# Initial investigation of generic management procedures for datapoor fisheries 

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#### Abstract

The vast majority of fish stocks in South Africa are not managed quantitatively as there is not sufficient data (such as an index of abundance) on which to base a resource assessment. In addition, these stocks are relatively "low-value", which renders dedicated scientific management too costly, and a generic approach is therefore required. The aim of this work is to design and test some very simple "off-the-shelf" management procedures (MPs) that can be applied to groups of data-poor fisheries that share some key characteristics in terms of demographic parameters. For this initial investigation, a selection of empirical MPs is simulation tested on a wide range of operating models ( OMs ) representing the underlying dynamics of the resource in order to ascertain how well the different MPs perform. While the data-rich MPs perform somewhat better than the data-poor ones, as would be expected, it seems that the very simple data-poor MPs are surprisingly robust to a wide range of uncertainty for key parameters and could well be candidates to manage the South African data-poor stocks, ensuring perhaps not optimum, but at least relatively stable sustainable future catches.


## 1. Introduction

Of the more than some 500 stocks fished in South Africa, only 11 are deemed "well-managed" in the sense of the data available allowing for detailed quantitative assessments (Colin Attwood pers. comm.). These 11 well-managed resources account for about $80 \%$ of the catch in terms of mass. Even so, there is a need for better management of the remaining $20 \%$ in order to maintain biodiversity as well as sustain the fishing communities that rely on these data-poor stocks. At present there are as yet no quantitative measures in place to manage those 500 stocks, mainly due to their relative low-value compared to other resources (such as hake) and also because of the lack of reliable data on which to base quantitative assessments. In order to manage these resources successfully some very simple harvesting rules are needed that will work (be robust) in the face of large uncertainty. Rather than attempt the impossible task of developing and simulation testing some 500 species-specific management procedures, it seems more reasonable to develop generic management procedures that can be applied to several similar data-poor low-value stocks. The aim of this work is therefore to design and test some very simple "off-the-shelf"
management procedures that could be applied to a group of data-poor fisheries termed "severely depleted" and sharing some key characteristics in terms of demographic parameters.

Building on preliminary work by Butterworth et al. (2010), this paper looks at more extensive comparative testing of a selection of empirical management procedures (MPs) on a wider range of operating models ( OMs ) representing the underlying dynamics of the resource. In the absence of an index of abundance, how well can these MPs perform?

Rather than test the MPs on data forthcoming from an existing fishery, data are generated by a range of operating models encompassing the extent of uncertainty expected in reality. For purposes of generic MP testing, stocks are grouped into three broad categories depending on the perceived level of resource depletion: "severely depleted" (current biomass $10 \%$ to $30 \%$ of its pre-exploitation level), "moderately depleted" (corresponding to a less pessimistic range for $B_{n}^{s p} / K^{s p}$ of $20 \%$ to $50 \%$ ) and "near target" (depletion in the range $40 \%$ to $70 \%$ of the pre-exploitation level.). A different set of operating models need to be developed for each of these categories, with different MPs appropriate in each case. However, as a first step, only OMs corresponding to the "severely depleted" scenario are considered here.

The operating models on which the MPs are tested include model uncertainty (by integrating over a range for current depletion, stock-recruitment parameter values, as well as other parameter values); this is in addition to "observation" error (by including stochastic components when generating index of abundance and length data), as well as incorporating past and future recruitment and fishing selectivity fluctuations for each simulation as in Butterworth et al. (2010).

As in Butterworth et al. (2010), the data-poor scenario is typified by the lack of any index of abundance (CPUE), with only mean length of catch data available as a quantitative though indirect indicator of trend in resource abundance. By contrast, the data-rich scenario corresponds to a fishery for which CPUE data are available. For the data-poor scenario, where stock assessments are not possible due to lack of quantitative data, a number of empirical MPs are simulation tested, ranging from a conservative constantcatch to a step up/down constant catch strategy depending on the level of current mean length, and to target type MPs based on current mean length as a function of the target mean length. For comparative purposes, empirical MPs corresponding to the data-rich scenario are also tested, including CPUE slope type MPs and CPUE target based MPs. Summary statistics and plots are shown to compare performance statistics of the candidate MPs.

## 2. Operating models

The technical specifications of the operating model, an age-structured production model (ASPM), used for the robustness trails can be found in Appendix 1 of this document. Simulations are generated by integrating over prior distributions for key model parameters such as current depletion $B_{n}^{s p} / K^{s p}$ (from which pre-exploitation equilibrium spawning biomass, $K^{s p}$, is back-calculated), "steepness" of the stockrecruit relationship, $h$, natural mortality rate, $M_{a}$, as well as selectivity and stock-recruit residuals. The prior distributions chosen reflect some qualitative information available for the resource, or group of resources, while still allowing for sufficient model uncertainty expected in reality. The range assumed
here for current depletion of $10 \%$ to $30 \%$ of the pre-exploitation level corresponds to the category of resources collectively termed "severely depleted".

Distributions assumed for key model parameters:

- Current depletion: $B^{s p} / K^{s p} \sim U[0.1,0.3]$
- Steepness: $h \sim U[0.5,0.9]$
- Natural mortality (age-independent): $M_{\alpha} \sim U[0.2,0.4]$
- Selectivity residuals: $\tau_{y, a} \sim N\left(0.0,0.4^{2}\right)$
- Stock-recruit residuals: $\zeta_{y} \sim N\left(0.0,0.5^{2}\right)$
where $a$ is age, $y$ is year and $n$ refers to the current year.

A large set of biomass trajectories are obtained by sampling from these distributions. Past and future data are generated for each simulation, which are then passed to the MPs to compute the TACs. In order to include the full extent of uncertainty expected in reality (and to ensure comprehensive sampling from the prior distributions), 8000 simulations were generated.

## 3. Management Procedures

A variety of management procedures (MPs) have been considered for illustratory purposes. Depending on the data that would typically be available from the fishery, MPs can be either fairly complex models or simple formulae. The model-based MPs are essentially resource assessments models which provide annual TACs according to some preselected target. The advantage of these models are that they can take all the available data into account in the model fitting process in order to estimate key resource abundance and target quantities that are then used to calculate the appropriate TAC. The downsides of these models are their complexity (i.e. not well understood by laymen) and the underlying minimization used for the model fitting can be unstable (leading to spurious results), particularly given the range of uncertainty assumed here for resource depletion. In addition, the simulation testing of model-based MPs is typically very computer time-intensive. For these reasons, and considering the nature of the inshore fisheries for which MPs need to be developed in the South African context, model-based MPs have not been implemented for the results considered here.

On the other hand, empirical-type MPs are generally simple to code and easily understood by all parties involved in the management of the resource. Limited data are used in the formulae to ascertain recent trend in resource biomass, with TACs being moved up or down depending on whether the perceived trend is positive or negative, or whether the resource index is above or below some target value. The disadvantage of this type of MP is that the small amount of data that are incorporated in the MP which could lead to unnecessarily large catch fluctuations, and that there are no estimates of resource abundance and other management quantities (eg related to MSY) on which to base TACs. Therefore, depending on trend in a limited subset of data (typically commercial catch rates, or mean length of catch) the yearly TAC is simply moved up or down from where it was the previous year without knowledge of where the resource might be in relation to its maximum sustainable level (MSY) or other management quantities. This may work well if the resource is not too far depleted and if recent TACs were set at appropriate
levels for the fishery. However if little is known about the resource status, as for example in the data-poor scenario for which an assessment is not possible, particular caution needs to be taken to avoid undue (and undetected) resource depletion as a result of unsustainable use of the stock. Thus the less fishery data available, the more conservative the approach needs to be.

In the absence of any estimates of $B^{s p} / B_{m s y}^{s p}$ there is no knowing whether the resource is above or below its maximum sustainable yield level, leading to uncertainty regarding whether the resource is currently under- or over-utilised. It is therefore important that the starting point of such an empirical MP is at an appropriate level of catch (TAC). While not problematic for the data-rich scenario for which estimates of resource depletion are readily available, this poses an obvious problem for the data-poor case for which there is not sufficient data to estimate current resource status which renders optimum resource management difficult if not impossible. The obvious advantage of these empirical MPs is that they can be efficiently simulation tested. Because of their inherent simplicity and the broad-stroke manner in which the apparent trend in resource is tracked, these MPs are often preferred to their model-based counterparts. More importantly, these simple empirical MPs present some (if not the only) quantitative way of managing the inshore data-poor fisheries of South Africa.

For illustrative purposes, empirical MPs are divided here into two classes depending on the quantitative data available:

- Data-poor: No quantitative data except for the catch history (which is assumed to be exact), and possibly some mean length of catch data;
- Data-rich: An index of abundance (CPUE) in addition to the above.

CPUE and mean length of catch data are generated by the operating model for each simulation, i.e. each generated data set corresponds to a different set of parameter values sampled from the prior distributions. Technical specifications for generating the pseudo data are given in Appendix 2.

For the data-poor case for which very little or no data are available, a variety of empirical rules are tested. A constant catch rule is tested to provide some idea of what level of TAC can be supported by the resource in the absence of quantitative data (in addition to the total historic catches) and thus to provide a benchmark against which to compare feedback-control MPs. The constant catch sought is that which would move the resource biomass to above the MSY level within the projection period of 10 years (see reference points at the beginning of results section). Constant catch strategies, where future TAC is fixed to some percentage $(100 \%, 90 \%, 80 \%$, etc.) of the average TAC over the last 5 years, were tested. The downside of this type of MP is that it may require an unacceptably large drop in TAC in the first year of implementation and, more importantly, that there is no feedback control.

