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Implications of efficiency and productivity change over the season for setting MEY-based trigger targets*

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The banana prawn component of Australia's Northern Prawn Fishery (NPF) is currently managed through the use of annually updated trigger catch rates as a means of achieving maximum economic yield (MEY) in the fishery, taking into account the estimated price and cost components for that season. The estimation of these target catch rates is based on the assumption of relative homogeneity of the fleet in terms of efficiency, productivity and cost structure. In this study, these assumptions are examined through the estimation of a stochastic production frontier. While technical efficiency varies between vessels, average efficiency is relatively constant over the fishing season. However, average productivity of the fleet increases, with smaller vessels (in terms of engine power) exiting the fishery earlier. This would likely increase the average cost of fishing towards the end of the season, with implications for setting the target catch rate. Based on a standard assumption as to the relationship between costs and vessel size, we find that the MEY target catch rates are most likely currently underestimated. However, the implementation of a precautionary minimum catch rate (which is above the MEY target catch rates for recent years) has maintained the fishery at a profitable level.

Key words: banana prawns, depleting fishery, efficiency, MEY trigger, Northern Prawn Fishery.

1. Introduction

The Australian Northern Prawn Fishery (NPF), running from the western end of Joseph Bonaparte Gulf in Western Australia to the tip of Cape York Peninsular in Queensland, is one of Australia's most valuable Commonwealth-managed fisheries with an annual value of production generally exceeding \$100 m in recent years (ABARES 2015). The fishery has two subfisheries that are managed using different approaches, but the different species are harvested by the same set of vessels. The banana prawn fishery,

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targeting common banana prawns (*Fenneropenaeus merguensis*), operates from April to June. The tiger prawn fishery, targeting two tiger prawn species (*Penaeus esculentus*, *P. semisulcatus*) with endeavour prawns (*Metapenaeus endeavouri*, *M. ensis*) caught as by-product, operates from April to November, with a mid-season closure usually from mid-June to the start of August.¹ The two components are spatially separate and also require different fishing methods. Given the shorter nature of the banana prawn season, fishing effort usually focuses on this component at the start of the year, with boats progressively moving onto the tiger prawns as banana prawn catch rates decline (Pascoe *et al.* 2015b).

Since 2007, the fishery has had an objective of achieving maximum economic yield (MEY) (Dichmont *et al.* 2010). The two subfisheries are subject to different management systems with different approaches to achieve MEY. Tradeable gear units and seasonal closures are used to manage the tiger prawn component with the target effort level (expressed in terms of both season length and gear units available) determined by a bioeconomic model of the fishery (Punt *et al.* 2010, 2011). The banana prawn component, in contrast, is managed through a catch rate trigger and seasonal closures. The banana prawn subfishery is characterised by a large recruitment at the start of the year that is largely environmentally driven (Vance *et al.* 1985). This is fished down over the season until a predefined catch rate triggers the fishery closure, at which time fishers are able to move to the tiger prawn component if they have not already done so (or the mid-season closure is in place which covers the entire fishery). An MEY-based trigger was introduced in 2013. Prior to this, the trigger was mainly based on a biological escapement target, with some limited consideration by the industry at the time as to what was profitable at boat level.

The MEY-based trigger for the banana prawn season is estimated largely using average catch, price and fishing cost information. As expanded upon in the following section, this effectively assumes that the average cost is equal to the marginal cost, which in turn implies that that structure and fishing behaviour of the fleet do not change over the season. The objective of this paper is to assess the extent of efficiency and productivity change over the banana prawn fishing season, and the implications of these changes, if any, on the setting of the MEY trigger/target catch rate. To this end, we estimate the technical efficiency of the boats operating in the banana prawn season and examine how average efficiency changes over the season. We also examine how fishing behaviour which may affect fishing costs also changes over the season. Implications of these changes for the estimation of the trigger are discussed.

¹ A third small subfishery targeting red-legged banana prawn (*Penaeus indicus*) in Joseph Bonaparte Gulf is exploited by a small number of NPF vessels between August and November. This fishery is not considered part of the banana prawn fishery covered in this study, which relates only to common banana prawns.

