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Comparison of TAC and current management for the White Banana Prawn fishery of the Northern Prawn Fishery

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Executive summary

This work addresses a request from the AFMA Commission to evaluate the relative performance of input and output controls for the white banana prawn (WBP) fishery of the Northern Prawn Fishery (NPF), investigating "specific aspects of a Management Strategy Evaluation (MSE)". This was achieved by developing a modelling framework for simulating a large number of plausible alternative annual WBP fisheries, over weekly time steps, and examining the economic performance of individual fisheries when these were subject to the different management approaches.

Specifying a range of fisheries consistent with historical observation in terms of the size of the available resource and amounts caught necessitated that we estimate fishable biomass, catchabilities and harvest rates, over the period 1987-2011, using depletion analyses. This work provides a new and valuable retrospective assessment of the fishery. A suite of approaches using daily logbook data captures observed effort patterns in the fishery; a binomial model was the best mimic of the pattern of effort observed in the fishery. This was also a set of work that could have future utility in analysis of the fishery.

In each of the WBP populations, we applied simulated population dynamics and fishing effort, letting the simulated fishery "run" over the full course of the season, and recording catch, effort, revenue and costs by week. Effort and catch values corresponding to a Maximum Economic Yield (MEY) criterion were derived for each simulated fishery. This required new economic analysis for the prediction of potential catch and information on the response of prices to catch volumes (both using information from separate concurrent work). These catch and effort values were then utilised in specifying management approaches with Total Allowable Catches (TACs) or a modified status quo approach that features an MEY-based catch rate stopping rule.

We sought to evaluate alternative policy choices for the WBP fishery, predicting and evaluating the relative performance of two TAC-based policies and a modified input control policy, compared with the status quo:

1. $TAC_{(MEY)}$ - a TAC set annually pre-season at an MEY target, developed using a rainfall-based prediction of "potential catch";
2. TAC-U – a TAC set annually as in $TAC_{(MEY)}$ but which is "updated" during the season using a predictor of potential catch based upon catch rates in the first three (simulated) weeks of each season. This was only applied if the TAC-U was greater than the $TAC_{(MEY)}$
3. SQ - The status quo, in which the WBP fishery is closed after catch rates for specific periods fall below a trigger of 500 kg/boat-day; and,
4. $SQ_{(MEY)}$ - A modification of SQ, in which the trigger catch rate is derived in keeping with an MEY target.

The management control rules, based on total catches, triggers, and season length, were applied to each of the simulated fisheries and so provided catch and effort for evaluation in terms of economic performance. The performance of the different management approaches could then be evaluated simply by comparing the profits or losses apparent at the point when the stopping rules would be applied.

Superficially, the different strategies produced similar performance, generating average annual profits of between \$10 and 11 million, but these were very variable (Standard Deviation, SD = \$8-9 million). Over longer time periods, performance was similar, with the differences between strategies emphasised. Differences in the performance of each of the strategies were more apparent when the simulations were grouped by the quality of fishing year (good, medium and bad). In bad years, the mean performance of the status quo-based strategies was noticeably better. In good years, the TAC strategy was marginally the worst performer, on average, but the updated TAC approach was a little better than the other approaches.

The variability of the WBP fishery is such that average performance over any time period conceals marked differences that are apparent from within-year comparisons. Such comparisons expose the potential risks or gains from adoption of a particular strategy.

A risk of significant loss in adopting a TAC based strategy was shown: although the performance of the status quo and the TAC-based approaches were similar in about half of comparisons, the TAC-based approaches led to a relative loss, sometimes several millions of dollars, in most of the other comparisons. This was largely due to error in the stock abundance measures from which the TACs were derived. An in-season update of the TAC tended to reduce the loss. In marked contrast, the MEY trigger strategy was consistently a good risk: in about half of the comparisons, it was more profitable than the status quo, by at least $1 million, in most of the remaining cases it was similarly profitable but only rarely worse (c.2%). The MEY trigger was less influenced than the TAC strategies by the initial catch prediction.

Relative performance depended upon year quality ("good" or "bad", corresponding to high or low fishable biomass). In bad years, the status quo was clearly more profitable than both of the TAC strategies. The risk of moving to either TAC approach was most clearly shown in sequences of bad years, where these strategies were likely to produce relative losses of about 50% (~$5 million) or more over a five year sequence. Updating the TAC in these years was not effective. In contrast, the status quo with an MEY trigger was predictably better than the status quo, with more than 50% of simulations producing a gain of $2 million or more relative to the status quo over five years.

In good years the TAC-U (but not the TAC) strategy usually performed better than status quo, again accentuated when sequences of good years were analysed. While substantially improving on the TAC strategy (which was very variable and mostly a poor performer relative to the status quo), and providing occasional very high profits, the TAC-U only rarely performed better than the status quo with MEY trigger. Even the in-season update relied on prediction (from the early season catch rates) and the MEY trigger would be much more sensitive to real abundance and prices and costs, rather than to predicted catches.

We conclude that there is substantial risk that introduction of a TAC strategy would lead to poorer profit performance than the status quo. The risk would be even greater if the fishery were to experience a series of environmentally-driven bad years – a drought. This is in marked contrast to the small differences that would be apparent if only long-term average or total profits from the different strategies were considered.

While it might be feasible to improve the performance of TAC approaches by investigating better rules for their application, the risk in these strategies is largely derived from the inability to provide accurate indicators for stock abundance. In the short term at least, this uncertainty is a serious flaw for a TAC-based management strategy for the NPF WBP fishery.

This work also shows that the MEY-based trigger has significant potential for the WBP fishery. However, the concept has only recently been introduced to the management of the fishery, and the implications and practicalities of applying a new management tool such as this to the fishery have yet to be thoroughly explored. Nevertheless, the broader utility of this approach might be examined for application in this and other fisheries where catches and recruitment are highly variable and it is difficult to provide estimates of biomass or other management reference points.

1 Background

This work addresses a request from the AFMA Commission (4 May 2012), asking that AFMA "work with the Northern Prawn Fishery Resource Assessment Group (NPRAG) and the Northern Prawn Fishery Management Advisory Committee (NORMAC) to further investigate specific aspects of a Management Strategy Evaluation (MSE)". The request requires, specifically, a comparison of the status quo management of the banana prawn fishery, with a Total Allowable Catch (TAC) control, under a Maximum Economic Yield (MEY) target. This project was developed with the direct input and review of the NORMAC, in framing objectives and the form of outputs, and comprises a team that includes scientific, management and industry participants. The intention is to evaluate the relative performance of TACs provided via a new approach to white banana prawn (WBP) catch prediction (Venables et al. 2011; Buckworth et al. 2013). This in turn will inform management of the potential benefits/losses of adopting output controls relative to existing input controls and is in keeping with the policy objective of maximising fishery economic returns.

Consistent with the April 2012 decision of the AFMA Commission, the Northern Prawn Fishery (NPF) will potentially move to output controls in 2014. However, there has been substantial debate over whether this move is likely to provide the economic benefits expected with output control. The debate mostly centres on the ability to set defensible TACs, which provide the maximum economic advantage, relative to the current input control system (which limits boat numbers and gear and uses seasonal closures and catch rate trigger limits). For WBP in particular, TACs being set too low in high recruitment years was considered to be a particular risk (NPRAG, March 2012). WBP are an "annual crop", the fishery being almost totally dependent upon annual recruitment. Annual catches have varied between less than 2000 to more than 12,000 tonnes, related to water flow and the strength of the annual Wet Season. Although this volatility is environmentally-driven, and statistical relationships between rainfall and subsequent catches have been described at fairly fine spatial scales (Vance et al. 1985), these relationships have not been temporally stable, and have not been extended to larger spatial scales (e.g. Staples and Maliel 1994;Vance et al. 2003). The lack of a good predictive tool has hamstrung previous evaluations. A new study (Venables et al. 2011), however, has shown substantial predictive ability, potentially as the basis of a defensible TAC. But it should be evaluated whether it might actually be worth moving to some form of TAC, a modified form of the status quo, or just staying with the status quo. By simulation, the work reported here provides a comparison, in terms of difference in operating profits (i.e. revenues minus variable operating costs) between the status quo and a TAC-based management control system that addresses an MEY target.

2 Need

AFMA policy requires that the NPF will adopt output controls in 2014, unless there are strong reasons that this should not be so. There has been considerable debate about the policy centring on the choice of credible, defensible TAC targets, and the economic benefits of output control relative to status quo input controls. Estimation of TACs for NPF target prawn species is especially a challenge: the fishery for WBP, *Penaeus merguiensis*, annually depends upon environmentally-dependent, new recruitment. There is a many-fold inter-annual variation in recruitment, and catches. Landings have ranged from less than 2000 to more than 12,000 tonnes (Woodhams et al. 2011). This considerable variation, as well as confounding between spatial ecological and operational factors, obscures the spawner-recruitment relationship. Hence, a standard fishery assessment, relying upon a fishery model and prediction of annual recruitment relative to spawning stock, is not feasible at this time. Despite high exploitation rates (Zhou et al. 2007), the good catches that usually follow high Wet Season rainfall indicate escapement is sufficient to ensure optimal egg production and subsequent recruitment.

Recently, promising statistical modelling of potential WBP catches, based on rainfall information (Venables et al. 2011), prompted further work (FRDC 2011-239, Buckworth et al. 2013) to ensure predictions are robust and accurate, to incorporate the maximum information, and to detail uncertainties. With economic input, the revised model could be the basis of TAC calculations supporting MEY as a target reference point.

Projected economic performance for the WBP fishery under output controls has been a concern. Cost-benefit analyses indicated that there could be a positive mean improvement in economic performance, over a long time horizon, with output controls relative to existing input controls. But there have been strong concerns that there would be foregone catches and profits in years when potential catches are underestimated, seriously affecting short term performance. Industry advice at NORMAC in relation to the scope of the project was that they hoped the project would produce results identifying a tangibly better management system, that improves profits and provides fair access to the fishery. The debate patently needs clear resolution.

3 Objectives

1. Develop a modelling framework for comparing the performance of proposed alternative management controls for the NPF White Banana Prawn fishery.
   Outcome: This objective was achieved, and the framework is detailed in this report;

2. Quantify risk to profitability of the white banana prawns fishery by the alternative management controls, TACs and the current input control policy.
   Outcome: This objective was achieved; and,

3. Report predicted relative performance of proposed input and output controls, in terms of short and long-term catches, revenues and costs.
   Outcome: This objective was achieved

4 Methods

4.1 Methods overview

A full management strategy evaluation (MSE; e.g. for NPF tiger prawns, Dichmont et al. 2012) would typically comprise, as an operating model, a detailed stock model including the population and fishery dynamics, and would evaluate the performance of management policy alternatives against limit and target reference points, and other criteria, over time series.

As the WBP fishery does not have a suitable stock model, and it is generally agreed that the fishery provides sufficient escapement to ensure optimal recruitment each year, we assume that there is no relationship between this year's catch and next year's stock. Therefore each year can be treated independently. Without trade-offs over time, we were able to address the objectives of this study with a modified approach in which we analysed the results for annual fisheries. Our approach was thus, firstly, to generate a large set of simulated, possible annual banana prawn fisheries. These were to be as consistent as possible with historical observations of the WBP fishery. This large set of fisheries was initially represented by a set of fishable biomass values estimated from the NPF catch and effort logbook data set. Each biomass was considered the starting point of an annual fishery. To each of these WBP populations, we then applied simulated population dynamics and fishing effort, letting the fishery "run" over the full course of the season. The response of fishing effort to catch rates was also chosen to be consistent with observations over the history of the fishery but was modified to reflect the smaller fleet since 2006. The different management controls were represented by different stopping rules applied to otherwise identical fisheries. The management control rules, based on total catches, triggers, and season length, were applied to each of the simulated fisheries and so provided catch and effort for evaluation in terms of economic performance. The process involved the following components:

1. Estimating annual "fishable biomass" using a hierarchical Bayesian model (HBM). The HBM also estimated catchability in each year. Harvest rates were derived from observed catch and estimated biomass;
2. The biomass estimated in step 1 was paired with a "potential catch" drawn from the confidence distribution around the potential catch estimates of the fishery, provided by the authors of Buckworth et al. (2013). This value was later used in the calculation of MEY values for the management control rules (below);
3. Deriving fishing effort pattern based on observations in recent years with a limited fleet size.
4. Building a population dynamics model and applying fishing effort pattern, catchability in recent years, as well as natural mortality to the annual fishable biomass. Daily and weekly catch data were obtained.
5. Calculating revenue, marginal cost, and profit in each time step by applying economic variables to the catch.
6. Applying alternative management rules to these simulated data:
   a. Status quo with a maximum season length of 12 weeks and a trigger of 500 kg/boat-day;
   b. A pre-season TAC based on predicted potential annual catch from rainfall and economic parameters;
   c. An in-season TAC update predicted from historical catch rate in the first 3-weeks;
   d. An MEY-based trigger rule as a modified status quo;
7. Retrieving results (catch and profit) that provide for evaluation of relative performance of the different controls; and,
8. The process is repeated 1000 times, including a range of uncertainties. The final results are presented figures and tables.

The following sections detail these steps.

4.2 Data sources

Various data were used in this study.

Commercial logbooks from 1970 to 2012 contain daily catch and effort information. From logbook data we derived weekly and annual catch, effort, catch-per-unit-effort (CPUE), and their temporal patterns.

Predictions of annual potential catch were produced from modelling the relationship between catch and rainfall (Venables et al. 2011). Confidence distributions of catch predictions were provided from Buckworth et al. (2013).

Economic data, including price flexibility, base price information and cost data estimates were derived from Buckworth et al. (2013). These were to ensure consistency between the two studies.

4.3 Estimation of fishable biomass at the beginning of each fishing season, catchability and harvest rate

To provide a set of biomass estimates for each year of the fishery, it was necessary to divide the log book data time series into two sets, pre-1987, and 1987 onwards. In 1986-87 and subsequently, the fishery was annually subject to a complete closure, usually in the period December to March. This meant that, for these years, a depletion analysis could be used to estimate fishable biomass, as well as harvest rate and catchability, for each year. For each simulated fishery for years prior to 1987, a harvest rate estimate derived from the depletion analyses for years 1987-2011 was applied to observed catch, to provide a consistent fishable biomass.

Zhou et al. (2007, 2008) estimated annual biomass, catchability, and harvest rate for three common banana prawn stocks (southeast Gulf of Carpentaria, east Gulf of Carpentaria, and Albatross Bay) from 1987 to 2007. These three stocks compose just a fraction of the 11 stock regions (Dichmont et al. 2001). Similar work has not hitherto been attempted for the entire NPF stock. Because fishing effort, as well as prawn abundance and their distribution, may differ among stock regions, it is necessary to estimate biological parameters for the whole NPF. The method used in this study is essentially the same as in Zhou et al. (2007, 2008) and is briefly described as follows.

We first used data from 1987 to 2011 because the year-around fishing permitted before 1987 obscured the population depletion process. It also made it difficult to define "initial biomass at the beginning of the fishing season". Since 1987 the WBP fishing season has usually begun in April, and has been largely confined to a period of less than two months each year. Such a short, defined but intensive fishing season provides ideal data for a depletion analysis.

