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Factors Affecting the Technical Efficiency Level of Inshore Fisheries in Kuala Terengganu, Malaysia

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Abstract

The objective of this study is to determine factors affecting the technical efficiency of the inshore fisheries in Kuala Terengganu. Data for the study was collected from a survey conducted between June and August 2007 where 100 fishermen in 14 villages were chosen by stratified sampling. Data envelopment analysis (DEA) and Tobit analysis were employed to determine the technical efficiency level and factors influencing technical efficiency among the fishermen. Results of the study show that, most fishing units exhibit a low degree of technical efficiency. This implies that either fishing inputs were used inefficiently or insufficient inputs were used in fishing activities. The mean technical efficiency for the sample was estimated to be 55% for the peak season and 40% for the non peak season. About 37% and 62% of the fishermen had less than 40% level of technical efficiency in peak season and non peak season respectively. Management variables (planning, staffing and controlling) and demographic variables (size of horsepower, size of family and formal education) exert positive effects on technical efficiency of inshore fisheries in Kuala Terengganu. These findings suggest that there is much room for improvement in efficiency among a large segment of the inshore fishermen. With appropriate training and using more advanced technologies, fishermen' level of technical efficiency can be raised.

Keywords:
Fishermen, Technical efficiency, Data envelopment analysis.

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INTRODUCTION

From ancient times, fishing has been a major source of food for humanity and a provider of employment and economic benefits to those engaged in this activity. The marine capture fisheries in Malaysia and in Terengganu have developed from an inshore traditional fishery to its present mix of inshore traditional and commercial, and deep-sea fishery sub-sectors. Although the bulk of the marine fish landings come from the inshore commercial and the deep sea fishery sub-sectors, the inshore traditional fishery is no less important. A number of factors are believed to have contributed to the inefficiency of the inshore traditional fishery such as vessel size, age of fishermen and vessel horsepower.

In the year 2009, the fisheries sector contributed 3.4% to the Malaysia GDP. Terengganu is one of the Malaysian state which is situated in north-eastern Penisular Malaysia and, is bordered in the east by the South China Sea. In Terengganu, production from marine captures fisheries in the year 2007 contributed 81,007 tonnes (5.86%) of the nation's fish production valued at RM 384million. It also provides employment to 8,651 (5,884 are local workers and 2767 are foreign workers) fishermen who work on 2,422 units of licensed fishing vessels. Total landings in Terengganu decreased by 16.50% from 111,394 million in 2006 to 81,007 million tonnes in 2007. The decline of capture fisheries in Terengganu is a symptom of many complex problems that have no easy solutions. In general, problems and constraints faced by small scale fisheries in most countries in the region are similar, only varying from one country or village to another in terms of local importance. In contrast to large-scale commercial fisheries, inshore fisheries are owner-operated and labor intensive, employing rudimentary technologies. Inshore fisheries harvest the sea from comparatively small vessels, powered by sail, paddles or outboard motors of limited power, have limited fishing range and generally deploy passive fishing gears that are set and later retrieved (Squire and Hj Omar, 1998). In Terengganu, about 1909 of the fishermen working on licensed vessels used traditional fishing gear and the dominant gear type used is hooks and lines.

In the Eight Malaysia Plan (2001-2005), marine fisheries achieved only 0.6% in average annual growth rate from targeted 5.9%. It means the fisheries subsector recorded a positive but slow growth rate. The measurement of efficiency has long been a subject of study for many economists and hence is of great interest to policy planners. It is important as a first step in identifying the process for resource saving and how to increase productivity. In an economy, where resources are scarce and opportunities of new technologies are lacking, efficiency study will be able to show the possibility of raising productivity by improving efficiency without increasing the resource base or developing new technologies. A firm is technically efficient if it produces a higher level of output as compared to another firm at the same level of input, Yotopoulos and Lau (1973).

The Fisheries Comprehensive Licensing Policy (FCLP) divides Malaysian fishing waters into four zones:

Zone A: 0-5 miles from shore, reserved for traditional fisheries;

Zone B: 5-12 miles from shore, for commercial fisheries that uses gear such as trawls and purse-seines below 40 GRT (Gross Registered Ton);

Zone C: 12-30 miles from shore, for commercial fisheries that uses boats above 40 GRT;

Zone C2: 30 miles from the shore and beyond, for commercial fisheries that uses boats 70 GRT and above.

