participants working in Fisheries Department of Nghia Hung district were invited to carry out the survey. These members have well understanding about the status of aquaculture activities, fisheries mechanism, culture as well as social, graphically condition in the study site. Besides, selected interviewers was also trained for understanding and acquainted of questionnaire, special language in aquaculture, economic and social issue relating to topic. On the other hand, this job also helped them understood purpose of this research as well as goal of this questionnaires and then in turn made the field survey smoothly.

Sampling method: Households were selected randomly from a listed farms provided by Fisheries Department of Nghia Hung district before carrying out field survey and considered as decision making unit since four-eye sleeper farms in the research area are operated by household term. In Nghia Hung district, four-eye sleeper cultivation is concentrated on three communes as Nghia Thang, Nam Dien and Rang Dong in which four-eye sleeper poly-culture is performed in Nam Dien and Rang Dong while in Nghia Thang is only cultivated four-eye sleeper mono-culture pattern and have few four-eye sleeper farming household as well. Thus, only of Nam Dien commune and Rang Dong were chosen for sampling. Throughout field survey, the interviewers went to each household and meet household head to interview face to face, although most of farmers did not have accounting book to note their cultivation activities about input and output in detail, the farmers could recall all inputs expenses, output quantity as well as some information in the questionnaire in general as at period time for interviewing farmers, luckily it was just time the end crop of 2009 year thus almost aquaculture activities especially related inputs and output categories were quite fresh for farmers. Therefore, all questions in the questionnaire was available.

Sample size: Spending two weeks on field survey, the final total sample were 77 four-eye sleeper poly-culture households collected in two communes in which of 35 households came from Rang Dong ward and the rest of 42 was from Nam Dien commune since the more farms in Nam Dien compared to Rang Dong. However, data editing and checking for outliers is an important task that could have serious influences on final results (Coelli et al., 2005). Thus, after checking and analyzing data sets, the total 7 out of 77 surveyed respondents were eliminated from data sets. Because, there were two households provided insufficient data with missing information about the number of year of aquaculture experience and the number of times attending training course, respectively. In addition, one more household also was as outlier because of getting too many training course times and can be seen abnormal and suspected observation. Moreover, there were 4 households also had been removed from data sets as outliers since these ones whether may faced seriously disease or provided unreliable information. The criteria for observation elimination is that all farms with too low or too high of output/seed cost ratio, output/labor ratio and output/feed cost ratio were considered as outliers (Sharma and Leung 1998; Sharma, 1999; Coelli et al., 2005). Finally, a total sample size of 70 surveyed households were retained and analyzed for the present study.

5.2. Data description

5.2.1. Variables of DEA stage

For the efficiency analysis, the input and output variables were identified. In which five most important inputs as area, labor, fingerling, feed and other cost which were assumed to adequately represent the four-eye poly-culture technology in the sample area and outputs used in estimating technical efficiency score were aggregated to two kind of output both measured in kilogram per crop. All output and input variables were measured in per crop of household term. The output and input variables for efficiency analysis for a sample of fish poly-culture producer in Nam Dinh province, Vietnam are described below and their summary statistics are provided in Table 5.1 and Table 5.2.

Output variables for efficiency analysis are:

Quantity of four-eye sleeper harvested by farmer in 2009: y_1 (kg).

Harvested quantity of tiger shrimp in 2009: y_2 (kg).

According to farmers in study site, these outputs commonly are harvested by several times per crop for both four-eye sleeper and especially in tiger shrimp, it take many times to harvest all tiger shrimp when they get market size. This species is harvested after breeding by four to five months later, and harvest selectively before fish harvesting. If fish get market size about 12 individuals per kilogram, farmer start harvest and mainly, it take two months later they then harvest the rest of fish in their pond. Although, this is poly-culture pattern with two kind of species, tiger shrimp is minor species comparing to four-eye sleeper in term of value and quantity contribution for farmer. Because, most of farmer said that survival rate of tiger shrimp usually is too low therefore total output quantity of tiger shrimp is rather low. Additionally, when farmer culturing fingerling and tiger shrimp post larva in their pond they can reduce wasted feed because the later species of tiger shrimp is unnecessary to feed separately as this species also can use redundant feed that is not consumed by fingerling. Based on this characteristic, farmer only feed four-eye sleeper while keep feeding tiger shrimp.

Source: Google image and field survey, respectively.

Figure 5.1: Image of tiger shrimp *(Peneaus monodon)* and four-eye sleeper *(Bostrichthys sinensis Lacépède, 1801)*

Similarly, the inputs involved in cultivating are also aggregated into five variables to calculate technical efficiency score as area, labor, seed, feed, and other costs in which:

Area (x_1) represents real cultured area, measured in m^2.

Labor (x_2) is expressed as total working hours included both household labor and hired labor who might work full-time and part-time measured in total working hours. Labor is mainly used to prepare fish feed, feed four-eye sleeper everyday and harvest in the end of crop and prepare pond for new crop such as moving out mud at the bottom of pond, fixing edge of pond and liming.

Seed (x_3) represents total value of seed including fingerlings and tiger shrimp seed released to pond, measured in thousand VND. Because if each kind of seeds are measured separately will increase the number of constraints which make the efficiency score of sample farms higher since frontier becomes tighter (Sharma et al; 1999). Thus in this research, seeds are measured in total value.

Feed (x_4) indicates total feed cost, measured in thousand VND. The feed for feeding four-eye sleeper is mainly trash-fish from marine species, farmer usually buy trash-fish from inshore vessel and the number of moth per crop is quite long so they can not memorize how many kilogram of trash-fish they bought for a crop instead of total feed cost. Thus this input is measured in total feed cost.

Other costs (x_5) represents other variable inputs including used chemical and antibiotic for treating fish and shrimp disease, lime for water treating, fuel and electricity for pumping water out, measured in thousand VND.

Table 5.1: Descriptive statistics of input and output variable for DEA analysis

Variables	Mean	Std. Deviation	Min	Max
Outputs:				
Four-eye sleeper: y_1 (kg/crop)	1,347.14	1,067.11	200	7,500
Tiger shrimp: y_2 (kg/crop)	134.89	113.06	10	500
Inputs:				
Area: x_1 (m^2)	8,405.71	5,686.82	1,440	34,000
Labor: x_2 (hours/crop)	1,960.29	989.35	560	7,400
Seed cost: x_3 (1000 VND/crop)	108,481.07	87,697.81	21,000	648,000
Feed cost: x_4 (1000 VND/crop)	53,228.57	59,346.48	4,000	480,000
Other cost: x_5 (1000 VND/crop)	6,917.14	5,455.16	600	31,000

Source: Field survey.

Table 5.1 summarizes the sample descriptive statistics of used inputs and output in cultivating four-eye sleeper and tiger shrimp. To estimate farm technical efficiency, data of households were collected with two outputs as quantity of four-eye sleeper and tiger shrimp in crop 2009. Besides, some main inputs were also conducted to estimate technical efficiency. The sample households produced more than 1,300 kilograms four-eye sleeper per crop and 134.89 kilograms tiger shrimp per crop, on average. The minimum of fish and tiger shrimp production were 200 kilograms and 10 kilograms, respectively. While the outputs maximum of fish and tiger shrimp production household were 7,500 and 500 kilograms, respectively. To reach their present level of production, households used more than 8 thousand m^2 of pond area, approximately two thousand working hour for pond preparation, feeding, pond maintenance and harvest, and 108 million VND for seed cost, more than 53 million VND for feed cost, and approximately 7 million VND for other cost, on average. From Table 5.1, seed cost is considered mainly expenses in four-eye sleeper poly-culture and following feed cost, in general.

Besides, the correlation between input and output, input and input, are illustrated in Appendix 5.1. The results show that the correlation between the total seed cost and the output of four-eye sleeper, the correlation between total feed cost and four-eye sleeper output were rather high. This reveals that output production and two important inputs as feed and seed was quite strict. In line with real aquaculture activity, the correlation between total seed cost and total feed cost was also high and it can be sated that the more seed farmer rear, the more feed cost they have to invest (Appendix 5.1).

5.2.2. Variables in regression analysis stage

In this stage, results of super efficiency score that was estimated in the first stage was used as dependent variable, and then regressed these super efficiency score on farm and farmer specific variables as age, education level and experience of farm operator, aquatic stocking densities; and the access to institutions/public good that all defined above.

Table 5.2: Descriptive statistics of OLS variables

Variables	Definition	Mean	Std. Dev.	Max	Min
$TE^{\text{Super-efficiency}}$	Super-efficiency score	0.955	0.035	2.000	0.489
AGE (years)	Age of household head	41.257	1.223	63.000	22.000
EDU(years)	Year of schooling of household head	8.943	0.234	12.000	5.000
EXP(years)	Experience of household head	9.757	0.497	20.000	1.000
DENF(fingerling/m^2)	Number of fingerling per square meter	3.265	0.272	16.250	0.417
DENS (individual/m^2)	Number of post larva per square meter	5.246	0.441	20.833	1.111
FEED (1000VND/kg)	Feed cost to output ratio	40.179	2.046	120.000	17.391
TRAIN (times)	Number of time attending training course	3.100	0.411	15.000	0.000
DEBT	Bank debt to total expense ratio	0.347	0.031	0.928	0.000

Source: Field survey.

In the research area, the age of farm operators were moderate of 41 years while the education level and the experience of farm operator were also rather high with approximately 8.9 years and 9.7 of year, respectively. Generally speaking, the education level of farm operators in Viet Nam is quite high such as: education level of Pangasius farm operators in An Giang province, Southern Viet Nam was 9.623 of year (Hanh, 2009) and the number year of schooling of prawn poly-culture farm operators in Tam Giang lagoon, Central of Viet Nam was 6.5 (Au, 2009), and the number of schooling year of prawn farmers in Mekong Delta, Southern Viet Nam was 5 years (Den et al., 2007). In this study, farmers cultivating four-eye sleeper poly-culture in Nam Dinh, Northern Viet Nam have the number of year in schooling was quite high of 8.9 years. Besides, the number of year schooling of trout farm operators in Black Sea Region, Turkey was relatively low, 3.28 of year (Cinemre et al., 2006). While, the number of year schooling of tilapia operators in Philippines was 11 years (Dey et al., 2000).

