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Original Article

Estimating productivity, technical and efficiency changes in the Western Pacific purse-seine fleets

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The purse-seine tuna fleet in the Western Pacific Ocean has undergone an accelerated expansion since the 1980s. The fishery is primarily managed using fishing effort limits. Constraining effort to ensure the biological health of the stock, while enhancing economic benefits generated by the fishery, is a major challenge faced by fisheries managers in this region. To maintain effort levels that achieve those objectives, there is a need to take into account technical and efficiency changes over time that influence the productivity of fleets. This study evaluates how the productivity of four of the region's purse-seine fleets has changed year on year between 1993 and 2010 using a robust bootstrapped Malmquist index approach. This index is separated into: technical change, which represents the change in productivity due to the introduction of new technology and efficiency change, the change in productivity resulting from a change in the level of efficiency in the use of inputs. The results show that half of the 56 purse-seine vessels examined displayed significant gains in productivity, which appeared to be driven primarily by technical change. The technical efficiency of fleets showed less marked changes, potentially due to the practical inability to maximize performance in the face of dramatic technological advances.

Keywords: DEA, fishing efficiency, Malmquist index, tuna, Western And Central Pacific Ocean.

Introduction

Tuna and tuna-like species support some of the most socially, economically, and ecologically valuable fisheries worldwide. This is particularly true for the Western and Central Pacific Ocean (WCPO), where ~2.6 million metric tonnes were caught in 2013, representing over half of the world's total tuna catch. The area has seen a rapid increase in catch since the turn of the century (FFA, 2014), which has led to growing concern about the impact of fishing on these species (Hampton *et al.*, 2005; Juan-Jordá *et al.*, 2011).

The majority, ~80%, of the WCPO tuna catch in recent years has been taken by purse-seine vessels (which involves using a net to encircle fish in the surface waters down to ~300 m), which landed over 2 million tonnes in 2014 and which operate mainly in tropical waters between 5°N and 10°S and from 135°E to 150°W, targeting skipjack (*Katsuwonus pelamis*) and yellowfin (*Thunnus albacares*) tunas (Williams and Terawasi, 2015). Historically, the main purse-seine fleets have been flagged to the United States (US), Korea (KR), Japan (JP), and Chinese Taipei (TW) although the number of vessels flagged to other nations, including those of the Pacific Islands, has increased in recent years with the fleet doubling in size since the late 1980s (Williams and Terawasi, 2015).

Within the region, purse-seine fishing has been managed through effort limits, within the Western and Central Pacific Fisheries Commission (WCPFC) and by the Parties to the Nauru Agreement (PNA); around three quarters of the WCPO purse-seine catch is taken from Exclusive Economic Zones (EEZs) of the eight tropical countries (Figure 1). Since 2007, the PNA has managed the purse-seine fishery through the Vessel Day Scheme, which aims to control purse-seine effort through a limit on the number of fishing days that can be utilized in their EEZs (referred as the total allowable effort; Shanks, 2010). The purse-seine fishery is vital to PNA member economies in many ways, including contributions to government revenue from access fees levied on foreign

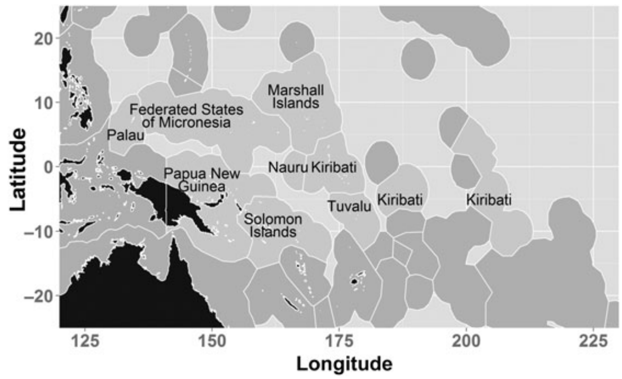

Figure 1. Parties of the Nauru Arrangement (PNA) Exclusive Economic Zones (EEZs).

purse-seine fishing operators (in 2012 contributing up to 60% of government revenue for some members, Bell *et al.*, 2015) and employment generated by the onshore processing sector. Given the stock's importance to these countries, PNA members have also put forward a target reference point (TRP) to the WCPFC that meets their objectives of stock sustainability, employment, and fishery revenue (PNA, 2015) around which the stock would be managed via effort control.

Management through input controls requires monitoring and adjustment for increases in the efficiency of that input to remain effective. For example, the onset of improved technology has allowed the fleet to fish the deeper thermocline found in the WCPO (Bertignac *et al.*, 2000). The use of helicopters, satellite maps, and bird radar has increased vessels' ability to find free swimming schools of tuna. In addition, adoption of advanced technologies in exploiting tunas in association with floating objects has increased the success rate of fishing (Coan *et al.*, 1998). This latter process is ongoing with the growing use of more sophisticated acoustic devices that allow for increasing levels of information on the size and composition of the fish aggregation below the Fish Aggregation Device (FAD) to be relayed to the fishing company and/or vessel. Quantifying increases in productivity (where productivity is the level of outputs for a given level of inputs within the production process) is therefore important for WCPO fisheries management. In this study, productivity refers to economic productivity rather than biological productivity which is the capacity of the stock to rapidly recover when depleted (Arrizabalaga *et al.*, 2011). Information on the relationship between fishery inputs (e.g. fishing effort) and outputs (e.g. catch or the exploitation rate) and how that relationship has changed over time is required.

The economic theory of total factor productivity (TFP) accounts for the portion of the output produced by a company that is not explained by the quantity of inputs (e.g. labour and capital) behind a company's production. It represents a useful tool to determine productivity changes in fisheries (Squires and Reid, 2004; Hoff, 2006; Oliveira *et al.*, 2009, 2013), but does not require difficult-to-obtain input and output economic variables such as revenues and costs. TFP may also relate to changes in stock biomass or regulations rather than any changes in the fleet. For example, Squires and Reid (2004) investigated productivity changes within the Korean purse-seine fleet in the WCPO between 1997 and 2002 using a deterministic approach that incorporated environmental factors, stock biomass (hence accounting for changes in stock levels), and a multioutput production of skipjack and combined yellowfin and bigeye tuna catch weights. The authors found that during this period, TFP was reasonably modest and was mainly driven by process innovation (e.g. improvements to vessel electronics or adoption of efficient brailling systems). Given the potential consequences of increases in fleet productivity since 2002, there is a need to fully inform regional management when developing management measures and maintaining stocks relative to TRP biomass levels.

