Effective fisheries management with few data: A Management Procedure Approach

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Thesis presented for the degree of
Doctor of Philosophy
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South Africa

April 2014

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The financial assistance of the National Research Foundation (NRF) towards this research is hereby acknowledged. Opinions expressed and conclusions arrived at, are those of the author and are not necessarily to be attributed to the NRF

To Nikolaus and Christina

Declaration

The work reported in this thesis has been performed in close consultation with my supervisor, Doug Butterworth. No assistance has been received to perform these analyses, except from normal guidance by my supervisor and as stated below:

- The generic data-poor Management Procedure (MP) analysis reported in this thesis is an extension of a related study published by Butterworth, Johnson and Brandao (2010). An earlier version of the work reported in Chapter 3 was presented at the International Fisheries Stock Assessment Review Workshop held in Cape Town in 2010 (Geromont and Butterworth 2010). Comments and suggestions by international panellists and participants attending the workshop led to improvements to Chapter 3.
- The retrospective studies of data-rich fish stocks were commenced as a direct result of interest and suggestions by Charlie Edwards (Imperial College, London). An earlier version of the work reported in Chapter 4 was presented at the ICES WGMG held in Vigo, Spain in 2011 (Geromont and Butterworth 2011). Comments and suggestions by the the participants at this international workshop lead to improvements and extensions to these analyses.

Two of the chapters have recently been accepted for publication in journals:

Geromont, H.F. and D.S. Butterworth. 2014. Generic management procedures for data-poor fisheries: forecasting with few data. ICES Journal of Marine Science, doi:10.1093/icesjms/fst232.

Geromont, H.F. and D.S. Butterworth. 2014. Additional data and more complex assessments: do these provide improved fisheries management advice? ICES Journal of Marine Science, doi:10.1093/icesjms/fsu017.

I know the meaning of plagiarism and declare that all of the work in the thesis, save for that which is properly acknowledged, is my own.

Signed at …………………. On the …….day of ………………………………………………………

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ABSTRACT

Complex stock assessments which typically rely on a comprehensive set of age or length data are traditionally seen as an essential requirement for sound fisheries management. An alternative process less commonly adopted for the provision of reliable on-going management advice is called the Management Procedure (MP) approach. This approach is pro-active and strategic rather than reactive and tactical, and lends itself well to forecasting and long-term fisheries management. This thesis investigates the application of the MP approach to data-poor as well as data-rich stocks.

The majority of fish stocks worldwide are not managed using quantitative analysis as there are not sufficient data on which to base a resource assessment. Often these stocks are relatively “low-value”, which renders dedicated scientific management too costly, and a generic approach applicable across a range of stocks is therefore desirable. The aim of the first line of analysis in this thesis is to illustrate the design and testing of some very simple “off-the-shelf” management procedures (MPs) that could be applied to groups of data-poor stocks which share similar key characteristics in terms of demographic parameters. For this initial investigation, a selection of empirical MPs is simulation tested over a wide range of Bayes-like operating models (OMs) representing the underlying dynamics of resources classified as “depleted”, in order to ascertain how well these different MPs perform. The moderately data-poor MPs (based on an index of abundance such as provided by a survey or reliable CPUE) perform somewhat better than the extremely data-poor ones (based on the mean length of catch data) as would be expected. Nevertheless the very data-poor MPs perform surprisingly well across the wide range of uncertainty considered for key parameters.

The second line of analysis in this thesis focuses on high-value data-rich marine resources: which of the two management paradigms is more suitable where sufficient data for annual stock assessments are readily available? This question is addressed through a retrospective study of management performance over the last twenty years for four North Atlantic fish stocks. The actual assessment advice for these stocks was provided on the basis of complex assessment methods making use of age data. The outcomes are compared to what could have been achieved with much simpler MPs based upon age-aggregated survey indices alone. Even for some of these stocks whose assessments exhibit retrospective patterns, these MPs can achieve virtually equivalent catch and risk performance, with much less inter-annual TAC variability, compared to what actually occurred over the past twenty years.

Despite the simplicity of the harvest control rules simulation tested in this thesis, these MPs could well provide the basis to develop generic MPs to manage data-poor stocks, ensuring if not optimal, at least relatively stable sustainable future catches. Moreover, these initial results suggest that simple empirical MPs could provide a defensible, simpler and less costly alternative approach to the provision of scientific management advice for high-value data-rich resources. The advantages of

adopting a procedural paradigm for fisheries management purposes are highlighted and rationale is offered as to why it may be prudent (better aligned with the precautionary approach) to adopt an MP approach, even in circumstances where reliable data, expertise and financial support are readily available to perform annual assessments.

Chapter 1 Introduction

1.1 Fisheries management: What, why and by whom?

In the words of Hilborn and Walters (1992), the fisheries of the world are managed for the benefit of mankind, not the fish, and as such we would like to know how well we are doing. In essence, the aim of fisheries management science, not to be confused with fisheries biology, is to evaluate different trade-offs in an attempt to maximise the biological and economic yield of which marine resources are capable while at the same time reducing the risk of undue resource depletion due to overfishing.

Within this paradigm, it is the role of fisheries management scientists to evaluate these risks and rewards quantitatively and give scientific management advice to marine resource regulatory bodies on the appropriate management actions (such as appropriate catch or effort levels) required to achieve the trade-offs that maximises the biological, economic and social benefits from the fishery. These quantitative scientists rely on fishery data, collected by fisheries agencies, to develop often quite complex mathematical models used to compute/predict resource impacts resulting from a variety of possible management actions. After much scientific analyses, scientists typically propose a selection of plausible management choices to the appropriate regulatory body for selection and eventual implementation. These choices would ideally include a selection of management strategies that should give acceptable long-term yields (in terms of annual catches) while at the same time ensuring that resource abundance is maintained at, or rebuilt to, healthy levels. Ultimately marine resource management authorities have to make the final choice of “how much”, based on the quantitative analyses conducted by fishery scientists.

Marine resource governing bodies are responsible for regulating fish resources in a sustainable manner to maximise long-term economic and social benefits by ensuring on-going supply of food, income and employment. They must seek a fine balance between often opposing strategies and objectives: how much fishing development to encourage or allow in order to satisfy social and economic objectives; how much restraint to be placed on fishing activity and methods (such as catch/effort limits and closed areas) to satisfy biological objectives; how much financial resources to spend on monitoring and enforcement of regulations to ensure compliance (Hilborn and Walters 1992)? Typically, these regulatory bodies can either function on a national level (for example the Ministry of fisheries of a particular country), or be inter-governmental organisations for those resources located in international waters and fished by fleets from different countries (examples are the Commission for the Conservation of Antarctic Marine Living Resources (CCAMLR), the International Whaling Commission (IWC) and the International Commission for the Conservation of Atlantic Tuna (ICCAT)).

The success, or otherwise, of fishery management is largely dependent on this quantitative advice, in the form of options presented to the governing bodies by fishery scientists. Bad management advice can lead to the overexploitation of a stock, eventual economic collapse of the fishery due to catch rates dropping too low for the fishery to remain profitable, with associated loss of employment which in turn may lead to serious social and economic problems. Likewise, bad management advice can lead to wasteful under-utilisation of resources. As such, fisheries scientists have the responsibility to ensure that their advice is unbiased, their methods are scientifically justifiable and that they use the best quantitative tools available to analyse resource data. These scientists need to be able to assess which data to include in models, based on information content, and which to discard as noise, get a quantitative “handle” on the level of risk associated with the management measures being applied to a particular stock, determine which uncertainties are key in influencing the performance of different management strategies, etc. The resultant advice (management choices) given to the fishery regulatory bodies must have a sound scientific basis and be quantitative in order for managers to compute the long and short-term costs associated with the different trade-off strategies. Furthermore, all management options proposed by fishery scientists must have undergone rigorous simulation testing to ensure that they would work in practice, i.e. all options presented must be shown to be robust to uncertainty in line with the precautionary approach requirements of the Food and Agriculture Organisation of the United Nations (FAO 1996).

This work concerns only those aspects of fishery management that pertain to the role fishery scientists play in the exploitation of marine resources.

1.2 Management objectives and trade-offs: how much is too much?

In fisheries management, a number of objectives often compete in the struggle for long-term biological, economic and socio-political sustainability.

- Biological: Maintain marine bio-diversity, restore marine eco-systems, re-build overfished stocks to target levels, minimise environmental impact, maximise sustainable biological yield, optimal monitoring and data-collection, effective research.
- Economic: Ensure sustainable economic growth, rebuild fisheries, maximise sustainable economic yield, maximise net economic benefits, maximise export revenue, enlarge market share.
- Social and Political: Poverty reduction, job creation, facilitate access, secure food production, secure subsistence catch, develop infra-structure, appropriate policy development.

Obviously none of these objectives can be realised while a resource is in an overexploited state, frequently caused by over-capacity in fishing fleets. Beddington *et al.* (2007) argue that economic and social objectives will not be met if the biological objectives are ignored and, conversely, biological objectives are unlikely to be met without proper consideration of economic and social objectives. Good fisheries management therefore entails evaluating and balancing trade-offs amongst all three objectives to ensure optimal long-term biological, economic, as well as social benefits.

To illustrate, if the goal were to maximise short-term resource yield by not enforcing any limit on the catch or restrictions on effort, the result would be an increase in fishing effort which in turn would lead to an increase in total fish landed, resulting in an increase in revenue, as well as jobs and infrastructure — all positive. This unrestricted increase in fishing effort would deplete the fish population abundance and likely flood the market with produce. A market over-supply would in turn lead to a decrease in unit price, with overall revenue maintained only by increases in catches rather than profit margin. With sustained pressure on the fish stock, the resource would become depleted below its maximum production level, called the maximum sustainable biological yield (MSY), eventually falling below the level that would ensure adequate stock renewal. In turn, without adequate stock renewal, the catch-per-unit-effort (CPUE) would decrease, resulting in decreases in overall operational profitability until the cost of fishing exceeds the revenue, corresponding to a situation where the fishery produce zero or negative net economic benefits. This would then lead to eventual closures of fisheries and factories with associated job losses. With the consequent decrease in fishing effort, the resource may again recover to profitable CPUE levels where, in the absence of enforced catch or effort limits, fishing effort would again increase until the bionomic equilibrium of zero net profit is reached. If left to its own devices, an unregulated fishery will fluctuate about an undesirable equilibrium of zero economic return because of over-capacity which leads to low catch-rates (Gordon 1954, Clark 1985, Beddington *et al.* 2007).

The reason why an unregulated fishery will operate at this uneconomic equilibrium is mainly due to property rights, or rather the lack thereof: if any one fishing company reduces fishing effort in an attempt to increase stock abundance with the aim to improve catch-rates in order to operate more profitably, there is no guarantee that another operator will not catch the surplus fish. Therefore, in an unregulated open-access fishery, each individual operator will endeavour to maximise his/her own profit, rather than the profitability of the fishery as a whole, collectively reducing the total net returns of the fishery to zero (Anderson and Seijo 2010).

In contrast, good long-term resource management will endeavour to maximise the sustainable catch by regulating total fishing effort in an attempt to re-build, or maintain, stock abundance levels at peak productivity to maximise potential long-term yield, thus optimising catch-per-unit-effort (CPUE), increasing profitability, and avoiding fluctuations in catch and effort to the extent possible.

1.3 Biological objectives: traditional management targets

While fishery scientists generally have a good idea of biological objectives in terms of target levels of abundance, the problem is estimating current stock status. Are we dealing with an overexploited stock, and if so, to what degree? Is the resource currently well managed at, or above, the target level of abundance? Once there is reasonable confidence regarding the estimate of current resource abundance in relation to the desired target level, some long-term management plan can be adopted. Graphically, this is best illustrated by means of the simple "Kobe" plot in Figure 1.1 (Tuna Report 2007), which gives a measure of stock status in terms of biomass (*B*) and fishing mortality (*F*) relative to the maximum sustainable biological yield (MSY) related reference points, F_{MSY} and B_{MSY}.

The phase diagram illustrates the management actions required in a broad brush manner. Fish stocks are categorised in terms of the four quadrants of the plot below. The management action required to move the stock to the desired levels of exploitation can then be determined.

1. Bottom right-hand green[1] zone: a healthy underexploited resource with biomass above B_{MSY} , and currently under-fished with fishing pressure below F_{MSY}.
2. Top right-hand yellow zone: an historically underexploited stock with biomass above B_{MSY}, and currently under excessive fishing pressure above F_{MSY} ;
3. Top left-hand red danger zone: an historically overexploited resource, with biomass estimated to be below B_{MSY} , and which continues to be overfished with fishing pressure remaining above F_{MSY};
4. Bottom left-hand yellow zone: a historically overexploited stock which is currently in a rebuilding phase (current fishing pressure reduced to a level that would ensure biomass recovery to MSY level).

The aim of fisheries management is to move a resource to just inside the green zone, i.e. keep fishing mortality as high as possible without resource abundance dropping below its MSY level - easier said than done. In reality, we never know exactly where on the plot a resource lies because of difficulties in estimating current abundance, *B*, current fishing mortality rate, *F*, and the associated reference points in terms of MSY. Due to unavoidable uncertainty regarding resource status, long-term safe management therefore dictates that we err on the side of caution by aiming above the biomass reference point, B_{MSY}, by keeping fishing mortality below the associated F_{MSY} reference point, thereby effectively enlarging the red danger zone and shrinking the green zone.

[1] Colours, while perhaps not visible in the printed format, can be seen in the electronic version.

