ICES Journal of Marine Science (2011), 68(5), 972–981. doi:10.1093/icesjms/fsr039

Among-stock comparisons for improving stock assessments of data-poor stocks: the "Robin Hood" approach

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Punt, A. E., Smith, D. C., and Smith, A. D. M. 2011. Among-stock comparisons for improving stock assessments of data-poor stocks: the "Robin Hood" approach. – ICES Journal of Marine Science, 68: 972–981.

Received 7 October 2010; accepted 24 February 2011

An approach is outlined for conducting stock assessments in which parameters are estimated for multiple stocks at the same time. Information from data-rich stock assessments, e.g. trends in fishing mortality, and values for parameters of selectivity functions are provided to data-poor assessments in the form of penalties on the estimated parameters, which leads to stock assessments for the most data-poor stocks being informed by those for the most data-rich stocks. The method is applied for example purposes to data for nine stocks in Australia's southern and eastern scalefish and shark fishery. The results of the application confirm that results for data-rich stocks are little impacted by being assessed in conjunction with data-poor stocks and that the results for data-poor stocks can be qualitatively different when information for data-rich stocks is taken into account.

Keywords: Australia, catch-at-age analysis, data-poor stocks, stock assessment.

Introduction

There is an increasing expectation by decision-makers in jurisdictions such as Australia, New Zealand, and the United States that there should be quantitative stock assessments for most, if not all, exploited fish and invertebrate stocks, especially if they are managed using output controls. The assessments should provide estimates of quantities such as historical and current biomass, and the ratio of current biomass to target or limit reference points, the basis for applying harvest control rules that aim to achieve prespecified management objectives. The need to provide an increasing number of stock assessments places increased demands on fisheries scientists, especially when data-collection schemes were not designed for the stocks for which the assessments are now needed. This is particularly the case in long-established multispecies fisheries where sophisticated stock assessments exist for major species, but virtually nothing is known about other species, although management advice is needed for all stocks owing, for example, to changes in harvest policy such as has transpired in Australia in recent years (Smith *et al.*, 2008, 2009). One consequence of this situation is increased interest in methods to provide management advice for data-poor stocks, here defined as stocks with catch estimates but little or no information on relative abundance and few or no samples of age and length from the fishery.

Two common ways to provide management advice for data-poor stocks are (i) to base management advice not on the outcomes from stock assessments, but rather on those of empirical decision rules (e.g. NPFMC, 2007; Smith *et al.*, 2008; Wayte and Klaer, 2010), and (ii) to place stocks into groups and to either conduct group assessments (e.g. Rogers *et al.*, 1996) or assume that all stocks in a group have the same dynamics as one member of the group. The concerns with assessing stocks as a group or assuming that the status of all stocks in a group are identical to that of an assessed stock is that it ignores any data that are available for the stocks in the group and implicitly assumes that all stocks in the group have the same dynamics.

In recent years, two ways have arisen in which allowance can be made for the data for one stock to influence the results of assessments for other stocks, instead of assuming that the status of the unassessed stocks equals those of assessed stocks. The first of these ways relates to the use in assessments of prior probability distributions, which can be used to summarize the information about the value of a parameter based on the results of assessments of other stocks or species. Prior probability distributions are used most naturally and straightforwardly when conducting stock assessments using Bayesian methods (McAllister *et al.*, 1994; Punt and Hilborn, 1997; McAllister and Kirkwood, 1998), although prior distributions can also be incorporated in non-Bayesian assessments by using them as penalty functions or as bounds (Punt and Butterworth, 2002). The second way in which the results from an assessment of one stock can influence that of another is when population models for multiple stocks are fitted at the same time. For example, Francis *et al.* (2002) assessed two stocks of blue grenadier (hoki, *Macruronus novaezelandiae*) off New Zealand within the same assessment framework, because some of the indices of abundance pertain to more than one stock. Similarly, Punt *et al.* (2000) conducted assessments of the school shark *Galeorhinus galeus* off southern Australia using a population dynamics model that included two stocks. Pribac *et al.* (2005) assessed gummy shark *Mustelus* *antarcticus* off southern Australia using an assessment model in which some of the key population dynamics parameters were assumed to be the same for several stocks of gummy shark.

The approaches taken by Francis *et al.* (2002), Punt *et al.* (2000), and Pribac *et al.* (2005) all involved multiple stocks of the same species. Here, we extend these approaches by fitting population models for multiple stocks of several species within the same optimization. It is clearly not possible to share the values of life-history parameters, such as age-at-maturity, among different species. However, it seems plausible that if multiple stocks/species are exploited by the same fleet (where a fleet is defined as a group of vessels fishing using the same gear in essentially the same fishing grounds at the same time), the trend in fishing mortality for that fleet should be similar for all stocks/species in the area fished. This assumption is the same as that underlying multispecies yield-per-recruit analysis (Pikitch, 1987; Murawski, 1996). However, it is not only trends in fishing mortality by fleet that might be expected to be common across stocks/species. It also seems possible that the annual deviations in recruitment about the stock–recruitment relationship for different stocks/species would be correlated (positively or negatively) as a result of the impact of common environmental variables (Myers *et al.*, 1995; Klaer, 2010) and that selectivity as a function of length (before discarding) should be relatively similar across fleets that use similar gear.

Although it seems plausible that, for example, the time-trend in fishing mortality for a given fleet should be similar across stocks/species, there are also good reasons, related to the behaviour of fishers and fish, why this time-trend would not be identical. The approach outlined below therefore allows for stock-specific values for all model parameters, but adds penalties on how the values for these parameters may differ among stocks. The objective function minimized for parameter estimation therefore contains contributions from the fit to the data for each stock, but there are also contributions to the objective function related to the pattern of fishing mortality over time among stocks for given fleets, and differences in selectivity-at-length among fleets. As a result, this approach to stock assessment has to be applied to all stocks at the same time. The approach here is based on the Integrated Analysis paradigm of fisheries stock assessment (Fournier and Archibald, 1982; Methot, 2005), *inter alia* because it is more straightforward to impose penalties on model parameters using this approach.

