Fisheries Research 171 (2015) 20–32

Contents lists available at ScienceDirect

Fisheries Research

journal homepage: www.elsevier.com/locate/fishres

An evaluation of an iterative harvest strategy for data-poor fisheries using the length-based spawning potential ratio assessment methodology

Adrian R. Hordyk[a,*], Neil R. Loneragan[a], Jeremy D. Prince[a,b]

[a] Centre for Fish and Fisheries Research, School of Veterinary and Life Sciences, Murdoch University, 90 South Street, Murdoch, WA 6150, Australia
[b] Biospherics, P/L, South Fremantle, Western Australia, Australia

ARTICLE INFO

Article history:
Received 28 February 2014
Received in revised form
11 December 2014
Accepted 18 December 2014
Handling Editor A.E. Punt
Available online 28 January 2015

Keywords:
Stock assessment
Per-recruit model
Length-based spawning potential ratio (LB-SPR)
Management strategy evaluation
Fisheries management

ABSTRACT

Data on the length structure of exploited stocks are one of the easiest sources of information to obtain for data-poor fisheries, and have the potential to provide cost-effective solutions to the management of data-poor fisheries. However, incorporating the results from stock assessments into a formal harvest strategy, defined here as a harvest management system that incorporates monitoring, assessment, and decisions rules for a specific fishery, usually requires information on the total catch or catch-per-unit effort, data that are not available for many data-poor fisheries. This paper describes and tests a harvest strategy where only length composition data of the catch and knowledge of basic biological parameters are available. The harvest strategy uses a recently developed methodology for stock assessment that estimates the spawning potential ratio (SPR) for an exploited stock from the length structure of the catch (the length-based SPR model; LB-SPR), and uses an effort-based harvest control rule to iteratively drive fishing pressure towards a target level of SPR (40%). A management strategy evaluation framework was used to explore the behaviour of various parameterizations of the harvest control rule for three species with a diverse range of life-histories and *M*/*k* ratios ranging from 0.36 (unfished population dominated by large fish) to the Beverton–Holt invariant *M*/*k* of 1.5 (unfished population dominated by smaller fish). For all three species the harvest strategy was able to guide the fisheries towards the target SPR, although the time taken for the SPR to stabilise at the target SPR was greatest for the species with the greatest longevity and the lowest *M*/*k*. The results of this proof-of-concept study demonstrate that the combination of the LB-SPR assessment model with an iterative, effort-based harvest control rule can successfully rebuild an overfished stock back to sustainable levels or fish down a stock to the target SPR without significantly overshooting the target.

1. Introduction

During its development, fisheries science has tended to focus on large-scale stocks and industrial-scale fisheries, and fisheries management often relies on technically challenging mathematical and statistical models to estimate the current stock status and the exploitation rates of a fishery (Hilborn and Walters, 1992). These models often include hundreds of estimated parameters, require substantial amounts of data, are based on numerous assumptions, require considerable technical expertise to develop and run, and are often poorly understood by policy makers and other stakeholders (Cotter et al., 2004; Hilborn, 2003). In the last 15 years, the need to develop simple data-driven harvest policies that are understood by all stakeholders has received increasing recognition (Cotter et al., 2004; Hilborn, 2012, 2003; Kelly et al., 2006; Prince et al., 2011).

In addition to the issues arising from the complex nature of modern assessment models, the collection and analysis of the extensive data required for these models can be prohibitively expensive (Berkes et al., 2001). Many fisheries are small-scale and data-poor, and lack the data and the funds required for conventional assessment techniques (Berkes et al., 2001; Mahon, 1997; Stanford et al., 2013). Furthermore, the necessary resources for full quantitative stock assessments of many low value fisheries and stocks are often not available. In recent years, research on developing assessment techniques for data-poor fisheries has increased, and a suite of tools is evolving for scientists and managers to assess and manage stocks with limited data (Kelly et al., 2006; Klaer et al., 2012; MacCall, 2009; Wayte and Klaer, 2010). However, many of these

* Corresponding author. Tel.: +61 8 9360 6685; fax: +61 8 9360 6303.
E-mail address: a.hordyk@murdoch.edu.au (A.R. Hordyk).

http://dx.doi.org/10.1016/j.fishres.2014.12.018

methods still require considerable amounts of data from the fishery or regarding the biology of the target species, including a time-series of historical catch, catch-per-unit-effort (CPUE) trends, or information on the age structure of the stock, all of which are difficult to obtain for many data-poor fisheries.

Hordyk et al. (2014a) linked the expected size composition of a stock under equilibrium conditions and various levels of exploitation to two ratios: the ratio of fishing mortality to natural mortality (F/M), and the ratio of natural mortality to the von Bertalanffy growth parameter (M/k). They demonstrated that, in the unfished state, the proportion of large fish in a stock is determined by the M/k ratio. For example, the unfished length structure of stocks with very low M/k (e.g., 0.3) is dominated by large individuals distributed around the asymptotic size (L_∞), while unfished stocks with high M/k (e.g., 3.0) are dominated by smaller fish and relatively few larger individuals, with few fish attaining the asymptotic size. Hordyk et al. (2014b) extended these ideas to develop a model to estimate the spawning potential ratio (SPR) from the length structure of the catch, referred to as the length-based SPR (LB-SPR) model.

In general, the SPR is defined as the ratio of the total reproductive production at equilibrium for a given level of fishing mortality divided by the reproductive production in the unfished state (Goodyear, 1993; Mace and Sissenwine, 1993; Walters and Martell, 2004). This metric is usually referred to as *static* or *equilibrium* SPR (Slipke et al., 2002), and represents the expected equilibrium SPR if a stock was held indefinitely at the given fishing mortality and recruitment was constant. It is a direct function of instantaneous fishing mortality (F), the selectivity of the fishery, and the maturity schedule for the species. The equilibrium SPR is the most commonly used form of SPR, and is often routinely estimated in stock assessment software (e.g., Stock Synthesis; Methot and Wetzel, 2013).

Another, less common, use of the term SPR is the *transitional* SPR, which refers to the current *per capita* reproductive output compared to that in the unfished state (Parkes, 2001). While static SPR is proportional to fishing mortality, the transitional SPR reflects the history of fishing pressure over the life-time of each of a population's component cohorts, and thus represents a moving average of the fishing mortality rates (Parkes, 2001; Slipke, 2010). At equilibrium, the static and transitional SPR are identical, but when the fishery is undergoing change, they will diverge. For example, if a stock was at equilibrium and overfished, the static and transitional SPR would both be the same. If managers decided to close the fishery, or significantly reduce catches to almost zero, F approaches 0 and the static SPR approaches 1 instantaneously, because if no catch is taken for an indefinite period, the stock will rebuild back to the unfished equilibrium condition. In reality, however, a number of years are required for the previously fished year classes to grow through the stock and be replaced by unfished cohorts so that the actual reproductive potential of the stock, as measured by the transitional SPR, recovers more slowly. Compared to the static SPR, the estimate of the transitional SPR may be a more useful metric as it provides an estimate of the current stock status rather than the expected equilibrium status of the stock. Like other length-based methods that estimate SPR, or its proxies on the basis of size composition (e.g., Ault et al., 2005; O'Farrell and Botsford, 2006, 2005), the LB-SPR method is expected to estimate transitional SPR better than the static SPR. This must be kept in mind whenever comparing the estimates of one of these methods to the output of models such as Stock Synthesis, which present the static SPR (Methot and Wetzel, 2013).

The LB-SPR model estimates the SPR by comparing the observed length structure to the expected unfished length composition and has the advantage of requiring only minimal data: i.e., a representative length sample of the stock and estimates of the life history parameters: the M/k ratio, the asymptotic length (L_∞), a measure of the variability in length-at-age ($CV_{L\infty}$), and estimates of the size at maturity (Hordyk et al., 2014a,b). Information on the length structure of an exploited stock is often one of the cheapest and easiest data sets to collect (Quinn and Deriso, 1999). Furthermore, the biological parameters required for the LB-SPR method (Hordyk et al., 2014a,b) can either be obtained with relatively simple biological studies, or "borrowed" from other similar species by meta-analysis (Prince et al., 2014). Because the LB-SPR model has few data requirements and is relatively simple to understand and apply, the method has potential as a valuable tool for the assessment and management of data-poor fisheries. For example, the technique has been enthusiastically received by the fishing community in the Pacific island nation of Palau. Local studies to determine the size-at-maturity parameters for tropical reef species identified a high proportion of immature fish in the catch, and very few individuals that were actually mature, resulting in legislated management changes to increase the size at capture and rebuild the SPR (Prince et al., 2015). In this study, simulation modelling was used to provide a proof-of-concept that the LB-SPR assessment method can be used in harvest control rules to iteratively adjust fishing effort levels so that stocks achieve a target SPR.

The use of harvest strategies, or management plans and procedures, that contain biological reference points and robust decision rules are becoming increasingly common in fisheries management around the world (Punt, 2006). Three essential elements of a formal harvest strategy include: a monitoring and data collection programme, an assessment routine, and one or more decision rules, which are also known as harvest control rules (Smith et al., 2008, 2014). Harvest strategies provide a transparent mechanism for scientifically linking changes in management to the estimated status of the stock (Punt, 2006; Smith et al., 2008, 2014). Harvest control rules (HCRs) are essential for quota-managed fisheries, and typically HCRs are used to determine the annual total allowable catch (TAC) or recommended biological catch (RBC) by comparing the estimate of the current biomass (B) or fishing mortality (F) with a reference point (e.g., B_{MSY} or F_{MSY}) (Smith et al., 2008). However, these harvest strategies are often data-intensive, and typically rely on the output of age-structured assessment models, conditioned on a time-series of catch data, together with an estimate of the current biomass, to provide a recommendation for the adjustment to the TAC. Furthermore, the calculation of biomass-based reference points requires detailed information on the biology of the species, including knowledge of the underlying stock–recruitment relationship, which can be difficult to estimate (Hilborn and Walters, 1992; Myers, 2001).

An alternative approach is to use a harvest strategy which does not have a pre-defined biomass-based reference point, but rather uses an iterative harvest control rule to incrementally adjust fishing mortality until the stock stabilises at a target level; analogous to the "*find which direction to go in and take a small step that way*" approach advocated by Graham (1956, as cited in Holt (2009)). For example, Prince et al. (2011) describe an approach which uses information on catch rate and size composition to iteratively adjust the level of catch until size indices stabilised at the target levels. Likewise, Klaer et al. (2012) describe a method which estimates the current exploitation rate from the mean length in the catch, and adjusts the annual quota according to the ratio of the estimated and target exploitation rates. However, both these methods require estimates of total catch, the natural mortality rate, and CPUE trends, which are difficult to obtain in many data-poor fisheries.

