Asian Fisheries Science **30** (2017):169−184
©Asian Fisheries Society
ISSN 0116-6514
E-ISSN 2073-3720
https://doi.org/10.33997/j.afs.2017.30.3.003

Technical Efficiency of Municipal Fisherfolk in Maasim, Saranggani Province, Philippines: A Stochastic Frontier and Data Envelopment Approach

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Abstract

This study assessed the level of technical efficiency of municipal fisherfolk in Maasim, Saranggani Province, Philippines. Multi-stage sampling procedure was employed to select 284 small-scale fishers in the area. The primary data on tuna landings per trip, effort days per trip, crew size, fishing ground distance, engine horsepower and operating cost per trip were analysed using Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). Results of the study show that the average technical efficiency of Maasim fisherfolk using the said approaches were 0.57 and 0.43, respectively. Using Tobit regression, hypothesised factors affecting technical efficiency of these fishers such as their socio-demographic profiles, attributes of the vessels and factors associated with fishing operations were considered. Among these determinants, the technical efficiency model indicated that age of the boat, engine horsepower, crew size, effort days, fishing ground distance and choice of unloading port were found to affect the technical efficiency of Maasim fishers.

Keywords: Technical efficiency, municipal tuna fisheries, stochastic frontier analysis, data envelopment analysis

Introduction

Fishery is one of the most notable sectors in the economy of the Philippines. In fact, according to FAO (2014), the country ranked as one of the major fish producing countries in the world in 2012. However, the country's total production has been experiencing a decline for the past few years from 5.1 million tonnes in 2010 to 4.7 million tonnes in 2014 (BFAR, 2014).

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With that, the economic contribution of the country's fishing industry has been falling (PSA, 2015). In 2016, based on the data of PSA or the Philippine Statistics Authority (2016), among the country's food items, fish has the second highest inflation rate after vegetables and this could be caused by increasing demand relative to supply. Also, for many years, among the Philippines basic sectors, fishermen have long been known to be the poorest in the country. According to the PSA (2012), on the 2012 official poverty statistics for the country's basic sectors, fishermen displayed the highest poverty incidence.

The decline in the fishery production can be attributed to the decrease in the production from three subsectors (aquaculture, municipal fisheries and commercial fisheries) wherein, based on the recent update, these three sectors had negative growth rates during the second quarter of 2016. Among these groups, municipal fisheries which operates with a boat capacity of 3 GT and below has the least share of production, contributing 26.41 % of the total output. However, in terms of employment, 85 % or 1,371,676 of the total number of fishing operators employed were from municipal fisheries (BFAR, 2014). According to Anticamara and Go (2016), over the last three decades, fishers belonging to these communities have been experiencing a low level of income due to the declining trend in the fish production especially at the local level. One of the prevailing problems that the small-scale fishers encounter is the intrusion by commercial fleets into municipal waters. According to Siason et al. (undated), there are local government units that allow commercial fishers to fish in the 10–15 km zone with fishery rentals. Furthermore, overfishing, destructive fishing practices, fewer options for alternative sources of income, as well as too much fishing effort are observed to be causing the decline in fisheries production.

The decrease in fisheries production in the Philippines has been replicated in the country's tuna industry which has seen yearly declines in production of the five major tuna species (yellowfin, bigeye, skipjack, frigate and eastern little tuna) (PSA, 2015). Tuna fishing was one of the prevailing livelihoods of the Filipinos considering that there is abundance of production in some areas in the country, especially in the southern Philippines provinces. In fact, in 2003, the country became the fourth largest producer of tuna and tuna-like species in the world (Vera & Hipolito, 2006). Surrounded by the Moro Gulf, the Celebes Sea and Saranggani Bay, the SOCCSKARGEN region was known to be the country's top producer of certain species of tuna such as yellowfin and skipjack (CountrySTAT, 2016). Located in the said region, Saranggani province has also been a major source of tuna production and the area comprises a considerable number of municipal fisherfolk. The province's coastal community has offered livelihood to most of the people specifically in terms of fishing. Each species caught in the said province has seen a downward trend in production volume (PSA, 2015).