Here, TFP is explored for the WCPO purse-seine fishery using a non-parametric algorithm (Oliveira *et al.*, 2009, 2013). First, we apply data envelopment analysis (DEA), a non-parametric frontier method that assumes no functional form on production, to estimate the productivity of vessels over time. From these, Malmquist indices (MIs) are developed as measures of relative TFP change. Those MIs are divided into two components: total efficiency (TE change; that is, changes in productivity due to changes in efficiency of the use of inputs; for example, a skipper who becomes better at locating fish schools over time will also be making much more efficient use of his crew over time) and technical change (TC; that is, changes in productivity due to the introduction of new technology, for example, sonar, satellite maps, or FADs) using a series of linear programming algorithms. Confidence intervals are developed by bootstrapping resulting DEA estimators to develop robust estimates of the population distribution of the MI (Simar and Wilson, 1998, 1999, 2007; Hoff, 2006). This approach is applied to develop fleet-specific changes in TFP for four of the main WCPO purse-seine fleets, the US, TW, JP, and KR over an 18-year period, 1993–2010. Changes in TFP are divided into those attributable to TE, and those to TC.

Methods

Data

The Pacific Community's Catch and Effort query System database for fishing activity (detailed commercial logsheet data by fishing event, unfortunately detailed high seas information was unavailable) and the Pacific Islands Forum Fisheries Agency fleet register were used to develop a time-series of commercial purse-seine catch estimates and vessel characteristic data for vessels flagged to the US, KR, JP, and TW operating in the PNA EEZs between 1993 and 2010 (∼105–135 vessels). The fleet register contains information on vessel characteristics such as engine power in Horse Power (HP), vessel length, and vessel age (Figure 2). While other vessel-related characteristics were also available from the fleet register database (e.g. storage capacity, number of crew, fuel capacity, number of auxiliary boats, gross tonnage, and if a helicopter was present), after a thorough investigation of available variables, other potentially relevant covariates were either absent for some vessels or did not span the time-series, and hence were omitted from the analysis.

As the estimation of the MI requires pairs of productivity information from successive years by the same vessel to calculate cross-period distance functions and to estimate productivity changes between 1993 and 2010, vessel-specific information was selected based on the presence of vessels in the fishery over the whole 18-year period. Unique vessels were identified by their registered call sign. Fifty-six vessels identified as fishing across the whole period under the same flag were included in the analysis. Catch and effort trends of the whole fleet and the sample of selected vessels (Figure 2) were comparable, and hence the subsets of vessels were considered representative of the fleet as a whole when constructing the MI.

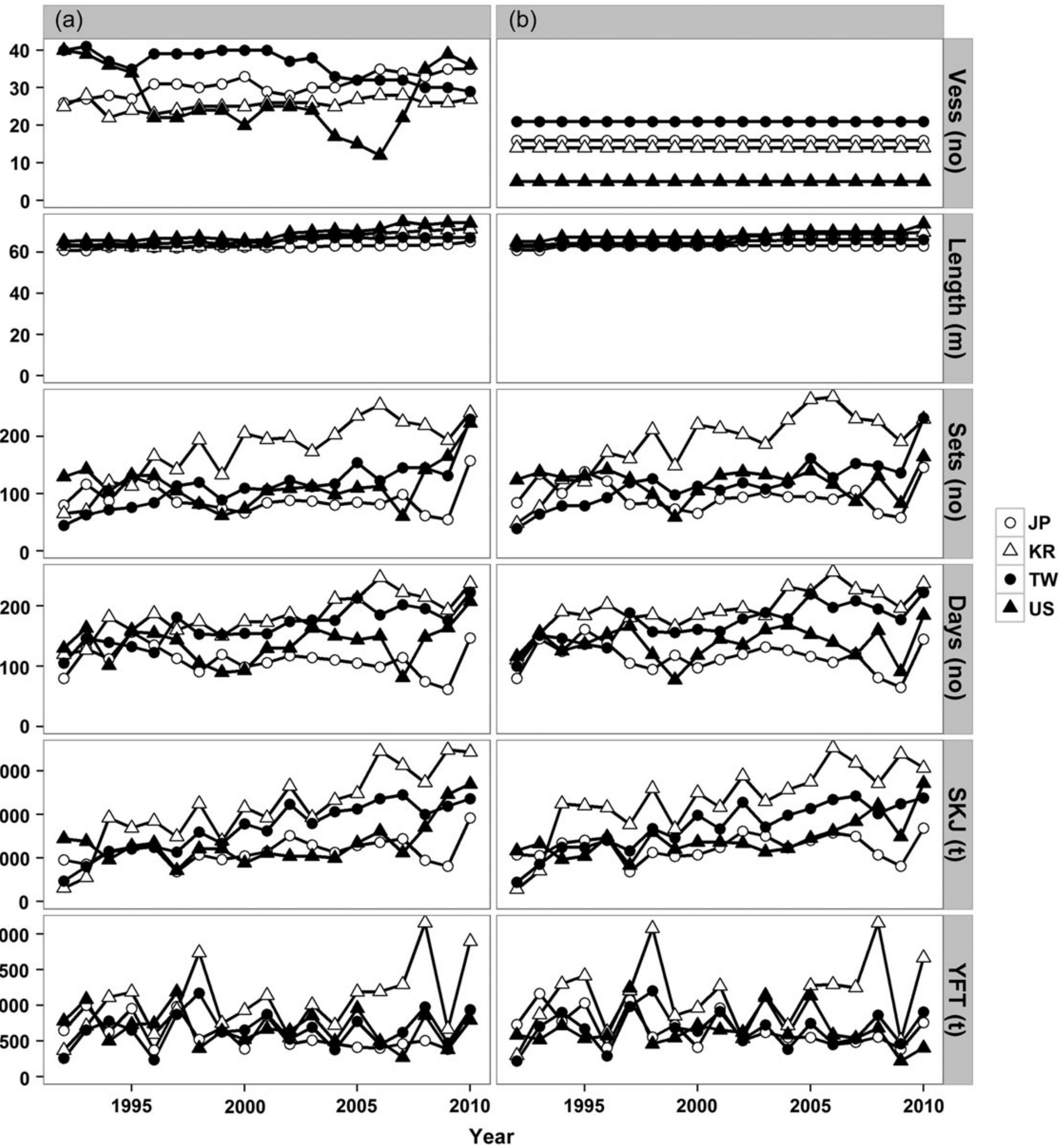

Figure 2. Summary statistics of the study fleets fishing in PNA EEZs. Column (a) represents effort (number of days fished), mean vessel length (m) from the whole of each fleet, effort (number of fishing sets), the mean skipjack (skj) catch (mt), number of vessels, and yellowfin (yft) catch (mt), and column (b) those statistics from the sample of vessels that fished throughout the 18-year period (where JP, Japan; KR, Korea; TW, Chinese Taipei; US, United States).