When mean length of catch data are available, empirical rules are employed in which the mean length of fish caught is taken to be an indirect index of abundance (see equilibrium per recruit plots in Figure 4). These include a simple constant catch strategy in which the TAC is stepped up or down by a fixed amount depending on whether certain thresholds are reached. The idea is that unless there is a strong quantitative signal from the length data, the TAC is better left where it is, i.e. to avoid tracking noise in a data-poor
situation. Target-based MPs, similar in form to those investigated in Wayte (2009) for tier 4 stocks, are tested for comparison. For this class of MPs, the TAC is adjusted up or down depending on whether the recent mean length is above or below the target mean length.

For the data-rich case where CPUE data are available, model-based MPs were excluded at this time due to their complexity and the time required to simulation test them. Rather some simple empirical MPs based on target CPUE were considered. While these MPs would normally not be applicable to data-poor resources, they were included here in an attempt to illustrate the possible benefit of the availability of an abundance index for management purposes.

Technical specifications of the Management Procedures are given in Appendix 3.

| Data | Type MP | Description |
| :--- | :--- | :--- |
| Data-poor | Constant catch | CC: Future catch set at a percentage of recent average <br> catch. |
| Data-poor | Mean catch length | LstepCC: step up/down constant catch depending on <br> recent mean length. |
| Data-poor | Target length | Ltarget: TAC adjusted up or down if recent mean <br> length is above or below target length |
| Data-poor/data-rich | Target CPUE | CPUEtarget: TAC adjusted up/down if recent CPUE <br> is above/below target CPUE. |
| Data-rich | CPUE slope | CPUEslope: TAC adjusted up/down if the trend in <br> recent CPUE is positive or negative. |

## 4. Results and discussion

Robustness trials were performed for each of the MPs summarized in the table above. Control parameters used to tune the MPs were chosen to achieve adequate biomass recovery for a "severely depleted" stock within the 10 year projection period. The spawning biomass target and limit reference points proposed in Smith at al. (2009) were adopted here. Specifically, the MP sought is that which would move the resource biomass to $20 \%$ above the MSY level (i.e. $1.2 B_{m s y}^{s p}$ ) within the projection period of 10 years. In terms of risk of further resource depletion, the MP must ensure that the spawning biomass is maintained at above $50 \%$ of $B_{m s y}^{s p}$ for $90 \%$ of the time. Therefore, assuming that $B_{m s y}^{s p}$ is achieved when the resource biomass is at approximately $40 \%$ of its pre-exploitation biomass level $K^{s p}$, the target biomass (in median terms) at the end of the projection period is about $50 \% K$, with a $10 \%$-ile of $20 \% K^{s p}$ to meet the risk threshold.

Tables 1-4 of results show medians and $90 \%$ probability intervals for some pertinent performance statistics. Lower $10 \%$-iles corresponding to the target reference points are also given. Management quantities that are equal or above the target and limit reference points are shown in bold. In all cases 8000 simulations were performed with a projection period of 10 years.

### 4.1 Constant catch harvesting strategy

At the one extreme where no quantitative data (other than the historic total catches) are available, constant catch strategies were tested to ascertain what level of catch is required to ensure recovery in median terms of the resource to $20 \%$ above $B_{m s y}$ level given the uncertainty inherent in a data-poor fishery, particularly one termed "severely depleted". When the current level of TAC is maintained for future years the spawning biomass is estimated to increase in median terms. However, looking at the lower $90 \%$ probability interval in Table 1 (first column) it is clear that there is the risk of unacceptably low resource depletion under this harvesting strategy (spawning biomass depleted to levels as low as $3 \%$ of its preexploitation level). On the positive side, the average variation in catch is zero. Reducing the future catches to $90 \%$ of its recent average ( 450 tons - column 2 ) leads to some improvement in terms of the $5 \%$-ile for final depletion (now $7 \%$ ) but not nearly enough.

Fixing the future catches to $80 \%$ of the recent average ( 400 tons - column 3 ) achieves the target values for $B^{s p} / B_{m s y}^{s p}$ in median terms as well as at the $10 \%$-ile level of 1.2 and 0.5 respectively. However, while the median estimate for spawning biomass depletion has improved to $44 \%$ of $K^{s p}$ for this MP, the target of $0.5 K^{s p}$ is not quite reached. A further reduction in future catch to $70 \%$ of previous levels ( 350 tons column 4) does however ensure resource biomass recovery to nearly $50 \%$ of $K^{s p}$ in median terms and a much improved $5 \%$-ile value for depletion of $B^{s p} / K^{s p}=0.18$ at the end of the 10 year projection period.

However, to achieve all the targets set out above, the future catch needs to be reduced to $60 \%$ of recent levels ( 300 tons - last column). In particular, spawning biomass is estimated to recover to above $50 \%$ of
$K^{s p}$ in median terms, while ensuring recovery to above $20 \%$ of $K$ at the lower $\%$-iles. Therefore, from a risk point of view, lowering the future catch to $60 \%$ of recent levels ( 300 tons) is sustainable and resource recovery is ensured. However, this low level of catch may be wasteful in terms of the maximum sustainable yield statistics in Table 1 (biomass well above $50 \%$ of $B_{m s y}^{s p}$ at the $5 \%$-ile level, with the median biomass estimated to be $60 \%$ above $B_{m s y}^{s p}$ ). Furthermore, the sudden large drop in TAC of $40 \%$ under these strategies is not desirable. Therefore, of the MPs shown in Table 1, setting the future catch in the region of $70 \%$ to $80 \%$ of recent levels appears to achieve most management objectives in terms of minimizing risk of further resource depletion while ensuring reasonable future catches. This provides a benchmark against which to compare the feedback based MPs that follow.

### 4.2 Step-wise constant catch strategy

For the scenario when some catch-at-length data are available to manage the fishery, simple empirical MPs were tested which attempt to react to trend information while not responding to noise. In contrast to the previous constant catch MPs, the difficulty here is to restrict the average variation in catch from year to year, but still react quickly enough to indications in the length data that the resource might be under undue pressure. A first attempt therefore is to react to an increase/decrease in average mean length only once a threshold is reached (Table 2). Here a $5 \%$ increase and $2 \%$ decrease thresholds were used, i.e. faster reaction when there is a negative trend. Once the threshold is reached, the TAC is increased/decreased by a step ( $5 \%$ of the average recent catch). The TAC is further reduced by a step if a second negative threshold is reached. The latter was necessary in cases of severe current resource depletion of $10 \%$ of the pre-exploitation level.

The results in column 1 correspond to a starting value used in the MP formula of $100 \%$ of recent catch ( 500 tons). The lower $5 \%$-ile for final spawning biomass estimate is unacceptable low ( $5 \%$ of $K^{s p}$ ) for this option. While $B_{m s y}^{s p}$ is reached in median terms within the projection period, another concern is that the median target of $20 \%$ above $B_{m s y}^{s p}$ if not achieved and that $10 \%$-ile is below the desired target value of 0.5. Lowering the starting value, $T A C^{*}$, to $90 \%$ of the average of recent catches ( 450 tons) results in an increase in the median spawning biomass to well above $B_{m s y}^{s p}$ at the end of the 10 year projection period; however the spawning biomass does not recover sufficiently in median terms and risk related target levels are not reached.

A starting point of $80 \%$ of recent catches ( 400 tons) performs much better in terms of resource recovery, with a median estimate for final depletion of 0.42 and the lower 5 and $10 \%$-iles at 0.12 and 0.20 respectively. To ensure that the resource biomass recovers to about $50 \%$ of the pre-exploitation target level, a more conservative starting point for this MP is required. For a starting point of $70 \%$ of recent catches ( 350 tons), all targets are achieved except that the median spawning biomass depletion reaches only $46 \%$. Similarly to the constant catch strategies, a starting point of $60 \%$ of average recent catches (300 tons) achieves all the risk related objectives, but seems overly conservative in terms of (over)reaching maximum sustainable yield targets. The main concern here is the possible large (>15\%) inter annual variations in catch. For this class of MPs no inter-annual TAC constraint was applied as these

MPs increase/decrease with predefined steps. In addition, large reductions in catch may be required for resources defined as "severely depleted" in order to avoid commercial extinction.

### 4.3 Target mean length harvest strategy

Performance statistics for the target-type MPs based on mean length are given in Table 3. The first column corresponds to a target of $5 \%$, the second one of $10 \%$, and the third one of $15 \%$ above an historical average for mean length of catch data. While a length target of only $5 \%$ above past average mean length does not achieve management objectives in terms of resource recovery to above $50 \%$ of preexploitation level, increasing the target to $15 \%$ above past average does succeed in increasing the median spawning biomass from $20 \%$ to $50 \%$ of $K$ at the end of the projection period, as well as ensuring that the biomass is more than $20 \%$ above the maximum sustainable yield level ( $B^{s p} / B_{m s y}^{s p}=1.54$ ).

However, this comes at a price in terms of total average catch which in median terms decrease from 470 tons to 321 tons with an increase in target mean length of $5 \%$ to $15 \%$ above historic average. In addition, the average inter-annual variation in catch can be as high as $26 \%$, which is hardly desirable. In order to decrease year-by-year fluctuations in catch a limitation of $15 \%$ is imposed on the inter-annual TAC variation (column 4 of table 3). This has minimal negative effect on the risk management statistics, but manages to reduce the fluctuations in future TACs, as well as increasing the future catches at the lower end of the probaility interval.

### 4.4 Data-rich harvesting strategies

Table 4 shows management statistics for data-rich MPs which calculate the annual TAC based on information in the CPUE data. Columns 1 and 2 give pertinent management quantities for the CPUE slope-type MP, while columns 3,4 and 5 show estimates for CPUE target-type MPs. For the slope-type MP, a conservative starting value of $60 \%$ of past catches was assumed combined with low values for $\lambda$ of 0.4 and 0.2 which leads to minimal inter-annual variation. No TAC constraint was therefore necessary for these MPs.