The approach is applied for exemplification to data for nine stocks in Australia's southern and eastern scalefish and shark fishery (SESSF; Smith and Smith, 2001). Two of these stocks, blue grenadier and the eastern stock of gemfish *Rexea solandri* are considered to be data-rich, and quantitative stock assessments have been produced. Three of the stocks (the eastern and western stocks of pink ling *Genypterus blacodes* and silver warehou *Seriolella punctata*) are considered data-moderate, whereas the remaining four stocks (mirror dory *Zenopsis nebulosus*, king dory *Cyttus traversi*, offshore ocean perch *Helicolenus percoides*, and the western stock of gemfish) are data-poor.

The value of the approach is determined by (i) whether the assessments for the data-poor stocks seem more realistic (and precise) than when integrated analysis is applied to the data for them without constraining parameters based on assessments for other stocks, and (ii) whether the assessments for the data-rich and data-moderate stocks are impacted by assessing them in conjunction with the data-poor stocks more than might be expected given the uncertainty associated with their assessments.

Methods

Multistock assessment method: population dynamics

The population dynamics for each stock are governed by the standard age-structured population dynamics equations, except that catches by each fleet are assumed to be taken sequentially rather than simultaneously for computational ease (see the Supplementary material for full specifications). Recruitment is assumed to be governed by a stochastic Beverton–Holt stock–recruitment relationship [Equation (S2)], and catches are assumed to be taken in the middle of the year after half of the annual natural mortality has been applied, i.e. Pope's approximation (Pope, 1972). Allowance is made for a range of selectivity assumptions, and discarding of undesirable (generally small) animals is also taken into account.

Multistock assessment method: parameter estimation

The values for the free parameters of the population dynamics model are estimated by minimizing an objective function that contains two components. The first is the likelihood of the data included in the assessment: catch and discard rates, survey indices of relative and absolute abundance, and length and age frequencies for the landed catch for the example application. The second component relates to the various penalties imposed on the parameter values (priors when interpreted in a Bayesian context). The first penalty pertains to the recruitment deviations:

$$P_1 = \sum_s \frac{1}{2(\sigma_R^s)^2} \sum_y (\varepsilon_y^s)^2, \tag{1}$$

where ε_y^s is the recruitment deviation for year y and stock s, and σ_R^s is the extent of variability in recruitment about the stock–recruitment relationship for stock s.

A second penalty is placed on the differences for each fleet in the length-at-50%-selectivity among stocks:

$$P_2 = \frac{1}{2\sigma_S^2} \sum_f \sum_s (L_{50}^{s,f} - \overline{L_{50}^f})^2, \tag{2}$$

where $L_{50}^{s,f}$ is the length-at-50%-selectivity for fleet f on fish of stock s, $\overline{L_{50}^f}$ the mean (across stocks) length-at-50%-selectivity for fleet f, and σ_S^2 the among-stock variance in the length-at-50%-selectivity. The summations in Equation (2) are restricted to combinations of fleets and stocks for which it is likely that selectivity should be similar.

The final penalty is placed on the relative trend in the exploitation rate:

$$P_3 = \frac{1}{2\sigma_f^2} \sum_f \sum_s \sum_y \left(\frac{F_y^{s,f}}{\overline{F^{s,f}}} - \overline{\overline{F_y^f}} \right)^2, \tag{3}$$

where σ_f determines how similar the trends in the exploitation rate will be, $F_y^{s,f}$ the exploitation rate on fully selected animals of stock s by fleet f during year y, $\overline{F^{s,f}}$ the mean (over years) exploitation rate by fleet f on stock s, and $\overline{\overline{F_y^f}}$ the mean (over stocks) value of $F_y^{s,f}/\overline{F^{s,f}}$. The summations over year, stock, and fleet in Equation

(3) are again restricted to those combinations of fleet, stocks, and years for which it is plausible that the trend in the exploitation rate is similar among stocks. Equation (3) does not imply that the absolute level of the exploitation rate should be the same for all stocks, but rather that the stock-specific trend in the exploitation rate for fully selected animals is distributed about a common trend for all stocks. The value for σ_f has to be selected based on *a priori* arguments related to how similar the trends in the exploitation rates are. In principle, the value for this parameter could be determined by assessing all the data-rich and data-moderate stocks separately and calculating the standard deviation about $\overline{\overline{F}}{}_y^f$.

Application to the SESSF

The example application is based on the fishery on the upper continental slope in southeastern Australia [see Tilzey (1994) and Smith and Smith (2001) and papers therein for a summary of the species taken in the fishery, along with a description of the various fleets and where and how the fleets interact with the various fish stocks]. The application involves seven species in the fishery (blue grenadier, gemfish, pink ling, silver warehou, mirror dory, king dory, and offshore ocean perch). Gemfish and pink ling have been divided into two stocks (eastern and western) for assessment purposes (Tuck, 2009), so the example application is based on a total of nine stocks (see Table 1 for a summary of the biological characteristics of the nine stocks). Management advice for the data-rich and data-moderate stocks is based on the results of population-model-based stock assessments. Management advice for mirror dory, ocean perch, and western gemfish is based on empirical control rules that use the available catch age/size compositions or trends in the standardized catch rates (see Table 1 for a summary of the management tiers for each stock).

Fleets can be defined in many ways. Ideally, they should be defined as a group of vessels with common fishing practices, fishing in common areas. However, this could lead to a large number of fleets in the SESSF. The process of selecting fleets when conducting stock assessments therefore involves a balance between selecting a large number of fleets to capture the behaviour of fishers adequately and a small number of fleets to avoid having very few data for each fleet. Six fleets are considered in the example application. Fleets 1 and 2 consist of trawlers in summer (January–May and September–December) and winter (June–August), respectively, in the east (Figure 1), fleet 3 consists of trawlers in zone 50 all year round and in zone 40 during summer, fleet 4 of trawlers in zone 40 during winter, fleet 5 of non-trawlers (primarily longliners) in the east all year round, and fleet 6 consists of non-trawlers in the west all year round. The temporal split of the fishery in the east is needed to separate the fishery that targeted primarily eastern gemfish during their winter spawning migration from the fishery that targeted non-spawning gemfish. This is because the length composition of the landings during the spawning and non-spawning fisheries for eastern gemfish differs markedly. The split of the fishery in the western sector allows the winter fishery for spawning blue grenadier to be treated as a separate fishery. Not all fleets catch all stocks (e.g. fleets 1 and 2 do not capture the western stock of gemfish; Table 1) and there are differences in targeting even within fleets as defined here.

