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Technical efficiency study on Japanese marine fisheries applying stochastic frontier analysis and data envelopment analysis approaches

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Abstract
Technical efficiency analysis was carried out targeting Japanese marine fishery production in 2013, applying both Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) approaches. Results showed the technical efficiency estimate of Japanese marine fishery production in 2013 was 0.783, 0.559 and 0.666 by means of SFA, DEA-CRS (constant returns to scale) and DEA-VRS (variable returns to scale), respectively. This indicates that a range of 22%-44% potential scope still exists for improving the current Japanese marine fishery production with the given inputs. Analysis of region-specific efficiencies showed Ehime Prefecture was the most efficient irrespective of estimation methods, while Osaka and Yamaguchi Prefectures were the least efficient using different analytical approaches. Comparison of the results between SFA and DEA shows that technical efficiency estimates applying SFA were closely associated with those by DEA, although the efficiency scores were higher by SFA approach.

Keywords: Japanese marine fishery, technical efficiency, stochastic frontier analysis, data envelopment analysis

1. Introduction

After World War Ⅱ, Japanese fisheries developed rapidly with the expansion of its economic growth and reached the peak in early 1980s. The largest production volume of Japanese marine fishery (the combination of marine capture fishery and marine aquaculture) was seen in 1984 as 12.6 million tonnes [1] (Figure 1). Nevertheless, this high-level did not continue and kept dropping since 1989 till now, with few exceptions. The total marine production volume in 2014 declined to only 37.5% of the quantity in the peak year 1984 [1]. The breakdown of total marine fishery production into different categories (Figure 1) indicates that the decrease in Japanese marine fishery production can be more attributed to the changes in the offshore and pelagic fisheries. The rapid decrease in Japanese fishery production is usually concluded to be caused by two changes, the collapse of Japanese sardine (*Sardinops melanostictus*) and the shrink of Japanese distant water fishery after the introduction of the 200 nautical miles exclusive economic zones [2].

The recession of Japanese marine fishery can also be reflected in the change of fishery workers and fishing vessels, which are further explained below. Based on the statistical data published by Ministry of Agriculture, Forestry and Fisheries (abbreviated as MAFF), the quantity of fishery workers experienced a 75% drop from 699,200 in 1961 to 173,030 in 2014 [3]. Furthermore, the age distribution of Japanese fishery workers is skewed, with 48.2% of them older than 60 years in 2014 [3]. In terms of vessels quantity operating in marine fishery, it was reduced from 293,578 in 1949 to 152,998 in 2013 [4]. Gross tonnage of the motor-powered marine fishing vessels decreased by 53.5% from 1963 to 2013 [4]. Similar with fishery workers, fishing vessels in Japan also display an aging trend, as pointed out in White Papers on Fisheries [5].

The decline of Japanese marine fishery has attracted great concerns from Japanese government, fishing industry as well as from fisheries scientists. Extensive discussions and researches have been conducted aiming at finding the most appropriate management framework for achieving sustainable fisheries in the future [6]. In the report published by Fisheries Research Agency (abbreviated as FRA) in 2009, the scenario of ecosystem mosaic was finally considered as appropriate for managing Japanese fishery [6], which sets efficiency enhancement as the priority in policy design concerning offshore and high seas fisheries. Improving efficiency of Japanese fishery is also emphasized in previous literatures [7, 8].

Although efficiency improvement is not the sole consideration or solution when dealing with the declining trend of Japanese fishery, evaluating the efficiency in Japanese marine fisheries should be part of the focuses.

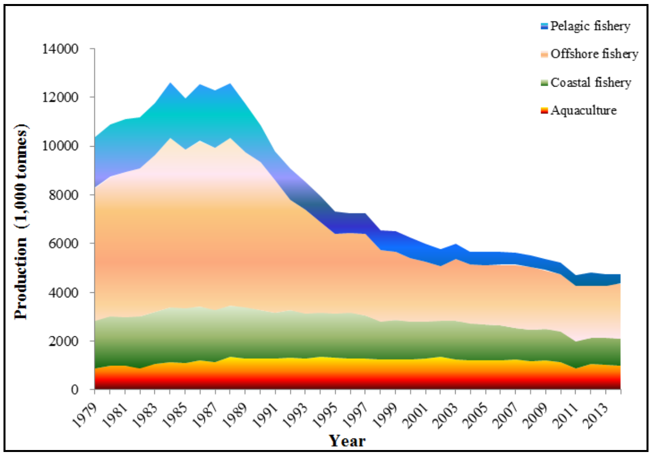

Fig. 1: Production volume of Japanese marine fishery from 1979 to 2014 [1]