The third column in Table 4 lists performance statistics for the CPUE target MP corresponding to a target of only $50 \%$ higher than an average historical CPUE. This results in median spawning biomass estimates well below the target reference point. Increasing the target to double an average historical CPUE (column 4 Table 4) results in an increased average future catch of 416 tons and median estimates of spawning biomass in excess of $20 \%$ above maximum sustainable yield level. However, for these catches the median biomass does not quite recover to $50 \%$ of the pre-exploitation level ( $B^{s p} / K^{s p}=0.42$ ), although the limit reference point requited for the $10 \%$-ile, that of being above $20 \% K^{s p}$, is reached. Increasing the CPUE target to $250 \%$ of past average improves the risk statistics somewhat at the expense of a drop in average catch in median terms from 416 to 337 tons (last column in Table 4). The inter-annual variation in catch was restricted to below $15 \%$ for the CPUE target-based MPs.

### 4.5 Results in graphical form

A subset of 30 simulations are shown in the worm plots (Figures 2, 3, 4, 5, and 6) depicting biomass trajectories and TACs for a selection of MPs tested. These plots reflect the extent of variation and uncertainty inherent in the resource biomass very clearly. The plots in Figure 2 depict different constant catch harvesting strategies. Given the extent of uncertainty encompassed by the operating models, particularly in terms of the extent of current resource depletion, it is clear that keeping the catch at a $100 \%$ of recent levels ( 500 tons) could lead to unacceptably low resource depletion. Lowering the future TAC to $60 \%$ of recent catches ( 300 tons) results in even the most pessimistic biomass trajectories increasing during the projection period.

Spawning biomass trajectories (Figure 3) for MPs based on a threshold length fare slightly better that the constant catch MPs for the equivalent TAC* $=70 \%$, with biomass estimates a little less spread at the end of the projection period for this MP. However there is a price to pay in terms of inter annual variability in the TAC.

Spawning biomass and TAC trajectories corresponding to the target length-based MPs, which adjust the future TAC depending on whether the mean length of the catch data is above or below the preselected target, are shown in Figure 4. To illustrate how mean length of catch varies with the level of resource biomass, the equilibrium spawning $B^{s p} / B_{m s y}^{s s}$ is plotted for increasing values of fishing mortality, $F$, in Figure 1. For the range of natural mortality rate assumed in the operating models ( 0.2 to 0.4 ), the values for equilibrium mean length at $B^{s p} / B_{m s y}^{s p}=1$ range from about 30 to 36 cm . Based on these values the target mean length was chosen as a percentage of historical mean length in the range 105 to $115 \%$. The worm plots corresponding to a mean length target of $115 \%$ of an average historic mean length are shown in Figure 5. Compared to the TAC trajectories in Figure 4, these show slightly more inter-annual variability, while biomass trajectories increase under this MP from the low current levels.

Biomass and catch trajectories corresponding to the CPUE slope MP are shown in Figure 5. The spread of the future catches is clearly reduced for this MP because of the low value of $\lambda$, although no TAC change constraints were applied. Figure 6 shows the biomass and catch trajectories when applying a CPUE target MP. These are very similar to the target mean length MP.

### 4.6 Comparison of MPs

Pertinent management quantities in Tables 1 to 4 are also shown visually in Figure 7 to facilitate comparison of the different MPs. The key statistics shown are medians and $90 \%$-iles of average future TAC (top), spawning biomass depletion $B^{s p} / K^{s p}$ (middle) and $B^{s p} / B_{m s y}^{s p}$ (bottom) at the end of the 10 year projection period. The thick horizontal line indicate the target depletion for $B^{s p}$. When ignoring the results corresponding to the constant catch harvesting strategies in the top plot, the target mean length strategy with a stepwise constant catch seems to perform best of the data-poor MPs, with comparatively narrow probability intervals for average TAC. However, when considering the data-rich candidates as well, the CPUE slope MP outperforms the others in terms of TAC spread.

When comparing the depletion probability intervals in the middle plot, the data-rich MPs have slightly narrower intervals than the data-poor ones. In particular, the CPUE target strategy seems to outperform its neighbours here as well as in the bottom plot, for $B^{s p} / B_{m s y}^{s p}$.

While these plots give useful information regarding spread of results under different strategies, Figure 8 is a better visual aid when comparing risk/return performance statistics. Median average future TAC is plotted against the $10 \%$-ile estimates for spawning biomass depletion under different harvesting strategies. If the objective is to maximize future catch while at the same time minimizing resultant resource depletion, then we are looking for those values that lie furthest to the right and to the top of the plots in Figure 8 . From the top plot it is apparent that the mean length constant catch strategy outperforms the other data-poor MPs. Of the three, the constant catch MP performs the worst as would be expected. The bottom plot compares performance of the two best data-poor MPs with that of the data-rich target CPUE harvesting strategy. It is evident from this plot that the data-rich MP achieves a higher yield, in terms of median average TAC, for the same level of risk of resource depletion than the data-poor ones. In terms of the limit reference point, to ensure that the spawning biomass is maintained above $20 \%$ of the preexploitation level for $90 \%$ of the time, a median future TAC of 450 tons is achievable by the CPUE slope MP, while the corresponding yield for the target length and stepwise constant catch MPs are 400 and 425 tons respectively.

## 6 Conclusions

The results thus far accentuate the importance of the role of an abundance index such as CPUE data for fishery management purposes. This is particularly evident when considering median estimates of average future TACs (rewards) plotted against the $10 \%$-ile values (relating to "risk") for final resource depletion in Figure 8. It is clear from the lower of these plots that the data-rich MP based on CPUE data outperforms the data-poor ones: in the absence of CPUE data (data-poor) the median average future TAC needs to be reduced by about 50 tons to maintain the same level risk.

In order to choose which data-poor MPs are best suited in terms of the performance statistics we need to consider the upper plot in Figure 8. While constant catch strategies perform well in terms of minimising inter-annual variation in catch, they cannot be considered for management purposes as they lack feedback control. Indeed, they are included here merely as a benchmark against which to compare the other MPs. It is not surprising that the stepwise constant catch based on mean length data outperforms the fixed constant catch MPs in terms of the risk/reward plot in Figure 8, ensuring higher median future TACs for less risk of further resource depletion at the $10 \%$-ile level. However, the target length-based MP perform only slightly better than the constant catch strategies and not nearly as well as the stepwise MPs, with a somewhat larger variation in catch from year to year.

While the data-rich MPs perform somewhat better than the data-poor ones as would be expected, from these initial results it seems, however, that the very simple data-poor MPs are surprisingly robust to a
wide range of uncertainty for key parameters and could well be candidates to manage the South African data-poor stocks, ensuring perhaps not optimum, but at least relatively stable sustainable future catches.

## 7 Future work

The objective of this work is to implement generic MPs for data-poor in-shore fisheries in South Africa. In its present form this document constitutes an initial theoretical consideration of possible harvesting strategies. However, in order to move towards practical implementation, a first step would be to attempt to group fisheries in terms of shared characteristics in terms of similar demographic parameters and level of perceived depletion. For example, stocks could be grouped into three main categories: "severely depleted", "moderately depleted" and "near target". Furthermore, resources with similar demographic parameters such as natural mortality rates could also be grouped, and so forth.

Based on available quantitative and qualitative data, different sets of generic operating models then be specified for the different groups of fisheries. Having defined the operating models that would encompass the uncertainty associated with a selection of fisheries, robustness trials could then be performed for the chosen set of MPs depending on typical data available. The generic MP appropriate for a group of fisheries sharing similar characteristic could then be chosen by comparing performance statistics.

The range of operating models used for robustness trials in this document correspond to "severely depleted" resources that have hake-like characteristics. While a large range of uncertainty was reflected in these operating models, no allowance was made for systematic bias (and particularly for trends in such bias) in the data. In addition, robustness to systematic changes in fishing selectivity also needs to be simulation tested. Furthermore, total historic catches were assumed to be exact for these calculations, which is unrealistic. Uncertainty regarding the growth parameters also needs to be considered. Importantly the extents of these uncertainties that are considered in the operating models needs to be related to reality, which requires close evaluation of the data sets available for the fisheries potentially subject to such a management approach.

| Data-poor MPs: No quantitative data |  |  |  |  |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :---: |
|  | MP: CC 100\% <br> of $\overline{T A C}$ | MP: CC 90\% <br> of $\overline{T A C}$ | MP: CC 80\% <br> of $\overline{T A C}$ | MP: CC 70\% <br> of $\overline{T A C}$ | MP: <br> $\mathbf{6 0 \%}$ <br> $\overline{T A C}$ |  |

Table 1: Medians (with 5\% and 95\%-iles in parenthesis) shown for pertinent management quantities for the case were no resource monitoring data are taken into account in the MP. The $10 \%$-iles for biomass depletion estimates are also shown to compare with target values for these quantities. Constant catch MPs are used starting with keeping the TAC at a $100 \%$ of the recent average TAC of 500 tons, and more conservative options of reducing the TAC to $90 \%, 80 \%, 70 \%$ and $60 \%$ of recent levels ( $450,400,350$ and 300 tons). No TAC constraints applied. 8000 simulations were performed.

