The Extent, Dynamics, and Potential Predictors of Technical Efficiency and Capacity Utilisation in Small-Scale Fisheries in Oman

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Abstract

This paper investigates the extent, dynamics, and factors influencing technical efficiency (TE) and capacity utilisation (CU) in small-scale fisheries (SSF) using a two-stage data envelopment analysis (DEA) approach covering the period 2010–2012. A considerable extent of boat-level technical inefficiency, capacity underutilisation and scale inefficiency were evident. On average, TE and CU levels under the constant returns to scale (CRS) and variable returns to scale (VRS) models declined over time. The TE and CU scores of 2010 remained unaltered with the addition of 'fishing time' as an input to the model. The proportion of boats with unitary scale efficiency (SE) decreased from 26 % in 2010 to 12 % in 2012. The underutilisation rates of the inputs 'crew' and 'fishing time' ranged from 15.5 % to 31.6 % and 15.8 % to 28.6 %, respectively. Among the species category, the extent of excess capacity was 70 % to 156 % and 47 % to 119 % under the CRS and VRS models, respectively. The second-stage DEA results indicated that the explanatory variables 'fishing location', 'catch per unit of effort' (CPUE), 'fuel costs' and 'crew share' significantly influenced CU under the CRS model. In contrast, the significant influence of subsidies and other operating costs were noted under the VRS model. For the TE case, 'age', 'education', 'subsidy' and 'CPUE' were found to be significant under the CRS and VRS models. Other significant variables were found in the study under CRS and VRS models. Finally, the results from the descriptive and empirical analysis under the two-stage DEA model are discussed together with policy implications.

Keywords: DEA, scale efficiency, excess capacity, Tobit regression, input utilisation

Introduction

The sustainability of small-scale fisheries (SSF) is a growing concern as failure to SSF will have adverse socio-economic implications for both local and global communities and will seriously affect the livelihoods of small-scale fishers (FAO, 2017). This consensual concern necessitated the assessment of technical efficiency (TE), of harvesting capacity and capacity utilisation (CU) in SSFs. Such assessments should provide direction to decide on the future course of actions to make meaningful progress towards sustainability (Sharma and Leung, 1998; Tingley and Pascoe, 2005) and to correct inefficient use of economic resources (Kirkley and Squires, 2003).

In the light of the above context, the assessment of TE and CU is of practical importance for the Sultanate of Oman (hereafter Oman), as the fisheries sector, especially the traditional SSF sector, plays a vital socio-economic role in the country's development and economic diversification campaigns (MNE, 2007a; Bose et al., 2010). In 2019 SSF produced 555 thousand tons (about 96 % of total landings) with a gross value of approximately US$750 million. They provided direct employment to 50,405 small-scale fishers and contributed to foreign exchange earnings of about US$270 million (MAF, 2020). The sector has been managed through five-year development plans (MNE, 2007b) aimed at enhancing socio-economic benefits through: sustainable utilisation of fisheries resources, improving fleet performance, and governance mechanisms (MNE, 2007a). 'Vision 2040' for the fisheries and aquaculture sector envisions a profitable and ecologically sustainable fisheries sector in Oman (World Bank, 2015).

However, a lack of knowledge about existing fleet capacity and the CU rate is a major issue (World Bank, 2015). There are insufficient empirical studies on the assessment of fleet performance in Oman. Such studies could provide scientific evidence on the time dynamics of TE and CU, capacity output, and the extent of excess capacity, which are of central interest to policy makers.

This paper has the following objectives. Firstly, to examine the dynamics of the TE and CU measures for the boats sampled each year and for the boats that appeared consistently in the sample (hereafter, as 'common boats'). Secondly, to examine the sensitivity of the average TE and CU scores reported by Al-Siyabi and Bose (2018) after the inclusion of an additional variable input ('fishing time') into the model. For this purpose, the identical representative sample of 97 boats used by Al-Siyabi and Bose (2018) for 2010 was retained. This helps the consistency of the model's results and strengthens the findings reported by Al-Siyabi and Bose (2018). Thirdly, to measure the scale efficiency of the representative boats and their trend over the study period. Fourthly, to estimate the extent of capacity output and excess capacity for each species category. Finally, to examine the statistical significance of a set of potential variables affecting the CU and TE scores of the common boats as mentioned above.

This paper is the first to investigate the time dynamics of TE, CU, measure the extent of economies of scale and the excess capacity in the SSF sector in Oman. In addition, the paper has global relevance as a country-specific case study to exemplify the recommendation of the FAO 'Code of Conduct' in relation to the effective management of fishing capacity (FAO, 1995). Furthermore, this case study complements a comparatively limited global literature on the economic performance of SSF in developing countries (Salas et al. 2007; Pomeroy, 2012).