The measurement of efficiency in modern economics follows the ideas of Farrell [9]. According to Farrell, efficiency of a decision-making unit (DMU) can be decomposed into two components: technical efficiency (TE) and allocative efficiency (AE) [9]. TE evaluates the capacity of a DMU to maximize its output with the given inputs or minimize the inputs with the given output [10]. Although a large body of literatures have been published concerning the technical efficiency of fisheries since the introduction of Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) approaches [11-19], the TE analysis in the context of Japanese fishery is still insufficient [20, 21].

Therefore, an analysis of the technical efficiency of Japanese marine fishery will be carried out on a prefecture-basis in this study. The methods for estimation are the two most widely applied approaches, i.e. SFA as well as DEA. This study aims to estimate the technical efficiency of Japanese marine fishery (includes capture fishery as well as aquaculture) which indicates the potential scope for improvement, to clarify the variations of efficiency in different geographical regions, and to compare the results obtained using different estimation methods.

2. Materials and Methods

2.1 Analytical data

As described above, technical efficiency is an indicator to measure the capacity of a DMU to maximize outputs given inputs or minimize inputs given outputs. Thus, in order to carry out the technical efficiency analysis of Japanese marine fishery production, related data on the output and inputs should be collected. Marine fisheries in Japan are rather complicated, composed of capture fisheries as well as aquaculture. Marine capture fisheries can be further divided into a wide range of subgroups, and so is marine aquaculture. Hence, a comprehensive analysis of Japanese marine fishery requires an inclusion of input-output data on various fishery types if fishing vessels are considered as the DMUs, which is data-demanding and impracticable. The prefectural governments engaging in marine fishery production are therefore taken as the DMUs in this study.

To clarify the current status of the technical efficiency regarding Japanese marine fishery, the latest available data in 2013 are selected. Production value of marine fishery by each prefectural government in 2013 is selected as the output variable; while gross registered tonnage (GRT) of motor-powered vessels and quantity of fishery workers used by each prefecture in 2013 are chosen as the two input variables [1, 4]. Marine fishery workers are defined as those with an age of more than 15 and engaging in marine fishery production for more than 30 days in one year [4]. Although the output data on marine capture fishery as well as aquaculture in each prefecture are available, a separate analysis is infeasible due to insufficient information of inputs. Therefore, the overall marine fishery production value is adopted as the output variable, which is measured in million Japanese Yen (JPY). Adoption of production value rather than volume as the output variable is a standard practice in cases of multi-products DMUs [12]. A summary statistics of the inputs and output variables is provided in Table 1.

As shown in Table 1, in 2013, the total marine fishery production value of each prefecture ranged from 2,653 million JPY to 298,444 million JPY, with the mean value as 34,722 million JPY; GRT of motor-powered vessels used in marine fishery distributed from 1,741 GRT to 71,377 GRT, with a mean of 15,699 GRT; and the total number of fishery workers differed from 343 persons to 29,652 persons, averaging as 4,641.

Table 1: Summary statistics of the variables used in the technical efficiency analysis of Japanese marine fishery in 2013

Variable	Unit	Description	Mean	Max	Min	SD
Production	million JPY	Marine fishery production value	34,722	298,444	2,653	48,516
Ton	GRT	Tonnage of motor-powered vessels used in marine fishery	15,699	71,377	1,741	13,891
Man	person	Total quantity of fishery workers engaged in marine fishery	4,641	29,652	343	5,004

2.2 Analytical methodology: SFA

The general stochastic frontier production function model can be written as follows [22]:

$$y_i = f(x_i;\beta) + \varepsilon_i,$$

$$\varepsilon_i = v_i + u_i,$$

$$TE = y_i/[f(x_i;\beta) + v_i] \quad i = 1, \cdots, N \text{ DMUs}$$

Where $f(x_i;\beta)$ represents the maximum output attainable by the i^{th} DMU, y_i denotes the real output by the i^{th} DMU, x_i is a vector of inputs applied by the i^{th} DMU, and β represents the vector of unknown parameters to be estimated. Here, ε_i designates the difference between real output and potential maximum output, which is composed of two error components, v_i and μ_i. v_i represents the symmetric disturbance out of the control of decision-making units, while μ_i is assumed to be distributed independently of v_i and represents the deviation from potential maximum output caused by technical inefficiency which is under the control of decision-making units.