| Data-poor MPs: Mean length of catch data |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\begin{aligned} & \text { MP: LstepCC } \\ & T A C^{*}=100 \% \overline{T A C} \end{aligned}$ | $\begin{array}{\|l} \hline \text { MP: LstepCC } \\ T A C^{*}=90 \% \overline{T A C} \end{array}$ | $\begin{aligned} & \text { MP: LstepCC } \\ & T A C^{*}=80 \% \overline{T A C} \end{aligned}$ | $\begin{aligned} & \text { MP: LstepCC } \\ & T A C^{*}=70 \% \overline{T A C} \end{aligned}$ | $\begin{aligned} & \text { MP: LstepCC } \\ & T A C^{*}=60 \% \overline{T A C} \end{aligned}$ |
| $B_{\text {current }}^{s p} / K^{s p}$ | $\begin{aligned} & \hline \mathbf{0 . 2 0} \\ & (0.11,0.29) \end{aligned}$ | $\begin{aligned} & \hline \mathbf{0 . 2 0} \\ & (0.11,0.29) \end{aligned}$ | $\begin{aligned} & \hline \mathbf{0 . 2 0} \\ & (0.11,0.29) \end{aligned}$ | $\begin{aligned} & \hline \mathbf{0 . 2 0} \\ & (0.11,0.29) \end{aligned}$ | $\begin{aligned} & \hline \mathbf{0 . 2 0} \\ & (0.11,0.29) \\ & \hline \end{aligned}$ |
| $B_{\text {final }}^{s p} / K^{s p}$ | $\begin{aligned} & \hline 0.35 \\ & (0.04,0.70) \\ & \hline \end{aligned}$ | $\begin{array}{\|l\|} \hline 0.38 \\ (0.07,0.72) \\ \hline \end{array}$ | $\begin{aligned} & \hline 0.42 \\ & (0.12,0.75) \\ & \hline \end{aligned}$ | $\begin{array}{\|l\|} \hline \mathbf{0 . 4 6} \\ (0.18,0.80) \\ \hline \end{array}$ | $\begin{array}{\|l\|} \hline 0.49 \\ (\mathbf{0 . 2 2}, 0.82) \\ \hline \end{array}$ |
| $\begin{aligned} & 10 \% \text {-ile } \\ & B_{\text {final }}^{s p} / K^{s p} \end{aligned}$ | 0.10 | 0.14 | 0.20 | 0.24 | 0.28 |
| $B_{\text {current }}^{s p} / B_{m s y}^{s p}$ | $\begin{aligned} & \hline 0.61 \\ & (0.33,0.95) \\ & \hline \end{aligned}$ | $\begin{array}{\|l\|} \hline 0.61 \\ (0.33,0.95) \\ \hline \end{array}$ | $\begin{aligned} & \hline 0.61 \\ & (0.33,0.95) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.61 \\ & (0.33,0.95) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.61 \\ & (0.33,0.95) \\ & \hline \end{aligned}$ |
| $B_{\text {final }}^{s p} / B_{m s y}^{s p}$ | $\begin{aligned} & \hline 1.08 \\ & (0.12,2.28) \end{aligned}$ | $\begin{array}{\|l\|} \hline 1.19 \\ (0.22,2.35) \\ \hline \end{array}$ | $\begin{aligned} & \hline \mathbf{1 . 3 1} \\ & (0.37,2.47) \end{aligned}$ | $\begin{aligned} & \mathbf{1 . 4 4} \\ & (\mathbf{0 . 5 2}, 2.65) \end{aligned}$ | $\begin{aligned} & \hline \mathbf{1 . 5 3} \\ & (\mathbf{0 . 6 2}, 2.72) \end{aligned}$ |
| $\begin{aligned} & 10 \%-\mathrm{ile} \\ & B_{\text {final }}^{s p} / B_{m s y}^{s p} \end{aligned}$ | 0.30 | 0.42 | 0.58 | 0.71 | 0.81 |
| $\overline{T A C}{ }_{\text {future }}$ | $\begin{aligned} & \hline 520 \\ & (335,638) \end{aligned}$ | $\begin{array}{\|l\|} \hline 475 \\ (293,588) \\ \hline \end{array}$ | $\begin{aligned} & \hline 435 \\ & (250,538) \end{aligned}$ | $\begin{array}{\|l\|} \hline 388 \\ (210,488) \end{array}$ | $\begin{aligned} & \hline 338 \\ & (163,438) \end{aligned}$ |
| $\begin{aligned} & \text { Change in } \\ & \overline{T A C}_{\text {future }} \end{aligned}$ | $\begin{aligned} & \hline 0.03 \\ & (0.01,0.09) \end{aligned}$ | $\begin{array}{\|l\|} \hline 0.04 \\ (0.02,0.11) \end{array}$ | $\begin{aligned} & \hline 0.05 \\ & (0.03,0.12) \end{aligned}$ | $\begin{aligned} & \hline 0.07 \\ & (0.04,0.15) \end{aligned}$ | $\begin{aligned} & \hline 0.09 \\ & (0.05,0.19) \end{aligned}$ |

Table 2: Medians (with 5\% and 95\%-iles in parenthesis) shown for pertinent management quantities for the stepwise constant catch MP where only mean length of catch data are taken into account. $10 \%$-iles are shown for the risk statistics. No TAC constraints applied. 8000 simulations were performed.

| Data-poor MPs: Mean length of catch data |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  | MP: Ltarget $l_{t \text { arget }}=105 \% \tilde{l}_{\text {past }}$ | MP: Ltarget $l_{t \operatorname{arget}}=110 \% \tilde{l}_{\text {past }}$ | MP: Ltarget $l_{t \text { arget }}=115 \% \tilde{l}_{\text {past }}$ | $\begin{aligned} & \text { MP: Ltarget } \\ & l_{t \text { arget }}=115 \% \tilde{l}_{\text {past }} \\ & T A C_{\text {change }} \leq 15 \% \end{aligned}$ |
| $B_{\text {current }}^{s p} / K^{s p}$ | $\begin{aligned} & \mathbf{0 . 2 0} \\ & (0.11,0.29) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline \mathbf{0 . 2 0} \\ & (0.11,0.29) \\ & \hline \end{aligned}$ | $\begin{array}{\|l\|l} \hline \mathbf{0 . 2 0} \\ (0.11,0.29) \\ \hline \end{array}$ | $\begin{aligned} & \hline \mathbf{0 . 2 0} \\ & (0.11,0.29) \\ & \hline \end{aligned}$ |
| $B_{\text {final }}^{s p} / K^{s p}$ | $\begin{aligned} & \hline 0.37 \\ & (0.08,0.73) \end{aligned}$ | $\begin{aligned} & \hline 0.45 \\ & (0.18,0.79) \end{aligned}$ | $\begin{aligned} & \mathbf{0 . 5 0} \\ & (\mathbf{0 . 2 2}, 0.83) \end{aligned}$ | $\begin{aligned} & \hline 0.48 \\ & (\mathbf{0 . 2 1}, 0.82) \end{aligned}$ |
| $10 \% \text {-ile } B_{\text {final }}^{s p} / K^{s p}$ | 0.14 | 0.23 | 0.28 | 0.27 |
| $B_{\text {current }}^{s p} / B_{\text {msy }}^{s p}$ | $\begin{aligned} & \hline 0.61 \\ & (0.33,0.95) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.61 \\ & (0.33,0.95) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.61 \\ & (0.33,0.95) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.61 \\ & (0.33,0.95) \\ & \hline \end{aligned}$ |
| $B_{\text {final }}^{s p} / B_{m s y}^{s p}$ | $\begin{aligned} & 1.16 \\ & (0.26,2.34) \end{aligned}$ | $\begin{aligned} & \mathbf{1 . 3 9} \\ & (\mathbf{0 . 5 2}, 2.57) \end{aligned}$ | $\begin{aligned} & \mathbf{1 . 5 4} \\ & (\mathbf{0 . 6 5 , 2 . 7 5 )} \end{aligned}$ | $\begin{aligned} & \mathbf{1 . 5 0} \\ & (\mathbf{0 . 6 1 , 2 . 7 1 )} \end{aligned}$ |
| $10 \% \text {-ile } B_{\text {final }}^{s p} / B_{m s y}^{s p}$ | 0.43 | 0.70 | 0.85 | 0.79 |
| $\overline{T A C}_{\text {future }}$ | $\begin{aligned} & \hline 470 \\ & (271,699) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 380 \\ & (224,564) \end{aligned}$ | $\begin{array}{\|l} \hline 321 \\ (194,472) \end{array}$ | $\begin{array}{\|l\|} \hline 330 \\ (243,470) \\ \hline \end{array}$ |
| Change in $\overline{T A C}_{\text {future }}$ | $\begin{aligned} & \hline 0.10 \\ & (0.05,0.24) \end{aligned}$ | $\begin{aligned} & \hline 0.11 \\ & (0.05,0.25) \end{aligned}$ | $\begin{aligned} & \hline 0.12 \\ & (0.06,0.26) \end{aligned}$ | $\begin{aligned} & \hline 0.10 \\ & (0.06,0.14) \end{aligned}$ |

Table 3: Medians (with 5\% and 95\%-iles in parenthesis) shown for pertinent management quantities for the target length MP where only mean length of catch data are taken into account. $10 \%$-iles are shown for the risk statistics. A 15\% inter-annual TAC constraint was applied for the last column of results. 8000 simulations were performed.

