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Bioeconomic adaptive management procedures for short-lived species: A case study of Pacific saury (*Cololabis saira*) and Japanese common squid (*Todarodes pacificus*)

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ABSTRACT

Short-lived fisheries stocks are subject to large fluctuations in abundance and respond rapidly to many factors including changes in oceanographic conditions, biological interactions and fishery exploitation. Management of such species requires a flexible, adaptive framework that responds rapidly to a changing environment, although such schemes are rarely operationalized. In this article, we develop a set of bioeconomic adaptive management schemes that respond to changes in economic conditions, stock abundance and catchability, using as case studies the fisheries targeting short-lived Japanese common squid (*Todarodes pacificus*) and Pacific saury (*Cololabis saira*). We suggest that such adaptive schemes have the potential to support the successful implementation of profit maximizing (MEY-based) harvest policies for borderline profitable fisheries targeting short-lived species.

1. Introduction

Populations of small pelagic fish and coastal squid support important fisheries worldwide. These species are typically short-lived, have rapid growth rates, and play an important role in the marine food web. Severe challenges arise in the management of short-lived species because the populations tend to expand rapidly in abundance when feeding and spawning conditions are favourable, but decline rapidly when ocean conditions change (EUR-OCEANS, 2008). Consequently the prediction of future abundance for short-lived species is very difficult and the management of such species faces many challenges (Caddy, 1983; Fréon et al., 2008; Patterson, 1992; Pierce and Guerra, 1994). In addition, the fishing industries targeting short-lived species are prone to over-capitalization (Fréon et al., 2008), because industry investment grows rapidly in response to periods of high stock abundance, while disinvestment does not occur to the same degree during periods of low biomass. This makes the industry vulnerable to external economic factors such as changes in fish prices and fuel costs.

Conventional static harvesting policies, such as annual constant catch or total allowable catch (TAC) based on maximum sustainable yield (MSY) are not necessarily helpful as they have little flexibility and are potentially unsuitable for a dynamic system whose parameters are known imprecisely and subject to large natural variability. A policy based on a similar equilibrium concept, that of maximum economic yield (MEY), suffers additional complexity due to the additional variability in economic parameters. The difficulty of sensibly estimating MEY and implementing an MEY-based harvest policy (including constant fishing mortality that produces MEY; or F_{MEY}) for dynamic and short-lived animals was recently highlighted by Dichmont et al. (2010). They argued that different assumptions concerning prices and costs can result in differing estimates of MEY and its associated effort trajectories, and such a "moving target" introduces additional issues to an already complex system.

As an alternative to stationary policies, adaptive management or adaptive control of the fisheries system has been proposed in the form of feedback control rules (Walters, 1986; Walters and Hilborn, 1976). Adaptive management does not rely on a fixed state of knowledge, but rather uses a learning process where new knowledge is gained over time, models are updated, and management decisions are adapted accordingly. Despite adaptive management

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having been advocated by various authors in the fisheries literature and beyond (Parma and NCEAS Working Group on Population Management, 1998), it has rarely been operationalized in the real world. One notable exception, for a short-lived species, is the Falkland Islands squid fishery, where weekly in-season fishery data are used to provide resource managers with up-to-date abundance indices of the resource, and the fishing effort is adjusted within the season (Basson et al., 1996). The management of pilchard and anchovy stocks in the South African purse-seine fishery is also adaptive, and since 1991 in-season surveys have been used to adjust anchovy TAC and total allowable bycatch (TAB) for pilchard (De Oliveira and Butterworth, 2004). While these existing examples, mainly "passive adaptive" management (Sainsbury et al., 2000; Walters, 2007; Walters and Hilborn, 1978), provide useful guidance on how to implement an adaptive management scheme in practice, there has been little exploration of dynamic or adaptive schemes that respond to both economic and biological conditions. As more fishery products have entered into international markets in recent years, many fisheries are exposed to external economic factors, which make it imperative that future adaptive management considers economics explicitly.

This article proposes bioeconomic adaptive management schemes for short-lived species which adapt to changes in both economic and biological conditions. We highlight the advantages of such schemes relative to traditional stationary approaches, using the empirical examples of fisheries targeting the stocks of Pacific saury (*Cololabis saira*) and Japanese common squid (*Todarodes pacificus*) off the coast of Japan. These fisheries are ideal candidates for designing and testing such bioeconomic adaptive schemes aiming to improve the economic performance of a fishery, since the industry has been suffering from low profitability and therefore there is a clear need for management tools to help improve profitability. This article first describes the structure and parameter values of the operating model, which mimics the true dynamics of the fisheries systems. Secondly, we propose a set of bioeconomic adaptive management procedures, where target effort is set at the level that maximizes the net present value (NPV) of profits (hereafter denoted E^*). The procedures are based on historical data in the first instance, but then adapt to changes in abundance, catchability and economic conditions. This is done by using the results of a within-season stock assessment for common squid, and pre-season surveys for Pacific saury. Finally, the performance is compared of an output-based management approach (TAC based on constant F), similar to the current practice; constant effort-based management which maintains the target effort at E^*; adaptive effort-based management. This comparison is done using a simulation-based management strategy evaluation (MSE) framework.

The aim is not to provide a performance evaluation of the current management regime, but rather to use real fisheries examples to develop adaptive management schemes which explicitly include economics, and demonstrate the comparative advantages of such a scheme, including the ability to quantify the economic value of scientific information. We suggest that such schemes have the potential to support the successful implementation of profit maximizing (MEY-based) harvest policies for borderline profitable fisheries targeting short-lived species.

2. Materials and methods

2.1. Source of empirical data

Pacific saury and common squid are thought to live up to 2 years and 1 year, respectively (Kidokoro et al., 2006; Ueno et al., 2006). The parameter estimates for these stocks were obtained from the Resource Assessment Report, published annually by the Fisheries Research Agency of Japan (FRA) (http://abchan.job.affrc.go.jp/index1.html). Income and expenditure data were obtained from the Annual Survey Report on Fishery Business Management (1985–2005) of the Ministry of Agriculture, Forestry and Fisheries (MAFF) (http://www.maff.go.jp/j/tokei/kouhyou/gyokei/index.html). These reports are based on sampling surveys. These data are aggregated to the fishery level, and reported either the sum or the average values for each fishery. Thus, the calculation of fishing costs is based on aggregated average cost data from sampled vessels and operators. The major cost items include labour, fuel, engine and electrical parts and their maintenance, gears and nets, ice, bait, service fees, depreciation of capital and miscellaneous items. To account for the effects of inflation, economic data were adjusted using the consumer price index (CPI) reported by the Statistics Bureau of Japan (http://www.stat.go.jp/data/cpi/).

The commercial fisheries in Japan exploit stocks of Pacific saury using stick-held dip nets (SHDN) from August to December, and common squid (there are two sub-stocks, but here we refer to a combined stock, see details in Appendix) using mainly angling gear. For saury the vessels over 100 gross tonnage (GT) dominate the catches in terms of volume, accounting for approximately 90%, and small numbers of saury are caught in the gill nets and drift net fisheries. In the Pacific, common squid is mainly caught by a small-scale (less than 30 GT) coastal angling fleet, but are also caught in gill nets and by the bottom trawl fishery. A medium-size angling fleet (vessels of 30–185 GT) dominates the catch of the common squid in the Sea of Japan, although overall the small-scale coastal angling fleet received the largest share (about 30% in 2005) of the TAC for common squid. Both fisheries are of significant socioeconomic importance. The squid angling fisheries alone, for instance, employ about 18,000 workers, contributing significantly to employment in coastal communities (Mori and Nagasawa, 2006). Although Japan dominates the global catches of both stocks, they are straddling stocks and are also harvested by neighbouring countries, including Russia, Taiwan (China), and South Korea. Due to the limited availability of cost data, our economic analyses focus on the "dominant fleet" alone, here defined as a large-scale SHDN fleet (100–200 GT class) for saury and a small-scale coastal angling fleet (10–30 GT class) for squid, respectively. Other Japanese fleet elements (e.g. gill nets) and the fleets from other nations are defined as "external fleets" in the following sections.

These stocks have experienced large fluctuations in abundance, strongly influenced by environmental factors, including sea surface temperature and a possible link with climatic regime shifts in the Kuroshio region (Sakurai, 2001; Tian et al., 2004). Such fluctuations have had a major impact on the price of saury, but a lesser impact on squid prices. The ex-vessel price of saury in Japan is highly variable and the price declines substantially during good fishing seasons; prices ranged from 66 yen/kg to 211 yen/kg (real prices) over the period 1990–2005. On the other hand, the arithmetic mean ex-vessel price of Japanese common squid appears to have been around 200 yen/kg over the period between 1992 and 2004 with random fluctuations between 149 yen/kg and 343 yen/kg (real prices) and no apparent trends. Historically, squid prices were much higher in the mid-1980s than recently due to the low levels of catch during that period, but stock recovery in the early-1990s together with the expansion of alternative squid fisheries (i.e. the fishery targeting *O. bartrami*) and increases in cheap imported squid products coincided with a sharp decline in common squid prices in the period 1986–1991. This has contributed to the low profitability of squid angling fisheries over the last 20 years. More detailed information on the case study fisheries can be found in Kidokoro et al. (2006), Mori and Nagasawa (2006) and Ueno et al. (2006, 2008). The time series of estimated
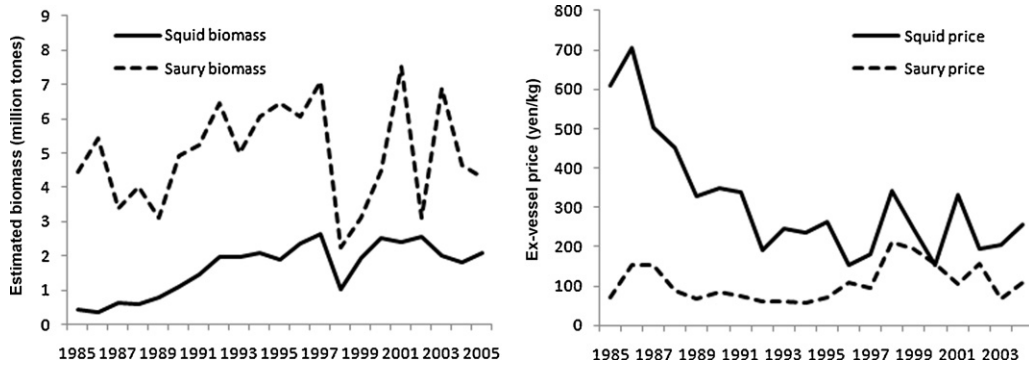
Fig. 1. Estimated stock biomass (left, million tonnes) and ex-vessel price (right, yen/kg) of Pacific saury and Japanese common squid, 1985–2005. Data on biomass obtained from Ueno et al. (2005, 2006), Mori and Nagasawa (2006) and Kidokoro et al. (2006). Data on ex-vessel price obtained from Annual Report of Fish Marketing Statistics. MAFF, 1961–2005.

biomass and ex-vessel prices for the case study stocks are given in Fig. 1.