Materials and Methods

Study area

Dhofar is one of the eight coastal Governorates of Oman (the other seven are: Musandam, North Al Batinah, South Al Batinah, Muscat, South Ash Sharqiyah, and AlWusta). It has ten Wilayahs (provinces) of which seven (Shalem & Al Halaniyat, Sadah, Mirbat, Taqah, Salalah, Rakhyut and Dhalkut) are coastal (Fig. 1). Dhofar's productive marine ecosystem is influenced by strong upwelling from seasonal monsoon winds (Anderson and Prell, 1993).

Total fish landings in Dhofar increased from 25,679 tons in 2010 to 74,359 tons in 2019; an annual growth rate of about 12.5 %, the increase predominately in demersal and pelagic species. In the same period, gross value increased from about US$42.6 million to US$104 million, an annual growth rate of about 10.4 %.
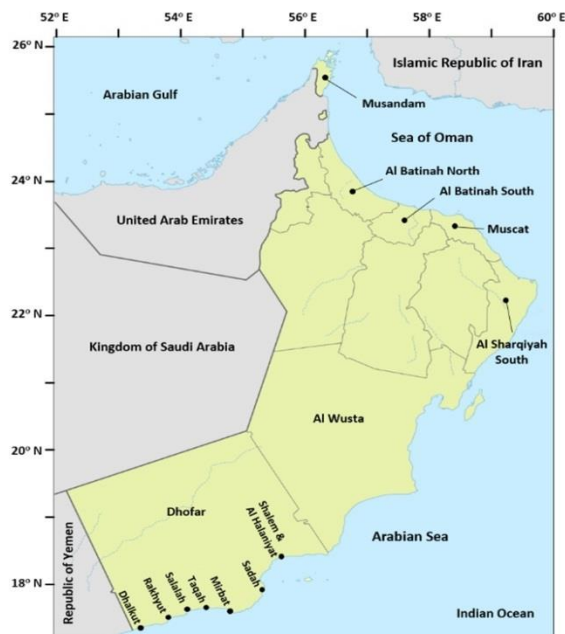

Fig. 1. Map of Sultanate of Oman, showing Dhofar Governorate and its coastal Wilayahs depicting the study area on the extent, dynamics, and factors influencing technical efficiency and capacity utilisation in small-scale fisheries.

The number of boats increased from 3,758 to 4,651; an annual growth rate of about 2.4 % over the same period (MAF, 2020). The registered small-scale fishing boats and dhows in 2019 represented about 19 % of the national fishing fleet and are dominated by fibreglass boats operating in coastal waters and carrying out daily fishing trips.

The number of fishers increased from 8,157 in 2010 to 11,394 in 2019; an annual growth rate of about 3.8 %. In 2019, the CPUE measured by number of boats and fishers were about 16 ton.boat^{-1} and 6.5 ton.fisher^{-1}, respectively.

Al-Siyabi (2018) noted that Dhofar surpassed the annual national growth rate with regard to the number of fishers, boats and landings. Using a non-parametric test, Al-Siyabi (2018) observed significant variability in landings (but not in gross value) between provinces. Further details on Dhofar fisheries can be found in Al-Siyabi (2018).

Empirical model

The measurement of TE and CU in fisheries found its theoretical origin in Farrell (1957). DEA- a non-parametric linear programming approach pioneered by Charnes et al. (1978) and further developed in Färe et al. (1994), is routinely used to measure the degree of TE and CU in fisheries in both developed and developing countries (Al-Siyabi and Bose, 2018). The concept of TE is inherently linked to the economic profitability of a fisher, a decision-making unit (DMU), as it measures the ability of a DMU to harvest the

maximum level of output for a given set of inputs and a given state of production technology (Farrell, 1957). The TE measure (expressed as a percentage) represents a boat's efficiency within a group relative to the observed best performing (i.e. fully technically efficient) boats in that group.