This study uses a management strategy evaluation (MSE) framework to develop and explore a harvest strategy that uses a harvest control rule and the LB-SPR assessment method to iteratively adjust fishing effort until the stock stabilises at the target level for SPR. It demonstrates that without estimates of catch and effort, biomass or the current exploitation rate, an incremental harvest strategy based entirely on monitoring size composition data can rebuild or fish-down a stock and stabilise it around a selected SPR reference point.

2. Methods

2.1. Harvest strategy

The length-based harvest strategy described in this paper involves the empirical estimation of the stock status together with a harvest control rule to iteratively adjust the level of fishing effort until the stock has stabilised around a target level. The application of the length-based harvest strategy has three main components:

1. an assessment method that uses length composition data to estimate the current stock status (current SPR);
2. a suitable SPR target that results in an equilibrium spawning stock biomass at a biologically sustainable level, while simultaneously providing a sufficient level of catch; and
3. an iterative harvest control rule (HCR) that adjusts fishing effort in each year in response to the difference between the estimated SPR and the target SPR.

The harvest strategy uses length composition data to estimate the current SPR of the exploited stock, which, when compared to a target level, is used to adjust the level of fishing effort by a certain amount in the appropriate direction; i.e., increasing, decreasing, or not changing the fishing effort, depending on the estimated SPR compared to the target level. Once stabilised at the target level, this approach effectively results in a constant fishing mortality (F) harvest policy and catches would be expected to be a constant proportion of the population, with annual fluctuations that reflect variability in the available biomass.

2.1.1. Estimation of current SPR

The harvest strategy developed and tested in this study uses the recently developed LB-SPR model to estimate the SPR from the observed size composition of the catch. The inputs to the LB-SPR model are: M/k, the mean asymptotic length (L_∞), the coefficient of variation of the asymptotic length ($CV_{L\infty}$), as well as parameters for the size-at-maturity (L_{50} and L_{95}, which correspond to the lengths at which 50% and 95% of the stock are expected to be mature). Given assumed values for the M/k and L_∞ parameters and length composition data from the catch of an exploited stock, the LB-SPR model uses maximum likelihood methods to simultaneously estimate the selectivity-at-length parameters, assumed to follow a logistic curve, and the relative fishing mortality (F/M), which are then used to calculate the SPR (Hordyk et al., 2014a,b).

Like many length-based methods, the LB-SPR model is an equilibrium based method, and relies on a number of important assumptions, including: (i) stock is in steady state, with constant recruitment, (ii) natural mortality and growth rates are constant for fish that are vulnerable to the fishery, (iii) selectivity has an asymptotic form, (iv) growth is adequately described by the von Bertalanffy equation, (v) both sexes have the same growth curve and the sex ratio of the catch is parity, or the model uses the biological parameters and length composition of female fish only, and (vi) the lengths-at-age are normally distributed. Furthermore, simulation testing of the LB-SPR model has shown that it is sensitive to non-equilibrium population dynamics, particularly high variability in recruitment, and miss-specification of the life history parameters, especially variation in the asymptotic length (Hordyk et al., 2014a,b).

In the length-based harvest strategy described in this paper, the LB-SPR assessment model was applied to length composition data of the catch at the end of each year. Violations of the assumptions of the LB-SPR method, in particular the equilibrium assumptions, can result in considerable error in the estimates of SPR (Hordyk et al., 2014a,b). In the LB-SPR model the stock status in each year is estimated independently of the stock status in previous years. To account for some of the uncertainty in the estimated SPR, after the first five years, the annual estimates of SPR were smoothed by an exponentially weighted five-year moving average.

2.1.2. Target SPR level

Ideally, the SPR target should be such that the spawning stock biomass (SSB) is maintained at a sustainable level, while still providing a reasonable level of catch (Clark, 2002). The relationship between SPR and the equilibrium SSB depletion level ($\%SSB_0$) is determined by the steepness parameter (often denoted as h) in the stock–recruitment model. Assuming a stock–recruit relationship that is described by the Beverton–Holt model, depletion can be described by:

$$\%SSB_0 = \frac{4h\text{SPR} + h - 1}{5h - 1} \tag{1}$$

If the steepness is equal to 1 (i.e., recruitment is completely independent of the size of the spawning stock biomass), under equilibrium conditions, the $\%SSB_0$ and SPR are equivalent (Cordue, 2012; Walters and Martell, 2004). The steepness parameter can also be used to calculate the level of SPR that corresponds to the extinction of the stock ($\%SSB_0 = 0$) (Brooks et al., 2010).

The stock–recruitment relationship and the steepness parameter are difficult to estimate and unlikely to be known with any certainty for data-poor stocks. Several studies have explored the levels of SPR to be used as reference points, and it is generally accepted that a SPR of 35–40% is sustainable for most species (Clark, 2002, 1993; Mace and Sissenwine, 1993), although a risk-adverse target SPR may be higher for species thought to have low steepness (e.g., Dorn, 2002). For this study, the SPR target (SPR_{targ}) was set to 0.40, which corresponds to a %SSB of ~30–40% for the most commonly observed values of steepness ($h \geq 0.6$; (Clark, 2002; Myers et al., 2002).

2.1.3. Harvest control rule

The harvest control rule (HCR) is an important component of the harvest strategy. The HCR developed and tested in this study was an iterative effort-based harvest control rule, which the fishing effort at the beginning of each year was adjusted by the recursive equation:

$$E_t = E_{t-1}V_t \tag{2}$$

where E_t is the level of fishing effort in year t, and V_t is the effort modifier, calculated at the beginning of year t, and defined by:

$$V_t = \varphi_1\left(\frac{\text{SPR}_{\text{curr}}}{\text{SPR}_{\text{targ}}} - 1\right)^3 + \varphi_2\left(\frac{\text{SPR}_{\text{curr}}}{\text{SPR}_{\text{targ}} - 1}\right) \tag{3}$$

where SPR_{curr} is the smoothed estimate of SPR from year $t-1$, and φ_1 and φ_2 are parameters that control the slope and shape of the harvest control rule. To avoid large changes in effort over short periods of time, the maximum change in fishing effort in any year in either direction was set to 30%.

The shape and slope of the HCR are flexible, and to explore the properties of this iterative HCR we examined three sets of HCRs; referred to as the "linear", "cubic" and "cubic polynomial" HCRs. As the name suggests, the Linear HCR, which is obtained by setting φ_1 to zero, had a constant slope, where effort was increased or decreased as a linear function of the estimated SPR. We explored five different slopes for the Linear HCR ($\varphi_1 = 0$, $\varphi_2 = 0.1 - 0.3$ in increments of 0.05; Fig. 1a). A harvest control rule that decreases

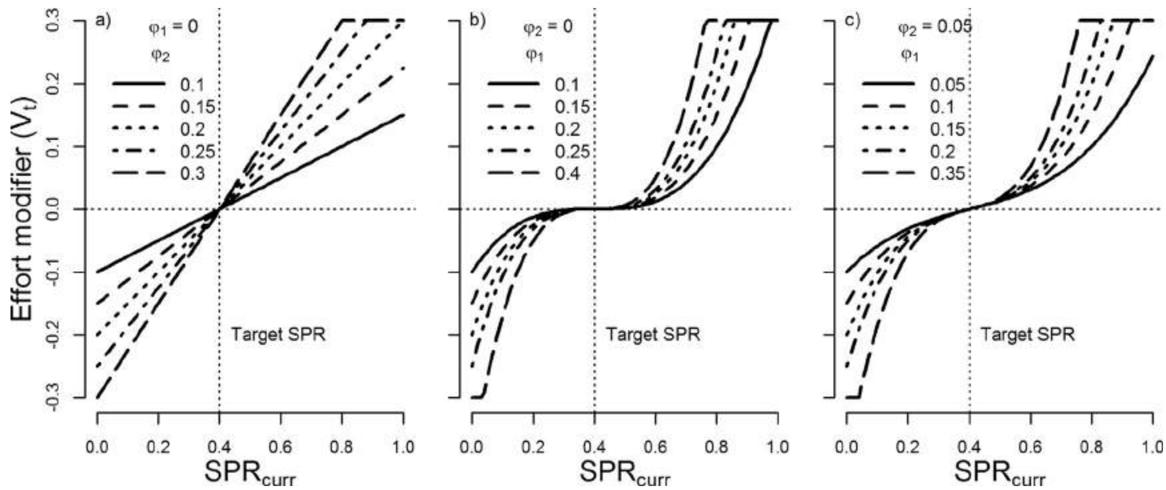

Fig. 1. The three sets of harvest control rules (HCR) examined in the management strategy evaluation based on: (a) the linear HCR, (b) the cubic HCR and (c) the cubic polynomial HCR. The performance of the length-based iterative harvest strategy was evaluated with five different slopes at the origin for each set of HCRs.

the rate of change in fishing effort as the estimated SPR approaches the target may be more appropriate than a linear control rule, and we explored the behaviour of the model with the Cubic HCR with five different slopes (φ_1 ranging from 0.1 to 0.4, $\varphi_2 = 0$; Fig. 1b). One potential weakness of the Cubic function is that the slope of the curve approaches zero as the estimated SPR approaches the target (Fig. 1b). The final set of HCRs that we examined was based on a cubic polynomial function. This HCR was similar to the Cubic HCR except that the φ_2 parameter was set to 0.05 (i.e., increased slope near the target SPR; Fig. 1c).

Although many other variations of the HCR are possible, we concentrated on these three sets to explore the general behaviour of the iterative harvest strategy. These values for the control rule parameters were selected to cover a range of different shaped HCRs, from a rule where the value of the effort modifier ranges from ±10% when the stock is estimated to be at low or high levels of SPR, to a rule where effort is modified by ±30% at lower or higher levels of SPR (Fig. 1).

2.2. Management strategy evaluation

We used a typical MSE, comprised of four main components: (i) an operating model (OM) that describes the population dynamics, (ii) a data generation model that simulates the collection of data from the fishery, (iii) an assessment model that assesses the stock status, and (iv) a management model that implements a harvest control rule which feeds back to influence the population dynamics (Fig. 2).

2.2.1. Operating model

The population dynamics were modelled with a single-gender, age-structured model, with the assumption that the population is closed with respect to immigration and emigration. The time component of the operating model was on a quarterly basis (i.e., every three months), with recruitment occurring at the beginning of the third quarter each year. The operating model was run for an initial period of 100 years, with random annual recruitment deviations and a constant fishing mortality rate. The model was then projected forward for 60 years (i.e., 240 quarters), with the LB-SPR assessment methodology and the iterative harvest control rule applied on an annual basis.