2.2. Developing a bioeconomic operating model

An MSE framework typically involves the construction of an underlying model of system dynamics termed an operating model (OM), simulation of the management decision making processes, implementation of the management actions, and evaluation of the outcomes of the management (Kirkwood and Smith, 1996; Punt and Smith, 1999). The process from data collection to the determination of management actions is termed a management procedure (MP; Butterworth and Punt, 1999). A conceptual diagram of the processes involved in an MSE, including the candidate MPs considered, is given in Fig. 2. The OM used in this paper is bioeconomic, consisting of three components: population dynamics; fishery exploitation dynamics; and economic dynamics. We used FLR (Kell et al., 2007), an open source toolbox, for all of the parameterizations and simulation modelling.

2.2.1. Population dynamics

We specified the population dynamics in the OM as an age-structured (up to 2 age classes), quarter-year model. Each quarter corresponds to a specific season consisting of winter (1), spring (2), summer (3) and autumn (4). The number of animals in year t at age j in season s can be written as:

$$N_{t,j,s} = N_{t,j,s-1}(1 - \psi_{t,j,s-1})e^{-M/4} \tag{1}$$

where $\psi_{t,j,s}$ is the total exploitation rate by all fleets (including non-Japanese fleets), and M is the annual rate of natural mortality. For squid, the maximum age is 0 and for saury it is 1, and no plus group is assumed in either case, so the assumption is that all animals die after reaching the end of the maximum age class. For age 0, it is assumed that $N_{t,0,s} = 0$ in the seasons prior to recruitment. For the seasons following recruitment, it is:

$$N_{t,0,s} = N_{t,0,s-1}(1 - \psi_{t,0,s-1})e^{-M/4} \tag{2}$$

For age 1, which only applies to Pacific saury, the number of animals in the first season ($s = 1$) is:

$$N_{t,1,1} = N_{t-1,0,4}(1 - \psi_{t,0,4})e^{-M/4} \tag{3}$$

and the numbers in the following seasons ($s = 2,3,4$) are:

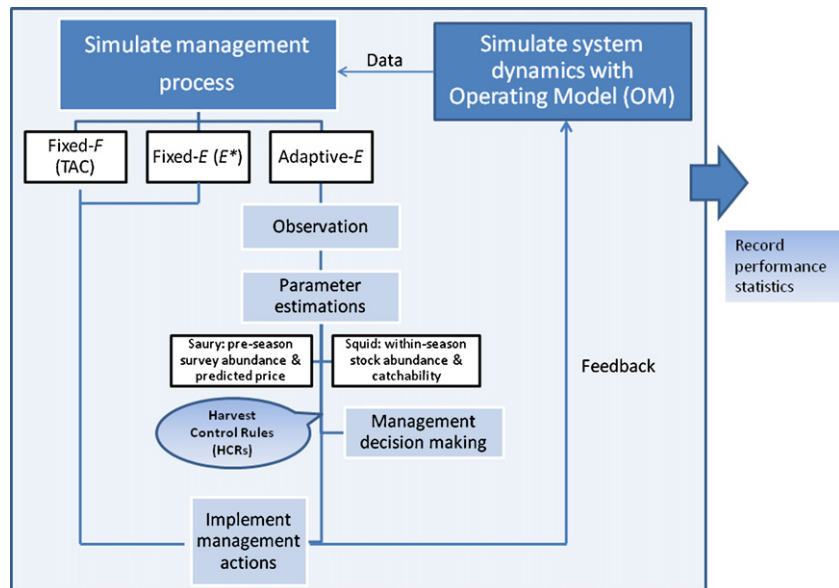$$N_{t,1,s} = N_{t,1,s-1}(1 - \psi_{t,1,s-1})e^{-M/4} \tag{4}$$

Fig. 2. Conceptual diagram of the MSE processes.

Table 1
Parameters related to the operating model.

Parameter	C. saira	T. pacificus
Recruitment		
Steepness, h	0.245	0.516
Standard deviation in recruitment, σ_R	0.3	0.3
Virgin recruitment biomass, R_0 (billions)	123.3	23.49
Carrying capacity, SSB_0 (million tonnes)	8.15[a]	3.81
Biological parameters		
Natural mortality, M (year^{-1})	0.67[a]	0.60[b,c]
Mean weight, w (g)	39 (across all ages and seasons)	280 (season 4)[b]
Maturity at age, m_j	0.5 (age0),1 (age1)	1
Maximum age in the population, J (years)	1	0
Fisheries parameters		
Effort elasticity, α	1	1
Biomass elasticity, β	1	0.61 (s.e. 0.004)
Mean log catchability coefficient, $\log(q)$, $\log(Q)$	−8.279	−4.69
CV for $q(Q)$, CV_Q (CV_Q)	0.1 (baseline), 0.2, 0.3	0.1 (baseline), 0.2, 0.3
Mean external harvest rate, μ_{Ext} (year^{-1})	0.034	0.213
Standard deviation in external harvest rate, σ_{Ext}	0.026	0.015
Observation error parameters		
CV_{CPUE}	–	0, 0.1, 0.25
CV_{Survey}	0.1, 0.2, 0.3, 0.4	–
CV_A	0.1	0.1
Economics		
Unit cost, c (million yen/operator)	166.8 ± 15%	22.3 ± 15%
Unit price, p (yen/kg)	Variable	257 ± 15%
Maximum and minimum price, P_{max}; P_{min} (yen/kg)	211; 58	–
Standard deviation in price, σ_p	24.5	–
Inverse demand function parameters, η (tonnes); n	122500; 3.741	–
Discount rate, δ (year^{-1})	0.04	0.04

[a] Ueno et al. (2005, 2006).
[b] Kidokoro et al. (2006).
[c] Mori and Nagasawa (2006).

The number of recruits is modelled using the following Beverton–Holt relationship:

$$N_{t,0,1} = \frac{4hR_0\,SSB_{t-1,4}}{(1-h)SSB_0 + (5h-1)SSB_{t-1,4}}e^{\varepsilon_t^R} \tag{5}$$

where R_0 is the virgin recruitment observed in the absence of fishing, and h is the steepness parameter of the S–R relationship, $SSB_{t-1,4}$ is the spawning stock biomass in the spawning season (4), and ε_R is the normally distributed error term with mean $-\sigma_R^2/2$ and standard deviation σ_R. For Japanese common squid, estimates of the S–R parameters are available from stock assessment reports. For Pacific saury, we estimated them from available life history parameters, following the method detailed in Myers et al. (1997); see Appendix. The parameter values related to the OM, both estimated and obtained from the available literature, are listed in Table 1.

2.2.2. The sub-OM to simulate data for the depletion model

For the common squid case study, a weekly time-step depletion model is used to estimate catchability and abundance at the start of the summer fishing season, given the weekly catch and CPUE data of the dominant fleet. Given that such fine scale data are not currently available from commercial fisheries, the data necessary for the depletion analysis were generated through simulation. For this purpose, a secondary feature (sub-OM) was built into the biological component of the OM to simulate the true weekly dynamics of the common squid stock. Ideally, a weekly OM would be preferable to

having a separate sub-OM, but there was no detailed information about spawning and recruitment patterns at such a fine temporal scale. The sub-OM applies in the third quarter (summer season) only when no spawning or recruitment occurs, thereby making it highly unlikely that any such unknown fine-scale reproductive dynamics would affect the assumptions made in the weekly sub-OM.

For the Japanese dominant fleet, weekly CPUE, I_w^J can be written as:

$$I_w^J = \frac{Y_w^J}{E_w} = Q_t(S_{w-1}(X_1 - C_{w-1}))^\beta e^{\varepsilon_{CPUE}} \tag{6}$$

where S_w is the weekly natural survival probability (defined later), C_w is the cumulative total catch biomass to week w, and ε_{CPUE} is the observation error of the CPUE with mean zero and variance σ_{CPUE}^2. The standard deviation σ_{CPUE} can be expressed as follows:

$$\sigma_{CPUE} = \sqrt{\log(1 + CV_{CPUE}^2)} \tag{7}$$

where CV_{CPUE} is the coefficient of variation (CV) of the observation error in CPUE. In (6), X_1 is the exploitable abundance at the start of season three, which is taken from the main OM. In practice, the catchability Q_t need not be the same as the "true" catchability q_t—this depends on how fishing effort is defined on the weekly scale. However, for our purposes effort is defined in the same manner throughout, so $Q_t = q_t$. We assumed fluctuations in Q_t during the projection period were purely random without major shifts, and an arbitrary coefficient of variation (CV_Q) of 0.1 was used as a baseline scenario to simulate year to year changes in Q_t.