To meet the research objectives outlined above, a two-stage DEA model was utilised. In the first stage, two sub-models used by Al-Siyabi and Bose (2018) were employed along with an additional input variable ('fishing time') to estimate TE, $CU_{observed}$, $CU_{unbiased}$, and SE scores under the constant returns to scale CRS and variable returns to scale VRS assumptions respectively. The description of various constraints under CRS and VRS conditions represented by these two sub-models, representation of parameters and variables involved, and the formula for calculating TE, $CU_{observed}$ and $CU_{unbiased}$ are detailed in Al-Siyabi and Bose (2018). A non-parametric test was performed to check whether the distributional pattern of TE measures under both the CRS and VRS models differed over the study period. The test results allowed the calculation of the SE scores. Following Färe et al. (2001) and Tingley and Pascoe (2005), a non-increasing return to scale (NIRS) condition was imposed into the second sub-model of the first-stage DEA model. TE scores were then obtained to calculate the SE measure - as a ratio of TE estimates under the CRS and NIRS models - to assess the status of the scale of operation of DMUs. Lastly, the input utilisation rate (IUR) variable, which is defined as the level of variable input usage required to operate at full capacity utilisation, was also calculated to assess whether the variable inputs were fully utilised. The DEA models were estimated using the general algebraic modelling system (GAMS) optimisation package. A review of various aspects of non-parametric efficiency literature in fisheries and some examples of empirical research on TE and CU in fisheries can be found in Pascoe and Greboval (2003) and Al-Siyabi and Bose (2018), respectively.

In the second-stage of DEA, the CU and TE scores obtained for the common DMUs in the first-stage and for the combined species category were regressed on a set of explanatory variables (age, education, experience, subsidy, costs, crew share, and stock productivity) using the Tobit regression model. In a comparative study, Hoff (2007) observed the adequacy of Tobit's model in representing the second-stage DEA model.

Description of data

The data for outputs and inputs used in the first-stage DEA were obtained from the Ministry of Agriculture and Fisheries (MAF). Data for individual boat characteristics such as length (in feet) and engine power (in horsepower) were for 2010–2014. Data on species landings and value, gear types, duration of fishing trips (hours) and crew for the period 2010–2012

were collected from routine surveys using the probability sampling procedure proposed by the FAO in the 1980s.

Initial scrutiny of the survey data for the period 2008-2018 revealed that the boat-level information was relatively better for the period 2010–2012 in selecting representative boats based on the frequency of fishing trip. The data revealed that the identification (ID) number was missing for a considerable number of boats (about 91 % of 5283 observations in 2010), so these boats were removed from the data. Boats that appeared less frequently in the 2010, 2011 and 2012 survey data and with zero catch of either large pelagic (e.g. yellowfin tuna *Thunnus albacares* (Bonnaterre, 1788), longtail tuna *Thunnus tonggol* (Bleeker, 1851), large jacks of family Carangidae, kawakawa Scombridae, kingfish *Scomberomorus commerson* (Lacepède, 1800)), demersal (e.g. emperor of family Lethrinidae, seabream Sparidae, grouper Serranidae, croaker Sciaenidae) or other species (such as sardine of family Clupeidae, Indian mackerel Scombridae, anchovy Engraulidae, small jacks Carangidae, cuttlefish Sepiidae) were also removed to reduce the potential bias due to noisy observation in the data set (Holland and Lee, 2002). Following Al-Siyabi and Bose (2018), the trip-level catch for each DMU was aggregated to obtain annual data for each DMU. This process resulted in 97 boats in 2010, 84 boats in 2011 and 57 boats in 2012 for the empirical analysis. Only 24 boats consistently appeared in the sample common across the study period and 22 boat owners were available for interview. The data were also unbalanced concerning the number of observations per boat in the survey. However, the sample sizes used in the first-stage (97, 84, and 57) and second-stage (22) DEA models meet the 'degrees of freedom' requirement of 21 observations calculated using the formula proposed by Cooper et al. (2006) as follows:

Number of observation $(N) \geq \max \{n \times m, 3(n+m)\}$

where n = number of inputs and m = number of outputs in the model.

Data for explanatory variables such as 'age', 'fisher education', 'fisher experience', 'costs of fishing' and 'subsidies' (received by fisher) used in the second-stage DEA analysis were collected using a questionnaire survey during March and April 2017. In addition, the CPI for fish (2007 = 100) for Dhofar Governorate was collected from the National Centre for Statistics and Information (NCSI) for the years 2010–2012. Two of the twenty-four common DMU fishers were not available for interview. Therefore, 22 DMUs were used in the final analysis. These 22 DMUs belong to four homeports, namely: Mirbat (5), Salalah (3), Rakhyut (3) and Dhalkut (11). Twelve out of the twenty-two received subsidies from the MAF.

The survey data for the variables included in the second-stage analysis were adjusted to the study

periods (2010–2012) by scaling down some variables (such as 'age' and 'experience') and by expressing other variables (such as 'price' and 'costs') in constant prices. The cost of fuel was calculated based on fuel prices between 2010 and 2012, which was found to be fixed at 0.114 OMR/litre (1 Omani Rial (OMR) ≈ 2.59 US$), and the CPI for fish and seafood products (2007 = 100) was used as a proxy for price. Both CPUE and the Malmquist index (MI) were experimented as proxies for stock conditions in the Tobit model.