Table 1 lists the selectivity patterns assumed for the various fleets. It is not feasible to estimate selectivity patterns for all combinations of stock and fleet because of a lack of data on the

Table 1. Biological parameters for the nine stocks.

Stock	Natural mortality, M[a] (year^{-1})	Growth rate, κ[a] (year^{-1})	Length-at-maturity (cm)/proportion spawning	Fleets	Selectivity assumptions	Recruitments estimated for	Tier level
Blue grenadier	0.25/0.25	0.2219/0.2219	70/0.77	1–6	1–3 (dome-shaped), 4–6 (increasing logistic)	1979–2006 ($h = 0.9$; $\sigma_R = 1$)	1[d]
Gemfish (east)	0.6/0.4	0.18/0.212	[b]/1	1, 2, 5	1 (declining logistic), 2 and 5 (increasing logistic)	1968–2006 ($h = 0.5$; $\sigma_R = 0.6$)	1[d]
Pink ling (east)	0.23/0.23	0.135/0.135	71.2/1	1, 2, 5	1 and 2 (increasing logistic), 5 (increasing logistic)	1986–2006 ($h = 0.75$; $\sigma_R = 0.75$)	1[d]
Pink ling (west)	0.23/0.23	0.135/0.135	71.2/1	3, 4, 6	3 and 4 (increasing logistic), 6 (increasing logistic)	1986–2006 ($h = 0.75$; $\sigma_R = 0.75$)	1[d]
Silver warehou	0.25/0.25	0.372/0.372	36.6/1	1–6[c5,6]	1, 2, and 5 (increasing logistic), 3, 4, and 6 (increasing logistic)	1986–2006 ($h = 0.75$; $\sigma_R = 0.6$)	1[d]
Mirror dory	0.3/0.3	0.2/0.2	18.6/1	1–6[c4,5,6]	1–6 (increasing logistic)	1986–2006 ($h = 0.75$; $\sigma_R = 0.6$)	3
Ocean perch	0.12/0.12	0.07/0.07	30.7/1	1–6[c4,6]	1–6 (increasing logistic)	1986–2006 ($h = 0.75$; $\sigma_R = 0.6$)	4
King dory	0.1/0.1	0.1/0.1	37.1/1	1–4	1–4 (increasing logistic)	1986–2006 ($h = 0.75$; $\sigma_R = 0.6$)	Not applicable
Gemfish (west)	0.6/0.4	0.19/0.19	60.2/1	3, 4, 6	3, 4, and 6 (increasing logistic)	1986–2006 ($h = 0.75$; $\sigma_R = 0.6$)	4

The symbols for the selectivity patterns indicate the fleets and pattern shapes (e.g. for blue grenadier the selectivity patterns for fleets 1–3 are a dome-shaped function, whereas the selectivity patterns for fleets 4–6 are an increasing logistic function). The column to the right indicates the Tier level used when determining management advice for each stock.

[a]Males/females.

[b]Set to the selectivity pattern for females during the winter (spawning) fishery.

[cx,y]Negligible <1% of total for fleets *x*, *y*, etc.

[d]Stock assessments used for management advice.

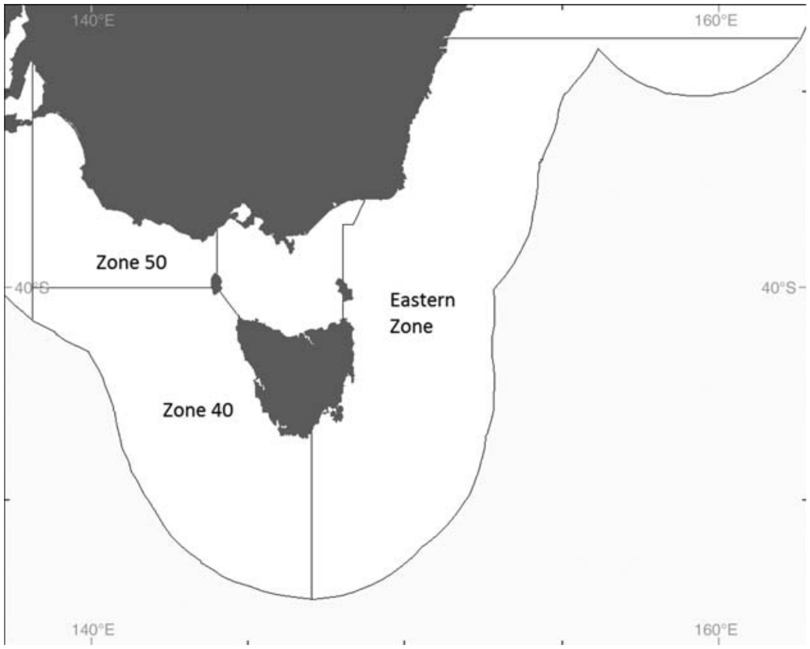

Figure 1. Map of southeastern Australia showing the zones used in the example application.

age/length composition of the landings (Table 2), so selectivity was assumed to be the same for several groups of fleets for each stock (Table 1), with the groups of fleets based on data availability, visual examination of length frequency distributions, and preliminary applications of the model. As expected, more selectivity patterns are estimated for the data-rich and data-moderate stocks than for the data-poor stocks. This does not imply that selectivity is independent of fleet for the data-poor stocks, but rather that the data for those stocks are insufficient to support estimation of more than one selectivity pattern (most assessments of SESSF stocks pool data across the fleets defined for the example application, so estimate even fewer selectivity parameters than is the case here; see, for example, Tuck, 2009). The shapes of the various selectivity patterns (dome-shaped, declining/increasing logistic functions) were also selected based on preliminary analysis and, where applicable, matched the selections in the most recent stock assessments.