|  | CPUE slope $\begin{aligned} & C P U E^{*}=60 \% C P U E_{\text {past }} \\ & \lambda=0.4 \\ & \sigma=0 \end{aligned}$ | CPUE slope $\begin{aligned} & \text { CPUE }^{*}=60 \% \text { CPUE }_{\text {past }} \\ & \lambda=0.2 \\ & \varpi=0 \end{aligned}$ | CPUE target $\begin{aligned} & \text { CPUE }_{\text {tayg }}=150 \% \text { CPUE }_{\text {past }} \\ & \varpi=0.5 \\ & T A C_{\text {change }} \leq 15 \% \end{aligned}$ | CPUE target $\begin{aligned} & \text { CPUE }_{\text {tayget }}=200 \% \text { CPUE }_{\text {pat }} \\ & \varpi=0.5 \\ & T A C_{\text {change }} \leq 15 \% \end{aligned}$ | CPUE target $\begin{aligned} & \text { CPUE }_{\text {tagye }}=250 \% \text { CPUE }_{p a} \\ & \varpi=0.5 \\ & T A C_{\text {change }} \leq 15 \% \end{aligned}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $B_{\text {current }}^{s p} / K^{s p}$ | $\begin{array}{\|l} \hline 0.20 \\ (0.11,0.29) \\ \hline \end{array}$ | $\begin{aligned} & \hline 0.20 \\ & (0.11,0.29) \\ & \hline \end{aligned}$ | $\begin{aligned} & 0.20 \\ & (0.11,0.29) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.20 \\ & (0.11,0.29) \\ & \hline \end{aligned}$ | $\begin{array}{\|l\|} \hline 0.20 \\ (0.11,0.29) \\ \hline \end{array}$ |
| $B_{\text {final }}^{s p} / K^{s p}$ | $\begin{aligned} & \hline 0.47 \\ & (0.22,0.77) \end{aligned}$ | $\begin{aligned} & \hline 0.49 \\ & (0.22,0.80) \end{aligned}$ | $\begin{aligned} & \hline 0.34 \\ & (0.09,0.63) \end{aligned}$ | $\begin{aligned} & \hline 0.42 \\ & (0.19,0.71) \end{aligned}$ | $\begin{array}{\|l\|} \hline 0.47 \\ (\mathbf{0 . 2 3}, 0.76) \end{array}$ |
| $\begin{aligned} & 10 \% \text {-ile } \\ & B_{\text {final }}^{s p} / K^{s p} \end{aligned}$ | 0.27 | 0.28 | 0.14 | 0.24 | 0.29 |
| $B_{\text {current }}^{s p} / B_{\text {msy }}^{s p}$ | $\begin{aligned} & \hline 0.61 \\ & (0.33,0.95) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.61 \\ & (0.33,0.95) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.61 \\ & (0.33,0.95) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.61 \\ & (0.33,0.95) \\ & \hline \end{aligned}$ | $\begin{array}{\|l\|} \hline 0.61 \\ (0.33,0.95) \\ \hline \end{array}$ |
| $B_{\text {final }}^{s p} / B_{m s y}^{s p}$ | $\begin{array}{\|l\|} \hline \mathbf{1 . 4 6} \\ (\mathbf{0 . 6 2}, 2.56) \\ \hline \end{array}$ | $\begin{aligned} & \mathbf{1 . 5 4} \\ & (\mathbf{0 . 6 2}, 2.70) \\ & \hline \end{aligned}$ | $\begin{aligned} & 1.02 \\ & (0.30,2.02) \end{aligned}$ | $\begin{aligned} & \mathbf{1 . 2 9} \\ & (\mathbf{0 . 5 7 , 2 . 3 1 )} \end{aligned}$ | $\begin{aligned} & \mathbf{1 . 4 5} \\ & (\mathbf{0 . 6 9}, 2.52) \end{aligned}$ |
| $\begin{aligned} & 10 \% \text {-ile } \\ & B_{\text {final }}^{s p} / B_{m s y}^{s p} \end{aligned}$ | 0.79 | 0.81 | 0.44 | 0.71 | 0.84 |
| $\overline{T A C}_{\text {future }}$ | $\begin{array}{\|l\|} \hline 365 \\ (296,457) \end{array}$ | $\begin{aligned} & \hline 332 \\ & (298,374) \end{aligned}$ | $\begin{aligned} & \hline 510 \\ & (249,942) \end{aligned}$ | $\begin{array}{\|l\|} \hline 416 \\ (248,717) \\ \hline \end{array}$ | $\begin{array}{\|l\|} \hline 337 \\ (231,610) \end{array}$ |
| $\begin{aligned} & \text { Change } \quad \text { in } \\ & \overline{T A C}_{\text {future }} \end{aligned}$ | $\begin{aligned} & 0.08 \\ & (0.06,0.11) \end{aligned}$ | $\begin{aligned} & 0.06 \\ & (0.05,0.07) \end{aligned}$ | $\begin{aligned} & 0.13 \\ & (0.08,0.15) \end{aligned}$ | $\begin{aligned} & 0.12 \\ & (0.07,0.15) \end{aligned}$ | $\begin{aligned} & \hline 0.13 \\ & (0.09,0.15) \end{aligned}$ |

Table 4: Medians (with 5\% and 95\%-iles in parenthesis) shown for pertinent management quantities for the data-rich case where CPUE are taken into account in the MP. A $15 \%$ inter-annual TAC constraint was applied to CPUE target MPs only. A total of 8000 simulations were performed.




Figure 1: Equilibrium spawning biomass and yield per recruit plots with corresponding mean length and mass targets. The MSY is assumed to be given by the $F$ for which $\operatorname{SSB}(F)=0.35 \operatorname{SSB}(F=0)$ for simplicity. The following selectivity vector was used for the yield-per-recruit calculations: $S_{a}=[0,0.2,0.4,0.6,0.8,1.0,1.0,1.0$, $1.0,1.0,1.0]$.







Figure 2: Spawning biomass (top 5 plots) and TAC (bottom) trajectories for 30 simulations out of a total of 8000 simulations are shown for various constant catch MPs for a starting values ranging from $\mathbf{1 0 0 \%}$ to $\mathbf{6 0 \%}$ of the recent average TAC.



Figure 3: Spawning biomass (top) and TAC (bottom) trajectories for 30 simulations out of a total of 8000 simulations are shown for the length-based stepwise constant catch MP for a starting value of $\mathbf{7 0 \%}$ of recent TAC.



Figure 4: Spawning biomass (top) and TAC (bottom) trajectories for 30 simulations out of a total of 8000 simulations are shown for the target length-based MP for a target value of $\mathbf{1 1 5 \%}$ of historical mean length. A $\mathbf{1 5 \%}$ restriction on TAC variability was imposed for this MP.



Figure 5: Spawning biomass (top) and TAC (bottom) trajectories for 30 simulations out of a total of 8000 simulations are shown for a CPUE slope-based MP. No inter-annual TAC restriction was imposed.



Figure 6: Spawning biomass (top) and TAC (bottom) trajectories for 30 simulations out of a total of 8000 simulations are shown for a CPUE-based MP with a target of $\mathbf{2 5 0 \%}$ of the historic average CPUE. A $\mathbf{1 5 \%}$ restriction on TAC variability was imposed for this MP.




Figure 7: Medians and $\mathbf{9 0 \%}$-iles for average future TAC (top), final spawning biomass depletion (middle) and final spawning biomass in terms of the MSY level (bottom) under various MPs considered. The thick horizontal line corresponds to the target reference point for median depletion.


Figure 8: Median average future TAC plotted against $10 \%$-ile estimates for final spawning biomass depletion for various MPs: the three data-poor MPs (top) and two data-poor MPs compared with a data-rich MP (bottom). Linear trendlines are shown for each MP.

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## Appendix 1: Operating model for generic MP testing

### 1.1 The age-structured production model (ASPM)

The resource dynamics are modeled by the following equations, depending whether a continuous or pulse fishery is assumed. For the Baranov approximation (continuous fishing throughout year), the resource dynamics are modeled by the equations

$$
\begin{align*}
& N_{y+1, a \min }=R_{y+1}  \tag{1.1}\\
& N_{y+1, a+1}=N_{y, a} e^{-\left(M_{a}+S_{y, a} F_{y}\right)}=N_{y, a} e^{-Z_{y, a}} \text { for } a_{\min } \leq a<m-2  \tag{1.2}\\
& N_{y+1, m}=N_{y, m-1} e^{-\left(M_{m-1}+S_{y, m-1} F_{y}\right)}+N_{y, m} e^{-\left(M_{m}+S_{y, m} F_{y}\right)} \tag{1.3}
\end{align*}
$$

When employing the Pope approximation (assuming a mid-year pulse fishery), the resource dynamics are modeled by the equations

$$
\begin{align*}
& N_{y+1, a+1}=N_{y, a} \exp ^{-M_{a}}-C_{y, a} e^{-M_{a} / 2} \quad \text { for } a_{\min } \leq a<m-2  \tag{1.4}\\
& N_{y+1, m}=N_{y, m-1} e^{-M_{m-1}}-C_{y, m-1} e^{-M_{m-1} / 2}+N_{y, m} e^{-M_{m}}-C_{y, m} e^{-M_{m} / 2} \tag{1.5}
\end{align*}
$$

where
$N_{y, a}$ is the number of fish of age $a$ at the start of year $y$,
$M_{a}$ denotes the natural mortality rate on fish of age $a$,
$S_{y, a}$ is the age-specific selectivity for year $y$,
$F_{y}$ is the fishing mortality for year $y$,
$m$ is the maximum age considered (taken to be a plus-group), and
$a_{\text {min }}$ is the minimum age considered ( 0 in this case).

The number of recruits at the start of year $y$ (for $y>1$ ) is related to the spawning stock size by a stockrecruitment relationship

$$
\begin{equation*}
R_{y}=\frac{\alpha B_{y-a \min }^{s p}}{\beta+\left(B_{y-a \min }^{s p}\right)^{\gamma}} e^{\varsigma_{y}} \tag{1.6}
\end{equation*}
$$

where
$\alpha, \beta$ and $\gamma$ are spawning biomass-recruitment parameters ( $\gamma=1$ for a Beverton-Holt and $\gamma>1$ for a Ricker-like relationship, and can either be input or treated as an estimable parameter), $\varsigma_{y}$ reflects fluctuation about the expected recruitment for year $y$, and $B_{y-a \min }^{s p}$ is the spawning biomass at the start of year $y-a_{\text {min }}$, given that:

$$
\begin{equation*}
B_{y}^{s p}=\sum_{a=0}^{m} f_{a} w_{a} N_{y, a} \tag{1.7}
\end{equation*}
$$

where $w_{a}$ is the begin-year mass of fish of age $a$ and $f_{a}$ is the proportion of fish of age a that are mature.