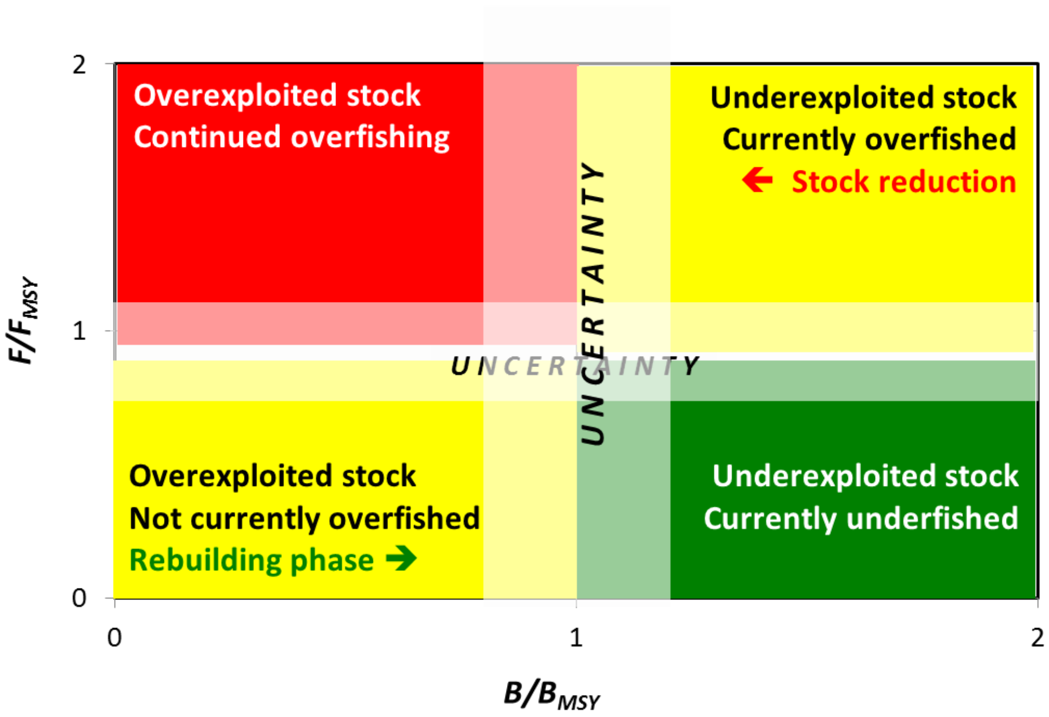

Figure 1.1: A phase diagram showing the quadrants reflecting four possible states of a stock in terms of the stock biomass and fishing mortality rate compared to the associated maximum sustainable yield (MSY) levels.

An unexploited fish stock will fall in the extreme lower right-hand corner of the green block. As a fishery develops, the resource status will move upwards and leftwards, beyond the target reference points. Under insufficient monitoring and management, a fishery would eventually move into the danger red zone signifying overexploitation coupled with sustained overfishing. Once in the red zone, good (albeit somewhat belated) management would entail regulating fishing mortality, F, to reduce the level of fishing pressure to well below MSY, in an attempt to move the resource into the yellow zone (historically overexploited but currently recovering) and eventually into the safe green zone.

However, scientific fisheries management is unfortunately not an exact science. Because of natural fluctuations in resource dynamics (e.g. in annual recruitment), coupled with high levels of uncertainty regarding population models and data, the fisheries scientist cannot possibly plot a direct course to MSY and expect to maintain it. Rather, the best case scenario corresponds to rebuilding, or maintaining, a resource in a target zone where annual biomass and fishing pressure estimates will unavoidably fluctuate about the pre-selected target levels.

Indeed, the great extent of uncertainty associated with estimates of stock status necessitates choosing biological targets above maximum sustainable yield. In terms of the precautionary approach, the biomass target reference point, B_{target}, is chosen at some percentage above B_{MSY}, with the associated fishing mortality target, F_{target}, lying below F_{MSY}. To avoid the possibility of stock collapse due to continued overfishing, limit reference points are typically also defined to serve as "no-go" zones. The biomass limit reference point, B_{lim}, chosen at some percentage below B_{MSY} , corresponds to the level of spawning stock abundance below which the reproductive capacity becomes impaired, called recruitment overfishing (Sissenwine and Shepherd 1987). The corresponding fishing mortality rate limit reference point, $F_{lim} > F_{MSY}$, is defined as the fishing mortality rate that would result in resource biomass to fall below B_{lim}.

In line with the precautionary approach (FAO 1996), higher levels of uncertainty regarding resource biomass levels would in turn necessitate higher associated biomass target and limit reference points. Typical precautionary biological reference points correspond to 25% above and 50% below B_{MSY} for B_{target} and B_{lim}, respectively (Smith *et al.* 2009). Due to frequent difficulties encountered when attempting to estimate B_{MSY}, proxy values for the limit and reference points are often used in terms of the pre-exploitation biomass level, K^{sp}. Assuming that B_{MSY} is reached when the spawning biomass is approximately 40% of its pre-exploitation biomass level, K^{sp}, typical biomass target and limit reference points would then correspond to 50% and 20% of K^{sp}, respectively (Beddington and Cooke 1983). Figure 1.2 redefines the quadrants in Figure 1.1 in terms of typical biological target and limit reference points (Beddington *et al.* 2007).

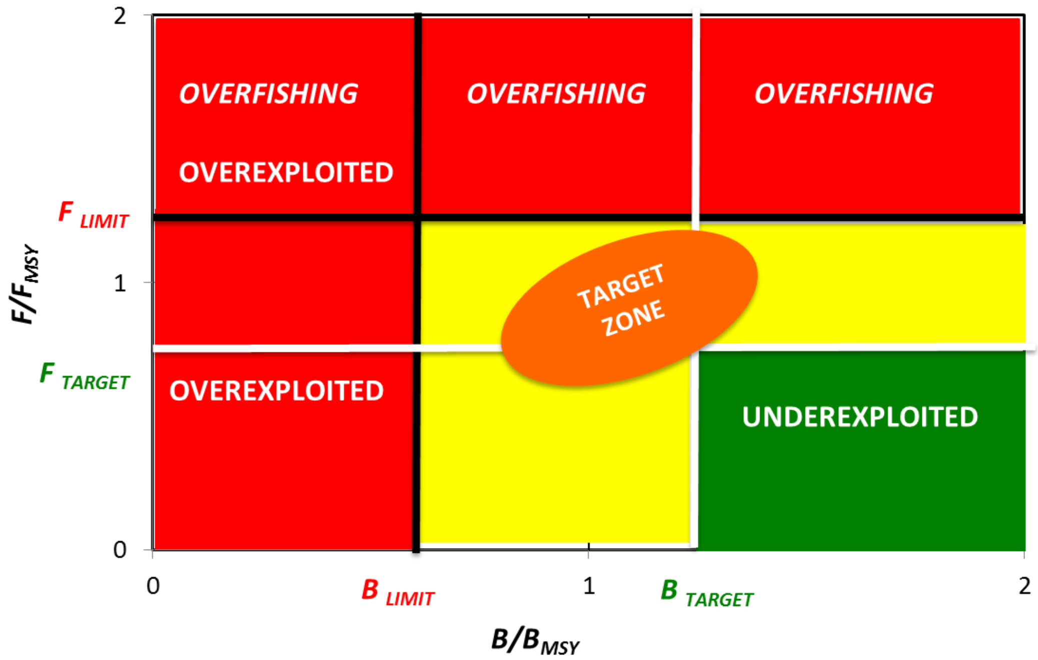

Figure 1.2: Stock status zones in terms of target and limit reference points.

1.4 Economic targets: same beast, different animal?

In simple terms, maximum sustainable biological yield (MSY) corresponds to the maximum yield, or catch, that can be taken from a renewable resource over an indefinite time period. Maximum sustainable economic yield (MEY), also called the optimum sustainable yield, pertains to the level of effort that maximises economic profit of the harvested resource, i.e. maximising the difference between total revenue and total cost (Gordon 1954, Schaefer 1954).

According to the Gordon-Schaefer model (Gordon 1954, Clark 1976) depicted in Figure 1.3, maximum economic yield occurs at a lower level of fishing effort than maximum sustainable biological yield ($F_{MEY} < F_{MSY}$). Correspondingly, the biomass that maximises economic yield is greater than the biomass that maximises biological yield ($B_{MEY} > B_{MSY}$) as shown in Fig 1.4. Therefore, when fishing pressure exceeds the maximum economic yield (MEY) level, the resource becomes economically overfished, even though the fish stock may be healthy and the associated fishery biologically sustainable.

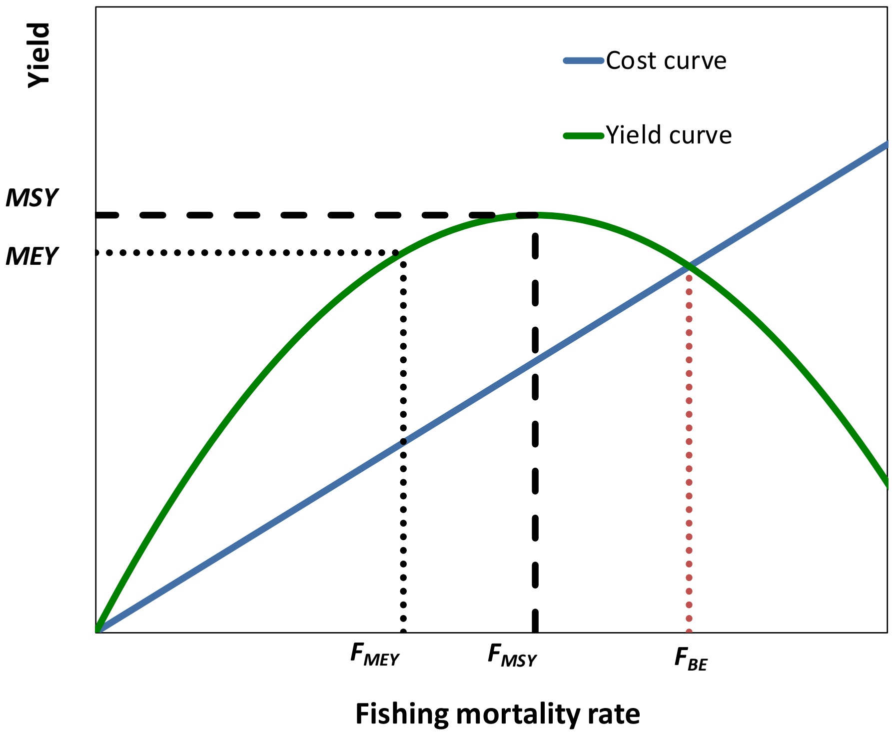

Figure 1.3: The static Gordon-Schaefer cost-yield model: when fishing effort exceeds that which corresponds to the maximum sustainable economic yield, F_{MEY}, economic overfishing occurs (Gordon 1954).

Net economic benefits from a fishery are usually measured in terms of economic rents. The inefficiency of a fishery can be measured as the difference between maximum potential rents obtainable from a fishery and the actual rents obtained (World Bank 2009). In terms of the cost-yield curves of Figure 1.3, the net economic benefits from a fish stock can be visualised by the area between the yield and cost curves: when yield (green curve) exceeds costs (blue curve), positive rents are produced. However, at higher fishing effort levels, the cost curve lies above the yield curve, resulting in negative rents. The maximum positive rent is produced at F_{MEY} when the difference between yield and cost is greatest. When fishing effort exceeds the point of maximum economic yield, economic overexploitation is evident. The bionomic equilibrium, *BE*, where the cost and yield curves intersect, corresponds to the point of zero net economic benefits. Past this point, too much effort, associated with over-capacity in the fishing fleet, will therefore result in negative net economic benefits. If the economic objective of a fishery is to maximise the sustainable net returns, or profits, then biomass levels need to be maintained above that corresponding to maximum sustainable biological yield, MSY. Using the more conservative static MEY as a management target is therefore beneficial from biological point of view.

In terms of the cost-yield curves in Figure 1.3, fish stocks will become economically overfished before biological overexploitation occurs, because the value of the increase in catch is less than the cost of extra fishing effort needed to catch it. Furthermore, biological extinction cannot occur, simply because it becomes too expensive (fuel costs, vessels/fishers not working at full capacity, etc.) to find and catch the last remaining fish. Too much effort for too little return means loss of revenue and industry will either move fishing effort to other resources, or simply sell out and invest elsewhere in the search of bigger profit margins.

However, life is not that simple. Gordon's cost-yield model does not account for dynamic effects such as discounting. Clark (1976, 1985) showed that the optimal stock biomass level, B^*, lies somewhere between the bionomic equilibrium, B_{BE}, and Gordon's static optimum, B_{MEY}, as indicated in Figure 1.4. On the one hand, higher costs will push the optimum biomass above maximum sustainable yield level, while on the other hand, discounting effects will tend to push the optimum biomass lower. At a zero discount rate, the dynamic MEY is equivalent to Gordon's static MEY, with an optimum biomass of B_{MEY}. As the discount rate increases, the optimum biomass approaches the bionomic equilibrium B_{BE}. Sufficiently large discount rates can therefore result in biological overexploitation because the fishery operator has little concern for potential profits to be earned in the future, but rather attempts to maximise his/her current annual yields at the current stock size. Taken to the extreme, at an infinite discount rate, it is optimal to maximise current profits without regard to the stock size. However, given that the real discount rate is probably much less than infinity, it follows that the optimum biomass would likely be much higher the than the bionomic equilibrium stock size B_{BE}.