From 1987, a typical declining trend in CPUE can be observed in each fishing season. We assume that recruitment into the catchable population and migrations into and out of the fishing grounds were negligible during the relatively short fishing season.

Let $B_{y,t}$ be the biomass of the white banana prawn in the NPF area in year y and time period t, $B_{y,1}$ the biomass at the beginning of the fishing season, $C_{y,t}$ the estimated catch, q_y the catchability, $Z_{y,t}$ the total mortality during the time period t, $F_{y,t}$ the fishing mortality, M the natural mortality, then we estimate catch and CPUE as:

$$C_{y,t} = \frac{q_y E_{y,t}}{Z_{y,t}} B_{y,1}[1 - \exp(-Z_{y,t} t)]$$

$$CPUE_{y,t} = \frac{C_{y,t}}{E_{y,t}} = q_y \frac{B_{y,t}[1 - \exp(-Z_{y,t})]}{Z_{y,t}}$$

Where $Z_{y,t} = F_{y,t} + M = q_y E_{y,t} + M$. Here weekly instantaneous natural mortality is assumed to be M = 0.05 week^{-1} (Lucas et al. 1979).

Biomass in the next time step is

$$B_{y,t+1} = B_{y,t}\exp\left(-Z_{y,t}\right)$$

We modelled these quantities and rates on a weekly time step. We use a hierarchical Bayesian technique to estimate model parameters. We treat the annual catchability coefficient q_y and the initial biomass $B_{y,1}$, as having random effects and assume they were drawn from the same probability distribution:

$$q_y \sim \text{lognormal}\left(\mu_q, \tau_q\right)$$

$$B_{y,1} \sim \text{lognormal}(\mu_B, \tau_B)$$

where μ and τ are the mean and precision (where precision is the reciprocal of variance, i.e. $\tau = 1/\sigma^2$), respectively. We set the hyper-priors as μ_q ~ normal(M_q, T_q) and μ_B ~ normal(M_B, T_B), where M and T are constants. We chose hyper-parameter M_q and M_B to be close to expected log(q) and log(B_1) while we chose small T_q and T_B (e.g., 0.01) to make these two prior distributions relatively uninformative but still proper (integrated to 1).

This model was run using the WinBUGS software (Spiegelhalter et al. 2003), where the Gibbs sampler, a special Markov chain Monte Carlo (MCMC) technique, was used for sampling parameters from the joint distribution. This was done by using each of the one-dimensional full conditional posterior distributions in turn to generate a sample from the joint posterior distribution of all the unknown parameters. We set up two Markov chains and ran 5,000 iterations of the Gibbs sampler before taking observations. We examined trace plots of the sample values versus iterations to ensure that the simulation had stabilised and that convergence had taken place. For statistical reference, we performed the sampling for an additional 60,000 iterations and thinned the chain by taking every 10th observation for the two chains.

The hierarchical Bayesian model captures the observed CPUE trend well (Figure 1). We also examined the reliability of the estimated biomass and catchability by simulating population dynamics and fishery processes. The simulated catch follows the historical trend of the observed catch well (Figure 2). A slightly low catch in the simulations is because a trigger at 500 kg/boat-day is applied instantaneously. In the fishery, the trigger is applied with a time lag, so that observed CPUE at the end of season is always lower than this trigger (and so more prawns are caught than if the trigger were applied instantaneously).

The posterior median biomass ranges from 2,990 to 11,940 tonnes (Table 1).

It appears the stock size has increased significantly since 2008 (Figure 3), presumably in response to favourable environmental conditions. The posterior median catchability varies from 0.00024 in 1990 to 0.00092 in 2007 (Table 2). The tendency of increase in catchability over time can also be observed (Figure 4).

For years prior to 1987, biomass at the beginning of the WBP fishery season is derived as

$$B_{y,1} = \frac{\sum_t c_{y,t}}{u_{87-11}}$$

Where $c_{y,t}$ is the observed catch, and $u_{87\text{-}11}$ is a sample from estimated harvest rates in 1987 to 2011.

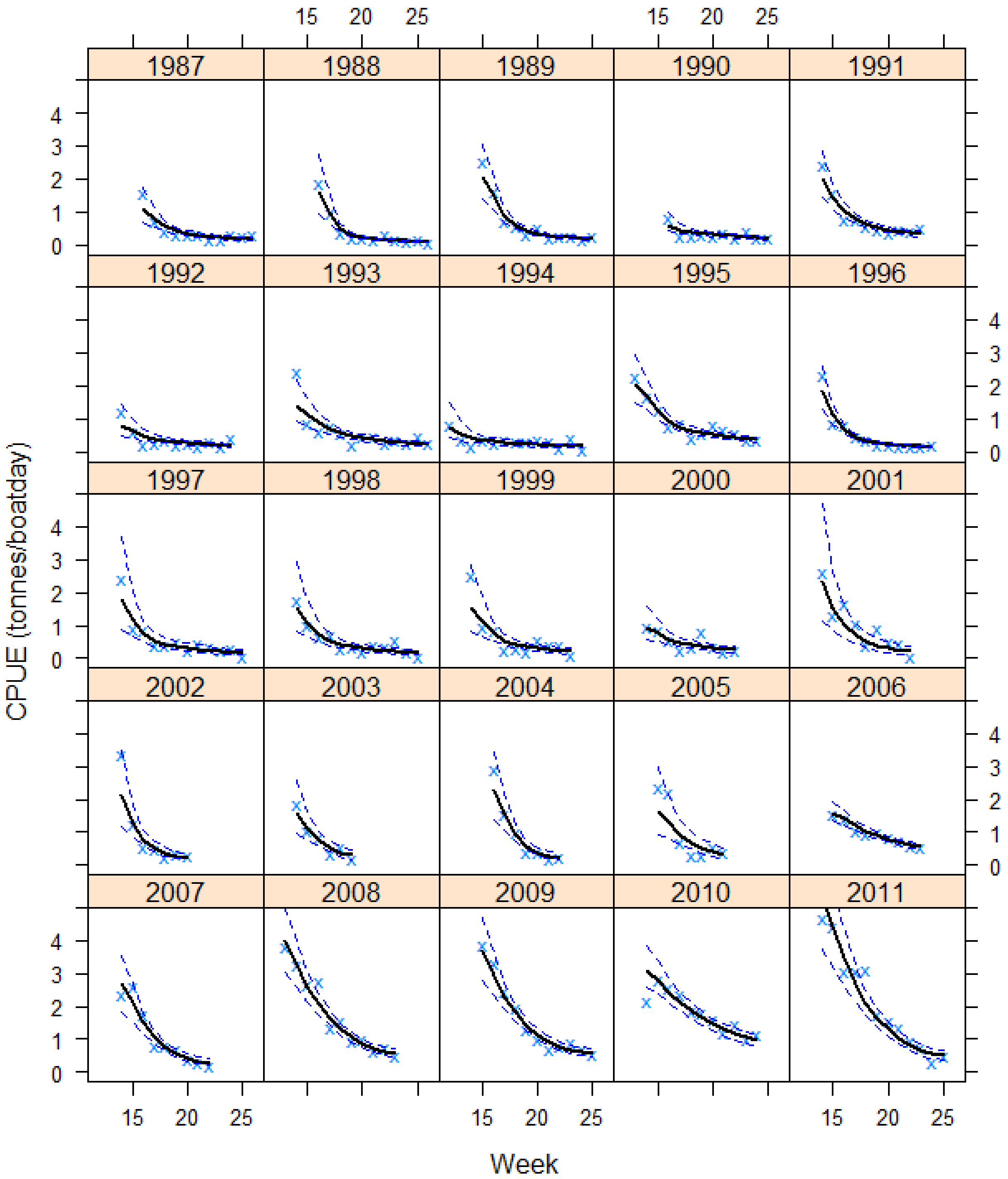

Figure 1. Observed and posterior CPUE for the NPF white banana prawn fishery from 1987 to 2011. Dark thick line = posterior median, dashed line = 95% CI, x = observed CPUE.

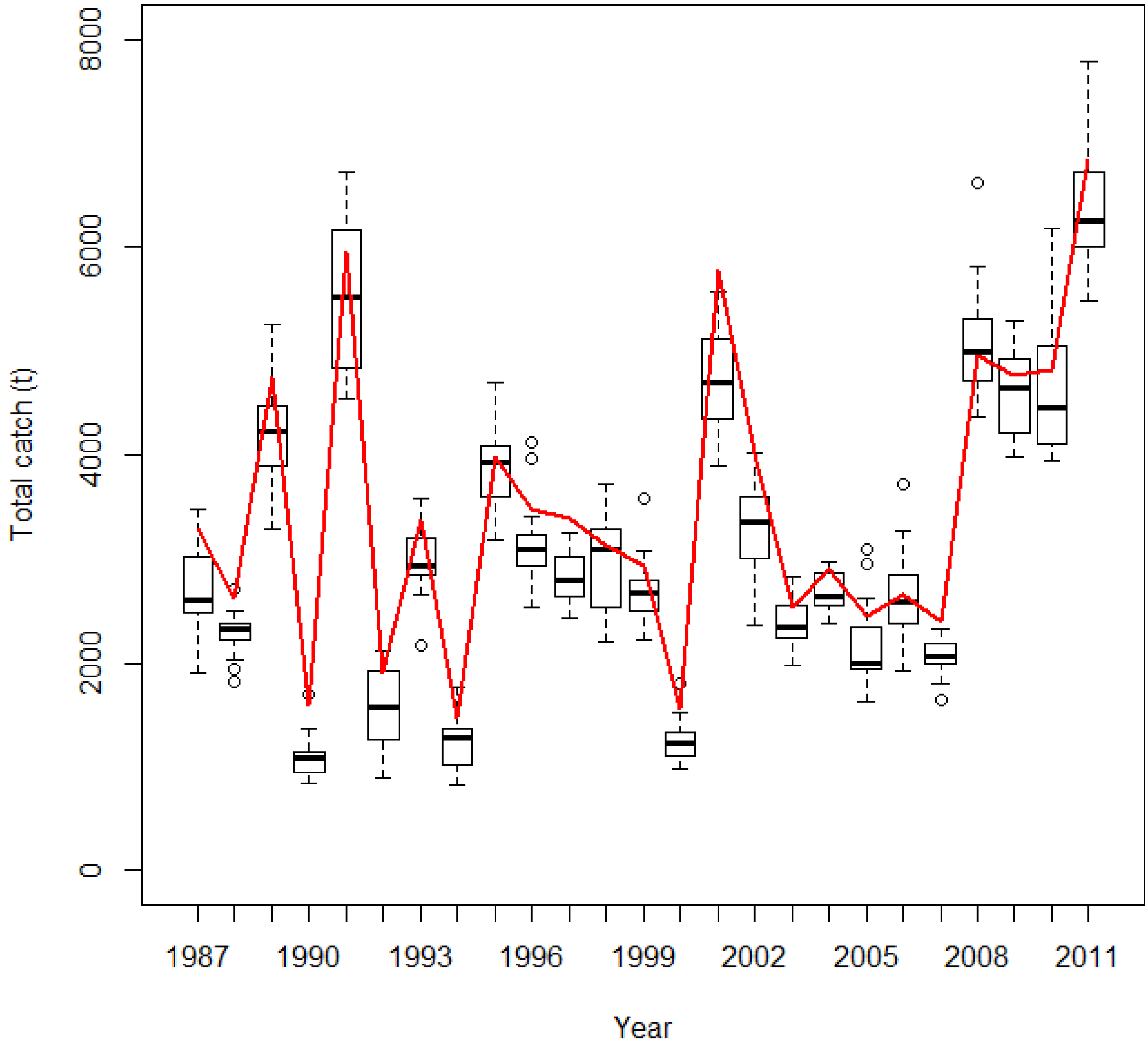

Figure 2.Simulated annual catch (boxplot) and observed catch (red line), NPF white banana prawn fishery. Trigger = 500kg.

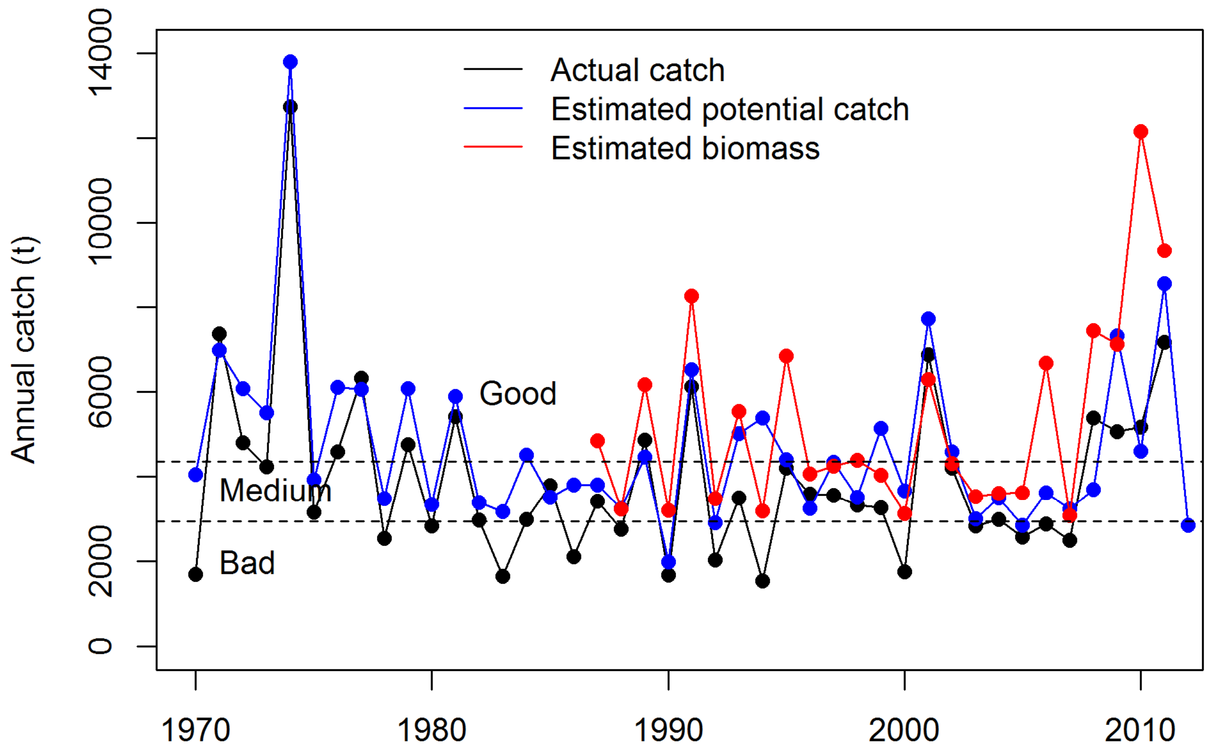

Figure 3. Actual catch from logbook data (black), estimated potential catch from the rainfall model (blue) and estimated biomass from the depletion analysis (red).
Year quality is split into three classes (Bad, Medium, Good) based on tertiles of the actual catch (2935t, 4352t).