The data available for assessment purposes for the nine stocks included landings, catch rates standardized using General Linear Modelling techniques (Maunder and Punt, 2004), discard rates, length frequencies and age compositions by fleet and stock, values for biological parameters, and survey estimates of abundance for blue grenadier. The discard rates and survey indices of abundance were assumed to be lognormally distributed with prespecified coefficients of variation (*CV*s), as is standard when conducting stock assessments of SESSF stocks (Tuck, 2009). The length and age data were assumed to be distributed according to the robust normal for proportions distribution (Fournier *et al.*, 1990).

Several of the parameters that could be estimated by fitting the model (e.g. natural mortality and growth) were prespecified for the purposes of the example application (Table 1). The estimable parameters of the model are therefore (i) average recruitment in the absence of exploitation, (ii) the parameters of the selectivity functions, and (iii) recruitment deviations. The values for the steepness of the stock–recruitment relationship (h) were prespecified, as is common practice for assessments of SESSF stocks (see, for example, the assessments in Tuck, 2009), and the parameters determining the probability of being discarded as a function of length were also prespecified by fitting a logistic function to data on the proportion of fish retained by length for each species and fleet from on-board observers. Allowance was made for age-reading error when fitting the age frequencies. The age-reading error matrices were estimated using the method of Punt *et al.* (2008).

Scenarios

A large number of scenarios can be constructed by varying the assumptions regarding among-stock penalties, choices regarding forms of selectivity, weights on data components, and penalties. However, the number of scenarios is limited to five for this paper to keep the volume of results to a reasonable level. The scenarios, which evaluate different types of penalty and level of information for mirror dory, are listed below.

1. A scenario with no among-stock penalties but with a penalty constraining the recruitment deviations within each stock [Equation (1)], equivalent to conducting assessments for each stock separately.
2. A scenario in which penalties are placed on the within-stock recruitment deviations and the among-stock differences in the relative exploitation rate for three groups of stocks, but no among-stock penalties are imposed on selectivity. Penalties on the exploitation rate (with $\sigma_f^2 = 1/50$) are imposed on fleet 1 (summer trawl fishery in the east) targeting pink ling and ocean perch (1992–2007; the period from the introduction of the TAC system for the SESSF), on fleet 2 (winter trawl fishery in the east) targeting eastern gemfish and mirror dory (1977–1998), and on fleet 3 (trawl fishery in zones 40 and 50) targeting blue grenadier, silver warehou, king dory, western gemfish, and pink ling (1992–2007).

Table 2. Data-related specifications for the nine stocks.

Stock	Catch rates (number of data points, assumed CVs)	Discard rates (number of data points; assumed $CV = 1$)	Survey indices	Age data per fleet 1	2	3	4	5	6	Length data per fleet 1	2	3	4	5	6
Blue grenadier	2 series (44) 0.15 / 0.15	4 series (36)	2 egg indices, 2 acoustic indices	17 (25)	13 (25)	16 (25)	12 (25)	0	0	Not used					
Gemfish (east)	2 series (43) 0.1 / 0.15	2 series (28)	None	17 (10)	15 (50)			0		15 (10)	15 (50)			0	
Pink ling (east)	1 series (21) 0.2	2 series (25)	None	11 (10)	9 (10)			11 (10)		Not used					
Pink ling (west)	2 series (44) 0.2 / 0.2	2 series (11)	None			11 (10)	0		3 (10)	Not used					
Silver warehou	4 series (88) 0.2 / 0.2 / 0.2 /0.2	4 series (44)	None	15 (10)	14 (10)	14 (10)	8 (10)	0	0	Not used					
Mirror dory	1 series (22) 0.3	4 series (42)	None	1 (5)	1 (5)	0	0	0	0	15 (5)	18 (5)	0	0	0	0
Ocean perch	None	4 series (40)	None	3 (5)	3 (5)	0	0	0	0	7 (5)	6 (5)	0	0	0	0
King dory	None	3 series (23)	None	n/a						0	0	6 (5)	0	0	0
Gemfish (west)	1 series (22) 0.3	1 series (14)	None	n/a								6 (5)	0		0

The information on fish age and length for each fleet is the number of years with data and the assumed effective sample size (in parenthesis). n/a denotes that there are no data of the type concerned, and not used indicates that the length data were not used because there were age data for the same years.

These choices were made because (i) ocean perch and pink ling are caught in similar depths during the summer trawl fishery, (ii) mirror dory is a key bycatch species in the winter fishery for eastern gemfish (the penalty is not imposed after 1998 because the winter fishery for eastern gemfish was closed by then), and (iii) the largest landings of blue grenadier, silver warehou, king dory, western gemfish, and pink ling are made by the fishery in zones 40 and 50.

3. A variant of scenario 1 in which the catch-rate data for mirror dory are ignored, making that stock more data-poor.
4. As for scenario 3, except that there are among-stock penalties as in scenario 2.
5. As for scenario 2, except that an additional penalty is placed so that the lengths-at-50%-selectivity for pink ling in the east and west are constrained to be similar.

Scenarios 1 and 2 explore the implications of adding penalties, scenarios 3 and 4 examine this question when mirror dory is more data-poor, and scenario 5 explores how adding a second type of penalty to scenario 2 impacts the results. The results for each scenario are summarized by the time trajectories of spawning biomass (in absolute terms and relative to the unfished level) and by the subset of the time trajectories of the exploitation rate for fleets 1–3 on which penalties are placed. The former set of results is shown because management recommendations for SESSF stocks depend primarily on the estimates of spawning biomass relative to the unfished level (Smith *et al.*, 2008), whereas the exploitation rates are shown because they are being constrained using Equation (3) in some scenarios.

The impact of imposing penalties on parameters is also evaluated using the asymptotic *CV*s for terminal spawning biomass relative to the unfished level, where the associated standard errors are computed using the delta method, in which the variance–covariance matrix for the parameters is obtained by inverting the Hessian matrix at the best estimates for the parameters. The *CV*s assumed for the indices of abundance and the effective sample sizes for the data on age and length (Table 2) were selected to be roughly comparable with the residual variation that arises when the model is fitted to the data. Therefore, the asymptotic *CV*s should only be considered meaningful in an among-scenario manner, rather than in an absolute sense.