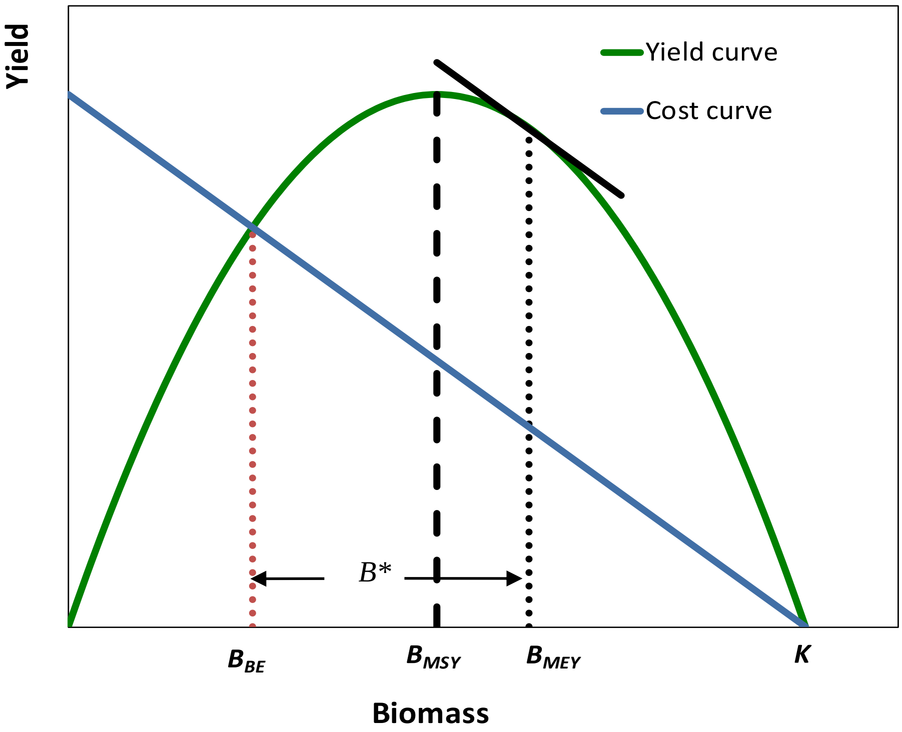

Figure 1.4: The dynamic optimal biomass lies between B_{MEY} , the static optimum stock size, and B_{BE} , the bionomic equilibrium stock size, as the discount rate increases from 0 to infinity, where *K* is the pre-exploitation biomass.

In terms of resource management, setting practically achievable targets that satisfy long-term biological and economic objectives can be tricky when discount rates are large. To satisfy biological objectives, a long-term strategy associated with a low discount rate and a higher optimum biomass is required, while the fishery operator is typically more concerned with short-term survival associated with a higher discount and a lower optimum biomass. A key question from a fisheries management point of view is where B_{MEY} lies in relation to the biological optimum B_{MSY}. If dynamic MEY is produced at a lower stock biomass than MSY, what should the resource management target be?

However, Grafton *et al.* (2007) show that the largest discounted economic profits are produced at a stock size that exceeds B_{MSY}, even in fisheries with quite high discount rates. In later studies, Grafton *et al.* (2010 and 2012) show that the optimal economic biomass exceeds the biological target, B_{MSY}, under a wide range of conditions, including the case where the discount rate exceeds the intrinsic growth rate. Anderson and Seijo (2010), who developed an age-structured bioeconomic model, suggest that, depending on the system parameters, there is likely very little difference between the static and dynamic optimum biomass. Therefore, using B_{MEY} as the target biomass can be advantageous from both an economic and biological point of view. Indeed a win-win scenario as both the static and dynamic MEY optimum stock sizes are likely to be above the biological optimum corresponding to MSY. In these cases, biological and economic management objectives are therefore not in opposition, but rather are mutually beneficial.

Different fisheries have different cost and yield curves associated with them. A high-value coastal resource with low associated harvesting costs will generate more potential rent than a low-value offshore fishery, mainly because of high fuel and capital costs associated with the latter. Offshore fisheries are therefore generally in better biological shape than inshore fisheries as the bionomic equilibrium (*BE*) is reached at higher levels of stock abundance. The aim of commercial fisheries is presumably not to operate at zero or negative profit margins, and therefore to keep abundance well above the B_{BE}, which in turn would prevent stocks from excessive biological overexploitation.

There are of course exceptions. Subsidies (fuel subsidies, grants for fishing vessels, subsidies to enable an uneconomic fishery to remain active) result in pulling down the cost curve in Figure 1.3 so that negative economic rents are only produced at fishing efforts high enough to deplete the resource abundance to dangerously low levels. Thus, by reducing the cost of harvesting by means of subsidies, fishing continues at effort levels that would normally not be economically viable, thereby removing the financial constraint that guards against overexploitation of fish stocks. Accordingly, subsidies incentivise overfishing, fleet over-capitalisation, reduced economic efficiency and resource rent dissipation (World Bank 2009).

Therefore, if the overriding focus of the resource manager is short-term social and political benefit, without regard to the long-term economic and biological objectives and trade-offs, biological overexploitation may well occur because long-term profitability, or otherwise, of the fishery is no longer the key factor that determines the level effort expended. While subsidies may be motivated by laudable socio-political intentions, they rarely have desirable long-term effects as they foster over-capacity in a fishery. Indeed, the only form of subsidy that could possibly benefit fisheries in the long-run is financial support for better fisheries research and management.

Circumstances under which a resource can also become severely overexploited are when a black market for the product exists. An example is the South African abalone resource (DAFF 2012): this fishery is currently dominated by illegal catch and export to a black market in the East. Conventional economic principles where maximum profitability is reached at biomass levels close to MSY level are not applicable here as the illegal fishery, which is by default unregulated and effectively open-access, maximises their short-term yields, depleting the stock down to the levels approaching to the bionomic equilibrium. The problem is exacerbated by high market prices which completely overshadow total costs of harvesting (including penalties and legal costs). These augmented profit margins pull down the cost curve in Figure 1.4, so that the bionomic equilibrium is only reached at very low abundance levels. Thus, for a largely illegal and unregulated fishery, coupled with a high price-cost ratio, the optimum biomass will only be reached after the resource is severely biologically overexploited.

1.5 Current state of world fisheries

According to the United Nations Food and Agriculture Organization (FAO 2010), only 10% of the world's exploited fish stocks are assessed, albeit not always regularly, accounting for about 80% of the total declared landings, with little or no information available regarding the stock status for the rest of the 90% of exploited fish resources worldwide. Based on data of the 10% of monitored fish stocks, the state of exploitation of the world's fishery resources has remained relatively stable since the 1990's, with 25% of the stocks monitored by FAO estimated to be under- to moderately-exploited, while approximately half of stocks monitored are deemed fully-exploited, producing close to their maximum sustainable biological yield, and the remaining 25% are estimated to be either overexploited (17%), depleted (7%) or recovering from depletion (1%) (FAO 2010). These estimates have since then been updated to only about 15% of fish stocks considered under-to moderately exploited and an increase in overexploited, depleted or recovering stocks to over 30% of total stocks monitored (FAO 2012).

Visually, in terms of the phase plot depicted in Figure 1.2, this translates to approximately 15% of the world's fish stocks that fall in the green zone, about half in the yellow zone, with the remaining stocks falling into the red zone. In other words, approximately half the stocks monitored by the FAO are underperforming in terms of potential yield, with the majority of these in dire need of stock rebuilding strategies to move stocks closer to higher yield levels by reducing fishing pressure.

However, the picture is even less positive when seen from an economic perspective. According to the study conducted by the FAO and the World Bank (2009) the majority of the world's marine fish stocks is estimated to be economically overfished. The Sunken Billions study reports that marine capture fisheries are an underperforming global asset, with the difference between potential and actual net economic benefits estimated at approximately $50 billion annually ─ equivalent to roughly half the global seafood trade (World Bank 2009). This huge economic loss can likely be recovered by reducing global fishing effort, which in turn would lead to an increase in productivity and profitability of the fisheries on the one hand, and to resource recovery to higher levels of sustainable biological and economic yields, on the other (World Bank 2009).

In a study conducted by Worm *et al.* (2009), which estimates current exploitation rates and biomass levels for 166 fish stocks around the world, most of these stocks were estimated to lie in the top red and bottom yellow blocks in Figure 1.1 in terms of their biological reference points. Of the ten eco-systems studied, average exploitation rates have declined recently to levels corresponding to, or below, MSY[2] in seven systems. However, to ensure adequate recovery of an estimated 63% of the fish stocks assessed in this study, fishing pressure needs to be decreased somewhat more drastically in order to move stocks from the bottom-left yellow zone to the green zone on the right of the phase plot in Figure 1.1. This study has recently been updated by Ricard *et al.* (2012). Of the 214 stocks in the RAM Legacy Stock Assessment Database for which MSY related reference points could be evaluated, most were found to be overfished, with 58% of these assessed stocks estimated to be below the biomass required to achieve MSY, and 30% subject to continued overfishing with fishing mortality rates exceeding those corresponding to MSY.

Of the 81 US fisheries investigated in the Ricard *et al.* study, the majority fall into the bottom-left yellow zone which corresponds to stock rebuilding, with some fisheries falling into the green (healthy to underexploited) block, while very few lie in the red danger zone of Figure 1.1. The situation is somewhat less optimistic for the 48 European fisheries investigated this study. The majority of fisheries in this region have been, and are currently, biologically overexploited with the biomass for most stocks estimated to be below the MSY level, and current fishing mortality at or above F_{MSY}. Given that the maximum economic sustainable yield, MEY, is generally produced at higher stock abundance levels than the biological reference point, MSY, it follows that most of these fish resources currently suffer from considerable economic overexploitation. It therefore comes as no surprise that global fisheries have been found to be operating below their maximum economic potential, and that there is an estimated $50 billion loss per annum in lost economic benefits from the fishing sector (World Bank 2009).

Further south, in South Africa, the situation is perhaps slightly more optimistic. Of the more than 500 stocks fished in South Africa, about a dozen are under formal scientific (quantitative) management which account for approximately 80% of total landings in terms of mass. Of these scientifically managed resources, the most valuable fisheries such as Cape hakes, anchovy and sardine lie in the yellow zone of Figure 1.5 below, corresponding to stocks for which management has adopted long-term rebuilding plans in order to move the stock abundance to higher productivity levels or, alternatively, to those stocks which are considered to be fully-exploited at, or about, MSY level. Indeed, according to the latest report on the status of the South African marine fishery resources (DAFF 2012), most of South Africa's offshore resources are in fairly good shape biologically, falling into the green and yellow zones of Figure 1.5 associated with well-managed, albeit mostly recovering resources. This, of course, does not imply that they are necessarily optimally-managed from an economic point of view.

[2] It should be born in mind that estimates of stock status related to the biomass at which MSY is achieved are generally subject to great uncertainty as biological reference points are difficult to estimate, even for data-rich stocks.

However, the same cannot be said about South Africa's inshore resources. Owing to their close proximity to the coast (which corresponds to a flattened cost curve in Figure 1.4) many inshore stocks have been exploited to the point of biological "collapse" (DAFF 2012). For example, abalone, locally called perlemoen, remains under enormous fishing pressure due to illegal fishing encouraged by high prices, and is firmly positioned in the red danger zone of Figure 1.5, which corresponds to overexploited and currently overfished resources with $B < B_{MSY}$ and $F > F_{MSY}$. Many of the linefish species have also been heavily overexploited historically because of inadequate management and enforcement (DAFF 2012). Even though emergency effort reducing measures were introduced in 1998 and again in 2003, most stocks continue to be overexploited in the absence of reliable quantitative management advice and enforcement thereof to reduce fishing effort sufficiently to move these vulnerable inshore species to more healthy levels of abundance. While not perhaps of great economic value, good quantitative management and adequate monitoring are nevertheless required to ensure that long-term biological and social objectives are met in terms of maintaining bio-diversity, ensuring sustainability of subsistence and recreational catches, job creation and poverty reduction.

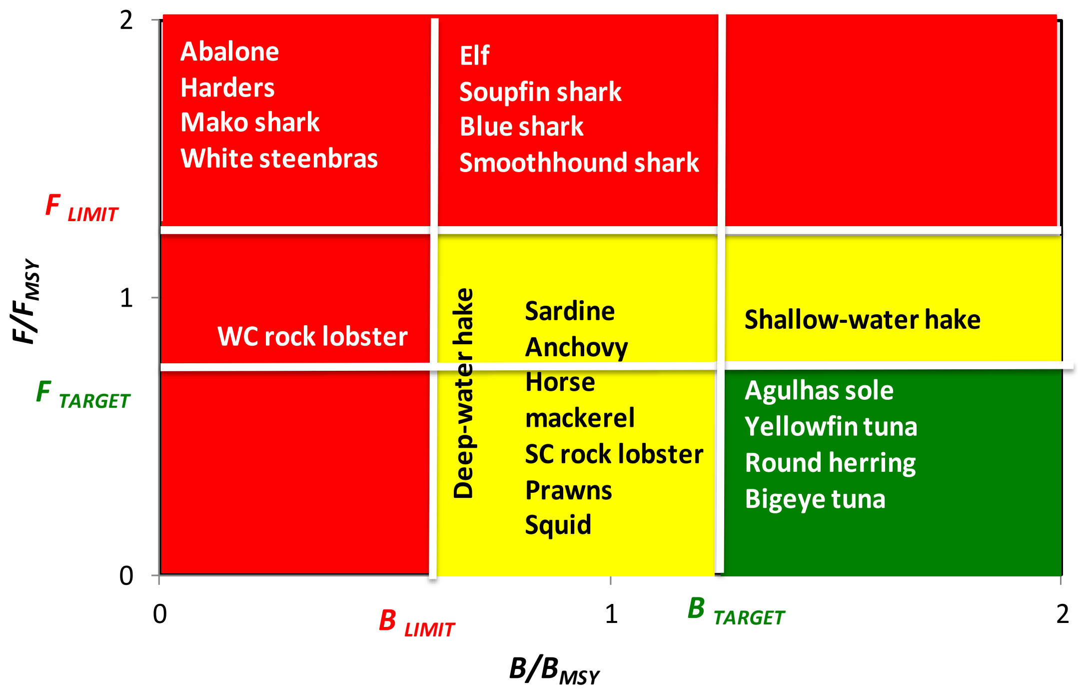

Figure 1.5: The status of South African fishery resources (DAFF 2012).

1.6 Quantitative marine resource management: methods

The majority of the world's most valuable marine resources are currently managed on the basis of advice generated using quantitative scientific techniques. These quantitative approaches provide the basis for scientific recommendations which aim to ensure the long-term sustainable exploitation of fish stocks. The traditional and widely used approach for the provision of such scientific advice is stock assessment, where statistical and mathematical models which describe the underlying resource dynamics are fitted to fisheries data to produce estimates of current stock abundance (or status, if expressed in terms of some reference level) and sustainable yield.