To construct the DEA, information on the productivity of each vessel based on given input and output variables is needed. For this analysis, vessel length was used as a fixed input to represent a vessel's capital stock (capacity index or the total physical capital existing in the fishery at any moment of time). Although vessels can change lengths to increase capacity (Gillett *et al.*, 2002; Figure 2), the length of vessels selected for analysis has remained fairly consistent over time, particularly compared with available data on vessel HP, which for a vessel could change markedly and sporadically over time due to, for example, engine refits. Fishing effort (days fishing) and number of purse-seine sets (fishing events) made were used to represent variable input measures (i.e. reflecting inputs dependent on the level of fishing effort) as vessel-specific economic data were not available.

The output variable selected for the analysis was tuna catch. As changes in catch may relate to changes in stock biomass levels rather than any change in the productivity of the fleet, estimated skipjack and yellowfin biomass were incorporated into the productivity evaluation. This was done by specifying output as the annual stock exploitation rate for each vessel (Figure 3), that is, vessel

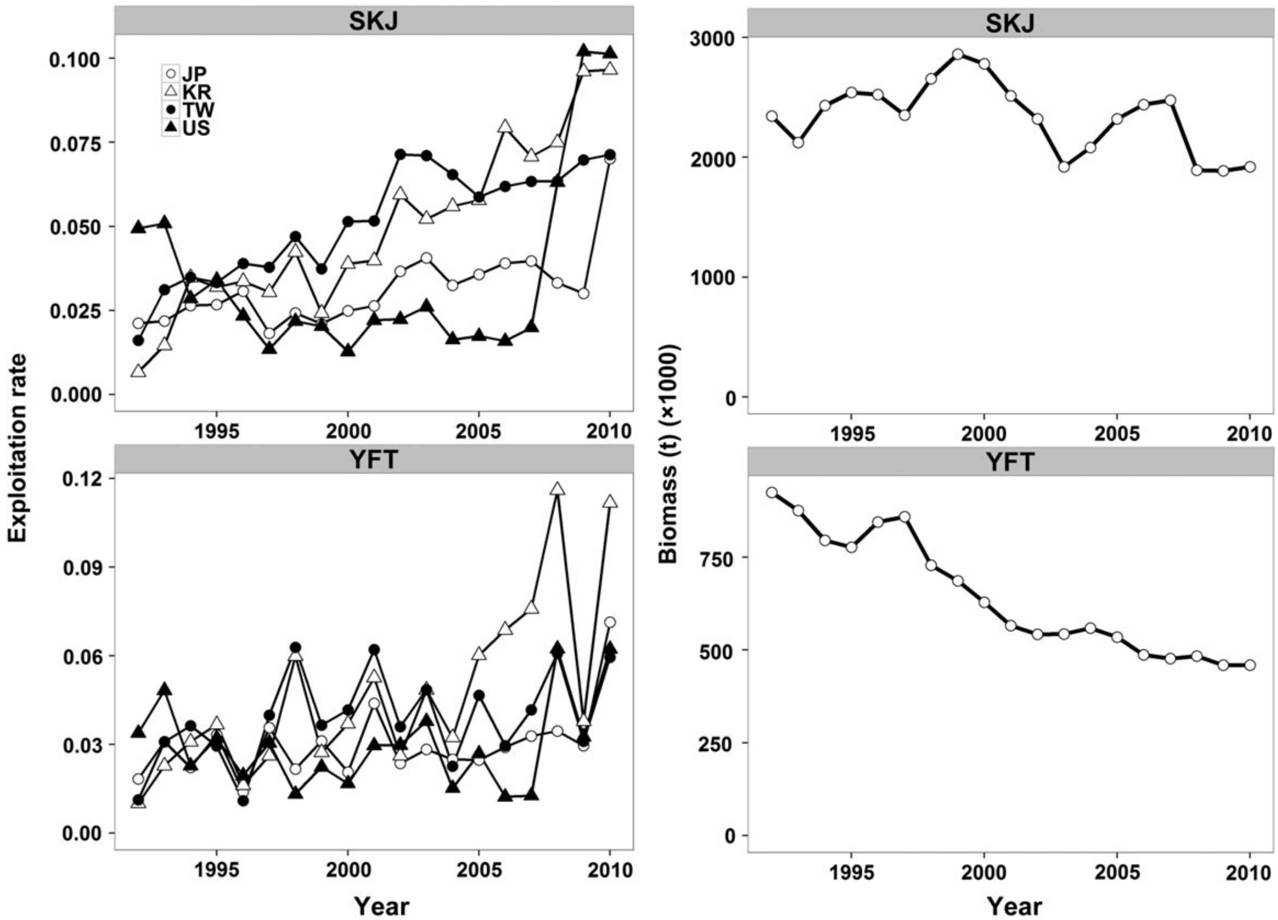

Figure 3. Annual exploitation rates (catch/aggregated exploitable stock biomass for each region encompassing the PNA EEZs by year) for skipjack and yellowfin tuna by fleet (left), and exploitable biomass estimates, respectively (right).

catch/aggregated exploitable stock biomass over all set-types for each region encompassing the PNA EEZs for each year. As the purse-seine catch is comprised predominately of skipjack and yellowfin (over 90% of the catch is typically of these two species), vessels were assumed to produce two outputs, the skipjack exploitation rate and the yellowfin exploitation rate. Exploitable biomass estimates for tropical waters for skipjack and yellowfin tuna stock were obtained from the latest skipjack and yellowfin stock assessments (Davies *et al.*, 2014; Rice *et al.*, 2014). In summary, fixed inputs were specified as the vessel's length, variable inputs as the number of sets made, and the number of fishing days expended in a given year, while vessel output was the annual exploitation rate of skipjack and yellowfin tuna. The estimated MI provides a measure of the annual increase in the exploitation rate.