The abundance, N, of animals at age a in quarter t is given by:

$$N_{a,t} = \begin{cases} R_t & \text{if } a = 1 \\ N_{a-1,t-1} e^{Z_{a-1}} & \text{if } 1 < a \le a_{\max} \end{cases} \quad (4)$$

where both a and t are in quarter–annual time-steps, R_t is the recruitment at time t, Z_a is the total mortality for age-class a, and $a_{\max}$ is the maximum age. The initial recruitment (R_0) was set to one million individuals.

Total mortality at age is given by:

$$Z_a = M + S_a F \quad (5)$$

where M is the quarterly instantaneous natural mortality rate (assumed independent of age and size), S_a is the selectivity at age a, and F is the quarterly instantaneous rate of fishing mortality.

Maximum age (in quarters) was calculated by:

$$a_{\max} = \frac{-\ln(0.01)}{M} \quad (6)$$

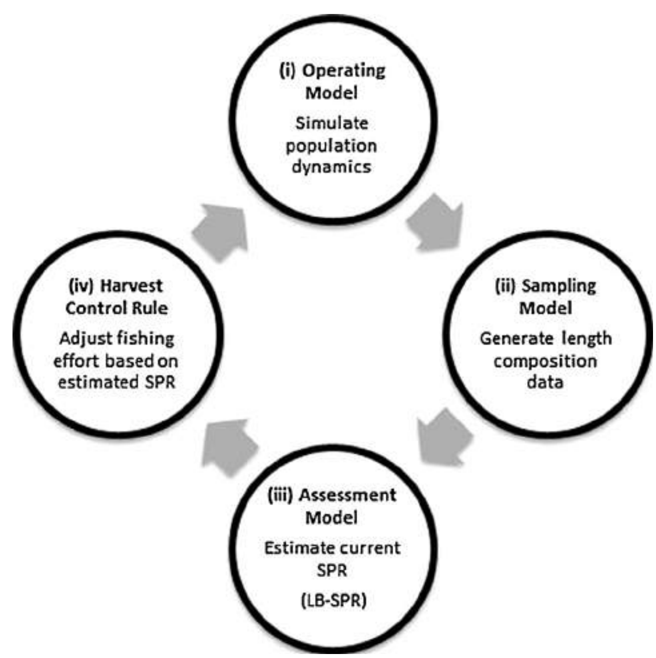

Fig. 2. Flow chart describing the management strategy evaluation process used in this study to investigate the utility of the length-based spawning potential ratio assessment methodology (LB-SPR) as a suitable tool for the management of data-poor fisheries. SPR = spawning potential ratio.

The catch-at-age (C_a) was calculated using the Baranov equation:

$$C_{a,t} = \frac{F_a}{Z_a} N_{a,t}(1 - e^{Z_a}) \quad (7)$$

Recruitment was assumed to be described by the Beverton–Holt stock–recruitment function with log-normally distributed recruitment deviations (σ_r), with recruitment occurring at the beginning of third quarter of each year:

$$R_t = \begin{cases} \dfrac{\mathrm{SSB}_{t-1}}{\delta + \rho \mathrm{SSB}_{t-1}} e^{\epsilon_t - (\sigma_R^2/2)} & \text{if}(t+1) \bmod 4 = 0 \\ 0 & \text{if}(t+1) \bmod 4 \neq 0 \end{cases} \quad (8)$$

where SSB_t is the spawning stock biomass at time t, δ and ρ are parameters of the stock–recruit function, and ε_t is the recruitment residuals at time t that is normally distributed with mean 0 and variance σ_R^2. The δ and ρ parameters were re-parameterised in terms of steepness (h), which is defined as the fraction of virgin recruitment R_0 obtained when the spawning biomass is 20% of the unfished spawning biomass. For this study, steepness was assumed to be 0.7.

Maturity-at-length (Mat_l) was modelled as:

$$\mathrm{Mat}_l = \frac{1}{1 + \exp((-\ln(19)(l - L50))/(L_{95} - L_{50}))} \quad (9)$$

where L_{50} and L_{95} are the length at which 50% and 95% of the individuals are mature respectively. Maturity-at-length was converted to maturity-at-age (Mat_a) by:

$$\mathrm{Mat}_a = \int_{l=0}^{l=\infty} \mathrm{Mat}_l \frac{1}{\sigma_{La}\sqrt{2\pi}} e^{-(l-La)^2/2\sigma_{L_a}^2} \quad (10)$$

where $\sigma_{L_a}^2$ is the variance of length-at-age a. Selectivity was assumed to be asymptotic and size-dependant, and was modelled by replacing L_{50} and L_{95} in Eq. (9) with the lengths at 50% and 95% selection (S_{L50} and S_{L95}).

Length-at-age (L_a) was modelled with the three-parameter von Bertalanffy function:

$$L_a = L_\infty(1 - e^{-k(a-t_0)}) \quad (11)$$

where L_∞ is the mean asymptotic length, k is the growth coefficient, and t_0 is the theoretical age when length is zero (assumed to be equal to zero for this study). Variation of length-at-age was assumed to be normally distributed, with variance increasing with increased mean length:

$$\sigma_{L_a}^2 = \sigma_{L_\infty}^2 (1 - e^{-k(a-t_0)})^2 \quad (12)$$

$$\sigma_{L_\infty}^2 = (CV_{L_\infty} L_\infty)^2 \quad (13)$$

Spawning stock biomass was calculated as:

$$\mathrm{SSB}_t = \sum_a N_{a,t} \mathrm{Mat}_a W_a \quad (14)$$

where W_a is the mean weight-at-age, calculated by:

$$W_a = \alpha L_\alpha^\beta \quad (15)$$

where α and β are constants. Egg production at age EP_a was assumed to be proportional to weight:

$$\mathrm{EP}_a \propto \mathrm{Mat}_a W_a \quad (16)$$

Fishing mortality (F) at full selectivity was assumed to be linearly related to effort (E), with log-normally distributed error on the catchability coefficient (q):

$$F_t = E_t q e^{\varepsilon_q - \sigma_q^2/2} \quad (17)$$

where $\varepsilon_q \sim N(0, \sigma_q^2)$ and $\sigma_q = 0.2$. The model was not tuned to real data, and the q parameter was set to an arbitrary value of 0.1. Likewise, the effort was defined on an arbitrary scale, with the initial effort determined from the initial fishing mortality.

The transitional SPR was calculated in each time step as:

$$\mathrm{SPR}_t = \frac{\sum_a \mathrm{EP}_a N_a / R_{t-a+1}}{\sum_a \mathrm{EP}_a e^{-\mathrm{M}a}} \quad (18)$$

2.2.2. Data generation

The data collection model assumed that the lengths of 1000 individuals were randomly sampled from the catch at the end of each year. The sampled catch-at-age data were generated by summing the quarterly catch-at-age data for the year, and then sampling 1000 ages with the probability of each age corresponding to the proportion of each age in the catch.

An age-length transition matrix of the population was constructed from the assumptions of mean length-at-age and the variation of length-at-age, where the probability of an individual at age a being in length class i is given by:

$$P_{i,a} = \begin{cases} \phi\left(\dfrac{l_{i+1}^{\mathrm{lo}} - L_a}{\sigma_{L_a}}\right) & \text{if } i = 0 \\ \phi\left(\dfrac{l_{i+1}^{\mathrm{lo}} - L_a}{\sigma_{L_a}}\right) - \phi\left(\dfrac{l_i^{\mathrm{lo}} - L_a}{\sigma_{L_a}}\right) & \text{if } 1 < i \le I \\ 1 - \phi\left(\dfrac{l_i^{\mathrm{lo}} - L_a}{\sigma_{L_a}}\right) & \text{if } i = I \end{cases} \quad (19)$$

where ϕ is the standard normal cumulative distribution, l_i^{lo} is the lower bound of length class i, and I is the total number of length classes. The width of the size classes was 5 mm, with the upper bound of the maximum size class set to $1.5L_\infty$ (rounded to the upper 5 mm).

The age-length probability matrix of the catch $\dot{P}$ was calculated by modifying P to account for the selectivity-at-length by multiplying the age-transition matrix by the selectivity-at-length class i (S_i; calculated using a formula similar to Eq. (9)) and re-standardising so that the probability of an individual at age a being in one of the I length classes was 1:

$$\dot{P}_{i,a} = \frac{P_{i,a} S_i}{\sum_a P_{i,a} S_i} \quad (20)$$

Finally, the size composition of the sampled catch at time t was generated by randomly sampling with replacement for each age in the catch from the catch length-at-age matrix $\dot{P}$.

2.2.3. Test species

The M/k ratio is a major determinant of the shape of the unfished size composition in populations under equilibrium (Hordyk et al., 2014a,b; Prince et al., 2014), and the biological parameters for the MSE were based on three species that covered a range of M/k ratios (Table 1): (i) Pacific mackerel (*Scomber japonicus*), a small pelagic species that is wide-spread throughout the Indo-Pacific with $M/k = 1.5$, a population dominated by small individuals and growth that continues through life (Carvalho et al., 2002), (ii) the silver warehou (*Seriolella punctata*), a demersal species caught off south-eastern Australia and New Zealand, with $M/k = 0.97$, a population which, in the unfished state, has a mix of individuals distributed across all size classes and growth that reaches an asymptote (Day et al., 2012), and (iii) crimson snapper (*Lutjanus erythropterus*) a long-lived reef species that is wide-spread throughout the Indo-West Pacific, with $M/k = 0.36$, a population with an accumulation of fish at maximum size and growth that reaches an asymptotic size relatively early in life (McPherson et al., 1992; Newman et al., 2000) (Table 1). For simplicity, these species are

Table 1
The biological and selectivity parameters for the three test species (Species I: Pacific mackerel *Scomber japonicus*[a]; Species II: Silver warehou *Seriolella punctata*[b]; Species III: Crimson snapper *Lutjanus erythropterus*[c]) used in the management strategy evaluation of the length-based iterative harvest strategy.