Results and Discussion

Table 1 presents the results of descriptive statistics about the input and output variables used in the analysis. Table 1 shows that the representative DMUs are comparatively more homogeneous in boat length, crew members, and fishing time than engine power. The apparent heterogeneity in engine power reflects the choices made by individual fishers of using more than one engine with different horsepower. Higher variability (measured by the standard deviation) in output variables compared to input variables may be due to seasonality and should not be treated as noise in the data (Al-Siyabi and Bose, 2018).

Table 2 presents the mean estimates of capacity (θ_1) and efficiency (θ_2) parameters, along with the average

score of TE and CU (biased and unbiased) measures under the CRS and VRS assumptions. The mean TE score under the VRS model was higher than that of the CRS case. The result indicates that the presence of the convexity constraint under VRS caused more boats to be identified as technically efficient. The mean TE score (less than unity) under the CRS and VRS models indicates that the representative boats were on average operating in a technically inefficient manner, which implies that output can be increased without increasing variable input use. The findings are in line with other studies such as Tsitsika et al. (2008), Ceyhan and Gene (2014), and Pham et al. (2014).

The average CU$_{unbiased}$ estimate under the CRS model indicated inefficiency in using variable inputs (i.e. 'crew' and 'fishing time') by the representative DMUs across the study period. The average CU measure suggests that output can be increased without incurring any additional physical capital costs. The inclusion of additional variable inputs in the first-stage DEA did not change the extent of TE and CU scores of 2010, as reported by Al-Siyabi and Bose (2018). This is perhaps due to the low level of variability in fishing time across the study period.

Apart from the average estimates, the TE and CU measures' frequency distributions at the DMU-level displayed in Figure 2 indicate a considerable degree

Table 1. Statistics summary of the inputs and outputs in the first-stage data envelopment analysis for 2010–2012.

Year	2010				2011				2012			
Number of DMU boats (N)	97				84				57			
	Min	Max	Mean	(SD)	Min	Max	Mean	(SD)	Min	Max	Mean	(SD)
					Fixed inputs							
Boat length (feet)	17	25	21	2.54	17	26	22	2.35	17	26	22	2.45
Boat power (hp)	40	150	56	23.08	30	120	56	21.84	30	130	55	18.98
Variable inputs												
Number of crew (person)	1	3	2	2.04	1	3	2	0.62	1	4	2	0.66
Fishing time (h)	3	8	6	1.11	3	8	5	0.82	3	6	5	0.81
Outputs												
Catch of large pelagic (kg)	0.33	178.90	28.93	35.71	0.7	169.4	32.85	36.38	0.77	311.11	27.30	45.36
Catch of demersal (kg)	4.39	193.75	66.64	50.26	2.0	296.0	68.86	60.58	0.39	252.42	69.37	51.64
Catch of other fish (kg)	0.50	495.46	51.93	101.46	0.2	769.6	52.45	99.74	0.23	300.00	26.02	43.78

Table 2. Estimates of technical efficiency, capacity utilisation, and scale of efficiency measures under the constant returns to scale and variable returns to scale conditions.