2. The banana prawn MEY trigger

The MEY trigger is based on traditional microeconomic theory of the firm. Assume the catch function can be given by $C = qx_0E^\lambda$, where q represents the (constant) proportion of the stock removed by one unit of fishing effort, E , and x_0 is the starting stock size with zero effort. The stock decreases as effort is applied, so that the marginal catch rate declines as effort increases, that is $dC/dE = \lambda qx_0E^{\lambda-1}$. Given such a catch function, and assuming constant prices and costs per unit of effort, the profit function is given by $\pi = pqx_0E^\lambda - cE$, where p is the constant price and c is the constant cost per unit effort. Profits are maximised when $\lambda pqx_0E^{\lambda-1} = c$, which is essentially when marginal revenue (pdC/dE) is equal to marginal cost.

Deriving the appropriate parameters to implement this relationship in the fishery is complicated. Foremost of the complications is that the size of the starting stock is not known with any accuracy at the start of the season (Venables *et al.* 2011; Buckworth *et al.* 2014), and only few attempts have been made to estimate stock sizes ex post (Zhou *et al.* 2007, 2015). Recruitment to the fishery appears to be driven largely by environmental factors, particularly rainfall (Vance *et al.* 1985). Second, abundance is not constant over the season, as factors such as the moon phase affects the behaviour of the prawns and hence the catch per unit of fishing effort. The schooling behaviour of prawns also obfuscates the relationship between fishing effort and the rate at which the stock is reduced (Die and Ellis 1999; Zhou *et al.* 2007). Finally, heterogeneity in the fishery in terms of fishing costs and also technical efficiency of the individual vessels results in potential changes in the measure of fishing effort and also costs over the season. Few boats fish the full season, with weekly effort levels declining largely as a consequence of vessels ceasing fishing, reflecting differences in costs (either opportunity costs or financial costs) (Pascoe *et al.* 2015b).

Given this, a proxy estimate of the appropriate profit maximising level of fishing activity is derived based on simple stopping rule for fishing. Assuming marginal revenue is represented by the observed average catch per day in a given week, CPD_t , times the average price (assumed constant over the season), p , and assuming average costs per day fished, c , also a constant such that the average cost is equal to the marginal cost, then the 'optimal' stop fishing condition is $pCPD_t = c$, which gives a 'target' catch rate of $CPD_t = c/p$.

For the purposes of estimating the target catch rate, only variable costs are considered. These include fuel costs, f (\$/day); a portion of repairs and maintenance, rm , \$/day (Pascoe *et al.* 2015a); crew costs, cs , as a proportion of revenue; and marketing costs, m , \$/kg catch. The latter two cost components are related to the quantity of catch, while the first two are related to the number of days fished. To factor these into the target, the price component is modified to reflect the catch related cost items, and the proxy target catch rate given by $CPD_t = [f + rm]/[p(1 - cs) - m]$ where the

denominator effectively represents the net price received after crew and marketing costs have been removed.

Information on the appropriate cost and prices are estimated in collaboration with the industry at the start of the season. Fuel costs per day are estimated based on average fuel use per day (derived from a survey of fishers in previous seasons) and the price of fuel paid by fishers at the start of the season. Repairs and maintenance costs are derived from actual costs in the previous season and assumed to stay the same for the current season. Similarly, crew share and marketing costs are based on values derived from a survey of fishers in the previous season. The average prawn price used in the analysis is provided by industry based on expectations for the current season.

Prior to the introduction of the MEY target catch rate, the fishery was subject to a minimum escapement-based trigger catch rate of 500 kg/day. This was a precautionary limit agreed to by industry reflecting the uncertainty in the stock-recruitment relationship. This led to a precautionary limit on harvesting the species. With the introduction of a MEY target catch rate, industry was concerned that a lower catch rate than the precautionary catch rate may result in longer term costs to the industry, while a substantially higher catch rate may provide lost opportunities to parts of the industry if the target was inappropriate (i.e. lower cost or more efficient vessels were still able to fish profitably at lower catch rates than 'average' costs would imply). Hence, a buffer was placed on the MEY target to be no more (or less) than 15 per cent above (or below) the original precautionary catch rate.