Results

The fits of scenarios 1 and 2 to the various data sources are comparable with those for the actual assessments of these stocks, i.e. for those stocks that are assessed, and noting that most of the actual assessments are not based on as many fleets as are the analyses of this paper and that the actual assessments are not based on exactly the same datasets and assumptions as the multistock model of this paper. Because of the very large quantity of data involved, the fits are not shown. The fits to the indices of abundance were generally good, whereas the fits to some of the age and length distributions were rather poor because of the small sample sizes, e.g. those for ocean perch, king dory, and mirror dory.

Impacts on stock assessments for data-rich and data-moderate stocks

The time trajectories of spawning biomass for the five data-rich and data-moderate stocks are robust to whether or not among-stock penalties are imposed when spawning biomass is expressed

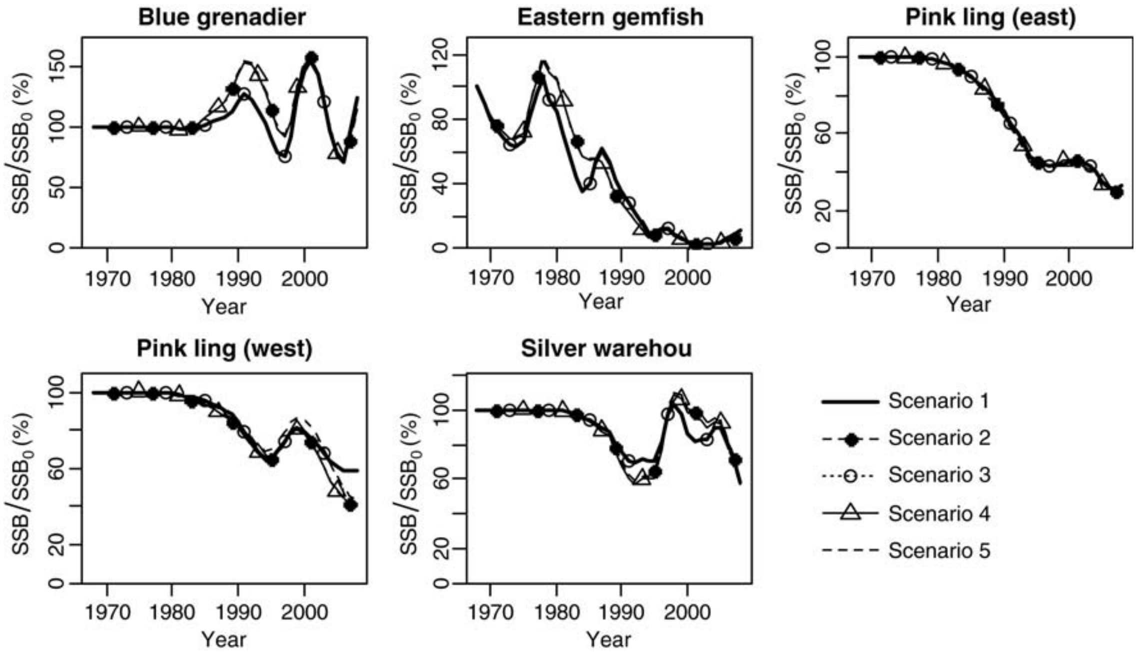

Figure 2. Time trajectories of spawning biomass as a percentage of the unfished level for the data-rich and data-moderate stocks.

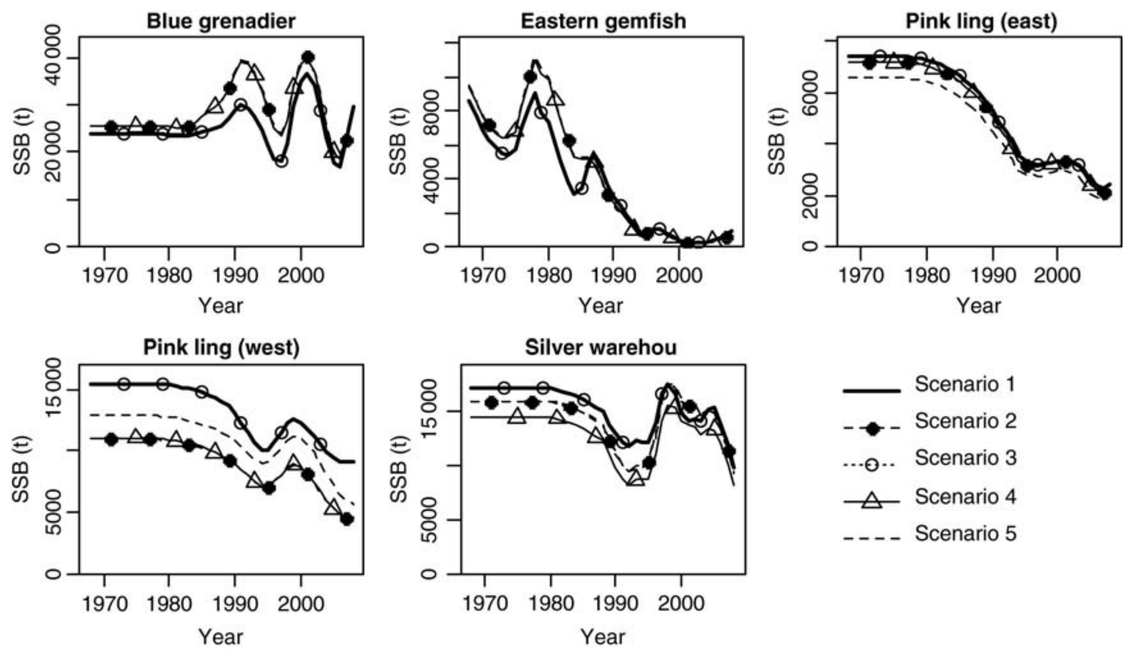

Figure 3. Time trajectories of spawning biomass for the data-rich and data-moderate stocks.

relative to the unfished level (Figure 2). The differences in spawning-biomass trajectories in absolute terms are greater than in relative terms (Figure 2 vs. Figure 3), with the difference in results greatest for the western stock of pink ling.

The estimates of spawning biomass for the two stocks of pink ling are not markedly different between scenarios 2 and 5, because sufficient age data are available (Table 2), and although a penalty was imposed on between-stock differences in the length-at-50%-selectivity, the estimates of selectivity-at-length still differed substantially.