In order to work with estimable parameters that are more meaningful biologically, the stock-recruitment relationship is re-parameterised in terms of the pre-exploitation equilibrium spawning biomass, $K^{s p}$, and the "steepness" of the stock-recruitment relationship (recruitment at $B^{s p}=0.2 K^{s p}$ as a fraction of recruitment at $B^{s p}=K^{s p}$ )
$\alpha=\frac{\left(5-0.2^{\gamma-1}\right) h R_{1}\left(K^{s p}\right)^{\gamma-1}}{5 h-1}$
and
$\beta=\frac{\left(K^{s p}\right)^{\gamma}\left(1-h 0.2^{\gamma-1}\right)}{5 h-1}$
where
$R_{1}=K^{s p} /\left[f_{0} w_{0}+\sum_{a=a \min +1}^{m-1} f_{a} w_{a} e^{-\left(\sum_{a \leq a \min }^{a-1} M_{a^{\prime}}\right)}+f_{m} w_{m} \frac{e^{-\left(\sum_{a^{\prime}=a \min }^{m-1} M_{a^{\prime}}\right)}}{1-e^{-M_{m}}}\right]$
Note: A Beverton-Holt stock-recruitment relationship is assumed for the analyse reported in the main texts, i.e. $\gamma=1$.

For the Baranov approximation, the total number of fish caught of age $a$ in year $y$ is given by

$$
\begin{equation*}
C_{y, a}=N_{y, a} \frac{S_{y, a} F_{y}}{Z_{y, a}}\left(1-e^{-Z_{y, a}}\right) \tag{1.11}
\end{equation*}
$$

where the fishing mortality $F_{y}$ cannot be calculated directly, so is computed using the bisection method.

When assuming a Pope approximation, the number of fish caught of age $a$ in year $y$ is given by

$$
\begin{equation*}
C_{y, a}=N_{y, a} S_{y, a} F_{y} e^{-M_{a} / 2} \tag{1.12}
\end{equation*}
$$

where the estimate fishing mortality is simply $F_{y}=C_{y} / B_{y}^{\exp }$
The corresponding catch by mass for each year is given by
$C_{y}=\sum_{a=a_{\min }}^{m} w_{a+1 / 2} C_{y, a}$
where $w_{a+1 / 2}$ denotes the mid-year mass of fish of age.
The model estimate of the exploitable ("available") component of biomass is given by $B_{y}^{\mathrm{exp}}=\sum_{a=a \min }^{m} w_{a} S_{y, a} N_{y, a} \quad$ for begin-year biomass, and
for the mid-year biomass
$B_{y}^{\exp }=\sum_{a=a \min }^{m} w_{a+1 / 2} S_{y, a} N_{y, a} e^{-Z_{y, a} / 2}$ for the Baranov approximation, or
$B_{y}^{\exp }=\sum_{a=a \min }^{m} w_{a+1 / 2} S_{y, a} N_{y, a} e^{-M_{a} / 2}$ for the Pope approximation.

It is usually assumed that the resource is at the deterministic equilibrium that corresponds to an absence of harvesting at the start of the initial year ( $B_{1}^{s p}=K^{s p}$ ). However, the initial spawning biomass ratio to this pristine level can also be fixed (input) such that $B_{1}^{s p}=r^{s p} K^{s p}$ where $r^{s p} \neq 1$. Whatever the value of $r^{s p}$, the age-structure of $B_{1}^{s p}$ is taken to be that corresponding to the equilibrium with no fishing mortality.

Note: The Baranov approximation was assumed for the calculations reported in the main text.

### 1.2 Model parameters:

Natural mortality: An age-independent mortality rate, drawn from a uniform prior distribution for $M_{a} \sim U[0.2,0.4]$ is assumed, consistent with that of a species of intermediate longevity, such as horse mackerel or hake.

Fishing selectivity: An age-dependant fishing selectivity of
$S_{a}=[0,0.2,0.4,0.6,0.8,1.0,1.0,1.0,1.0,1.0,1.0]$
is assumed. Log-normally distributed variability about these values is assumed to be both age and year correlated (Butterworth et al. 2001), such that:

$$
\begin{equation*}
S_{y, a}=S_{a} e^{\tau_{y, a}-\sigma_{t}^{2} / 2} \tag{1.18}
\end{equation*}
$$

where
$\tau_{1, a_{\text {min }}} \sim N\left(0, \sigma_{\tau}{ }^{2}\right)$ is the log-residual for the first year and minimum age,
$\tau_{y, a}=\rho \tau_{y, a-1}+\sqrt{1-\rho^{2}} \chi_{y, a}$ is the log-residual for year $y$ and year $a$, which is estimated for ages $a=a_{\text {min }}+1$ to $m$ and years $y$,
$\tau_{y, a_{\min }}=\rho \tau_{y-1, a_{\min }}+\sqrt{1-\rho^{2}} \chi_{y, a_{\min }}$ is the residual for the minimum age $a_{\text {min }}$ and all years $y$.
$\chi_{y, a} \sim N\left(0, \sigma_{\tau}^{2}\right)$,
$\sigma_{\tau}$ is the standard deviation of the log-residuals, which is input ( $\sigma_{\chi}=0.4$ is used here), and $\rho$ is the serial correlation coefficient, which is input ( $\rho=0.5$ is assumed for these calculations).

Initial spawning biomass ratio: $r^{s p}=B_{1967}^{s p} K^{s p}$ is input ( $r^{s p}=1$ is assumed for these analyses).

Minimum and maximum age: $a_{\min }$ is taken to be $0 ; m$ is taken as a plus-group and set to 10 .

Age-at-maturity: The proportion of fish of age a that are mature is input. For the reference case this is approximated by $f_{a}=1$ for $a>3$.

Mass-at-age: The mass ( $w$ ) of a fish at age $(a)$ is assumed to fit a von Bertalanfy growth equation:

$$
\begin{equation*}
w_{a}=\alpha\left[l_{\infty}\left(1-\exp \left(-\kappa\left(a-t_{0}\right)\right)\right)\right]^{\beta} \tag{1.19}
\end{equation*}
$$

where the following values are assumed here (consistent with the values used in Butterworth et al.(2010))

$$
\begin{aligned}
& \alpha=0.0078 \mathrm{~g}, \\
& \beta=3.0, \\
& l_{\infty}=54.56 \mathrm{~cm}, \\
& \kappa=0.183 \mathrm{yr}^{-1}, \text { and } \\
& t_{0}=-0.654 \mathrm{yr} .
\end{aligned}
$$

### 1.3 Management statistics

Four statistics are used to compare performance by the various MPs considered in the main text:

- $B_{\text {final }}^{s p} / K^{s p}$, the final biomass depletion where $B_{\text {final }}^{s p}$ is the spawning biomass in the last year of the projection period, given by equation Error! Reference source not found..
- $B_{\text {final }}^{s p} / B_{m s y}^{s p}$, the spawning biomass at the end of the 10 year projection period as a fraction of $B_{m s y}^{s p}$, the equilibrium spawning biomass at which maximum sustainable yield is achieved, given by
$B_{m s y}^{s p}=R \sum_{a=a_{\text {min }}}^{m} f_{a} w_{a} N_{a}^{e q}$
where $N_{a}^{e q}$ are the equilibrium population numbers corresponding to $F_{m s y}$ (the fishing mortality at which the maximum yield is obtained), $S_{\text {current }, a}$ (the fishing selectivity vector at the start of the projection period), and $M_{a}$ (the natural mortality vector), and $R$ is the number of recruits which is given by
$R=(\alpha-\beta / S S B)^{*} S S B^{1-\gamma}$
where $S S B$ is the equilibrium spawning biomass per recruit at $F_{m s y}$ and $\alpha, \beta$ and $\gamma$ are the stock-recruit parameters. Note that a different $B_{m s y}^{s p}$ is computed for each simulation, corresponding to different values for $M_{a}$ and $S_{\text {current }, a}$ (which are re-sampled per simulation) as well as the stock-recruit parameters $\alpha$ and $\beta$ (which are re-computed for different values of $K^{s p}$ and $h$ ).
- $\overline{T A C}_{\text {future }}$, the average future TAC, given by

$$
\overline{T A C}_{\text {future }}=1 / 10 \sum_{y=n+1}^{n+10} T A C_{y}
$$

where $n$ is the current year.

- change $\overline{T A C}_{\text {future }}$, the average inter-annual variation in future TAC given by

$$
\text { change } \overline{T A C}_{\text {future }}=1 / 10 \sum_{y=n+1}^{n+10} \frac{\left|T A C_{y-1}-T A C_{y}\right|}{T A C_{y-1}}
$$

## Appendix 2: Generated data

For purposes of this exercise, a pseudo stock is selected that has been depleted to well below the maximum sustainable level (MSYL), with historic catches high at the start of the fishery after which they are reduced later on to prevent further resource depletion. Historic catches assumed for the pseudo fishery for the period under investigation (1970 to 2009) are given in Table A-1.

### 2.1 CPUE data:

The CPUE data are generated assuming that the abundance index is log-normally distributed about its expected value such that
$I_{y}=\hat{I}_{y} e^{\varepsilon_{y}}$
where
$I_{y}$ is the generated abundance index for year $y$,
$\hat{I}_{y}=\hat{q} \hat{B}_{y}$ is the corresponding model estimate, where $B_{y}^{\text {exp }}$ is the model estimate of exploitable resource biomass, given by equations (1.15), (1.16) and (1.17),
$\hat{q}$ is the constant of proportionality for abundance series (effectively the multiplicative bias if the series reflects abundance in absolute terms) which is set equal to 1.0 here, and $\varepsilon_{y} \sim N\left(0, \sigma_{\text {CPUE }}^{2}\right)$ where $\sigma_{\text {CPUE }}$ is the coefficient of variation (CV) associated with the resource abundance index. A value of $\sigma_{\text {CPUE }}=0.2$, consistent with what might be expected in practice, is assumed for data generation purposes.