Parameter	Test species			
	I	II	III	Definition
L_∞ (mm)	575.2	504.1	584.8	Asymptotic size
$CV_{L\infty}$	0.1	0.1	0.1	Coefficient of variation of L_∞
M	0.3	0.3	0.14	Natural mortality
k	0.2	0.31	0.39	von Bertalanffy growth coefficient
M/k	1.50	0.968	0.359	M/k ratio
A_{max}	15	15	33	Maximum age (in years) used in the model. $A_{\max}$ was calculated from M
L_{50}	277.8	370	468	Length at 50% maturity
L_{95}	308	400	480	Length at 95% maturity
L_{S50}	194	259	327	Length at 50% selectivity
L_{S95}	246	320	384	Length at 95% selectivity

Data from:
[a] Carvalho et al. (2002).
[b] Day et al. (2012).
[c] McPherson et al. (1992) and Newman et al. (2000).

referred to throughout this study as Species I, II and III respectively. These species were chosen to represent species showing a range of M/k values from the Beverton–Holt Life History Invariant (BH-LHI) ratio of 1.5 (Jensen, 1996) to those with a much lower M/k of 0.36 (Table 1). To ensure that the catch contained a reasonable number of length classes, the selectivity-at-length curve was shifted towards smaller fish than the maturity-at-length curve for each species, and assumed constant for each species across scenarios.

2.2.4. Scenarios considered in the MSE

Five different scenarios were considered for each species, with each scenario consisting of a set of specifications for the operating model (Table 2). The first two scenarios compare two different levels of initial equilibrium stock levels; Scenario 1 the low initial stock equilibrium (SPR = 0.15) and Scenario 2 the high initial stock equilibrium (SPR = 0.85). The aim in evaluating these two scenarios is to test the behaviour of the iterative HCR in conditions that involve both rebuilding and fishing-down to the target level of SPR.

Sensitivity testing of the LB-SPR assessment model identified that the method is sensitive to violations of the equilibrium assumption, with increased recruitment variability resulting in increased error in the estimates of SPR (Hordyk et al., 2014a,b). The iterative HCR uses estimates of the current SPR from the LB-SPR method, and any error or bias in these estimates are likely to impact the performance of the iterative harvest strategy. Thus Scenarios 3 and 4 examined the the consequences of increased violations of the equilibrium assumption by: increasing recruitment variability in the operating model (Scenario 3) and auto-correlating recruitment error (Scenario 4).

The HCR we describe adjusts fishing effort in relation to size composition targets, however, it is widely recognised that the measures used for managing fishing effort can be counter-acted by the incentives for fishers to increase their own fishing efficiency when management is based on effort quotas. Thus in Scenario 5, we examined the impact of increasing catchability (q) on the capability of the HCR to iteratively adjust and maintain fishing effort at levels corresponding to the SPR target. In this scenario, the catchability parameter was increased by cumulative lognormal random increments of mean 5% every 5 years:

$$q_y = 1.05 q_{y-5} e^{\dot{\varepsilon}_q - \dot{\sigma}_q^2/2} \quad \text{for } y = 6, 11, 16, \ldots \tag{21}$$

where $\dot{\varepsilon}_q \sim N(0, \sigma_q^2)$ and $\dot{\sigma}_q = 0.05$.

2.2.5. Comparison and performance of HCRs

The relative performance of the 15 different HCRs (Fig. 1) was examined by running one hundred iterations of the model for each of the three test species, using each HCR, for both Scenarios 1 and 2, and comparing the trajectory of the transitional SPR over the 60-year projection period. The results of this comparison were used to select a particular set of control rule parameters (φ_1 = 0.20 and φ_2 = 0.05), and one hundred iterations of the model were then run for the remaining scenarios (Table 2). The rationale for choosing this set of parameters was based on the criteria of minimising the amount of time for the stock to first reach the target level, while simultaneously minimising the risk of overshooting the SPR target, and this particular parameterization of the HCR appeared to perform well for the three test species (see Section 3). The median, 5th and 95th percentiles of the transitional SPR over the projection period were calculated for each scenario, and the relative error of the estimated model outputs (F/M, SPR, and the two selectivity parameters) in the final year of the projection period were calculated to compare the relative performance of the iterative length-based harvest strategy under the five scenarios.

3. Results

3.1. Behaviour of the harvest control rules for Scenarios 1 and 2

The results of the comparison of the three sets of harvest control rules for Scenarios 1 and 2, the low and high initial stock scenarios respectively, are summarised by time-trajectories (median, 5th and 95th percentile) of the transitional SPR values from the operating model. At low starting stock size (Scenario 1), each parameterization of the iterative HCR was successful in reducing effort and rebuilding the fishery towards the SPR target level. At high starting stock abundances (Scenario 2) the HCR likewise successfully increased fishing effort and reduced the SPR to the target level (Figs. 3–5).

The pattern of the SPR trajectories for each of the three species was broadly similar with respect to each HCR, with all displaying a direct relationship between the slope of the harvest control rule and the number of years for the SPR to first reach the target level. Although the stock was rebuilding, it failed on average to reach the target SPR level for all three species within the 60 year projection period when the two curves of the Cubic HCR with the lowest slope (φ_1 = 0.10 and 0.15) were used with the low initial stock (Scenario 1; Figs. 3f and g, 4f and g and 5f and g). Conversely, the linear HCR with the steepest slope resulted in the stock first reaching the target level in the shortest time, approximately 10 years for all three species under both Scenario 1 (low initial stock) and Scenario 2 (high initial stock; Figs. 3e, 4e and 5e).

Table 2
The five scenarios used in the management strategy evaluation of the length-based iterative harvest strategy for the three test species with different life history strategies (see Table 1).

Scenario	Description	σ_R	Initial SPR	Rationale
1	Low initial stock equilibrium and moderate recruitment variability	0.6	0.15	Examine performance of the LB-SPR assessment method and the iterative HCR to rebuild over-fished stock to SPR target level.
2	High initial stock equilibrium and moderate recruitment variability	0.6	0.85	Examine performance of the LB-SPR assessment method and the iterative HCR to fish down stock to SPR target level.
3	Low initial stock equilibrium and increased recruitment variability	0.9	0.15	Examine sensitivity of the LB-SPR assessment method and the iterative HCR to increased violations of the equilibrium assumption.
4	Low initial stock equilibrium and auto-correlated recruitment variability	0.6	0.15	As Scenario 3, examine impact of increased violations of the equilibrium assumption.
5	Low initial stock equilibrium, moderate recruitment variability, and increasing catchability by cumulative lognormal random increments every 5 years	0.6	0.15	Examine effect of increasing catchability on the performance of the iterative HCR.

In many of the simulations, the SPR of the stock tended to overshoot the target before returning towards, and continuing to oscillate around, the target. This feature of the iterative rule was especially pronounced with the steeper linear HCRs, and the magnitudes of the oscillations were distinctly greater for Species III (Fig. 5c–e), which had the lowest *M*/*k* and the longest lifespan compared with Species I and II.

The tendency to overshoot the target was much less marked for the HCRs based on the cubic and cubic polynomial HCRs, or the linear HCR with a low slope (Figs. 3a, b, f–o, 4a, b, f–o and 5a, b, f–o). The cubic HCR performed similarly across the three species. However, many of the SPR trajectories under this rule tended to stabilise slightly below the SPR target (Figs. 3f–j, 4f–j and 5f–j). The increased slope of the cubic polynomial HCR around the target SPR appeared

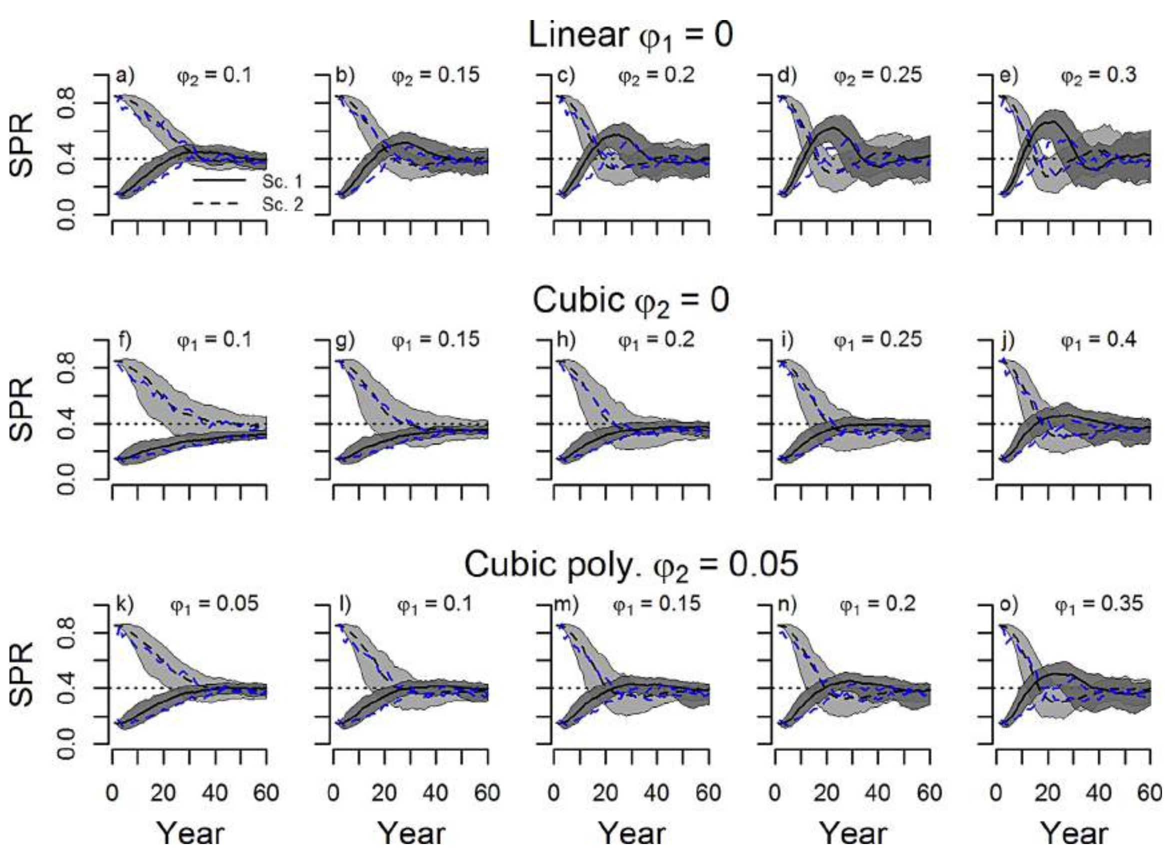

Fig. 3. The trajectories (median, 5th and 95th percentiles) of the transitional SPR of Species I (*M*/*k* = 1.5, *Scomber japonicus*) for Scenario 1 (low initial stock equilibrium (SPR = 0.15), median as solid black line and dark grey shading showing 5th and 95th percentiles) and Scenario 2 (high initial stock equilibrium (SPR = 0.85), median as dashed black line and light grey shading showing 5th and 95th percentiles) for the 15 different harvest control rules shown in Fig. 1(a–e) the linear HCR, (f–j) the Cubic HCR, and (k-o) the cubic polynomial HCR. The median estimated SPR for Scenarios 1 and 2 are shown as dashed blue lines. (For interpretation of the references to color in this legend, the reader is referred to the web version of the article.)