The average catch rate in the fishery is monitored over the season, with critical time periods at 6, 8 and 10 weeks into the season (AFMA 2016). The fishery is opened in early April (usually the first, but this varies). Catch and effort data relating to weeks 4 and 5 are assessed and if the average of these values over this period is below the target catch rate, the fishery is closed in week 6. If the target catch rate is exceeded on average over this period, fishing continues and a further assessment is made for week 8 relating to catch and effort in weeks 6 and 7. Similarly, if the target catch rate is exceeded at this point, fishing continues and a further assessment is made for week 10 relating to the proceeding 2 weeks. If the target catch rate is still exceeded, the fishery remains open until the preset closure date (in mid-June) (AFMA 2016). Hence, that target catch rate is also the trigger that leads to closing the fishery for the season.

The initial derivation of the trigger catch rate rules (Buckworth *et al.* 2013) included an allowance for further declines in the catch rate between the 2-week monitoring period and the following decision week. That is, the trigger catch rate was initially proposed to be 1.63 times higher than the target to allow for the decline in catch rates over the 2-week period, based on observed changes in the fishery over recent previous years. This was opposed by industry who argued that lower cost and more efficient vessels could continue

to fish profitably at lower average catch rates than the average trigger value. As result, no adjustment was made to increase the trigger above the target catch rate.

3. Methods

The study involves two key questions: First, does the average technical efficiency of the fleet change over the season?; and second, are variable costs per day fished likely to be constant over the season? The first research question is addressed using a stochastic production frontier approach, from which estimates of individual vessel technical efficiency can be derived. The second research question is more complex, as ideally a cost function should be estimated. In the absence of appropriate information to estimate such a function, a simpler approach is adopted that is indicative of cost changes over the season. These approaches are outlined below.

3.1 Stochastic production frontier and efficiency estimation

Stochastic production frontiers are econometric models that estimate the output of a vessel as a function of a number of inputs (fixed and variable) as well as a measure of the relative inefficiency of the vessel. These have been applied in a wide range of fisheries internationally (Kirkley *et al.* 1995; Pascoe *et al.* 2001; Pascoe and Cogan 2002; Zen *et al.* 2002; Herrero and Pascoe 2003; Squires *et al.* 2003; Tingley *et al.* 2005) as well as other prawn fisheries in Australia (Greenville *et al.* 2006; Pascoe *et al.* 2017). In the northern prawn fishery, the approach has been used to assess technical efficiency in the tiger prawn fishery (Pascoe *et al.* 2012) as well as the banana prawn fishery (Kompas *et al.* 2004).

A number of different functional forms for the production frontier exist, although the most flexible is the translog production frontier (Aigner *et al.* 1977; Meeusen and Van den Broeck 1977), given by:

$$\ln y_i = \beta_0 + \sum_k \beta_k \ln x_{k,i} + 0.5 \sum_k \sum_j \beta_{k,j} \ln x_{k,i} \ln x_{j,i} - u_i + \varepsilon_i, \quad (1)$$

where y is the quantity of output produced, x is a vector of inputs, u is a one-sided error term ($u \geq 0$) representing the level of inefficiency of the vessel, and ε is a random error term. The technical efficiency (TE) of the i -th vessel is given by $TE_i = \exp(-u_i)$. In order to separate the stochastic and inefficiency effects in the model, a distributional assumption about the inefficiency term has to be made. In this study, both a half normal distribution and truncated normal distribution were tested (Battese and Coelli 1988), along with the potential for time-variant efficiency (Cornwell *et al.* 1990).