And the number of education year of freshwater aquaculture operators in Tripura, India was 6.74 years (Singh. K., et al., 2009).

Besides, personal characteristics of farm operators as age, education level and experience are seem to be various factors influencing to technical efficiency. Some factors as stocking densities and access to institution/public good also may be considered causing impacts on technical efficiency of four-eye sleeper poly-culture in this area. From Table 5.2, the stocking densities of seed four-eye sleeper and tiger shrimp were 3.27 and 5.25 on average, respectively. While the maximum stocking densities were 16.3 and 20.8, respectively for fish and tiger shrimp. In contrast, the minimum stocking densities were quite low 0.4 for fish and 1.1 for tiger shrimp. From the Table 5.2, interestingly to realize that in order to produce one kilogram of four-eye sleeper, farmer had to cost 40 thousand VND for feed cost, on average. This variable is expected to impact on technical efficiency negatively, it means that the higher feed cost to output ratio households get, the less technical efficiency farmer are.

In the research area, the farm operator were trained moderately measuring by the times attending training course hosting by local government institutions. On average, the number of times attending of farm operator was 3.1 times with maximum and minimum attendance times of 20 and zero, respectively. They also used rather high credit, measuring in total debt to total expenses ratio. The mean of this index was 0.347, this index implies that if farmers in this area expensed 100 million VND for spending on their cost expense in farming such as feed cost, seed cost, other cost they had to borrow capital from bank 34.7 million VND. Moreover, this index also indicates available capital of farmer their own. Both factors training and debt are expected influence on technical efficiency positively.

6. Results

This chapter consists of two main sections. First, technical, scale efficiency scores in overall, technical scale and efficiency score by pond size are presented both under CRS and VRS. Second, then the relationship between farm super efficiency scores based the assumption of CRS and some specific factors including three categories of farm operator characteristic, access to institutions/public goods, stocking density are presented in detail.

The software DEA Excel Solver written by Zhu was used in estimating technical and super efficiency (Zhu, 2003). The Microsoft Excel was used for ANOVA, and econometric software package of Eviews 6.0 was used for regression and testing.

6.1. Technical and scale efficiency results

6.1.1. Technical and scale efficiency results in overall

Farm technical efficiency (TE) scores under the assumptions of CRS and VRS and scale efficiency (SE) scores were estimated using DEA input oriented model. The distributions of the scores are presented in Figure 6.1 and Table 6.3. Meanwhile, mean, standard deviation, minimum, and maximum levels of TE and SE scores in overall are shown in Table 6.1.

Table 6.1: Technical and scale efficiency score in overall

TE score	Mean	Std deviation	Max	Min	No. efficiency farms	Percentage (%)
TE - CRS	0.8644	0.1460	1.00	0.4893	26	37.14
TE - VRS	0.9024	0.1259	1.00	0.5687	34	48.57
SE	0.9566	0.0756	1.00	0.5563	26	37.14

Source: Field survey.

From Table 6.1 above, the mean technical efficiency under CRS and VRS, and scale efficiency were 0.8644, 0.9024 and 0.9566, respectively. The mean technical efficiency under CRS or overall technical efficiency was 0.8644 means that poly-culture four-eye sleeper in Nghia Hung district, Nam Dinh province could reduce used input by almost 14 percent while keep unchanging output. Under CRS approach, there were 26 full efficiency farms out of 70 in the total sample size accounted for 37.14 percent, the other were technical inefficiency farms. The least technical inefficiency farm only got score of 0.4893.

Besides, under VRS the mean technical efficiency or pure technical efficiency was 0.9024 in which the minimal technical inefficiency was only 0.5687. It means that when VRS approach was applied, the farmers could reduce proportionally by nearly 10 percent input used while maintaining the output level. In this case, there were 34 fully technical efficiency farms accounted for 48.57 percent in total. Moreover, the mean scale efficiency score was 0.9566 in which 26 farms were fully scale efficiency estimated 37.14 percent or another ways, 44 out of 70 farms in total were not operated at optimal scale. There is a difference between VRS and CRS technical efficiency indicates existence of scale inefficiency in four-eye sleeper aquaculture in Nghia Hung district.

The total quantity of excess inputs used by all inefficiency farms in the sample is presented in Table 6.2. This criteria implies that all inefficiency farms could save their used inputs by proportionally reduction input used if they increase their productivity to efficiency level get by frontier farms. Table 6.2 shows that all inefficiency farms of 44 farms under CRS approach could saved total inputs used as area, total working hours, total seed cost, total feed cost and total other cost by 122,245 m^2; 31,388 hours; 1,226,052 thousand VND; 757,389 thousand VND and 139,738 thousand VND, respectively while keep unchanging their output.

Similarly, for case of VRS all inefficiency farms of 36 farms also could reduce their input used without reducing their output. From Table 6.2 below, total excess inputs used of area and total working hours were 97,391 m^2 and 21,928 hours, respectively. In term of total seed cost, total feed cost and total other cost, the total excess input used were 932,720 thousand VND; 531,901 thousand VND and 109,699 thousand VND, respectively.

Table 6.2: Available saved inputs by all inefficiency farms under CRS and VRS

Saved inputs	Area (m2)	Total working hours (hours)	Total seed cost (1000 VND)	Total feed cost (1000 VND)	Total other cost (1000 VND)
Total input used by all farms	588,400	137,220	7,593,675	3,726,000	484,200
Total saved input: CRS	122,245	31,388	1,226,052	757,389	139,738
Total saved input: VRS	97,391	21,928	932,720	531,901	109,669

Source: Field survey.

Table 6.3 indicates total input slack for some farms. There may also be non-proportional input reduction available for some frontier farms or best practice farms in the sample observations. This issue means that some frontier farms or efficiency farms could reduce their non-proportional inputs used or non-radial reduction while keep being efficiency farms. This non-proportional reduction can be seen as input slack. The problem arose because of the sections of the piece-wise linear frontier that run parallel to the axes (Coelli et al., 2005).

From Table 6.3 below, the total input slack of area and working hours were 37,962 m^2 and 11,395 hours, respectively under CRS approach. While under VRS approach, these numbers were 31,020 m^2 and 7,107 hours, respectively. For total seed cost, feed cost and other cost, the total input slack of them were 218,907 thousands VND, 251,505 thousands VND and 66,462 thousands VND, respectively under CRS. But, there was slight difference occurrence when applying VRS, the total amount of input slack were 202,774 thousands VND, 199,599 thousands VND and 54,153 thousands VND, respectively.

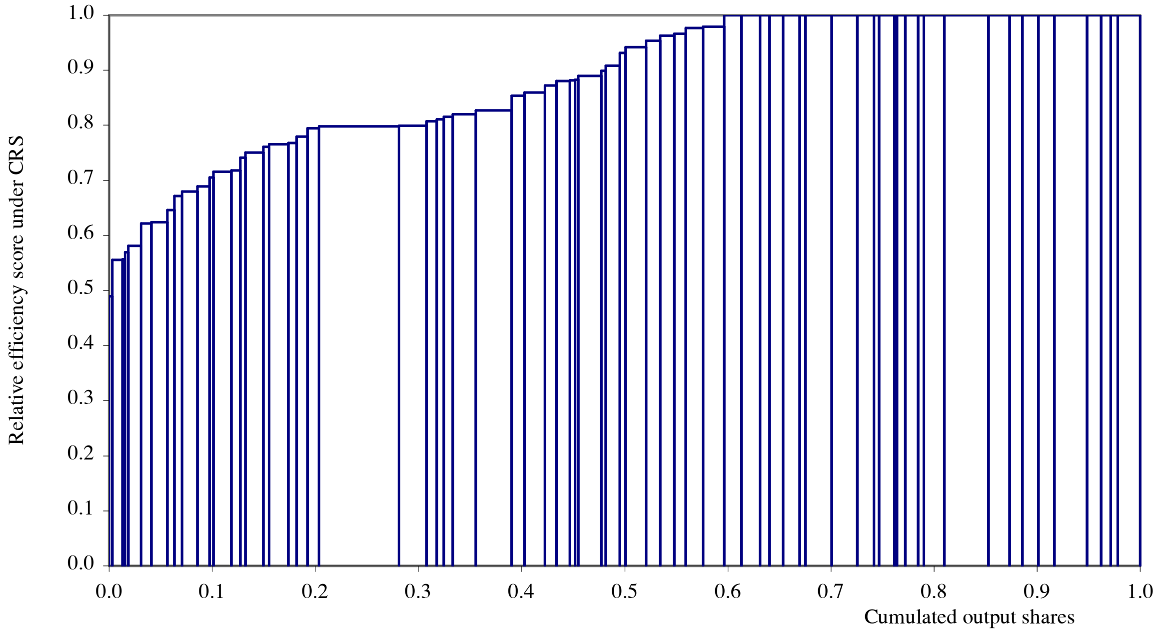
Table 6.3: Total input slack under CRS and VRS

Input slack	Area (m2)	Total working hours (hours)	Total seed cost (1000 VND)	Total feed cost (1000 VND)	Total other cost (1000 VND)
Total inputs used by all farms	588,400	137,220	7,593,675	3,726,000	484,200
Total input slack: CRS	37,962	11,395	218,907	251,505	66,462
Total input slack: VRS	31,020	7,107	202,774	199,599	54,153
Slack as of total resource: CRS	6.5%	8.3%	2.9%	6.8%	13.7%
Slack as of total resource: VRS	5.3%	5.2%	2.7%	5.4%	11.2%

Source: Field survey.