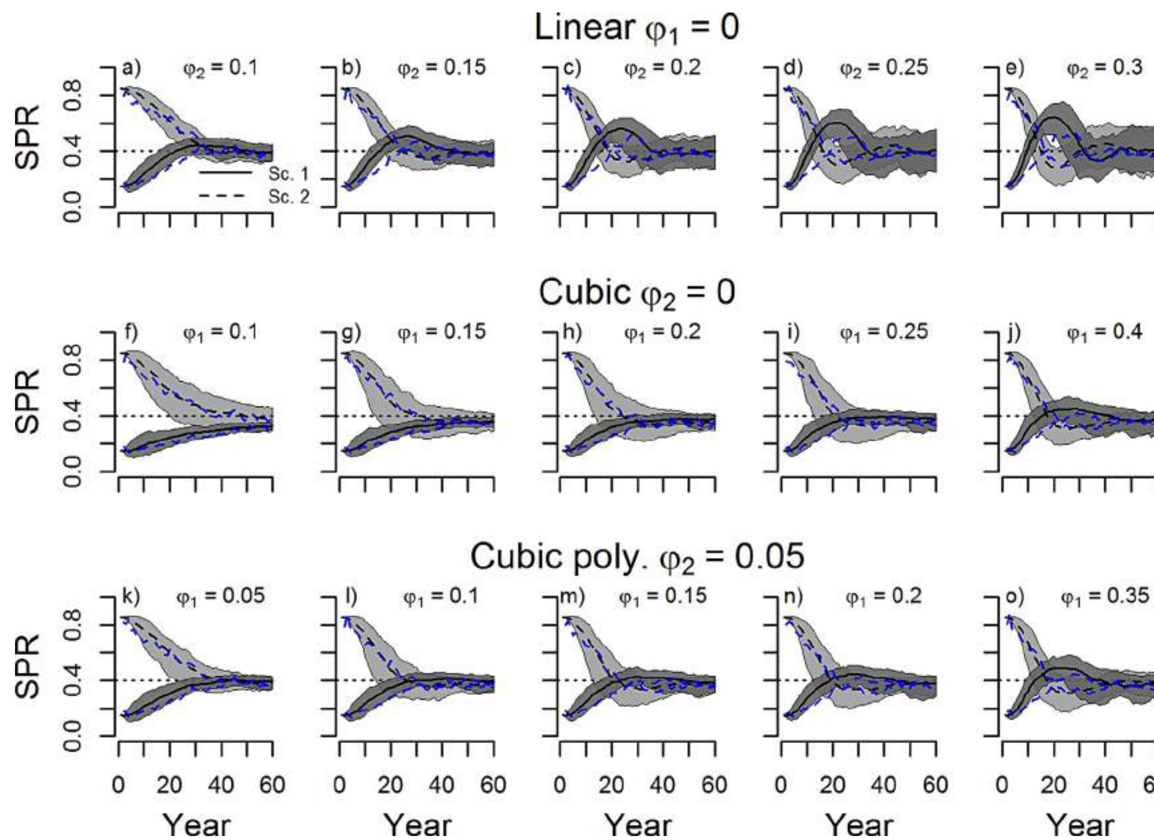

Fig. 4. The trajectories (median, 5th and 95th percentiles) of the transitional SPR of Species II (M/k = 0.968, *Seriolella punctata*) for Scenario 1 (low initial stock equilibrium (SPR = 0.15), median as solid black line and dark grey shading showing 5th and 95th percentiles) and Scenario 2 (high initial stock equilibrium (SPR = 0.85), median as dashed black line and light grey shading showing 5th and 95th percentiles) for the 15 different harvest control rules shown in Fig. 1: (a–e) the linear HCR, (f–j) the Cubic HCR, and (k–o) the cubic polynomial HCR. The median estimated SPR for Scenario 1 and 2 are shown as dashed blue lines. (For interpretation of the references to color in this legend, the reader is referred to the web version of the article.)

to rectify this issue, with the SPR of the stock tending to gradually rebuild (Scenario 1) or decrease (Scenario 2), before stabilising at or close to the target level (Figs. 3k-o, 4k-o and 5k-o).

The longer lifespan of Species III compared to the other two species means that a longer time period is required for the stock to reach equilibrium and the stock tends to oscillate around the target, especially when a steeper HCR was used (Fig. 5). However, the magnitude of the oscillations tended to decrease with time, and would be expected to gradually stabilise near the target level.

The LB-SPR assessment method appeared to track the transitional SPR reasonably well, with the median estimated SPR following the median transitional SPR in most cases (dashed blue lines in Figs. 3–5). In particular, the method appeared to track the transitional SPR very well during the fish down phase of Scenario 2 (high initial stock). However, there was a distinct lag between the estimated SPR and the transitional SPR during the rebuilding phase (Scenario 1), especially when a steeper HCR was used (e.g., Figs. 3e, 4e and 5e). This lag between the estimated and actual SPR during the rebuilding phase would contribute to the considerable overshooting of the target observed in these simulations.

The comparison of the harvest control rules demonstrates that a trade-off exists between the various parameterizations of the rule. A steep-sloped linear harvest control rule results in the quickest time for the stock to reach the target level, but also results initially in a considerable overshoot of the SPR target, as well as a longer time for the stock to reach equilibrium. Additionally, the rapid response of the steep HCR results in a lag between the estimated and transitional SPR, and higher variability in the SPR of the stock. While deciding on an optimum HCR would require a clear specification of management objectives, the cubic polynomial family of HCRs appeared to perform the best in terms of the trade-off between reaching the SPR target in the quickest time, and minimising fluctuations around the target. The fourth curve of this set (φ_1 = 0.20 and φ_2 = 0.05; Figs. 3n, 4n and 5n) was used to examine the performance of the iterative harvest strategy under the remaining scenarios presented in Table 2.

3.2. Relative performance under additional scenarios

The results of the projections using the cubic polynomial HCR with φ_1 = 0.20 and φ_2 = 0.05 are presented as time-trajectories (median, 5th and 95th percentiles) of the actual SPR of the operating model (solid lines and dark grey shading) and the estimated SPR from the LB-SPR model (dashed lines and light grey shading) (Fig. 6).

While the estimated SPR from the LB-SPR method for the three species varied considerably (Fig. 6 light grey shading), the actual SPR of the operating model was much less variable (Fig. 6 dark grey shading), and the iterative method appeared to successfully adjust fishing effort until the stock approached the SPR target level.

With the low initial stock size (Scenario 1), the iterative harvest control rule rebuilt the stock to the target level in approximately 20 years (Fig. 6a, f and k). During the rebuilding phase, the estimated SPR tended to lag behind the transitional SPR, but the two measures of SPR appeared to converge after approximately 28 years for Species I and II (Fig. 6a and f) and 41 years for Species III (Fig. 6k). By the end of the 60 year projection period, the SPR of Species I and II stabilised just below the target level (Fig. 6a and f). In contrast, the SPR of Species III had not stabilised at the end of 60 years, although it was very close to the target level (Fig. 6k).

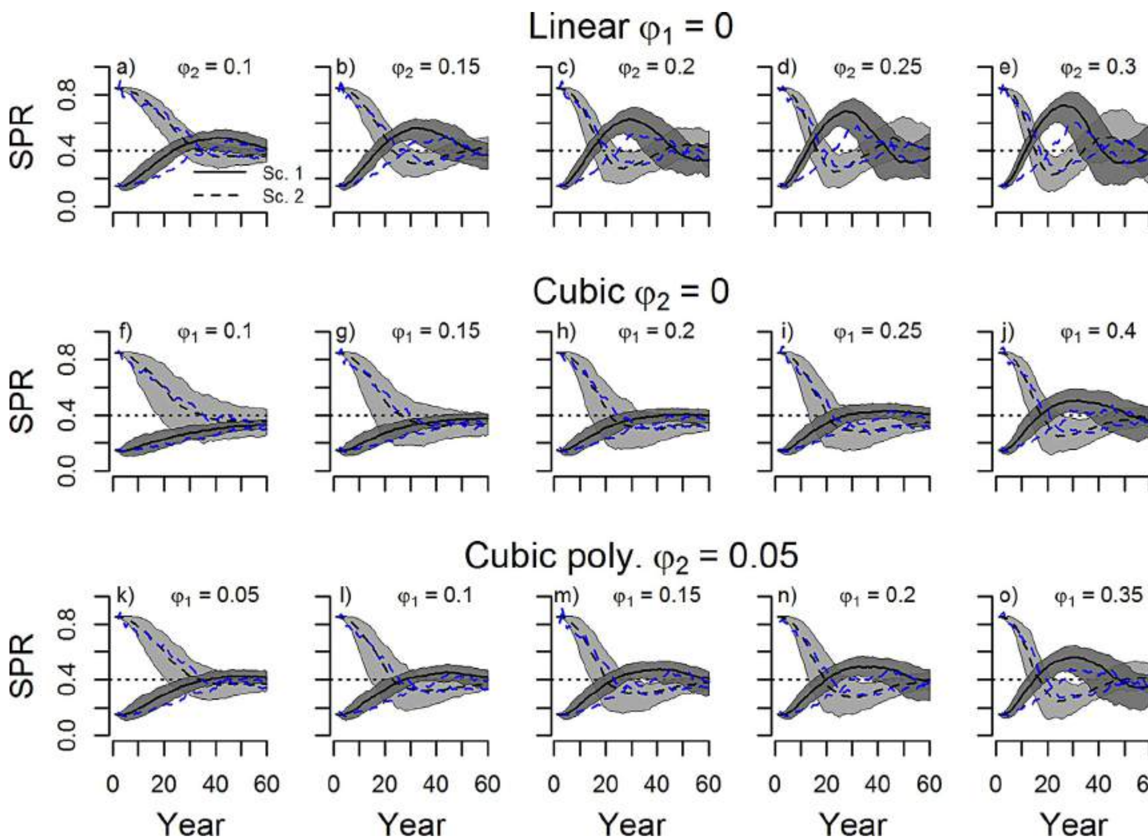

Fig. 5. The trajectories (median, 5th and 95th percentiles) of the transitional SPR of Species III (M/k = 0.359, *Lutjanus erythropterus*)for Scenario 1 (low initial stock equilibrium (SPR = 0.15), median as solid black line and dark grey shading showing 5th and 95th percentiles) and Scenario 2 (high initial stock equilibrium (SPR = 0.85), median as dashed black line and light grey shading showing 5th and 95th percentiles) for the 15 different harvest control rules shown in Fig. 1: (a–e) the linear HCR, (f–j) the cubic HCR, and (k–o) the cubic polynomial HCR. The median estimated SPR for Scenarios 1 and 2 are shown as dashed blue lines. (For interpretation of the references to color in this legend, the reader is referred to the web version of the article.)