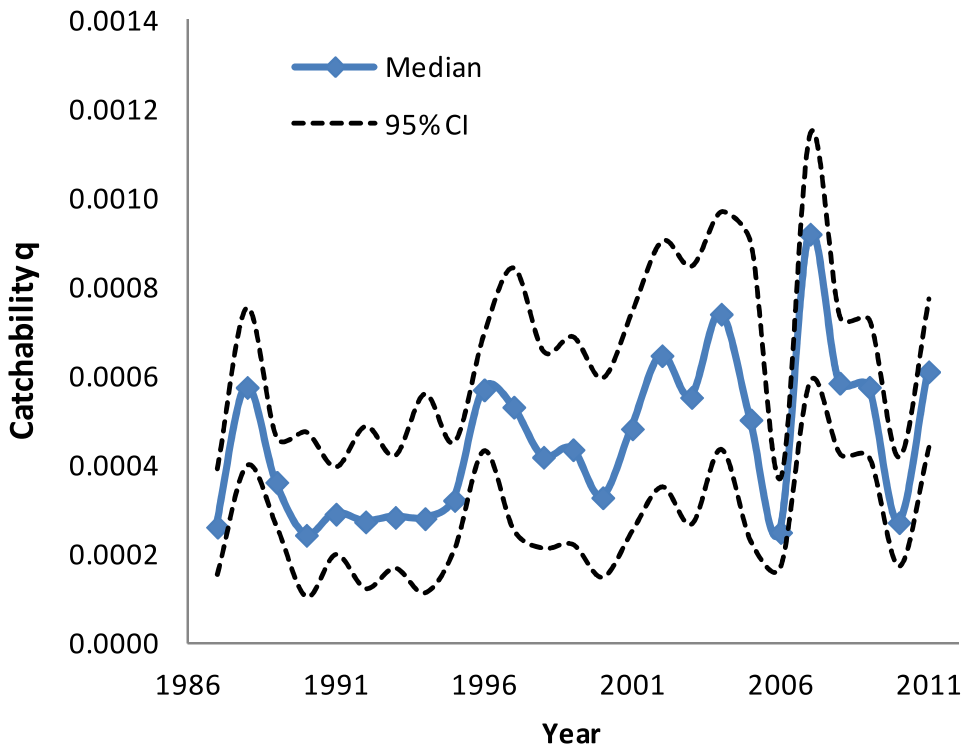

Figure 4. Posterior catchability from hierarchical Bayesian model.

Table 1. Posterior biomass at the beginning of the white banana prawn fishing season from 1987-2011.
Harvest rate *u* based on median biomass is included.

Year	Mean	SD	2.5% CI	Median	97.5% CI	u
1987	4847	588.4	3816	4802	6123	0.683
1988	3236	527.2	2395	3168	4473	0.829
1989	6166	657	4983	6128	7570	0.774
1990	3197	726.2	2299	3044	5012	0.523
1991	8258	736.6	6869	8231	9788	0.724
1992	3475	661.1	2512	3373	5072	0.563
1993	5537	665.4	4375	5483	7017	0.614
1994	3182	693.1	2181	3069	4858	0.476
1995	6849	663	5666	6803	8302	0.584
1996	4063	413.5	3336	4035	4971	0.863
1997	4250	845.2	2914	4139	6216	0.820
1998	4384	756.8	3114	4306	6103	0.727
1999	4037	677	2928	3960	5570	0.739
2000	3123	724.7	2122	2990	4908	0.520
2001	6288	1434	3925	6141	9609	0.942
2002	4314	652.4	3224	4248	5811	0.945
2003	3527	596.7	2639	3433	4979	0.736
2004	3595	462.5	2802	3554	4622	0.815
2005	3612	848.3	2420	3466	5681	0.706
2006	6675	911.5	5087	6599	8676	0.402
2007	3083	295.8	2608	3051	3764	0.784
2008	7445	532.9	6454	7419	8616	0.669
2009	7117	494.3	6204	7093	8180	0.672
2010	12160	1980	8915	11940	16600	0.404
2011	9331	815.1	7754	9316	10990	0.734

Table 2. Posterior catchability q from 1987 to 2011 for the entire NPF white banana prawn population.

Year	Mean	SD	2.5% CI	Median	97.5% CI
1987	0.000263	5.95E–05	0.000154	0.000260	0.000388
1988	0.000574	8.89E–05	0.000397	0.000574	0.000751
1989	0.000361	4.99E–05	0.000262	0.000361	0.000459
1990	0.000253	9.47E–05	0.000104	0.000242	0.000471
1991	0.000291	4.92E–05	0.000199	0.000290	0.000392
1992	0.000280	9.27E–05	0.000122	0.000272	0.000484
1993	0.000285	6.37E–05	0.000168	0.000282	0.000418
1994	0.000294	0.000116	0.000112	0.000279	0.000557
1995	0.000323	6.05E–05	0.000211	0.000320	0.000448
1996	0.000567	6.57E–05	0.000431	0.000569	0.000693
1997	0.000535	0.000150	0.000253	0.000530	0.000841
1998	0.000422	0.000113	0.000212	0.000418	0.000653
1999	0.000440	0.000120	0.000221	0.000434	0.000686
2000	0.000338	0.000115	0.000148	0.000326	0.000593
2001	0.000485	0.000127	0.000252	0.000481	0.000744
2002	0.000640	0.000139	0.00035	0.000646	0.000901
2003	0.000551	0.000147	0.000267	0.000552	0.000845
2004	0.000729	0.000133	0.000434	0.000739	0.000967
2005	0.000517	0.000173	0.000227	0.000501	0.000895
2006	0.000253	4.97E–05	0.000171	0.000248	0.000368
2007	0.000907	0.000137	0.000586	0.000919	0.001144
2008	0.000581	7.67E–05	0.000423	0.000584	0.000731
2009	0.000573	7.71E–05	0.000414	0.000574	0.000723
2010	0.000276	6.29E–05	0.000172	0.000270	0.000414
2011	0.000609	8.39E–05	0.000438	0.000610	0.000771

4.4 Effort and its pattern over time

Effort patterns were analysed using daily logbook data from 1987–2011 (Figure 5). We considered several models in an attempt to establish which might best mimic the pattern of effort observed in the fishery. Over the history of the fishery, the size of the fleet has changed considerably (from 218 boats in 1998 to 52 boats in 2011; see Figure 5), so that the total effort in recent years is very different from earlier years. Nevertheless, the general pattern has been intense effort in the first few weeks involving almost the entire fleet, followed by differing rates of decline. Sometimes the decline is long-tailed, as in 1990, where most boats stopped fishing after about two weeks, leaving a smaller fleet that stayed for a further seven weeks[1]. Sometimes the decline is fairly linear, as in 1993, where the effort dropped steadily over nearly 12 weeks. In later years, the effort has remained high throughout the season with a fairly abrupt fall occurring at the end of the season (e.g. 2007, 2011).

For the purpose of this study, possible future effort patterns need to be simulated. Our first approach was to characterise effort patterns by their shape over days of the season. A weighted least-squares polynomial fit,

$$E_d/N = 1 + a\,d + b\,d^2$$

where *d* is day of season, *N* is fleet size, and *a* and *b* are coefficients, yields the blue curves in Figure 5. These capture the shape of patterns for historical data, though not the whole complexity in some years (e.g. 1995). However, it is necessary to able to generate patterns of effort under a range of possible future conditions of white banana prawn biomass. Using the polynomial model, the strategy would be to establish a relationship between the coefficients *a* and *b* and the underlying biomass, as predicted in section 3.2. Unfortunately, no convincing relationship was found, making this approach unviable.

A second approach was to attempt to model the fleet behaviour in terms of CPUE, since this is what is actually observed by the fishing fleet, and appears to be the main driver. Daily CPUE is likely to be too variable as a basis for modelling base behaviour, therefore the moving average over the previous seven days was used as a driver of behaviour. A range of formulas for effort were tried including the following relationship,

$$E_d/N = 1 + a\,\mathrm{CC} + b\,\mathrm{CC}^2$$

where CC is the cumulative CPUE over the season. The rationale for using CC is that the *change* in effort (dE/dt) should depend on CPUE and therefore *E* should depend on the integral of CPUE. The quadratic term was included for greater flexibility. The relationship also fits the data (Figure 5, green curve) and, in some cases, is more convincing than the polynomial. However the main benefit of this model is that it could be used for simulating future patterns because it depends on the prior CPUE, which will in turn depend on the simulated biomass. Other dependencies on CPUE were also considered, but this was the most convincing. It is possible that the exact choice of model for effort is not critical, provided only that it depends on CPUE.

[1] About 20 boats stayed with banana prawns throughout season 1. A further 40-50 switched between banana prawns and tiger prawns. The remaining 130 or so fished tiger prawns almost exclusively after about 2 weeks.

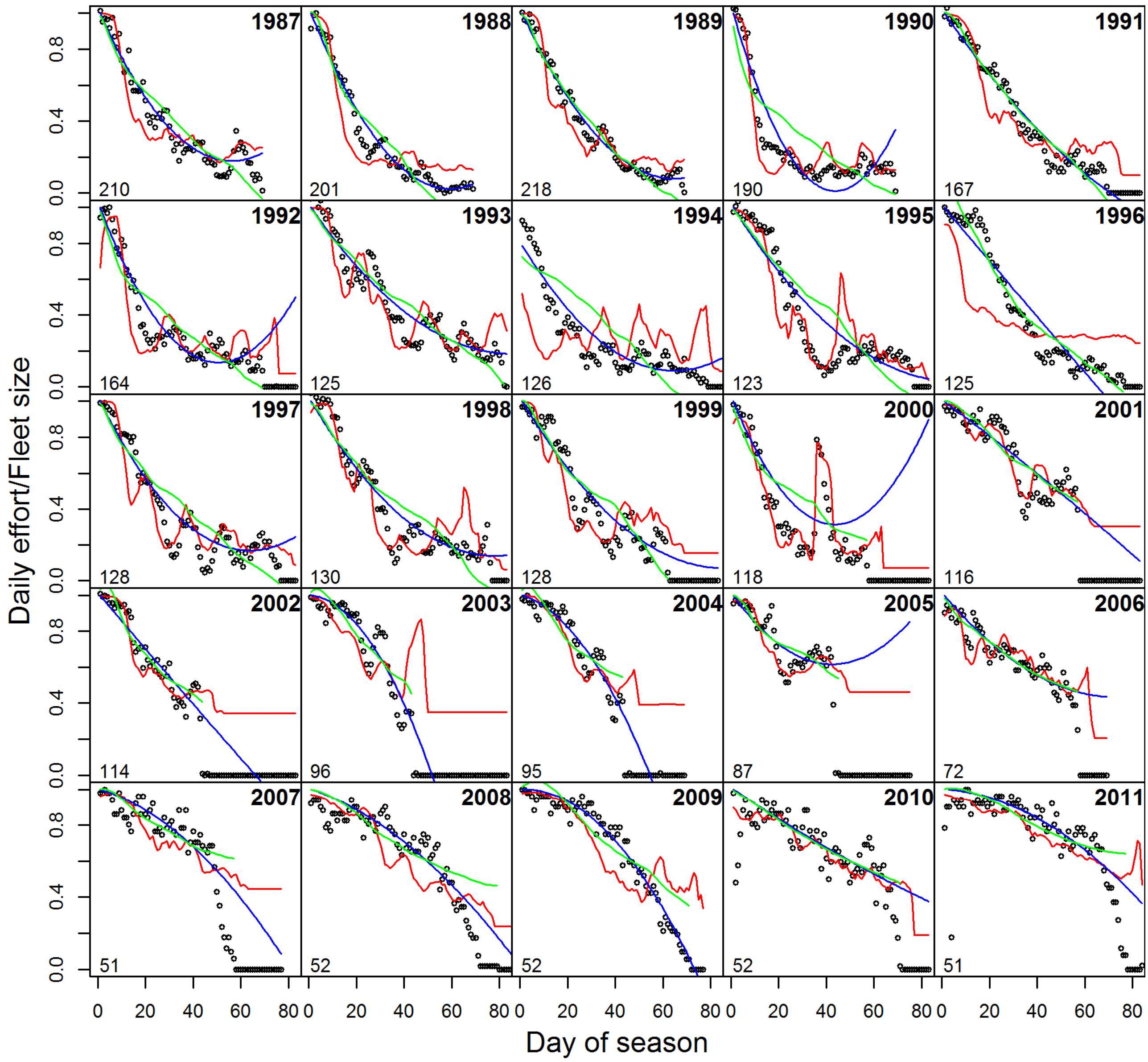

Figure 5. Daily patterns of effort over 1987–2011.
The vertical scale represents effort as a proportion of the number of boats fishing for white banana prawns on that day. The number of boats in the fishery is given in the bottom-left corner. The blue curves are a simple polynomial fit weighted towards higher effort in the earlier part of the season. The green curves are the fit based on cumulative CPUE, CC. The red curves are the fit from the binomial model. All models use separate coefficients for each year.

A final attempt to capture the patterns of effort seen in the fishery was to apply a binomial model using simple logistic regression:

$$\log[P/(1-P)] = a_y + b_y \text{ CPUE}.$$

Here, each boat makes a choice whether to fish for bananas with probability P, where CPUE is mean catch (over the previous seven days) divided by mean effort (also over the previous seven days). The parameters a_y and b_y depend on year. In some instances this model was more realistic than the other models (Figure 5, red curves). For instance, some of the mid-season re-entry behaviour in 2000 and 2005 was faithfully captured by the binomial model. Moreover, the binomial model did not need to be artificially constrained to give a number between 0 and N, unlike, say, the polynomial model in 2004.

All of the results reported here use the binomial model. However, runs were also carried out using the cumulative CPUE model, and the results were in broad agreement with respect to comparisons among the strategies. The values of the coefficients of each of the three models are shown in Table 3.

Table 3. Coefficients of the various effort models discussed. The units of CPUE are t per boat day.

Year	Binomial model		Cumulative CPUE		Polynomial	
	a_y	b_y	a_y	b_y	a_y	b_y
1987	−2.01	3.86	−0.004	−0.0008	−0.030	0.00027
1988	−2.28	3.82	0.008	−0.0019	−0.034	0.00029
1989	−2.28	3.16	0.000	−0.0006	−0.029	0.00022
1990	−3.24	5.74	−0.054	0.0006	−0.046	0.00054
1991	−2.18	2.51	0.002	−0.0003	−0.019	0.00007
1992	−2.52	5.35	−0.041	0.0000	−0.035	0.00035
1993	−2.21	3.88	−0.003	−0.0003	−0.019	0.00011
1994	−2.35	4.67	−0.028	−0.0003	−0.025	0.00017
1995	−3.31	3.52	−0.005	−0.0002	−0.021	0.00011
1996	−1.13	1.02	0.017	−0.0008	−0.016	0.00000
1997	−2.34	3.00	−0.001	−0.0003	−0.026	0.00021
1998	−2.70	4.46	−0.007	−0.0004	−0.022	0.00014
1999	−1.70	2.66	0.004	−0.0006	−0.022	0.00013
2000	−2.54	4.71	−0.036	0.0002	−0.032	0.00038
2001	−0.82	1.59	0.001	−0.0001	−0.010	−0.00001
2002	−0.65	1.59	0.010	−0.0004	−0.016	0.00001
2003	−0.61	2.06	0.009	−0.0006	−0.002	−0.00036
2004	−0.44	2.01	0.010	−0.0005	−0.004	−0.00027
2005	−0.15	1.46	0.000	−0.0003	−0.019	0.00022
2006	−1.35	2.19	−0.011	0.0000	−0.016	0.00011
2007	−0.22	1.43	0.001	−0.0001	−0.004	−0.00010
2008	−1.17	1.11	0.000	0.0000	−0.005	−0.00008
2009	−1.18	1.37	0.004	−0.0001	0.000	−0.00019
2010	−1.46	1.20	−0.003	0.0000	−0.009	0.00002
2011	−0.12	0.67	0.001	0.0000	−0.001	−0.00008

4.5 Population dynamics and fishing process

With estimated fishing effort, initial biomass, and catchability, we can simulate the population dynamics process and fishing process using similar models to those in the biomass and catchability estimation. The formulations are as follows:

$$F_{y,t} = qE_{y,t}$$

$$Z_{y,t} = F_{y,t} + M$$

$$C_{y,t} = \frac{qE_{y,t}}{Z_{y,t}} B_{y,1}[1 - \exp(-Z_{y,t}t)]$$

$$B_{y,t} = B_{y,1}\exp\,(-Z_{y,t}t)$$

$$CPUE_{y,t} = \frac{C_{y,t}}{E_{y,t}} = q\,\frac{B_{y,t}[1 - \exp\,(-Z_{y,t})]}{Z_{y,t}}$$

where q comes from Table 2.