2.2.3. Defining exploitation rates

In order to create a feedback loop between the management actions affecting the population and the economic dynamic models, the exploitation rate needs to be defined. The current management of the two case study fisheries uses annual TACs – an output-based harvest control – while our proposed alternative harvest control rules are effort-based. Therefore, the exploitation rate, $\psi_{y,j,s}$ is defined in two ways. The input-based exploitation rate can is defined as:

$$\psi_{t,j,s} = q_t E_{t,s}^\alpha X_{t,s}^{\beta-1} + \xi_t^{Ext} \tag{8}$$

where q_t is the catchability coefficient with a log-normal distribution and mean q (see Table 1) and an assumed CV_q. $E_{t,s}$ is the effort by the dominant fleet in year t and season s, α is the effort elasticity, ξ_t^{Ext} is the external harvest rate (other than by the dominant fleet) with a log-normal distribution with known mean μ_{Ext} and variance σ_{Ext}^2 derived from the historical ratio of external catch to exploitable biomass, β is the biomass hysteresis term (elasticity) from the production function, and finally $X_{t,s}$ is the exploitable stock biomass that is available to the fishing gear:

$$X_{t,s} = \sum_{j=0}^{J} w_{j,s} \cdot N_{t,j,s} \tag{9}$$

where J is the maximum age-class in the population. Selectivity is assumed to be independent of age, season and time. The output-based exploitation rate is defined as the ratio of the dominant fleet's catch biomass, $Y_{t,s}$, to total exploitable stock biomass, and written as:

$$\chi_{t,j,s} = \frac{Y_{t,s}}{X_{t,s}} \tag{10}$$

The total exploitation rate on the population is therefore written as $\psi_{t,j,s} = \chi_{t,j,s} + \xi_t^{Ext}$.

2.2.4. Economic dynamics

Although we accounted for the exploitation of the stock by fleets other than the dominant fleet in the biological and exploitation dynamics models above, we have no economic data for the other external fleets, thus the economic feedbacks are modelled only for the dominant fleet. The economic consequences of management actions were calculated using the profit function, production function, and inverse demand function (for saury), given the levels of catch taken or effort of the dominant fleet calculated from the management actions and stock biomass generated by the biological component of the OM. The annual profit, π_t, for the dominant fleet is defined as:

$$\pi_t = p_t Y_t - c_t E_t \qquad (11)$$

where p_t and c_t are the price and cost at time t, respectively, and Y_t is the yield of the dominant fleet summed over the fishing seasons. For both fisheries models, effort is expressed as the number of operators in any given year, since the key economic cost data are expressed as average annual operating cost per operator.

While ex-vessel prices of common squid have changed over time, there is no clear historical relationship between the price and harvested quantity of squid in the Japanese market. We therefore specified squid price as a random variable with a uniform distribution centred around the fixed level in 2004 $\pm 15\%$. Similarly, the unit cost for a squid operator is treated as a random variable around the unit cost in 2004 with a $\pm 15\%$ error range. These fixed levels coincide with the median values of these parameters between 1985 and 2005. For Pacific saury, there is a clear downward-sloping demand relationship. Using a generalization of the 1-parameter nonlinear inverse demand function used in Grafton et al. (2000) and Sandal and Steinshamn (2001), the following 2-parameter inverse demand function was fitted to the data:

$$P_t(Y_t) = \frac{P_{max}\eta^n + P_{min}Y_t^n}{\eta^n + Y_t^n} + \varepsilon^P \qquad (12)$$

In (12) Y_t is the yield of saury for the dominant fleet, P_{max} and P_{min} are the maximum and minimum observed prices of fresh saury in the Japanese market, respectively, η and n are the parameters to be estimated. The reason that only the catches of the dominant fleet are used to predict price is that they are the key supplier of fresh saury, accounting for over 90% of the total fresh saury catch sold in Japan, while the catches from non-Japanese vessels are imported either in frozen or processed form, and have little influence on the price of fresh saury in the Japanese market. The ε^P are assumed to be normally distributed random variables. The predicted vs observed ex-vessel prices of Pacific saury are shown in Fig. A.1. The estimated inverse demand curve fits relatively well under the 2-parameter model, with a residual standard error of 24.5. Both η and n, are highly significant components of the fitted relationship ($P < 0.005$), and their values, along with the estimated random variation in this relationship (the variance of the ε^P), were used to define a stochastic relationship between price and catch biomass. The unit cost assumption for the Pacific saury fishery is the same as for the common squid.

To relate the outputs (harvest) of the fishing operators to the levels of their effort and to biomass, a general Cobb–Douglas production function (Eq. (8)) was assumed for both fisheries. The details of how the production function parameters were estimated are given in Appendix.

2.3. Developing adaptive management procedures (AMPs)

Here we propose two types of bioeconomic adaptive management procedure (AMPs): a model-based and an empirically based procedure. The model-based AMP uses an in-season stock assessment to specify the effort level for the second half of the fishing season (the fourth quarter in the OM), while the empirical AMP uses a pre-season stock survey. The default target effort levels (E^*) that serve as a basis for the AMPs were computed using the current "best" assessment models and the estimation process is detailed in Appendix. Note that because the stock assessment models are different from the OM, E^* is not necessarily the effort which maximizes profit in the OM. The parameters related to the AMPs are listed in Table A.1.

2.3.1. Model-based AMP for common squid

For the Japanese common squid fishery, the target effort level is adjusted within a fishing season based on a set of pre-defined rules, termed harvest control rules (HCR; Rademeyer et al., 2007). The HCR for the common squid fishery utilizes the information from a within-season stock assessment based on the Leslie–Delury depletion method similar to those used in assessments of other cephalopod species (Agnew et al., 1998; Basson et al., 1996; Rosenberg et al., 1990; Young et al., 2004) as well as changes in economic conditions. This effort adjustment scheme was designed to capture the annual variation in both stock abundance and the catchability coefficient—a key parameter for most stock assessments which is often assumed constant, despite evidence to the contrary (Arreguín-Sánchez, 1996; Ricker, 1975). Catchability variation can be caused by a number of factors, including daily or seasonal cycles, changes related to stock abundance, changes in the efficiency of the fishery (e.g. improved gear), changes in regulations, fishers' behaviour, and environmental factors (Gulland, 1983; Hannesson, 1983; Wilberg et al., 2010), but the greatest sources of variation in catchability are essentially random (Gulland, 1983). Higher catchability means that fish are easier to catch on average given the same level of inputs, which in turn has an important economic implication. The proposed adaptive scheme also enables regulators to make the necessary adjustments when economic conditions (e.g. fish price, fuel price) change for the worse. In this way, higher profitability might be obtained from the fishing operation while meeting the stock conservation objectives. A potential issue is obtaining unbiased estimates of catchability separately from biomass, given that there is a known negative correlation between them (Hilborn and Walters, 1992). However, the depletion assessment method is embedded in the MSE framework, as is the simulation of observation error in the key input data, so this potential bias is already factored into the evaluation process.

The AMP for the Japanese common squid fishery was set up as follows: prior to the start of the summer fishing season (start of the third quarter), when the population abundance of squid is unknown, fishing effort is based on the profit maximizing target effort, E^*, estimated from historical data. Once fishing has started, and data are available for assessment, at the start of the autumn fishing season (fourth quarter) in-season adjustments of effort are made once, based on the changes detected in the estimated stock abundance, catchability coefficient and economic conditions.

In the depletion assessment model, the expected total catch biomass from all fleets at week w is defined as:

$$\hat{Y}_w = \hat{Q}_t E_w \hat{X}_w^\beta + \xi_w^{Ext}\hat{X}_w \qquad (13)$$

where $\hat{Q}_t$ is the estimated catchability coefficient, E_w is the effort at week w, $\hat{X}_w$ is the estimated exploitable biomass at week w, and ξ_w^{Ext} is the weekly external harvest rate (defined as $1 - \sqrt[52]{1 - \xi_t^{Ext}}$ so that weekly and annual external harvest rates are comparable over the same time-scale). The estimated biomass $\hat{X}_t$ is distinguished from the "true" biomass X_t in the OM, because the assessment process involves observation and estimation errors. The biomass $\hat{X}_w$ can be expressed in relation to the initial exploitable biomass:

$$\hat{X}_w = S_{w-1}(\hat{X}_1 - C_{w-1}) \qquad (14)$$

where S_{w-1} is the proportion surviving to week w (defined as $S_w = \exp(-M/52)$), and C_{w-1} is the cumulative total catch biomass taken prior to week w. Non-linear least squares methods are used to estimate $\hat{Q}_t$ and $\hat{X}_1$ for use in the AMP. The objective function is the sum of squares of model-predicted minus observed log-scale weekly CPUE of the dominant fleet.

2.3.1.1. Defining a HCR for the model-based AMP.

Let us assume that $\hat{Q}_t$ (the depletion model estimate of the true catchability, Q_t) can be expressed as $\hat{Q}_t = \bar{Q}(1 + \varphi_t)$, where $\bar{Q}$ is the mean catchability coefficient observed in the past few years, and φ_t represents the annual proportional change. The HCR which defines the effort in the fourth quarter can then be specified as follows:

- Target effort is zero if the unit harvesting cost exceeds the unit harvesting revenue ($P_t \hat{Q}_t \hat{X}_t^\beta < c$, where $\hat{X}_t$ is the depletion model estimate of the biomass at the start of summer season in year t)
- If $\varphi_t > 0$ and positive profit is expected ($c \le P_t \hat{Q}_t \hat{X}_t^\beta$), the effort is increased by a fixed multiplicative factor equal to $1 + \theta$.
- Otherwise, the effort level is maintained at E^*.