|	2010		2011		2012	
	Mean	(SD)	Mean	(SD)	Mean	(SD)
CRS						
Capacity parameter (θ_1)	2.854	2.372	3.771	2.745	3.298	1.882
Efficiency parameter (θ_2)	2.401	1.674	2.955	2.110	2.739	2.225
Technical efficiency (TE)	0.567	0.275	0.492	0.279	0.513	0.262
Capacity utilisation (CU)						
CU$_{biased}$	0.519	0.275	0.403	0.257	0.435	0.249
CU$_{unbiased}$	0.896	0.119	0.818	0.173	0.847	0.146
VRS						
Capacity (θ_1)	2.435	2.081	3.105	2.325	2.798	2.096
Efficiency (θ_2)	1.740	1.126	2.181	1.431	1.882	1.304
Technical efficiency (TE)	0.727	0.273	0.622	0.296	0.685	0.267
Capacity utilisation (CU)						
CU$_{biased}$	0.608	0.299	0.487	0.286	0.520	0.278
CU$_{unbiased}$	0.835	0.229	0.784	0.228	0.753	0.209
Scale efficiency (SE)	0.797	0.237	0.816	0.236	0.770	0.239
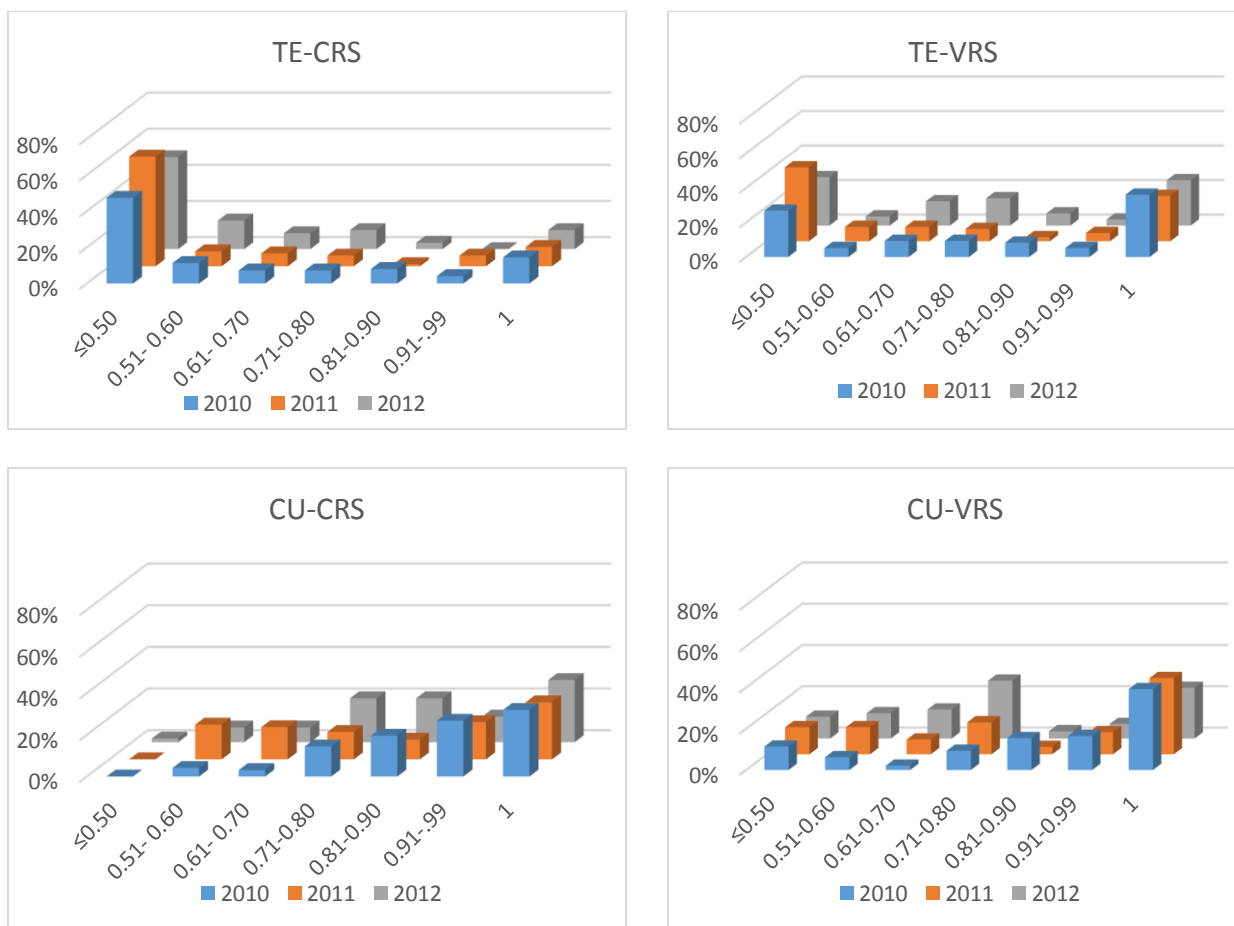
Fig. 2. The frequency distribution of capacity utilisation unbiased and technical efficiency scores for the small-scale fisheries in Oman.

of technical inefficiency and capacity underutilisation over the study period.

The non-parametric Wilcoxon signed-rank test revealed that the distributional pattern of TE measures under both the CRS and VRS models differ significantly at the 5 % level indicated by the corresponding Z-scores (-7.374, P < 0.0001), (6.955, P < 0.0001) and (-6.154, P < 0.0001) for 2010, 2011, and 2012, respectively. The significant differences between the TE measures under the CRS and VRS conditions led to scrutiny of the SE measure, as the differences possibly indicate that the representative boats were not operating at an optimum scale. The results showed that the SE-scores of 74 %, 76 %, and 88 % of the representative boats were less than in 2010, 2011, and 2012, respectively. With reference to the utilisation rate of variable inputs, the results indicated that the underutilisation rate for 'crew' ranged from 15.5 % to 31.6 %, while the range for 'fishing time' was 15.8 % to 28.6 % over the study period.

Table 3 presents the estimates of capacity output and excess capacity for all species categories under the CRS and VRS models. The excess capacity estimate (in percentages) indicated that the sampled boats failed to fully utilise their capacity over the period.