Impacts on stock assessments for data-poor stocks

The results for the assessments of the four data-poor stocks are markedly different when among-stock penalties are imposed on the trends in exploitation rates. In particular, mirror dory and ocean perch are assessed to be more depleted when there are no among-stock penalties on the exploitation rate (Figure 4a and b). The results for mirror dory also differ markedly between scenarios 2 and 4 (Figures 4a and 5a), because scenario 4 ignores the catch-rate data for mirror dory and bases inference on stock status almost solely on inferred trends in the exploitation rate.

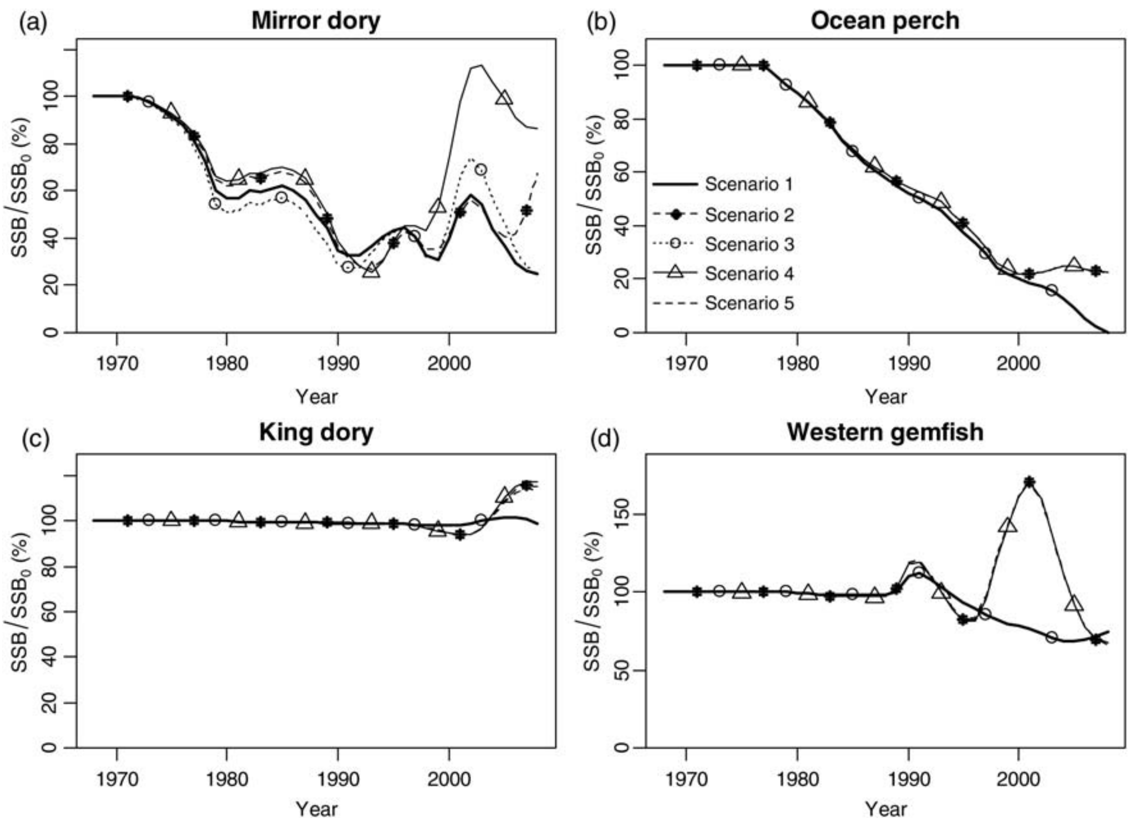

Figure 4. Time trajectories of spawning biomass as a percentage of the unfished level for the data-poor stocks.

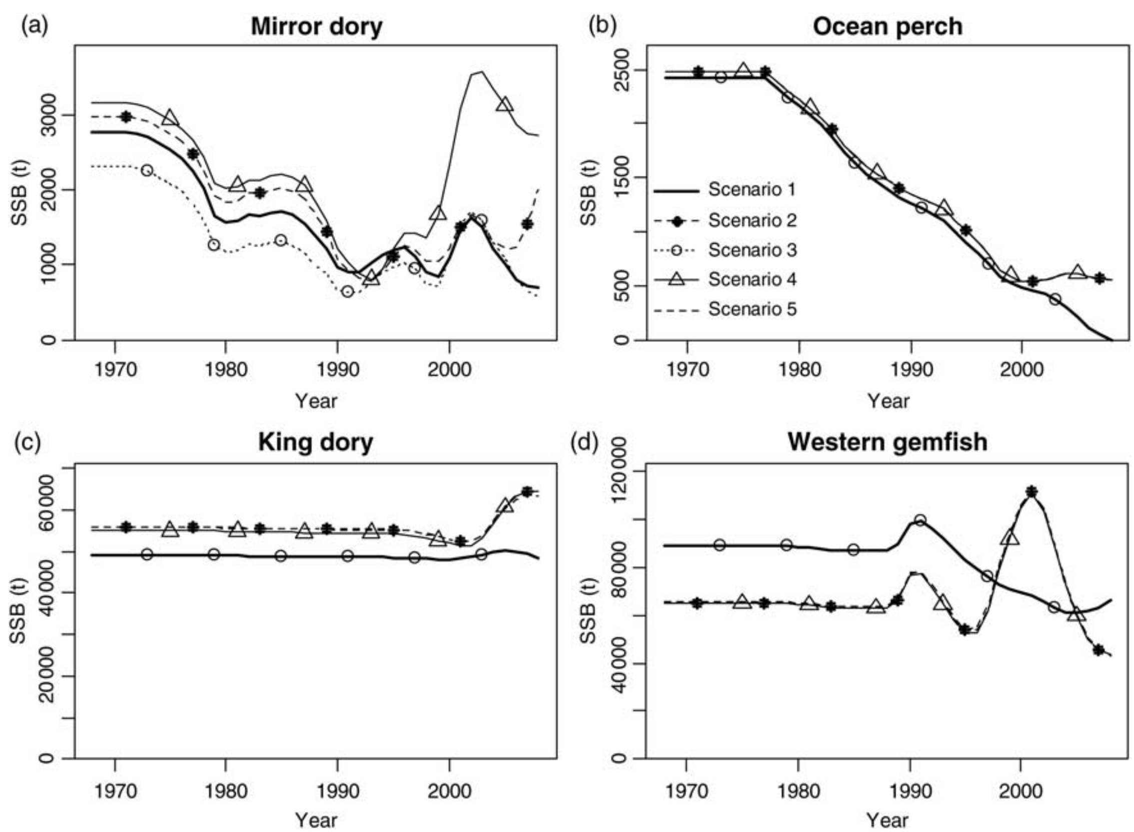

Figure 5. Time trajectories of spawning biomass for the data-poor stocks.