For profit maximisation, economic theory requires that the translog production function be monotonically increasing (i.e. $\partial y_i / \partial x_i \geq 0 \forall i, x$), and

quasi-concave for all inputs (Lau 1978; Sauer and Hockmann 2005; Sauer 2006; Sauer *et al.* 2006). To ensure this, we have adopted an approach developed by Henningsen and Henning (2009) which combines parametric and nonparametric estimation of the model coefficients. This involves first estimating the stochastic translog production frontier and extracting the unrestricted parameters $\hat{\beta}$ and their covariance matrix $\hat{\Sigma}_{\beta}$. Second, we estimate restricted $\hat{\beta}^0$ parameters through a minimum distance approach, given by:

$$\hat{\beta}^0 = \text{argmin}(\hat{\beta}^0 - \hat{\beta}) \sum_{\beta}^{-1} (\hat{\beta}^0 - \hat{\beta}), \quad (2)$$

subject to:

$$\frac{\partial f(x, \beta^0)}{\partial x} \geq 0 \forall i, x. \quad (3)$$

This is solved using quadratic programming to find the revised set of coefficients $\hat{\beta}^0$ that conform to the monotonicity assumption. Finally, the stochastic frontier model is re-estimated as:

$$\ln y_i = \alpha_0 + \alpha_1 \ln \tilde{y} - v_i + \varepsilon_i, \quad (4)$$

where $\tilde{y} = f(x, \hat{\beta}^0)$. That is, the only input is the estimated frontier output based on the restricted parameters. The parameters α_0 and α_1 represent final adjustments to the parameter estimates. An advantage of the three-stage approach is that the parameter values estimated in the first stage provide appropriate starting values while the variance-covariance matrix limits the degree to which these parameters are altered when imposing monotonicity in the nonparametric component. While not imposed, convexity is tested *ex post*. Henningsen and Henning (2009) argue that there is less need to impose the convexity constraints when estimating production frontiers as these are based on the assumption that producers aim to maximise output for a given set of inputs rather than profit maximisation *per se*, and suggest that only monotonicity be imposed.

3.2 Changes in fishing costs

As noted above, the target catch rate in the fishery is given by $CPD_t = [f + rm]/[p(1 - cs) - m]$, where f are fuel costs (\$/day); rm is a portion of repairs and maintenance (\$/day); cs are the crew share of revenue; and m are marketing costs (\$/kg catch). These parameters are derived as averages from an economic survey of the industry. Fuel and repairs and maintenance costs are estimated as an average cost per day. However, fishing activity within a day varies over the season. At the start of the season, catch

rates are high and nets are filled with relatively short sets/hauls. However, towards the end of the season catch rates are lower and hours trawled per day tend to be longer. As a result, fuel use per day is likely to be higher towards the end of the season. Changes in fleet composition over the season may also result in changes in average fuel and repairs/maintenance cost per day fished.

The data available are insufficient to estimate the change in cost per day, but an assumption was made that these would be proportional to the relative number of hours trawled per day and the average engine power of boats fishing in each week.² An index (I_w) was developed based on the product of the average number of hours trawled in a given week relative to the average number of hours trawled over all weeks and the average engine power in a given week relative to the average engine power over all weeks, given by:

$$I_w = \frac{\sum_{i \in i(w)} h_{i,w}/n_w}{\sum_w \sum_i h_{i,w}/\sum_w n_w} \frac{\sum_{i \in i(w)} kW_i/n_w}{\sum_w \sum_i kW_i/\sum_w n_w}, \quad (5)$$

where $i(w)$ is the set of boats operating in week w , $h_{i,w}$ is the hours trawled in week w by boat i , kW_i is the engine power of boat i , and n_w is the number of boats operating in week w . This index was applied to the currently used fuel and repairs and maintenance costs, such that a modified minimum catch rate for a given week could be estimated as $CPD_{t,w} = I_w[f + rm]/[p(1 - cs) - m]$.