The extent of excess capacity increased for each species category over the period under the CRS and VRS models. This result is not unusual. In Alaska, Felthoven et al. (2002) found for the crab fishery that the excess capacity estimate ranged from 133.47 % to 325.18 % in 2001.

Second-stage DEA: Tobit regression

The descriptive statistics of $CU_{unbiased}$ and TE scores for the twenty two DMUs and independent variables used in the Tobit model are presented in Table 4.

The extent of the underutilised capacity and technical inefficiency in harvesting operations was noted from the results. Higher variability in various cost elements compared to other explanatory variables may be due to the nature of fishing operations adopted by fishers, and the variability in crew's share is influenced by the amount of catch. Further scrutiny of the TE scores of the common DMUs revealed that in the majority of the cases they were declining under the CRS and VRS assumptions over the study period. In addition, an increasing trend in scale inefficiency was observed.

Tables 5 and 6 present the model results for CU and TE under the CRS and VRS assumptions. The final selection of the model was determined by the

Table 3. Fleet capacity output and excess capacity under the constant returns to scale and variable returns to scale conditions.

Year	Species category	Catch (ton.year⁻¹)	Technical efficient output (ton.year⁻¹)		Capacity output (ton.year⁻¹)		Excess capacity (ton.year⁻¹)		Excess capacity (%)	
			CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS
2010	Large pelagics	648.3	1144.2	915.8	1319.5	1145.0	671.2	496.7	103.5	76.6
	Demersal	1493.1	2585.9	2155.6	2868.3	2549.1	1375.2	1056.0	92.1	70.7
	Other fish	1163.6	1777.1	1491.9	1981.0	1710.6	817.4	547.0	70.3	47.0
2011	Large pelagics	626.4	1197.6	1010.5	1446.5	1288.4	820.0	661.9	130.9	105.7
	Demersal	1313.0	2647.1	2189.2	3364.0	2881.6	2051.1	1568.7	156.2	119.5
	Other fish	1000.2	2089.4	1755.9	2369.8	2113.7	1369.6	1113.6	136.9	111.3
2012	Large pelagics	367.3	745.0	563.2	857.6	742.6	490.4	375.3	133.5	102.2
	Demersal	933.2	1693.6	1372.4	2056.9	1845.5	1123.7	912.3	120.4	97.8
	Other fish	350.1	679.1	530.5	840.6	749.8	490.5	399.7	140.1	114.2

Table 4. Descriptive statistics of the variables used in the Tobit Model (n = 22): 2010–2012.

Variable	Assumptions	Mean	Max	Min	SD
Dependent		Aggregate species model			
$CU_{unbiased}$	CRS	0.915	1.000	0.530	0.124
TE		0.640	1.000	0.253	0.248
$CU_{unbiased}$	VRS	0.883	1.000	0.300	0.214
TE		0.796	1.000	0.309	0.253
Independent					
Age (years)		45	61	29	8
Experience (years)		26	39	13	7
CPUE (kg/boat)		7.115	7.759	6.751	0.461
MI (productivity index)		1.016	2.39	0.41	0.373
CPI (price index)		229.067	242.7	217	10.631
Price (OMR)		0.766	1.258	0.14	0.207
Cost (OMR)	Fuel	2077.794	2989.333	1437.667	413.323
	Other operation	6826.818	10541.95	3325.931	1926.078
	Maintenance	111.147	262.76	26.581	56.221
	Crew share	3417.806	18403.81	0	4723.957

OMR: Omani Rial; SD: standard deviation.

Table 5. Regression results for capacity utilisation under the constant returns to scale (CRS) and variable returns to scale (VRS) assumptions.

Variable	CRS			VRS		
	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.
Constant	1.3950	0.5286	0.0083	3.9670	1.6037	0.0134
Location	-0.0619	0.0193	0.0014	-0.0997	0.0546	0.0677
Age	-0.0070	0.0075	0.3484	-0.0311	0.0186	0.0950
Education	-0.0058	0.0434	0.8934	-0.0269	0.1044	0.7968
Experience	-0.0054	0.0057	0.3403	-0.0039	0.0170	0.8167
Subsidy	0.0497	0.0566	0.3800	0.3826	0.1555	0.0139
CPUE	-0.3139	0.1066	0.0033	-0.2369	0.2715	0.3828
Costs of fuel	0.0003	0.0001	0.0001	0.0003	0.0003	0.3685
Other operation costs	7.07E-06	1.31E-05	0.5884	0.0001	3.23E-05	0.0417
Maintenance costs	-0.0008	5.80E-04	0.1722	0.0004	0.0018	0.8235
Crew share	1.21E-05	5.67E-06	0.0331	1.65E-05	1.91E-05	0.3886
CPI	0.0083	0.0043	0.0547	-0.0012	0.0125	0.9231
Summary statistics and diagnostics						
SE of regression	0.1082	AIC criterion	0.3069	0.1946	AIC criterion	1.1677
SSE	0.6209	Schwarz criterion	0.7382	2.0080	Schwarz criterion	1.5990
Log likelihood	2.8721	H-Q criterion	0.4773	-25.5340	H-Q criterion	1.3381
RMSE	0.0969	LR test	37.191 (0.0001)	0.1744	LR test	27.2405 (0.0042)

Table 6. Regression results for technical efficiency under the constant returns to scale (CRS) and variable returns to scale (VRS) assumptions.