This is to protect the juveniles of fish that are concentrated in the inshore waters from the intensive fishing pressure of these commercial gears. This study was focused on fishermen from Zone A only which is the vessel can go to 0-5 miles from shore and this zone only reserved for traditional fisheries such as hook and lines.

MATERIALS AND METHODS

Source of data

The data collection was carried out from June to July 2007. The data collected were based on fishing activities from January until December 2006. 14 villages in Kuala Terengganu were selected for this study. Survey respondents consisted of 100 fishermen engaged in inshore fisheries in Kuala Terengganu were chosen based on a stratified random sampling method. The 100 respondents were chosen randomly from each village using the lists of fishermen made available by Department of Fisheries DOF Terengganu officer.

A structured questionnaire was used to guide the interview with the respondents. The questionnaire covers six sections: vessels details, socio-economic and demographic profile, fishing activities, income and operation cost, activities of vessel's owner and lastly, management inventory.

Management inventory variables are based on the five management functions adapted from Hellriegel *et al.*, (2002). Management aspects included were planning, organizing, staffing, directing and controlling as follows:

Planning - Fishermen visions, objectives setting, creativity in problem solving, and ability in choosing the right alternative, as well as attention to details are indicators of their skills in planning.

Organizing - The fishermen's skills organizing are detected by their ability in delegating responsibility and accountability among their staff/workers and providing clear working procedures.

Staffing - The fishermen skill of staffing are detected by their ability in telling their workers to do the right thing, providing proper training, setting an appropriate wages and salary, evaluating workers skills, and recruiting workers.

Directing - Evaluating fishermen skills in directing is done through the structured question regarding job instruction, description and delegation as well as workers awareness of activity problems and successes.

Controlling - Evaluation of fishermen skills in controlling is done through the structured question regarding performance assessment, the extent of report utilization for fishing activities control, workers understanding of performance standard and corrective actions for control purpose.

All these aspects of management inventory are set in positive and negative questions and are arranged in such a way as to facilitate the determination of management inventory.

The data was grouped into two, peak season and non-peak season. Peak season is start from April to September which is most of fishermen go for fishing. Non-peak season is start from October to March which is called rainy season and number of trip for fishing will reduce.

Theoretical Framework

Generally, technical efficiency means that there is no waste of resources in production. Farrell (1957) explained that the concept or technical inefficiency refers to the amount by which output is less than the potential output for a given combination of inputs used in a production process. The potential output is a maximum output attainable from a given sets of inputs. A fishing vessel's technical efficiency is a measure of its ability to produce relative to the fleet's best practice frontier, the maximum output possible from a given set of inputs and production technology (Aigner *et al.,* 1977 and Meeusen and van den Broeck, 1977).

For the purpose of this study, the non-parametric estimation is used to estimate the level of technical efficiency of fishermen as compared to the parametric approach due to several reasons. Non-parametric estimation is used for this study because it can evaluate the efficiency of relative homogeneity of organization. Data envelopment analysis (DEA) is the powerful aggregate comparative method for assessing the productivity of an organization with multiple incomparable inputs and outputs. The input-output regression of ordinary least square model invariably result in average or expected level of outcome given certain inputs, instead of the desired maximum achievable outcome (Soteriou *et al.*, 1998). Moreover, econometric approach used in evaluating efficiency is based on the assumption that all decision making units are operating efficiently and would not be appropriate if technical efficiency assumption is dropped (Fukuyama, 1993).

Non-parametric analysis does not require a priori functional specification of the unknown technology or distribution assumptions about the error term that may cause potential specification error. The multiple outputs and variable return to scale of production provide meaningful technical and scale efficiency measures for each decision making units without having data on input price and costs. Non-parametric approach also identifies sources of production growth, hence provides recommendation for performance improvement (Fukuyama, 1993; Grabowski *et al.,* 1994). Non-parametric analysis also avoids the problem arising from multicollinearity among variables (Elyasiani and Mehdian, 1993).

Model specification

The methodology used in this study is a two-stage process commonly used in the literature. The efficiency scores are estimated in the first stage and then the scores are used as dependent variables in the second stage. In the first stage, the data envelopment analysis (Charnes *et al*., 1978) or DEA is used to estimate the level of technical efficiency. For the second stage, Tobit regression is used to find the factors that influence the technical inefficiency.