4. Data

4.1 Vessel data

Data for the analysis were derived from logbook and vessel registry information covering the period 2010–2015. While earlier data were available, changes in fishery management arrangements prior to 2010 may have influenced behaviour. Prior to 2010, fishers were prohibited from taking tiger prawns in the first season (making it uniquely a banana prawn fishery). With the recovery of the tiger prawn stock, fishers were permitted to switch to tiger prawns during the first season from 2010. This created an opportunity cost³ which resulted in a number of vessels moving from banana prawns to tiger prawns (Pascoe et al. 2015b) towards the end of the first season as banana prawn catch rates declined, changing the fleet composition over the first season with subsequent changes in average efficiency and cost structure.

The original data were daily catch and effort for each individual vessel, with the latter recorded total hours (including searching) and hours trawled

² Ideally, a cost function or frontier would be estimated to test this assumption. While economic data are collected biannually on the fishery (e.g. ABARES 2016), only aggregated fleet level information is made available.

³ This opportunity cost will vary from year to year with changes in relative stock abundance, prices and fishing costs. An example of this opportunity cost is shown in Figure S1, estimated for the 2015 and 2016 fishing years.

separately. This was aggregated into weekly values for each vessel, with a further measure of effort as days fished each week. Other vessel characteristics such as engine power (kW) and length (m) were also available and merged with the catch and effort data. While some vessels used quad gear (quad nets) and others twin gear (two nets), records were incomplete and were not used in the analysis (and is likely to manifest itself in terms of differences in technical efficiency). While 52 licences are available for the fishery at any one time, over the period examined 62 different vessels reported fishing activity. A summary of the key data used in the analysis is given in the Supporting Information (Table S1).

All data were logged and normalised, such that their mean value was equal to zero (i.e. $\ln(\bar{x}) = 0$). Correlation between the logged variables is given in the Supporting Information (Table S2). Engine power and vessel length are highly correlated, so including both measures into a production function would be inappropriate. Of the two, catch is most highly correlated to engine power, so this was selected as a covariate in the production function. Correlation between the different effort measures is generally low, with only a moderate correlation between the number of days fished per week and the total number of hours per week (including searching time). Of the different effort measures, catch was most highly correlated with days fished. As catch per day is the basis of the trigger, this was considered the most appropriate effort measure to be used in the analysis.

4.2 Imputation of a stock index

Catch rate decline over the season is largely a consequence of stock decline. Estimates of biomass change over the season are not routinely undertaken for the banana prawn component of the fishery, although are integral to the tiger prawn bioeconomic model (Punt *et al.* 2011). Zhou *et al.* (2015) estimated biomass changes in the banana prawn stock over the period 1981–2011 using a population depletion analysis which also simultaneously estimated natural mortality and changes in fishing power.

In this study, we employ a productivity based approach, namely the Malmquist productivity index (Caves *et al.* 1982), and more specifically the technical change component of the Malmquist index. This was shown by Pascoe and Herrero (2004) to provide a useful stock index for the purposes of subsequent estimates of fisheries production frontiers. The index is not purely an index of stock size, but captures changes in availability due to factors such tides. A subset of 26 boats that fished for at least 62 of the 68 weeks of data was selected for the analysis to remove the effect of changing fleet structure on the estimate. Over the short (6 years) time frame, it was assumed that there was no substantial technical change in these vessels, and hence any shift in the frontier was due to size or availability of the stock. As the index is a cumulative measure, each year was assessed separately to reduce the effects of compounding error, with the first week of 2010 applied in every estimation so

that all estimates are relative to a common starting point. The derived stock index estimates are shown in the Supporting Information (Figure S2).

5 Results

5.1 Production function and efficiency analysis

5.1.1 Econometric analysis

The results of the production frontier estimation are given in Table 1. The initial model (Step 1) included assumptions of a truncated normal and time-variant distributions, both of which were found to be significant. Most of the other input parameters were also found to be significant, including key cross-product coefficients. Given the significance of the cross-product terms, a Cobb Douglas production function was not tested, and the translog production function was accepted as the more appropriate functional form. The model was also tested against the assumption of no technical inefficiency and found to be significant, indicating that heterogeneity in inefficiency exists, and hence a frontier rather than a standard production function is a more appropriate specification.