Given the declining trend in the Philippine fisheries production, particularly in the tuna industry in Maasim in Saranggani province, and the prevailing poverty concerns in this sector, this paper tries to address the problems through assessing the technical efficiency of these municipal fisherfolk, identifying the sources of inefficiency and suggesting solutions for optimised operation.

Technical efficiency according to Kumbhakar and Lovell (2000) can be defined as the ability to produce a certain level of output using a minimum quantity of inputs under a given technology or the ability to produce maximum output given the current level of inputs. This can be modelled using the deterministic or stochastic production frontier. Assuming that two decision-making units (DMUs) have the same set of inputs, it is possible that they acquire different levels of output resulting in variations in the level of efficiency.

The said efficiency can be measured using two common methodologies: the stochastic production frontier (SPF) analysis and data envelopment analysis (DEA). Using these approaches, several studies on fishery were conducted by Esmaeili 2006, Tingley et al. 2005, Pascoe and Coglan 2002, Eggert 2000, and Jamnia 2015. Both of these methods involve a parametric and non-parametric approach respectively and are commonly used to describe the efficient production frontier and estimate the efficiency scores. Stochastic production frontier makes use of the specification of production function. It also includes the effect of both technical inefficiency and random shocks (such as labour or capital performance) to the model. The DEA approach, however, ignores the effect of these random errors considering that any deviation of the observed output to the maximum possible output is only assumed to be attributed to technical inefficiency.

Materials and Methods

The primary data used in the study was collected from the municipality of Maasim in Saranggani province. It was based on cross-sectional data collected during the 2015 production season in the area. The sampling involved three stages: selection of the municipality, then barangays and finally the fisherfolk. Although Maasim does not have the highest number of fishers, the municipality was chosen as the study area due to the fact that it has the most number of registered boats. Using stratified sampling, a total of 284 fisherfolk were included in the study. A structured questionnaire was used to gather relevant information from these respondents.

The dominant functional specification of the stochastic production frontier model in the literature based on the work of Battese and Coelli (1995) may be expressed as:

$$Y_{it} = x_{it}\beta + (V_{it} - U_{it}) \quad \textbf{(1)}$$

where Y_{it}, is the (logarithm of) production of the i^{th} firm in the t^{th} period; x_{it}, is a kx1 vector of input quantities of the i^{th} firm in the t^{th} period; β is a vector of unknown parameters; V_{it} is the random error and U_{it} are non-negative random variables assumed to account for technical inefficiency. Given that U_i is the error associated with technical inefficiency, a model which estimates the factors that affect the technical efficiency is shown in equation 2:

$$U_i = z_i\delta + w \quad \textbf{(2)}$$

where z_i denotes a vector of hypothesised efficiency determinants; δ is the parameter to be estimated and w is the unobservable random variable. However, if U_i does not exist in equation 1, the stochastic frontier production function reduces to a traditional production function (Tijani, 2006).

In this paper, the SFA approach was utilised to measure the technical efficiency of municipal fisherfolk in Maasim, Saranggani Province. The said method was preferred since it has the advantage of allowing statistical inference where different hypotheses on estimated parameters of the production frontier can be tested (Mastromarco, 2008). In addition, SFA can also accommodate functional forms such as Cobb-Douglas and translog production functions. The sources of technical inefficiency, on the other hand, were analysed using Tobit regression. However, in this case, technical efficiency scores from DEA were utilised as the dependent variable for the said regression.

Using the formula stated in equation 1 and assuming Cobb-Douglas and translog production functions, cross-sectional data that was used in the study could be expressed as follows (Coelli et al., 2005):

$$lnY = \beta_0 + \beta_1 \ln(CS_i) + \beta_2 \ln(ED_i) + \beta_3 \ln(FGD_i) + \beta_4 \ln(HP_i) + \beta_5 \ln(OC_i) + (V_i - U_i) \quad \textbf{(3)}$$