In order to have more comprehensive about individual farm technical efficiency related to their output, the results of TE under both CRS and VRS are presented in more detail individually in Figure 6.1 and Figure 6.2 below. The efficiency scores in the range between zero and one are measured along the vertical axis and each histogram represents an individual farm with the width of the histogram proportional to its share of total output production. The Figure 6.1 and Figure 6.2 show the distribution of TE under CRS and VRS where the TE were sorted by increasing efficiency.

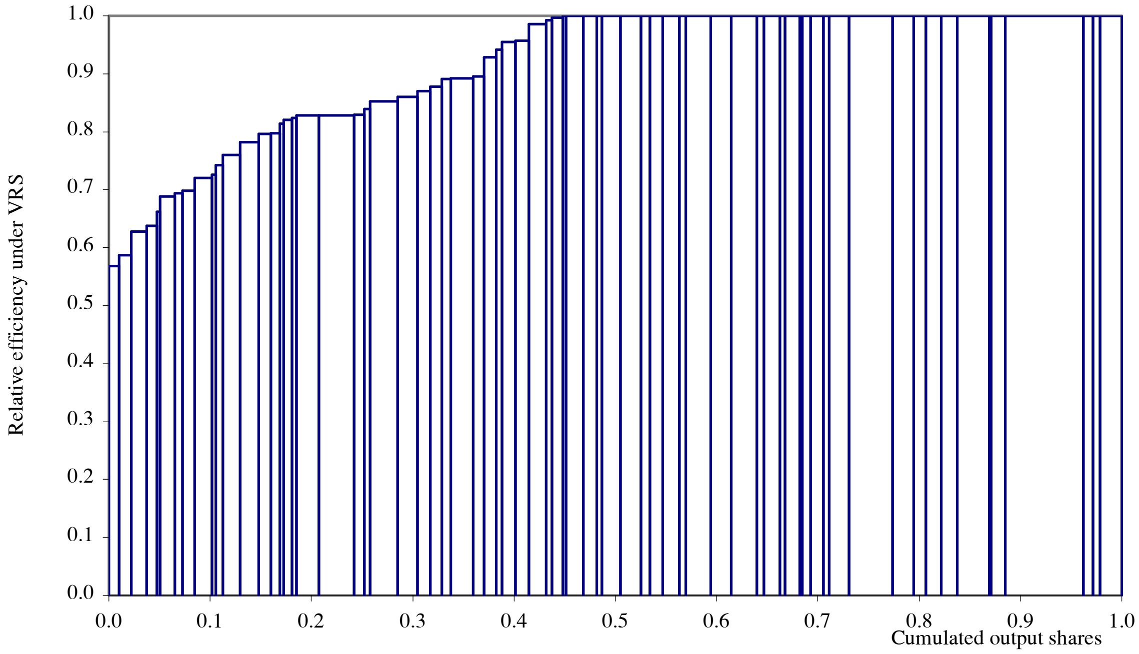
When specifying CRS, the Figure 6.1 reveals that more than 40% of total output production were produced by efficiency farms. The largest total output production farm was not TE farm, and its TE was about 80 percent.



Source: Field survey.

Figure 6.1: Salter diagram: Relative total production and TE under CRS

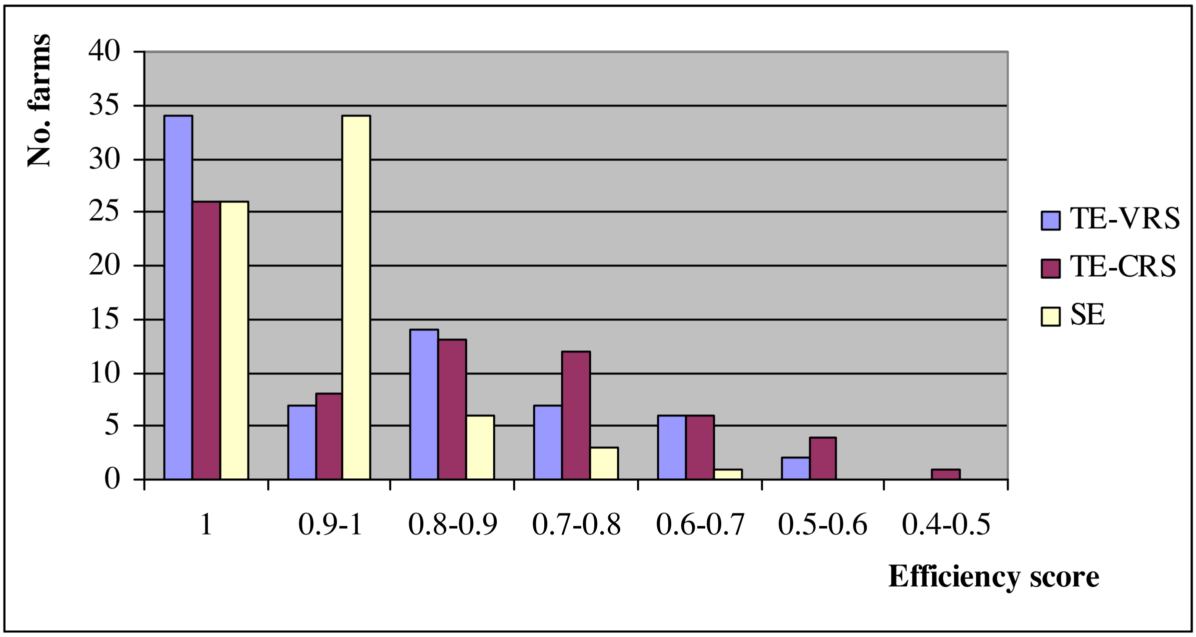
When specifying VRS the picture changes considerably, firstly the largest total output production farm was TE farm and the second largest ones was also TE farm. The second is that it was more than 55% of total output production were produced by farms being 100% efficiency and the large total output production farms being TE was dominant.



Source: Field survey.

Figure 6.2: Salter diagram: Relative total production and TE under VRS

The Figure 6.3 and Table 6.4 present distribution range of technical and scale efficiency score under CRS and VRS. In the case of CRS evaluation, the technical efficiency score were bounded from 0.4 to 1 of score in which the number of farms get score from 0.6 to 0.9 was 39, mainly. And only 5 farms out of 70 farms had score ranged from 0.4 to 0.6, accounted for 7 percent in total. Similarly, under VRS evaluation the technical efficiency score varied between 0.5 to unity in which most of farms gained efficiency level from 0.6 to 1, accounted for 68 out of 70 farms in total or approximately to 97 percent.



Source: Field survey.

Figure 6.3: Distribution of technical and scale efficiency score

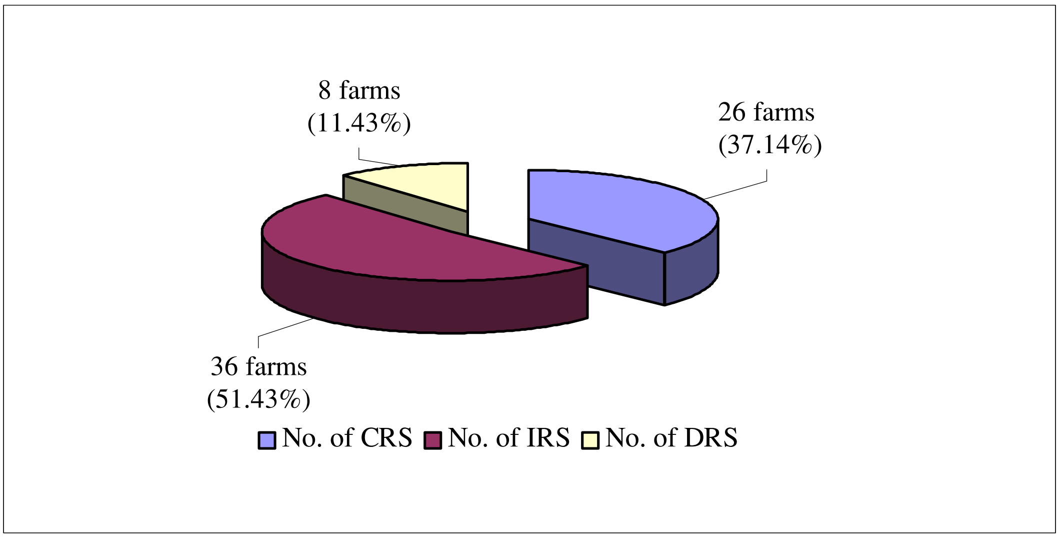
Besides, the scale efficiency score can be seen rather high with bounded range from 0.6 to 1 of score. The majority of scale efficiency score distributed from 0.7 to unity of score with 69 out of 70 farms in sample, accounted for more than 98 percent in which 34 farms reached scale efficiency score from 0.9 to 1 accounted for 48 percent and 6 out of 70 farms accounted for 8 percent reached efficiency score from 0.8 to 0.9 of score. Merely, there were only 4 farms get scale efficiency score from 0.6 to 0.7. As can be seen in the Table 6.4 below.

Table 6.4: Distribution of technical and scale efficiency score

TE score	TE-VRS (No. farms)	%	TE-CRS (No. farms)	%	SE (No. farms)	%
1	34	48.57	26	37.14	26	37.14
[0.9-1)	07	10.00	08	11.43	34	48.57
[0.8-0.9)	14	20.00	13	18.57	06	08.57
[0.7-0.8)	07	10.00	12	17.14	03	04.29
[0.6-0.7)	06	08.57	06	08.57	01	01.43
[0.5-0.6)	02	02.86	04	05.71	00	00.00
[0.4-0.5)	00	00.00	01	01.43	00	00.00
Total	**70**	**100**	**70**	**100**	**70**	**100**

Source: Field survey.