The initial model did not fully satisfy the monotonicity requirements, especially in relation to engine power, so the second and third stages described in the methodology were implemented. The coefficients estimated through the minimum distance approach (second stage) were not statistically different from the initial estimates (based on the standard errors of the initial coefficients). The final estimates were derived by the scaling coefficient estimated in the final step (given in Table S3). As expected, the intercept term in the final step was not significantly different from zero, whereas the scaling coefficient was not significantly different from 1 suggesting that no substantial bias has been introduced through the three-step process (Henningesen and Henning 2009).

5.1.2 Efficiency distributions

The distribution of technical efficiency over the whole data period is shown in the Supporting Information (Figure S3). A high proportion of the fleet had relatively high technical efficiency scores (i.e. >0.9), although some vessels had very small efficiency scores (i.e. <0.5) which impacted on the overall average. Factors driving the level of inefficiency were not examined as the focus of the study was on the distribution of the efficiency scores, and may be an area for further investigation. In the tiger prawn fishery, the use of quad gear, vessel age, company size and the number of other boats fishing were all found to have a significant impact on efficiency (Pascoe *et al.* 2012), so may have similar impacts on efficiency in the banana prawn fishery.

The average technical efficiency over the fishing season in each year is shown in Figure 1. In 2010, 2011 and 2014, average efficiency was relatively constant over most of the year with a small increase towards the end of the

Table 1 Initial and final parameter estimates

	Step 1			Step 2			Step 3
	Initial estimate	Std. error	Sig	Minimum distance coefficients	<i>t</i> Statistic	Pr(> <i>t</i>)	Final estimates
Constant	0.333	0.043	***	0.299	0.781	0.198	0.307
ln(Engine)	0.697	0.236	**	0.988	-1.234	0.126	0.986
ln(Days)	0.690	0.104	***	0.640	0.477	0.259	0.639
ln(Stock)	1.157	0.037	***	1.151	0.144	0.312	1.149
ln(Engine) ²	-5.323	2.011	**	-2.462	-1.423	0.105	-2.457
ln(Engine) × ln(Days)	0.262	0.387		0.170	0.238	0.301	0.170
ln(Engine) × ln(Stock)	-0.399	0.200	*	-0.347	-0.259	0.298	-0.346
ln(Days) ²	-0.342	0.292		-0.507	0.565	0.241	-0.506
ln(Days) × ln(Stock)	0.407	0.105	***	0.323	0.802	0.194	0.322
ln(Stock) ²	0.100	0.083		0.104	-0.052	0.317	0.104
Sigma ²	2.246	0.547	***				
Gamma	0.790	0.057	***				
Mu	-2.664	1.119	*				
Time	-0.015	0.004	***				
Log Likelihood	-1,587.6						-1,589.8
Monotonicity (%)							
ln(Engine)	76.4						100
ln(Days)	99.7						100
ln(Stock)	99.9						100
Quasi-concavity (%)	99.9						99.9
Mean efficiency	0.79						0.78

Note: *** significant at 0.1%, ** significant at 1% and * significant at 5%

year. In the other 3 years, average efficiency declined sharply at the end of the season, although in the case of 2012 this was preceded by an increase in average efficiency. Both 2013 and 2015 were characterised by lower than average total catches, 2013 more so, which may have resulted in different (more efficient vessels) leaving the fishery earlier to fish for tiger prawns. However, the total number of vessels fishing each week were fairly similar in each year of the data (as seen in the Supporting Information Figure S4).

5.2 Productivity impacts on catch rates

While no clear trends in efficiency were observed, both average hours trawled and average engine power increased over the season (Figure 2). The former of these is not directly captured in the production function, which is specified with days fished as the effort measure, but is likely to influence the catch per day for a given biomass level. Engine power is specifically captured in the production function. From the production function, the responsiveness of catch to engine power – the production elasticity⁴ – varies with the average level of engine power, days fished each week and stock size. While stock size declines over the season, the engine power elasticity remains relatively

⁴ The production elasticity is given by $\partial \ln C / \partial \ln kW$.