$$\begin{aligned} lnY = {} & \beta_0 + \beta_1 \ln(CS_i) + \beta_2 \ln(ED_i) + \beta_3 \ln(FGD_i) + \beta_4 \ln(HP_i) + \beta_5 \ln(OC) \\ & + 0.5\,\beta_6 \ln CS_i^2 + 0.5\,\beta_7 \ln ED_i^2 + 0.5\,\beta_8 \ln FGD_i^2 + 0.5\,\beta_9 \ln HP_i^2 \\ & + 0.5\,\beta_{10} \ln OC_i^2 + 0.5\,\beta_{11} \ln(CSED_i) + 0.5\,\beta_{12} \ln(CSFGD_i) \\ & + 0.5\,\beta_{13} \ln(CSHP_i) + 0.5\,\beta_{14} \ln(CSOC_i) + 0.5\,\beta_{15} \ln(EDFGD_i) \\ & + 0.5\,\beta_{16} \ln(EDHP_i) + 0.5\,\beta_{17} \ln(EDOC_i) + 0.5\,\beta_{18} \ln(FGDHP_i) \\ & + 0.5\,\beta_{19} \ln(FGDOC_i) + 0.5\,\beta_{20} \ln HPOC_i^2 + (V_i - U_i) \end{aligned} \quad \textbf{(4)}$$

The Cobb-Douglas model in equation 3 specifies the input or explanatory variables of catch output as defined in Table 1 while translog specification in equation 4 involves the square and interaction terms of such inputs. Furthermore, the symbol $\boldsymbol{\beta}$ represents the vector of the unknown parameter, $\boldsymbol{v_i}$ represents the random error, and $\boldsymbol{\mu_i}$ is the error associated with technical inefficiency. Given functional assumptions, the values of the unknown coefficients in equations (3) and (4) can be obtained using the maximum likelihood method (ML).

Table 1. Description of variables included in the production function and technical efficiency model

Variables	Description
Inputs	
Crew size (*CS*)	Number of persons in the boat
Effort days/trip (*ED*)	Number of days spent for searching and fishing per trip
Fishing ground distance (in miles) (*FGD*)	Distance of the fishing ground from the municipal coastline.
Horsepower *(HP)*	Horsepower of the boat engine
Operating costs *(OC)*	Total operating costs consisting of ice, food and fuel costs
Determinants	
Age (age)	Age of the fisherman (in years)
Education ($educ$)	Dummy variable; takes value of 1 if the respondent reaches high school, 0 if otherwise
Years in fishing ($fyrs$)	Number of years involved in fishing operations
Age of the boat ($ageb$)	Age of the boat (in years)
Horsepower (hp)	Horsepower of the boat engine
Years boat owned by current owner ($yrsboatown$)	Number of years the boat was owned by the current owner
No. of fishing gears ($fgears$)	Number of fishing gears used during operation
Crew Size (cs)	Number of persons in the boat
Effort days/trip (ed)	Number of days spent for searching and fishing per trip
Fishing ground distance (in miles) (FGD)	Distance of the fishing ground from the municipal coastline.
Operating costs *(oc)*	Total operating costs consisting of ice, food and fuel costs
% Target volume – big tuna ($ptargetbig$)	Percentage of the fisher's target volume for big tuna e.g. yellowfin, bigeye
% Target Volume – Small tuna ($ptargetsmall$)	Percentage of the fisher's target volume for small tuna e.g. skipjack
Unloading port: General Santos Fish port ($GenSan$)	Dummy variable; takes the value of 1 if the respondent unloads in GenSan Port, 0 if otherwise
Unloading port: Maasim coastal area ($Maasim$)	Dummy variable; takes the value of 1 if the respondent unloads in Maasim coastal area, 0 if otherwise

On the other hand, in utilising Tobit regression, the dependent variable involved DEA-derived technical efficiency scores from each of the respondents. The explanatory variables included possible determinants of technical inefficiency such as the profiles of the fishers, attributes of the boat vessels and other determinants, as summarised above. Furthermore, δ represents the vector of the unknown coefficients to be estimated and *w* is the unobservable random variable. This model was measured using Tobit regression from STATA 12 software.