In this study, the stochastic frontier production function model of Japanese marine fishery can be specified as follows:

$$\ln y_i = \beta_0 + \beta_1 \ln ton_i + \beta_2 \ln man_i + v_i + u_i$$

$TE = y_i/[f(x_i;\beta) + v_i] \quad i = 1, \cdots, N$ DMUs

Where $\ln y_i$ represents the natural logarithm of yearly production value of marine fishery by the i^{th} prefecture (i =1,…,39) in 2013. The variable $\ln ton_i$ denotes the natural logarithm of total gross registered tonnage of motor-powered fishing vessels in marine fishery production by the i^{th} prefecture in 2013, and $\ln man_i$ is the natural logarithm of fishery worker quantity involved in marine fishery by each prefecture in that year.

2.3 Analytical methodology: DEA

DEA approach is a nonparametric method to calculate the technical efficiency scores of decision-making units, by constructing a production frontier using the observed input-output data. Unlike SFA, DEA is a linear programming method and can avoid the assumption of functional form in advance. In the work of Charnes et al. [23], the first original model of DEA was raised, also known as CCR model, assuming constant returns to scale (DEA-CRS model). Afterwards, the assumption of constant returns to scale was relaxed and variable returns to scale was adopted by Banker et al. [24]. This DEA-VRS model is also known as BCC model.

The general output-oriented DEA-CRS model for a single output is described as follows:

$\text{Max } \varphi_i$

Subject to:

$$\varphi_i\, y_i \le \sum_j \lambda_j\, y_j, \; i = 1, \cdots, N \text{ DMUs}, \; j = 1, \cdots, N \text{ DMUs}$$

$$\sum_j \lambda_j\, x_{j,k} \le x_{i,k}, \; k = 1, \cdots, m \text{ inputs}$$

$$\lambda_j \ge 0$$

And DEA-CRS model can be transformed into a more flexible DEA-VRS model by means of adding another constraint as follows:

$$\sum_j \lambda_j = 1, \; j = 1, \cdots, N \text{ DMUs}$$

Where the scalar φ_i measures the extent of potential output expansion if the i^{th} DMU performs at a 100% technical efficiency, ranging from 0 to 1; y_i denotes the output produced by the i^{th} DMU; λ_j is the weight assigned to the peers of the i^{th} DMU; $x_{i,k}$ represents the k^{th} input used by the i^{th} DMU.

Based on the results of φ_i estimated by DEA-CRS and DEA-VRS models, the technical efficiency score of the i^{th} DMU can be calculated, and the scale efficiency (SE) can also be measured as follows:

$$TE_i = \frac{1}{\varphi_i}$$

$$SE_i = \frac{TE_{i,CRS}}{TE_{i,VRS}}, \; i = 1, \cdots, N \text{ DMUs}$$

3. Results

3.1 Results of parameter estimates in SFA

The R programming language (version 2.14.2) was applied to perform the calculation and acquire the results. Based on the maximum likelihood estimation approach, the estimated results of stochastic production frontier are presented in Table 2. The coefficient of vessel tonnage is 0.89, which means it is positively related with marine fishery production value, significant at a 1% level or less. The quantity of fishery workers is also significantly and positively related with marine fishery production value, with the coefficient as 0.30. The variance of the one-sided component γ is 0.66, which can be used to calculate the relative contribution of the technical inefficiency effect to the total variance term. As Cobb-Douglas function form is adopted, the coefficients of parameters can be given an economic explanation. Theoretically, the value of Japanese marine fishery production in 2013 can be increased by 0.89% and 0.3% if the vessel tonnage and the fishery worker number increase by 1% respectively.