4.6 Profit estimation and MEY

In fisheries based on short lived species that are effectively depleted over a season, MEY is given by the general profit-maximising assumption that effort should increase in the fishery up to the point where the marginal revenue from fishing is equal to the marginal cost. In the case of the banana prawn fishery, there

is assumed to be no relationship between this year's catch and next year's stock, such that each year can be optimised separately. This is based on two key assumptions. First, that there is sufficient escapement to ensure no stock impacts due to fishing between years; and second, that the animals only live for one year so there is no benefit in delaying harvest. As there are no trade-offs over time, discounting is not relevant. Effectively there is an infinite discount rate as prawns not taken this year have no value beyond this year.

This simplifies the process of estimating the optimal effort and catch at MEY, and can be illustrated with a simple model. Assume the catch function can be given by $C = qx_0E^{\lambda}$, where *q* represents the proportion of the stock removed by one unit of effort (a constant), x_0 is the starting stock size with zero effort, E is effort and λ represents the effort elasticity. That is, the percentage change in catch due to a one percent change in fishing effort. The stock is assumed to become depleted as effort is applied, so that the marginal catch rate declines as effort increases. i.e. $dC/dE = \lambda qx_0E^{\lambda-1}$.

Assuming constant (exogenously determined) prices, 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 the marginal revenue $\left(p\,dC/dE\right)$ is equal to the marginal cost. From this, $E^{\lambda-1} = \dfrac{c}{\lambda pqx_0}$ and $E^* = \left(\dfrac{c}{\lambda pqx_0}\right)^{1/(\lambda-1)}$, where *E** is the level of effort that maximises profits given *c*, *p*, *q*, x_0 and λ . For a given *E**, the optimal catch is given by $C^* = qx_0E^{*\lambda}$.

There is evidence in the fishery that price varies with the quantity landed. With variable prices, and assuming a constant price flexibility *f*,[2] the profit function becomes $\pi = e^{[\ln p_0 - f\ln(qx_0E^{\lambda})]}qx_0E^{\lambda} - cE$. Profits to the industry are maximised when

$$\frac{d\pi}{dE} = \frac{-f\lambda qx_0E^{\lambda-1}}{qx_0E^{\lambda}}e^{\ln(P_o - f\ln(qx_oE^{\lambda}))}qx_0E^{\lambda} + e^{\ln(P_o - f\ln(qx_oE^{\lambda}))}\lambda qx_0E^{\lambda-1} - c$$
$$= \left(\lambda qx_0E^{\lambda-1}\right)e^{\ln(P_o - f\ln(qx_oE^{\lambda}))}(1-f) - c$$

from which

$$\left(E^{\lambda-1}\right)e^{\ln(P_o - f\ln(qx_oE^{\lambda}))} = \frac{c}{\lambda qx_0(1-f)}$$

From the above, when *f* is zero (i.e. demand is said to be perfectly elastic and prices perfectly inflexible), this collapses back to the constant price conditions with $p = P_1$.

Given a current quantity (Q_1) and price (P_1), we can approximate price P under different quantities Q as $P = P_1\left(1 + f\left(Q/Q_1 - 1\right)\right)$. This is a linear approximation of the logarithmic function above, and is valid for changes in quantities close to the current quantity. Substitution of this into the equation above gives

$$\left(E^{\lambda-1}\right)\left(1 - f\,\frac{qx_0E^{\lambda} - Q_1}{Q_1}\right) = \frac{c}{\lambda qx_0P_1(1-f)}$$

Again, when *f* = 0 this collapses back to the constant price condition (i.e. $\lambda pqx_0E^{\lambda-1} = c$).

[2] Price flexibility represents the percentage change in price given a one percent change in quantity landed.

4.6.1 Practical bioeconomic model

The above model is highly non-linear and needs to be solved numerically rather than analytically. It is also relatively restrictive in the assumptions about the relationship between catch and effort. Given this, the approach adopted was to estimate the components of the model separately and optimise profits for the fleet as a whole. The objective function of the model was given by Max $\pi = P^{*}C - c_e E$ where P^* is the effective price received for the prawns (net of crew share and also marketing costs), C is the catch level ($C = f(E, S)$, where S is the stock index, which is assumed to be exogenously determined independently between years), c_e is the variable fishing cost per unit of effort (i.e. fuel, repairs and gear costs) and E is the level of effort in the fishery. As we are optimising over a single year and are assuming that the fleet size is fixed and hence are not optimising vessel numbers as well as days fished, we ignore fixed and capital costs. The estimated profit is consequently not a true profit measure, but a measure of revenue less variable costs (i.e. the gross margin). This differs from the tiger prawn model (Dichmont et al. 2012) that optimises over time with lower bounds on profitability (i.e. non-negative profits) in any one year and consequently needs to consider all the costs, not just variable costs.

We estimate the effective price as $P^* = P(1-c_c) - o_c$, where P is the prawn price, c_c is the crew share of revenue (0.23) and o_c are other catch-based costs such as marketing, freight etc. The prawn price was estimated as $P = P_1\left(1 + f\left(Q/Q_1 - 1\right)\right)$, where P_1 is the price in the most recently available year (in this case 2011) and Q_1 is the quantity landed in that year (again 2011), and f is the price flexibility.

Catch is given by[3]

$$\ln C = \beta_0 + \beta_1 \ln S + \beta_2 \ln E + \beta_3 \ln^2 E + \beta_4 t + \sum_i \delta_i D_i$$

where t is a time index to capture technical change (or efficiency change) over time and D_i are a series of year-specific dummy variables that represented major management changes (e.g. buybacks, changes to gear units etc).

The catch model (Table 4) was estimated from daily catch and effort data during the targeted banana prawn season (i.e. excluding banana prawns caught during the tiger prawn season) over the period 1987-2011. The effort weighted (EW) "potential catch" estimated by the Buckworth et al. (2013) model was taken as the stock proxy.

The model captured around 93% of the variation in catch. The coefficient for the potential catch was less than one, indicating that catch did not increase linearly with the estimate of potential catch. That is, higher estimates of potential catch were greater over-estimates of stock abundance than lower estimates. The relationship between catch and effort decreases with increasing effort.

From the coefficient on the time variable, fishers' ability to catch banana prawns increased at an average 1.6% per year over the period examined.[4] This is broadly consistent with the increase in catchability observed in Table 2 and Figure 4.

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[3] A range of other specifications were also tested, including models with quadratic and cubic time terms, models without the quadratic effort term, models imposing a constant unitary stock elasticity, as well as models with interactions between the stock index, effort and also time. The identified model was the best given the data. The model was also estimated using data only from 2007 onwards based on suggestions at the November Northern Prawn Resource Assessment Group meeting. The coefficients on the effort variables were not significantly different to those estimated using the longer time series of data, although the coefficient on the stock measure was significantly lower. The model using the shorter time period suggests that changes in stock had little impact on catch. Given that abundances were high during most of this period this results was assumed spurious and the original model retained.

[4] As noted above, quadratic and cubic time trends as well as interaction terms were also considered but the linear model was the most appropriate.

Table 4. Regression results for bioeconomic model: catch equation.

	Estimate	Std. Error	t value	Sig
Intercept	−7.068	0.319	−22.131	***
lnEW	0.747	0.013	55.825	***
lnEffort	1.717	0.081	21.2	***
lnEffort2	−0.078	0.006	−13.677	***
time	0.016	0.001	20.876	***
Y1994	−1.039	0.018	−59.027	***
Y2000	−0.660	0.021	−31.356	***
Y2006	−0.267	0.022	−12.23	***
Y2007	0.043	0.022	1.908	.
Y2008	0.455	0.019	23.419	***
Adjusted R-squared	0.926			
F	2267.000			***
AIC	−1507.453			

Table 5. Economic parameters used in the TAC analysis and in the simulation.

Parameter	Value
P_1 (\$/tonne)	8000
CV_P	2%
q_1 (tonnes)	6835
f	−0.3
Fishing costs per day (\$/day) (fuel, repairs, gear)	3819
CV_C	16%
Crew share (%)	23
Marketing (\$/tonne)	1030

4.6.2 Estimates of the TAC at MEY

An equivalent total allowable catch at MEY was estimated for each year between 1987 and 2011, given the recent estimates of cost and price conditions. As these parameters were held constant, variations in the TAC at MEY were due solely to changes in the initial estimate of 'potential catch'.[5] The key parameters used in the analysis are given in Table 5. These are indicative values only as they will change for each year.

In the simulations uncertainty in price and cost was accounted for by introducing variability around the value assumed in the TAC analysis. Vessel-specific price data for the 2011 banana prawn season (provided by industry) showed variability across vessels with a 13% coefficient of variation (CV), which translates to a CV of 2% ($=13/\sqrt{51}$) for the fleet as a whole. The price variability was therefore modelled by a lognormal factor with mean 1 and coefficient of variation CV_P = 2%. Variability in costs was assumed to reside solely in the fishing costs per day, and derived from fishing cost information provided by industry for the tiger prawn assessments. An assumption was made that variability in banana prawn fuel costs would be equivalent to variability of tiger prawn costs. This was modelled by a lognormal factor with mean 1 and coefficient of variation CV_C = 16%. It is an important principle in management strategy evaluation that the operating

[5] Incorporating year-specific costs and prices would add greater variability to the analysis and additional confusion as to the extent that estimates of the 'potential catch' have on optimal catch and effort.

model should be independent of the management model, to guard against over-optimistic assessment of the efficacy of management strategies.

The resultant MEY effort and catch, and the underlying 'potential catch' (effort weighted, or EW) are shown in Figure 6 and detailed in Table 6. As would be expected, the variability in optimal catch is greater than the variability in optimal effort. Also as would be expected, optimal catch also closely follows the estimate of the potential catch.

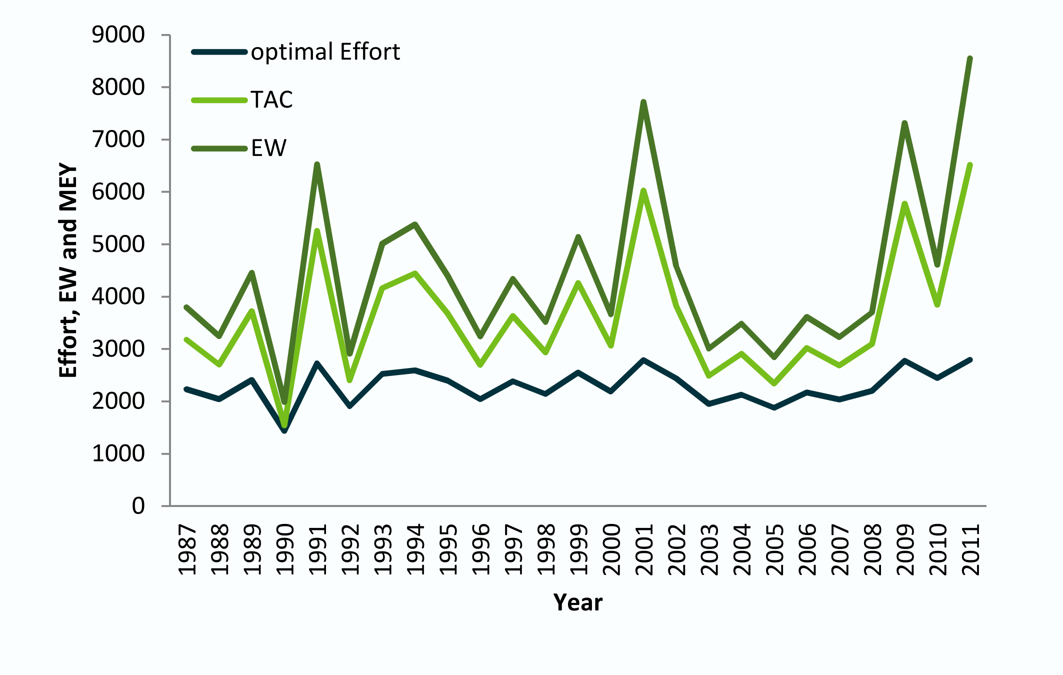

Figure 6. Optimal effort and catch with current prices and costs.
Effort is measured in total days fished; EW and MEY are measured in tonnes.

Table 6. Estimated TACs given current base prices and costs.

Year	EW	Optimal Effort (days)	TAC (MEY) (tonnes)	Price ($/tonne)	Effective price ($/tonne)	Effective revenue ($m)	Fishing costs ($m)	Operating Profit ($m)
1987	3795	2231	3178	9284	6119	19.4	8.5	10.9
1988	3248	2045	2704	9451	6247	16.9	7.8	9.1
1989	4456	2410	3724	9092	5971	22.2	9.2	13.0
1990	1988	1436	1542	9858	6561	10.1	5.5	4.6
1991	6528	2725	5258	8554	5556	29.2	10.4	18.8
1992	2911	1909	2403	9556	6328	15.2	7.3	7.9
1993	5014	2527	4163	8938	5852	24.4	9.7	14.7
1994	5380	2590	4441	8841	5777	25.7	9.9	15.8
1995	4404	2397	3682	9107	5983	22.0	9.2	12.9
1996	3241	2042	2698	9453	6249	16.9	7.8	9.1
1997	4339	2382	3629	9126	5997	21.8	9.1	12.7
1998	3514	2140	2936	9369	6184	18.2	8.2	10.0
1999	5140	2550	4260	8904	5826	24.8	9.7	15.1
2000	3662	2189	3064	9324	6150	18.8	8.4	10.5
2001	7721	2788	6026	8284	5349	32.2	10.6	21.6
2002	4584	2439	3826	9056	5943	22.7	9.3	13.4
2003	3006	1949	2489	9526	6305	15.7	7.4	8.2
2004	3486	2131	2912	9377	6191	18.0	8.1	9.9
2005	2844	1880	2342	9578	6345	14.9	7.2	7.7
2006	3610	2173	3020	9340	6162	18.6	8.3	10.3
2007	3226	2036	2684	9457	6252	16.8	7.8	9.0
2008	3696	2200	3093	9314	6142	19.0	8.4	10.6
2009	7318	2774	5776	8372	5416	31.3	10.6	20.7
2010	4606	2444	3844	9050	5939	22.8	9.3	13.5
2011	8552	2797	6514	8113	5217	34.0	10.7	23.3

4.6.3 Estimates of the MEY Trigger points

The current management system uses a series of catch rate trigger points in order to determine when to close the fishery. An equivalent set of trigger points can be established consistent with MEY.