Data envelopment analysis

The DEA method measures efficiency by comparing each individual production unit (fishing vessels) against all other production units within a group (e.g. fleet of fishing vessels that share the same fishing flag) given a set of input and output variables (Cooper *et al.*, 2000). The algorithm compares observations from those production units relative to a production frontier. The production units situated on the frontier are assigned an efficiency score (θ) of 1, and the subsequent units within that optimal frontier <1 (representing distances from the frontier). For example, an efficiency score of 0.75 implies that a company could in theory increase its outputs (that is, its exploitation rate) by 33% while keeping inputs the same (e.g. 1/0.75) if it performed as good as its best-performing peers [see Coelli *et al.* (1998)]. For a detailed explanation of the use of DEA to measure output efficiency, see Färe *et al.* (1989). Resulting indices from the estimates of DEA allow the calculation of MI from the TFP as ratios of two output distance functions (change in the MI of TFP over two periods) (Malmquist, 1953; Caves *et al.*, 1982). It has been suggested in the literature (e.g. Walden *et al.*, 2012) that to calculate MI correctly, the distance frontiers are estimated relative to constant returns to scale (CRS technology; i.e. doubling inputs will double outputs), which gives the global (TE) of the companies (Grifell-Tatjé and Lovell, 1995) and this was used in this study.

The output-oriented distance function, where relative efficiency is calculated, is given as [see Färe *et al.* (1989, 1994)]

Max θ,z

subject to

$$\theta y_{j,m} \le \sum_{j=1}^{J} z_j y_{j,m} \forall m, \tag{1}$$
$$\sum_{j=1}^{J} z_j x_{j,n} \le x_{j,n} \forall n,$$
$$z_j \ge 0 \forall j,$$

where θ is the efficiency measure ($\theta \ge 1$) determining how much production of each vessel (j) can increase for a given quantity (n)

of fixed (vessel length) and variable inputs [the number of fishing days and fishing events (sets)], ($x_{j,n}$), to give the feasible quantity (m), of outputs ($y_{i,m}$), in an efficient combination (maximum productivity), where (z_j) weighting factors measure the optimal linear combination of peers (frontier observations) that give the optimal performance of the unit in question. Vessels that are the most technically efficient operate along the frontier boundary (θ) and have a value of 1. Those that are less efficient operate within it and have a value of <1. A normalized distance (x, y) to the frontier for fixed input and output vectors is defined by the Shephard output distance $d_0(x,y)$ (Shephard, 1970) as follows:

$$d_0(x, y) \equiv \inf\{\theta > 0 | (x, \theta^{-1}y) \in P\}. \quad (2)$$

Malmquist indices

The difference in the TFP output orientated index d_0 between two periods, and hence the MI [see Färe *et al.* (1994)], was calculated as the geometric mean of d_0 in the two periods t and $t+1$ as follows:

$$M(x^{t+1}, y^{t+1}, x^t, y^t) = \overbrace{\frac{d_0^{t+1}(x^{t+1}, y^{t+1})}{d_0^t(x^t, y^t)}}^{\text{TE}} \overbrace{\sqrt{\frac{d_0^t(x^t, y^t)}{d_0^{t+1}(x^t, y^t)} \cdot \frac{d_0^t(x^{t+1}, y^{t+1})}{d_0^{t+1}(x^{t+1}, y^{t+1})}}}^{\text{TC}}. \quad (3)$$

If there is improvement in productivity between periods, then a value of >1 can be expected. In contrast, a value of <1 implies productivity has declined.

The MI [Equation (3)] can then be further decomposed into components of TE and TC by rewriting that equation as

$$\text{TC} = \sqrt{\frac{d_0^t(x^{t+1}, y^{t+1})}{d_0^{t+1}(x^{t+1}, y^{t+1})} \cdot \frac{d_0^t(x^t, y^t)}{d_0^{t+1}(x^t, y^t)}}, \quad (4)$$

where TC is a measure of the relative movement of the frontier between period t and $t+1$ and is a measure of technical improvements between the periods; and

$$\text{TE} = \frac{d_0^{t+1}(x^{t+1}, y^{t+1})}{d_0^t(x^t, y^t)}, \quad (5)$$

where TE is a ratio of the distance function for the observation under question between t and $t+1$.

DEA has in the past been criticized due to its lack of statistical grounding (i.e. it is difficult to make inference about the parameters or DEA scores) in that the distances to the frontier may be underestimated if the best-performing production units in the population are not included in the sample. To circumvent this important issue, Simar and Wilson (1998, 2000) proposed a bootstrapping method to provide measures of uncertainty [e.g. confidence intervals and standard errors; see Efron and Tibshirani (1993)]. In the present context, the DEA efficiency estimates θ were sampled 2000 times, with replacement, to develop bootstrapped distributions (Simar and Wilson 1999). However, resampling directly from the original dataset provides biased bootstrap estimates of the confidence intervals since distance estimation values are close to unity. To overcome this problem, the smoothing procedure proposed by Simar and Wilson (1998, 2000) was used, which was an adaptation of a reflective process devised by Silverman (1986).

The indices TC and TE can be decomposed from MI using Equations (3) and (4) [see Hoff (2006) for a detailed explanation of the MI bootstrapping approach]. An MI or TC or TE index was considered significant (indicating a significant change over that time-step) where the confidence intervals did not include 1. The DEA linear programming model developed in R software benchmarking (Bogetoft and Otto, 2011) was used to implement the above analysis.

Results and discussion

The results are examined first at the level of individual vessels, then at the level of the four fleets, and finally the overall trends are calculated based on the individual vessel data. The overall bias-corrected estimates of productivity change and corresponding decompositions of TC and TE for each vessel between 1993 and 2010 are presented by vessel in Table 1. To provide an explanatory example, the MI value of 3.15 for vessel KR2 indicates that the vessel was estimated to be over three times as productive in 2010 as it was in 1993; in other words, its exploitation rate increased by over 200% during the period.