A variety of stock assessment methods have been developed over the years. These typically include Virtual Population Analysis (VPA), integrated analysis (IA) and statistical catch-at-age (SCAA) models, which are based on age or length data obtained from annual surveys, as well as one or more indices of abundance. In the absence of catch-at-age data, simpler age-aggregated models such as production models (e.g. Schaefer or Pella-Tomlinson), fitted to one or more indices of abundance, are typically used to estimate pertinent management quantities. In an attempt to upgrade current stock assessments, the International Council for the Exploration of the Sea (ICES) recently launched the Strategic Initiative on Stock Assessment Methods "to assure that ICES scientists can apply the best methods when developing management advice" (ICES 2012a). "Best methods" evolve and improve with time and the ICES report emphasises that successful long-term application of the best method is necessarily an iterative, multi-step process. While classification of the best alternative assessment methods in terms of data availability is very useful, the question, which inevitably leads to endless debate at scientific meetings, remains what to do when confronted with several plausible hypotheses *sans* pertinent quantitative data to distinguish between them.

An alternative, called the Management Procedure (MP) approach, which was first developed by the International Whaling Commission's (IWC's) Scientific Committee (Punt and Donovan 2007), has found favour with marine scientists and fisheries managers seeking a more comprehensive resource management tool. Instead of a "best" assessment, this approach integrates over a variety of different plausible population models, called the operating models, representing different hypotheses regarding the resource. Different harvesting strategies are then simulation tested to ascertain which harvest control rule (HCR) would ensure that the desired long-term management goals are met in practice across this range of alternative models. While the "best" assessment approach typically allows for only one possible interpretation, or reality, of the resource, the MP approach incorporates different plausible interpretations, represented by a range of assessment or operating models. While the assessment approach is geared to short-term (annual) management advice based on the "best" estimates of current stock status, thereby attempting to answer the "where are we now?" question, the

MP approach is geared to reaching longer-term goals by means of implementing harvesting strategies, focussing rather on the questions "where are we going?" and "how will we get there?" (Anderson *et al.* 2010). In this manner, the MP approach entails a more comprehensive analysis of possible stock reaction to various management actions.

This approach has been adopted to provide scientific recommendations for management measures for the exploitation of some high-value stocks in the Southern Hemisphere, notably in South Africa, which has the longest experience with the successful implementation of MPs to provide total annual catch (TAC) recommendations for its most valuable fisheries (Geromont *et al.* 1999). For example, MPs have been used to manage the demersal hake fishery and the pelagic fishery for sardine and anchovy in South Africa for the last two decades (Punt 1992, Butterworth and Bergh 1993). More recently, the MP approach has also been adopted to regulate the South African south coast rock lobster, the South African west coast rock lobster resource (Johnston 1998), and further afield, the high-value Namibian hake fishery at the start of the millennium (Butterworth and Geromont 2001). In Australia, a more general form of the MP approach known as Management Strategy Evaluation[3] (MSE), provides a platform to simulation test a variety of management options for fish stocks ranging from data-rich to data-poor[4] (Wayte *et al.* 2009).

Compared to complex annual stock assessments on which annual management recommendations are based, MPs (harvest control rules that have been simulation tested to check robustness to uncertainty about resource dynamics) are often very simple empirical algorithms that are much more easily understood by stakeholders (such as the fishing industry), thus enhancing the credibility of fishery scientists with these stakeholders (Geromont *et al.* 1999). An additional advantage of the MP approach is its multiyear cyclical implementation, which is particularly advantageous for managing data-poor stocks for which scientific person-power and financial support for research are sorely lacking. One further advantage of the approach is related to the important resource management concern of long-term trade-offs between, for example, the mutually conflicting objectives of maximizing catch and minimising the risk of overexploitation of resource. These are fundamental to the MP selection process, though generally ignored in the traditional "best" assessment approach with its myopic view of the future. However, the key advantage of the MP approach, compared to the traditional annual stock assessment approach, is its ability to incorporate uncertainty in the modelling

[3] MSE in the broad sense involves evaluating the consequences of different management actions by means of simulation testing. The MP approach is a prescriptive form of MSE consisting of a number of steps that define the process: from prioritizing management objectives, defining the data available, specifying the suite of operating models on which candidate harvest control rules are simulation tested, and outputting performance statistics and trade-offs for inspection by stakeholders in a partnership approach.

[4] While it can be argued that all fish stocks are data-poor to some degree due to unavoidable uncertainty about resource models and data, "data-poor" refers here to "data-limited" stocks for which no formal assessment is possible due to lack of data.

exercise explicitly, thereby ensuring consistency with the precautionary approach (PA) (Butterworth 2007), which is an important consideration when dealing with all marine resources, and even more so with data-poor stocks.

1.7 Managing uncertainty: little we know, much we don't

In order to ensure sustainable long-term use of marine stocks, fisheries scientists need to model key features of the resource dynamics while taking cognizance of the most important uncertainties. A cornerstone of successful modelling is reliable data (e.g. accurate records of past catches). However, for most fish stocks, and particularly for low-value resources, reliable data are in short supply. With lack of knowledge and greater uncertainty associated with the majority of exploited marine stocks, sustainable resource management becomes difficult, if not impossible, if one seeks to base this on traditional stock assessment methods.

There are numerous sources of uncertainty in the management of marine resources. One important source of error is model uncertainty due to the lack of knowledge regarding the underlying fish stock and the model that would best describe its population dynamics. Another source of uncertainty is observation error due to errors in sampling and monitoring of the resource, as well as data capturing. Process error arises from natural fluctuations in the model parameters related to population abundance and recruitment. In addition, for those fish resources where harvest control rules are already in place, another important source of uncertainty is implementation error due to non-compliance to catch/effort limits due to lack of enforcement, political interference, market influences, and so forth (Hilborn 1996, Butterworth and Punt 1999, Punt and Donovan 2007). The above mentioned sources of uncertainty exclude key uncertainties regarding the economics of the fishery: harvesting costs, market share and saturation, export costs, taxes, levies, fluctuating exchange rates, etc., which are required in order to manage a fishery in an economically optimal manner.

A major concern associated with stock assessment is model uncertainty: how to choose the "best" model to apply to the data available for the species/stock under consideration. The choice of "best" population model with which to assess a stock depends not only on the scientific expertise at hand, but more importantly, on the type and information content of the data that are available. The Strategic Initiative on Stock Assessment Methods (ICES 2012a) was launched to aid scientists in selecting the most appropriate model given the data available. A simulation-based evaluation of model performance was conducted to compare the efficacy of the different assessment methods. An important conclusion drawn from the 2012 SISAM workshop was that, while application of multiple models may help to evaluate model uncertainty, having more than one model does not facilitate management advice. Furthermore, applying multiple models to real data cannot distinguish performance as they cannot be calibrated against the “truth”.

Wentzel and Punt (2011) conducted a comparative study to evaluate model performance of different methods when estimating of appropriate harvest levels for data-poor stocks. They concluded that simulation testing is essential to evaluate the risks associated with alternative methods to provide decision makers with the necessary information to set precautionary reference points and acceptable biological catches that accounts for uncertainty. However, comprehensive simulation studies that evaluate the performance of different assessment models against the data available are rarely conducted, even for high-value stocks under regular assessment. In contrast, the Management Procedure (MP) approach, presents a formal framework to take full quantitative recognition of underlying uncertainty by integrating over a range of assessment models, called the operating models, thereby ensuring that diverse plausible hypotheses are evaluated. The approach has its origins in the International Whaling Commission (IWC) where de la Mare (1986) conducted extensive simulation trials of the complete process used for the assessment and management of whale stocks. Cooke (1999) discusses the merits of applying a simulation approach to the developing of management algorithms (or MPs) and likens it to the design of passenger aircraft which first undergo extensive testing of components in wind tunnels before going into production.

Figure 1.6 gives a schematic representation of the different sources of uncertainty typically encountered by fisheries scientists, and the manner in which they are incorporated into an MP approach.

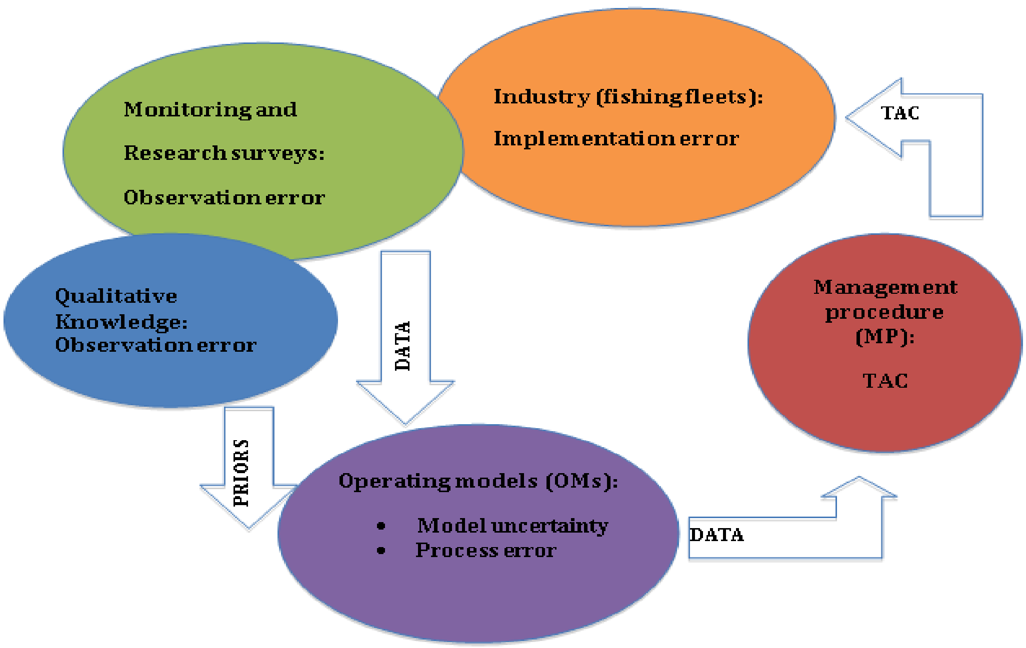

Figure 1.6: Taking account of uncertainty in a management procedure approach.

1.8 MP versus assessment: broad-brush or fine art?

For a relatively small group of high-value fish resources, termed data-rich, substantial funds and effort are allocated to annual data collection and analyses thereof. For most of these stocks complex scientific assessments are performed every year, fitted to age and length data, to estimate stock status and set appropriate catch/effort limits that would ensure sustainable and effective long-term exploitation. But how can we manage effectively in the absence of these data when traditional assessment techniques are not possible? And, even when comprehensive data are available, are biological and economic targets adequately met using traditional assessment techniques?

Scientific fisheries advice based on the Management Procedure (MP) approach is different to the traditional approach of “best” assessment in that it attempts to follow a more holistic style to fisheries management, involving full quantitative recognition of underlying uncertainty as well as including all stakeholders (scientists, industry and managers) in the management process, thereby ensuring that biological and economic goals are met in the long run. Bentley and Stokes (2009) compare these two management paradigms and highlight the potential of the procedural paradigm for application to data-poor resources in cases where the assessment paradigm has difficulty to provide fisheries management advice. However, for data-rich high-value fisheries for which the assessment paradigm has traditionally been favoured, an often overlooked advantage of the MP approach lies in the decision-making process which involves all stakeholders. This is particularly important when a fishery is in a rebuilding phase: a thorough understanding of long-term trade-offs and potential economic gains encourages compliance and is critical if biological, economic and social objectives are to be achieved.

Regardless of whether the fishery is data-sufficient or not, high-value or subsistent, once an MP for the resource has been selected by stakeholders to meet the desired management objectives, and has passed a rigorous set of robustness trials, it relies on feedback to adjust the management controls, such as the yearly TAC, up or down in order to move the resource abundance towards some pre-agreed target level, even if the “best” assessment were wrong. Indeed, past experience in resource management has shown that the current “best” assessment, while often complex and relying on substantial high quality data, is sometimes based on a dubious set of assumptions that is quickly rejected in favour of an alternative set, causing the resultant annual management recommendations to fluctuate more than necessary while models are continuously debated, discarded and replaced, in turn leading to enhanced data requirements and analysis in a never-ending quest for the “best” model. Therefore, fluctuations in management controls such as annual TAC recommendations based on current “best” assessment typically arise from noise in the data and annual (argued) improvements to assessment models rather than actual changes in resource abundance (Butterworth 2007). This ability to distinguish between noise and actual trends in abundance is the very essence of good scientific advice for fisheries management.

An example of the contrary is the highly controversial North Atlantic bluefin tuna resource (*Thunnus thynnus*), where two alternative "best" assessments gave notably different estimates of stock status at the 1998 ICCAT SCRS meeting held in Genoa, resulting in the adoption of a last-minute "compromise" assessment for management advice purposes (ICCAT 1999). The "compromise" assessment estimated the resource biomass to lie roughly between the estimates corresponding to the two highly debated and discarded "best" assessments, while a new "best" assessment was developed in time for the next ICCAT SCRS meeting (Geromont and Butterworth 2001). Almost a decade later, and after much controversy, the MP approach has been proposed as the preferred approach to regulate North Atlantic bluefin tuna (ICCAT 2006), and the MP development process has since commenced. Similarly, after years of bitter arguments leading eventually to international litigation regarding the appropriate basis for TAC recommendations for the southern bluefin tuna resource (*Thunnus maccoyii*), the Commission (CCSBT) agreed to commence work on the development of a management procedure as the basis for management recommendations at the beginning of the millennium (De Oliveira *et al.* 2009). The MP, known as the "Bali Procedure", was eventually adopted in 2011 (CCSBT 2012).