As noted before, the profit function for the fishery as a whole can be given by $\pi_y = (p_y(1-c_c)-o_c)C_y - c_e E_y$ where π_y is the profit in year *y*, p_y is the average price per kilogram, C_y is the total catch in year *y*, c_e are effort related variable cost per day (such as repairs and maintenance, fuel, and gear). We can approximate the profit maximising condition without reliance on catch-effort models by equating the revenue per unit effort with the cost per unit effort, such that $(p_y(1-c_c)-o_c)C_y/E_y = c_e$. From this, we can set an optimal target catch rate of

$$\frac{C_y}{E_y} = \frac{c_e}{(p_y(1-c_c)-o_c)}$$

For example, using the parameter values in Table 6 and assuming a constant price gives a target catch rate of 772 kg. Fishing beyond this catch rate (i.e. at lower catch rates) results in fishing costs exceeding revenues and total profits declining.

The target catch rate value can be estimated using either the most recent price or a variable price based on expected catch. This can have a substantial impact on the estimated optimal catch rate. For example, using the 2011 price of $8/kg as a constant price, and the model estimated price based on expected catches given changes in the 'potential catch' over the period 1987-2011 results in substantially different targets (Figure 7). This is because 2011 was a high catch year, and the optimal catches in the other years were

substantially lower, resulting in higher prices and hence a lower optimal minimum catch rate. Hence, while the target catch rate may be estimated without the use also of catch estimates, including these estimates results in a less conservative target catch when the base price is relatively low.

Figure 7. Target catch rates with high constant price and model-estimated prices.

The trigger mechanism in the current harvest strategy (i.e. for the status quo) closes the fishery one week after the trigger catch rate has been observed as a mean over defined two week periods. We applied this approach slightly differently with the MEY trigger. Catch rates two weeks apart from seven weeks into the season (i.e. assuming the trigger catch rates are observed from week 5) were compared and an average factor of 1.63 was found. This factor, however, has a substantial variability (standard error = 0.3). Consequently, while a target catch rate can be potentially readily identified, identifying an appropriate trigger catch rate two weeks earlier that will result in that target catch rate being achieved is more uncertain. If instead a one-week delay were implemented, the scaling factor would be smaller and subject to less variability.

4.6.4 In-season update

The initial TAC can be adjusted by an in-season update. The purpose of the update is to improve on the pre-season estimate of potential catch C_{pred} using catch-effort information from the early part of the season. The MRAG (2007) report used a Bayesian approach that was developed to provide a TAC in the absence of a predictive model. They also implemented a Bayesian in-season update based on a simple regression equation. Here a predictive model is available to provide a pre-season estimate, making the full Bayesian approach unnecessary. However, the regression idea is adopted here, and provides a fairly simple update rule that we judged to be similarly effective.

First, the annual catch is used as a surrogate for potential catch. Annual catch C_y is fit using the linear model

$$C_y = a + b\ CPUE_{w3}$$

where $CPUE_{w3}$ is the catch rate in the first 3 weeks and a and b are parameters. Using data from 1987 to 2011, we obtain a positive relationship between the annual catch and $CPUE_{w3}$ (Figure 8). Define C_{w3} as the estimate of potential catch after week 3. The simplest update rule is as follows:

Update rule: if $C_{w3} > C_{pred}$, recalculate the TAC using C_{w3} in place of C_{pred}.

The recalculation of TAC would follow the same method as described in section 4.6.2.

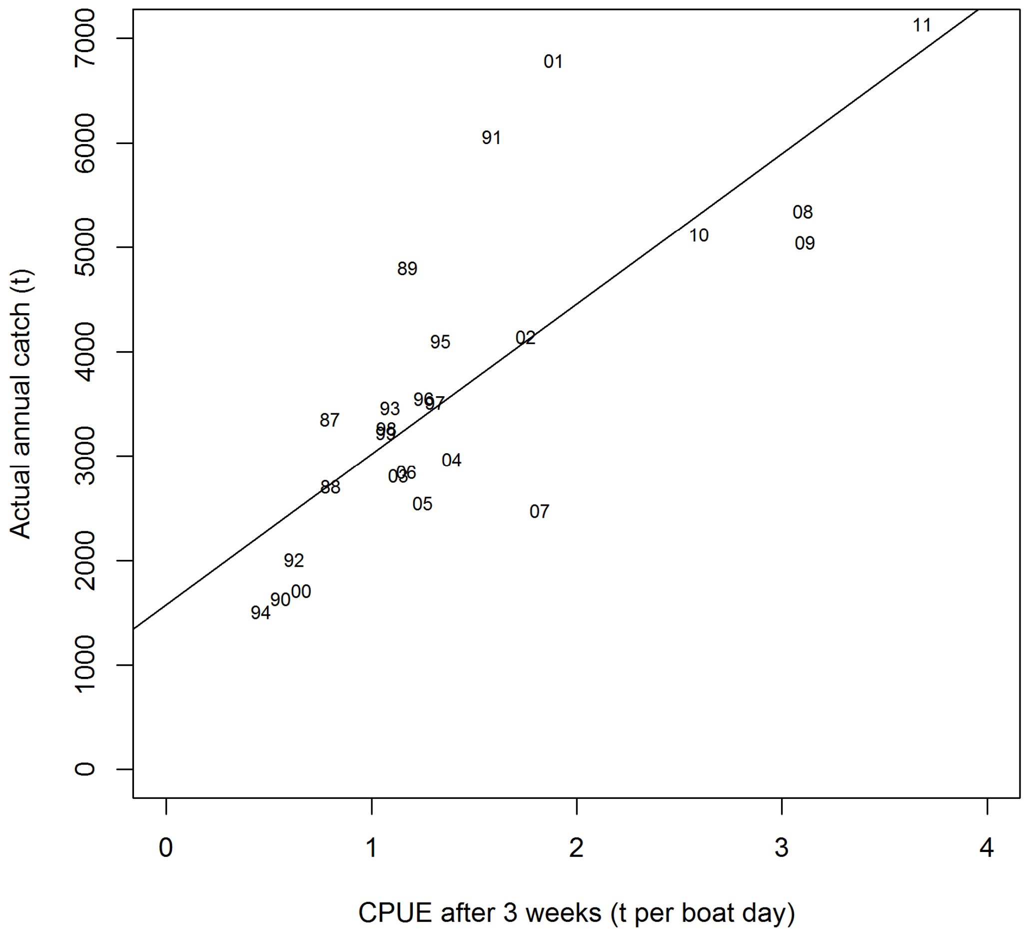

Figure 8. Relationship between actual annual catch C_y and CPUE in the first 3 weeks C_{w3}. The line is the linear regression. Labels denote year.

4.7 Status quo

The current banana prawn harvest strategy defines season length and a trigger. The season length is 13 weeks and the trigger is CPUE = an average of 500 kg/boat-day. In the actual fishery the trigger is only tested at the end of week 5 and every subsequent fortnight. If the average CPUE over the previous two weeks falls below the trigger, the fishery continues for one week and closes for the rest of the season.

In this report, the simulations tested the rule at the end of every week. This would only have a slight effect because triggering prior to week 5 was extremely rare, and additional testing on the even-numbered weeks would have the effect of shifting any closure forward by a week.

4.8 Simulation procedure

The simulation process is divided into two stages. In the first stage, the simulations are generated to the end of a 13-week fishing season in the absence of stopping rules. In the second stage, the management strategies are applied in parallel to the common set of simulated fishing seasons.

4.8.1 Generating simulated fishing seasons

The simulations aim to capture the full range of possible future scenarios based on situations seen in the past. For each simulation, two key choices are made:

1. a representative year y_B for describing the biology
2. a representative year y_E for describing the effort

The year y_B is randomly sampled from the range 1970–2011. This year is then used as the basis for choosing (i) the initial biomass and (ii) the pre-season TAC and MEY trigger.

i. Initial biomass

The initial biomass is derived from the depletion estimate of the biomass for year y_B. The value is sampled from the normal distribution with mean and standard deviation taken from columns 2 and 3 in Table 1. If $y_B < 1987$ (i.e. no depletion estimates exist), then the biomass is taken to be the catch for that year divided by a harvest rate *u* drawn at random from the last column in Table 1.

ii. Pre-season TAC and MEY trigger

An estimate of the potential catch C_{pred} is obtained by choosing a single value from the bootstrap distribution of the estimated potential catch for year y_B. We cannot re-use the values in Table 6, since these are based on the mean potential catch, not the *sampled* potential catch C_{pred} (which simulates uncertainty in the estimation process in future years). Given the C_{pred} , estimate, the effort E^* that maximises profit is found by numerical optimisation as described in section 4.6. The TAC is then the catch that would be caught at this level of effort according to the simple economic model (section 4.6.1).

The pre-season TAC calculations, providing the catch and effort values at which MEY is achieved, is then used to set an MEY trigger, as described in section 4.6.3.

The effort year y_E is randomly sampled from the range 2006–2011, as we considered that effort patterns from this period were likely to reflect any changes engendered by the fleet re-structure that occurred during 2006-7. This year was then used as the basis for choosing (iii) the catchability *q* and (iv) the effort pattern. The reason for restricting the choice to these years is that future fishing effort will be similar to recent years with respect to both behaviour and efficiency, especially considering the current small fleet size.

iii. Catchability *q*

Like the biomass, this is also derived from the depletion estimate of the catchability for year y_E. The value is sampled from the normal distribution with mean and standard deviation taken from columns 2 and 3 in Table 2.

iv. Effort pattern

The effort pattern is based on the binomial model with parameters a_y and b_y for year $y = y_E$ (section 4.4). In this report the non-stochastic version of the effort model was used: $E = NP$. A stochastic version would draw from the binomial $E \sim \text{Binom}(N,P)$.

Having initialised with these parameters, the fishing season is then simulated. It transpires that it is most convenient first to simulate a season in which no management rules apply, except for the finite limited season length.

Prior to the first day there is no CPUE information, and so the binomial model cannot be used to allocate effort. To get the season started, the first day is treated differently. A random number of vessels is allocated to the first day, where that number is drawn from the historical distribution of the proportion of the fleet fishing on the first day. This number is usually close to 51 in the simulations. Once the first day is fished, there is a CPUE value, which drives the effort model for subsequent days. Each day a 1-week and 2-week prior CPUE is recalculated.

Given effort on the day, the daily catch is calculated as well as the mortality and change in biomass according to the biomass-dynamic model (section 4.5). In addition the revenue and costs are also computed according to the economic model (section 4.6.1), taking into account price and cost variability (CV_P and CV_C; Table 5), a variation assumed fixed for the year. Because price depends on the landed catch, which is not known until after the season ends, the calculated revenue for each day represents the revenue that would be attained if the fishery closed on that day.

The calculation proceeds to the end of the season (90 days). A table of 90 records and 25 columns representing the various computed variables are then generated. (An example of the kind of outputs generated is shown in Figure 9). This is repeated 1000 times (with random variation) to allow the range of future situations to be explored, thus generating a table of 90,000 records, which forms the raw material for comparing strategies as described next.

4.8.2 Applying the strategies

The focus of this report is to compare the different management strategies. It is therefore convenient to generate the simulated seasons first, and then apply each strategy in turn. The only effective difference in each strategy will be when the stopping rule is applied. This is illustrated with reference to Table 7. In the table, the first five columns have been created using the fishing season simulation process; they hold the key quantities for the management strategies, but they are independent of those strategies, continuing uninterrupted to the 13th week.

The TAC set for this simulation was 3103 t. Allowing for implementation error (described below), a TAC strategy would have closed this season after week 4, implying an operating profit of \$16.74 million. The status quo MEY approach with a CPUE trigger value based on the pre-season TAC was 1.01 t/boat day. If this strategy were in effect, the rule would be triggered in week 7 (0.93 < 1.01) and the fishery closed 2 weeks later (in our implementation) leading to a profit of \$17.76 million. After week 3 the CPUE (based on weeks 1–3, not the one in the table) was sufficiently high to reset the TAC to 4781 t. If the TAC strategy with update rule were adopted, the TACU would have been achieved (again with implementation error) in week 10, yielding a profit of \$17.45 million. Finally, the status quo trigger would have gone off in week 10, leading to a closure a week later, giving a profit of \$17.07 million.

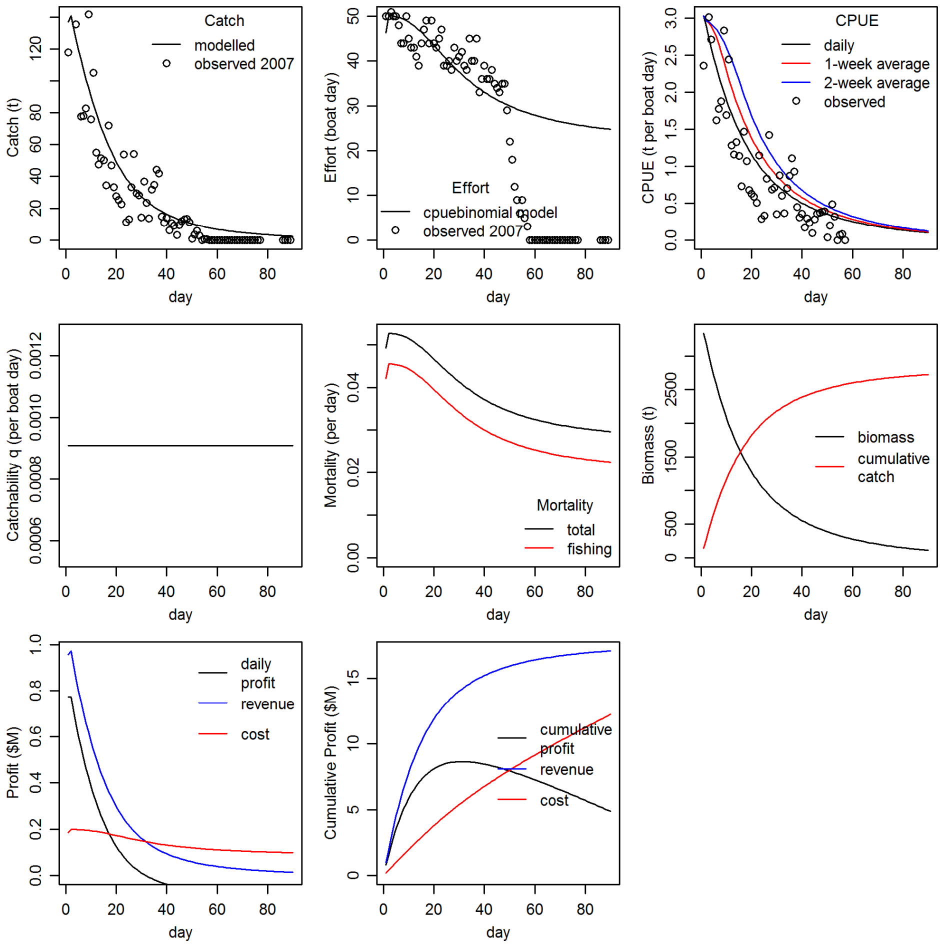

Figure 9. Example of time trajectories of various quantities that are tracked during a simulation. This uses y_E = 2007. The actual data from 2007 are overlaid in the top panels.