Of the 56 vessels sampled, 27 showed significant increases in productivity (as measured by the MI) at the 1% level of significance, one vessel at the 5% level, and three vessels at the 10% level. In contrast, two TW-flagged vessels showed a significant (at the 1% level) decrease in productivity over the period, suggesting that their fishing ability was getting worse. For the remaining 23 vessels, their change in the productivity over the period was found not to be statistically significantly different. These results indicate that for nearly half of the vessels examined in this study, their productivity had increased over the 18-year period, while that of 41% of vessels remained relatively constant. The level of significant positive changes in MI ranged from 11 to 215%, indicating that the degree of change was variable at the level of the individual vessel. In a similar study by Hoff (2006), Danish seiners (demersal trawling) fishing in the North Sea were assessed for productivity change at the individual vessel level. That fleet showed larger significant variations of positive change in productivity, ranging from 23 to 490%. This greater variability between vessels may be influenced by variability in the targeting between species, i.e. adjustment of some technical characteristics of the fishing gear to the ecology and biology of the target species.

Examining the individual components of the MI for each purse-seine vessel, the bias-corrected TC for 55 of the 56 vessels shows significant upward trends (at the 1, 5, and 10% levels). In contrast, the change in TE showed significant declines for 22 vessels and significant increases for 13 vessels. For the remaining 21 vessels, their TE showed no significant change over the period. These results indicate that the increased productivity of the vessels is strongly related to the adoption and use of new technology rather than improvements in the efficiency in the usage of the inputs. Stock biomass is generally declining (apart from peaks in 1995, 2000, and 2007 for skipjack; Figure 3); however, TFP and TC are on the increase, potentially indicating skippers' success in finding tuna concentrations or patches influences catchability, resulting in increases in productivity even with a potentially decreasing stock size (Hilborn and Walters, 1992). In the demersal Danish seine fishery, TFP increases are largely down to TE and fishing skill to pick up loosely aggregated fish (Squires and Kirkley, 1999), i.e. using less input to catch the same amount of fish. In comparison, for schooling pelagic tuna, detecting aggregations is an important element of fishing. Technical improvements, such as helicopter use and sonar buoys (able to estimate quantity and shoal movements), can help locate

Table 1. Estimated bias-corrected MI and decomposed indices over the period 1993–2010 by vessel (Vessel ID).

Vessel ID	MI	TC	TE
KR1	3.21	1.85***	1.73***
KR2	3.15***	2.1***	1.5***
KR3	2.53***	1.92***	1.31***
KR4	3.88	1.71***	2.25***
KR5	1.3	1.47	0.86***
KR6	1.93	1.94***	0.99
KR7	3.04***	2.42***	1.25*
KR8	2.55***	1.94***	1.31***
KR9	2.49***	2.47***	1
KR10	2.07	1.82***	1.12
KR11	2.93***	2.31***	1.25*
KR12	1.61	1.52***	1.04
KR13	1.52	1.96***	0.77***
KR14	2.11	2.17***	0.97
JP1	2.12***	1.98***	1.06
JP2	1.36	1.98***	0.69***
JP3	2.2***	2.3***	0.91
JP4	1.25***	1.47***	0.85*
JP5	1.83***	1.81***	1.01
JP6	1.65***	1.67***	0.98
JP7	2.21***	2.59***	0.81
JP8	1.68***	1.81***	0.92
JP9	1.59***	1.86***	0.86***
JP10	1.54***	1.77***	0.87*
JP11	1.11***	1.85***	0.6***
JP12	1.42***	1.92***	0.73***
JP13	1.34***	1.62***	0.82***
JP14	1.9***	2.01***	0.93
JP15	1.41***	1.74***	0.81**
JP16	1.65***	2.05***	0.79
TW1	1.46	1.66***	0.88*
TW2	1.14	1.55***	0.74***
TW3	1.3*	1.48***	0.88**
TW4	0.8***	1.22***	0.66***
TW5	1.51	1.61***	0.93
TW6	1.48	1.81***	0.82***
TW7	1.27	1.61***	0.79***
TW8	1.2	1.41***	0.85***
TW9	1.17	1.26***	0.93
TW10	2.09***	1.85***	1.13**
TW11	1.23	1.7***	0.72***
TW12	1.09	1.67***	0.65***
TW13	2.1***	1.42***	1.48***
TW14	2.15*	1.78***	1.18***
TW15	1.42	1.34***	1.05
TW16	1.92***	1.55***	1.24***
TW17	0.88***	1.29***	0.68***
TW18	0.91	1.47***	0.62***
TW19	1.69	1.79***	0.94
TW20	1.63*	1.67***	0.97
TW21	1.81	1.79***	1.01
US1	1.53	1.42***	1.07
US2	1.57***	1.78***	0.88**
US3	2.34***	1.62***	1.45***
US4	1.64***	1.4***	1.14
US5	2.06**	1.51***	1.37**

The asterisks denote that MI = change in productivity, TC = technical change, and TE = change in efficiency differ significantly from unity at: *statistical significance at 10% level, ** at 5% level, and *** at 1% level.

Table 2. Annual bias-corrected MI and decomposed indices by flag (US, KR, JP, and TW).