Variable	CRS			VRS		
	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.
Constant	1.4950	0.6390	0.0193	2.6108	0.9977	0.0089
Location	-0.1192	0.0243	0.0001	-0.0889	0.0463	0.0549
Age	-0.0377	0.0108	0.0005	-0.0620	0.0185	0.0008
Education	-0.1720	0.0623	0.0058	-0.4844	0.0990	0.0001
Experience	0.0130	0.0075	0.0811	0.0184	0.0131	0.1600
Subsidy	0.3144	0.0633	0.0001	0.6279	0.1360	0.0001
CPUE	0.3713	0.0591	0.0001	0.5625	0.1051	0.0001
Costs of fuel	0.0004	0.0001	0.0007	-1.19E-05	0.0002	0.9501
Other operation costs	2.93E-05	1.60E-05	0.0669	-4.08E-05	3.20E-05	0.2022
Maintenance costs	-0.0002	0.0007	0.7318	-0.0007	0.0013	0.5896
Crew share	-1.04E-06	5.97E-06	0.8612	-2.81E-05	1.07E-05	0.0084
CPI	0.0013	0.0018	0.4914	0.0102	0.0035	0.0038
Summary statistics and diagnostics						
SE of regression	0.1479	AIC criterion	-0.0056	0.1717	AIC criterion	0.8015
SSE	1.1599	Schwarz criterion	0.4257	1.5628	Schwarz criterion	1.2328
Log likelihood	13.1850	H-Q criterion	0.1648	-13.4494	H-Q criterion	0.9719
RMSE	0.1326	LR test (p value)	84.0885 (0.0001)	0.1538	LR test (p value)	64.1141(0.0001)

performance of the model selection criteria and the likelihood-ratio (LR) test. The estimated root-mean-square error (RMSE) value was used to measure the forecast performance of the models as the Tobit analysis does not produce a 'goodness-of-fit' measure.

With reference to the CU model under the CRS assumption, the variables of 'location', 'CPUE', 'fuel costs' and 'crew share' were statistically significant at the 5 % level. On the other hand, under the VRS model only two variables, 'subsidy' and 'other operation costs' were statistically significant at the 5 % level.

The model results for TE under the CRS and VRS assumptions indicated that six variables were statistically significant at the 5 % level, of which 'age', 'education', 'subsidy' and 'CPUE' were common in both models. Other significant variables were 'location' and 'costs of fuel' under the CRS model, and 'crew share' and 'CPI' under the VRS model (Table 6).

In comparing the results of the models for CU and TE, it was observed that the variables of 'location', 'costs', 'subsidy' and 'CPUE' are significant in both models. The significance of the location variable reflects variability in the performance of fishers from different geographical locations and is consistent with the findings of Al-Siyabi (2018). The positive influence of the fuel costs reflects the fact that an increase in fuel expenditure forced the DMUs to fish harder to cover the associated costs and hence improve CU and TE. The positive coefficient of the subsidy variable indicates that the subsidy program enhances CU and TE through technical improvements. With reference to the crew share and CPUE variables, sign reversals of the estimated coefficients were observed in the CU

and TE models. The CPUE variable generally embraces the supply-side factor, and encompasses the seasonal variability of catch and productivity change over the period. The crew share variable is influenced by the amount of catch and hence connected to CPUE. Dudley (2008) argued that the acceptable level of CPUE by fishers is influenced by the profitability of fishing and the expected price of the fish. While any improvement in CPUE positively affects the technical efficiency of DMUs, the present finding suggests that when small-scale fishers have earned their expected income through improved CPUE they may be reluctant to improve their boat capacity to their maximum potential.

The anecdotal information in relation to small-scale fishers' practices in Oman suggests that fishers are reluctant to stay longer at sea, which is evident from the average duration of the fishing trip (about 5.4 h).

With regard to the TE model, the education variable has a negative and significant influence on the technical efficiency of DMUs. This result is in contrast with Sharma and Leung (1998), Fousekis and Klonaris (2003), Esmaeili (2006), Shen and Shen (2013) and Jamnia et al. (2015), but is in line with Tingley et al. (2005). The result suggests that fishers with relatively better educational attainment considered fishing as a part-time profession which is a common occurrence in Oman.