In this particular example, there is no assumed difference between Q_t and q_t so we use a 10-year back-average, using our estimates of both q and $\hat{Q}_t$, to calculate the $\bar{Q}$ which yields φ_t. The obvious assumption in the OM is that the known estimate q is a good estimator for the future mean level of catchability even though it varies randomly from year to year. Also note that simulation evaluation explorations showed it was not possible to estimate $\hat{Q}_t$, $\hat{X}_t$ and the biomass elasticity, β, simultaneously in the depletion model framework so the value estimated for β from the squid production function (see Table 1) was assumed throughout. We selected a value of 0.15 for θ, because in practice, any larger year to year change in the target effort is unlikely to be accepted by stakeholders. In EU fisheries, for instance, year to year changes in quota are set at no more than 15% as a general rule, based on industry preferences (EC, 2007). The purpose of the HCR is to increase effort when catchability is higher, and decrease effort if the catchability and/or the stock biomass are low enough to suggest the continuation of the fishery is likely to be unprofitable. A conceptual diagram of the AMP is given in Fig. 3.

2.3.2. Empirically-based AMP for Pacific saury

For the Pacific saury fishery, the abundance estimates based on pre-fishing season surveys (abundance at the start of season three) and predicted prices were used to adjust the annual target effort levels. Pre-season surveys have already been used in an ad hoc manner as a part of stock assessment practices for Pacific saury in Japan, which makes the implementation of the proposed adaptive scheme feasible in practice. In order to account for imperfect survey precision, an observation error model was constructed:

$$X_t^{\text{Survey}} = X_{t,S} \exp\left(\varepsilon_t^S - \frac{\sigma_S^2}{2} \right) \tag{15}$$

where ε_S is the observation error from the survey with mean zero, and variance σ_S^2. Using the same equation as in (7), the standard deviation σ_S can be expressed in terms of variation in the survey coefficient $\text{CV}_{\text{survey}}$: ($\sigma_s = \sqrt{\log(1 + \text{CV}_{\text{survey}}^2)}$). We assumed that the survey biomass to stock biomass calibration had already been performed.

The adaptive scheme with a pre-season survey also involves predicting the price of fish given the survey-based estimate of stock biomass. However, the functional relationship between the price of fish and biomass as estimated from the survey data in a given year is unknown. As an alternative, we used the predicted harvest

Y_t^{Pred} of fish given the level of effort E^* and the survey biomass, X_t^{Survey}:

$$Y_t^{\text{Pred}} = qE^* X_t^{\text{Survey}} \tag{16}$$

Y_t^{Pred} was then used to predict the price of fish (P_t^{Pred}) using the inverse demand function for Pacific saury in Eq. (12). The annual expected profit based on the survey biomass is expressed as

$$\pi_t^{\text{Pred}} = qP_t^{\text{Pred}} Y_t^{\text{Pred}} - c_t E^*. \tag{17}$$

The HCR for the survey-based AMP is defined as follows: The fishery is closed when the predicted profit in Eq. (17) is negative or $qP_t^{\text{Pred}} X_t^{\text{Survey}} < c_t$. Otherwise, the target effort is maintained at E^*.

2.4. Defining alternative MPs for comparison

In addition to the above AMPs, two alternative MPs based on conventional fixed output and effort controls were considered for the purpose of comparison: (1) fixed output control management based on an annual TAC determined according to a pre-specified target fishing mortality (similar to current practice); (2) fixed input control based on an annual effort allocation with E^* as the target effort. The parameters related to the MPs are listed in Table A.1.

2.4.1. TAC-based MP with constant fishing mortality

Both case study stocks are managed according to an annual acceptable biological catch (ABC) level. The Fisheries Research Agency (FRA) considers the limit and target fishing mortality (F_{target}), which would be expected to produce the ABC limit and ABC target, to be F_{MSY} and 80% of F_{MSY}, respectively. The value of F_{MSY} for saury for all fishing nations was estimated by Ueno et al. (2005) at 0.32 in 2004. The FRA use a multiplier of 0.67 (5 year average Japanese catch share in total catches) to estimate the ABC available for Japan (ABC^J). The annual TAC is set based on ABC^J as well as socio-economic factors. TACs for Pacific saury have been set lower than ABC^J since the introduction of the TAC system, roughly around 70–80% of ABC^J (JFA 2008). To mimic this, a uniform random multiplier, κ, between 0.7 and 0.8 of ABC^J was used in setting the actual TAC. About 90% of the TAC was then allocated to the 100–200 GT class fleet, also to mimic the current system. In reality the values of F_{target} may vary over time. However, we assume F_{target} remains constant to demonstrate the comparative advantages of an adaptive bioeconomic scheme over a conventional biologically motivated fixed F_{target} policy.

$$\text{TAC}_{\text{saury } 100-200 \text{ GT}} = 0.9 \times \kappa \times 0.67 \times \frac{F_{\text{target}}}{M + F_{\text{target}}} (1 - e^{-F_{\text{target}} - M})$$
$$\times X_{t-1,4} e^{\varepsilon_t^A - \sigma_A^2/2} \tag{18}$$

For Japanese common squid, we assume the target F value for the combined stock to be between 0.3 and 0.5, based on the ABC advice applied to the two stocks in 2005. The ABC available for Japan (ABC^J) is $0.54 \times$ ABC. TACs for common squid have been almost identical to the Japanese ABC levels during 2004–2008, thus, we assume this in setting the TAC for Japanese fleet. About 30% of the TAC is then allocated to the dominant 10–30 GT class fleet, as per actual practice.

$$\text{TAC}_{\text{squid } 10-30 \text{ GT}} = 0.3 \times 0.54 \times \frac{F_{\text{target}}}{M + F_{\text{target}}} (1 - e^{-F_{\text{target}} - M})$$
$$\times X_{t-1,4} e^{\varepsilon_t^A - \sigma_A^2/2} \tag{19}$$

There has been a large gap between the TAC and actual reported harvest of both case study stocks, with the actual harvest being 42–57% of the TAC for common squid, and 72–83% for Pacific saury.
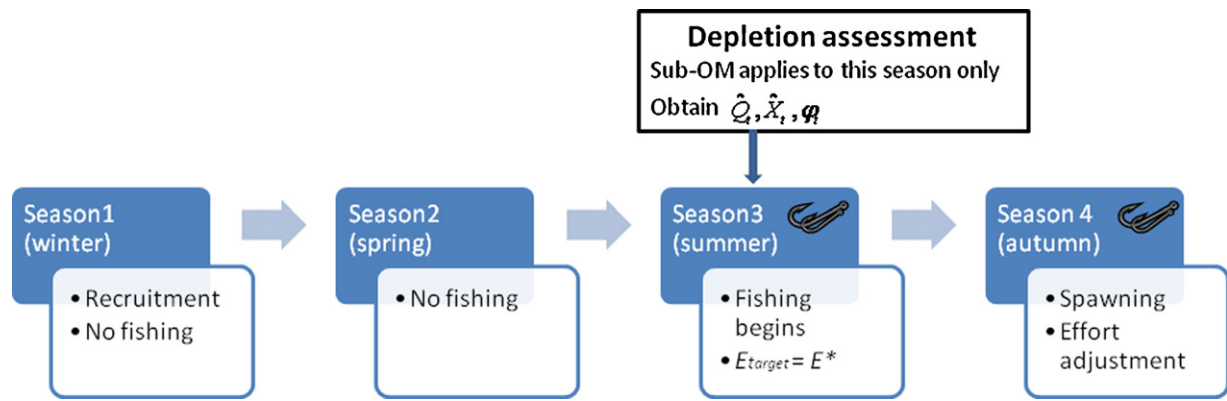
Fig. 3. Conceptual diagram of the AMP for common squid.

This discrepancy can be included as an implementation error if the purpose is to evaluate the performance of the actual management practice. However, this was not our main interest and, therefore, implementation error was not considered. A "stock assessment" parameter is included as an effectively random mis-estimation of the true stock biomass when setting the TAC in Eqs. (18) and (19). This is assumed to be unbiased with a coefficient of variation (CV_A) of 0.1 for both species, so that $\sigma_A = \sqrt{\log(1 + CV_A^2)}$ in both (18) and (19).

2.4.2. Constant effort-based MP

The mean estimate of E^* (see Appendix) defines the fixed total effort allocation per year and was split equally between the two fishing seasons.

2.5. Performance testing simulations

The spawning stock biomass (SSB) for both the stocks, as well as the NPV of annual profits from the fisheries at a 4% discount rate, were projected 10 years into the future, from 2004 to 2014. A thousand Monte Carlo (MC) trials were undertaken in all simulations. For the model-based AMP, observation error for the CPUE abundance index (CV_{CPUE}) was initially set to be negligible in order to simulate the performance of the depletion method for a perfect stock assessment. Indicative levels of observation error of $CV_{CPUE} = 0.1$ and 0.25 were then introduced for comparative purposes in order to investigate the sensitivity to CPUE observation error (which relates to the accuracy of the depletion method) when assessing the performance of the AMP. For the empirically based AMP, values of survey CV (CV_{survey}) between 0.1 and 0.4 were explored when simulating the precision of the pre-season surveys (Table A.1). This allows us to potentially quantify the economic value of improving the survey precision.

2.5.1. Performance indices

Five indices were used to evaluate the performance of each MP. Biologically-based indices were the probabilities that, after 10 years of management, the SSB in season 4 (the spawning season) in the final year either dropped below 20% of SSB_0 (index 1: recruitment overfishing threshold) or was greater than 50% of SSB_0 (index 2: sustainability threshold). Economically based indices were the sum of the NPV of annual profits at a 4% discount rate over a 10 year period (index 3): this summary of NPV includes both the median and inter-quartile range of the sum of the NPV over the projection period, as well as the inter-annual CV of discounted revenue and cost as proxies for the inter-annual CV of NPV, because the direct measurement of this CV encountered scaling issues as the mean NPV frequently approaches very close to zero. We also include the

probability of the annual NPV profits being negative (index 4). The total loss (sum of the negative profits projected from each MC sample) was also included as another economic performance measure (index 5) to see if the AMP worked to minimize the economic losses incurred in bad years. Index 3 is clearly economic but more specifically a measure of the overall positive performance of the AMP. Indices 4 and 5 can be seen as pertaining to industry vulnerability.