Other examples exist of contentious assessments that are under on-going attack from stakeholders who believe that the "best" assessment adopted by fishery scientists are either outdated, or based on the wrong set of assumptions regarding the population model and/or the data (Gulf of Maine Cod (Northeast Fisheries Science Center 2012), Atlantic Menhaden (Menhaden Report 2010)). As noted by De Oliveira *et al.* (2009), selection of a "best" assessment necessitates rejection of all other alternatives proposed by stakeholders even when they are near equally plausible. Indeed, rigorous healthy debate from different stakeholders, with sometimes apposing interests, has entered virtually all facets of fisheries management rendering the choice of a "best" assessment difficult if not impossible. A holistic approach that formally incorporates different plausible hypotheses in terms of resource dynamics, models and data, and which is inclusive of all stakeholders, would surely lead to improved scientific resource management.

An important advantage of the MP approach is the resolution of such debates by simply expanding the set of operating models, or plausible realities, which form the basis for the simulation testing exercise, thereby addressing all valid concerns and including sometimes disparate stock hypotheses. An important by-product of this approach is the identification of uncertainties that are key in terms of meeting biological and economic performance criteria (Butterworth 2007). A positive spin-off of sidestepping arguments via explicit incorporation of different points-of-view from different stakeholders in the MP process is the fostering of team spirit which in turn results in "buy-in" in an effort to maximise the long-term biological and economic yield that can be produced by the fishery on a sustainable basis.

Some fundamental questions that clearly distinguish between the two approaches are: to whom do fishery scientists aim resource management advice and what do resource managers need to make better decisions?

A resource manager would presumably prefer a selection of choices with trade-offs, preferably in simple numerical format that can be readily understood by decision makers who are unlikely to be mathematicians or statisticians. Choice is important as different objectives often compete in the unavoidable trade-off of win-here-lose-there. Decision makers want to "decide" – they hate being "told" – and as such scientists need to put different management options with probable outcomes on the table in an attempt to better inform decision making. Besides, fishery scientists are unlikely to be fully cognizant of pertinent social, economic and political factors that drive policy. In this respect, the MP approach is far more practical than the traditional assessment approach as different management actions are tested across a wide range of possible "realities" to ascertain which action fares better in terms of a set of performance criteria that is tailored to facilitate informed decision making. These would usually include, for a variety of harvesting strategies: potential short-, medium- and long-term yields, average short-, medium- and long-term fluctuation in future catch, as well as short-, medium- and long-term stock abundance levels in relation to a pre-selected target level. These performance statistics paint a simple yet clear picture of where the fishery is heading depending on the management action taken.

In contrast, the assessment-based management statistics usually consist of "best" estimates of current resource abundance in relation to a target level. That approach does not provide medium to long-term estimates of yield and risk corresponding to different harvesting strategies, but rather takes a very detailed look at what has happened before and where the stock is currently. It leaves the impossible task of deciding future strategy up to the decision makers without giving them a choice of feasible options, based on simulation testing, with the risk/reward trade-offs associated with different management actions. Much like telling a blind-folded person exactly where he is and then asking him to find the best route to some target destination: possible, but might entail a fair amount of wandering in circles. With the MP approach, all plausible avenues would first be analysed via simulation testing, after which the previously blind-folded person would be supplied with a map from which to select the best route to the destination.

There are of course negative aspects to the Management Procedure approach. Much like any worthwhile relationship, the MP approach is demanding: it requires substantial amounts of understanding, commitment and time.

- Understanding:

  The approach is generally not well understood by fisheries scientists, with frequent confusion of the MP (the harvest control rule that sets the TAC or TAE) and the OMs (the underlying population models). The MP approach is often rejected on the basis that the MP is too simple – scientists feel more comfortable with complex models on which to base management advice. However, an MP approach is generally a far more complex process than a typical stock assessment, incorporating a wider range population models in the analysis. Specialised expertise is therefore required.

- Commitment:

  All stakeholders need to commit to the process. This entails an investment of time and effort from all parties at various stages of the development process, full support of the approach and adherence to the outcomes.

- Time:

  The main disadvantage concerns the time investment that is required to develop and test the candidate MPs. Indeed, this is both a strength and a weakness of the approach: the success of the implemented MP relies on its robustness to a comprehensive range of uncertainty. However, the simulation testing process to show adequate robustness can be lengthy and effort-intensive if done properly. In order to avoid a lengthy development process and time-delays, a MP development schedule needs to be agreed and enforced, often to the chagrin of members of industry who value their manoeuvrability. The development process can take anything from one to two years, sometimes longer, compared to an annual assessment that often takes only a couple of months from start to finish. However, the time invested in the development stage is rewarded later on once the MP is implemented.

1.9 Current scientific initiatives

Some valuable initiatives have recently been taken with the aim of improving scientific advice for fisheries management. While mostly addressing traditional stock assessment methods, they have important applications in the MP arena in terms of forming the basis for the set of operating models on which robustness testing is performed. The main reason for some of these initiatives is the current lack of adequate quantitative management for the large number of moderately to very data-poor stocks for which no quantitative assessment exists at present. With the aim of moving the vast number of global fisheries to optimum biological and economic levels, a generic approach is sought which would employ a selection of state-of-the-science methods to provide robust scientific advice for the sustainable use of the world's marine resources.

Below is a list of some fisheries management initiatives currently underway:

- *Strategic Initiative on Stock Assessment Methods (SISAM):*
  This ICES initiative entails the classification of stock assessment methods according to the amounts and/or types of data required. This classification will serve to guide fisheries scientists to the selection for the most appropriate stock assessment methods given the data available (ICES 2012a).

- *Workshop on the Development of Assessments based on LIFE history traits and Exploitation Characteristics (WKLIFE):* This ICES initiative is focussed on developing a methodology for providing assessments and advice on data deficient stocks. Stocks are classified into categories according to the quantity and quality of the data and methods available. The aim is to move data-deficient stocks into data-adequate category over time (ICES 2012b).

- *Assessment for All (A4A):*
  This initiative aims to develop assessment methods for approximately 200 moderately data-poor stocks (landings and CPUE data, but no age/length data are available and limited biological data) which are presently not assessed. In order to be able to give quantitative advice for these stocks, a group of standardised methods is sought that can be applied rapidly (Jardim *et al.* 2013).

- *Southern Hemisphere Collaboration (SHC):*
  The focus of this collaboration between South Africa, Australia and New Zealand is the Management Procedure approach (or MSE in the broader sense), with the aim to improve all aspects of quantitative fisheries management, thus ensuring long-term biological and economic sustainability by incorporating key stakeholders into the process. More specifically, the aim is to design, develop and simulation-test a set of MPs for data-poor fisheries which are not currently managed quantitatively (Butterworth and Geromont 2010).

- *Marine Stewardship Council (MSC):*
  While not a new initiative (originally started in 1997), this has gained momentum in establishing itself as the most recognisable global eco-label in the market place. The objective of this international fish produce ecolabelling and certification program is to contribute to the health of global fish stocks by transforming global seafood markets to stock seafood from sustainable sources, and influencing buyers to make informed choices when buying seafood. The MSC has developed standards for sustainable fishing and seafood traceability.

1.10 Thesis objectives and outline

The central thesis of this work revolves around seeking a more effective and efficient way to manage fisheries, both data-poor and data-rich, towards biological and economic sustainability given the high levels of uncertainty. In particular, given the extent of uncertainty inherent in all aspects of fisheries management, are there simpler, more robust, scientific techniques that would better address the current woes in global fisheries?

In an attempt to answer this question, the traditional annual assessment-based management is compared to the Management Procedure approach. A double-pronged investigation is followed in an attempt to ascertain which approach is more likely to lead to better long-term management of renewable data-poor and data-rich fish resources. For data-rich resources, a simple retrospective comparative study is conducted to see if very simple MPs (simulation tested harvest control rules) could have outperformed the annual assessment based management employed to regulate some high-value stocks fished in the North Atlantic. Would these simple harvest strategies, or MPs, have resulted in better scientific management of these resources over the long-term? However, the yet untapped value of the MP approach lies in its ability to be applied to extremely data-poor, highly uncertain resources for which standard population assessments cannot be carried out due to lack of data to which to fit assessment models. A simple generic MP approach is suggested and simulation tested here for possible future application to data-poor stocks.

Chapter 2 gives a general description of the MP approach.

Chapter 3 looks at applications to data-poor stocks and compares performance for a variety of harvest control rules to determine which generic catch control rules perform best given the uncertainties involved.

Chapter 4 considers the application of the MP approach to data-rich stocks for which comprehensive data-sets are available. The simple generic harvest control rules introduced in Chapter 3 are employed here to ascertain how well they perform compared to the actual catches resulting from assessment based management.

Chapter 5 concludes with a general discussion on the advantages and shortcomings of the MP approach as applied to data-poor and data-rich stocks and offer some suggestions for further work to be undertaken.

Chapter 2 The Management Procedure Approach

2.1 Introduction

Following extensive discussion and analyses in its Scientific Committee from the mid-1980s, the International Whaling Commission (IWC) first introduced the management procedure approach early in the 1990s with the aim to manage commercial and aboriginal subsistence whaling (Kirkwood 1997).

An earlier phase of this process was initiated when the IWC first adopted a harvest control rule in 1974, called the New Management Procedure (NMP), to provide clear-cut scientifically based management advice on catch limits for commercial whaling. The NMP (though not a complete "Management Procedure" as the approach has now come to be understood) was revolutionary in that it sought to automate decision making, thereby attempting to sidestep political interference, combined with a high protection level of 54% of carrying capacity below which catch limits were set to zero, in addition to a maximum catch of 90% of MSY, thus attempting to ensure that whale stocks were maintained above the maximum sustainable yield level (MSYL) while at the same time maximising continuing yield (Butterworth and Best 1994).

However, due to problems with the NMP, in particular difficulties in agreeing on the inputs required, such as population size and on how to take scientific uncertainties into account, the IWC declared a moratorium on commercial whaling in 1982, which commenced some years later. As a consequence of the moratorium, development of the Revised Management Procedure (RMP) was initiated in 1987 to address this uncertainty aspect in particular. The development process was lengthy and it was only finalised seven years later in 1994. Although the RMP has not been implemented by the IWC, the process has nevertheless been invaluable as a learning vehicle as documented in Punt and Donovan (2007).

Based on this experience gathered at the IWC, the MP approach gained popularity for fisheries in many parts of the world (Punt 2006). In Southern Africa, MPs have been developed and implemented successfully for the most valuable data-rich fish resources, for example the South African hake (*Merluccius capensis and M. paradoxus*), sardine/anchovy (*Sardinops sagax* and *Engraulis encrasicolus*) and rock lobster (*Jasus lalandii*) resources (Punt 1992, Johnson 1998, Geromont *et al.* 1999 , De Oliveira 2003 and 2004, Rademeyer 2012) and for a time for the Namibian hake resource (Butterworth and Geromont 2001). A more general form of the approach has found favour in Australia, where it is better known as Management Strategy Evaluation (MSE), and has been adopted by the Australian Fisheries Management Authority (AFMA) partnership to ensure stakeholder involvement in all key areas of fisheries management (Smith *et al.* 1999). Since 2005, a formal harvest strategy framework using an MSE approach has been adopted in the Southern and Eastern Scalefish and Shark Fishery (Wayte 2009). In New Zealand, the MP approach has been adopted to provide TAC recommendations for their rock lobster fisheries (Starr *et al.* 1997). With the aim to combine expertise between these three countries, share experiences and set up a framework to facilitate future MP development, a Southern Hemisphere Collaboration was formed in 2010 (Butterworth and Geromont 2010). Further afield, an MP approach has recently been adopted for Southern bluefin tuna (CCSBT 2012) and is planned for North Atlantic bluefin tuna (ICCAT 2006) and krill (CCAMLR 2006). Initiatives are underway to introduce the MP approach in Europe and the USA (De Oliveira *et al.* 2008), with MPs having been formally adopted in Iceland to manage Icelandic cod (ICES AGICOD Report 2009), haddock (ICES 2013a) and saithe (ICES 2013b).

While the end-product (the MP that is eventually implemented to provide fisheries management advice) is often deceptively simple, the development process can be elaborate and complex. This is partly due to the holistic nature of the approach whereby different stakeholders are involved in the various phases of the development process. The mathematical complexity, however, is mostly hidden from stakeholders and resides in the underlying operating (or assessment) models on which the simulation testing of the MPs, or harvest control rules, are based. The practical success of the end-product is largely dependent on the thoroughness of this simulation testing exercise, an essential element of the MP approach, which can be very time-consuming if done properly. As such, the management procedure development process is generally far more labour and time intensive than the traditional assessment approach. However, the time and expertise invested during the development process are rewarded later on once the MP runs as if on autopilot and avoids the lengthy annual debates on assessment updates. Typically, an MP has a development cycle of 1 to 2 years followed by an implementation cycle of 4 to 5 years.

An example to the contrary is the MP development cycle for Namibian hake which took only a couple of months, including a series of high-level stakeholder meetings (attended by the then Minister of Fisheries and his scientific advisors, key members of industry and their scientific advisors and of course a contingent of local fishery researchers) to ensure buy-in from all parties throughout the condensed and intense development process. The eventual management procedures selected for implementation, called the IMP, remained in place for 3 years (Butterworth and Geromont 2001).

The MP approach, or MSE in the broader sense, is a system that encompasses all aspects of fisheries management, from defining the management objectives for the fishery, to data collection and analysis, the development of harvest control rules that can be shown to be robust to key uncertainties via simulation testing, as well as monitoring (Punt 2006). Furthermore, the most compelling reason to use the MP approach is to take formal account of uncertainties as required by the Precautionary Approach and in line with the FAO Technical Guidelines for Responsible Fisheries (FAO 1996). Following a rigorous process of simulation testing by scientists and evaluation by key stakeholders, the end product, the chosen MP, is essentially a simulation-tested feedback-control decision rule for fisheries management based on a pre-specified set of data (Butterworth 2007). The feedback-control feature ensures that management controls are adjusted in order for the resource to move towards the pre-selected long-term target levels.

2.2 The process

In practice, an MP approach comprises of a number of equally important steps as discussed by Punt and Donovan (2007) and De Oliveira *et al.* (2008). A diagrammatic presentation of these steps and the iterative processes involved is shown in Figure 2.1.