$$U_I = \delta_0 + \delta_1 agef_i + \delta_2 educ_i + \delta_3 fyrs_i + \delta_4 ageb_i + \delta_5 hp_i + \delta_6 yrsboatown_i + \delta_7 fgears_i + \delta_8 cs_i + \delta_9 ed_i + \delta_{10} fgd_i + \delta_{11} oc_i + \delta_{12} ptargetbig_i + \delta_{13} ptargetsmall_i + \delta_{14} GenSan_i + \delta_{15} Maasim_i + w_i \quad \textbf{(5)}$$

The estimates of the stochastic frontier production function using FRONTIER 4.1 were used for the validation of the hypotheses such as the assumption of having a half-normal distribution, the absence of the technical inefficiency effects and the adequacy of the Cobb-Douglas production function. Prior to that, these tests are conducted using the generalised likelihood-ratio test (LR test) following Coelli et. al (2005) which can be defined as:

$$LR = -2\{\log[L(H_0)] - \log[L(H_1)]\} \qquad \textbf{(6)}$$

Results

The adequacy of half-normal distribution which was validated by the first null hypothesis, stated as H_o: $\delta_0 = 0$, was not rejected since the LR statistic values 1.16 and 0.72 of both Cobb-Douglas and translog functions, respectively, are less than the critical value, 2.706, as seen in Table 2. The second null hypothesis, that is H_o: $\gamma = 0$, which indicates that the inefficiency effects in the frontier model are not present, however, was rejected still by both functions. Finally, in the third hypothesis, with the critical value greater than the LR statistic, the adequacy of the Cobb-Douglas production functions is not rejected. With that, the said production function was used in this study.

Table 2. Hypothesis testing between Cobb Douglas and Translog Production function models through generalised likelihood ratio tests on half normal distribution adequacy, presence of inefficiency effects and Cobb Douglas production adequacy.

Hypothesis	Log Likelihood			Degrees of freedom (alpha)	Critical Value*	Decision
	Null (H_0)	Alternative (H_1)	LR statistic			
H_o: $\delta_0 = 0$						
Cobb-Douglas	-328.07	-327.49	1.16	1 (0.05)	2.706	Fail to reject H_o
Translog	-316.00	-315.64	0.72	1 (0.05)	2.706	Fail to reject H_o
H_o: $\gamma = 0$						
Cobb-Douglas	-330.13	-328.07	4.12	1 (0.05)	2.706	H_o rejected
Translog	-318.67	-316.00	5.34	1 (0.05)	2.706	H_o rejected
H_o: $\beta_7 = ... = \beta_{27} = 0$						
Cobb-Douglas vs. Translog	-328.07	-316.00	24.14	15 (0.05)	25.00	Fail to reject Ho

*According to the critical value determined by Kodde and Palm (1986)

The estimation of technical efficiency shows the given model presented in Table 3. All of the inputs have positive coefficients and are mostly significant at 5 %. The estimated elasticities of mean output with respect to operating cost, crew size, effort days, fishing ground distance and horsepower are 0.14, 0.25, 0.20, 0.42 and 0.27 respectively. This means that the operating costs, as the model suggests, expectedly imply a direct relationship, indicating that a 10 % increase in the spending for the operation, such as for food, ice and fuel, will create an increase of level of output of 1.4 %.

Fishing capacity of the boat is also one of the essential factors that contribute to obtaining higher levels of output. A 10 % increase in the crew size increases fish landings by 2.5 %. Also, an increase of 2 %, 4.2 % and 2.7 % in level of tuna output would be generated through a 10 % increase in effort days, fishing ground distance and horsepower, respectively.

Table 3. Estimated elasticities of the stochastic frontier parameters including the mean output and inputs through Maximum-likelihood estimates.

lnOutput	Coefficient	Std. Err.	t-ratio	
Constant	-1.05	0.697	-1.51	
lnCS	0.25	0.127	2.00	***
lnED	0.20	0.097	2.08	***
lnFGD	0.42	0.093	4.53	***
lnOC	0.14	0.032	4.40	***
lnHP	0.27	0.137	1.95	**
Variance Measures				
sigma-squared	1.054	0.183	5.75	***
gamma	0.679	0.120	5.67	***

*T-test for Cobb-Douglas (2-tail, df = 283/∞); @10 % 1.645, @5 % 1.96, @1 %

On the other hand, based on the results of the MLE estimates, gamma, which is the ratio of the variance of the technical inefficiency effects to the variance of random errors, has a coefficient of 0.68 and is also significant. This suggests that 68 % of the variation in tuna output is attributed to the differences in technical efficiencies among municipal fisherfolk.