The Figure 6.4 results express return to scale of farm. The empirical results show that, there were 26 farms out of 70 farms were operating at constant return to scale accounted for 37.14% in total. This result means that if these 26 farms increase or decrease their proportionally used input will lead to increase or decrease output level by the same amount of increase or decrease of input, respectively. In addition, the number of farms had increasing return to scale was 36 farms in total sample, accounted for 51.43%, it means that if a proportionate increase inputs leads to a more than proportionate increase in output production. While the minority of 8 farms out of 70 farm in the total had decreasing return to scale, accounted for 11.43%, it also implies that if a proportionate increase in all inputs results in a less than proportionate increase in output production.



Source: Field survey.

Figure 6.4: The results of return to scale

In general, technical efficiency of four-eye sleeper poly-culture in Nghia Hung district, Nam Dinh province could be improved by using appropriately inputs like best practices farms in the sample and adjusting production scale to become optimal scale farms.

6.1.2. Technical and scale efficiency by pond size

In order to examine how efficiency scores vary with pond size, the pond size in the sample were classified into 3 size categories after running DEA model under CRS and VRS this can be seen in Table 6.5. Following paragraph presents technical and scale efficiency of three pond sizes.

Table 6.5: Technical efficiency under CRS and VRS according to farms size

Farm size (m^2)	**Total no. farms**	**Mean TE**			**Min TE**			**No. efficiency farms**		**No. scale efficiency**
		CRS	VRS	SE	CRS	VRS	SE	CRS	VRS	
Area ≤ 5000	24	0.8125	0.8927	0.9067	0.4893	0.6623	0.5563	5	8	5
5000 <Area<10000	21	0.9351	0.9503	0.9839	0.6218	0.6377	0.8106	13	15	13
Area ≥ 10000	25	0.8548	0.8715	0.9815	0.5552	0.5687	0.7985	8	11	8

Source: Field survey.

Looking at the Table 6.5 above, the technical efficiency farm of the smallest pond size group had technical efficiency score in both case CRS and VRS were 0.8125 and 0.8927, respectively. The number of farms got fully technical efficiency under CRS and VRS was 5 and 8 farms, respectively. The scale efficiency score of this category was 90.67% with 5 scale efficiency farms.

In the medium size pond group from 5000 m^2 to 10,000 m^2, the technical efficiency under CRS and VRS were greatest comparing to other pond size groups, with level score of 93.51% and 95.03%, respectively. Moreover, the number of fully scale efficiency farm in this group was 13 farms out of 21 farms in total. Meanwhile, the number of technical efficiency farm based CRS and VRS approach was 13 and 15 farms, respectively.

Finally, the largest size pond category got efficiency score under CRS was 85.48% while this index was 87.15% for this pond size group under VRS approach. The number of farms got fully technical efficiency under CRS and VRS, and scale efficiency were 8, 11 and 8 farms, respectively.

In summary, under both CRS and VRS approaches the average technical efficiency farms as well as scale efficiency of medium size group is higher than other groups. Following medium size group, the TE score under CRS of the largest pond size group was 85.48%, its score was higher than the smallest pond size group's score but less than the medium pond size group's score. Conversely, under VRS approach, TE of the smallest pond size group was higher than the medium pond size group. The highest SE belongs to medium pond size then following were largest and smallest ones, respectively. This is also true for case of the number of fully efficiency farm it means that the number of farm get fully TE of medium pond size is highest following largest and smallest pond size ones.

In order to compare mean of technical efficiency score between pond size groups, some tests were implemented. The question is that there is equality technical efficiency in average between different pond size groups. To test this hypothesis, ANOVA F-tests were used for testing by using Microsoft Excel and its results are presented in Table 6.6, Table 6.7 and Table 6.8.

Null hypothesis H_0: There are no differences in the average technical efficiency under CRS approach between three farm size groups.

Table 6.6: Mean of technical efficiency scores between different pond size group under CRS and F-test results

Farm size (m^2)	No. of farms	Technical efficiency (CRS)
Area ≤ 5000	24	0.8125
5000 <Area<10000	21	0.9351
Area ≥ 10000	25	0.8548
$\mathbf{F}_{\text{Critical}}$		3.134
$\mathbf{F}_{\text{Value}}$		4.433
$\mathbf{P}_{\text{Value}}$		0.016

Source: Field survey.

The results of the F-test show that the equality of means for all three pond sizes for TE under CRS is rejected at the 5% significance level. As can be seen that $F_{\text{Value}} > F_{\text{Critical}}$ at $\alpha = 0.05$ significance level or $P_{\text{Value}} = 0.016$ less than $\alpha = 0.05$. Therefore, the null hypothesis is rejected at $\alpha = 0.05$ significance level. It can be interpreted that there are statistically differences of average technical efficiency between pond size groups under CRS approach.

Null hypothesis H_0: There are no differences in the average technical efficiency score under VRS approach between three farm size groups.

Table 6.7: Mean of technical efficiency scores between different pond size group under VRS and F-test results

Farm size (m^2)	No. of farms	Technical efficiency (VRS)
Area ≤ 5000	24	0.8927
5000 <Area<10000	21	0.9503
Area ≥ 10000	25	0.8715
F $_{\text{Critical}}$	2.384	
F $_{\text{Value}}$	2.438	
P $_{\text{Value}}$	0.095	

Source: Field survey.

For TE under VRS, the equality of the means TE is rejected at the 10% significance level as magnitude of F_{Value} is greater than its F_{Critical} at 10% significance level or $P_{\text{Value}} = 0.095$ is less than $\alpha = 0.1$. Thus, the null hypothesis is rejected at $\alpha = 0.1$. It means that there are statistically differences of mean TE between groups under VRS approach.

Null hypothesis H_0: There is equality in mean of scale efficiency between three farm size groups.

Table 6.8: Mean of scale efficiency scores between different pond size groups and F-test result

Farm size (m^2)	No. of farms	Scale efficiency
Area ≤ 5000	24	0.9067
5000 <Area<10000	21	0.9839
Area ≥ 10000	25	0.9815
F $_{\text{Critical}}$	4.937	
F $_{\text{Value}}$	10.029	
P $_{\text{Value}}$	0.0002	

Source: Field survey.

The results of the F-test are presented in the Table 6.8 above. The results show that equality of the mean scale efficiency is also rejected at level of 1% significance as the value of F_{Value} is greater than its F_{Critical} or $P_{\text{Value}} = 0.0002$ is less than $\alpha = 0.01$. This result indicates that average SE scores are statistically differences between all of three pond sizes at 1% significance level.

6.1.3. Super-efficiency results

The results of input orientated super-efficiency DEA model under CRS and VRS are presented in Table 6.9. The maximum super efficiency score under CRS was 2.0 while minimum one was only of 0.489, these numbers show considerable various range among farms. Similarly, in the case of VRS, the super-efficiency score were bounded from 0.4 to 5.0. From Table 6.9 can be seen that when super efficiency DEA models were applied allow some efficiency farms in CCR (1974) and BCC (1984) models got score more than unity, it means that efficiency farms can increase their input usage by amount equal to its super-efficiency score minus one and then still being efficiency farms within the technology defined by other farms in the sample. In fact that, the number of farms captured super-efficiency under CRS and score higher than unity were equal to the number of fully technical efficiency farms in CCR (1974) and BCC (1984), respectively.

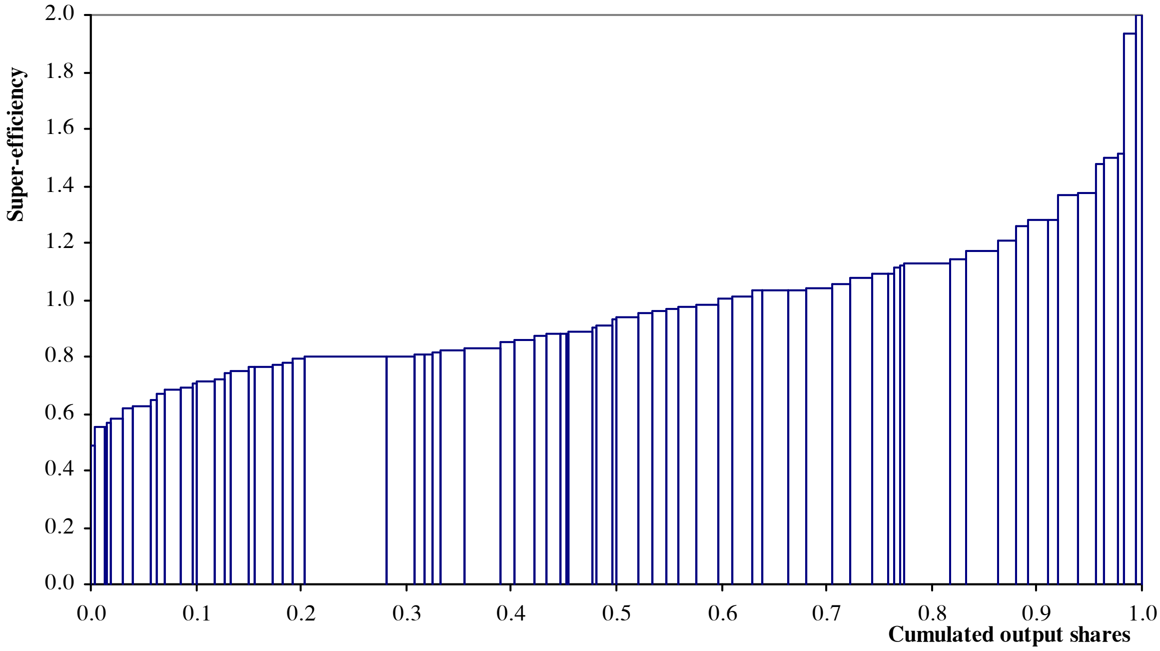
Table 6.9: Distribution of super-efficiency score under CRS and VRS.