Table 2: Parameter estimates of the stochastic production frontier model for Japanese marine fishery in 2013

Parameter	Symbol	Coefficient
Constant	β_0	-0.55
ln(ton)	β_1	0.89***
ln(man)	β_2	0.30***
Sigma-squared	σ^2	0.17**
Gamma	γ	0.66**
Log-likelihood		-9.52

Note: * designates statistically significant at 10% level or less, ** means statistically significant at 5% level or less, and *** means statistically significant at 1% level or less.

3.2 Results of technical efficiency in SFA

Results of TE estimates calculated by SFA model are presented in Table 3. In 2013, the technical efficiency of Japanese marine fishery was 0.783 on an average, ranging from 0.516 to 0.918, with a small standard deviation as 0.094. Frequency distribution in Table 3 indicated that nearly half of the 39 prefectures (43.6%) exhibited a technical efficiency between 80% and 90% and more than one-third (35.9%) performed at a 70%-80% level of the maximum capacity. In another word, a majority of the prefectures (84.6%) showed a technical efficiency over 0.7. Among the 39 prefectures, Ehime was the most technically efficient with a score as 0.918, while Osaka was the least technically efficient with a score as 0.516. The technical efficiency estimates of each prefecture are listed in Table 4.

In Figure 2, the mean technical efficiencies of Japanese marine fishery in 2013 divided by geographical regions are represented. The 39 prefectural governments are usually divided into five geographical regions from the north to the south, i.e. Hokkaido region, Honshu region, Shikoku region, Kyushu region and Okinawa region. Results showed that Hokkaido region was the most technically efficient, followed by Shikoku, Kyushu and Okinawa, and Honshu was the least technically efficient.

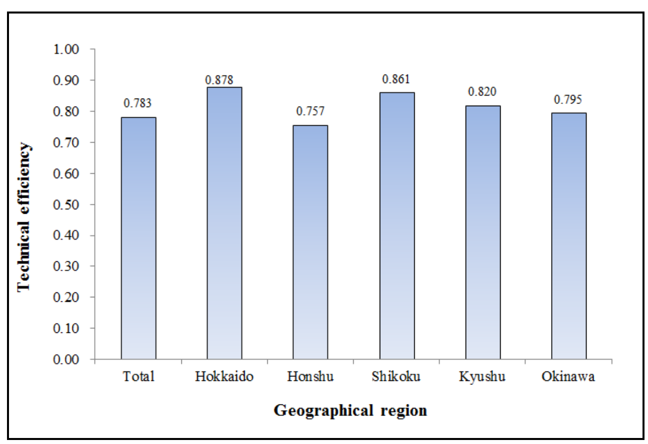

Fig 2: Mean technical efficiencies of Japanese marine fishery in 2013 divided by geographical regions (SFA)

Table 3: Frequency distributions of technical efficiency and scale efficiency (SE) of Japanese marine fishery in 2013 using SFA, DEA-CRS and DEA-VRS

Frequency	SFA		DEA-CRS		DEA-VRS		SE	
1.00			2	(5.1%)	5	(12.8%)	3	(7.7%)
[0.90, 1.00)	2	(5.1%)	3	(7.7%)	3	(7.7%)	13	(33.3%)
[0.80, 0.90)	17	(43.6%)	1	(2.6%)	2	(5.1%)	14	(35.9%)
[0.70, 0.80)	14	(35.9%)	1	(2.6%)	4	(10.3%)	5	(12.8%)
[0.60, 0.70)	3	(7.7%)	6	(15.4%)	7	(17.9%)		
[0.50, 0.60)	3	(7.7%)	9	(23.1%)	12	(30.8%)		
[0.40, 0.50)			9	(23.1%)	3	(7.7%)	4	(10.3%)
[0.30, 0.40)			6	(15.4%)	3	(7.7%)		
[0.20, 0.30)			2	(5.1%)				
Total	39	(100%)	39	(100%)	39	(100%)	39	(100%)
Mean	0.783		0.559		0.666		0.841	
Maximum	0.918		1.000		1.000		1.000	
Minimum	0.516		0.210		0.320		0.397	
Standard deviation	0.094		0.207		0.194		0.163	

Table 4: List of prefecture specific technical efficiency of Japanese marine fishery in 2013 using SFA, DEA-CRS and DEA-VRS