Step 1: Specify strategic objectives:

All key stakeholders (industry, fishery regulatory bodies and scientists) take part in these discussions to prioritise the most important biological, economic and social objectives.

Step 2: Decide on performance measures:

Quantify the qualitative management objectives identified in step 1 above.

Step 3: Agree on historic data sets and develop a suite of operating models (OMs):

These OMs must best represent the dynamics of the resource and fishery while incorporating the key uncertainties. This step is equivalent to identifying all plausible stock assessment models with their associated data sets. All stakeholders should be part of the data discussions to identify areas of concern and delineate different plausible hypotheses.

Step 4: Specify a set of management procedures (MPs):

Identify a range of candidate MPs, model-based and/or simple harvest control rules, with associated historic and future data required by each MP. An MP is essentially a formula for which the input is a pre-agreed set of resource monitoring data, and which outputs a regulatory measure such as a TAC or TAE value. The candidate MPs to be used in the projections should ideally span a range from simple empirical harvest control rules to model-based procedures if data allows. However, for data-poor stocks, candidate MPs should ideally be very simple empirical harvest control rules that are easily understood by all stakeholders and that rely on the regular availability of relatively few data.

Step 5: Simulation test each MP over the range of OMs:

This entails examining the candidates from step 4 in terms of the OMs developed in step 3 to determine which MP would best satisfy the management objectives defined in step 1, regardless of which OM might actually best describe the unknown underlying dynamics. These tests for robustness of performance, which involve forward projection of the resource dynamics under each OM with catches set by the candidate MP under simulated data which incorporate random observation error, are the foundation of the MP development process. The future success of the end-product relies on this step.

Step 6: Evaluate performance statistics:

During the simulation testing of each candidate MP, the summary statistics defined in step 2 are output for inspection, comparison, MP tuning[5] and candidate MP rejection purposes.

Step 7: Select MP for implementation:

Based on the performance statistics output for each candidate MP in the previous step, choose the best performing MP in terms of the objectives specified in step 1. All stakeholders should take part in the MP selection process to ensure that their pre-defined objectives are met to the extent possible in relation to the trade-offs which are acceptable, so as to promote understanding and collaboration between the different interest groups.

Drawing on lessons learned from the IWC MP development process (Punt and Donovan 2007, De Oliveira *et al.* 2009), as well as valuable experience gained with MP development and application in South Africa (Geromont *et al.* 1999, Butterworth 2008), some general recommendations when developing management procedures are listed below:

- The management objectives for the fishery need to be identified upfront and defined explicitly with the full support of key stakeholders to ensure subsequent buy-in and compliance. It is important to define the goals before the results become known, thereby effectively separating "wisdom" from "want", as well as long-term goals from short-term returns.

[5] Adjust parameters of the harvest control rules to achieve the required performance trade-offs.

- Uncertainty in all facets of the assessment and management of the fishery (observation, process, structural and implementation error[6]) needs to be identified and incorporated in the MP simulation testing exercise. Again, key stakeholders need to be consulted in order to ensure that a comprehensive range of uncertainty is incorporated in these simulation trials. Agreement by stakeholders about the most important sources of uncertainty (step 3) is required before performance statistics (step 6) are evaluated, to avoid a situation where the "tail wags the dog".
- A Bayes-like approach is advantageous when setting up the operating models, particularly when dealing with data-poor stocks where data and knowledge regarding stock structure and productivity are limited, as this admits the use of prior distributions for parameters based on information obtained from data-rich stocks. Prior distributions for pertinent population model parameters need to be specified in consultation with key stakeholders (statisticians, biologists, representatives from industry) to draw on their collective knowledge of the fishery.
- To achieve positive management collaboration, stakeholders need to be involved in determining management objectives, identifying areas of key uncertainty and performance statistics, and finally choosing the MP to be implemented. Fishery scientists, as well as representatives from industry and governmental and regulatory bodies, should take part in key meetings at different stages of the MP development process to ensure that biological, economic and socio-political objectives are met satisfactorily, thereby guaranteeing the success and longevity of the MP implemented. However, it is important to realise also that it will not be possible to achieve every objective as there will be conflicts, e.g. between maximising catches and minimising risk to the resource. An iterative process may be required as stakeholders are only able to fully grasp what ranges of trade-off choices are possible as computations proceed. Members of industry are far more likely to accept short-term decreases in catch in return for higher catch-rates later on if they understand the trade-offs and can look forward, with some measure of security, to potential long-term gains.
- Clear requirements for data to be input to the MP need to be specified, as well as pre-specified rules for when such data are not forthcoming. The MP process presents an ideal opportunity to motivate the need to collect certain data: trade-offs of potential yields (future catch) against data availability are standard performance statistics output for candidate MPs, thereby effectively highlighting which data are essential and which are of little benefit to long-term management goals. This is particularly important when considering the high cost of monitoring and scientific research, and the analyses of data collected. The trade-off of the

[6] Observation error due to errors in sampling and monitoring of the resource; Process error from natural fluctuations in the model parameters related to population abundance and recruitment; Structural uncertainty due to lack of knowledge of the underlying fish stock and the model that would best describe its population dynamics; Implementation error due to non-compliance to catch/effort limits due to lack of enforcement.

cost of data against the potential yield is essential to plan future fishery data requirements in the light of current financial constraints globally.

- Rules need to be established on when to over-ride the implemented MP and invoke "exceptional circumstances" if scenarios arise which were not included in the simulation testing. Tinkering with the MP or its outputs once implemented is counter-productive and must be avoided. The MP implemented should only be over-ridden if new evidence requires immediate management action in line with the precautionary principle. It is better to bring a full MP revision process forward if there are valid reasons to expect that continued application of the current MP will not satisfy the long-term management objectives. Keeping in mind that the main benefit of an MP approach is to long-term management, this objective is defeated if there is annual tinkering with the implemented MP. If stakeholders are intent on changing management recommendations every year, an assessment approach would suffice (though bring back with it all its attendant problems). The strength of the MP approach is to focus on long-term objectives and to automate management so as to avoid interference (see Chapter 4 for a comparative study of long-term compared to short-term management).
- An MP development schedule needs to be drawn up to pre-specify when different processes start and stop in the MP cycle. In order to avoid delays in the development, all attempts should be made to adhere to the predetermined schedule. Two key deadlines need to be established: the date after which no further data are submitted, and the date after which no additional OMs are introduced. New information/data forthcoming after a deadline should be deferred to the next MP cycle. Keeping in mind that less information/data usually translates to more conservative management, a fixed schedule puts the onus on the various stakeholders to attend meetings and produce on time, to avoid missing out until the next round. However draconian this may sound, the advantages of a well-planned, transparent and inclusive process far overshadow the disadvantages of being restricted by a time-line.

While all aspects of the MP development process are important from a fisheries management point of view, steps 3, 4 and 5 are perhaps the most challenging for the fisheries scientist. The choice of a range of OMs, similar to a suite of traditional stock assessment models, depends largely on the data available. Typically, OMs are age- or length-based population dynamics models fitted to one or more indices of abundance, and possibly age- or length-data from the fishery and/or surveys if available. In contrast, MPs can be either model-based, usually age-aggregated models, or simple empirical algorithms. Indeed, for the sake of thorough robustness testing, it is usually advantageous to use simple empirical MPs, or harvest control rules, and leave the complexity to the operating models which describe the underlying population dynamics. For purposes of this thesis, an age-structured production model is used as basis for setting up the operating models, as described in Section 2.3.

Technical descriptions of a range of empirical management procedures used for simulation testing are given in Section 2.4.

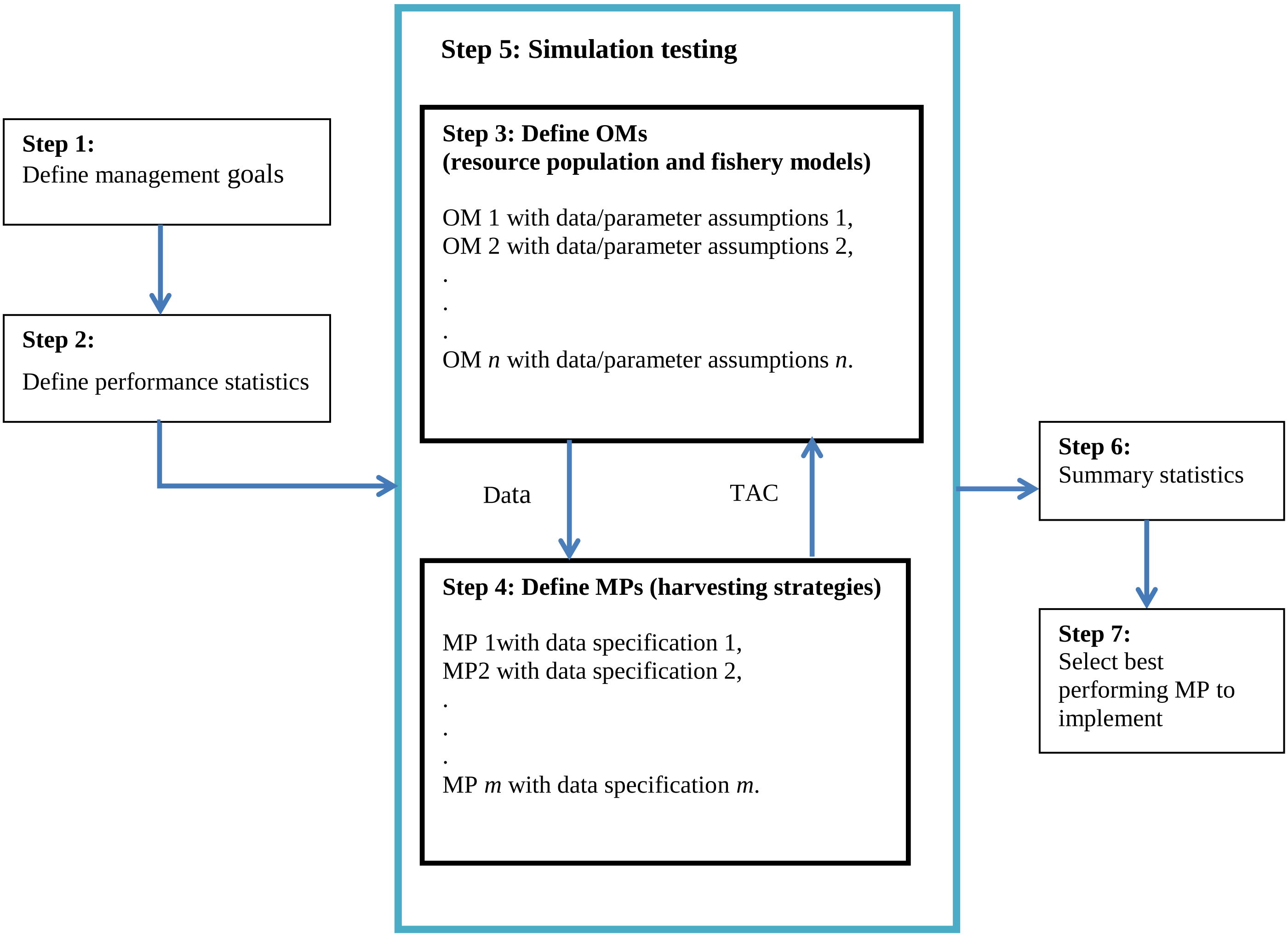

Figure 2.1: Schematic representation of simulation testing in a management procedure framework, where *n* denotes the number of operating models over which robustness is tested, and *m* denotes the candidate harvest control rules that output the total allowable catch (TAC), or similar management control measure such as total allowable effort (TAE), for each year of the projection period under consideration.

2.3 Operating models

An age-structured production model (ASPM) is used to model the resource dynamics of the populations considered in this thesis. Fishing is assumed to be continuous throughout the year, so that the population dynamics are described by the equations:

$$N_{y+1,a\min} = R_{y+1} \tag{2.1}$$

$$N_{y+1,a+1} = N_{y,a}e^{-(M_a+S_{y,a}F_y)} = N_{y,a}e^{-Z_{y,a}} \qquad \text{for } a_{\min} \le a < m-2 \tag{2.2}$$

$$N_{y+1,m} = N_{y,m-1}e^{-(M_{m-1}+S_{y,m-1}F_y)} + N_{y,m}e^{-(M_m+S_{y,m}F_y)} \tag{2.3}$$

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 for fish of age a ,

$S_{y,a}$ is the age-specific selectivity for year *y* and set to 1 for the age at which there is full selectivity,

F_y is the fishing mortality for year *y*,

m is the maximum age considered (taken to be a plus-group),

$a_{\min}$ is the minimum age considered (0 in this case), and

y denotes the year.

The total number of fish caught of age a in year *y* is given by the Baranov equation:

$$C_{y,a} = N_{y,a}\,\frac{S_{y,a}F_y}{Z_{y,a}}(1-e^{-Z_{y,a}}) \tag{2.4}$$

where $Z_{y,a} = M_a + S_{y,a}F_y$ is the total mortality for fish of age *a* in year *y*.

The corresponding total catch by mass for each year is given by

$$C_y = \sum_{a=a_{\min}}^{m} w_{y,a+1/2}\, C_{y,a} \tag{2.5}$$

where $w_{y,a+1/2}$ denotes the mid-year weights-at-age of fish caught in year *y*.