Super-efficiency score	**CRS**		**VRS**	
	No. Farms	Percentage (%)	No. Farms	Percentage (%)
[0.4-0.6)	5	0.071	2	0.029
[0.6-0.8)	18	0.257	13	0.186
[0.8-1.0)	21	0.300	21	0.300
[1.0-1.2)	15	0.214	14	0.200
[1.2-1.4)	6	0.086	8	0.114
[1.4-1.6)	3	0.043	2	0.029
[1.6-1.8)	0	0.000	2	0.029
[1.8-2.0)	2	0.029	3	0.043
[2.0-5.0)	0	0.000	4	0.057
Infeasible	0	0.000	1	0.014
Mean	0.955			
Std Deviation	0.292			
Minimum	0.489			
Maximum	2.000			

Source: Field survey.

Moreover, when applying super-efficiency models not only efficiency score of farms can be calculated but also its results give criteria to rank efficiency farms based on their super-efficiency score with attribute that the higher super-efficiency score, the better ranking. Under CRS approach, DMU29 was best efficiency farm with highest score of 2.0, following were DMU41, DMU20, DMU3 and so forth. In contrast, DMU4 was lowest super-efficiency score and can be seen worst performance farm with only 0.489 of super-efficiency score (Appendix 6.4).

To illustrate the relationship between large, small producers in term of total output production and super-efficiency score, Salter diagram of Figure 6.5 presents this relationship. From the Figure 6.5 below, it would be that highest super-efficiency score farm was not the largest producer in term of total output production and vice versa. Interestingly, the highest super-efficiency score was belong to small producer with 2.0 score. While the largest producer only got about 0.8 of efficiency score.



Source: Field survey.

Figure 6.5: Super-efficiency and relative total production

Beside, when VRS approach was applied, the rank and reference sets had been changed. The best efficiency farm was DMU37 with super-efficiency score of 4.286 and following were DMU10, DMU31, DMU29 and so forth (Appendix 6.5). It is remarkable that it is infeasible to rank DMU53 with input orientation super-efficiency under VRS model that proposed by Andersen and Petersen (1993) as this farm had at least one output strictly larger than a convex combination of that output among all farms in the reference set (Lovell and Rouse, 2003). For more detail of ranking and reference sets, the Appendix 6.4 and Appendix 6.5 provided whole picture of ranking and reference sets.

6.2. Regression analysis results

6.2.1. Test for misspecification model (Ramsey-Reset test)

The adequacy of specified model was tested by using RESET test. The RESET stands for "*Regression Specification Error Test*" and was proposed by Ramsey (1969). The fitted terms are the powers of the fitted values from the original regression, starting with the square or second power.

The RESET test is based on an augmented regression and it is an F tests whether the coefficients on the new regressors are zero with null hypotheses of the RESET test. Rejection of null hypothesis implies that the original model is inadequate and can be improved. In contrast, a failure to reject null hypothesis says the test has not been able to detect any misspecification. The F-test compares both regressions, the original one and the Ramsey's auxiliary one with F distribution with (m, n-m-k) degrees of freedom is

$$F[m, n-m-k) = \frac{[R_1^2 - R_0^2]/m}{[1-R_1^2]/[n-m-k]}$$

R_0^2 is the determination coefficient of the original linear model regression;

R_1^2 is the determination coefficient of the Ramsey's auxiliary regression;

n is the sample size, m is additional regressor and *k* is number of parameters in the Ramsey's model.

Table 6.10: Test for error specification (Ramsey-Reset test)

Ramsey-RESET test	**P-value**
RESET(2), F with DF1 = 1 and DF2 = 60	0.1442
RESET(3), F with DF1 = 2 and DF2 = 59	0.1262
RESET(4), F with DF1 = 3 and DF2= 58	0.1132

Source: Field survey.

From results table above, as the estimated p-values are more than 0.05, the null hypothesis of the coefficients on the new regressors are zero is not rejected by this test or no misspecification is not rejected then we can state that the estimated model is adequate.

6.2.2. Test for heterocedasticity

When variance for all observations are not the same it can be seen heteroskedasticity existed Heteroskedasticity is often encountered when using cross-sectional data (Hill et al., 2007). In order to detect heteroskedasticity there are several types of test have been suggested including informal and formal type.

White test was used in this research to test of the null hypothesis of homoscedasticity existence. The White test results is presented in Table 6.11 below.

Table 6.11: Test for Heteroskedasticity

Heteroskedasticity Test: White			
F-statistic	1.289404	Prob. F(8,61)	0.2659
Obs*R-squared	10.12499	Prob. Chi-Square(8)	0.2564

Source: Field survey.

From the results above, as P-value 0.2564 is greater than $\alpha = 0.05$ level of confidence. Thus, the null hypothesis of homoscedasticity is not reject and then we conclude that there is no the existence of heteroscedasticity in the sample data.

6.2.3. Ordinary least squares results

Ordinary least squares (OLS) estimates of the parameters of the model are shown in Table 6.12. The analysis results of R^2 value equal to 0.438 shows that the independent variables used in the model were able to explain about 43.8 percent of the variation in technical super-efficiency by the variation in farm operator characteristics, stocking density and their ability to access institution/public good.

Moreover, the Table 6.12 shows that the education level, experience year of four-eye sleeper poly-culture farmers, their accessing ability to extension services such as the number of time attending to training course, the feed ratio index and the differences in fingerling density were significant variables affecting super-efficiency of the whole farms in the study area. Conversely, the age of farmer, the stocking density of tiger shrimp per square meter of pond area and the debt ratio had no explanatory effect on technical super-efficiency.

Table 6.12: Parameter estimates and standard error of Ordinary least square model

Variable	Estimated coefficient	Std. Error	P value
Intercept	0.638422	0.195195	0.0018
Operator characteristic			
AGE	-0.00373	0.002991	0.2173
EDU	0.03269	0.015337	0.0371*
EXP	0.015366	0.008317	0.0695**
Stocking density			
DENF	0.024164	0.012754	0.0629**
DENS	-0.00444	0.008101	0.586
FEED	-0.00366	0.001787	0.0448*
Institutions/public goods:			
TRAIN	0.022774	0.010802	0.0391*
DEBT	0.140389	0.116815	0.2341
R^2 = 0.439			

Source: Field survey.

* *Statistically significant at the level of 5%*

** *Statistically significant at the level of 10%*

Individually, the results from the Table 6.12 indicates that in the category of operator characteristic, only age of farmer variable had not statistically significant impacted on super-efficiency, the sign of this explanatory variable had negatively influence on technical efficiency. Conversely, the variable of education and experience level had statistically significant impacted on super-efficiency at the 5 percent and 10 percent level, respectively. Both coefficient of education and experience variables were positively sign impact on technical efficiency and the results mean that if a increase in education and experience of farmer would increase technical efficiency of four-eye sleeper poly-culture.

It is regarded that the higher education and experience of farm operator will lead to increase level of technical efficiency of farming, this can be explained by increasing the education and experience level of farmer may lead to broaden knowledge of farmer, and help farmer easily access and familiar to modern technology, updated information, having more real practice in tackling as well as treating with fish disease and so forth and finally then may result in better performance of technical efficiency in farming. This empirical result is consistent with the expected result that increasing of education level may lead to increase of technical efficiency of four-eye sleeper poly-culture in this study area.

Interestingly, it is found that fingerling density stocking was statistically significant at 10 percent impacted on technical efficiency. This variable had positive influence on technical efficiency indicates that increasing stocking density of fingerling may lead to increase technical efficiency. This result can be explained that four-eye sleeper density in sampled households may not be reared at optimal density, the current stocking density in the sample observation may be less than optimal density. Thus the density can be increased while being technical efficiency. It can be stated that fingerling stocking density was quite low while water area was so large. Otherwise, as mentioned above that the cost in farming four-eye sleeper require much invested capital spending on seed and feed cost, especially. Therefore, most of farmer did not have enough desirable capital to invest in seed and feed cost in order to release desirable density of fingerling. A caution with this results that it is not true when fingerling density go up to infinity will lead to technical efficiency higher and higher. Thus, an issue arise in this finding is that how many maximumal stocking density of fingerling per square meter is appropriate while still maintains technical efficiency when farmer would like to increase their stocking density of fingerling. It is suggested that further study should focus on this finding.

In contrast, tiger shrimp density per square meter variable had positively influence on technical efficiency but no statistically significant.

Feed variable is expected negatively impact on technical efficiency, and consequently, this empirical result had negative influence technical efficiency and statistically significant at 5 percent level. The results indicate that increasing feed cost per a kilogram of output lead to decrease technical efficiency.

Finally, the variables of training course attendances and debt ratio regarding as extension service from local authorities had effect on technical efficiency of selected household in sample. Really, explanatory variable of train measured in the number of times attending to training course holding by local government had positive influence technical efficiency and statistically significant at level of 5 percent. This result implies that increase the number of times attending to training course will help farmer increase their technical efficiency farming. Meanwhile, debt ratio was not found statistically significant effect on technical efficiency.

7. Discussions and conclusions

This study estimated technical and scale efficiency of four-eye sleeper poly-culture in Nghia Hung district, Nam Dinh Province, Viet Nam by using data envelopment analysis approach. The result of estimated super-efficiency score was used as dependent variable in regression analysis of which farm operator characteristic, stoking density and ability to access institution and public good were regarded as exogenous explanatory variables.