Figure 1 Average technical efficiency scores over the fishing season.

Figure 2 Average (a) hours trawled and (b) engine power each week over the fishing season, 2010–2015.

constant for most of the season, increasing in the last few weeks (as seen in the Supporting Information Figure S5). The effect of this on vessel productivity (ignoring the stock decline) is that vessel productivity is roughly 10–20 per cent higher in the last couple of weeks that the fishery is open (Figure S5). This reduces the effect of declining stock levels of catch rates, resulting in average catch rates generally staying above the 500 kg level in most years from weeks 8 to 12 (Figure 3).

5.3 Changes in cost per day

The higher productivity of the fleet in the last 2 weeks resulting from the greater input use is also likely to have implications for the cost per day, and

consequently the appropriate trigger catch rate. The cost data used in the estimation of the trigger value is based on the average costs for the fleet in total over the whole season. The marginal crew cost and marketing costs per day are linked to the level of catch, which will decline as catch rates decline. However, these declines are implicit in the estimation of marginal revenue when deriving the trigger. In contrast, fuel and repairs and maintenance costs are assumed constant per day, but in reality may change as a result of changes in fleet structure over the season (as seen in Figure S3) and the change in the average hours per day and engine power of the vessels (Figure 2).

As noted in the methodology, the cost index is assumed to be proportional to average engine power and hours trawled each day, with the combined cost index assumed to be the product of the two input indexes, given in the Supporting Information Figure S6. From this, average variable running costs are expected to be below the annual average for the first 8 weeks of the season, and above this average for the remainder of the season. In weeks 11 and 12, running costs are potentially 45–55 per cent higher than the annual average. Given this, target catch rates are also expected to be higher if based on the average costs towards the end of the season. For example, based on the price and cost parameters used for the estimation of the 2015 target, the target catch rate in week 12 given the higher costs is estimated to be 351 kg/day compared with the value based on average costs of 221 kg/day (ignoring the buffer discussed previously) (Figure 4).

The effect of increasing the costs on the target catch rate for a range of prices is shown in Figure 5. The average cost index in week 12 (1.54, see Figure S6) was used to inflate the running costs (fuel and repairs and maintenance). As expected, the target catch rate increases as prawn prices decrease, but do not reach the lower buffer level (425 kg/day) even with

Figure 3 Average catch per day from weeks 8 to 12. The blue line represents the 500 kg catch rate.

Figure 4 Target catch rates based on factoring in the higher costs towards the end of the season (2015 price and cost parameters).

higher cost assumptions until prices fall to \$10.75/kg, and does not reach the upper buffer level (575 kg/day) until prices fall lower than \$8/kg.

6. Discussion

The objective of the study was to assess if changes in fleet composition over the year affects the estimation of the target and trigger MEY catch rate used to currently manage the banana prawn fishery. In principle, the trigger catch rate should be higher than the target, as there is a delay between when the trigger is observed and when fishing ceases. However, industry suggested that only the more efficient vessels fished at the end of the season, and the (assumed) lower cost of these vessels (compared with the average of the fleet as a whole) means that they can still fish profitably at lower catch rates. Given the uncertainty around the fleet and cost structure over the season, the trigger and target catch rates were considered to be the same (i.e. no allowance was made to reflect the decline in the stock over the period between when the trigger rate was observed and the fishing ceased).

Uncertainty around stock sustainability resulted in further modification to the MEY trigger. Prior to the implementation of the MEY trigger, an escapement target of 500 kg/day was set as a biologically oriented trigger catch rate. This was a precautionary target and not based on a detailed biological modelling of the fishery. Industry concern that catching at lower rates than this may affect future stock levels resulted in a catch rate buffer being implemented, such that the minimum acceptable MEY target catch rate (and trigger) would be no <15 per cent below the biological trigger rate. The estimated MEY target rate has fallen below this buffer since 2013, so the precautionary 425 kg/day has been implemented as the management trigger.