### 2.2 Mean length data:

The mean length data, when allowing for observation error, are given by
$l_{y}=\sum_{a=a_{\text {min }}}^{m} P_{y, a} l_{a}$
where
$l_{a}$ is the length of fish of age $a$ as per the von Bertalanfy growth curve given by equation (1.19),

$$
P_{y, a}=\frac{C_{y, a}}{\sum_{a=a_{\min }}^{m} C_{y, a}} e^{\varphi_{y, a}-\sigma_{l}^{2} /\left(2 P_{y, a}\right)} \text { is the normalized proportion of fish caught of age } a \text { in year } y,
$$

where
$C_{y, a}$ is the total number of fish caught of age $a$ in year $y$, given by equations (1.11) or (1.12), and
$\varphi_{y, a} \sim N\left(0, \sigma_{l}^{2} / P_{y, a}\right)$ where $\sigma_{l}$ is the coefficient of variation (CV) associated with the mean length data. A value of $\sigma_{l}=0.25$ is assumed which is consistent with fisheries such as that for South African hake.

| Year | Catch (tons) |
| ---: | ---: |
| 1 | 1000 |
| 2 | 1000 |
| 3 | 1000 |
| 4 | 1000 |
| 5 | 1000 |
| 6 | 1000 |
| 7 | 1000 |
| 8 | 1000 |
| 9 | 1000 |
| 10 | 1000 |
| 11 | 1000 |
| 12 | 1000 |
| 13 | 1000 |
| 14 | 1000 |
| 15 | 1000 |
| 16 | 1000 |
| 17 | 1000 |
| 18 | 1000 |
| 19 | 1000 |
| 20 | 1000 |
|  |  |


| year | catch(tons) |
| ---: | ---: |
| 21 | 950 |
| 22 | 900 |
| 23 | 850 |
| 24 | 800 |
| 25 | 750 |
| 26 | 700 |
| 27 | 650 |
| 28 | 600 |
| 29 | 550 |
| 30 | 500 |
| 31 | 500 |
| 32 | 500 |
| 33 | 500 |
| 34 | 500 |
| 35 | 500 |
| 36 | 500 |
| 37 | 500 |
| 38 | 500 |
| 39 | 500 |
| 40 | 500 |

Table A-1. Annual catches in tons assumed for these analyses.

## Appendix 3: Management Procedures

### 3.1 Data-poor

For scenarios where there are few data or where the quality of the available data is poor, simple empirical management procedures are probably best suited. A number of variations of empirical MPs are considered for the data-poor case characterized by the lack of an index of abundance such as provided by CPUE data. The first is a constant catch strategy appropriate when no data are available/suitable for use in the MP. This also serves as a base line for comparison with performance statistics forthcoming from other MPs which have feed-back control and therefore should be able to outperform the constant catch strategy.

### 3.1.1 Constant catch MP:

For the constant catch strategy, the future TAC is set equal to $T A C^{*}$

$$
\begin{equation*}
T A C^{*}=x \% \overline{T A C} \tag{1.22}
\end{equation*}
$$

where
$\overline{T A C}=1 / 5 \sum_{y=n-4}^{n} T A C_{y}$ is the average catch over the preceding 5 years, and
$x \%$ is some percentage of this recent average catch $(100 \%, 90 \%, 80 \%, 70 \%$ and $60 \%)$.

### 3.1.2 Stepwise constant catch MP:

The MP considered here is a simple constant catch strategy with a step up or down depending on whether some threshold is reached in terms of recent mean length of fish caught. The rationale for this type of conservative MP is increased uncertainty regarding the status of the resource coupled with the fact that mean length data are not a direct index of abundance and can be very noisy (i.e. limited information content). It is therefore not defensible to adjust the TAC up or down as the mean length increases/decreases as these fluctuations could bear little relation to resource population size, but rather be due to effects such as observation error and changes in fishing gear. No TAC smoothing was applied for this class of MPs as the stepsize should remain fixed, and large decreases in terms of double step downs may be necessary for severely depleted resources.

The following simple formula calculates the TAC for the next year
$T A C_{y+1}=T A C_{y} \pm$ step
where step $=5 \% \overline{T A C}$ where $\overline{T A C}$ is defined by equation (1.22), and for the first year $T A C_{y}=T A C^{*}$ is an appropriate "starting level" which is not necessarily equal to the actual TAC for that year. The TAC is only increased/decreased if the recent mean length is more than a predetermined percentage higher/lower than the average of past mean length values. A 5\% increase threshold and $2 \%$ decrease threshold were selected for these calculations to ensure faster reaction to negative indicators in the data to prevent heavy resource depletion. Let
$\tilde{l}_{\text {ratio }}=\frac{\tilde{l}_{\text {recent }}}{\tilde{l}_{\text {past }}}$
where

$$
\begin{aligned}
& \tilde{l}_{\text {recent }}=\frac{1}{5} \sum_{y^{\prime}=y-4}^{y} \tilde{l}_{y^{\prime}} \text { is the average mean length over the most recent } 5 \text { years, and } \\
& \tilde{l}_{\text {past }}=\frac{1}{10} \sum_{y^{\prime}=n-10}^{n-1} \tilde{l}_{y^{\prime}} \text { is an historic average mean length (which remains fixed for all future years). . }
\end{aligned}
$$

then the TAC is only increased by one step if $\tilde{l}_{\text {ratio }}>1.05$. On the other hand if $\tilde{l}_{\text {ratio }}<0.98$ the TAC is decreases by a step. As a precautionary measure multiple step-downs are permitted, for example, the TAC is decreased another step if $\tilde{l}_{\text {ratio }}<0.96$, etc. For this MP a higher upper threshold of $5 \%$ was assumed to ensure that the TAC does not increase too rapidly, possibly causing further stock decline. Lower upper threshold values may be appropriate for a resource for which the status is judged healthy. However, to ensure low inter-annual TAC variability, higher thresholds for both increasing and decreasing the TAC are necessary.

### 3.1.3 Target mean length target MP:

This MP is similar to the Tier 4 control rule based on a target CPUE tested in Wayte (2009), but here mean length of catch data is used in the absence of a CPUE index. A target mean length, $\tilde{l}_{\text {target }}$, is chosen with the intention to achieve some preselected reference point.

$$
\begin{equation*}
T A C_{y+1}=\varpi T A C_{y}+(1-\varpi) T A C_{y+1}^{\tilde{l}} \tag{1.25}
\end{equation*}
$$

and
$T A C_{y+1}^{\tilde{I}}=\overline{T A C} \frac{\tilde{l}_{\text {recent }}-\tilde{l}_{\text {lim }}}{\tilde{l}_{\text {target }}-\tilde{l}_{\text {lim }}}$
where $\quad \varpi$ is the TAC smoothing parameter (a value of 0.5 was used here),
$\overline{T A C}=1 / 5 \sum_{y=n-4}^{n} T A C_{y}$ is the average catch over the preceding 5 years,
$\tilde{l}_{\text {target }}=x \% \times \tilde{l}_{\text {past }}$ is the target length which is a certain percentage above the historic average mean length ( $x \%=5 \%, 10 \%$ and $15 \%$ were tested),
$\tilde{l}_{\text {lim }}=0.9 \times \tilde{l}_{\text {past }}$ is the limit mean length below which catches are set to zero,
$\tilde{l}_{\text {past }}=\frac{1}{10} \sum_{y^{\prime}=n-10}^{n-1} \tilde{l}_{y^{\prime}}$ is the historic average mean length,
$\tilde{l}_{\text {recent }}=\frac{1}{5} \sum_{y^{\prime}=y-4}^{y} \tilde{l}_{y^{\prime}}$ is the average mean length over the most recent 5 years, and
$n$ is the current year.

For this MP, in addition to the TAC smoothing effect of equation (1.25), additional TAC smoothing was to constrict the next year's TAC, $T A C_{y+1}$, to increase or decrease by at most $15 \%$ from that of the previous year, i.e. let
$T A C_{\text {change }}=\left(T A C_{y+1}-T A C_{y}\right) / T A C_{y}$

Then, if

$$
\begin{aligned}
& T A C_{\text {change }}>15 \%, T A C_{y+1}=T A C_{y}+15 \% T A C_{y}, \text { or } \\
& T A C_{\text {change }}<-15 \%, T A C_{y+1}=T A C_{y}-15 \% T A C_{y} .
\end{aligned}
$$

### 3.2 Data-rich

For these fisheries we assume that there is at least some index of abundance available, be it a CPUE series which is reasonably comparable over time, or a survey series. It is further assumed that these data have reasonable information content and that the observation error is reasonably small. Based on these premises it can be assumed that any trend in the CPUE data is a fairly reliable indicator of trend in resource abundance. For the data-rich case, two types of MPs are simulation tested for comparison with the data-poor ones: an empirical MP based on the slope of the CPUE data to calculate future TACs and a CPUE target based MP. To minimize inter-annual TAC variability a limit of $15 \%$ was imposed on how much the TAC might increase/decrease from year to year (see equation (1.27)).

The idea underlying the these empirical MPs is that the TAC each year is adjusted up or down from the previous year's TAC depending on the rate of increase or decrease in size of the resource as indicated by the index of abundance (eg CPUE). The success of this rule depends on how much information, rather than noise due to observation error, there is in the data series, i.e. whether the MP is reacting to trends in biomass or simply following noise.