Fig. 1 shows the technical efficiency distributions of Maasim municipal fisherfolk estimated using both parametric and non-parametric approaches. The mean technical efficiency using methods such as SFA and DEA are 0.57 and 0.43, respectively. By utilising the SFA approach, results have shown that over 50 % of the given sample of fishers was above the mean efficiency of the sample; nevertheless, only 3 % belong to the given highest efficiency scores bracket ranging only from 0.80–0.89. Furthermore, based on the said analysis, none of the surveyed respondents have achieved outstanding levels of technical efficiency scores from 0.90–1. Based on the DEA results, only an estimated 40 % of them are above the mean technical efficiency; however, about 36 fishers (13 % of Maasim fishers) are found to be fully efficient.

On the other hand, considering the low level of technical efficiency of Maasim fishers in both approaches, factors that contribute to this inefficiency were also identified in this study. The researchers have incorporated different aspects in identifying these factors. Fisher's profile, attribute of the vessels was used and other possible factors relating to the fishing operations have been included.

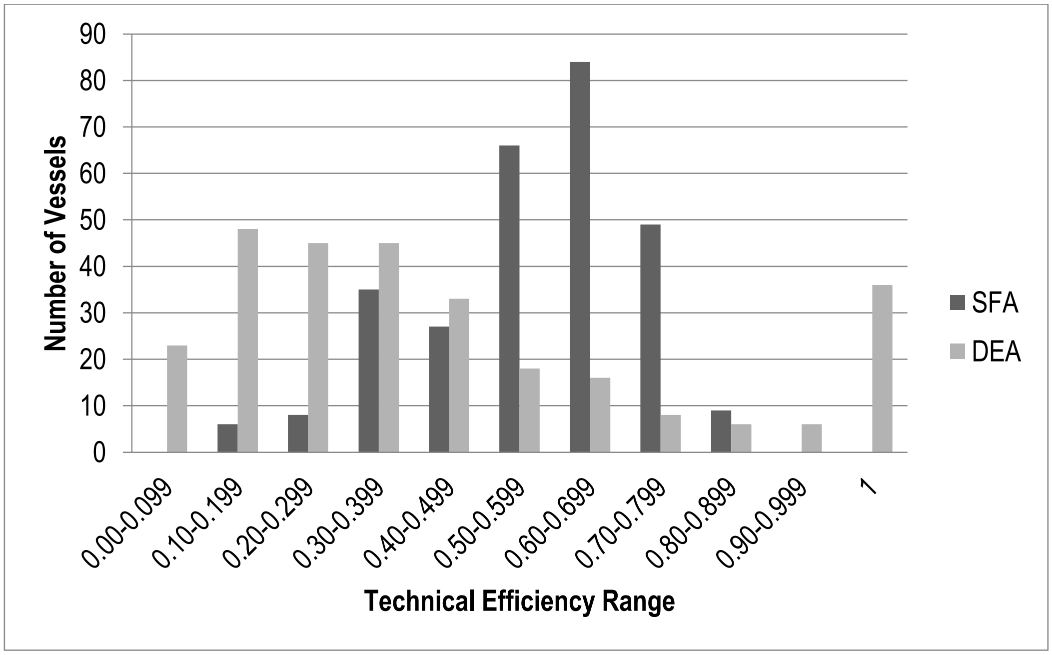

Fig. 1. Technical efficiency distribution of Maasim municipal fisherfolk using stochastic frontier analysis (SFA) and data envelopment analysis (DEA)

Discussion

The researchers considered varied components that might affect the efficiency of the fishers involved in the study. These factors are estimated using Tobit regression. Results of the model, shown in Table 4, reveal that few determinants are statistically significant. Some of the vessel attributes, such as the age of the boat and engine horsepower are also found to be major sources of technical inefficiency which are significant at 10 % and 1 %, respectively. Also, based on the model, the variables crew size, effort days as well as fishing ground distance, which are also included in the SFA production function, are found to be statistically significant in determining the sources of inefficiency. Furthermore, the variable which indicates GenSan Fish Port as the unloading port is perceived to affect the technical efficiency of Maasim fishers considering its significance in the model.