Figure 5 Target catch rates for a range of prawn prices based on 2015 cost parameters and higher costs assumptions towards the end of the season.

The results of this study found no clear pattern around efficiency changes over the season. While the number of vessels generally declined towards the end of the season, the average efficiency of those remaining was generally similar to that of the larger fleet earlier in the season. The model analysis used fishing days as the measure of variable fishing effort as this corresponds to the management system in place. However, days is potentially a poor measure of fishing effort as the amount of trawling time within the day varies over the season, and this may have affected the efficiency scores. The use of hours trawled as an alternative effort measure is also potentially problematic. At the start of the season when stocks and catch rates are high, low hours trawled per day may reflect a capacity constraint of the vessel in terms of its ability to process the catch. Towards the end of the season when catch rates were lower, longer trawling hours may be required to reach the capacity constraint.

While average efficiency did not change substantially in most years, productivity of the remaining vessels at the end of the season was generally greater than the fleet in the earlier weeks. The remaining vessels were generally larger in terms of engine power, and trawled more hours per day. This had the effect of maintaining catch rates at higher levels, and on this basis equating the target and trigger catch rates to be the same is a reasonable assumption. However, higher engine power and hours trawled also has implications for the costs of fishing. An assumption was made that running costs would be proportional to these inputs, and on this basis running costs at the end of the fishing season may be up to 55 per cent higher than the average values used in the current setting of the MEY trigger. While no cost functions have been estimated for the fishery, Zhou *et al.* (2012) found that, generally, fuel costs increased almost linearly with vessel length (which is highly correlated with engine power in the NPF) and at a diminishing rate with days fished, while repairs and maintenance costs were estimated to be linearly proportional to vessel length.

Even assuming higher costs at the end of the season, the MEY target catch rate is likely to be below the current buffer lower limit, and is likely to remain so unless banana prawn prices decrease substantially. However, if this buffer is to be removed or modified (subject to biological sustainability constraints), more detailed consideration will need to be given to changes in cost structure over the season. In such circumstances, estimating a cost function for the fishery may be beneficial.

The analysis has focused on the effects of changing efficiency and productivity levels on the existing MEY trigger estimation process. This process is based on the general economic principle that profits are maximised when the marginal cost of fishing is equal to marginal revenue. Studies of similar fisheries elsewhere, however, have found that the pattern of fishing effort earlier in the season can also have a substantial impact on fishery profitability as this affects the rate of change in marginal revenue (Huang and Smith 2014). Consequently, while the MEY trigger catch rate provides a proxy for implementing MEY in the fishery, it may not fully achieve MEY. Other factors may also affect MEY in the fishery, particularly the interaction with the tiger prawn fishery. For example, the level of fishing effort in the banana prawn fishery is affected by the tiger prawn price (Pascoe *et al.* 2015b). Ideally, given that vessels operate across both fisheries, MEY in each fishery should be assessed accordingly taking into consideration conditions in the other.

7. Conclusions

Given the changes in fleet productivity over the season, and the observed changes in catch rates as a result, equating the MEY target and trigger catch rates is a reasonable approach for pragmatic fisheries management. However, the likelihood of higher fishing costs at the end of the season suggest that the current MEY trigger estimates are too low. As the estimated target levels in recent years have been below the lower precautionary buffer, they have not affected the actual implemented target and trigger. Ideally, a fishery specific cost function should be estimated to refine these costs and improve the estimate of the trigger and target.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Figure S1. Estimated average net revenue per day (revenue less crew share and fuel costs) from targeting tiger or banana prawns, 2015 and 2016 fishing seasons.

Figure S2. Estimated stock index, banana prawn fishery.

Figure S3. Distribution of final technical efficiency scores.

Figure S4. Number of vessels fishing each week over the fishing season.

Figure S5. Engine power (a) production elasticity and (b) productivity.

Figure S6. Derived proxy cost index (i.e. the combined cost index).

Table S1. Weekly data summary, banana prawn fishery 2010–2015.

Table S2. Correlation between key variables (logged).

Table S3. Final stochastic frontier model (step three).