3. Results and discussion

3.1. Performance of the model-based AMP for common squid

3.1.1. Baseline case

Under baseline assumptions (scenario A in Table 2), no difference in biological performance indices was found among the candidate MPs. Due to the moderate levels of exploitation, and the productive nature of the population, the stock was maintained at high levels under all MPs.

The TAC-based MP with $F_{target} = 0.5$ yielded the highest NPV of profits over a 10-year projection period (approximately 46.7 billion yen). This was due to the higher exploitation rate relative to the two alternative MPs. The total loss over the projection period was, however, also the highest under this MP. The TAC-based MP with a lower target F level ($F_{target} = 0.3$) resulted in approximately the same performance as the fixed effort MP across most indices, except for the CV of the NPV. It may appear somewhat counterintuitive that the TAC-based MP with higher F levels (0.4 and 0.5) resulted in higher NPV than that of the profit-maximizing fixed effort MP with no apparent biological performance difference. Although this is partly due to the differences in time frame (the 10 year timeframe of the simulation versus the 100 year timeframe of the dynamic MEY estimation), it is mainly driven by the fundamental properties of the dynamic MEY estimation scheme: to obtain an estimate of the distribution of E^* we maximize the 100-year sum of NPV profits *along each* of the 500 future sample paths (see Appendix), not the expected NPV taken *across all* future sample paths. Our estimation scheme will tend to avoid higher estimates of effort that, while increasing average future profits, lead to a higher frequency of negative future profit trajectories. As a result, while the higher effort levels and exploitation rates associated with the target F levels of 0.4 and 0.5 gave larger median profits, they also give rise to a higher prevalence of negative profit trajectories and, as such, are rarely selected by the MEY estimation scheme.

The key improvement of the AMP over the fixed output and effort MPs was observed for the industry vulnerability indices (indices 4 and 5). For example, the expected total loss over 10 years was reduced from around 10.1 billion yen under the fixed effort MP and 10.0–14.7 billion yen under the TAC-based MP to

Table 2
Performance indices for Japanese common squid management scenarios. Indices 1 and 2 represent the probabilities of SSB in season 4 dropping below 20% of $SSB_{t,4}$, and being above 50% of SSB_0, respectively. Index 3 is the median sum of the NPV over a 10 year period (interquartile range in parentheses) and across-year CV for discounted revenue and cost, index 4 is the probability of the annual NPV being negative, and index 5 is the total expected losses over the 10 years and across 1000 Monte Carlo samples. CV_{CPUE} is the observation error CV from the depletion assessment model. Average effective exploitation rates over the fishing seasons are given in parentheses next to each MP scenario.

MP		Biological		Economic			
		$P(SSB_{t,4} < 20\% \, SSB_0)$ (index 1)	$P(SSB_{t,4} \geq 50\% \, SSB_0)$ (index 2)	NPV billion yen (index 3)		P(Neg. profits) (index 4)	Losses billion yen (index 5)
	(ave.expl. rate)			Median (25; 75%ile)	CV_{rev}; CV_{cost}		
(A) Baseline ($CV_Q = 0.1$, $\beta = 0.61$)							
TAC							
$F_{target} = 0.3$	(0.230)	0	0.991	25.5 (10.2; 43.3)	0.41; 0.42	0.292	9.95
$F_{target} = 0.4$	(0.237)	0	0.982	36.5 (14.4; 61.3)	0.41; 0.42	0.282	12.25
$F_{target} = 0.5$	(0.244)	0	0.992	46.7 (22.2; 72.2)	0.41; 0.43	0.291	14.71
Fixed-effort	(0.230)	0	0.987	27.7 (13.0; 45.2)	0.22; 0.14	0.282	10.07
Adaptive							
$CV_{CPUE} = 0$	(0.228)	0	0.985	37.3 (21.8; 52.9)	0.36; 0.24	0.267	6.00
$CV_{CPUE} = 0.1$	(0.228)	0	0.985	36.8 (21.3; 52.2)	0.34; 0.23	0.270	6.18
$CV_{CPUE} = 0.25$	(0.228)	0	0.985	36.5 (20.8; 51.9)	0.34; 0.24	0.271	6.50
(B) Larger values of CV_Q							
$CV_Q = 0.2$							
TAC: $F_{target} = 0.5$	(0.244)	0	0.986	39.5 (8.9; 67.2)	0.41; 0.45	0.326	23.11
Fixed-effort	(0.230)	0	0.991	32.9 (12.7; 51.9)	0.27; 0.14	0.313	12.93
Adaptive ($CV_{CPUE} = 0.25$)	(0.228)	0	0.986	41.4 (23.0; 59.3)	0.41; 0.26	0.302	7.73
$CV_Q = 0.3$							
TAC: $F_{target} = 0.5$	(0.244)	0	0.981	35.4 (−1.6; 67.9)	0.41; 0.49	0.352	34.21
Fixed-effort	(0.231)	0	0.990	38.7 (13.5; 64.3)	0.34; 0.14	0.342	16.64
Adaptive ($CV_{CPUE} = 0.25$)	(0.229)	0	0.986	49.3 (26.6; 71.4)	0.51; 0.29	0.335	9.73
(C) Incorrect assumption about β							
$\beta = 0.65$							
Fixed-effort	(0.232)	0	0.987	39.5 (17.4; 62.7)	0.34; 0.14	0.341	16.15
Adaptive ($CV_{CPUE} = 0.25$)	(0.231)	0	0.992	49.8 (33.4; 67.3)	0.31; 0.20	0.207	4.91
$\beta = 0.57$							
Fixed-effort	(0.231)	0	0.988	32.2 (14.3; 58.8)	0.35; 0.14	0.353	17.47
Adaptive ($CV_{CPUE} = 0.25$)	(0.226)	0	0.986	19.4 (6.2; 35.0)	0.37; 0.27	0.363	8.71

Note: Discount rate = 4%. Sum of the NPV and the total losses excludes the initial year.

around 6.0–6.5 billion yen under the AMP (Table 2, A). Moreover, the AMP yielded significantly higher (26–27%) NPV profits than the fixed effort-based MP, despite both having about the same exploitation rates. This was due to a combination of increased effort in years when catchability was detected to be higher than the average and fishery closure in the autumn fishing season (quarter four) in less profitable years. However, the inter-annual variability of NPV (inter-annual CVs of discounted revenue and cost, CV_{rev} and CV_{cost}) was higher for the AMPs than the fixed effort-based MP due to the adaptive nature of harvesting (Table 2, A).

Introducing indicative levels of observation error of 0.1 and 0.25 into the depletion stock assessment (CV_{CPUE}) did not change the estimated NPV levels, while increasing the losses slightly (by 3–8%) compared to the case with negligible observation error (Table 2, A), but the effect was minimal. More detailed work was undertaken in Hoshino (2010), exploring the interaction of observation error and exploitation rate in determining the precision and bias of the estimates of catchability and biomass in the depletion assessment. This showed that the CV_{CPUE} of the stock assessment input data would have to be at or above 0.25 to have any significant impact on the quality of the depletion assessment, given the current levels of exploitation rate. This is why there was such a minimal performance reduction from a CV_{CPUE} of 0.1 or 0.25 to a "perfect" ($CV_{CPUE} = 0$) assessment.

3.1.2. Effects of a larger CV_Q

In the above performance evaluations, the default magnitude of the year to year fluctuations in Q during the projection period was assumed to be moderate ($CV_Q = 0.1$), but we also considered larger values ($CV_Q = 0.2, 0.3$) to investigate the comparative advantage of the model-based AMP in improving economic performance under such conditions relative to the static MPs. As the levels of CV_Q increase, the range of NPV estimates becomes wider in both directions (negative and positive) under the static MPs, and for the TAC case in particular, while the increase in CV_Q values made the NPV estimates more positive under the AMP (scenario B in Table 2). The total losses under higher levels of CV_Q were considerably lower for the AMP than for the static MPs. This suggests that one comparative advantage of the AMP lies in its ability to minimize negative profits in the face of a highly uncertain environment. This provides evidence that the model-based AMP can significantly aid in minimizing losses from borderline profitable fisheries targeting fluctuating stocks. Although an in-season stock assessment is likely to increase the management costs, further investigation would be worthwhile of the trade-offs between increased management costs, adjustment costs by the industry, and the potential gains from minimizing the economic losses of the industry.

3.1.3. Effects of incorrect assumptions about β

We explored the impact of the actual value of the biomass elasticity β in the OM differing from the value of the effort-based MPs (0.61 ± s.e. 0.004) to see if this caused the performance of the AMP to deteriorate. There was no obvious difference in the biological performance indices but clear differences were found in the economic performance indices (scenario C in Table 2). If the true value of β was slightly higher than the baseline, summed NPV was generally higher for the fixed-effort MP (28–29% above the baseline), but the industry vulnerability indices (indices 4 and 5) were lower for the AMP. If the true value was less than the assumed value, the fixed-effort MP outperformed the AMP in terms of NPV, although the AMP still yielded much lower levels of total losses than the

Table 3
Performance indices for Pacific saury management scenarios. See the legend to Table 2 for explanations of the indices.