Table 4. Parameter estimates of efficiency model using Tobit regression

Determinants	Coefficient	t-ratio	
Age	-0.0003	-0.10	
Education	0.0356	0.99	
Years in fishing	0.0021	0.81	
Age of boat	-0.0080	-1.72	*
Engine horsepower	0.0200	-2.99	***
Years owned by current owner	0.0107	1.27	
Number of fishing gears	-.00395	-0.40	
Crew size	-0.0293	-2.27	**
Effort days	-0.0210	-3.05	***
Fishing ground distance	-0.0025	-2.08	**
Operating cost	0.000003	-0.29	
Target volume of big tuna	0.116	0.41	
Target volume of small tuna	0.159	0.56	
Unloading port: Gensan fish port	-0.2736	-2.17	**
Unloading port: Maasim coastal area	-0.1971	-1.56	
Constant	0.960	2.92	***

*T-test for Cobb-Douglas (2-tail, df= 285 /∞); @ 10 % 1.645, @ 5 % 1.96, @ 1 % 2.576

Age of boat

In this model, it was found that the coefficient of the variable pertaining to the age of boat (in years) has a negative effect on technical efficiency and is significant at 10 %. Having a boat that is used over a long period can sometimes affect its performance when used during fishing operations since the quality of the boat depreciates over time, depending on the materials used. In addition to that, older vessels are more likely to undergo repairs than new ones and fishers have the tendency to spend more on maintenance costs of fishing gears and for other components of the boat. The findings show that old boats have lower efficiency scores than the new ones. In addition, the budget for other necessary spending, more importantly for the operating cost which is essential in every fishing operation of the fishermen, will be affected. Operating or variable costs, identified by Bose & Sarma (2010) as consisting of berth charges, fuel cost, ice cost, salaries of the crew, food and water cost and other miscellaneous expenditure, are important factors since these things somehow affect and determine the level of tuna landings in every fishing trip. This finding is consistent with those of Lim et al. (2012) and Pascoe and Coglan (2002).

Table 5. Average fuel cost, ice cost, food cost, output level and technical efficiency scores according to the age of the boat.

	Age of the boat (in years)			
	0–5	6–10	10–15	≥16
Fuel cost/trip (in pesos)	1075.80	914.62	960.10	1143.33
Ice cost/trip (in pesos)	581.43	409.20	386.79	760.00
Food cost/trip (in pesos)	970.55	839.42	733.08	1016.67
Output (in kg)	45.93	41.53	38.43	67.81
Efficiency score	0.42	0.34	0.39	0.37

Engine horsepower

Engine horsepower has shown an inverse relationship with efficiency. Results indicate that boats with horsepower below 9 obtain an average of 0.46–0.51 efficiency ratios while those with 9 HP and above have lower mean technical efficiency ranging only from 0.37–0.42. In terms of input, fishers having vessels with high powered engines have higher operating costs specifically fuel costs resulting in farther fishing grounds which are about 29 miles from the coastline. However, these higher levels of inputs do not translate into maximum possible output. Also, boats with low powered engines, particularly 5–6.99 HP, attained better output than those with high powered engines. Additionally, average tuna landings of the boats with 11–12.99 HP are only higher by 2.4 kg compared to the lowest category of the boat's horsepower specified in this study.

This finding varies with the studies of Aisyah et al (2011), Moskness et al. (2009) and Viswanathan (2000) in which horsepower was found to have a positive relationship with technical efficiency. However, this result is consistent with the study of Al Kahtani et al. (2015). It was also supported by Fare (2006) who found that boats considered to be efficient according to results were found to have engines with lower horsepower as well.