The LB-SPR assessment method appeared to track transitional SPR better during the fish down phase of the high initial stock size (Scenario 2), with the iterative harvest control rule successfully increasing fishing effort until the stock approached the target level (Fig. 6b, g and l). In Scenario 2, the declining transitional SPR of the operating model tended to overshoot the SPR target, especially for the low M/k species (Species III) (Fig. 6l), before rebuilding to the target. Furthermore, the LB-SPR model appeared to underestimate the SPR of the stock in the early years of the projection period when the actual SPR of the stock was at high levels (Fig. 6b, g and l).

Scenarios 3 and 4 involved increased recruitment variability (σ_r = 0.9) and auto-correlated error in the recruitment trends respectively. The behaviour of the model was similar for these two scenarios, and was characterised by an increase in the variability in both the estimated and 'actual' transitional SPR (Fig. 6c, d, h, i, m and n). The LB-SPR model tended to under-estimate SPR, especially for Scenario 3 and Species III (low M/k), which resulted in the final transitional SPR of the stock being above the target (Fig. 6m). However, the SPR of all three species rebuilt to the target level in 20–25 years for these two scenarios, and the final SPR was at or above the target level.

The final scenario (Scenario 5) included a step-up in the catchability coefficient every five years. The estimated SPR appeared to track the transitional SPR of the operating model reasonably well, and the median transitional SPR reached the target level in just over 20 years for Species I and II, before declining and stabilising slightly below the target by the end of the 60 year projection period (Fig. 6e and j). Species III showed a similar trend, with the median SPR of the stock increasing above the target SPR level in years 25–40, before declining back down below the target (Fig. 6o). The median SPR in the final year was close to the target level however, indicating that the iterative harvest strategy was successful in recovering the overfished stock, but that given the increasing fishing effort over time, the harvest control rule was not re-active enough to complete the recovery.

For Species I (*S. japonicus*), the median relative error in the estimate of F/M in the final year of the projection period (year 60) was close to zero for most of the scenarios, although the model tended to over-estimate F/M, especially with increased recruitment variability, Scenario 3 (Fig. 7a). Corresponding to these estimates, the median relative error in SPR was under-estimated slightly, with particularly high variability in Scenarios 3 and 4 (increased and auto-correlated recruitment variability respectively; Fig. 7b). In general, the results of the LB-SPR model in the final year for Species II (*S. punctata*) were similar to those for Species I (Fig. 7e, f, g and h). The relative error in F/M for Species II was most pronounced for Scenario 3 (increased recruitment variability) (Fig. 7e). Likewise, the relative error in the estimates of SPR for this scenario demonstrate that the model tended to under-estimate the SPR of the stock, and hence was conservative, when recruitment variability was increased (Fig. 7f). As for Species I and II, with Species III (*L. erythropterus*), the LB-SPR model tended to over-estimate F/M and under-estimate the SPR for the scenario with increased recruitment variability (Scenarios 3; Fig. 7i and j). In Scenario 4 (auto-correlated recruitment deviations) the LB-SPR model tended to slightly under-estimate the F/M and over-estimate the SPR, although the final median estimated SPR was still close to the actual SPR of the stock (Fig. 7i and j). The median relative error for the final year for the three test species in the two selectivity parameters (SL_{50} and SL_{95}) was close to zero for all 5 scenarios. However, the model appeared

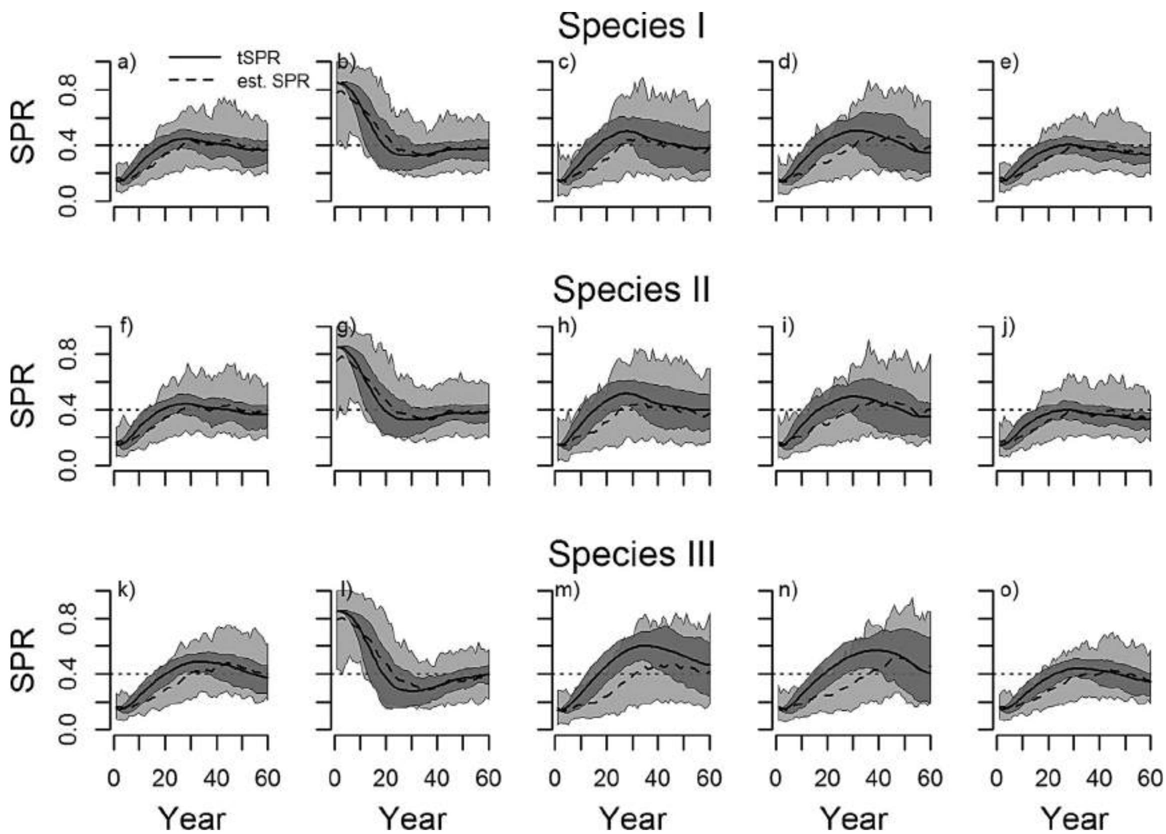

Fig. 6. The trajectories of the median transitional SPR (tSPR; solid line) and median estimated SPR (est. SPR; dashed line) as well as the 5th and 95th percentiles (transitional SPR = dark grey; estimated SPR = light grey shading), for the five scenarios of Species I (a–e), Species II (f–j) and Species III (k–o).

to slightly over-estimate these parameters (Fig. 7c and d, g and h, and k and l, for Species I, II and III respectively). Species I had the highest variability in relative error in the estimated selectivity parameters, particularly for Scenarios 3 and 4 (increased and auto-correlated recruitment variability respectively; Fig. 7c and d). In general, the two selectivity parameters were well estimated for Species II and Species III with the median relative error generally less than 3% and most estimates within 20% of the true values (Fig. 7i and j).

4. Discussion

4.1. Trade-offs for selecting HCRs

The value of a specific harvest control rule depends on the particular objectives of management in different situations. In some cases, there may be conflicts in the various management objectives, and management strategy evaluation can be used to identify the trade-offs among objectives for any chosen strategy (Sainsbury et al., 2000; Wiedenmann et al., 2013). For example, almost all of the harvest control rules used in the current study were successful, on average, in rebuilding the overexploited stocks back to, or above, the target levels of spawning potential ratio (SPR). However, the number of years for the stock to reach the target SPR, the fluctuations of the SPR around the target SPR, and the variability in the transitional SPR varied with the type of species and the shape and slope of the harvest control rule. The optimal parameterization of the harvest control rule for a particular fishery is likely to depend on the biological characteristics and life-history traits of the targeted species, as well as the specific objectives of the management and characteristics of the fishery, and should be explored with a case-specific simulation study (Deroba and Bence, 2008; Sainsbury et al., 2000; Wiedenmann et al., 2013).

4.2. Harvest strategy evaluation

The results from this examination of the length-based spawning potential ratio (LB-SPR) assessment model and an effort-based harvest control rule revealed that, under certain conditions, this methodology is able to rebuild an overfished stock back to sustainable levels. The LB-SPR assessment method combined with an effort-based harvest control rule requires little data compared with other stock assessment models, and uses a simple procedure to iteratively drive fishing effort to an appropriate level that results in the SPR approaching and stabilising at the target level. Such an approach may be valuable in data-poor situations, where little biological information is available on the stock, or the history of catches and exploitation rates of the fishery. With few data and technical requirements, the combination of the LB-SPR assessment model and an effort-based harvest control rule described in this paper offers a simple and transparent methodology for an initial quantitative assessment of an exploited stock, and provides fisheries managers and other stakeholders with a framework for beginning to manage a data-poor fishery.