MP	Biological			Economic			
	$P(SSB_{t,4} < 20\% \, SSB_0)$ (index 1)		$P(SSB_{t,4} \geq 50\% \, SSB_0)$ (index 2)	NPV billion yen (index 3)		P(Neg. profits) (index 4)	Losses billion yen (index 5)
	(ave. exp. rate)			Median (25;75%ile)	CV_{rev}; CV_{cost}		
TAC	0.088	0	0.616	−127.7 (−152.5; −97.9)	0.16; 0.26	0.944	128740.7
Fixed effort	0.044	0	0.837	50.2 (39.2; 59.9)	0.13; 0.14	0.018	111.2
Adaptive							
$CV_{survey} = 0.1$	0.044	0	0.842	49.1 (37.9; 58.6)	0.14; 0.15	0.003	10.63
$CV_{survey} = 0.2$	0.044	0	0.833	48.4 (36.3; 58.8)	0.15; 0.15	0.005	17.63
$CV_{survey} = 0.3$	0.043	0	0.830	44.5 (33.3; 56.0)	0.25; 0.19	0.009	46.72
$CV_{survey} = 0.4$	0.043	0	0.818	42.3 (29.0; 54.2)	0.40; 0.40	0.011	59.44

Note: The level of annual variability in catchability coefficient (CV_Q) was 0.1. Discount rate = 4%. The sum of the NPV and the total losses exclude the initial year.

fixed-effort scheme (Table 2, C). This result emphasises the importance of the non-linear terms in the production function since small mismatches between the assumed and true values of the biomass elasticity parameter can have a substantial effect on the behaviour and performance of bioeconomic MPs.

3.2. Performance of the empirically based AMP for Pacific saury

Ueno et al. (2006) reported that the prices of Pacific saury tend to drop in the Japanese market in years when the stock is abundant (hence, when there is a large supply), perhaps due to the lack of primary processing capacity to handle large quantities of fresh saury. Ad hoc advice to cut the fishing effort to avoid price drops in good seasons has already been provided by the Pacific saury fishermen's organization. The empirically based AMP developed here was designed to minimize industry vulnerability by taking into account the negative correlation between supply and demand and to enable managers to take actions proactively and more systematically. The advantages of such an approach are clearly demonstrated by the improvement in the vulnerability performance indices under the AMP (indices 4 and 5; Table 3). The results shows that the probability of annual profits being negative is substantially reduced; from 1.8% under the fixed effort MP to 0.3% for the AMP. This positive effect may seem too small in practice to justify the use of adaptive management if possible adjustment costs are high. However, we assumed that such costs are negligible for this particular fishery, given that pre–season surveys are already in place, and most participants in the dominant fleet are part-time operators. The AMP's ability to minimize the average total loss over 10 years largely depends on the survey precision. The total loss for the AMP with relatively good survey precision (CV_{survey} = 0.1) was 10.6 million yen compared to 111.2 million yen under the fixed effort MP, suggesting a 90% reduction in the total loss of profits. Under reduced survey precision (CV_{survey} = 0.4), a higher loss of 59.4 million yen was predicted, but it was still approximately 50% less than the loss from the fixed effort MP. There was a small decrease in the median NPV when moving from the fixed effort MP to the survey-based AMP, but the difference between the medians was not statistically significant.

All candidate MPs performed well in terms of the two biological indices (indices 1 and 2), with negligible risks of recruitment overfishing and a high chance of the final year SSB being above 50% of the virgin SSB level, although the two effort-based MPs performed significantly better than the TAC-based MP with respect to the sustainability index (index 2) due to its lower harvest rates (Table 3). The TAC-based MP performed poorly on the economic indices (indices 3–5), with negative profits projected for most years during the 10-year projection period, while both fixed and adaptive effort-based MPs generated positive profits over 10 years (Table 3). The fixed effort-based MP yielded a marginally larger NPV. This is

because the target effort was maintained regardless of the changes in economic conditions, while the AMP allows the fishery to be closed when it is not economical to continue fishing. This lack of flexibility in the fixed effort-based MP was reflected in its lower performance compared to the AMP when evaluated against the industry vulnerability indices (indices 4 and 5).

3.3. The economic value of scientific information

While we did not have specific and detailed cost information on the saury pre-season abundance surveys, we were able to perform semi-quantitative analyses to see whether our results could tell us anything about cost-effective levels of survey effort. The following assumes that the industry itself pays the survey costs, either directly or indirectly, otherwise it will always be worthwhile from the fisher's perspective to increase the survey effort, as this would decrease their losses at no extra cost to them. A common statistical assumption is that the survey effort, S, and the resultant survey CV are related as follows: $CV_{survey} \propto 1/\sqrt{S}$, i.e. the survey CV decreases with the square root of increasing survey effort. Assuming that the level of survey effort to achieve a CV_{survey} of 0.3 is $S_{0.3}$, then the proportional increase in this baseline-level survey effort required to reduce the CV_{survey} to levels of 0.2 and 0.1 are 2.25-fold and 9-fold, respectively. As noted before, there is a lack of any real statistically significant difference between the median NPVs for the various effort-based MPs, and so we focus our cost–benefit analysis only on the relative reduction in total losses. From Table 3 the reduction in total losses when the CV_{survey} is reduced from 0.3 to 0.2 and 0.1 was 29.1 and 36.1 million yen, respectively. The difference between these values is the economic value of additional scientific information through the improvement in the survey precision. Assuming that the total cost of the surveys, TC_{survey}, is a function of survey effort S, with stationary costs over 10 years, improving the survey precision from CV_{survey} 0.3–0.2 would be worthwhile if TC_{survey} is less than 29.1 million yen after discounting. However, the value of the additional survey precision is much less (7 million yen) when trying to achieve CV_{survey} 0.1 instead of 0.2. Given that a 9-fold increase in effort is required, the additional investment in survey effort may not be financially worthwhile. It would be interesting to investigate further the optimal level of survey precision (where marginal benefit equals marginal cost) if survey cost information becomes available.

For the in-season assessment-based AMP for squid, it is not in our control to directly influence the precision of the CPUE-based abundance index. However, any stock assessment process has an associated cost—from collecting the data, to analyzing it and processing and distributing the results. Clearly from Table 2, the depletion-based AMP outperforms the fixed effort MP in terms of average NPV profits and total losses. Using an indicative CV_{CPUE} of 0.1, a within-season assessment would be worth doing if it costs less

than 1.28 billion yen per year. The reality of actual management for Japanese common squid is a complex mixture of fixed F strategies, as already outlined, some of which give lower median profits and some higher, but all of which result in larger total losses than the AMP (Table 2). To really assess the financial utility of the proposed AMP for the squid fishery, it would be necessary to adequately simulate actual management practice, which was not feasible at present nor was it the focus of this work. Nevertheless, the ability to quantify the economic value of scientific information is one of the major advantages of a bioeconomic MSE.

Our study does not include social objectives, such as providing jobs in coastal communities or supplying fresh seafood to the local market. Social objectives are of key importance for coastal nations such as Japan. The comparative advantage of the bioeconomic AMP may be undermined by the relative importance of other objectives. For instance, if social objectives are more important than economic objectives, a stationary effort control strategy may be more appropriate. This may be the case for the Pacific saury fishery, because the fishery remains open at some level even when the expected profit is negative. There is further scope to investigate the performance of the candidate MPs using multiple (biological, economic, and social) objectives. Moreover, ecosystem dimensions (e.g. species interactions) and changes in fisher behaviour in response to biological, economic or regulatory conditions are not accounted for in this study. These are important factors to consider in future in order to further advance the practical implementation of bioeconomic adaptive management regimes.

4. Conclusions

In this article we have proposed a set of bioeconomic adaptive management schemes and have shown that such schemes have the potential to reduce economic vulnerability for borderline profitable fisheries targeting rapidly fluctuating stocks. We also suggest that such schemes are potentially useful in the practical implementation of MEY-based policies. Dichmont et al. (2010) argued that MEY is a moving target and its implementation is unlikely to be successful without stakeholder participation. If a management authority must update the target every year, this is likely to introduce major issues of shifting baselines, increased industry complaints and delayed actions due to a prolonged decision making process. Instead, the adaptive schemes developed here use a best estimate of target effort and a current best assessment of stock size, and adapt these estimates based on changing conditions using an adaptive feedback control rule within an MSE framework. The MSE process provides an opportunity to test adaptive schemes prior to implementation, allowing stakeholders to be involved with the design and evaluation processes. As the assumptions of the model and the rules for adaptive responses must be pre-agreed among scientists and stakeholders, this framework may help in minimizing conflicts and reducing the lengthy decision-making process involved in the implementation of MEY-based policy. Another interesting research avenue would be to compare the performance of a procedure involving yearly revisions of a given target and the more systematic adaptive control management approach tested here, in terms of industry stability and the time required to reach management decisions.

It must be noted that different protocols are required when fundamental shifts in the dynamics of the system occur that are outside the ranges tested in any MSE work. After the development, testing and eventual adoption of any MPs, the relevant scientific management body must have in place some kind of review process to assess how the MP is performing and whether there have been any significant changes that invalidate, or require updates to, the operating models used in the original MP testing process. This

may require subsequent minor changes to the key elements of the MP (such as the E^* effort levels). However the approach described here is still placed within a general MSE framework and retains the advantages outlined above, compared to the standard approach of re-estimating the profit-maximizing effort target based on an annual stock assessment process.

Acknowledgements

Appendix A. Parameterization of the OM

A.1. Estimating S–R parameters for Pacific saury

Using the available life history parameters and intrinsic rate of logistic growth for Pacific saury (Ueno et al., 2005, 2006, 2008), we extrapolated the S–R parameters for this stock to parameterize the OM, using the Euler–Lotka equation described by Myers et al. (1997), which is defined as:

$$\sum_{j}^{J} e^{-rj} e^{-M} m_j w_j \frac{4hR_0}{\mathrm{SSB}_0(1-h)} = 1 \tag{A.1}$$

where J is the maximum age in a population, e^{-M} is the probability of surviving to age j, m_j is the maturity at age j, w_j is the weight at age j, r is the intrinsic growth rate, and h is the steepness parameter of the S–R relationship that we want to estimate. We selected the value for m of 0.5 for age 0. At age 1 full maturity is assumed. The weight at age was derived from a time-specific (quarterly) weight relationship detailed in Ito et al. (2004). The estimate of SSB_0 (Table 1) is inferred from the estimate of K in Ueno et al. (2006); the estimate of R_0 is derived from SSB_0 and the unfished spawner biomass-per-recruit. This makes Eq. (A.1) a function of h, as all the other variables are known (Tables 1 and A.1), which is then solved to give the saury estimate of steepness of $h = 0.245$.