No.	Prefecture	SFA	Rank	DEA-CRS	Rank	DEA-VRS	Rank
Hokkaido	Hokkaido	0.878	6	0.960	4	1.000	1
Honshu region	Aomori	0.656	35	0.390	32	0.400	36
	Iwate	0.806	17	0.520	18	0.580	23
	Miyagi	0.779	26	0.610	13	0.690	15
	Akita	0.758	30	0.310	36	0.780	11
	Yamagata	0.846	8	0.430	30	1.000	1
	Fukushima	0.816	15	0.990	3	1.000	1
	Ibaraki	0.837	12	0.670	8	0.710	14
	Chiba	0.837	11	0.550	16	0.620	20
	Tokyo	0.906	2	1.000	1	1.000	1
	Kanagawa	0.584	37	0.340	35	0.390	37
	Niigata	0.824	14	0.470	25	0.660	18
	Toyama	0.799	20	0.570	14	0.630	19
	Ishikawa	0.793	22	0.500	21	0.560	26
	Fukui	0.766	29	0.380	34	0.540	29
	Shizuoka	0.733	32	0.560	15	0.690	15
	Aichi	0.777	27	0.440	29	0.520	30
	Mie	0.781	25	0.510	19	0.520	30
	Kyoto	0.792	23	0.390	32	0.910	7
	Osaka	0.516	39	0.210	39	0.460	35
	Hyogo	0.711	33	0.490	23	0.490	34
	Wakayama	0.600	36	0.300	37	0.380	38
	Tottori	0.844	9	0.650	10	0.730	12
	Shimane	0.800	19	0.510	19	0.570	24
	Okayama	0.807	16	0.430	30	0.590	22
	Hiroshima	0.752	31	0.460	26	0.500	33
	Yamaguchi	0.571	38	0.270	38	0.320	39
Shikoku region	Tokushima	0.803	18	0.460	26	0.560	26
	Kagawa	0.825	13	0.550	16	0.620	20
	Ehime	0.918	1	1.000	1	1.000	1
	Kochi	0.898	3	0.910	5	0.930	6
Kyushu region	Fukuoka	0.787	24	0.480	24	0.520	30
	Saga	0.871	7	0.640	11	0.720	13
	Nagasaki	0.685	34	0.500	21	0.570	24
	Kumamoto	0.840	10	0.620	12	0.680	17
	Oita	0.893	5	0.760	7	0.800	10
	Miyazaki	0.894	4	0.870	6	0.880	9
	Kagoshima	0.774	28	0.660	9	0.910	7
Okinawa	Okinawa	0.795	21	0.450	28	0.560	26

Table 5 shows the technical efficiencies of the top ten prefectures in terms of marine production value in 2013. Among these ten prefectures with large marine fishery production values, only three of them (Hokkaido, Ehime and Kochi) entered into the list of top ten technically efficient prefectures. The remaining seven prefectures were all ranked after the 20th place considering TE estimate, with four appearing in the bottom ten list of TE. Although Hokkaido showed an obvious superiority in marine production value, its TE was lower than Ehime and Kochi.

3.3 Results of technical efficiency and scale efficiency in DEA

As presented in Table 3, TE of Japanese marine fishery in 2013 estimated by DEA-CRS averaged as 0.559, ranging from 0.21 to 1, with a standard deviation as 0.207. Mean TE calculated by DEA-VRS was 0.666, ranging from 0.32 to 1. Table 3 also indicated that TE estimates by use of DEA model displayed a wide distribution. In DEA-CRS, prefectures with a TE range between 0.5 and 0.6 (also between 0.4 and 0.5) accounted for the largest ratio (23.1%); while in DEA-VRS, over one third of the prefectures (30.8%) fell into the range of 0.5 and 0.6. Two and five prefectures obtained a TE score of 1 in DEA-CRS and DEA-VRS models, respectively. As shown in Table 4, Ehime and Tokyo were fully efficient while Osaka was the least technically efficient in the case of DEA-CRS model; in the condition of DEA-VRS model, Yamaguchi obtained the lowest TE while Ehime, Tokyo, Fukushima, Yamagata and Hokkaido were all perfectly efficient.

As presented in Figure 3, in terms of different geographical regions by DEA-CRS model, Hokkaido region showed the highest TE, followed by Shikoku, Kyushu, Honshu and Okinawa, which was similar with the result by SFA model illustrated in Figure 2 except the reversed order of Honshu and Okinawa. By using DEA-VRS model, the rank of average TE in different geographical regions is the same with that in DEA-CRS.