Flag	Year	MI	TC	TE	Flag	Year	MI	TC	TE
US	1994	1.05	0.81	1.27	KR	1994	1.77***	1.51***	1.16
US	1995	1	1.02	0.98	KR	1995	1.04	1.32**	0.78
US	1996	1.13	1.22***	0.92	KR	1996	0.54***	0.44***	1.23
US	1997	1.19	1.11	1.08	KR	1997	1.23	1.13	1.09
US	1998	1.29	1.28***	1	KR	1998	1.43	1.49***	0.96
US	1999	1.1	1.13***	0.97	KR	1999	0.61***	0.66***	0.91
US	2000	0.92	0.85	1.08	KR	2000	1.42***	1.4***	1.01
US	2001	0.95	0.9	1.06	KR	2001	1.02	0.9	1.12
US	2002	0.99	1.06	0.93	KR	2002	0.79	0.87	0.91
US	2003	1.24	1.38***	0.89	KR	2003	1.44	1.43***	1
US	2004	0.73***	0.69***	1.06	KR	2004	0.73***	0.65***	1.12
US	2005	1.41	1.36***	1.04	KR	2005	1.12	1.22***	0.92
US	2006	0.92	0.88	1.05	KR	2006	1.17***	1.19***	0.98
US	2007	1.29	1.35***	0.96	KR	2007	0.99	1.23*	0.8*
US	2008	1.11	1.03	1.08	KR	2008	1.5***	1.1***	1.35***
US	2009	0.73***	1.01	0.67	KR	2009	0.69	0.74	0.93
US	2010	1.27	1.04	1.19	KR	2010	1.28	1.25	1.03
JP	1994	1.07	1.02	1.05	TW	1994	1.12**	1.2***	0.94
JP	1995	0.94***	1.1**	0.85*	TW	1995	0.92	0.93	0.98
JP	1996	0.79***	0.71***	1.11	TW	1996	0.88	1.09	0.79
JP	1997	1.23	1.29	0.95	TW	1997	1.09	1.06	1.03
JP	1998	1.16	1.11***	1.04	TW	1998	1.39***	1.24***	1.12
JP	1999	0.98	0.89	1.1	TW	1999	0.86***	1.07	0.79
JP	2000	1	1.12***	0.9	TW	2000	1.17	1.15	1.01
JP	2001	1.41**	1.48***	0.95	TW	2001	1.2	0.95	1.25*
JP	2002	0.94	0.87	1.08	TW	2002	0.96	0.87	1.1
JP	2003	1.05	1.06**	0.99	TW	2003	1.01	1.04	0.97
JP	2004	0.86***	0.84***	1.03	TW	2004	0.94	0.9	1.05
JP	2005	1.05	1.21***	0.86	TW	2005	0.96	1.02	0.94
JP	2006	1.08	1.02	1.06	TW	2006	0.96	0.95	1.01
JP	2007	0.9***	0.86*	1.04	TW	2007	1.01	0.98	1.03
JP	2008	1.34***	1.18***	1.12	TW	2008	1.34***	1.38***	0.97
JP	2009	0.82***	0.87***	0.94	TW	2009	0.91	1.03	0.87
JP	2010	0.97	1.19***	0.81*	TW	2010	1.01	0.93	1.09

The asterisks denote that MI = change in productivity, TC = technical change, and TE = change in efficiency between years differ significantly from 1 at: *statistical significance at 10% level, ** at 5% level, and *** at 1% level. 'Year' denotes the last year of the year pair.

and localize schools and thus increase the vessels' productivity; however, one could suggest that the purse-seine fleet is generally technically inefficient and that the vessels are not as profitable as they could be if they were operating efficiently, which could be a concern for managers when setting TRPs due to the latent potential to increase output with no change in inputs.

At the fleet level (Table 2 and Figure 4), the evolution of productivity change over the period was comparable, with MI increasing for all fleets particularly after 1996 (as identified through cumulative/chained-sequential multiplication of interannual MI; Figure 4). There is some evidence of concurrent increases in productivity in the period after 1995 and again post 2005. Table 2 summarizes that large annual changes in productivity of over 77% (MI >1.70) were estimated for the Korean fleet in 1993–1994, and 42% in 1999–2000 (MI >1.4), and the TW fleet between 1997–1998 and 2007–2008. These increases in productivity in the earlier years are potentially due to FAD technology uptake during this period (Ben-Yami, 1994; it should be noted that there were under-reporting issues in the early years and so changes in those years could reflect elimination of under-reporting rather than technological change). Conversely, TE for both these fleets shows decreases that could amount to the fishers having difficulties adapting to the new technological processes.

Furthermore, in some instances, while TC was statistically significant, the change in productivity between years was not

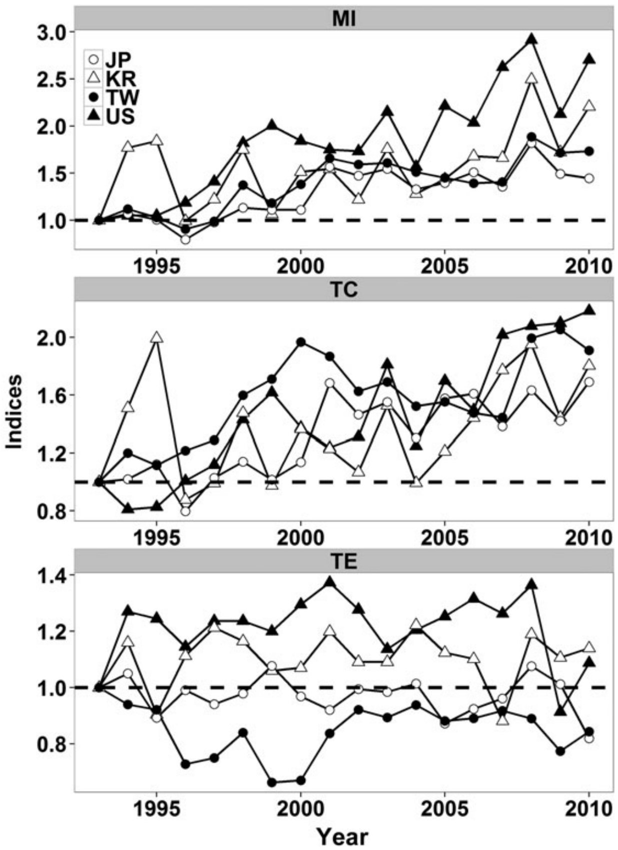

Figure 4. Average annual cumulative (chained) MIs calculated from individual year comparisons for the period 1993–2010 (where MI, Malmquist indices; TC, technical change; TE, technical efficiency change).

statistically significant, suggesting that the technological improvements observed were not accompanied by a significant increase in productivity (for example, JP 2004–2005, KR 1994–1995, 1997–1998, and 2002–2003, and US 1995–1996, 1997–1998, 1998–1999, 2002–2003, and 2006–2007). Nevertheless, what is evident from studying the year pairs in Table 2 is that in general, TC significantly affects MI, that is, when TC is low MI is also low and *vice versa*, and this can also be observed in the cumulative trends in Figure 4.