A.2. Fit of the inverse demand function

The estimated inverse demand curve and observed ex-vessel prices of Pacific saury is given in Fig. A.1.

A.3. Estimating production function parameters

Using the historical biomass and effort data, Cobb-Douglas function parameters (q, α and β in Eq. (8)) were estimated on a

Table A.1
Parameters related to estimation of E^* and the various management strategies. The catchability and economic parameters are common to both the estimation scheme for E^* and the OM and are not repeated here, but can be found in Table 1.

Parameters	C. saira	T. pacificus
Intrinsic growth rate, r (year^{-1})	0.474[a]	0.812
Standard deviation in biomass, σ_X	0.3	
Standard deviation in abundance, σ_N	–	0.3
F_{target} (year^{-1})	0.26	0.3, 0.4, 0.5
X_{MSY}^A (million tonnes)	–	1.05[b]
MSY^A (thousand tonnes)	–	428[b]

[a] Ueno et al. (2005, 2006).
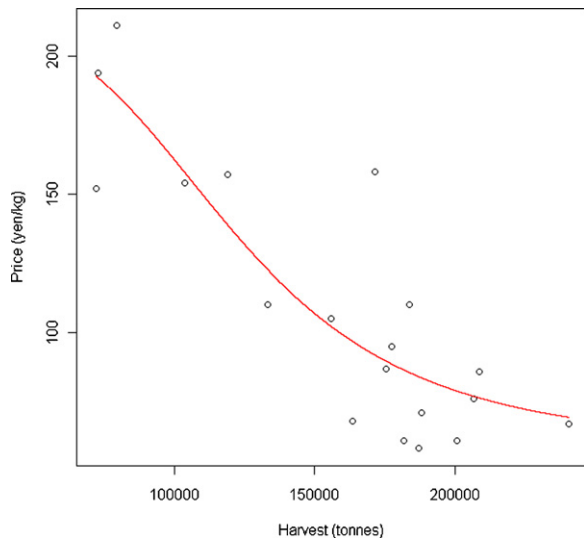[b] Kidokoro et al. (2006).

Fig. A.1. Inverse demand curve and observed ex-vessel prices of Pacific saury.

logarithmic scale assuming normal errors. For Pacific saury the estimates of α and β were not significantly different from one and were therefore assumed equal to one. With this reduced model (where $\alpha = 1$, $\beta = 1$) the estimate and SE of $\log(q)$ was −8.279, 0.06, respectively, with an adjusted $R^2 = 0.704$. For the Japanese common squid case α was not significantly different from 1 while the estimate of β was. With the model assuming $\alpha = 1$ the estimates (SEs) for $\log(q)$ was −4.69 (0.48), and β was 0.61 (0.004). The adjusted $R^2 = 0.838$ for this reduced model was greater than that obtained assuming the full model (0.835) and, henceforth, this reduced model was assumed for the squid. The predicted harvest by the selected model versus observed harvest is given in Fig. A.2. In order to detect the presence of autocorrelation in the residuals from the selected models for both fisheries, a Durbin–Watson test was carried out. The Durbin–Watson d-statistic was 2.087 (p-value of 0.51) for saury, 1.58 (p-value of 0.167) for squid, thus it was concluded that there was no evidence of autocorrelation. The resulting parameters were also used in estimating the default target level (E^*) below.
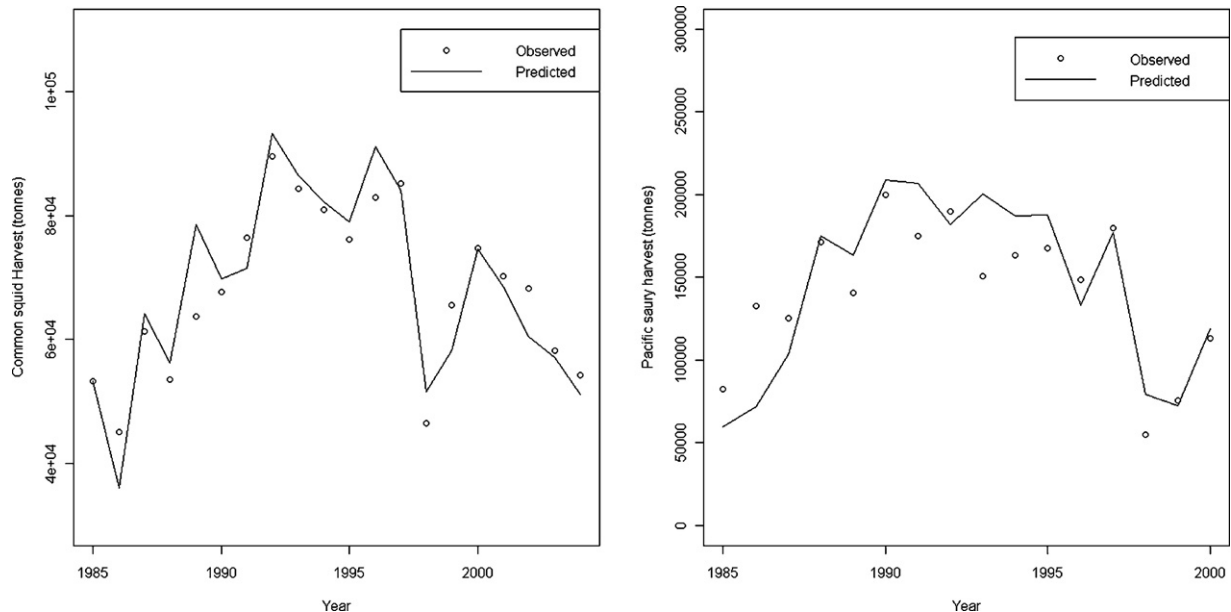
Appendix B. Estimating default target effort levels (E^*)

To identify the target effort levels (E^*) that maximize NPV profits, we constructed stochastic bioeconomic estimation models, based on the population models currently being used for the stock assessments of the resources, but incorporating random fluctuation of the stock abundance and economic variables. A Schaefer model and a Beverton–Holt discrete time age-structured model were used to define the population dynamics of Pacific saury and common squid, respectively. The parameter values used to estimate E^* were listed in Table A.1. The catchability and economic parameters used in the estimation scheme for E^* are already detailed in Table 1. The population models used here are simpler than those used in the OMs.

Due to the lack of availability of economic data for all participating fleet categories, the equilibrium conditions were derived for the dominant fleet only and the fishing mortality by other Japanese and non-Japanese fleets was specified as "external" and treated as a random variable, given historical estimates. These estimates were obtained from the historical ratio of external fleet catch to stock biomass. As the external fishing mortality cannot be known precisely, the equilibrium conditions for the fleet concerned are indicative, but are investigated for heuristic purposes to design and test the proposed effort-based adaptive schemes.

B.1. Model of population dynamics for Pacific saury in the estimation model

A stochastic difference equation is used to explain the dynamics of Pacific saury:

$$X_t = Z_t[X_{t-1} + F(X_{t-1}) - Y_{t-1} - \xi^{\text{Ext}}_{t-1} X_{t-1}] \qquad (A.2)$$

where $F(X_t) = rX_t(1 - X_t/K)$ is the logistic growth function, Y_t is the size of harvest by the dominant fleet (100–200 GT class), Z_t are random variables with $E\{Z_t\} = 1$. This can be written as $Z_t = e^{\varepsilon^X_t - \sigma^2_X/2}$, where ε^X are normally distributed error terms with mean zero and variance σ^2_X. In this formulation, the biomass X becomes a random variable. ξ^{Ext}_t is the external harvest rate expressed as a proportion of the modelled harvest with a log-normal distribution with known mean μ_{Ext} and variance σ^2_{Ext}. This was included to be able to account for the exploitation of the stock by fleets other than

Fig. A.2. Observed versus predicted harvest of common squid (left) and Pacific saury (right) by the selected models.

the dominant fleet for which we have no economic data. Based on the historical estimates of biomass (Ueno et al., 2005, 2006), the coefficient of variation, CV_X, was assumed to be roughly 30%. The (log-scale) standard deviation, σ_X, can be then calculated as follows: $\sigma_X = \sqrt{\log(1 + CV_X^2)}$, giving a value of 0.3 for σ_X.

B.2. Model of population dynamics for common squid in the estimation model

Japanese common squid stocks are managed as two separate sub-stocks: the winter spawning stock and the autumn spawning stock. As our intention is to estimate the equilibrium effort level for the coastal squid angling fleet (10–30 GT classes), which harvests both stocks indistinguishably, in this paper we use a single population model which can explain the population dynamics of both (combined) stocks, rather than having a separate biological model for each stock. Hoshino (2010) explored the sensitivity of this assumption and found such an assumption can potentially result in conservative estimates of E^* if effort is allocated predominantly to one of the sub-stocks.