The M/k ratio, coupled with the variability in length-at-age, determines the shape of the length composition of an unfished stock (Hordyk et al., 2014a,b), and is an important parameter for the LB-SPR methodology. The three species used in this MSE had M/k ratios that ranged from $M/k = 1.5$ (Species I *S. japonicus*), a species where unfished stocks are dominated by small sized individuals and large animals are relatively rare, to $M/k = 0.36$ (Species III *L. erythropterus*), where the unfished length composition is expected to be comprised of almost entirely adult sized animals (Hordyk et al.,

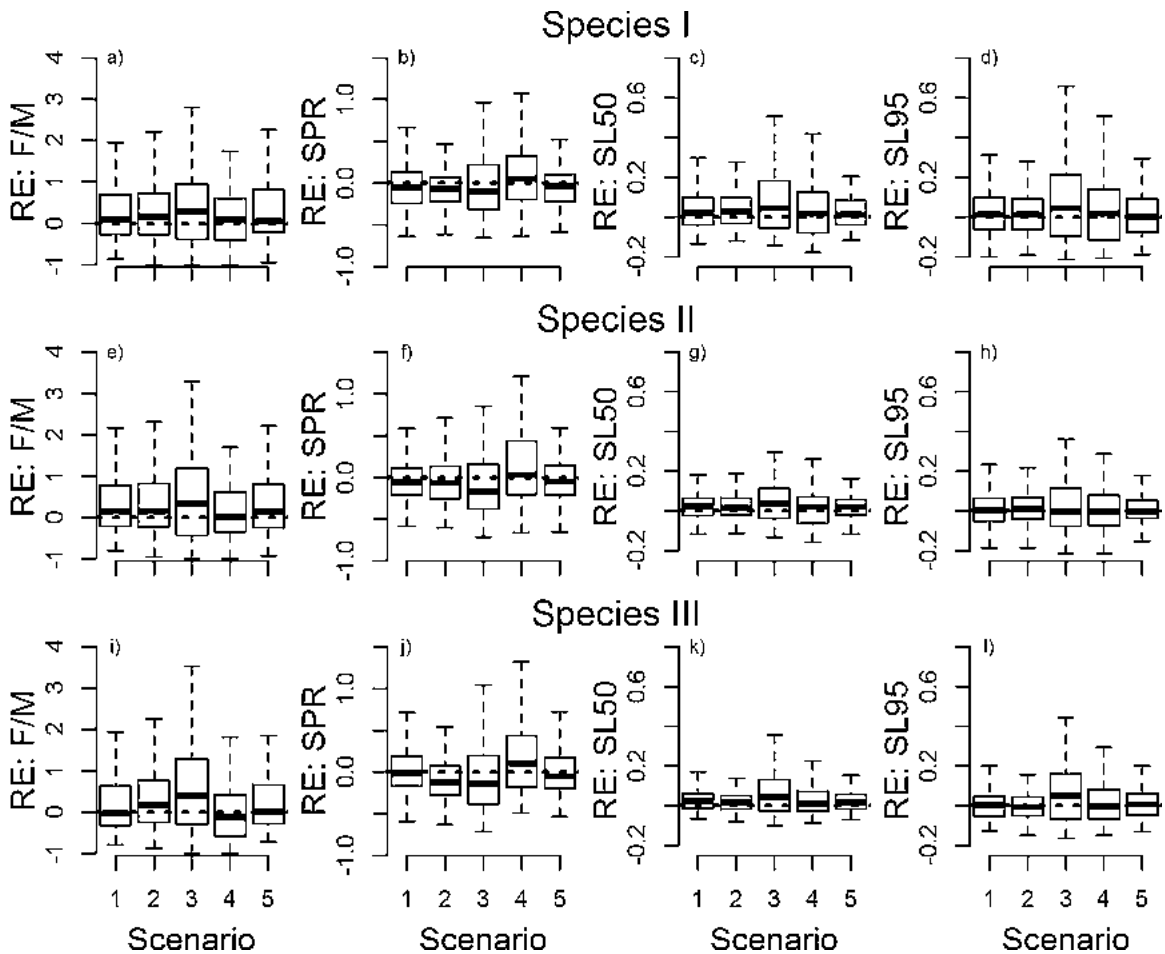

Fig. 7. The relative error in the four estimated parameters of the LB-SPR assessment method in the final year of the projection period for (a–d) Species I, (e–h) Species II, and (i–l) Species III. See Table 2 for definitions of the Scenarios. For the results shown the cubic polynomial HCR was used with control parameters $\varphi_1 = 0.20$ and $\varphi_2 = 0.05$.

2014a,b). These species represent a range of life histories that are common in marine species, although the *M/k* ratios for a number of species are considerably greater than 1.5 (e.g., up to 3.5; Prince et al., 2014). The species examined in this study were all relatively long-lived (maximum age of 15–33 years; Table 1). The performance of the LB-SPR harvest strategy has not, however, been examined in detail for shorter-lived species.

4.3. Data requirements of the harvest strategy

Information on the length structure of the catch is often one of the most accessible sources of data for fish stocks (Quinn and Deriso, 1999), and numerous methods have been developed to use this information to manage data-poor fish stocks. For example, Froese (2004) presented a simple method using the proportion of large fish in an exploited population as an indicator of stock status. Cope and Punt (2009) extended the application of this method, and demonstrated that the interpretation of length data is more complex, and requires some knowledge of life history and selectivity patterns. Other length-based techniques use length composition data to estimate the stock status and provide useful management advice (e.g., Ault et al., 2005; Gedamke and Hoenig, 2006; Klaer et al., 2012; O'Farrell and Botsford, 2006, 2005). The LB-SPR approach differs from many of these approaches by not requiring estimates of the individual parameters for natural mortality (*M*) and the von Bertalanffy growth coefficient (*k*), instead using the *M/k* ratio. By parameterising the model with the *M/k* ratio, it is possible to evaluate the length data and provide an estimate of stock status that can be compared against existing, widely accepted, reference points and incorporated into management decisions, without a complete understanding of the species' growth pattern and natural mortality rate. It could be argued that using the *M/k* ratio only transfers the problem from estimating the individual parameters to estimating the ratio. However, the ratio of *M/k* is known to vary less between species than either of the individual parameters in the ratio (Beverton, 1992; Prince et al., 2014). Meta-analysis and comparative studies may be useful for providing estimates of the *M/k* ratio for data-poor stocks without the need for expensive ageing studies.

One of the main underlying assumptions of the LB-SPR model is that the length frequency data are representative of the exploited stock. Although length data are one of the cheapest and easiest forms of data to collect, ensuring that the length composition data are representative of the exploited stock can be difficult, as the spatial distribution of fish is often not random which can lead to samples that are over-dispersed (Gerritsen and McGrath, 2006; Heery and Berkson, 2009; Hilborn and Walters, 1992). The simulation model used in this study generated multinomially distributed length composition data, which likely contain lower variability than would typically be observed in real-world samples. It is possible that the actual variation in the SPR when using the LB-SPR assessment was under-represented by this study. The importance and difficulty of collecting representative samples is common to all stock assessment methodologies. It is important to bear these considerations in mind when designing sampling regimes to collect length data for the LB-SPR model, and to ensure that sample sizes are large enough to adequately reflect the length structure of the population (Hordyk et al., 2014a,b; Erzini, 1990).

4.4. Initiating a process of assessment and management with LB-SPR

The iterative length-based harvest control rule developed and tested in this paper has the advantage of requiring little biological information and using relatively easily obtainable data. However, the simplicity of the technique means that the model is not likely to perform as well as more sophisticated assessment models and harvest strategies when more data are available. In data-poor situations, managers often have very little information on which to base their decisions. The harvest strategy outlined in this study provides managers and stakeholders with a simple and transparent framework for assessing and sustainably managing a data-poor fishery, while simultaneously identifying and prioritising key areas for further research and data collection. Under the scenarios examined in this study, the harvest control rule successfully decreased fishing effort and initially brought the spawning stock biomass of the depleted stocks back to sustainable levels in 10–20 years. The results of this study suggest that a suitably precautionary SPR target (e.g., $SPR_{target} \geq 0.4$) could be set initially, and a HCR combined with the LB-SPR method can be used to determine the initial management actions required to rebuild an overfished data-poor stock when no catch data are available.

It is important to recognise that the management strategy evaluation illustrated in this study is not proposed as a once-off solution to the assessment and management of data-poor stocks. Rather, our view is that the HCR combined with the LB-SPR methodology has potential as a cost-effective tool for initiating the assessment and management of a data-poor fishery with limited capacity to quantify or manage catch and effort. The simulations carried out in this study were projected over a 60 year period, and assumed no increase in knowledge of the fishery or stock during this time. In reality, this provides a significant time window to start a data collection programme that would refine and improve the assessment and management process and after time, allow other assessment methodologies to be applied. The initial application of the harvest strategy described in this study would help prioritise further research and data collection that could reduce the uncertainty of the assessment. For example, biological studies could be carried out to provide better estimates of the size of maturity and life history ratios needed for the LB-SPR model. If capacity is developed to collect representative size data annually and to adjust fishing pressure periodically, the additional resources required to collect annual catch and effort data are not very great. As more information is collected, and better estimates of the biological parameters of a stock become available, more sophisticated assessment methodologies become possible (Cope, 2013). For example, Prince et al. (2011) showed that size-based catch-per-unit-effort (CPUE) trends could be used to modify catch limits to iteratively drive a stock to a target level of SPR. Dick and MacCall (2011) demonstrated that a time-series of estimated catch, together with estimates of *M* and age-at-maturity, could be used to set sustainable catch recommendations for data-poor stocks. We envisage that an HCR based on the LB-SPR has potential to provide an 'entry point' for a data-poor fishery to the process of monitoring, assessment and management. Over-time, the results from these evaluations will provide directions for acquiring further information and a pathway to more sophisticated forms of assessment and management.

The harvest control rules we propose here adjust effort according to the size structure of a stock in relation to the SPR based target size structure. While this assumes that effective fishing effort can be adjusted, the results show that this HCR can be applied to fisheries for which estimating the magnitude of the catch is difficult, as it is for many recreational and small-scale fisheries, as well as for species taken as by-catch in other fisheries. The concept of harvest control rules has tended to pre-suppose that catches must be estimated, so that trends in CPUE and or biomass can be calculated, and often, that catches can be adjusted by management. We believe that this study is the first to demonstrate that as long as fishing pressure can be adjusted by some mechanism, it is possible to use harvest control rules to achieve target levels of SPR, without estimates of catch and effort. The logical extension of this work is to adapt this form of HCR based on the LB-SPR to fisheries for which the capacity exists only to manipulate selectivity with minimum size limits, the mesh size of nets, or the number and dimension of escape vents in traps; and fisheries that lack the capacity to monitor or directly manage effective effort and catch. We believe that these are important topics for understanding data-poor fisheries, and intend this to be the focus of future research.

Acknowledgements

We thank the David and Lucille Packard Foundation, the Marine Stewardship Council, and Murdoch University for funding and support of this study. We also thank D. Agnew, N. Gutiérrez, S. Valencia, K. Ono, K. Sainsbury, and R. Hillary for helpful comments and suggestions on various aspects of this work. We thank the two anonymous reviewers and the editor, David Sampson, for their constructive comments on the manuscript. This study formed part of the PhD research by Adrian Hordyk at Murdoch University.

References

Ault, J., Smith, S., Bohnsack, J., 2005. Evaluation of average length as an estimator of exploitation status for the Florida coral-reef fish community. ICES J. Mar. Sci. 62, 417–423.