In establishing the model specification, data envelopment analysis was adopted and tested. DEA is multi-factor productivity analysis model for measuring the relative efficiencies of a homogenous set of decision making units (DMUs). The general form of the model is:

$$\text{Efficiency} = \frac{\text{weighted sum of output}}{\text{weighted sum of inputs}} \quad (1)$$

Assuming that there are n DMUs, each with **m** inputs and **s** outputs, the relative efficiency score of a test DMU p is obtained by solving the following model proposed by Charnes *et al*., (1978):

$$\text{Maximize} \quad Z_0, \ \frac{\sum_{k=1}^{s} v_k y_{kp}}{\sum_{j=1}^{m} u_j x_{jp}}$$

$$\text{Subject to} \quad \frac{\sum_{k=1}^{s} v_k y_{ki}}{\sum_{j=1}^{m} u_j x_{ji}} \le 1 \forall i$$

$$v_{kv}, \quad u_j \ge 0 \quad \forall k, j, \quad (2)$$

Where
k = 1 to ***s***,
j = 1 to ***m***,
i = 1 to ***n***,
y_{ki} = amount of output ***k*** produced by fishermen ***i***,
x_{ji} = amount of input j utilized by fishermen ***i***,
v_k = weight given to output (catch per kg) k,
u_j = weight given to input (GRT, no of worker, distance from shore and expenditure per trip) j.

The fractional program shown as (2) can be converted to a linear program as shown in (3).

$$\text{Maximize} \quad Z_0, \ \sum_{k=1}^{s} v_k y_{kp}$$

$$\text{Subject to} \quad \sum_{j=1}^{m} u_j x_{jp} = 1$$

$$\sum_{k=1}^{s} v_k y_{ki} - \sum_{j=1}^{m} u_j x_{ji} \le 0 \quad \forall i$$

$$v_k, u_j \ge 0 \quad \forall k, j$$

(3)

The above problem is run n times in identifying the relative efficiency scores of all the DMUs. Each DMU selects input and output weights that maximize its efficiency score. In general, a DMU is considered to be efficient if it obtains a score of 1 and a score of less than 1 implies that it is inefficient.

Variables used in the DEA Model divided into two which is the dependent variable and independent variable. The dependent variable is total output (catch) in kilogram per month. While, for independent variables are vessel capacity measured by Gross Registered Tonnage (GRT), number of crew employed per vessel for fishing trip, including captain, input usage (diesel/petrol, lubricant and oil, ice, food and miscellaneous variable inputs) and distance traveled measured by nautical miles from shore line.

For the second stage, Tobit regression was used to determine which factors influence efficiency, using a log-linear form of the model. Tobit regression is an alternative to ordinary least squares regression (OLS) and is employed when the dependent variable is bounded from below or above or both, with positive probability pileup at the interval ends, either by being censored or by being corner solutions.

As DEA is a non-parametric method, no econometric tests are available to gauge the appropriateness of the estimated frontier and efficiency scores. In a probit model the variable of theoretical interest, y*, is unobserved; what is observed is a dummy variable, y, which takes on a value of 1 if y*i is greater than 0, and 0 otherwise. In contrast, devised what became known as the Tobit (Tobin's probit) or censored normal regression model for situations in which y is observed for values greater than 0 but is not observed (that is, is censored) for values of zero or less.

The standard Tobit model is defined as

$$y^*_i = x_i\beta + \epsilon_i$$

$$y_i = y^*_i \qquad \text{if} \qquad y^*_i > 0$$

$$y_i = 0 \qquad \text{if} \qquad y^*_i \leq 0 \qquad (1)$$

where y*i is the latent dependent variable, yi is the observed dependent variable, xi is the vector of the independent variables, β is the vector of coefficients, and the ϵi's are assumed to be independently normally distributed: ϵi ~ N(0,σ) (and therefore yi ~ N(xiβ,σ)). Note that observed 0's on the dependent variable can mean either a "true" 0 or censored data. At least some of the observations must be censored data, or yi would always equal y*i and the true model would be linear regression, not Tobit.

Tobit is chosen by assuming that the concentration of the dependent variable clusters toward the left limit (i.e., zero) and because it does not only explain the value of the dependent variable or the probability of limit (e.g. point of technical efficiency) and non-limit (e.g. points of technical inefficiency) responses, but also the size (e.g. value) of non-limit responses (Tobin, 1958). Tobit regression is an alternative to ordinary least squares regression (OLS) and is employed when the dependent variable is bounded from below or above or both, with positive probability pileup at the interval ends, either by being censored or by being corner solutions. In the former case (censored) observations outside the limiting interval are recorded as the border values. That is if the range is given by the interval [a;b], observed y < a is recorded as y = a, and likewise observed y > b is recorded as y = b. In the latter case (corner solutions) the observations are by nature limited from below or above or both with a positive probability at the 'corners' (interval ends). DEA scores are limited to the interval [0;1] and accordingly only has a positive probability to attain one of the corner values. As such the two-limit tobit model, which is generally used to model censored or corner solution data limited both from below and above, is necessarily a mis-specification when applied to DEA scores, as this method requires a positive probability to attain both corner values.