Table 7. Example simulation showing different timings of the stopping rule.

Week	Effort (boat days)	Catch (t)	Profit ($M)	CPUE (t/boat day)	Action
1	353	1349	7.79	4.15	
2	692	2313	12.45	3.47	
3	1010	2993	15.18	2.61	
4	1306	3479	16.74	1.97	TAC 3103 attained
5	1584	3831	17.58	1.51	
6	1845	4091	17.98	1.18	
7	2092	4286	18.08	0.93	
8	2327	4435	17.98	0.74	
9	2552	4550	17.76	0.59	MEY trigger 1.01 in week 7
10	2768	4640	17.45	0.48	TACU 4781 attained
11	2977	4711	17.07	0.39	SQ trigger 0.50 in week 10
12	3181	4768	16.64	0.32	
13	3351	4808	16.25	0.27	

Notes to table: The four quantities are evaluated at the end of the given week. Profit is the profit that would be achieved if the fishery closed in the given week. CPUE is the average CPUE over the current and previous week. The right-most column indicates in which week fishing stopped.

The example given was just one example out of 1000; we emphasise that this example was chosen for clarity, because all four strategies applied the stopping rule at different times. Most simulations did not have all four stopping rule applied at different times.

A different way of seeing the difference in the effect of the four strategies is to consider the time series of effort for a few simulations (Figure 10). In each of the four panels the trajectories of effort against time are the same except for their endpoint, beyond which they are not drawn. For example, the orange trajectory continues for 13 weeks for the trigger-based strategies whereas the stopping rule applies quite early in the season for the TAC strategies. The light blue simulation is stopped at different times by all four strategies (in order TAC, TACU, SQMEY, SQ) and in the dark blue simulation is only the SQMEY strategy applies its stopping rule.

Unlike the trigger-based strategies, where the fishery is closed at a definitive time, the closing due to a TAC is in fact a fleet-level approximation to the actual process in which individual fishers choose to stop fishing because they are close to their quotas. In reality fishers would stop at different times, a process which could only be faithfully described by individual vessel-based modelling. In this report, the uncertainty in stopping time is accommodated by an implementation error ε, where the rule becomes

TAC stopping rule: if total catch > TAC × (1+ ε) then stop fishing.

The implementation error is of a similar magnitude for that assumed in MSE for tiger prawns (Dichmont et al. 2012). However, we note that the proposed penalties for exceeding individual quotas are fairly punitive, and so ε is more likely to be negative than positive. Therefore a random ε is sampled as follows: $\varepsilon = s \times$ Uniform(0,0.15), where s is –1 with probability 2/3, otherwise +1.

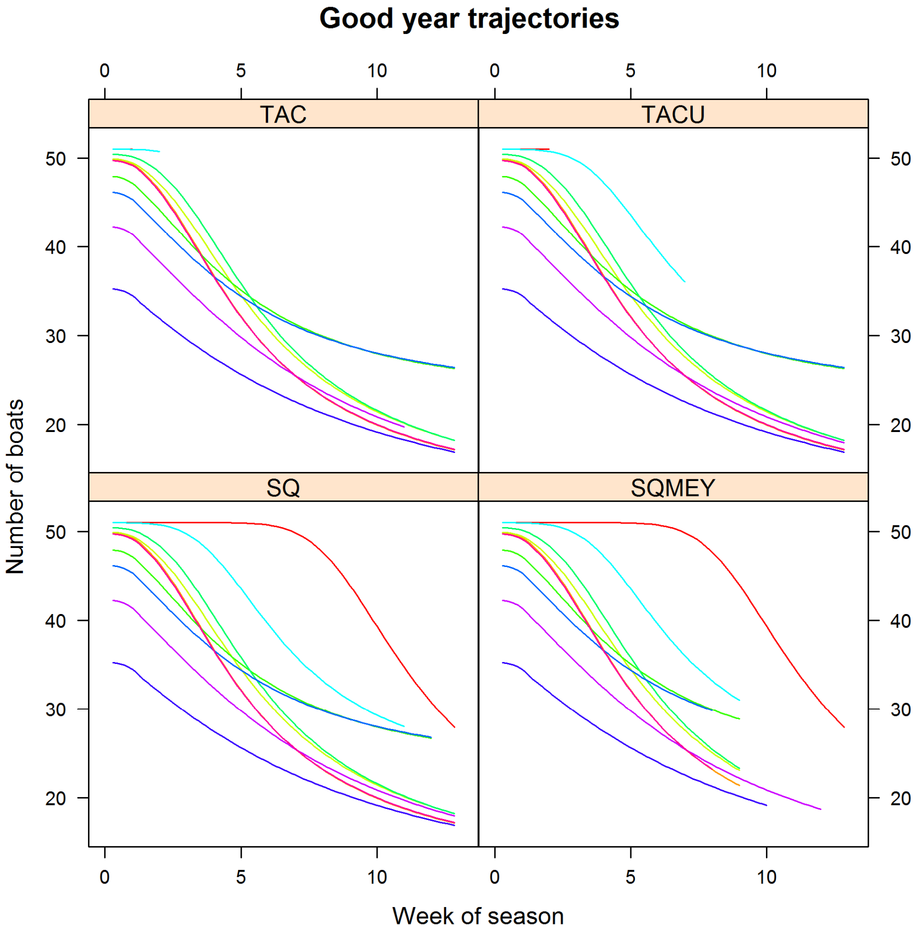

Figure 10. Time trajectories of daily effort for 10 random 'good' years for each strategy. The only difference among strategies is when the season ends.

5 Results

From each of the 1000 simulations, the operating profit (marginal revenue-marginal cost) was recorded for each of the four strategies. The results are summarised in the first row of Table 8. Superficially the four strategies are fairly similar, with expected annual profit around $10–11 millions but a rather large standard deviation of around $8 million. This range is evident also in the histograms of profit (Figure 11). The TACU strategy shows the largest variation including some high profits but also some negative profits (as does the TAC strategy).

The focus of this report is comparative, however, so it is more useful to look at the *differences* between strategies (Table 8, right-hand columns), which addresses the potential risks or gains from adoption of a particular strategy, as operating profit (or loss) in an annual fishery, relative to the status quo. This shows that the SQMEY trigger strategy consistently out-performs the status quo (SD < mean), and that status quo out-performs both TAC strategies on average, but with fairly large variation (mean < 0, but SD to mean ratio fairly large). The crude summaries in Table 8 mask the detailed comparison of relative performance which are better expressed in Figure 12. This shows that in about half of the simulations SQ and either TAC strategy perform about the same (bar at 0 difference with height ~ 0.5) but for the remainder of times the difference can be fairly large (several millions of dollars) and mainly in favour of SQ (more negative cases than positive cases). This Figure most clearly shows the risk associated with moving from SQ to a different strategy. In contrast, the SQMEY trigger strategy out-performs SQ by about $1 million for more than half of the simulations; and it is rarely worse than SQ (about 2%).

The differences among strategies vary depending on the quality (good, medium, bad) of the year (Table 8, rows 2–4). Although SQ is consistently slightly more profitable than the TAC, irrespective of season, its performance relative to TACU does depend on the season. In good years the TACU strategy performs better than status quo, which appears to arise from an earlier closing of the season (Figure 13, right). However in bad years the situation is reversed with SQ closing the season earlier and leading to greater profitability, whereas the TACU seems overly optimistic in the catch that can be achieved profitably (closure in week 13). The difference between SQMEY and SQ is very consistent across seasons; the improved profitability of SQMEY seems associated with a more timely closure about four weeks earlier in the season. The effect of the TAC update is to delay the stopping rule by about three weeks. The TACU strategy out-performs the TAC in good years but is slightly worse in bad years. The level of effort is determined by catch rates

The operation of the TACU strategy can be understood from Figure 14, which shows the updated TAC value against the pre-season value. In about half of cases the TAC is not updated because the 3-week estimate C_{w3} does not exceed the rainfall estimate of potential catch C_{pred}. These cases correspond to the diagonal 45° line. When the TAC is small (~ 3,000 t) the update rule is quite often invoked and the new TAC can be substantially larger, especially in good years. Given the relative performance of these two strategies, the update in good years appears to be warranted, whereas the update in bad years is over-optimistic. When the pre-season TAC is high the update rule is rarely invoked, except in a few good years. Given that the prediction based on C_{w3} estimates actual catch, this suggests that those high TACs are over-optimistic with respect to the actual stock situation.

Table 8. Mean (standard deviation) profit ($M) and difference in profit ($M) over all simulations and grouped by year quality.
The definition of year quality is given in Figure 3.

	Status quo (SQ)	SQ + MEY trigger (SQMEY)	Pre-season TAC (TAC)	TAC + update (TACU)	SQMEY – SQ	TAC – SQ	TACU – SQ
All simulations	10.72 (8.05)	11.30 (8.10)	9.99 (7.60)	10.60 (9.01)	0.58 (0.49)	–0.73 (3.24)	–0.12 (3.19)
Good years	18.05 (7.56)	18.65 (7.59)	17.10 (6.32)	19.20 (8.25)	0.60 (0.49)	–0.95 (5.34)	1.15 (5.10)
Medium years	8.83 (5.54)	9.41 (5.64)	8.41 (5.29)	8.33 (5.80)	0.58 (0.50)	–0.42 (1.26)	–0.49 (0.87)
Bad years	5.10 (4.15)	5.65 (4.23)	4.28 (4.47)	4.07 (4.47)	0.55 (0.47)	–0.83 (1.09)	–1.03 (1.01)

Given overall climatic conditions, especially the state of the Southern Oscillation Index, extended periods of dry or wet years are not uncommon. We see this mirrored in the historical catch record (Figure 3), when the period 2002–6 had relatively low catch whereas 2007–11 had relatively good catch. We therefore examined the difference in total profit over a contiguous sequence of similar years. For instance, to examine the profit over five good years, we randomly selected five of the 1000 simulations, computed the total profit over those five years, repeated the process 1000 times, and computed the mean and standard deviation. We carried this out for sequences of two, three, five, 10 and 20 years for good, medium and bad seasons and also for any kind of season (Table 9).

The differences discussed above tend to be accentuated when considered over several years. The mean differences grow linearly with the duration of the sequence, but the standard deviations grow more slowly. For instance over two good years the SQMEY strategy is fairly likely to out-perform SQ (SD is roughly half the mean difference) whereas after 10 years it is virtually guaranteed (SD roughly a quarter of the mean difference). Comparing the TAC strategies with SQ, an interesting feature arises: in bad years SQ emerges as clearly favourable especially after five years (SD/mean ~ 0.5), whereas in good years TACU is preferred but only with a large uncertainty (SD exceeds the mean difference). As before, these summary properties are more clearly understood from the histograms of bad year (Figure 15) and good year (Figure 16) differences. We see that over five bad years SQ almost always makes more profit than the TAC strategies; over five good years TACU beats SQ most of the time, as does SQ beat TAC; and SQMEY consistently beats SQ by a margin that is the same for good or bad years.

Table 9. Mean (standard deviation) total profit ($M) and difference in total profit ($M) over sequences of years of various quality.

Season quality	No. of years	Status quo (SQ)	SQ + MEY trigger (SQMEY)	Pre–season TAC (TAC)	TAC + update (TACU)	SQMEY – SQ	TAC – SQ	TACU – SQ
Any	2	21.12 (11.13)	22.29 (11.21)	19.65 (10.59)	20.92 (12.73)	1.17 (0.68)	−1.48 (4.12)	−0.20 (4.35)
	3	31.83 (13.72)	33.60 (13.86)	29.81 (13.21)	31.52 (15.29)	1.76 (0.85)	−2.02 (5.90)	−0.31 (5.85)
	5	53.09 (18.04)	56.00 (18.24)	49.44 (17.37)	52.40 (20.48)	2.90 (1.11)	−3.65 (7.35)	−0.70 (7.16)
	10	107.00 (24.51)	112.76 (24.67)	99.82 (23.35)	105.99 (27.30)	5.75 (1.51)	−7.18 (10.07)	−1.01 (9.76)
	20	213.55 (35.55)	225.05 (35.83)	198.87 (33.12)	211.38 (39.45)	11.5 (2.25)	−14.68 (16.07)	−2.17 (15.01)
Good	2	36.03 (10.70)	37.25 (10.77)	34.18 (8.92)	38.48 (11.75)	1.22 (0.69)	−1.85 (7.49)	2.46 (7.10)
	3	54.65 (12.80)	56.46 (12.85)	51.49 (10.70)	58.10 (14.46)	1.81 (0.86)	−3.16 (8.59)	3.45 (8.30)
	5	90.25 (16.83)	93.26 (16.96)	85.42 (13.50)	95.76 (18.13)	3.01 (1.13)	−4.83 (11.35)	5.51 (10.90)
	10	179.81 (23.75)	185.91 (23.85)	170.63 (20.01)	190.99 (25.62)	6.10 (1.57)	−9.18 (17.33)	11.18 (16.37)
	20	360.39 (33.20)	372.34 (33.28)	342.22 (29.06)	383.66 (38.06)	11.95 (2.14)	−18.17 (23.61)	23.27 (23.04)
Medium	2	17.48 (7.59)	18.65 (7.74)	16.70 (7.22)	16.47 (7.96)	1.18 (0.70)	−0.78 (1.62)	−1.01 (1.24)
	3	26.23 (9.29)	27.96 (9.42)	25.06 (8.94)	24.80 (9.71)	1.73 (0.86)	−1.17 (2.00)	−1.43 (1.51)
	5	44.71 (12.92)	47.63 (13.11)	42.54 (12.22)	42.35 (13.53)	2.92 (1.15)	−2.17 (2.87)	−2.36 (1.97)
	10	87.87 (17.93)	93.71 (18.25)	83.52 (17.05)	82.91 (18.81)	5.84 (1.66)	−4.35 (3.89)	−4.96 (2.71)
	20	175.44 (25.33)	187.12 (25.74)	166.71 (23.98)	165.52 (26.49)	11.69 (2.26)	−8.73 (5.82)	−9.92 (3.80)
Bad	2	9.95 (5.82)	11.04 (5.93)	8.31 (6.32)	7.84 (6.20)	1.09 (0.67)	−1.64 (1.53)	−2.11 (1.42)
	3	15.35 (7.29)	17.00 (7.44)	12.85 (7.81)	12.21 (7.82)	1.65 (0.82)	−2.50 (1.87)	−3.15 (1.74)
	5	25.46 (8.97)	28.18 (9.16)	21.21 (9.66)	20.23 (9.64)	2.72 (1.03)	−4.25 (2.43)	−5.23 (2.28)
	10	51.76 (13.68)	57.26 (14.02)	43.48 (14.78)	41.56 (14.85)	5.51 (1.52)	−8.28 (3.49)	−10.2 (3.18)
	20	102.02 (18.53)	113.10 (18.83)	85.62 (20.19)	81.36 (20.03)	11.08 (2.07)	−16.40 (4.8)	−20.66 (4.54)