The 'age' variable carried a negative sign which indicates that older fishers are inefficient compare to younger fishers. This is in line with other studies. For example, Fousekis and Klonaris (2003) found a negative influence of fishers' age (51 years and above) on TE while Tingley et al. (2005) showed age had

negative effects on the efficiency of potters and net-liner boats in the English Channel. Furthermore, the study by Esmaeili (2006) for fisheries in the Persian Gulf of Iran found that age was negatively influencing TE. Jamnia et al. (2015) found that age had a negative effect on the efficiency of the offshore vessels operating in Chabahar region of Iran. This finding reflects the fact that fishing is a hard and challenging profession as mentioned earlier (Belwal et al., 2015).

Some Policy Implications

Regardless of the CRS and VRS assumptions, the results from this study indicate: i) the existence of technical inefficiency in harvesting operation, ii) the underutilisation of fishing capacity, iii) an increasing trend in scale inefficiency, and iv) the underutilisation of variable inputs over the study period. These results have important economic implications with regards to policy-setting for the sector as they reflect inefficient use of resources which hinders the achievement of the intended economic objectives for the sector.

If the objective of economic efficiency in fisheries takes precedence over the objective of community welfare, then the management authority could use the existing subsidy program to enhance productivity (without undermining the long-term sustainability of the resource) by allocating such financial incentives to efficient fishers only. This approach would increase the operational costs of inefficient fishers and discourage them to stay in the fishery.

However, if social objectives take precedence over economic objectives then other strategic approaches such as the development of human capital in the form of skill development initiatives should be sought (Bose et al., 2013). This development initiative could be tied with the recent initiatives of aquaculture development by MAF to enable fishers to choose a related but alternative profession. Furthermore, as there are considerable opportunities to increase productivity with current production technology through more efficient use of available inputs, a convincing case can be made to support government investments, infrastructure developments, and human capital developments through fisheries extension programs. The signal of excess capacity can be used as a tool to attract private investment in the sector, which is one of its strategic goals. It should be noted that any effort to increase productivity must strike a balance with the status of the stock. The results of the 2007–2008 stock assessment survey of the Arabian Sea coast of Oman indicated that the contribution of marine capture fisheries could be enhanced through increased production (Shallard et al., 2010).

If the existing fleet capacity and the observed outputs are not in harmony with the future sustainability of fish stocks, the government should focus on the development of the post-harvest sector which offers considerable room to improve operational efficiency (Al-Jabri et al., 2015; Qatan et al., 2015; Al-Busaidi et al., 2016; Al-Busaidi et al., 2017). Fisheries development strategies in Oman have adopted such an economic approach. To promote efficiency and fairness in relation to pricing and the distribution of fish products, a central wholesale fish market with an electronic auctioning system has been in operation since April 2014 (Bose et al., 2010; Qatan et al., 2015; Al-Busaidi et al., 2016). This initiative is expected to address some fundamental distributional and pricing concerns with regard to fish products in the country. Furthermore, the 'trawl ban' that occurred in the demersal trawl fishery in 2010 led to the decision to modernise fishing operations through the development of 'coastal fishery' (Al-Masroori and Bose, 2016), with the expectation of enhancing productivity of the sector. This policy decision is unlikely to diminish the role of SSF in Oman.

Conclusion

One of the prime justifications for the economic management of small-scale fisheries (SSF) is to optimise economic benefits and reduce economic waste of fisheries resources. With this in mind, this case study has been primarily concerned with investigating the status of technical efficiency (TE) and capacity utilisation (CU) of sampled fishing boats along with the factors affecting the level of TE and CU using a two-stage two-stage data envelopment analysis model. Such quantitative information is important to formulate effective policies for achieving economic sustainability of the SSF sector and safeguarding the livelihoods of small-scale fishers and coastal communities. In this regard, the present case study demonstrates how economics can play an important role in analysing techno-economic performance of the representative fishing boats and contributes to the development of appropriate policies for the conservation and efficient management of SSF resources.

The results indicate inefficiency in harvesting practices, inefficient use of inputs and the presence of underutilised fishing capacity. However, the results should be interpreted within their scope as they relate to a specific case study and data sets and, therefore, should not be treated as an indicator of efficiency (or lack of it) for the fisheries sector of Oman as a whole. Despite these caveats, the empirical results of this study have important policy implications. They provide a strong rationale for a further in-depth study on the efficiency issue for the overall fisheries sector in Oman. Future work must scrutinise the sensitivity of empirical results by adopting a parametric approach.

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