### 3.2.1 CPUE slope harvest control rule:

This MP is similar to the one proposed for Namibian hake in Butterworth and Geromont (2001). The TAC for the next year is given by
$T A C_{y+1}=\varpi T A C_{y}+(1-\varpi) T A C_{y+1}^{\text {CPUEslope }}$
and

$$
\begin{equation*}
T A C_{y+1}^{\text {CPUEslope }}=T A C_{y}\left(1+\lambda s_{y}\right) \tag{1.29}
\end{equation*}
$$

where $\varpi$ is the TAC smoothing parameter (a value of 0 was used here),
$T A C_{y}$ is the TAC in year $y$ (note that for the first year an appropriate "starting level" $T A C^{*}$ must be chosen (not necessarily equal to the actual TAC that year),
$\lambda$ is a control parameter that reflects how strongly the TAC is adjusted in response to the perceived trend in resource biomass, whose value is pre-chosen ( $\lambda=1.0$ was used here), and $s_{y}$ is a measure of the trend in the abundance index given by the slope of the linear regression of $\ln C P U E_{y^{\prime}}$ against $y^{\prime}$ for years $y^{\prime}=y-p, y-p+1, \ldots, y$, and
$p$ is the number of years over which the slope is calculated. Note that if $p$ is too small the trend estimates would fluctuate too much (tracking noise) and if $p$ is too large the MP would not be
able to react quickly enough to recent trends in resource abundance. A value of $p=5$ was chosen for this class of MPs.

### 3.2.2 Target-based CPUE harvest control rule:

Based on the Tier 4 control rule based on a target CPUE tested in Wayte (2009), the target CPUE, $C P U E_{\text {target }}$, is chosen to achieve resource recovery in terms of the preselected reference points.

The TAC for the next year is given by
$T A C_{y+1}=\varpi T A C_{y}+(1-\varpi) T A C_{y+1}^{C P U E(t a r g e t)}$
and

$$
\begin{equation*}
T A C_{y}^{C P U E(t \text { arget })}=\overline{T A C} \frac{C P U E_{\text {recent }}-C P U E_{\text {lim }}}{C P U E_{\text {target }}-C P U E_{\text {lim }}} \tag{1.31}
\end{equation*}
$$

where $\quad \sigma$ is the TAC smoothing parameter (a value of 0.5 was used here),
$\overline{T A C}=1 / 5 \sum_{y=n-4}^{n} T A C_{y}$ is the average catch over the preceding 5 years,
$C P U E_{\text {recent }}=\frac{1}{5} \sum_{y^{\prime}=y-4}^{y} C P U E_{y^{\prime}}$ is the average CPUE over the most recent 5 years,
CPUE $_{\text {target }}=x \% \times C P U E_{\text {past }}$ is the CPUE target which is a certain percentage above an historic average CPUE ( $x \%=200 \%$ and $250 \%$ were tested), where
$C P U E_{\text {lim }}=0.8 \times C P U E_{\text {past }}$ is the limit mean length below which catches are set to zero, where
$C P U E_{\text {past }}=\frac{1}{10} \sum_{y^{\prime}=n-10}^{n-1} C P U E_{y^{\prime}}$ is the historic average mean length, and
$n$ is the current year.

### 3.2.3 Age-aggregated production model-based MP:

Note: Due to time constraints this class of MPs have not yet been simulation tested.
Here, an age-aggregated surplus production model (AAPM), fitted to CPUE data, is used to determine management quantities. The dynamics of the resource is modeled by the following equations

$$
\begin{equation*}
B_{y+1}=B_{y}+f\left(B_{y}\right)-C_{y} \tag{1.32}
\end{equation*}
$$

where $f\left(B_{y}\right)$ is the net growth function of the form:

$$
\begin{equation*}
f\left(B_{y}\right)=r B_{y}\left(1-\frac{\ln B_{y}}{\ln K}\right) \tag{1.33}
\end{equation*}
$$

for the Fox model, with corresponding
MSYL $=e^{-1} K$ is the maximum sustainable yield level, and
$M S Y R=r / \ln K$ is the maximum sustainable yield rate
where
$r$ is the intrinsic growth rate,
$K$ is the pre-exploitation equilibrium biomass, and $B_{y}$ is the resource biomass for year $y$.

When assuming the Pella-Tomlinson form of the growth function, we have:

$$
\begin{equation*}
f\left(B_{y}\right)=r B_{y}\left(1-\left(\frac{B_{y}}{K}\right)^{\mu}\right) \tag{1.34}
\end{equation*}
$$

with corresponding

$$
\begin{aligned}
& M S Y L=1 /(1+\mu)^{\frac{1}{\mu}} K \text { is the maximum sustainable yield level, and } \\
& M S Y R=\mu /(1+\mu)^{r} \text { is the maximum sustainable yield rate. }
\end{aligned}
$$

Note that the Schaefer form of the growth function is obtained by setting $\mu=1$ in equation (1.34), while the Fox form is obtained as $\mu \rightarrow 0$.

## The likelihood function

The model is fitted to abundance data (CPUE) to estimate model parameters. Contributions to the negative of the log-likelihood $(-\ln L)$ are as follows.

The likelihood is calculated assuming that the observed abundance index is log-normally distributed about its expected value
$I_{y}^{i}=\hat{I}_{y}^{i} e^{\varepsilon_{y}^{i}} \quad$ or $\quad \varepsilon_{y}^{i}=\ln \left(I_{y}^{i}\right)-\ln \left(\hat{I}_{y}^{i}\right)$
where
$I_{y}^{i}$ is the abundance index for year $y$ and series $i$,
$\hat{I}_{y}^{i}=q^{i} B_{y}$ is the corresponding model estimate, where $B_{y}$ is the model estimate of resource biomass, given by equation (1.32),
$q^{i}$ is the constant of proportionality for abundance series $i$ (effectively the multiplicative bias if the series reflects abundance in absolute terms), and

$$
\varepsilon_{y}^{i} \text { from } N\left(0,\left(\sigma_{y}^{i}\right)^{2}\right)
$$

The contribution of the abundance data to the negative of the log-likelihood function (after removal of constants) is given by:

$$
\begin{equation*}
-\ln L=\sum_{i}\left[\sum_{y} \ln \sigma_{y}^{i}+\left(\varepsilon_{y}^{i}\right)^{2} / 2\left(\sigma_{y}^{i}\right)^{2}\right] \tag{1.36}
\end{equation*}
$$

## Estimation of variance:

In this case, homoscedasticity of residuals is assumed, so that $\sigma_{y}^{i}=\sigma^{i}$, the standard deviation of the residuals for the logarithms of abundance index $i$ is estimated in the fitting procedure by its maximum likelihood value

$$
\begin{equation*}
\sigma^{i}=\sqrt{1 / n^{i} \sum_{y}\left(\ln I_{y}^{i}-\ln \hat{I}_{y}^{i}\right)^{2}} \tag{1.37}
\end{equation*}
$$

where $n^{i}$ is the number of data points for abundance series $i$.

The catchability coefficient $q^{i}$ for abundance index $i$ is estimated by its maximum likelihood value

$$
\begin{equation*}
\ln \hat{q}^{i}=1 / n^{i} \sum_{y}\left(\ln I_{y}^{i}-\ln B_{y}\right) \tag{1.38}
\end{equation*}
$$

## Harvest control rules:

Various harvesting strategies are considered, such as $f_{M S Y}, f_{0.1}$ and $f_{0.2}$, depending on the resource recovery desired. The TAC for the next year is given by

$$
\begin{equation*}
T A C_{y+1}=\varpi T A C_{y}+(1-\varpi) T A C\left(\mu, f_{0 . n}\right) \tag{1.39}
\end{equation*}
$$

where
$\varpi$ is a weight that acts as a TAC smoothing parameter where $\varpi=1$ corresponds to a constant catch strategy, and
$T A C\left(\mu, f_{o . n}\right)$ is the TAC resulting from fitting the surplus production model (e.g. Fox or
Schaefer, depending on the value of $\mu$ ) to the CPUE data when employing a particular $f_{0 . n}$ harvesting strategy.
A further constraint is imposed such that the TAC may not vary more than $15 \%$ from one year to the next in order to limit inter-annual variability.

The TAC according to the Schaefer and Fox models for the different $f_{0 . n}$ harvesting strategies is calculated from mid-year biomass in year $y+1$ using equations (1.33) and (1.34) with their corresponding estimates for $M S Y R$ defined above, such that
$T A C\left(\mu, T A C_{0 . n}\right)=x T A C\left(\mu, T A C_{M S Y}\right)$
where

$$
\operatorname{TAC}\left(\mu, f_{M S Y}\right)=\operatorname{MSYR}\left(B_{y+1}+B_{y+2}\right) / 2
$$

and $x$ is given by solving:
$(1-x)=0 . n$ for the Schaefer model ( $\mu=1$ ), and
$(1-x)=0 . n e^{x}$ when employing the Fox model $(\mu=0)$.

| $f_{0 . n}$ strategy | Schaefer | Fox |
| :--- | :--- | :--- |
| $f_{0.1}$ | $0.9 T A C\left(\mu=1, f_{M S Y}\right)$ | $0.782 T A C\left(\mu=0, f_{M S Y}\right)$ |
| $f_{0.2}$ | $0.8 T A C\left(\mu=1, f_{M S Y}\right)$ | $0.626 T A C\left(\mu=0, f_{M S Y}\right)$ |
| $f_{0.3}$ | $0.7 T A C\left(\mu=1, f_{M S Y}\right)$ | $0.504 T A C\left(\mu=0, f_{M S Y}\right)$ |
| $f_{0.4}$ | $0.6 T A C\left(\mu=1, f_{M S Y}\right)$ | $0.402 T A C\left(\mu=0, f_{M S Y}\right)$ |
| $f_{0.5}$ | $0.5 T A C\left(\mu=1, f_{M S Y}\right)$ | $0.315 T A C\left(\mu=0, f_{M S Y}\right)$ |

## Appendix 3: Table 1 The multiplicative values used for $x$ in calculating the TAC.