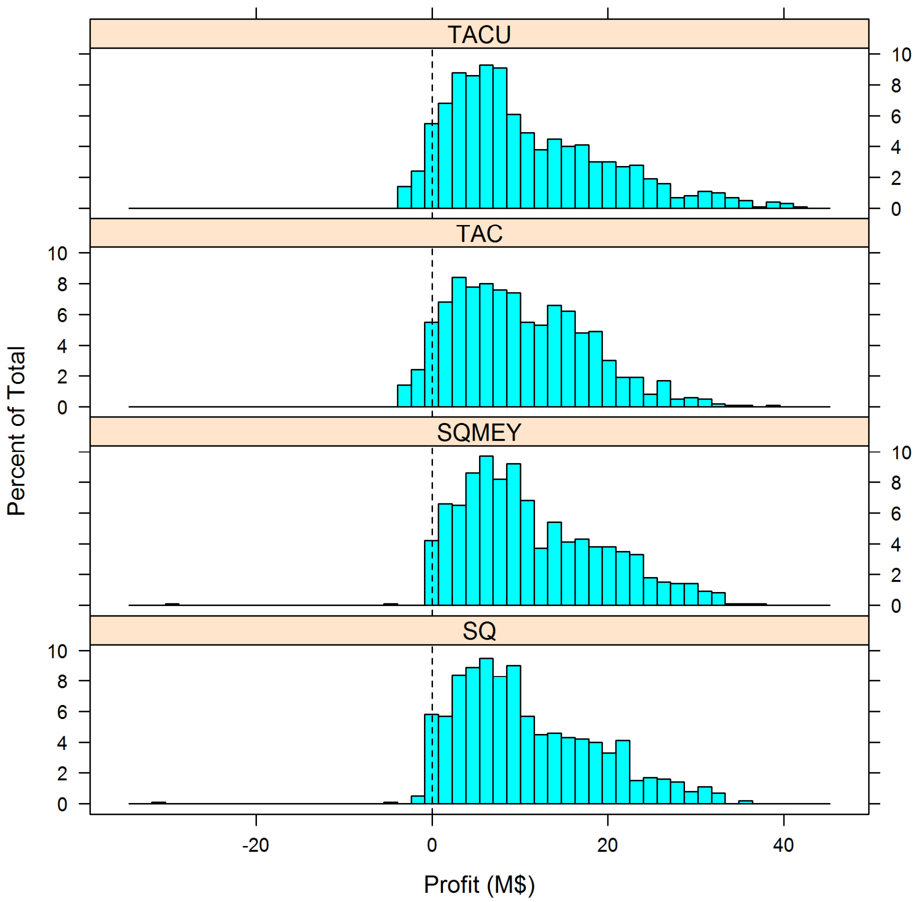

Figure 11. Histograms of annual profit for each strategy.
SQ, status quo; SQMEY, status quo with MEY-based trigger; TAC, pre-season TAC; TACU, as TAC with potential update.

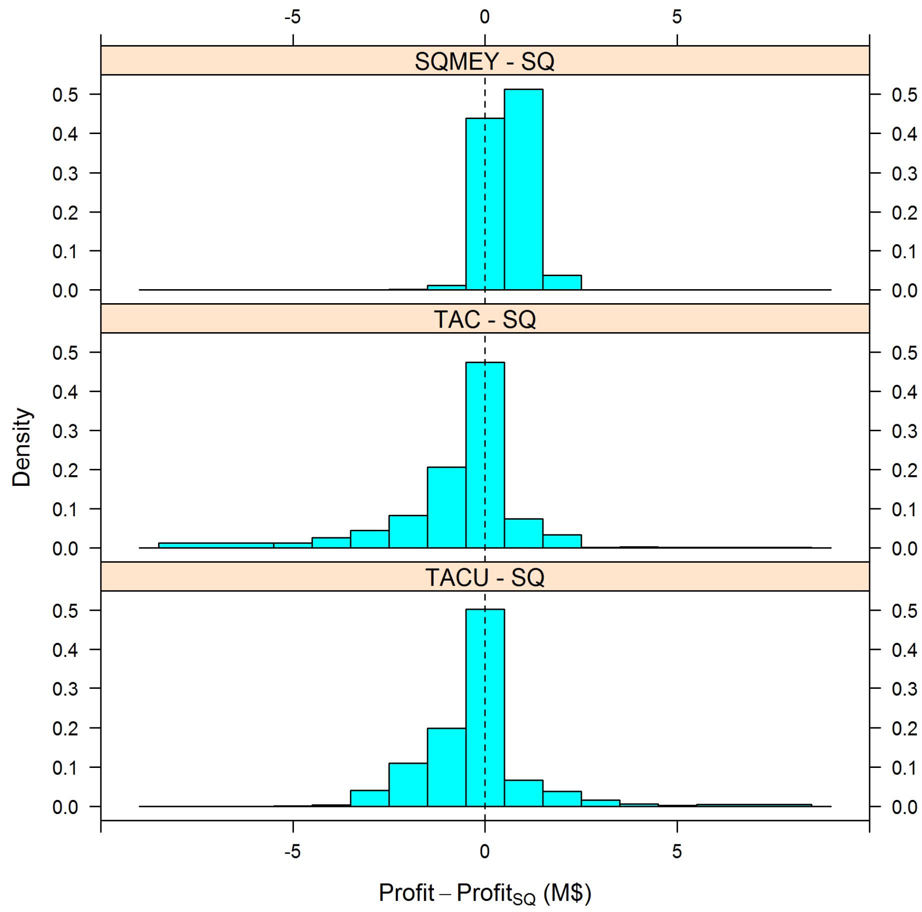

Figure 12. Histograms of difference in annual profit relative to status quo for each strategy.

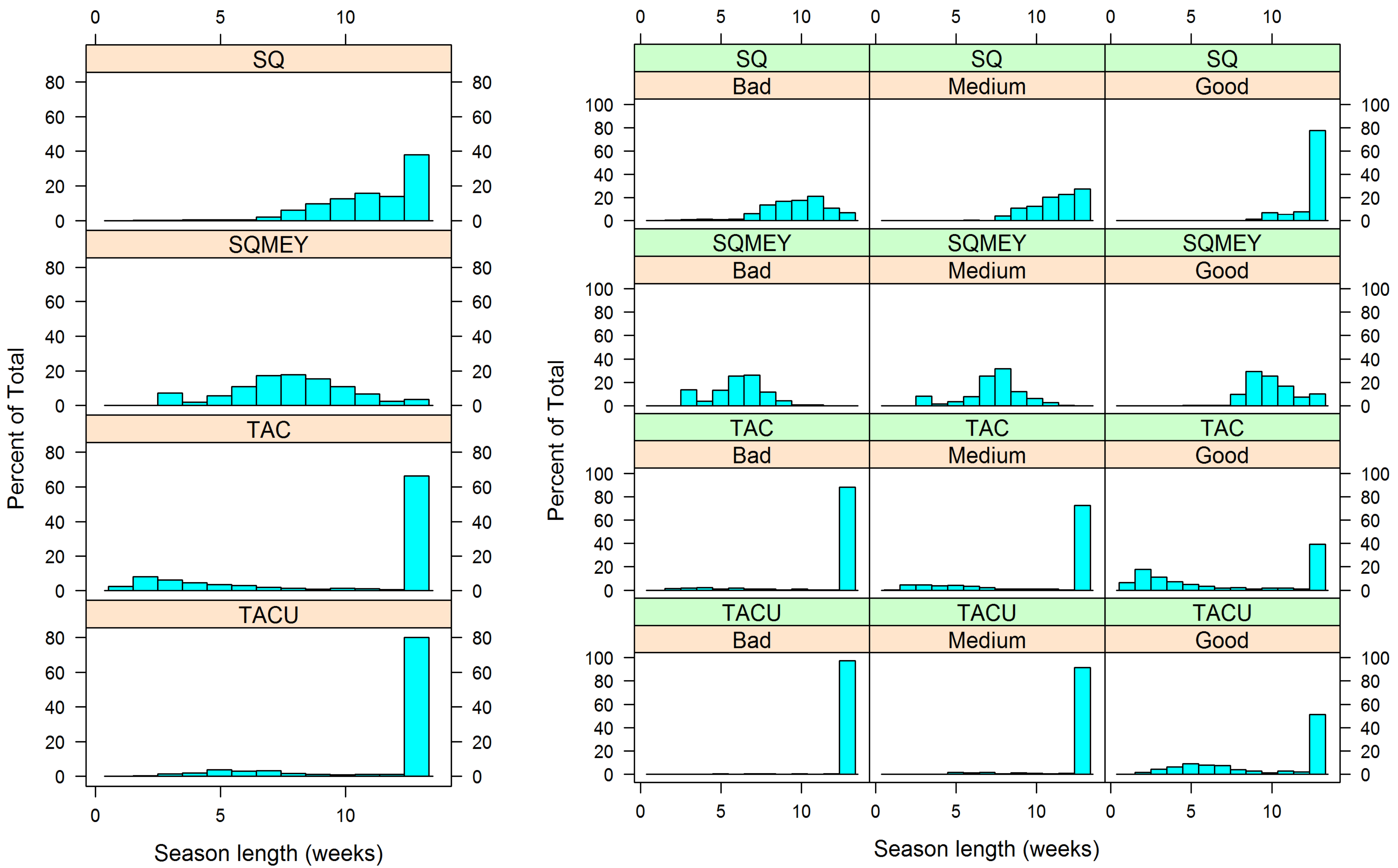

Figure 13. Histograms of season length for each strategy (*left*) for all simulations and (*right*) grouped by year quality.

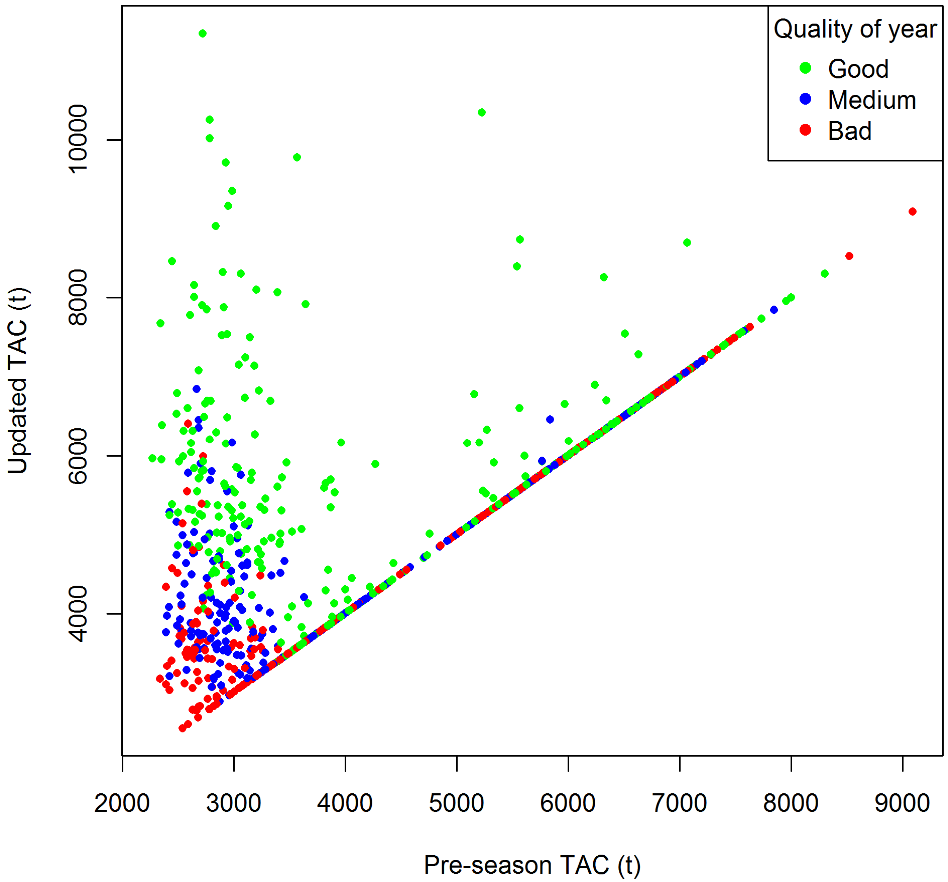

Figure 14. Updated TAC compared to pre-season TAC. In good years the update can be quite substantial.

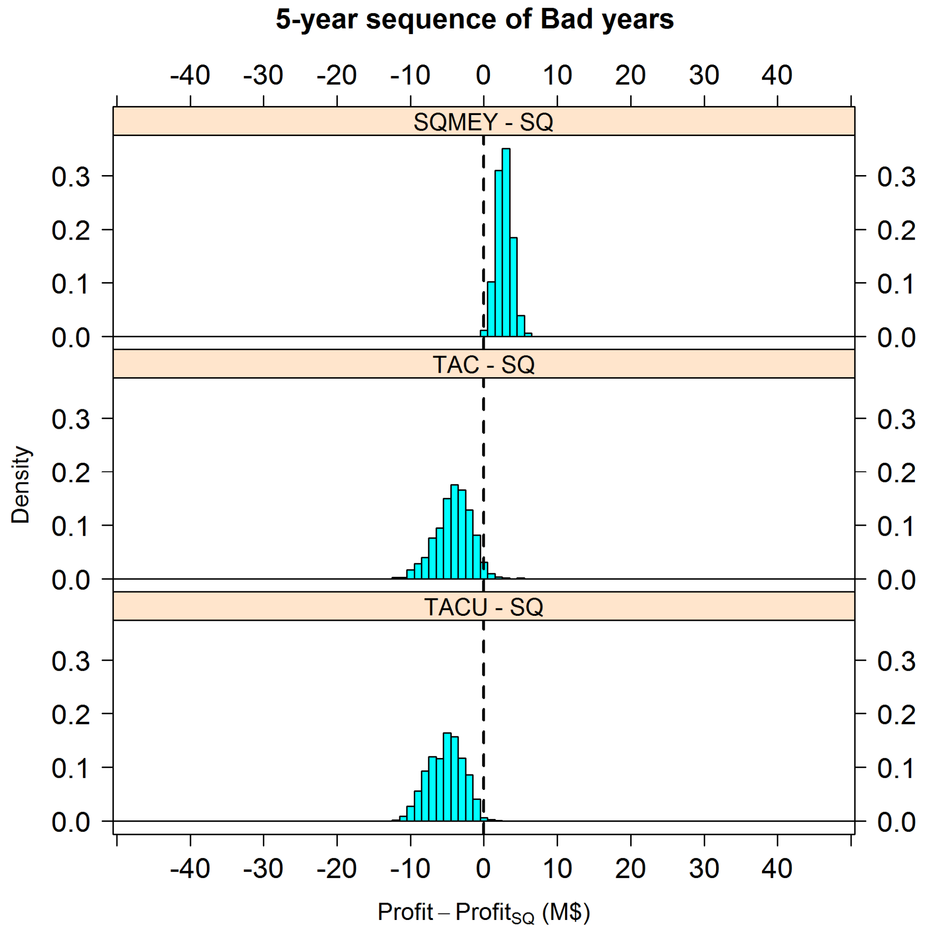

Figure 15. Histograms of difference in total profit over 5 'bad' years relative to status quo for each strategy.