Table 6 shows TE estimates and corresponding ranks of the top ten prefectures in terms of marine production value in 2013 using DEA. In DEA-CRS model, four of the top ten prefectures with the largest marine fishery production entered into the group of top ten technically efficient, i.e. Hokkaido, Ehime, Kagoshima and Kochi. Hokkaido showed an obvious superiority over Ehime in terms of marine production value, while its TE was lower than Ehime. In DEA-VRS model, four of the top ten prefectures with the largest marine fishery production were also the top ten considering TE (Hokkaido, Ehime, Kagoshima and Kochi), which agreed with the corresponding results in DEA-CRS model. Hokkaido showed an obvious superiority over Ehime in terms of marine production value and its TE was the same with that of Ehime.

Table 5: Technical efficiency ranking of the top ten prefectures in terms of marine fishery production value in 2013 (SFA)

Prefecture	Production value (million JPY)	Rank	TE	Rank
Hokkaido	298,444	1	0.878	6
Nagasaki	92,140	2	0.685	34
Ehime	84,912	3	0.918	1
Kagoshima	76,637	4	0.774	28
Miyagi	57,002	5	0.779	26
Shizuoka	51,634	6	0.733	32
Kochi	48,957	7	0.898	3
Mie	46,212	8	0.781	25
Aomori	46,125	9	0.656	35
Hyogo	38,303	10	0.711	33

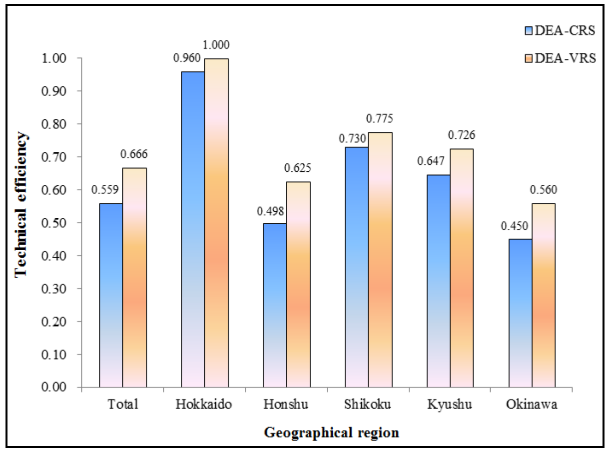

Fig 3: Mean technical efficiencies of Japanese marine fishery in 2013 divided by geographical regions (DEA)

Table 6: Technical efficiency ranking of the top ten prefectures in terms of marine fishery production value in 2013 (DEA)

Prefecture	Production value (million JPY)	Rank	DEA-CRS	Rank	DEA-VRS	Rank
Hokkaido	298,444	1	0.96	4	1.00	1
Nagasaki	92,140	2	0.50	21	0.57	24
Ehime	84,912	3	1.00	1	1.00	1
Kagoshima	76,637	4	0.66	9	0.91	7
Miyagi	57,002	5	0.61	13	0.69	15
Shizuoka	51,634	6	0.56	15	0.69	15
Kochi	48,957	7	0.91	5	0.93	6
Mie	46,212	8	0.51	19	0.52	30
Aomori	46,125	9	0.39	32	0.40	36
Hyogo	38,303	10	0.49	23	0.49	34

Table 3 also listed the frequency distribution of SE, which averaged as 0.841, changing from 0.397 to 1, with a standard deviation as 0.163. Three of the prefectures displayed full SE and prefectures with an SE range between 0.8 and 0.9 accounted for the largest ratio (35.9%). Nearly 90% of the prefectures showed an SE higher than 0.7.

3.4 Comparisons of technical efficiency in both SFA and DEA

As indicated in Table 3, the mean TE estimates of Japanese marine fishery in 2013 calculated by SFA are higher than those in DEA. Meanwhile, the TE scores of 39 prefectures in SFA concentrated in the range of 0.7 and 0.9, while those in DEA were distributed more widely. This difference can also be found from different standard deviations between SFA and DEA results. In terms of the prefecture with the highest TE, results were consistent between SFA and DEA; while with respect to the least efficient prefecture, results were the same between SFA and DEA-CRS while showed differences in DEA-VRS.