Berkes, F., Mahon, R., McConney, P., Pollnac, R., Pomeroy, R., 2001. Managing Small-Scale Fisheries: Alternative Directions and Methods. International Development Research Centre, Ottawa, Canada.

Beverton, R.J.H., 1992. Patterns of reproductive strategy parameters in some marine teleost fishes. J. Fish Biol. 41, 137–160.

Brooks, E., Powers, J., Cortés, E., 2010. Analytical reference points for age-structured models: application to data-poor fisheries. ICES J. Mar. Sci. 67, 165–175.

Carvalho, N., Perrotta, R.G., Isidro, E., 2002. Age, growth and maturity in the chub mackerel (*Scomber japonicus* Houttuyn, 1782) from the Azores. Life Mar. Sci. 19A, 93–99.

Clark, W., 1993. The effect of recruitment variability on the choice of a target level of spawning biomass per recruit. In: Kruse, G., Eggers, D.M., Jarasco, R.J., Pautzke II, C., Quinn, T.J. (Eds.), Proceedings of the International Symposium on Management Strategies for Exploited Fish Populations. University of Alaska, Fairbanks, Alaska, USA, pp. 233–246.

Clark, W., 2002. F35% revisited ten years later. N. Am. J. Fish. Manag. 22, 251–257.

Cope, J.M., 2013. Implementing a statistical catch-at-age model (stock synthesis) as a tool for deriving overfishing limits in data-limited situations. Fish. Res. 142, 3–14.

Cope, J.M., Punt, A.E., 2009. Length-based reference points for data-limited situations: applications and restrictions. Mar. Coast. Fish. 1, 169–186.

Cordue, P., 2012. Fishing intensity metrics for use in overfishing determination. ICES J. Mar. Sci. 69, 615–623.

Cotter, A.J.R., Burt, L., Paxton, C.G.M., Fernandez, C., Buckland, S.T., Pan, J.-X., 2004. Are stock assessment methods too complicated? Fish Fish. 5, 235–254.

Day, J., Klaer, N., Tuck, G., 2012. Spotted Warehou (*Seriolella punctata*) Stock Assessment Based on Data Up To 2011. Australian Fisheries Management Authority, Hobart, Australia.

Deroba, J.J., Bence, J.R., 2008. A review of harvest policies: understanding relative performance of control rules. Fish. Res. 94, 210–223.

Dick, E.J., MacCall, A.D., 2011. Depletion-based stock reduction analysis: a catch-based method for determining sustainable yields for data-poor fish stocks. Fish. Res. 110, 331–341.

Dorn, M., 2002. Advice on west coast rockfish harvest rates from Bayesian meta-analysis of stock–recruit relationships. N. Am. J. Fish. Manag. 22, 280–300.

Erzini, K., 1990. Sample size and grouping of data for length-frequency analysis. Fish. Res. 9, 355–366.

Froese, R., 2004. Keep it simple: three indicators to deal with overfishing. Fish Fish. 5, 86–91.

Gedamke, T., Hoenig, J.M., 2006. Estimating mortality from mean length data in nonequilibrium situations, with application to the assessment of goosefish. Trans. Am. Fish. Soc. 135, 476–487.

Gerritsen, H.D., McGrath, D., 2006. Precision estimates and suggested sample sizes for length-frequency data. Fish. Bull. 106, 116–120.

Goodyear, C.P., 1993. Spawning stock biomass per recruit in fisheries management: foundation and current use. In: Smith, S.J., Hunt, J.J., Rivard, D. (Eds.), Risk Evaluation and Biological Reference Points for Fisheries Management. Canadian Special Publications of Fisheries Aquatic Sciences, pp. 67–81.

Heery, E.C., Berkson, J., 2009. Systematic errors in length frequency data and their effect on age-structured stock assessment models and management. Trans. Am. Fish. Soc. 138, 218–232.

Hilborn, R., 2003. The state of the art in stock assessment: where we are and where we are going. Sci. Mar. 67, 15–20.

Hilborn, R., 2012. The evolution of quantitative marine fisheries management 1985–2010. Nat. Resour. Model 25, 122–144.

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

Holt, S., 2009. Sunken Billions – but how many? Fish. Res. 97, 3–10.

Hordyk, A., Ono, K., Sainsbury, K., Loneragan, N., Prince, J., 2014a. Some explorations of the life history ratios to describe length composition, spawning-per-recruit, and the spawning potential ratio. ICES J. Mar. Sci., http://dx.doi.org/10.1093/icesjms/fst235.

Hordyk, A., Ono, K., Valencia, S.R., Loneragan, N.R., Prince, J.D., 2014b. A novel length-based empirical estimation method of spawning potential ratio (SPR), and tests of its performance, for small-scale, data-poor fisheries. ICES J. Mar. Sci., http://dx.doi.org/10.1093/icesjms/fsu004.

Jensen, A.L., 1996. Beverton and Holt life history invariants result from optimal trade-of of reproduction and survival. Can. J. Fish. Aquat. Sci. 53, 820–822.

Kelly, C.J., Codling, E.A., Kelly, J.C., Codling, A.E., 2006. Cheap and dirty fisheries science and management in the North Atlantic. Fish. Res. 79, 233–238.

Klaer, N.L., Wayte, S.E., Fay, G., 2012. An evaluation of the performance of a harvest strategy that uses an average-length-based assessment method. Fish. Res. 134–136, 42–51.

MacCall, A.D., 2009. Depletion-corrected average catch: a simple formula for estimating sustainable yields in data-poor situations. ICES J. Mar. Sci. 66, 2267–2271.

Mace, P., Sissenwine, M.P., 1993. How much spawning per recruit is enough? In: Smith, S.J., Hunt, J.J., Rivard, D. (Eds.), Risk Evaluation and Biological Reference Points for Fisheries Management. Canadian Special Publication of Fisheries and Aquatic Sciences, pp. 101–118.

Mahon, R., 1997. Does fisheries science serve the needs of managers of small stocks in developing countries? Can. J. Fish. Aquat. Sci. 54, 2207–2213.

McPherson, G.R., Squire, L., O'Brien, J., 1992. Reproduction of three dominant *Lutjanus* species of the Great Barrier Reef inter-reef fishery. Asian Fish. Sci. 5, 15–24.

Methot, R.D., Wetzel, C.R., 2013. Stock synthesis: a biological and statistical framework for fish stock assessment and fishery management. Fish. Res. 142, 86–99.

Myers, R., 2001. Stock and recruitment: generalizations about maximum reproductive rate, density dependence, and variability using meta-analytic approaches. ICES J. Mar. Sci. 58, 937–951.

Myers, R.A., Barrowman, N.J., Hilborn, R., Kehler, D.G., 2002. Inferring Bayesian priors with limited direct data: applications to risk analysis. N. Am. J. Fish. Manag. 22, 351–364.

Newman, S.J., Cappo, M., Williams, D.M., 2000. Age, growth, mortality rates and corresponding yield estimates using otoliths of the tropical red snappers, *Lutjanus erythropterus*, *L. malabaricus* and *L. sebae*, from the central Great Barrier Reef. Fish. Res. 48, 1–14.

O'Farrell, M.R., Botsford, L.W., 2005. Estimation of change in lifetime egg production from length frequency data. Can. J. Fish. Aquat. Sci. 62, 1626–1639.

O'Farrell, M.R., Botsford, L.W., 2006. Estimating the status of nearshore rockfish (*Sebastes* spp.) populations with length frequency data. Ecol. Appl. 16, 977–986.

Parkes, G., 2001. Understanding SPR and Its Use in U.S. Fisheries Management. Report of MRAG Americas, Inc. to The Ocean Conservancy, Washington, DC.

Prince, J.D., Dowling, N.A., Davies, C.R., Campbell, R.A., Kolody, D.S., 2011. A simple cost-effective and scale-less empirical approach to harvest strategies. ICES J. Mar. Sci. 68, 947–960.

Prince, J., Hordyk, A., Valencia, S.R., Loneragan, N.R., Sainsbury, K., 2014. Revisiting the concept of Beverton–Holt life-history invariants with the aim of informing data-poor fisheries assessment. ICES J. Mar. Sci., http://dx.doi.org/10.1093/icesjms/fsu011.

Prince, J.D., Victor, S., Kloulchad, V., Hordyk, A., 2015. Length based SPR assessment of eleven Indo-Pacific coral reef fish populations in Palau. Fish. Res. 171, 42–58.

Punt, A., 2006. The FAO precautionary approach after almost 10 years: have we progressed towards implementing simulation-tested feedback-control management systems for fisheries management? Nat. Resour. Model 19, 441–464.

Quinn, T.J., Deriso, R.B., 1999. Quantitative Fish Dynamics. Oxford University Press, New York.

Sainsbury, K., Punt, A.E., Smith, A.D.M., 2000. Design of operational management strategies for achieving fishery ecosystem objectives. ICES J. Mar. Sci. 57, 731–741.

Slipke, J., Martin, A., Pitlo, J.J., Maceina, M.J., 2002. Use of the spawning potential ratio for the upper Mississippi River channel catfish fishery. N. Am. J. Fish. Manag. 22, 1295–1300.

Slipke, J.W., Maceina, M.J., 2010. Fishery Analysis and Modeling Simulator (FAMS 1.0). American Fisheries Society, Bethesda, MD, vii+154pp.

Smith, A., Smith, D., Haddon, M., Knuckey, I.A., Sainsbury, K.J., Sloan, S.R., 2014. Implementing harvest strategies in Australia: 5 years on. ICES J. Mar. Sci. 71, 195–203.

Smith, A.D.M., Smith, D.C., Tuck, G.N., Klaer, N., Punt, A.E., Knuckey, I., Prince, J., Morison, A., Kloser, R., Haddon, M., Wayte, S., Day, J., Fay, G., Pribac, F., Fuller, M., Taylor, B., Little, L.R., 2008. Experience in implementing harvest strategies in Australia's south-eastern fisheries. Fish. Res. 94, 373–379.

Stanford, R., Wiryawan, B., Bengen, D.G., Febriamansyah, R., Haluan, J., 2013. Exploring fisheries dependency and its relationship to poverty: a case study of West Sumatra, Indonesia. Ocean Coast. Manag. 84, 140–152.

Walters, C.J., Martell, S.J.D., 2004. Fisheries Ecology and Management. Princeton University Press, Princeton, USA.

Wayte, S.E., Klaer, N.L., 2010. An effective harvest strategy using improved catch-curves. Fish. Res. 106, 310–320.

Wiedenmann, J., Wilberg, M.J., Miller, T.J., 2013. An evaluation of harvest control rules for data-poor fisheries. N. Am. J. Fish. Manag. 33, 845–860.