Findings of the research showed that the surveyed farms under the assumption of constant returns to scale (CRS), the technical efficiency was 0.844 on average ranged from minimum of 0.4893 to maximum of unity. Estimated technically efficient under the assumption of variable returns to scale (VRS) was 0.9024 with TE-VRS ranged between 0.5687 and unity. And scale efficiency was 0.9566 with minimum score of 0.5563 and maximum of unity (Table 6.1). Minimum and maximum values of efficiency score showed considerable variability among farms. Mean technical efficiency under CRS suggested that the inputs used by poly-culture farms potentially can be reduced by 16% while producing the same level of output. When VRS was applied, many farms had a higher level of VRS technical efficiency, 0.9024 on average, it means that all farmers can reduce potentially by 10% their used input in producing while keep unchanged their produced output. The difference between VRS and CRS technical efficiency scores means that scale inefficiency was the main cause of the CRS technical inefficiency.

Moreover, the individually analysis indicate that there were 26 farms out of 70 farms in total accounted for 37% farms were constant return to scale or operating at optimal scale and the others were increase return to scale and decrease return to scale of 36 and 8 farms, respectively. An other ways, there were 36 farms in total should expand their production scale to improve their productivity since if these farms increase their input used level by 1% will make their outputs increase greater than 1% unit of output. In contrast, there were 8 farms in total accounted for 11.4% in total should not expand their production scale since if any farm in these decreasing return to scale increase their input used by 1% will make their output produced increase by less than one percent.

Besides, the results of the ANOVA F-tests for whether the existence a impact of pond size on the efficiency showed that the equality of means for all three pond size groups for technical efficiency under CRS assumption was rejected at the 5% significance level.

Under CRS approach, the farms in the medium size group: farm size from 5000 m^2 to 9000 m^2 had the highest average technical efficiency score then following was largest farm size: farm size greater or equal to 10,000 m^2, and the least mean TE was smallest farm size group.

Otherwise, under VRS approach, the farms in the mediate size group still was most TE in average, the second and the last ones were the smallest farm size groups and the largest farm size groups, respectively. Moreover, the results of F tests indicated that there had statistically significant difference between farm size groups in term of mean technical efficiency at 10% significant level. Tests for equality of the mean scale efficiency was rejected at 1% significant level thus there was statistically difference between mean scale efficiency among these farm groups. The smallest size group achieved the smallest scale efficiency score while the mediate size group got the highest score and the medium size group caught mediate score. This results of study implies that farm size area should be limited at given level and appropriate area so that farmer can control disease spread-out if it happen, and monitor input used as well as water quality easier.

In regression analysis stage, the results showed that almost 43.8 percent of the variance in technical super-efficiency was explained by the variance in farm operator characteristics, stocking density and ability to access to extension services of training course and capital source. The education level of household head had positively influence technical efficiency indicates that the higher education level of farmer, the more efficiency that farmer will get. This result confirmed results of some earlier studies, which suggested a positive relationship between schooling year and efficiency as Cinemre (2006); Dey et al, (2000); Chiang et al. (2004). Moreover, the experience of farm operator measured by the years of farming activities had statistically positive effects on technical efficiency indicates that the more experiences the farmers have in aquaculture, the more efficiency those farms will have. Similar results were suggested by Cinemere (2006); Kaliba and Engle (2006), Chiang et al., (2004); Den et al., (2007); Au (2009) and Hanh (2009).

The significant positive relationships were also found between technical efficiency and stocking density of fingerling per square meter. This finding implies that the higher stocking density of fingerling per square meter, the better technical efficiency those farm will gain but this one should be interpreted with caution. As can be seen there might be an optimal stocking density higher than the present level of stocking density. Therefore, further research should find out optimal stocking density.

Feed to output ratio was also found negatively effect to technical efficiency and had statistically significant at 5% level. Being less feed cost to output ratio will lead to increase super-efficiency. Otherwise, it can be stated that increase the feed ratio will make super-efficiency decrease.

Technical efficiency was positively influenced by the number of attending to training course that was held by local government. This relationship was found statistically significant at 5% level. Increasing training course to learn aquaculture skill, modern technology and scientific method in farming might lead to better performance of super-efficiency. The result showed that increasing the number of time attending to training course could enable to improve technical efficiency. Therefore, this institutional service should be held and regarded by local government or responsible institutions.

In this study, there was a positive sign relationship between technical efficiency and debt ratio but total debt to total expenses ratio had not been found statistically significant. It means that farmer's debt regarding as their capital capacity was not influenced to their performance of efficiency. This finding was not consistent with some earlier studies as Cinemre et al., (2006), Helfand and Levine (2003), and Hanh (2009) these authors found statistically significant relationship between credit and performance of technical efficiency. Thus result related to issue in this study should be investigated further for future study.

Based on the case study, the results of technical efficiency stage indicates that the overall technical efficiency could be increase by 16% or input used could reduce by 16 percent while unchanging their output level. There were also 44 farms should adjust their production scale to become optimal scale farms then efficiency could be increased. The observed technical inefficiency can be eliminated by eliminating the problem of increasing return to scale and decreasing return to scale to be optimal scale producing and by adapting to the best practices of efficiency farms.

Moreover, with quite high of pure technical and scale efficiency, 0.9024 and 0.9566 (Table 6.1), respectively show that the technology production of four-eye sleeper poly-culture was quite efficiency but their input used can be reduced by almost 10 percent while maintaining their recent output. This farming pattern should be paid attention for future developing as well as being as reference for other provincial areas. Furthermore, from finding results of ranking efficiency farms, there were some less super-efficiency score farms should apply and refer to their benchmark or reference sets for aquaculture activities. However, applying input orientation of super-efficiency under VRS arose infeasible problem, thus to get fully ranking farms, more advance model should be explored.

The results investigating relationship between technical efficiency and exogenous explanatory variable of personal characteristic, stocking density and extension service as training course, debt show that educational and experience of farmer had positive statistically significant impacted on super-efficiency. Hence, sharing experience in four-eye sleeper poly-culture should be done to improve the knowledge of farmers, and in order to learn aquaculture technique among farmer also. Besides, enhancing education level for farmer is also better in order to capture more efficiency farming.

Additionally, stocking density of fingerling had positive relationship influence super-efficiency, this implies that most farms should increase the fingerling stocking density to the optimal level to improve their technical efficiency. Due to the limitation of time and effort, this study could not show how many fingerling per square meter is appropriate density. Therefore, further study in the future is recommended for investigating this issue. From the finding results, the goal of reducing feed cost to output ratio is also recommended to increase efficiency for farmer. Finding fresh stable source of trash-fish as well as nearby farm could be a one of appropriate ways to get this goal.

The results of this research also suggest that technical efficiency could be improved if farmer have chance to participate training course more frequently and have chance to access capital source even if the debt variable was not found statistically significant but it is in line with high required capital amount in context of farming activities of farmer since mentioned above, stocking density had statistically impacted on technical efficiency thus a increase fingerling density to get more efficiency require these farmers more capital for buying seed while their budget is limited. Therefore, outsource requirement as capital sources is necessary for improving efficiency poly-culture in Nghia Hung district, Nam Dinh province, Vietnam.

8. References

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9. Appendices

Appendix 2.1: General fisheries information in Nam Dinh province

Year	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Total amount fisheries (tons)	15905	19143	24557	28976	38384	43946	46850	51609	55071	60231	60118	65254	71555	76195	-
Total amount aquaculture (tons)	6562	9723	12897	13497	16866	17627	20089	22609	22714	28074	28419	33571	37547	39682	-
Total amount harvest (tons)	9343	9420	11660	15479	21518	26319	26761	29000	32357	32157	31699	31683	34008	36513	-
Total farmed fish (tons)	6488	5692	9403	9594	10392	10088	11260	12623	11262	13620	15276	17268	19171	21125	-
Total aquaculture area (ha)	9533	11016	9758	9910	11017	11600	12300	12700	13200	13100	14000	14200	15200	15300	-
Aquaculture productivity (tons/ha)	0.6883	0.8826	1.3217	1.3620	1.5309	1.5196	1.6333	1.7802	1.7208	2.1431	2.0299	2.3642	2.4702	2.5936	
Total offshore vessel (vessel)						50	50	56	56	50	23	78	89	111	-
Total capacity of offshore vessel (1000 CV)						16.6	15.5	17.5	18.7	16.6	8	12.8	14.6	23	-
Total exported value (million USD)					4.2	9.6	14.2	20	25.19	30.1	-	-	-	-	-
Total amount of four-eye sleeper (tons)*													500	700	715

Source: GSO. Available from http://www.gso.gov.vn/default.aspx?tabid=430.

(*) Source: Agriculture and rural development Department of Nam Dinh.