To further verify the association of the results obtained by means of SFA and DEA, Spearman rank correlation analysis [25] was conducted and the coefficients were listed in Table 7. The coefficients were all larger than 0.7, designating strong correlations among the ranking results of SFA, DEA-CRS and DEA-VRS. And the TE ranking using SFA showed the best agreement with that applying DEA-VRS.

Table 7: Spearman rank correlation matrix of technical efficiency rankings of prefectures

	SFA	DEA-CRS	DEA-VRS
SFA	1.000	0.745	0.759
DEA-CRS	0.745	1.000	0.716
DEA-VRS	0.759	0.716	1.000

4. Discussion
Results of mean technical efficiency of Japanese marine fishery indicate that it still has considerable room to improve the efficiency as the TE score was less than 0.8 regardless of estimation methods. The TE score of overall Japanese marine fishery derived in this study was lower than that of offshore bottom trawl fishery in Hokkaido studied by Sakai et al. [21], which showed an average TE as 0.892. They concluded that the offshore bottom trawl fishery in Hokkaido operated with a high technical efficiency. The gap between the TE score in our study and that in Sakai et al. [21] can be possible because our study target is the overall Japanese marine fishery, which may include efficient fisheries as well as inefficient fisheries. Meanwhile, TE estimates of the fishery in other countries can also be found in previous literature despite a small quantity. For instance, a meta-analysis of TE in global aquaculture was conducted [26] and it was concluded that the mean TE of aquaculture operations was 0.64 for Asia, 0.71 for Africa, 0.80 for Europe, and 0.73 for the U.S. Kim et al. [27] estimated the TE of Korean coastal composite fishery in 2005 and found the TE score ranged from 0.48 to 0.74. Comparison among these results indicates that Japanese marine fishery does not demonstrate superiority over other fishing counties in terms of technical efficiency.

With regard to the prefecture-specific TE, results showed that Ehime was the most efficient applying both SFA and DEA approach. This could be explained by the importance of Ehime in Japan's marine fishery production. As shown in Table 5 and 6, the TE of some traditional marine fishing region was not as high as being expected, revealing that large marine production does not guarantee high technical efficiency. This can be easily understood because TE evaluates a DMU's capacity in maximizing output or minimizing inputs. If a prefecture with large fishery production uses excessive inputs to achieve an abundant production, it may be less technically efficient than a prefecture with small fishery production but using the appropriate amount of inputs.

Technical efficiency estimates derived from SFA approach were larger than those from DEA, which corresponds with several previous works [28, 29]. This is reasonable because DEA attributes the deviation of real output from potential maximum output to inefficiency, without taking into account random error; while SFA considers both. Despite of the variation in TE scores, results in this study indicate that TE estimates applying SFA are closely associated with those by DEA, which was also pointed out in previous works [27-29].

5. Conclusion
By selecting the input and output data on Japanese marine fishery production in 2013, this study adopted SFA and DEA approaches to estimate the TE scores of each prefectural government engaging in marine fishery production. Yearly production value of marine fishery by each of the 39 prefectural governments was chosen as the output, and the gross registered tonnage of motor-powered vessels and the overall quantity of marine fishery workers were considered as two input variables.

Results showed that the mean TE of Japanese marine fishery production in 2013 was 0.783, 0.559 and 0.666 using SFA, DEA-CRS and DEA-VRS, respectively. Irrespective of estimation methods, Ehime showed the highest TE. Adopting SFA and DEA-CRS, Osaka showed the lowest efficiency; while using DEA-VRS, Yamaguchi was the least efficient. Although TE estimates were different, there exist strong correlations among the results by SFA, DEA-CRS and DEA-VRS.

As the technical efficiency studies on Japanese fishery are extremely insufficient and comparison of results between SFA and DEA is even much scarcer, this study is significant and meaningful, providing important insights into the current status of Japanese marine fishery production. Despite of this, limitations can be found such as the combination of capture fishery and aquaculture. When input and output data are available, a separate analysis of the technical efficiency of marine capture fishery as well as marine aquaculture will be carried out which is expected to derive more accurate results. Meanwhile, another aspect of efficiency, i.e. allocative efficiency, will also be analyzed targeting Japanese marine fishery in future works.

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