Also of note are the significant low MI/TC for Korean and US fleet in 2004, which was potentially due to vessels shifting their distribution eastwards influenced by significant declines in catch rates for both yellowfin and skipjack, a drop in skipjack prices (Williams and Reid, 2005), and the continual increases in fuel prices (Krampe, 2006) (Figure 2 shows decreases in the number of sets and days and declines in catches in 2004 compared with 2003). Figure 4 shows that the TE of the Japanese fleet slightly decreased (around −1%) over the study period. These potential declines in efficiency may be due to a combination of factors. The first was disputes over access costs in the late 1980s with Papua New Guinea (which represented particularly productive fishing grounds) (Petersen, 2003). The fleet ceased fishing in this area until around 2006 and during this time operated mainly in less productive high sea areas and via bilateral agreements with other countries (Gillett and Lewis, 2003). There were also changes in the pattern of fishing techniques such as log sets, drifting FADs, and free school fishing (Gillett and Lewis, 2003) all of which encapsulate the fishing skill component of "learning by doing" (Squires and Kirkley, 1999; Squires and Reid, 2004).

Examining the long-term trends (Figure 4), the US fleet showed the greatest increase in productivity, over 150% across the 18-year period. This fleet showed the most consistent and greatest year-on-year increase since 1996. This fleet also showed corresponding TC of over 100% across the period, while the TE change over time was above 20%. In comparison, the Korean fleet that showed the second greatest increase in productivity over the period (>100%) exhibited a relatively rapid increase in productivity after 2005, lifting this fleet above the productivity of the Japanese and TW fleets. TE change for the Korean fleet was on average slightly below 20%, and the interannual variability was fairly consistent over years, except for 2 years when TC was at its highest and TE at its lowest. In contrast, the improvement in productivity for the Japanese and TW was lower; there was also less interannual variability in their MI. The lower interannual variability may relate to slower uptake of technological advances as their TE showed peak declines in between 19 and 33% over the period, and were operating inefficiently relative to the other fleets. An explanation for the similarities in trends for these two fleets could be that historically, the Korean fleet mostly fished on free schools as with the US fleet, while the TW followed the Japanese approach of fishing on a mix of logs and free schools and switching to a mix of free school/FADs by late 1990s/early 2000s (Gillett and Lewis, 2003). Nevertheless, both the latter fleets fished in different areas; the Japanese fleet fishing more to the west while vessels from TW were geographically widespread in their operations. Regarding the above, Table 1 summarizes that overall there were three individual TW vessels displaying significant productivity change (∼100% change in productivity) throughout the period. Six vessels within the Korean fleet (>150%) were potentially the drivers for the annual fleet-level changes in MI, while for the US (ranging from 57 to 134%) and JP (ranging from 11 to 121%) productivity generally improved for all vessels in the sample.

Given the desired management aims of achieving a TRP level, and hence limiting effective effort within input controls, understanding the level of change over time is important. To this end, using the results of the cumulative chained analysis (Figure 4), an overall annual rate of change in fleet productivity can be estimated annually as the compounded MI rate (changes in fishing power) over the 18-year period. The results show that US had a 5.6% annual increase (TC = 4.4%, TE = 0.5%), followed by KR at 4.4% increase (TC = 3.3%, TE = 0.7%), 3.1% for Taiwan (TC = 3.6%, TE = −0.9%), and 2.1% for JP (TC = 3.0%, TE = −1.0%). For the whole fishery, an estimate of a 3.8% annual increase in fishing power was calculated along with a TC of 3.6% and TE of −0.2%.

To conclude, the results of this study indicate that there was an increase in productivity (MI) over the period 1993–2010 for all flags, with an average increase in the productivity of vessels of 3.8% per year across the four fleets (range 5.6% for the US fleet, down to 2.1% for the Japanese fleet). This equates to an increase over 10 years of over one-third, that is, the rate at which vessels are currently exploiting the available stock per unit of effort is one-third greater in 2015 than it was in 2006. This clearly illustrates the necessity of accounting for, and obtaining robust estimates of, productivity change when setting management limits in the WCPO purse-seine fishery. Most of this productivity increase was attributable to TC; while there were significant interannual changes in TE in many vessels within a fleet, the annual statistical trends generally were not significant. Understanding the drivers behind changes in TC is also important, so that future changes in fleet characteristics can be adjusted for within the management regime. Future studies will look at vessel history data post 2010 to identify the vessel characteristics driving change. In particular, the inclusion of detailed observer information from vessels which acquired new FAD technologies will further enrich the analysis. In addition, studies will research the entry and exit of vessels, particularly changes in fishing capacity resulting from the arrival of newer efficient vessels to replace older inefficient vessels (Tidd *et al.*, 2011).

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References

Arrizabalaga, H., De Bruyn, P., Diaz, G. A., Murua, H., Chavance, P., De Molina, A. D., and Kell, L. T. 2011. Productivity and susceptibility analysis for species caught in Atlantic tuna fisheries. Aquatic Living Resources, 24: 1–12.

Bell, J. D., Allain, V., Allison, E. H., Andréfouët, S., Andrew, N. L., Batty, M. J., Blanc, M., *et al.* 2015. Diversifying the use of tuna to improve food security and public health in Pacific Island countries and territories. Marine Policy, 51: 584–591.

Ben-Yami, M. 1994. Purse Seining Manual. Fishing News Books, London. 406 pp.

Bertignac, M., Campbell, H. F., Hampton, J., and Hand, A. 2000. Maximizing resource rent from the Western and Central Pacific Tuna Fisheries. Marine Resource Economics, 15: 151–177.

Bogetoft, P., and Otto, L. 2011. Benchmarking with DEA, SFA, and R. Springer, New York.

Caves, D., Christensen, L., and Diewert, E. 1982. Multilateral comparisons of output, input, and productivity using superlative index numbers. Economic Journal, 92: 73–86.

Coan, A. L., Sakagawa, G. T., Prescott, D., and Yamasaki, G. 1998. Changes in the U.S. purse seine fishery for tropical tunas in the central-western Pacific Ocean. *In* Proceedings of the 49th Annual Tuna Conference, Lake Arrowhead, CA, USA, 18–21 May 1998. 76 pp.

Coelli, T., Rao, D., and Battese, G. 1998. An Introduction to Efficiency and Productivity Analysis. Kulvwer Academic Publishers Group, London.

Cooper, W. W., Seiford, L. M., and Tone, K. 2000. Data Envelopment Analysis, A Comprehensive Text with Models, Applications, References and DEA-solver Software. Kluwer Academic Publishers, Dordrecht.