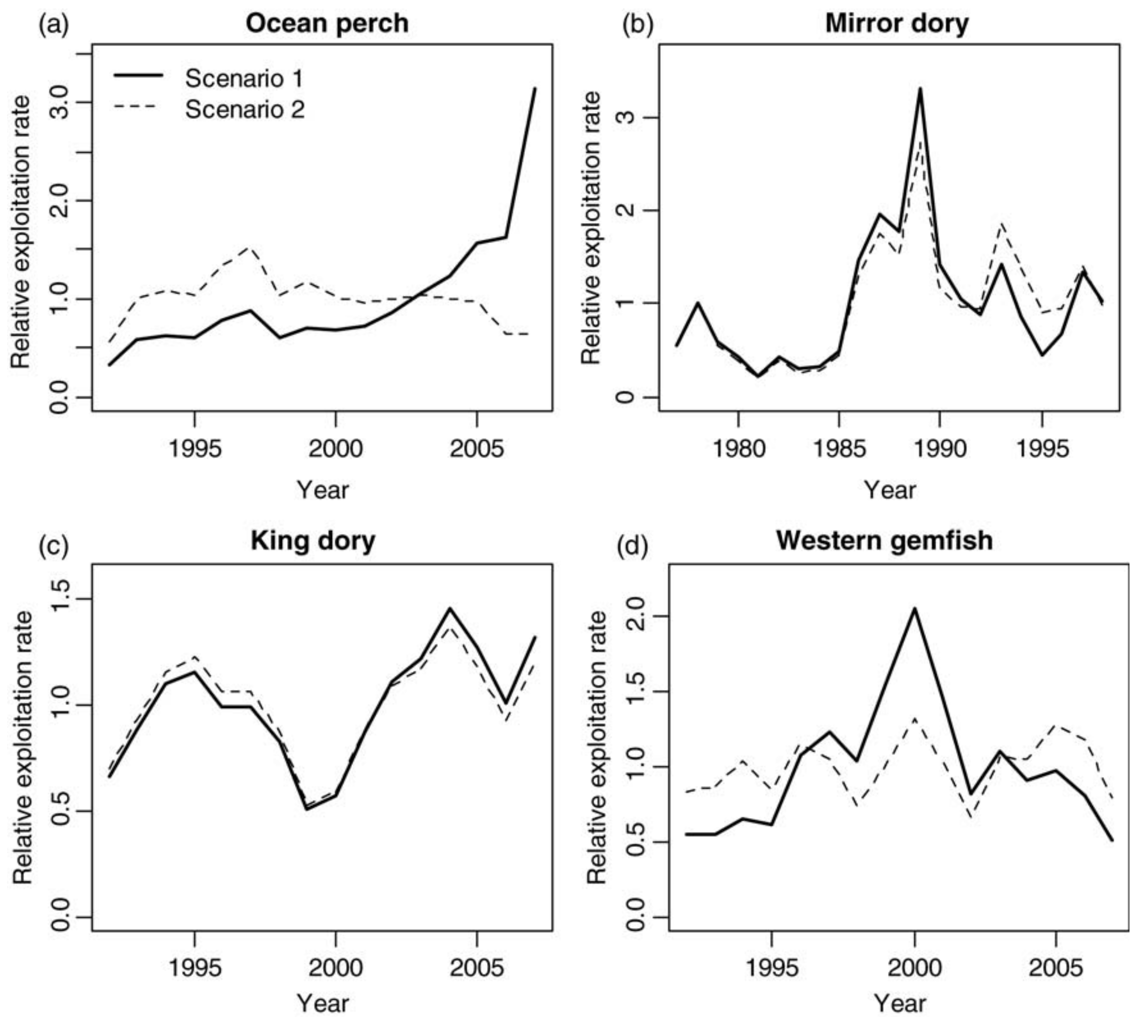

Figure 6. Estimated time trajectories of the exploitation rate (expressed relative to the average exploitation rate) for the fleets on which exploitation-rate penalties are placed for the four data-poor stocks.

Table 3. Asymptotic *CV*s (%) for terminal spawning biomass as a percentage of the unfished level.

Stock	Scenario 1	Scenario 2
Blue grenadier	13.8	9.3
Gemfish (east)	11.5	10.5
Pink ling (east)	11.4	11.0
Pink ling (west)	10.1	8.7
Silver warehou	7.4	7.0
Mirror dory	23.5	18.7
Ocean perch	20.3	18.3
King dory	8.1	7.4
Gemfish (west)	12.0	6.4

Figure 6 shows the time trajectories of exploitation rates expressed relative to the average exploitation rate (for the fleets for which among-stock penalties are imposed) for the four data-poor stocks. Ocean perch differ most between scenarios 1 and 2. Rather than the exploitation rate increasing markedly towards the end of the time-series for that stock, it declines slightly when penalties are imposed on exploitation rates.

Table 3 contrasts the asymptotic *CV*s for terminal spawning biomass as a percentage of the unfished level for scenarios 1 and 2 (with and without penalties). Higher *CV*s for terminal biomass imply lower confidence in assessment outcomes and perhaps the need to reduce TACs to account for increased uncertainty. The asymptotic *CV*s are lower for scenario 2 for all stocks.