Appendix 3.1: Technical efficiency in aquaculture summary

No	Authors	Aquaculture activities	Country	Methodology	Mean efficiencies (%)	Factors effected on technical efficiency
1	Sharma, K. R. and P. S. Leung, (1998)	Carp production	Nepal	SPF	TE (213 intensive and 73 extensive): 77	Regular fish, water, and feed management activities
2	Sharma et al., (1999)	Fish poly-culture	China	DEA	TE: 83; AE: 87 and RE or EE : 74	Farm size
3	Sharma et al., (1999)	Carp production	Pakistan	SPF	TE (semi-intensive/intensive): 67.3 and TE (extensive): 56.1	Seed, labor, and organic manure
4	Iinuma et al., (1999)	Carp ponds	Malaysia	SPF	TE: 42 (intensive/ semi-intensive : 57, extensive: 24)	Age, ownership, intensive culture
5	Dey et al., (2000)	Tilapia ponds	Philippines	SPF	TE: 83	Farm area, education and age of the farmers
6	Chiang et al., (2004)	Milkfish production	Taiwan	SPF	TE: 84	Fresh water, location, education, experience labor
7	Cinemere et al., (2006)	Trout farms	Turkey	DEA	TE: 82, AE: 83, CE: 68	Pond tenure, farm ownership, experience, education, extension service, off-farm income, credit availability

No	Authors	Aquaculture activities	Country	Methodology	Mean efficiencies (%)	Factors effected on technical efficiency
8	Kaliba and Engle, (2006)	Catfish farms	Arkansas	DEA (weight restricted)	TE: 57, AE: 67, CE: 49	Experience, extension contacts
9	Alam and Murshed-e-Jahan, (2008)	Prawn-carp poly-culture	Bangladesh	DEA	TE: 85; AE: 58 and CE: 49	Pond size
10	Poulomi, (2008)	Shrimp farming	India	SPF	TE: 49 (traditional pattern); TE: 61 (scientific pattern)	
11	Singh, K., et al., (2009)	Small-scale fish production	India	SPF	TE: 66	Seed quality Experience of the operators (positively effect on technical inefficiency)
12	Den et al., (2007)	Prawn farms (intensive and extensive)	Vietnam	SPF	TE: 48 (extensive), TE: 35 (intensive)	Age, experience
13	Au, (2009)	Prawn poly-culture	Vietnam	DEA (two stages approach)	TE: 91	Experience of farmers, attending times to aquaculture training course, stocking density of prawn
14	Cuong, (2009)	Intensive tiger shrimp	Vietnam	DEA	TE: 91.1	
15	Hanh, (2009)	Pangasius farms	Vietnam	DEA (two stages approach)	TE: 59.5	Farm investment, experience of household head, debt to asset ratio, debt to equity ratio

Appendix 5.1: Correlation between input, output and input

Correlation	Area : x_1	Total working hours: x_2	Total seed cost: x_3	Total feed cost: x_4	Total other cost: x_5	Output1: y_1	Output2: y_2
Area: x_1	1						
Total working hours: x_2	0.7371	1					
Total seed cost: x_3	0.7729	0.7540	1				
Total feed cost: x_4	0.7392	0.7804	0.9128	1			
Total other cost: x_5	0.5855	0.6331	0.6884	0.6700	1		
Output 1: y_1	0.7470	0.7700	0.9470	0.9123	0.6725	1	
Output 2: y_2	0.5175	0.5121	0.4943	0.4893	0.4948	0.5682	1

Source: Field survey.

Appendix 6.1: Technical and scale efficiency under CRS and VRS by pond size (area ≤ 5000 m^2)

No.	DMU Name	Area	TE:CRS	TE:VRS	SE	RTS
1	DMU1	1,440	0.8826	1.0000	0.8826	Increasing
2	DMU17	2,000	0.9318	0.9928	0.9386	Increasing
3	DMU29	2,000	1.0000	1.0000	1.0000	Constant
4	DMU32	2,000	1.0000	1.0000	1.0000	Constant
5	DMU50	2,160	0.5563	1.0000	0.5563	Increasing
6	DMU4	2,500	0.4893	0.6623	0.7389	Increasing
7	DMU9	3,000	0.8990	1.0000	0.8990	Increasing
8	DMU12	3,000	0.8159	0.8908	0.9159	Increasing
9	DMU31	3,000	1.0000	1.0000	1.0000	Constant
10	DMU40	3,000	0.9662	0.9971	0.9691	Increasing
11	DMU61	3,000	0.7058	0.8143	0.8668	Increasing
12	DMU3	4,000	0.8074	0.8297	0.9730	Increasing
13	DMU28	4,000	1.0000	1.0000	1.0000	Constant
14	DMU58	4,000	0.6720	0.7422	0.9054	Increasing
15	DMU59	4,000	0.7183	0.7976	0.9005	Increasing
16	DMU45	4,500	0.7613	0.8392	0.9071	Increasing
17	DMU8	5,000	0.6462	0.6941	0.9310	Increasing
18	DMU13	5,000	0.5696	0.7256	0.7850	Increasing
19	DMU33	5,000	1.0000	1.0000	1.0000	Constant
20	DMU42	5,000	0.7685	0.8203	0.9369	Increasing
21	DMU49	5,000	0.7798	0.8950	0.8712	Increasing
22	DMU64	5,000	0.8811	0.9417	0.9357	Increasing
23	DMU66	5,000	0.7411	0.8241	0.8993	Increasing
24	DMU68	5,000	0.9084	0.9569	0.9493	Increasing
Mean		3,650.00	0.8125	0.8927	0.9067	
Std. Deviation		1,224.73	0.1543	0.1132	0.0992	
Min		1,440.00	0.4893	0.6623	0.5563	
Max		5,000.00	1.0000	1.0000	1.0000	

Source: Field survey.

Appendix 6.2: Technical and scale efficiency under CRS and VRS by pond size (5000<area<10000)

No.	DMU Name	Area	TE: CRS	TE: VRS	SE	RTS
1	DMU34	5,400	1.0000	1.0000	1.0000	Constant
2	DMU35	5,400	1.0000	1.0000	1.0000	Constant
3	DMU16	5,600	1.0000	1.0000	1.0000	Constant
4	DMU6	6,000	0.8802	0.9282	0.9483	Increasing
5	DMU25	6,000	0.8106	1.0000	0.8106	Increasing
6	DMU30	6,000	1.0000	1.0000	1.0000	Constant
7	DMU43	6,000	1.0000	1.0000	1.0000	Constant
8	DMU65	6,000	1.0000	1.0000	1.0000	Constant
9	DMU18	6,400	1.0000	1.0000	1.0000	Constant
10	DMU7	7,000	0.9631	1.0000	0.9631	Increasing
11	DMU41	7,000	1.0000	1.0000	1.0000	Constant
12	DMU63	7,000	0.8540	0.8697	0.9820	Increasing
13	DMU46	7,500	1.0000	1.0000	1.0000	Constant
14	DMU2	8,000	1.0000	1.0000	1.0000	Constant
15	DMU10	8,000	1.0000	1.0000	1.0000	Constant
16	DMU22	8,000	1.0000	1.0000	1.0000	Constant
17	DMU55	8,000	0.8727	0.8774	0.9947	Increasing
18	DMU51	8,500	1.0000	1.0000	1.0000	Constant
19	DMU36	9,000	0.6218	0.6377	0.9751	Increasing
20	DMU56	9,000	0.6802	0.6887	0.9877	Increasing
21	DMU60	9,000	0.9541	0.9545	0.9996	Decreasing
Mean		7,086	0.9351	0.9503	0.9839	
Std. Deviation		1,241	0.1114	0.1038	0.0422	
Min		5,400	0.6218	0.6377	0.8106	
Max		9,000	1.0000	1.0000	1.0000	

Source: Field survey.

Appendix 6.3: Technical and scale efficiency under CRS and VRS by pond size (area ≥ 10000 m^2)

No.	DMU Name	Area	TE:CRS	TE: VRS	SE	RTS
1	DMU11	10,000	0.9418	1.0000	0.9418	Decreasing
2	DMU14	10,000	0.7509	0.7594	0.9889	Increasing
3	DMU19	10,000	1.0000	1.0000	1.0000	Constant
4	DMU26	10,000	0.7163	0.7203	0.9945	Decreasing
5	DMU27	10,000	0.9762	0.9860	0.9901	Increasing
6	DMU47	10,000	1.0000	1.0000	1.0000	Constant
7	DMU48	10,000	0.6891	0.6985	0.9865	Increasing
8	DMU57	10,000	0.7661	0.7820	0.9796	Increasing
9	DMU69	10,000	0.8893	0.8920	0.9970	Increasing
10	DMU70	10,000	1.0000	1.0000	1.0000	Constant
11	DMU15	11,000	0.7996	0.8528	0.9377	Decreasing
12	DMU52	11,000	0.8201	0.8278	0.9907	Decreasing
13	DMU20	12,000	1.0000	1.0000	1.0000	Constant
14	DMU23	12,000	0.9796	1.0000	0.9796	Increasing
15	DMU24	12,000	1.0000	1.0000	1.0000	Constant
16	DMU38	13,000	1.0000	1.0000	1.0000	Constant
17	DMU44	15,000	0.6239	0.6281	0.9932	Increasing
18	DMU67	15,000	0.7941	0.7965	0.9969	Decreasing
19	DMU54	17,000	1.0000	1.0000	1.0000	Constant
20	DMU5	20,000	0.8595	0.8602	0.9993	Increasing
21	DMU21	20,000	0.5552	0.5687	0.9763	Increasing
22	DMU37	20,000	1.0000	1.0000	1.0000	Constant
23	DMU39	20,000	0.5813	0.5873	0.9899	Increasing
24	DMU62	20,000	0.8273	0.8287	0.9983	Decreasing
25	DMU53	34,000	0.7985	1.0000	0.7985	Decreasing
Mean		14,080	0.8548	0.8715	0.9815	
Std. Deviation		5,708	0.1447	0.1458	0.0416	
Min		10,000	0.5552	0.5687	0.7985	
Max		34,000	1.0000	1.0000	1.0000	

Source: Field survey.