Crew size

Based on the findings, crew size or the number of people in the boat, a factor included in the stochastic frontier production function, has a negative impact on technical efficiency, considering that it is strongly significant at 5 %. Results reveal that the level of output gets higher as the number of persons in the boat increases. However, in terms of efficiency, boats with only one person with mean TE score of 0.56 are more efficient than boats with crew size of 2, 3 and 4 which have mean TE scores of only 0.32, 0.36 and 0.42, respectively. This can be associated with diminishing marginal returns wherein additional labour somehow increases the total level of output, however, at a decreasing rate. The productivity of each of the person in the boat tends to diminish as their number increases.

Based on the results, lower levels of efficiency can be attributed not only to the number of persons in the boat but also the corresponding resources brought by or associated with having that number of crew such as expenditure on consumption and other possible factors. With that, it can be implied that these inputs can be utilised more efficiently in order to achieve the maximum possible level of output.

Table 6. Mean DEA-derived efficiency scores, output level, effort days, fishing ground distance, fuel cost, ice cost and food cost according to crew size

Crew size	TE scores	Output (in kg)	Effort days	FGD (in miles)	Fuel cost (Php)	Ice cost (Php)	Food cost (Php)	Total Operating cost
1	0.56	26.94	5	24	804.75	327.67	542.92	1,674.71
2	0.32	53.55	6	30	1039.18	510.99	999.48	2,549.66
3	0.36	73.18	7	35	1281.30	1203.22	1484.78	3,969.30
≥4	0.42	84.16	7	40	2627.14	1412.14	2528.57	6,567.86

Effort days

Using Tobit regression, fishing duration in days, also known as the fisherman's effort days, was also found to have an inverse relationship with technical efficiency and was significant at 1 %.

Results show that the output and input variables, have a positive relationship with each other. As the fishers stay longer at sea, farther fishing grounds are more likely to be reached. In addition to that, they would also need more people to accompany them in fishing. Thus, food expenses are expected to be higher. Output per trip as well as the total sales per trip showed a positive relationship with the number of effort days and other given inputs; however, average technical efficiency scores obtained using DEA indicate a declining value which implies that even fisherfolk with a greater number of fishing days are more likely to be less technically efficient compared to those who fish for a shorter time duration. It is observed that fishers categorised with 6–10 and 11–15 effort days have a lower mean efficiency of 0.37 and 0.45, respectively compared to those who stay in the sea for only 1–5 days attaining an average TE ratio of 0.49. Generally, these fishers, more specifically those who have greater resources, can still improve their operations further to maximise output.

Table 7. Mean crew size, fishing ground distance (FGD), food cost, output and TE scores according to effort days

	Effort Days		
	1–5	6–10	11–15
Crew size	2	2	3
FGD (in miles)	24.90	31.76	33.07
Food cost/trip (in Php)	734.93	1051.73	1728.57
Output/trip	30.17	59.85	77.58
Sales/ trip (in pesos)	2,970.60	5,568.02	5,628.08
DEA-derived TE score	0.487514	0.366951	0.446643

Fishing ground distance

The distance of the fishing ground from the municipal coastline was also revealed to be a source of Maasim fishers' inefficiency. These municipal fishers have an average fishing ground distance of 28 miles from the coast. Nevertheless, the farther the area that these boats reach, the higher the level of inputs needed.

Highest technical efficiency and lowest operating costs were attained by those who only fish in the nearest fishing grounds such as in Centro Kablacan, Centro Malbang, Centro Colon, and Lumasal area where distances range from 1–10 miles from the coastline only. These fishers have a mean technical efficiency ratio and operating cost of 0.66 and Php 1,283.27 respectively. The farthest areas where Maasim fishers usually fish are located in Centro Kiamba, Centro Kabatiol, Saranggani Bay and Celebes Sea, which are 45–75 miles from the Maasim coastline. With these distances, fishers obtain much lower efficiency scores and operating costs averaging 0.41 and Php 3,308.90, respectively.