Stock-recruitment relationship

The number of recruits at the start of year y is related to the spawning stock size by a stock–recruitment relationship. Two forms of such a relationship are considered. The first is a Beverton-Holt form:

$$R_y = \frac{\alpha\, B^{sp}_{y-a\min}}{\beta + B^{sp}_{y-a\min}} e^{\varsigma_y - \sigma_R^2/2} \tag{2.6}$$

where

α and β are spawning biomass-recruitment parameters,

$\varsigma_y \sim N(0, \sigma_R^2)$ reflect fluctuations about the expected recruitment for year y,

σ_R is the standard deviation of the log-residuals, which is input, and

$B^{sp}_{y-a\min}$ is the spawning biomass at the start of year $y - a_{\min}$, given that:

$$B^{sp}_y = \sum_{a=a\min}^{m} f_a w_a N_{y,a} \tag{2.7}$$

where w_a is the begin-year mass of fish of age a (spawning is assumed to take place at the start of the year) 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^{sp} , and the "steepness" of the stock–recruitment relationship, h (recruitment at $B^{sp} = 0.2K^{sp}$ as a fraction of recruitment at $B^{sp} = K^{sp}$)

$$\alpha = \frac{4h R_K}{5h-1} \tag{2.8}$$

and

$$\beta = \frac{K^{sp}(1-h)}{5h-1} \tag{2.9}$$

where the pristine equilibrium recruitment R_K is given by

$$R_K = K^{sp} / [\ f_0 w_0 + \sum_{a=a\min+1}^{m-1} f_a w_a e^{-(\sum_{a'=a\min}^{a-1} M_{a'})} + f_m w_m \frac{e^{-(\sum_{a'=a\min}^{m-1} M_{a'})}}{1-e^{-M_m}}\ ] \tag{2.10}$$

Note: A Beverton-Holt stock–recruitment relationship is assumed for the analyses reported in Chapter 3 of this thesis.

The second is a two-line (or "hockey stick") form:

$$
\begin{aligned}
B_y^{sp} \geq B^0: &\quad R_y = \alpha e^{\zeta_y - \sigma_R^2/2} \\
B_y^{sp} < B^0: &\quad R_y = (\alpha B_{y-1}^{sp} / B^0) e^{\zeta_y - \sigma_R^2/2}
\end{aligned}
\tag{2.11}
$$

where B^0 is the spawning biomass limit point below which recruitment becomes impaired (decreases to zero).

Note: A two-line stock–recruitment relationship is assumed for the analyses reported in Chapter 4 of this thesis.

Biomass

The model estimate of the exploitable ("available" to the fishing fleet) component of biomass is given by:

$$B_y^{\exp} = \sum_{a=a\min}^{m} w_{y,a} S_{y,a} N_{y,a} \tag{2.12}$$

for begin-year biomass, and for the mid-year biomass:

$$B_{y+1/2}^{\exp} = \sum_{a=a\min}^{m} w_{y,a+1/2} S_{y,a} N_{y,a} e^{-Z_{y,a}/2} \tag{2.13}$$

where $w_{y,a}$ denote the begin-year weights-at-age of fish caught in year y, and $w_{y,a+1/2}$ are the mid-year weights-at-age.

The model estimate of the survey biomass is given by

$$B_y^i = \sum_{a=a\min}^{m} w_{y,a} S_a^i N_{y,a} \tag{2.14}$$

where $w_{y,a}$ denote the population weights-at-age for each year, and

S_a^i is the fishing selectivity corresponding to survey index *i*.

It is usual to assume that the resource is at the deterministic equilibrium that corresponds to an absence of harvesting at the start of the initial year ($B_1^{sp} = K^{sp}$). The age-structure of B_1^{sp} is taken here to be that corresponding to the equilibrium with no fishing mortality.

2.3.1 Bayesian approach

In the traditional stock assessment, and adopting a strictly frequentist's viewpoint, the data alone must inform the model, necessitating a comprehensive set of data from which to estimate the model parameters that describe the underlying resource dynamics. The Bayesian, however, measures plausibility given incomplete knowledge, using prior knowledge as well as data to assign probabilities to different plausible hypotheses regarding the resource dynamics.

Limited data is an unfortunate reality in most fisheries management. For data-poor fisheries, the situation is more extreme and assessments under the frequentist paradigm relying on a full set of data from which to estimate model parameters become impossible. When confronted with few data, or considerable but unreliable data, fisheries scientists have little choice but to make use of expert judgement and inferences drawn from other stocks and species to fill the gaps.

Less quantitative data require a statistical approach that more readily admits qualitative information. The Bayesian approach allows the fishery scientist to incorporate information from alternative species and stocks into the modelling exercise, in this manner taking account of model uncertainty in a formal manner. This approach works particularly well in a management procedure development environment: parameter values are sampled from prior distributions to give a range of plausible alternative realities, each an alternative operating model. Reliable quantitative data are included to inform the model, but need not be as extensive. In addition, a Bayesian approach allows for priors to be added in order to ensure that model parameter estimates fall in plausible ranges based on expert judgement.

Prior distributions for pertinent model parameters can be based on qualitative knowledge of the resource, as well as knowledge borrowed from similar fish stocks and fisheries. However, care must be taken when constructing these prior distributions as badly chosen priors may lead to dubious management conclusions (Punt and Hilborn 1997). It is therefore advisable to include the various stakeholders in this process to ensure that priors are consistent with expert knowledge gained through the collective resource and fishery experience and that the prior distributions encompass the uncertainty associated with model parameters.

2.3.2 Management performance statistics

Four main statistics are used to compare performance of the various MPs considered in this work:

i. B^{sp}_{final} / K^{sp}, the final biomass depletion where B^{sp}_{final} is the spawning biomass for the last year of the projection period, and B^{sp}_{y} is calculated using equation (2.7).

ii. $B^{sp}_{final} / B^{sp}_{msy}$, the spawning biomass at the end of the projection period as a fraction of B^{sp}_{msy}, the deterministic equilibrium spawning biomass at which maximum biological sustainable yield is achieved, given by:

$$B^{sp}_{msy} = R \sum_{a=a_{\min}}^{m} f_a w_a N^{eq}_a$$

where N^{eq}_a are the equilibrium population numbers per recruit corresponding to F_{msy} (the fishing mortality at which the maximum yield is obtained), for $S_{n,a}$ (the fishing selectivity vector at the end of the pre-management period) and M (the natural mortality), with R the number of recruits which is given by:

$$R = (\alpha - \beta / SPR)$$

where SPR is the equilibrium spawning biomass per recruit at F_{msy}, and α and β are the Beverton-Holt stock–recruitment parameters. Note that a different B^{sp}_{msy} is computed for each simulation, corresponding to different values for M and $S_{n,a}$ (which are re-sampled per simulation) as well as the stock–recruitment relationship parameters α and β (which are re-computed for different values of K^{sp} and h).

iii. $\overline{TAC}$, the average future total annual TAC, given by

$$\overline{TAC} = 1/p \sum_{y=n+1}^{n+p} TAC_y$$

where n is the current year (last year of the pre-management period) and p is the number of years in the projection period .

iv. AAV, the average inter-annual variation TAC given by

$$AAV = 1/p \sum_{y=n+1}^{n+p} \frac{\left| TAC_y - TAC_{y-1} \right|}{TAC_{y-1}}$$

Target and limit reference points for the projections performed in Chapter 3 are chosen to lie 20% above and 50% below the biological target, MSY, as discussed in Section 1.3. This is also consistent with managing a resource in terms of an economic target, MEY, as discussed in Section 1.4, which is assumed to lie 20% above the MSY target for simplicity, i.e:

$$B^{target} = B_{MEY} = 1.2 B_{MSY}^{sp}$$

Assuming that maximum sustainable biological yield, MSY, is produced when the spawning biomass is at 40% of pre-exploitation level, K^{sp}, a proxy for the target reference point in terms K^{sp} is given by:

$$B^{target} = 0.5 K^{sp}$$

The limit reference point, below which the stock is considered overexploited, is assumed here to occur at 50% of MSY level, and 20% of the pre-exploitation spawning biomass, K^{sp}, such that:

$$B^{\lim} = 0.5 B_{MSY}^{sp} = 0.2 K^{sp}$$

2.4 Management procedures (MPs)

A variety of management procedures (MPs) have been considered for illustrative purposes. Depending on the data that would typically be available from the fishery, MPs can either involve fairly complex models or be very simple formulae. The model-based MPs are essentially resource assessment models which provide annual TACs according to some preselected target. The advantage of these models is that they can be structured to take most, even all, of 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, or other appropriate management control. The disadvantages of this model-based approach are its complexity (the models are not well understood by all stakeholders) and the underlying minimization used when fitting the model to data can be unstable (leading to spurious results because the thousands of fits involved in simulation testing cannot each be checked for convergence in the same way as would a single best assessment). In addition, the simulation testing of model-based MPs is typically very computer time-intensive. For these reasons 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 trends in relative levels of 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. Because of their inherent simplicity and the broad-stroke manner in which the apparent trend in resource abundance is tracked, these MPs are often preferred to their model-based counterparts, even when dealing with data-rich resources (Punt 1993, Rademeyer 2012). More importantly, these simple empirical MPs present some defensible quantitative way of managing data-poor fisheries.

The potential disadvantages of this type of MP are the relatively few data that are incorporated in the harvest control rule, which could lead to unnecessarily large catch fluctuations, and the lack of estimates of resource abundance and other management quantities (e.g. 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 (MSYL or MEYL) or other customary management reference points. This may work well if the resource is not depleted too far and if recent TACs have been set at appropriate levels for the fishery. However if little is known about the resource status, as for example in a 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 (and/or less reliable) fishery data available, the more conservative the management approach needs to be.

The following sections provide details of the MPs which have been considered in the analyses of the Chapters that follow.

Extremely data-poor (no direct index of abundance):

2.4.1 Constant Catch

The first MP considered is a constant catch strategy which is appropriate when no data, other than the annual catches, are available/suitable for use in the MP and none are likely to become so in the short or medium term. While a constant catch harvest control rule is not desirable in reality, it serves as a base line for comparison with performance statistics forthcoming from other MPs that have feed-back control and which should therefore result in better performance than this constant catch strategy.
For the constant catch strategy, the future TAC is set equal to TAC^*:

$$TAC_{y+1} = TAC^* = (1-x)C^{ave} \tag{2.15}$$

where

$C^{ave} = 1/5 \sum_{y=n-5}^{n-1} C_y$ is the average historic catch over the preceding 5 years,

x is the proportional difference between the future catch and the average historic catch (values for x of 0, 0.1, 0.2, 0.3 and 0.4 are considered for data-poor applications in Chapter 3), and n is the current year.

2.4.2 Stepwise Constant Catch

For extremely data-poor fisheries for which no reliable index of abundance exists, data may be available for the average individual length or mass of the fish caught each year. Rather than using the constant catch control rule described above, which has no feed-back control mechanism, to set yearly TACs or some similar management control measure, the mean length or mass of fish harvested could be used as an indicator of the level of depletion of the resource (see Figure 2.2 which plots mean length of fish caught as a function of resource depletion for typical values of natural mortality for fish of intermediate life-spans).

This MP is a simple constant catch strategy with a step up or down depending on whether some threshold is reached in terms of the recent mean length of fish caught (Geromont and Butterworth, 2010). The rationale underlying this type of MP arises from considerable uncertainty regarding the status of the resource coupled with the fact that mean length data do not constitute a direct index of abundance and can be very noisy (consequently having limited information content). It is therefore not defensible to adjust the TAC up or down annually as the mean length increases/decreases because these fluctuations could bear little relation to resource population size, but rather arise from effects such as observation error. For this MP, the TAC is left unchanged until overwhelming evidence (in terms of a large change in mean length of the resource harvested) suggests that the TAC should be increased or decreased. Given this inertia in the interests of stability, clearly such MPs need to be tuned to be conservative (risk averse).

No TAC smoothing was applied for this class of MPs as the step-size should remain fixed, and large decreases in terms of double step downs may be necessary for severely depleted resources.

$$TAC_{y+1} = TAC_y \pm step \tag{2.16}$$

where TAC_y is the TAC in year y,

$step = 5\%C^{ave}$, and

C^{ave} is defined by equation (2.15).

For the first year of the projection period an appropriate "starting level", TAC^*, must be chosen (which is not necessarily equal to the actual TAC of the previous year) — see equation (2.15).

The TAC is increased/decreased only if the recent mean length is more than a predetermined percentage higher/lower than the average of historic mean length of catch. Let:

$$L_y^{ratio} = \frac{L_y^{recent}}{L^{ave}} \tag{2.17}$$

where

$L_y^{recent} = \frac{1}{5}\sum_{y'=y-4}^{y} L_{y'}$ is the average mean length over the most recent 5 years, and

$L^{ave} = \frac{1}{10}\sum_{y'=n-10}^{n-1} L_{y'}$ is an average historic mean length, which remains fixed over the projection years, and serves as a proxy for the target mean length[7],

then the TAC is only increased by a single step for year y+1 if $L_y^{ratio} > 1.05$. On the other hand if $L_y^{ratio} < 0.98$ the TAC is decreased by a step. As a precautionary measure multiple step-downs are permitted: thus, the TAC is decreased a second step if $L_y^{ratio} < 0.96$, etc. For this MP a greater upper threshold of 5% is set to ensure that the TAC does not increase too rapidly, which runs the risk of unintended resource overexploitation. An additional safeguard may be necessary to limit the number of consecutive increases in TAC to avoid over-exploitation of a vulnerable stock. Lesser upper threshold values may be appropriate for a resource for which the status is judged to be healthy given a coarse preview of the history of the fishery. However, to ensure adequately low inter-annual TAC variability, higher thresholds for both increasing and decreasing the TAC may be necessary.

2.4.3 Target mean length

This MP is similar to the Tier 4 control rule for Australian fisheries, which is based on a target CPUE level as tested in Wayte (2009); here, however, annual mean length of fish caught is used as an indirect index of resource abundance in the absence of a CPUE or survey index. A target mean length, L^{target}, is chosen with the intention to achieve some associated target level of abundance:

$$TAC_{y+1} = TAC^{target}\left[w + (1-w)\frac{L_y^{recent} - L^0}{L^{target} - L^0}\right] \qquad \text{if } L_y^{recent} \geq L^0 \tag{2.18}$$

and

$$TAC_{y+1} = wTAC^{target}\left[\frac{L_y^{recent}}{L^0}\right]^2 \qquad \text{if } L_y^{recent} < L^0 \tag{2.19}$$

where

$w = 0.5$ is the TAC smoothing parameter,

[7] Rather than use the average historical length as target, an alternative option for the target mean length is the equilibrium mean length when fishing at a rate, *F*, equal to, *M*, the natural mortality rate (ICES 2012b).