When the dependent variable y is limited to the interval [0;1] it may be described by the model:

$$y_i^* = \sum_{k=1}^{n} \beta_k\, x_k + u_i, \qquad (1)$$

$$y_i = \left[\frac{1+sign\,(y*_i)}{2}\right].\min(1, y_i^*),$$

$$\text{sign}\,(y_i^*) = \begin{cases} 1; & y_i^* \geq 0, \\ -1; & y_i^* < 0, \end{cases}$$

where u_i ~ N (0, σ) are independent and identically normal distributed (iid.) residuals of the observations and x = (x_i, ..., x_n) is the vector of explanatory variables. Thus

$$y = \begin{cases} y^*; 0 \leq y^* \leq 1 \\ 0;\ y^* < 0; \\ 1;1 < y^* \end{cases} ; \quad y^* = \sum \beta_k x_k + u.$$

(2)

The probability that a recorded y is equal to 0 is given by

$$P\,(y = 0) = F(-\Sigma\beta_k x_k \mid 0, \sigma)$$

$$= \frac{1}{\sqrt{2\pi\sigma^2}} \int_{\infty}^{-\Sigma\beta_k x_k} e^{-t^2/(2\sigma^2)}\, dt \qquad (3)$$

Given the basic iid. assumption for the residuals

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u. F ($x|$ μ, σ) is the density function. Likewise:
P (y =1) = F(-(1-Σ$\beta_k x_k$)$|$ 0, σ)

$$= \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{-(1-\sum \beta_k x_k)} e^{-t^2/(2\sigma^2)} dt. \tag{4}$$

Finally when the recorded y is between 0 and 1 the probability to observe y is given by

$$P\ (y_i | 0 < y_i < 1) = f\left(y_i - \sum \beta_k x_k \,\middle|\, 0, \sigma\right)$$

$$= \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{-(1-\sum \beta_k x_k)} e^{-t^2/(2\sigma^2)} dt. \tag{5}$$

where $f(x|$ μ, σ) is the N (μ,σ) frequency function. Thus the combined likelihood function for the recorded censored dataset is given by

$$L = \prod_{y_i=0} P(y_i = 0) \prod_{y=1_i} P(y_i = 1) \prod_{0<y_i<1} P\ (y_i | 0 < y_i < 1) \tag{6}$$

This shows why the two-limit tobit model is mis-specified when applied to DEA scores, as the scores only have a positive pileup at the right hand side of the interval [0;1]. As none of the scores are equal to zero the first multiplication in (6) will be left out.

RESULTS

Data Envelopment Analysis

The technical efficiency represents the degree of success to produce maximum output from given levels of inputs. One percent technical efficiency means that the fishermen could have produced one percent more output from existing level of inputs. Range 80% and above are indicated as the most efficient level of technical efficiency. While 40% and below are categorized as a very low efficiency. For the peak season, the technical efficiency for individual fishermen ranged from 0.073 to 1

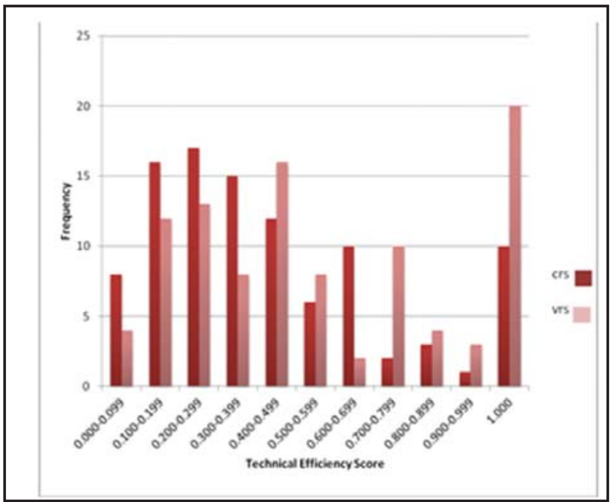

Figure 1: Frequency distribution of technical efficiency index for peak season.