Unloading port

Fishers' preference for the port where they unload their tuna landings was also perceived to be one of the sources of technical inefficiency based on the model's estimations. Results show that fishers unloading their tuna in GenSan fish port are more likely to experience lower efficiency than those who prefer to unload in the Maasim Coastal Area. This could be due to higher levels of input consumption such as fuel and ice cost since it is a longer distance to the main port (GenSan) compared to the coastal area within their municipality. Since these fishers' fishing grounds are located just within the municipal waters and in the south-west areas of Maasim (whereas GenSan Fish Port is in the north-west of Maasim), they could unload their tuna directly in the nearby coastal area, with less expenses incurred for the said input.

These fishers could also save on the port fees which is usually charged in GenSan Port. According to FAO, the catch from the municipal fisheries subsector is typically unloaded in the traditional landing sites or in municipal fish ports. Based on the data, it was found that 63 % of the Maasim fishers unload their catch in the Maasim Coastal Area while only 37 % of them unload in GenSan Fish Port.

Table 8 summarises the discussion on the correlation between the level of inefficiency variables to the level of technical efficiency of the Maasim municipal fishers. As observed in the figures, the identified continuous variables such as age of the boat, engine horsepower, crew size, effort days and fishing ground distance as well as the dummy variable pertaining to GenSan fish port as the fishers' preferred unloading port have an inverse relationship with the level of technical efficiency. As the level of such determinants increase, technical efficiency decreases.

Table 8. Correlation between level of inefficiency variables and technical efficiency

Inefficiency variables		Technical Efficiency
Variables	**Level**	**Level**
Age of boat	↑	↓
Engine horsepower	↑	↓
Crew size	↑	↓
Effort days	↑	↓
Fishing ground distance	↑	↓
Unloading Port: GenSan fish port		↓

*The symbol (↑) represents increasing level and (↓) represents decreasing level

Conclusion

Fishing operations are considered essential in terms of providing food supply and sustaining livelihoods of most people in local communities especially those located in the country's coastal areas. Keeping in mind the difficult situation of the small-scale fishermen, their basic operations, especially the utilisation of primary inputs, were examined to assess their technical efficiency as well as to identify the various factors contributing to their inefficiency.

Given the mean technical efficiency ratio of 57 % and 43 % based on the study using stochastic and deterministic models, it is clear that the Maasim municipal fishermen still have so much more to improve in terms of efficiency of operations per fishing trip. With that, tuna landings of these fishers specified in the study area can still be increased by 43–57 % given the current level of inputs.

According to the findings of the study, inputs such as the number of crew, days spent fishing, distance of the fishing ground, boat horsepower as well as the operating costs affect the level of output. As these inputs increase, the level of tuna landings also increases. Moreover, both methods also indicate that there is an inefficiency problem within the Maasim municipal fishery. Inefficiency brought about by increasing to a certain level of crew size and effort days in every operation is attributed primarily to diminishing returns on labour and capital.

Based on the study, with possible increase of efficiency, current high fishing effort such as days of fishing and operational costs can be reduced while still attaining an optimised level of output. With a substantial reduction in the cost of fishing, decrease of the country's fish market price might be achieved for the benefit of the Filipino consumers.

On the other hand, while a major problem on overexploitation in the Philippine fisheries resources exists, the national government, especially the local government units and other stakeholders should consider implementing precise and strict policies to address the problems of destructive fishing practices, coastal area management, as well as controlling and setting allowable fishing efforts and capacity of the local fishers in the community. In the case of Maasim fishers, the results of this study can be used in establishing necessary policies. With that, participation of municipal fishers especially in Maasim, Saranggani should be guided through conducting programmes and seminars on understanding the policies that will be established and more importantly for increased awareness of the current situation of the country's fisheries sector.

Acknowledgements

This research was facilitated through the funding of the Sustainable Development of the Philippine Tuna Value Chain project under the Higher Education Regional Research Centre XI of the Commission on Higher Education. The researchers would also want to acknowledge the local government unit of the Municipality of Maasim, Sarangani Province, Philippines for the support provided during the conduct of the study.

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Received: 11.11.2016; Accepted: 06.07.2017 (MS 16-72)