Davies, N., Harley, S., Hampton, J., and McKechnie, S. 2014. Stock assessment of yellowfin tuna in the western and central Pacific Ocean Noumea, New Caledonia: Secretariat of the Pacific Community. WCPFC-SC10-2014/SA-WP-04.

Efron, B., and Tibshirani, R. J. 1993. An Introduction to the Bootstrap. Chapman and Hall, New York.

Färe, R., Grosskopf, S., Lindgren, B., and Roos, P. 1989. Productivity developments in Swedish hospitals: A Malmquist output index approach. *In* Data Envelopment Analysis: Theory, Methodology and Applications, pp. 253–272. Ed. by A. Charnes, W. W. Cooper, A. Lewin, and L. Seiford. Kluwer Academic Publishers, Boston.

Färe, R., Grosskopf, S., and Lovell, C. A. K. 1994. Production Frontiers. Cambridge University Press, New York.

FFA. 2014. Economic Indicators Report (Interim). Forum Fisheries Agency, Honiara.

Gillett, R. D., and Lewis, A. 2003. A Survey of Purse Seine Fishing Capacity in the Western and Central Pacific Ocean, 1988 to 2003. Gillett, Preston and Associates, Lami.

Gillett, R. D., McCoy, M. A., and Itano, D. G. 2002. Status of the United States Western Pacific Tuna Purse Seine Fleet and Factors Affecting its Future. Publication 02-01, School of Ocean and Earth Science Technology, University of Hawaii at Manoa.

Grifell-Tatjé, E., and Lovell, C. A. K. 1995. A note on the Malmquist productivity index. Economics Letters, 47: 169–175.

Hampton, J., Sibert, J. R., Kleiber, P., Maunder, M. N., and Harley, S. J. 2005. Fisheries: Decline of Pacific tuna populations exaggerated? Nature, 434: E1–E2, discussion E2.

Hilborn, R., and Walters, C. J. 1992. Quantitative Fisheries Stock Assessment: Choice, Dynamics and Uncertainty. Chapman and Hall, New York. 570 pp.

Hoff, A. 2006. Bootstrapping Malmquist Indices for Danish Seiners in the North Sea and Skagerrak. Journal of Applied Statistics, 33: 891–907.

Juan-Jordá, M. J., Mosqueira, I., Cooper, A. B., Freire, J., and Dulvy, N. K. 2011. Global population trajectories of tunas and their relatives. Proceedings of the National Academy of Sciences, 108: 20650–20655.

Krampe, P. 2006. Rising Fuel Prices and Its Impact on the Tuna Industry. Tuna 2006—9th Infofish World Tuna Trade Conference, 27 May, Bangkok.

Malmquist, S. 1953. Index numbers and indifference curves. Trabajos de Estatistica, 4: 209–242.

Oliveira, M. M., Camanho, A. S., and Gaspar, M. B. 2013. The influence of catch quotas on the productivity of the Portuguese bivalve dredge fleet. ICES Journal of Marine Science, 70: 1378–1388.

Oliveira, M. M., Gaspar, M. B., Paixão, J. P., and Camanho, A. S. 2009. Productivity change of the artisanal fishing fleet in Portugal: A Malmquist index analysis. Fisheries Research, 95: 189–197.

Parties to the Nauru Agreement (PNA). 2015. Draft Conservation and Management Measure on the Target Reference Point for WCPO Skipjack Tuna. WCPFC-SC11-2015/MI-WP-02. http://www.wcpfc.int/system/files/MI-WP-02%20Draft%20TRP%20SKJ%20CMM.pdf (last accessed 19 October 15).

Petersen, E. 2003. The catch in trading fishing access for foreign aid. Marine Policy, 27: 219–228.

Rice, J., Harley, S. J., Davies, N., and Hampton, J. 2014. Stock Assessment of Skipjack Tuna in the Western and Central Pacific Ocean. Rev 1 25 July 2014. WCPFC-SC10-2014/SA-WP-01.

Shanks, S. 2010. Introducing a transferable fishing day management regime for Pacific Island countries. Marine Policy, 34: 988–994.

Shephard, R. W. 1970. Theory of Cost and Production Functions. Princeton University Press, Princeton.

Silverman, B. W. 1986. Density Estimation for Statistics and Data Analysis. Chapman and Hall, London.

Simar, L., and Wilson, P. W. 1998. Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. Management Science, 44: 49–61.

Simar, L., and Wilson, P. W. 1999. Estimating and bootstrapping Malmquist indices. European Journal of Operational Research, 115: 459–471.

Simar, L., and Wilson, P. W. 2000. Statistical inference in nonparametric frontier models: The state of the art. Journal of Productivity Analysis, 13: 49–78.

Simar, L., and Wilson, P. W. 2007. Estimation and inference in two-stage, semi-parametric models of production processes. Journal of Econometrics, 136: 31–64.

Squires, D., and Kirkley, J. E. 1999. Skipper skill and panel data in fishing industries. Canadian Journal of Fisheries and Aquatic Sciences, 56: 2011–2018.

Squires, D., and Reid, C. 2004. Using Malmquist indices to measure changes in total factor productivity of purse-seine vessels while accounting for changes in capacity utilization, the resource stock and the environment. SCTB17 Working Paper. FTWG-5.

Tidd, A. N., Hutton, T., Kell, L. T., and Padda, G. 2011. Exit and entry of fishing vessels: an evaluation of factors affecting investment decisions in the North Sea English beam trawl fleet. ICES Journal of Marine Science, 68: 961–971.

Walden, J. B., Kirkley, J. E., Färe, R., and Logan, P. 2012. Productivity change under an individual transferable quota management system. American Journal of Agricultural Economics Advance Access, 94: 913–928.

Williams, P., and Reid, C. 2005. Overview of Tuna Fisheries in the Western and Central Pacific Ocean, Including Economic Conditions. Western and Central Pacific Fisheries Commission. WCPFC-SC1/GN WP-1, Noumea, New Caledonia.

Williams, P., and Terawasi, P. 2015. Overview of Tuna Fisheries in the Western and Central Pacific Ocean, Including Economic Conditions—2014. WCPFC-SC11-2015/GN WP-1.

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