Management implications

Management advice for SESSF stocks is based on applying a set of control rules in which 20 and 48% of the unfished spawning biomass are, respectively, the limit and target reference points (Smith *et al.*, 2008). The status of the data-rich and data-moderate stocks relative to these reference points is insensitive to the imposition of among-stock penalties. However, this is not the case for data-poor stocks. Mirror dory are assessed to be just above and ocean perch well below the limit reference point when no among-stock penalties are imposed, but well above the target reference point (mirror dory) and slightly above the limit reference point (ocean perch) when such penalties are imposed (Figure 4a and b). The status of king dory relative to the reference points is insensitive to whether or not penalties are imposed (management advice is, however, not currently provided for that stock because it is not part of the SESSF quota system).

Discussion

The approach outlined here implements the notion that stocks found (and caught) together exhibit similar, but not identical, trends in the exploitation rate. It therefore allows assessments for data-poor stocks to "borrow strength" from assessments for data-rich stocks and could lead to more stability and precision for data-poor assessments, with little impact on the results of assessments for data-rich stocks. The expectations of improved stability and precision are largely borne out in the example application: trends in the abundance of ocean perch and mirror dory differ when among-stock penalties are taken into account, but the results for the data-rich stocks are generally insensitive to among-stock penalties. Moreover, the precision of some of the key outputs from an assessment (the trends in spawning biomass and spawning biomass expressed relative to the unfished level) for the data-poor stocks is greater when among-stock penalties are taken into account. In particular, the results in Figures 4 and 5 show that constraining assessments for data-poor stocks using results from data-rich stocks should reduce the chance of assessments following noise in a small dataset, e.g. for ocean perch. The result that the exploitation rate for ocean perch increased markedly towards the end of the assessed period when no among-stock penalties were imposed (Figure 6a, solid line) is unrealistic, whereas the trend in the exploitation rate for that stock from the multistock model is not unreasonable given auxiliary information (admittedly somewhat anecdotal).

The example application here could be extended in several ways. Specifically, in relation to "borrowing strength", additional penalties could be imposed, such as on among-stock differences in the value for the steepness parameter of the stock–recruitment relationship, e.g. using the approach of Dorn (2002), or by allowing for among-stock correlations in the deviations about the stock–recruitment relationship, as might be expected if recruitment deviations are driven by common environmental factors (Klaer, 2010). The residuals about the fits to the data are assumed to be independent among stocks. Allowance could be made for among-stock correlation in residuals about the fits to, for example, catch rates (McDonald *et al*., 2001). Correlations among stocks in the residuals about the fits to catch rates, related to changes in availability rather than abundance, have been observed for some SESSF species.

The example application is based on a simple age-structured model, whereas most assessments for Tier 1 SESSF stocks are now based on stock synthesis (Methot, 2005). Stock synthesis has been selected as the basis for stock assessment for the SESSF because it is flexible, can estimate the growth curve internally to the stock assessment, and has been thoroughly evaluated. Stock synthesis would need to be extended, however, to allow for multiple stocks to implement the approach outlined in this paper. The results shown in Figures 2–5 do not always match those on which management advice is currently based. This is particularly the case for blue grenadier, because the analyses here do not take time-varying growth into account, and this can have a marked impact on assessment outcomes (Punt *et al*., 2001).

The approach is, however, not without disadvantages. Although it would be expected that fleets operating in similar areas and times would have similar impacts on the stocks they encounter, subtleties in fine-scale targeting practice will violate this expectation, to some extent at least. A common difficulty when conducting assessments is how to weight different data sources, especially when those sources are potentially in conflict. This problem is exacerbated in the current method because not only is it necessary to specify weights for the various data sources, but it is also necessary to specify the weights on the penalties related to the extent to which trends in exploitation rates and selectivity are similar among stocks. Setting the weights to values that are too high will lead to changes (perhaps major) in the results of data-rich assessments, whereas setting values for these weights that are too small will effectively mean that no information is shared among stocks. In principle, the weights could be estimated by conducting assessments for all data-rich assessments independently, then setting the weights based on the variance in the exploitation rate and selectivity among stocks.

The focus of this paper is on the point estimates of spawning biomass and exploitation rate (the exception being Table 3, where uncertainty is quantified in terms of asymptotic *CVs*), although ideally the uncertainty associated with estimates of biomass should be accounted for when setting catch limits. The analyses herein are based on maximizing a penalized likelihood function. Bayesian methods, e.g. using Markov chain Monte Carlo sampling could be used for parameter estimation and to quantify uncertainty using posterior distributions. In principle, the weights applied to each penalty could be estimated within a Bayesian estimation framework.

Finally, although the approach outlined here is not ideal, it does add to the toolbox of methods for data-poor stocks (see Smith *et al*., 2009, for a list of the methods proposed and used to provide management advice for data-poor stocks in Australia). This toolbox is increasingly being used in jurisdictions where catch limits need to be set for most harvested stocks (as is now the case in the United States and Australia). When augmented by an appropriate catch control rule, the approach described here could be used to compute catch limits and hence to replace methods that use catch data alone (e.g. NPFMC, 2007; MacCall, 2009; Dick and MacCall, 2010), which is the default approach for providing management recommendations for many data-poor stocks. In the SESSF, data-poor species such as mirror dory and ocean perch are currently managed using either Tier 3 or Tier 4 methods that do not use formal quantitative stock assessments. Adoption of the methods developed here could allow such stocks to be managed using Tier 1 rules, perhaps with some appropriate discount factor applied to take account of the additional uncertainty. However, it will be necessary to evaluate the ability of such an approach to satisfy management goals using management strategy evaluation (Butterworth and Punt, 1999; Punt, 2006; Rademeyer *et al*., 2007; Smith *et al*., 2008) before adopting control rules that use the results from the approach described here, as is now standard practice in the SESSF (Wayte and Klaer, 2010). Similarly, simulation could be used to evaluate the impact of having a different mix of data-rich and data-poor stocks than is the case for the SESSF.

Supplementary material

Supplementary material with the specifications of the model is available at the *ICESJMS* online version of this paper.

Acknowledgements

This work was supported by FRDC project 2002/094 and CSIRO. Geoff Tuck and Rich Little (CSIRO), José De Oliveira (Cefas), the editor (Sarah B. M. Kraak), and an anonymous reviewer are thanked for their comments on a draft of the manuscript, and Ian Knuckey (Fishwell Consulting) for suggesting the term "Robin Hood" for the method.

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