The model describing the population dynamics of *T. pacificus* is based on the work by Kidokoro et al. (2006). A Beverton–Holt discrete time age-structured model was used to define the population dynamics for the combined stock of *T. pacificus*. The spawner–recruit relationship can be expressed as:

$$N_t = \frac{4hR_0N_{t-1}e^{-M-F_t-F_t^{\text{Ext}}}}{(1-h)R_0e^{-M}+(5h-1)N_{t-1}e^{-M-F_t-F_t^{\text{Ext}}}} \quad (A.3)$$

where N_t is the number of recruiting squid at the beginning of time period t, h is the steepness of the stock–recruit (S–R) relationship, R_0 is the virgin recruitment, M is the rate of natural mortality at time t, F_t is the rate of fishing mortality by the dominant fleet at time t, F_t^{Ext} is the rate of external fishing mortality at time t, and $e^{-M-F_t-F_t^{\text{Ext}}}$ is the proportional survivorship. As before, Z_t are random variables with $E\{Z_t\} = 1$ and $Z_t = e^{\varepsilon_t^N - \sigma_X^2/2}$, where ε^N are normally distributed error terms with mean zero and variance σ_N^2. The external fishing mortality, other than the mortality from the dominant fleet, has known mean μ_{Ext} and variance σ_{Ext}^2. The S–R parameters are constant, but a variance term (log-normal deviations) was included to account for the uncertainty in the S–R relationship. Kidokoro et al. (2006) estimated $\sigma_N = 0.238$ for the autumn spawning stock. We considered a higher level of σ_N (0.3) as a baseline for the combined stock to account for the higher level of inter-annual fluctuation of the winter spawning stock.

The catch in weight in period t is given by the Baranov (1981) catch equation:

$$Y_t = \frac{F_t}{F_t + M}(1 - e^{-M-F_t})N_tw_t \quad (A.4)$$

where w_t is the average squid weight at period t. We used the reported S–R parameters for the autumn stock to extrapolate the indicative S–R parameters for the combined stock, assuming that the both stocks have the same steepness of $h = 0.516$. In general, the estimation of steepness can be informed by estimates from related stocks (Myers et al., 1999; Punt and Hilborn, 2001; Rose et al., 2001; SFSC, 2009).

To obtain an estimate of the global unfished spawner biomass (SSB_0) and virgin recruitment level (R_0), we made use of the available estimates of biomass time-series for both the autumn and winter stocks, and the estimates of MSY^A and the biomass at MSY (X_{MSY}^A) for the autumn stock (Table A.1), derived from a production model by Kidokoro et al. (2006).

We first estimated the autumn stock carrying capacity, K^A as follows:

$$K^A = 2X_{\text{MSY}}^A = \frac{4MSY^A}{r} \quad (A.5)$$

With this we estimated K^A at 2.1 million tonnes; r at 0.812. It was assumed that the winter and, hence, combined stocks have the same value of r as the autumn stock. The carrying capacity for the winter spawning sub-stock, K^W, was estimated by multiplying K^A by a factor of 0.8, the average ratio of the winter sub-stock biomass and autumn sub-stock biomass during 1985–2005, since the levels of catches as a proportion of stock biomass are similar between the two stocks. An estimate of the global carrying capacity (K) for the combined stock was the sum of K^A and K^W, which was 3.81 million tonnes. We assumed that K is equal to the global unfished spawner biomass, SSB_0, given there is only ever one cohort in the population. The virgin recruitment number, R_0 is estimated by SSB_0 divided by the SSB-per-unit-recruit, $\rho = w\exp(-M)$ and w is the mean weight with the rate of natural mortality, M. Finally, the S–R parameters for the combined stock were calculated using the values of SSB_0, R_0, and h. This approach assumes that the equilibrium yield-biomass curve for the model defined by Eqs. (A.3) and (A.4) is comparable to that of the Schaefer model as in Eq. (A.5), from which the MSY estimates were derived. In reality, the ratio of the spawner biomass at which MSY is achieved relative the unfished level was around 0.35–0.4, given a steepness of $h = 0.516$ and the other life-history parameters, not 0.5 as is the case for the Schaefer model. An alternative approach would be to take the MSY and biomass at MSY estimates in Table A.1 from Kidokoro et al. (2006) and estimate both steepness and virgin recruitment using Eqs. (A.3) and (A.4) but one still has the problem of a potential lack of comparability between this yield-biomass curve and that of the Schaefer model from which the MSY estimates were derived. Moreover, the data used to estimate S–R parameters for the autumn stock in Kidokoro et al. (2006) were concentrated around the gradient at the origin with little or no information on recruitment levels at higher spawner abundance, which made the reliable extrapolation of the autumn stock virgin recruitment difficult. Ultimately, the lack of definitive information on the key population parameters for both the autumn and winter stocks forced us to make certain assumptions about the equivalence of alternative population models, suggesting a level of uncertainty in our estimates of the unfished global population size.

B.3. Economic model

The sum of NPV of profits was defined according to:

$$\text{NPV} = \sum_{t=1}^{T} \pi_t(1+\delta)^{-t} \quad (A.6)$$

where δ is the discrete discount rate. The optimization approach taken here was Monte Carlo (MC) in nature not deterministic, projecting population dynamics forward for a time horizon parameter T, and finding the long-term effort and associated catch levels that maximize the sum of NPV of annual profits, subject to the population and price dynamics over the period and for each simulated future population and fishery trajectory. This allows us to obtain many possible future values for E^* and their distribution, given the time horizon parameter T. To ensure quasi-equilibrium and sustainability conditions were met we chose a suitably large value of T (100 years). In all cases 500 MC trials were performed.

The estimates of equilibrium effort and harvest are given in Table A.2 and the distribution of the E^* estimates are given in Fig. A.3. We also considered a more traditional optimization approach, which identifies the value of E^* that maximizes the average NPV over all sample paths. For Pacific saury, the result for E^*

Table A.2
Estimates of equilibrium effort E^* and corresponding harvest Y^* for the major Japanese fleet for Pacific saury (*C. saira*) and Japanese common squid (*T. pacificus*).

	C. saira			*T. pacificus*		
	Median (mean)	5%ile	95%ile	Median (mean)	5%ile	95%ile
E^* (operators)	43.7 (43.6)	38.4	49.8	0 (1291)	0	6837
Y^* (1,000 tonnes)	82.0 (81.7)	70.8	93.1	0 (108)	0	561
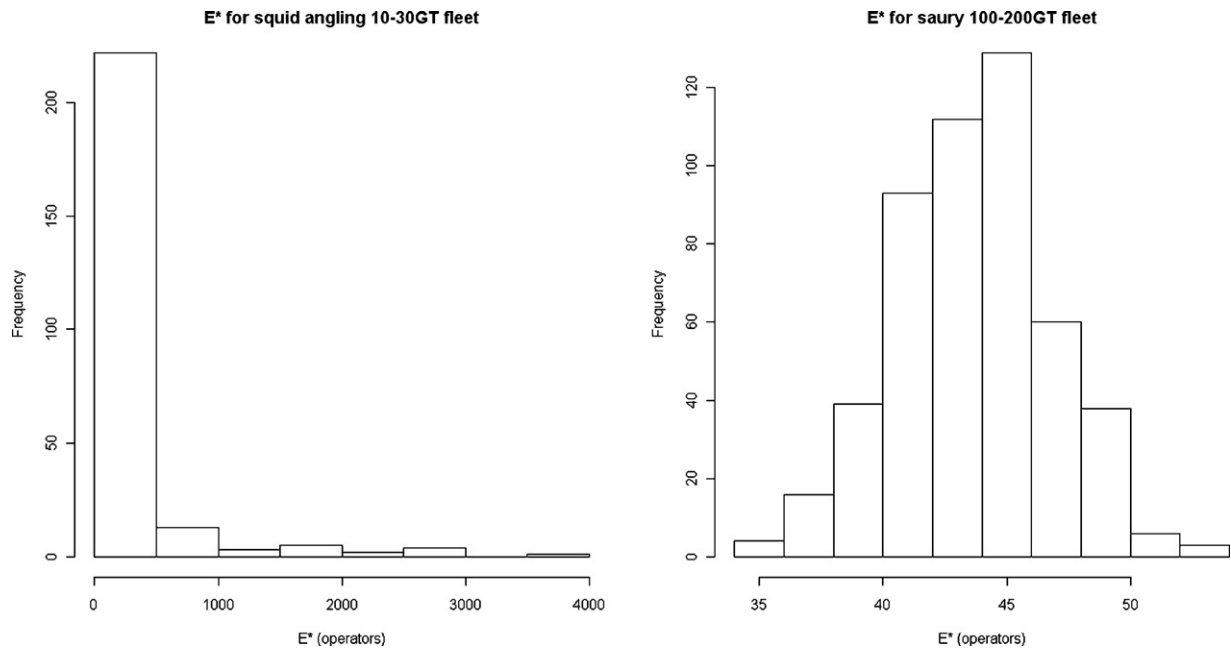
Fig. A.3. Distribution of the E^* estimates from the best assessment models and historical data.

calculated in this way was identical to the mean E^* obtained from the above method, while it was zero for squid as the large economic losses outweighed the perceived profits. Therefore, we selected the mean E^* obtained from the above method as the default target effort.

B.4. Distribution of E^*

The distribution of the E^* estimates for the Pacific saury 100–200 GT class fleet was roughly normally distributed around a mean and median value of approximately 44 operators for a 4% discount rate, with $\sigma_X = 0.3$ (Table A.2 and Fig. A.3). This is approximately 60% of the number of operators in 2004. In contrast, the distribution of E^* for the Japanese common squid 10–30 GT class fleet shows a bimodal pattern with the highest frequency around zero, and a median of zero. The mean value (1291 operators) is more than 40% larger than the observed level in 2004. The positive value of the mean of E^* implies that the coastal squid angling fishery can be profitable when economic and recruitment conditions are favourable, but there is a large probability (0.64) that the fishery becomes unprofitable when conditions are unfavourable and E^* is therefore zero. In fact, negative profits are common for this fishery. Based on the average annual revenue and expenditure data from sampled operators between 1985 and 2004, negative profits were experienced approximately 40% of the time. The results for common squid indicate that estimating E^* is highly uncertain. Finding the "right" level of initial target effort for fluctuating stocks is challenging, and this was clearly the case for the Japanese common squid fishery.

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