Appendix 6.4: Result of input orientation super-efficiency score under CRS and ranking

No	Ranking	Super Efficiency-CRS	Reference sets				
1	DMU29	2.000	DMU10				
2	DMU41	1.932	DMU11	DMU30			
3	DMU20	1.511	DMU10	DMU54			
4	DMU51	1.499	DMU33	DMU54			
5	DMU32	1.478	DMU33	DMU47			
6	DMU28	1.373	DMU29	DMU30	DMU47		
7	DMU35	1.367	DMU28	DMU32	DMU46	DMU70	
8	DMU54	1.280	DMU20	DMU51			
9	DMU10	1.277	DMU18	DMU31	DMU41		
10	DMU33	1.256	DMU32	DMU46	DMU51		
11	DMU46	1.209	DMU10	DMU16	DMU33		
12	DMU47	1.174	DMU10	DMU28	DMU33	DMU46	
13	DMU43	1.143	DMU24	DMU35	DMU37		
14	DMU37	1.125	DMU2	DMU24	DMU41	DMU43	DMU46
15	DMU31	1.120	DMU10	DMU16			
16	DMU65	1.116	DMU30	DMU37			
17	DMU34	1.090	DMU10	DMU20	DMU51		
18	DMU30	1.090	DMU10	DMU28	DMU37	DMU41	
19	DMU70	1.079	DMU18	DMU35	DMU41		
20	DMU19	1.055	DMU10	DMU20	DMU37	DMU41	DMU46
21	DMU22	1.038	DMU35	DMU37	DMU47		
22	DMU2	1.034	DMU37	DMU46	DMU65		
23	DMU24	1.033	DMU33	DMU37	DMU43		
24	DMU16	1.032	DMU10	DMU31	DMU46		
25	DMU38	1.009	DMU2	DMU65			
26	DMU18	1.005	DMU10	DMU35	DMU41	DMU70	
27	DMU23	0.980	DMU24	DMU35	DMU37		
28	DMU27	0.976	DMU30	DMU37	DMU65		
29	DMU40	0.966	DMU28	DMU32	DMU35	DMU47	
30	DMU7	0.963	DMU24	DMU37	DMU43	DMU46	
31	DMU60	0.954	DMU2	DMU37	DMU65		
32	DMU11	0.942	DMU28	DMU30	DMU37	DMU41	
33	DMU17	0.932	DMU32	DMU33	DMU35	DMU47	
34	DMU68	0.908	DMU22	DMU35	DMU37	DMU43	DMU47
35	DMU9	0.899	DMU10	DMU20	DMU30	DMU65	
36	DMU69	0.889	DMU10	DMU28	DMU35	DMU37	DMU47
37	DMU1	0.883	DMU32	DMU35	DMU46		
38	DMU64	0.881	DMU37	DMU65			
39	DMU6	0.880	DMU37	DMU43	DMU46	DMU47	
40	DMU55	0.873	DMU2	DMU10	DMU37	DMU65	
41	DMU5	0.860	DMU24	DMU35	DMU43		
42	DMU63	0.854	DMU2	DMU22			
43	DMU62	0.827	DMU2	DMU22	DMU37		
44	DMU52	0.820	DMU24	DMU33	DMU35	DMU37	DMU43
45	DMU12	0.816	DMU28	DMU35	DMU47		
46	DMU25	0.811	DMU41	DMU46	DMU51	DMU54	
47	DMU3	0.807	DMU32	DMU33	DMU35	DMU46	
48	DMU15	0.800	DMU28	DMU33	DMU35	DMU43	DMU47

49	DMU53	0.799	DMU28	DMU35	DMU43	DMU47	
50	DMU67	0.794	DMU30	DMU37	DMU65		
51	DMU49	0.780	DMU28	DMU35	DMU41	DMU43	
52	DMU42	0.768	DMU2	DMU37	DMU46	DMU47	
53	DMU57	0.766	DMU33	DMU37	DMU41	DMU46	DMU47
54	DMU45	0.761	DMU30	DMU37	DMU65		
55	DMU14	0.751	DMU30	DMU37	DMU47		
56	DMU66	0.741	DMU2	DMU10	DMU65		
57	DMU59	0.718	DMU22	DMU37	DMU47		
58	DMU26	0.716	DMU2	DMU10	DMU35	DMU41	DMU46
59	DMU61	0.706	DMU2	DMU10	DMU46		
60	DMU48	0.689	DMU2	DMU35	DMU46		
61	DMU56	0.680	DMU2	DMU10	DMU35	DMU46	DMU47
62	DMU58	0.672	DMU33	DMU35	DMU46	DMU47	
63	DMU8	0.646	DMU2	DMU10	DMU35	DMU46	
64	DMU44	0.624	DMU18	DMU35	DMU41	DMU46	DMU70
65	DMU36	0.622	DMU2	DMU10	DMU46		
66	DMU39	0.581	DMU30	DMU37	DMU65		
67	DMU13	0.570	DMU2	DMU65			
68	DMU50	0.556	DMU37	DMU47			
69	DMU21	0.555	DMU2	DMU46			
70	DMU4	0.489	DMU22	DMU37	DMU47		

Source: Field survey.

Appendix 6.5: Result of input orientation super-efficiency score under VRS and ranking

No	Ranking	Super Efficiency-VRS	Reference sets						
1	DMU53	infeasible							
2	DMU37	4.286	DMU53						
3	DMU10	2.207	DMU11	DMU37	DMU41				
4	DMU31	2.154	DMU1	DMU20					
5	DMU29	2.154	DMU1	DMU28	DMU30				
6	DMU1	1.954	DMU17	DMU31					
7	DMU41	1.937	DMU11	DMU25	DMU30				
8	DMU51	1.803	DMU33	DMU46	DMU54				
9	DMU54	1.676	DMU19	DMU20	DMU51				
10	DMU20	1.669	DMU31	DMU41	DMU50	DMU54			
11	DMU32	1.569	DMU1	DMU17	DMU33	DMU47			
12	DMU35	1.408	DMU22	DMU28	DMU47	DMU70			
13	DMU47	1.391	DMU22	DMU33	DMU37	DMU53			
14	DMU28	1.379	DMU29	DMU30	DMU35	DMU47			
15	DMU46	1.327	DMU33	DMU37	DMU47				
16	DMU33	1.273	DMU32	DMU46	DMU51				
17	DMU11	1.240	DMU10	DMU37	DMU41				
18	DMU43	1.208	DMU7	DMU24	DMU33	DMU35	DMU41		
19	DMU34	1.201	DMU1	DMU20	DMU32	DMU41	DMU51		
20	DMU65	1.201	DMU9	DMU10	DMU20	DMU30	DMU64		
21	DMU70	1.135	DMU10	DMU35	DMU37	DMU41			
22	DMU50	1.105	DMU1	DMU20	DMU31				
23	DMU30	1.097	DMU9	DMU10	DMU28	DMU37	DMU41		
24	DMU9	1.094	DMU1	DMU29	DMU30	DMU31	DMU65		
25	DMU24	1.067	DMU33	DMU37	DMU43				
26	DMU19	1.066	DMU10	DMU37	DMU41	DMU46	DMU51	DMU54	
27	DMU2	1.058	DMU1	DMU31	DMU35	DMU37	DMU65		
28	DMU16	1.043	DMU10	DMU31	DMU46	DMU70			
29	DMU22	1.038	DMU2	DMU35	DMU37	DMU47			
30	DMU38	1.013	DMU37	DMU65					
31	DMU7	1.012	DMU33	DMU35	DMU41	DMU43			
32	DMU18	1.008	DMU10	DMU31	DMU35	DMU41	DMU70		
33	DMU25	1.005	DMU1	DMU33	DMU41	DMU43			
34	DMU23	1.001	DMU7	DMU24	DMU35	DMU37	DMU43		
35	DMU40	0.997	DMU1	DMU28	DMU32	DMU35			
36	DMU17	0.993	DMU1	DMU32	DMU35	DMU47			
37	DMU27	0.986	DMU2	DMU30	DMU37	DMU65			
38	DMU68	0.957	DMU1	DMU2	DMU28	DMU35	DMU37	DMU43	DMU47
39	DMU60	0.954	DMU2	DMU37	DMU38	DMU65			
40	DMU64	0.942	DMU1	DMU31	DMU65				
41	DMU6	0.928	DMU1	DMU37	DMU41	DMU43	DMU46		
42	DMU49	0.895	DMU1	DMU28	DMU35	DMU41	DMU43		
43	DMU69	0.892	DMU10	DMU28	DMU30	DMU35	DMU37	DMU41	
44	DMU12	0.891	DMU1	DMU28	DMU35				
45	DMU55	0.877	DMU2	DMU10	DMU30	DMU37	DMU65		
46	DMU63	0.870	DMU1	DMU2	DMU22	DMU65			
47	DMU5	0.860	DMU7	DMU24	DMU35	DMU43			
48	DMU15	0.853	DMU35	DMU37	DMU47	DMU53			
49	DMU45	0.839	DMU1	DMU9	DMU10	DMU30	DMU65		

50	DMU3	0.830	DMU1	DMU2	DMU35	DMU46	DMU47		
51	DMU62	0.829	DMU2	DMU22	DMU37				
52	DMU52	0.828	DMU24	DMU35	DMU37	DMU43	DMU47		
53	DMU66	0.824	DMU1	DMU2	DMU31	DMU65			
54	DMU42	0.820	DMU1	DMU2	DMU22	DMU47	DMU65		
55	DMU61	0.814	DMU1	DMU2	DMU31	DMU46	DMU65		
56	DMU59	0.798	DMU1	DMU2	DMU22	DMU28	DMU30		
57	DMU67	0.797	DMU10	DMU30	DMU37	DMU65			
58	DMU57	0.782	DMU1	DMU33	DMU37	DMU41	DMU43	DMU46	DMU47
59	DMU14	0.759	DMU2	DMU9	DMU30	DMU47	DMU65		
60	DMU58	0.742	DMU1	DMU33	DMU41	DMU43	DMU46	DMU47	
61	DMU13	0.726	DMU1	DMU31	DMU65				
62	DMU26	0.720	DMU10	DMU35	DMU37	DMU41	DMU46	DMU70	
63	DMU48	0.699	DMU2	DMU31	DMU35	DMU46			
64	DMU8	0.694	DMU1	DMU2	DMU9	DMU10	DMU30	DMU41	
65	DMU56	0.689	DMU1	DMU2	DMU10	DMU35	DMU46	DMU47	
66	DMU4	0.662	DMU1	DMU31	DMU65				
67	DMU36	0.638	DMU2	DMU10	DMU31	DMU46	DMU65		
68	DMU44	0.628	DMU31	DMU35	DMU41	DMU46	DMU70		
69	DMU39	0.587	DMU2	DMU9	DMU30	DMU65			
70	DMU21	0.569	DMU2	DMU31	DMU46	DMU65			

Source: Field survey.