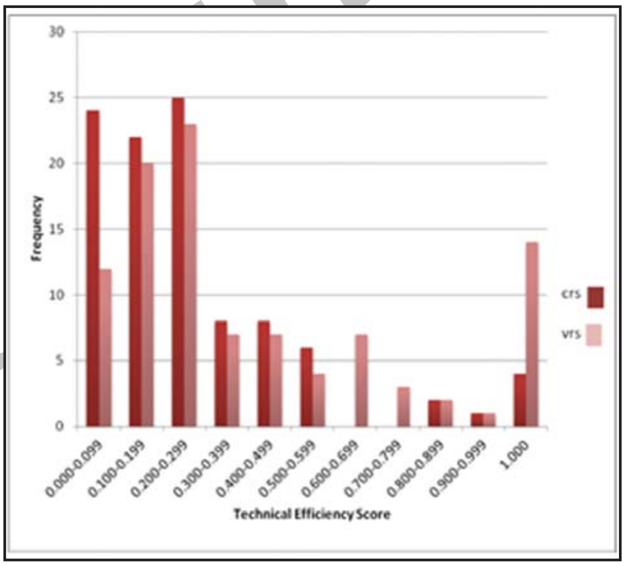

Figure 2: Frequency distribution of technical efficiency index for non peak season.

with a mean of 0.5469. The most striking result obtained by the study is the variation of technical efficiency by season. Most vessel are technically inefficient (below 0.4) during peak season. In this season, there are two regimes, low efficiency (below 0.4) or very high efficiency (above 0.8) figure 1.

During the non peak season, there are also two efficiency regimes that are slightly different from each other. The lower level regime (below 0.4) dominates the higher level regime (above 0.8) giving a very low overall efficiency (figure 2). Technical efficiency for each individual fisherman ranged from 0.025 to 1 with a mean of 0.401.

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Table 1: Estimated technical inefficiency function for the peak and non peak season

	Peak Season			Non Peak Season		
Variables	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.
Intercept	0.241384	0.589132	0.6820	0.309043	0.607469	0.6109
Age of fishermen	-0.001428	0.003739	0.7025	0.005306	0.004276	0.2146
Horsepower	-0.530796	0.186765	0.0045	-0.320788	0.073901	0.0303
Trip	0.004026	0.005539	0.4673	0.000522	0.005873	0.9292
Household	0.001221	0.011453	0.9151	-0.031021	0.012403	0.0344
Ownership	0.039246	0.116423	0.7360	0.108585	0.116797	0.3525
Education	-0.040293	0.092198	0.0421	-0.130203	0.103580	0.2087
Management variables						
Planning	-0.028901	0.012684	0.0227	-0.036081	0.014199	0.0110
Organizing	-0.001886	0.012711	0.8821	-0.014900	0.014267	0.2963
Staffing	-0.004620	0.016805	0.7834	-0.037948	0.018743	0.0429
Directing	-0.005902	0.018307	0.7472	-0.013732	0.019389	0.4788
Controlling	-0.008175	0.015851	0.6060	-0.035009	0.016630	0.0353

Tobit Regression

Table 1 provides the estimated technical inefficiency function, where the dependent variable is technical inefficiency as opposed to technical efficiency. Thus, a negative sign indicates a decrease in technical inefficiency or an increase in technical efficiency. The statistically significant variables in the technical inefficiency function are education, horsepower and planning for a peak season and horsepower, household, planning, staffing and controlling for a non peak season.

CONCLUSION

The empirical results of the study show that 20% of the fishermen had an impressive efficiency index greater than 90% during the peak season. On the other hand 39% of them had an efficiency index of less than 40%. During the non peak season, the number of fishermen declined from 20% to 15% for the most efficient vessels efficiency score and about 63% of the fishermen surveyed had less than 40%. The mean technical efficiency for the sample were estimated to be 54.6% for the peak season and 40.1% for the non peak season implying that more effort can still be done to increase the efficiency level. For the technical inefficiency test, there were 8 inefficiency variables shown to have significant impact against technical efficiency. They are: formal education, horsepower engine and planning for the peak season and size of family, horsepower engine, planning, staffing and controlling for non peak season.

The findings of this study suggest that there exists room for improvement in efficiency among a sizeable proportion of the fishermen studied. With appropriate training and introduction of more advanced technologies fishermen' efficiency level can be raised. Also higher level of engine power to steam in different fishing grounds and thus conducts more fishing operations than smaller horsepower in a given trip. Hence fishermen should use bigger horsepower engine to increase their catch. This can be achieved through loans, subsidies and incentives from the government.

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