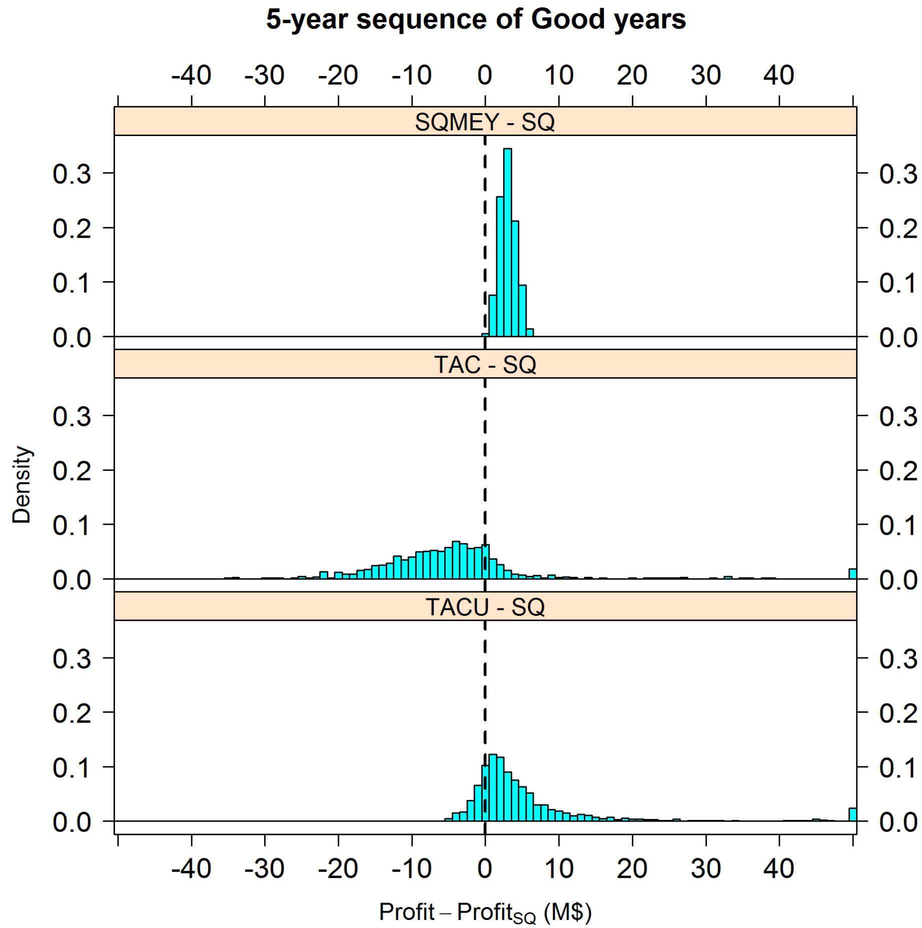

Figure 16. Histograms of difference in total profit over 5 'good' years relative to status quo for each strategy.

6 Discussion

In many ways, the NPF's white banana prawn fishery is an extreme fishery: it is a multi-stock, annual "crop" that is heavily fished during a short season, it is extremely variable, the prawns are very aggregated and highly targetted, and there may be seasonal changes in catchability. Producing a high-value product, the remote, tropical fishery is also subject to very high operating costs. The fishery has been the subject of almost continuous management change since its inception. All these attributes contribute to the difficulty in managing this fishery, as well as developing assessments and predicting its current status at any point.

A management system to include an annual TAC and ITQs has been proposed for the WBP fishery to reduce the potential need for management intervention, and to ensure the economic performance of the fishery. There are several potential benefits of such a system for the NPF, which have been elaborated in detail by MRAG (2007). In many fisheries, a TAC is developed simply by applying an optimal harvest rate to a prediction of fishable biomass (e.g. Hilborn and Walters 1992). In many fished species, where the fishery is usually made up of several year classes, that optimum harvest rate might be of the order of 10-20%, and a modest error in setting the TAC will be compensated for by opportunities to manage the harvest of those cohorts through the future. In the WBP fishery, we have shown that historical annual harvest rates have been between 40% and 94%. The stock is effectively annual, so that there are no opportunities to manage the harvest of a cohort for more than one year, and the high level of harvest rates puts great pressure on the choice of a suitable TAC.

In this fishery, the prediction of fishable biomass for WBP, or a proxy for it, had proven elusive until the work of Venables et al. (2011) demonstrated the feasibility of predicting "potential catch" for the whole of the WBP, from rainfall data, with development of more stable models and description of uncertainties by Buckworth et al (2013). This report addresses whether those predictions can be used as a suitable basis for a TAC system for the WBP fishery.

Being presented with the mean outputs of the analyses undertaken here, it might have been easy to conclude that the performance of the various management strategies tested was similar: although rather variable (as are catches in the NPF banana prawn fishery), the mean profits of the fishery under the different strategies were fairly close. This certainly attests to the potential utility of the Venables et al. (2011) approach.

Further analysis was fruitful. Some of the differences between strategies were a little more apparent in mean profit over longer time periods. However, these differences were subtle, less than the standard deviations. Differences in the performance of the strategies were more apparent when the simulations were grouped by the quality of fishing year (good, medium and bad). In bad years, the mean performance of the status quo-based strategies was noticeably better. In good years, the TAC strategy was marginally the worst performer, on average. At the same time, the updated TAC approach was marginally better than all of the other strategies in these years.

Direct comparison of the performance of the different strategies on individual, simulated fishing years was the most informative approach. The structure of the modelling system in this work readily allowed for this analysis. We were able to calculate profit due to each management approach simply by evaluating cumulative catches and effort at the point where each management approach would cause the fishery to stop. This was a very good approach for exposing the potential risks or gains from adoption of a particular strategy and within-year comparisons revealed important differences between the strategies.

In this form of analysis, we were able to indicate that a SQMEY strategy would be a potential and reliable improvement on status quo. While it performed much the same as the status quo on about half of occasions – incidentally showing that the status quo currently often delivers something near MEY– it rarely performed a little worse than the status quo, but outperformed the status quo (by about $1 million/ year) the remainder of the time.

The SQMEY management approach has only recently been suggested for the WBP fishery, and while offering significant utility, should also be subject to some scrutiny. The MEY point was calculated simply as that point at which mean marginal costs and revenues were equalised.

It would be worth exploring whether the variability within the fleet of prices obtained and operating costs were such that this was the appropriate criterion for setting the trigger point. An extension of this work might thus be to undertake similar analyses using the individual vessel catchabilities, costs and prices to see what MEY would be achieved if individual rules were applied (varying ITQs, and catch rate triggers according to the vessels characteristics, to maximise individual profitability). We note that such an individualised system might be difficult for management to implement. In the simulation, we back-calculated the trigger catch rates to be two weeks prior to the point at which MEY would be achieved. This prediction would be improved, perhaps substantially, if the time lag were reduced to one week, as in the current catch rate trigger arrangements. The dependence of the price of banana prawns on amounts landed meant that the SQMEY strategy used the potential catch prediction from Buckworth et al. (2013); however, as the calculation was only weakly sensitive to that prediction, the performance of this approach was not substantially hampered.

The status quo outperformed, on average, both of the TAC-based strategies (but this was variable). Again, in about half of years, the performances of SQ and both TAC approaches were much the same. Differences in other years were at times large (several $ million), mostly in favour of the SQ strategy. Clearly a move to a TAC strategy, even with an in-season update, would be a poor risk.

The differences among strategies varied depending on the quality (good, medium, bad) of the year.

In sequences of five bad years – which is within the recent experience of the fishery – the difference between the status quo and TAC approaches was very clearly shown by the in-year differences: either TAC approach would most often produce $1-2 million profit/ year less than the status quo. The SQMEY approach, in contrast, again performed consistently better than the status quo.

In sequences of five good years, the TAC strategy still largely underperformed compared to the status quo and SQMEY strategies, indicating that in this context, again, this strategy would be a poor risk for the fishery. That this risk arose from the prediction of potential catch from rainfall is shown by the improved performance of the TAC with an in-season update. Use of an in-season update was shown to be a way to improve application of a TAC control in the fishery, but only in good years. In sequences of five good years, the TACU strategy was a bit more profitable on average than the SQMEY and the status quo, but it was very variable, with occasional, very profitable years, that captured the full variability of the banana prawn resource. The prediction from catch rates early in the season was obviously more effective for good years – when the season could be allowed to run much of its length – than in bad years, when the optimum probably would see the season constrained to the first few weeks.

It is difficult to predict what fisher behaviour might be under either of the TAC systems. Chasing of TAC in bad years might be an artefact, particularly if the catch predictions from the rainfall model were especially optimistic, so that fishers might actually stop sooner, before achieving their TAC. This might account for some of the long seasons seen under TAC and TACU, and with the result that they operated worse in some years than the SQ. One way to counter this would be to assume hybrid behaviour, where the fishers will continue fishing for the TAC unless CPUE drops below the SQ trigger level, or some other. This would be attractive in ensuring the sustainability of the fishery –but it effectively means that the fishery would be operating as the status quo fishery. Conversely, underestimating the TAC in both good and bad years also results in a loss of potential benefits. Modifying the model to enable fishers to stop before the quota is exceeded will reduce the impacts of TAC overestimates in the model, but will not reduce the impacts of underestimates. Hence, while the distribution of profits in Figure 12 would shift closer to the centre (with a greater number of cases where TAC and SQ are equal), it would not eliminate the tail (due to the underestimate problem), and would not result in an increase in the number of cases where TACs exceeded the SQ.

There are probably ways in which update rules might be improved, such as updating only if C_{w3} exceeds C_{pred} by a finite margin. These would also need to consider effects on quota trading, even though TAC

provides the opportunity for increased profit, because fishers have already made investment decisions based on the original TAC.

The effort model does not model the end of the season as well as would be desirable. It is possible in any of the management options that a boat may cease fishing when it is perceived that it is no longer of value to do so. In addition to operating profit considerations, “value” might include fatigue, contractual obligations, and considerations for the crew and so on. These all may vary substantially among boats so that boats may leave the fishery despite remaining quota or fishing opportunity. This is partly because the WBP fishery at a boat level is episodic. At the end of the season a boat may typically go several days without a catch, perhaps when tidal conditions are not favourable, and then take a catch of several tonnes in a single day, when an aggregation is located. Additionally, the departure of boats from the fishery may depend more on information from other fisheries (the tiger prawn fishery, Torres Strait or East Coast prawn fisheries).

We were unable to use effort patterns directly derived from the fishery (as did Hutton et al. 2009), because of the large reduction in fleet size in 2007. We emphasise that our intention was to compare the performance of the management controls under as identical conditions as possible. Further work on the supply of effort in the banana prawn fishery is required, but this was beyond the scope and timeframe of this project. Not having this information does not detract from the current analysis, as these factors can be assumed for a given effort trajectory, and all management options were compared using common effort trajectories. However, for assessing future developments in the fishery, improved understanding of the drivers of the effort trajectory is important.

While adjustment of the effort model to include tidal effects or other improvements might improve performance, the ability to predict “potential catch” or any other proxy for fishable biomass is clearly the main barrier to developing a TAC-based approach for the WBP fishery. It is of concern too that unknowns cannot by definition be accounted for. Thus the “potential catch” or other measures of biomass available to the fishery are likely to be subject to more variation in the future than we have anticipated (e.g. the rainfall prediction model only uses information from the last four decades). The in-season update improved the performance of the TAC strategy relative to the status quo-based approaches but was really only effective in “good” years. The MRAG (2007) study also used a similar in-season update approach, based on a Bayesian update process. While not identical, the two processes are very similar and it is unlikely that such a process would produce a substantially different result. It is probably not appropriate to implement a management approach that is useful only in good years, so that further work with such a control would be required before it could be an effective improvement on a pre-season TAC. Until such improvements can be effected, the TAC approaches studied should be judged as a poor risk for the fishery at this time.

The analysis precludes potential benefits from quota trading, which were assumed to be considerable in the earlier cost-benefit analysis (Hutton et al. 2009). Neither, however does the analysis include the costs of implementing any of the systems described here. We do note that with the current smaller fleet, to maximise profits, in good years it is expected that all boats would be needed to participate in the fishery. In poor years, over-estimating the TAC would erode the benefits of quota trading as there would potentially be considerable excess quota available. This would reduce the efficacy of the quota market. This is an area for further consideration. A priori, it is expected that the efficiency gains from quota trading may not be sufficient to offset the problems associated with inaccurate TAC setting.

In this project we developed a deceptively simple system for modelling of the WBP fishery. Our intention was to create as clear a system as possible, in which the performance of the different strategies could be fairly appraised. While the system itself was simple, the work to support that simplicity was complex and extensive.

In order to provide estimates of fishable biomass that were consistent with that experienced in the fishery, a complex depletion analysis, an assessment of the fishery, was necessary. This importantly provided estimates of biomass that were not derived from the prediction of “potential catch”. While it has not been extensively examined in this report, the estimates of biomass and harvest rates indicate that the fishery has

at times been very heavily fished, with harvest rates exceeding 90% in some years. The outputs from this work deserve further study as providing understanding of the dynamics of the WBP population.

We addressed the modelling of effort in three different ways, in an attempt to capture the most realistic process for the simulations. Further investigation would be useful. A model that offers great promise is a Markov transition model. Here one estimates the transition probabilities p_{FF} (the probability of fishing today given fishing yesterday) and p_{NF} (the probability of fishing today given not fishing yesterday). By cascading these transition probabilities from an initial state of fishing on day 1, one can obtain the probability of fishing on each day. This then becomes a more general binomial model. After relating the transition probabilities to time-dependent covariates (CPUE, moon-phase, day), coefficients can be estimated by maximizing the likelihood using a nonlinear algorithm. One can go further still if the effort data are disaggregated to the level of individual boats. Then the data can be cast in the form of individual decisions to fish or not to fish. This is a special case of discrete choice modelling which can be addressed using the multinomial distribution. Such a model was used by Venables et al (2009) to describe fleet movement between regions within the NPF for the tiger fishery. Here, because the choice is dichotomous, the estimation could be achieved using simple logistic regression.

Factors underlying the increase in catchability over time found by both the depletion model and also the catch-effort relationships also require further investigation. This could reflect changes in average technical efficiency due to less efficient boats leaving the fishery during the key structural adjustment programs, and improvements in fishing equipment, but is confounded with change in management arrangements. These need to be investigated in order to determine appropriate future efficiency trajectories. If the fishery's management adopts, as intended, MEY-based TACs or catch rate triggers, then changes in catchability over time will need to be monitored, so that the changing relationship between catches and effort can be properly accommodated in MEY calculations.

Finally, we considered the exact definition of Maximum Economic Yield (MEY) that should apply to this work. The Commonwealth Fisheries Harvest Strategy Policy aims to "maximising the economic returns to the Australian community". However, the model as applied focuses on "maximize the economic returns to the fishing companies". This is consistent with how MEY has been interpreted in other fisheries. With non-zero price flexibility, it could be argued that benefits to consumers should also be considered, as lower catches result in higher consumer prices. This is an area for future consideration. However, given the nature of the fishery (i.e. harvesting a depleting stock), it is unlikely that fishers would continue to harvest just in order to supply cheaper prawns unless they were also benefiting. Given this, the definition of MEY applied (i.e. maximising industry profits) is more appropriate in this case.

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