TAC^{target} is a preselected target catch (i.e. TAC* in equation 2.15), chosen to correspond to the constant catch that would achieve the target biomass in the long term ,

$L^{ave} = \frac{1}{10} \sum_{y'=n-10}^{n-1} L_{y'}$ is the historic average mean length,

$L_y^{recent} = \frac{1}{5} \sum_{y'=y-4}^{y} L_{y'}$ is the average mean length over the most recent 5 years,

$L^{target} = (1+\delta)L^{ave}$ is the target length,

δ is the proportional difference between the target length and the average historic length (values for δ of 0.05, 0.1 and 0.15 are considered in Chapter 3 for "depleted" pseudo stocks),

$L^0 = 0.9L^{ave}$ is the limit mean length below which future catches are reduced quadratically rather than linearly with L and are set to zero if $w = 0$, and

n is the current year.

In addition, future TACs are restricted to increase/decrease less than a predetermined proportional amount from one year to the next. Let $\Delta^{\max}$ be the maximum allowable proportional difference in TAC, where the inter-annual variation in TAC is denoted by:

$$\Delta TAC_{y+1} = (TAC_{y+1} - TAC_y) / TAC_y \tag{2.20}$$

with the maximum allowable difference bounded in absolute terms such that $b_1 \le \Delta^{\max} TAC_y \le b_2$ to avoid over/under dampening of very small/very large future TACs. Then, for $b_1 \le \Delta^{\max} TAC_y \le b_2$, the maximum inter-annual variation in TAC in relative terms is defined by:

$$TAC_{y+1} = (1 \pm \Delta^{\max})TAC_y \quad \text{if } \Delta TAC_{y+1} \begin{cases} > \Delta^{\max} \\ < -\Delta^{\max} \end{cases}$$

Outside these bounds, the TAC for the next year can only be increased/decreased by an absolute maximum (pre-specified in metric tons).

For $\Delta^{\max} TAC_y < b_1$:

$$TAC_{y+1} = TAC_y \pm b_1 \qquad \text{if } TAC_{y+1} - TAC_y \begin{cases} > b_1 \\ < -b_1 \end{cases}$$

For $\Delta^{\max} TAC_y > b_2$:

$$TAC_{y+1} = TAC_y \pm b_2 \qquad \text{if } TAC_{y+1} - TAC_y \begin{cases} > b_2 \\ < -b_2 \end{cases}$$

Note: Relative bounds (without the additional absolute bounds) on inter-annual TAC variation of 15% are used in the catch control rules considered in Chapter 3.

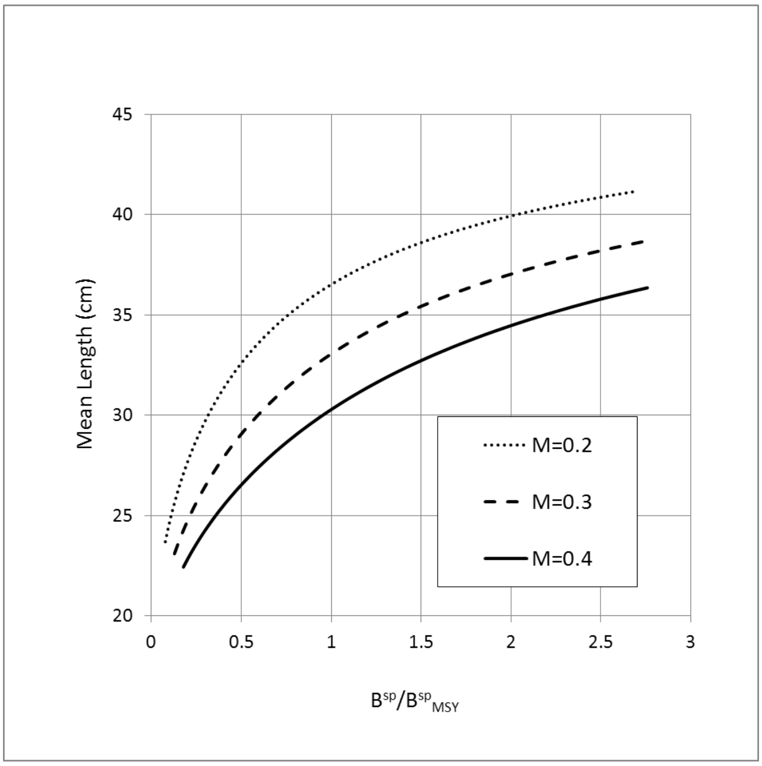

Figure 2.2: Equilibrium mean length of the resource harvested as a function of spawning biomass for age-independent natural mortality rates, *M*, of 0.2, 0.3 and 0.4 yr^{-1} (see Appendix A.4 for yield-per-recruit analysis).

Moderately data-poor and data-rich (one of more indices of abundance):

For this class of MPs, it is assumed that there is at least some index of abundance (I) 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 so that the observation error is not too large. Based on these premises it can be assumed that any trend in the index of abundance is a fairly reliable indicator of trend in resource abundance. The idea underlying these empirical MPs is that the TAC each year is adjusted up or down from the previous year's TAC depending on either the rate of increase or decrease in size of the resource as indicated by the index of abundance (e.g. CPUE), or the extent to which this index is above or below target level. The success of this rule depends on how much information, rather than noise due to observation error, the data series contains, i.e. whether the MP is reacting to real trends in abundance or simply following noise.

For moderately data-poor and data-rich stocks, slope- and target-type MPs, based on a direct index of abundance, are simulation tested. For these MPs, additional TAC smoothing in terms of equation (2.20) is applied to avoid undesirably large fluctuations in future TAC.

Note: If more than one index of abundance is incorporated in the slope and target MPs that follow, the yearly TAC is computed by averaging over the TAC contributions associated with each of the indices, so that:

$$TAC_{y+1} = 1/n \sum_{i} TAC_{y+1}(I^i)$$

where n is the number of abundance indices included in the MP.

2.4.4 Abundance index slope

This MP is similar to the one implemented for the Namibian hake fishery (Butterworth and Geromont 2001). The TAC for the next year is given by:

$$TAC_{y+1} = TAC_y(1+\lambda s_y) \qquad (2.21)$$

where TAC_y is the total annual catch for year y,

λ is a control parameter that reflects how strongly the TAC is adjusted in response to the perceived trend in resource biomass, and

s_y is a measure of the trend in the abundance index given by the slope of the linear regression of $\ln I_{y'}$ against y' for years $y' = y-p+1, y-p+2, ..., y$ for abundance index I, 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), but if p is too large, the MP would not be able to react sufficiently rapidly to recent trends in resource abundance.

For the first year of the projection period an appropriate "starting level", TAC^*, must be chosen (not necessarily equal to the actual TAC that year) given by equation (2.15). The choice of this starting point is important for the performance of the MP because a starting level that is too low will result in an unrealistically large drop in TAC in the first year of management (unrealistic because it would not be accepted in practice), while a starting point that is too high may necessitate subsequent severe cuts in the TAC. A more precautionary MP may be required for severely depleted resources, e.g. a larger value for λ when the slope, s_y, is negative to ensure quicker reaction to a decreasing trend in stock abundance.

2.4.5 Abundance index target

This type of MP is based on moving resource abundance to a chosen target level for some abundance index *I*. The TAC is adjusted up or down depending whether the most recent abundance index is above or below the target survey level.

$$TAC_{y+1} = TAC^{target}\left[w + (1-w)\frac{I^{recent} - I^0}{I^{target} - I^0}\right] \quad \text{if } I^{recent} \geq I^0 \tag{2.22}$$

and

$$TAC_{y+1} = wTAC^{target}\left[\frac{I_y^{recent}}{I^0}\right]^2 \quad \text{if } I^{recent} < I^0 \tag{2.23}$$

where

$I_y^{recent} = 1/p\sum_{y'=y-p-1}^{y} I_{y'}$ is the average survey or CPUE index of abundance over the most recent *p* years,

$I^{target} = (1+x^{tar})I^{ave}$ is the desired target value for the index of abundance,

$I^0 = (1-x^{\lim})I^{ave}$ is a lower survey or CPUE abundance index level below which future TACs are reduced quadratically to zero,

$I^{ave} = 1/q\sum_{y=n-q}^{n-1} I_y$ is an average past survey abundance index value over the last *q* years,

TAC^{target} is a preselected target catch (i.e. TAC* in equation 2.15), equivalent to the constant catch that would achieve the target biomass in the long term, and

w is a TAC smoothing parameter that defines the catch level when $I^{recent} = I^0$.

A simplified, commonly used form of equation (2.22), similar to the Tier 4 control rule in Wayte (2009), is obtained by setting *w*=0

$$TAC_{y+1} = TAC^{target} \frac{I_y^{recent} - I^0}{I^{target} - I^0} \tag{2.24}$$

Here, the catch is set to zero when the abundance index reaches its lower limit, I^0. At the other extreme, setting $w = 1$ results in a constant catch harvesting strategy.

The formulation given by equation (2.22) allows for a non-zero catch of $wTAC^{target}$ when $I^{recent} = I^0$, which has the effect of dampening the inter-annual variation in catches, thereby stabilizing the output from the MP. Setting $w = 0$ would necessitate a steeper slope of the linear relationship given by equation (2.24), leading to more variability in future catches. On the other hand, setting $w = 1$ would result in no inter-annual fluctuations in catch, but also no adjustment of catch in response to changes in survey abundance indices. To achieve a suitable trade-off between the level of feedback control and inter-annual catch variation, a value of $w = 0.5$ was chosen for the deterministic retrospective projections considered in subsequent chapters, so that equations (2.22) and (2.23) become:

$$TAC_{y+1} = 0.5TAC^{target}\left[1 + \frac{I^{recent} - I^0}{I^{target} - I^0}\right] \qquad \text{if } I_y^{recent} \geq I^0 \tag{2.25}$$

$$TAC_{y+1} = 0.5TAC^{target}\left[\frac{I_y^{recent}}{I^0}\right]^2 \qquad \text{if } I_y^{recent} < I^0 \tag{2.26}$$

Figure 2.3 illustrates three different forms of the harvest control rule when assuming different values (0, 0.5 and 1) for the control parameter *w*.

While a control parameter of *w*=0.5 should suffice in dampening the inter-annual variations adequately, an additional constraint on TAC variation, as per equation (2.20), may be required when developing MPs for extremely data-poor resources with large uncertainty about current levels abundance, as is the case for MPs tested in Chapter 3.

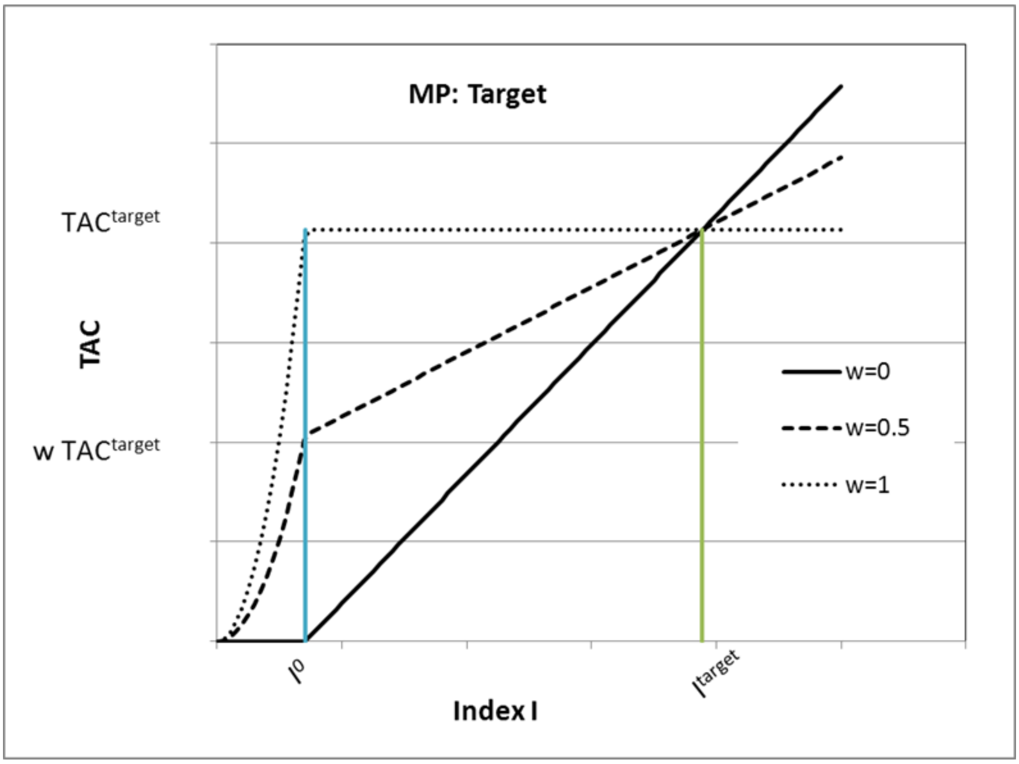

Figure 2.3: Different target-type MPs for three values of the control parameter *w*: the dashed lines correspond to equations (2.25) and (2.26), while the solid black line corresponds to equation (2.24). The vertical lines indicate the zero and target survey values, while the horizontal dotted line corresponds to a simple constant catch rule when $w = 1$. To ensure adequate precaution against over-exploitation, the value chosen for w may need to be less than I^0 / I^{target}; a value of $w = 0$ may therefore be advisable.

Chapter 3 Data-poor stocks: forecasting with few data

3.1 Introduction

At present there are as yet no quantitative measures in place to manage the majority of low-value fish stocks worldwide, mainly due to the lack of reliable data on which to base quantitative assessments. The FAO (2010) has highlighted the need for the development of scientific management methods and procedures for an estimated 90% of exploited stocks worldwide that are currently not assessed. Due to the high costs of data collection, these methods and procedures need to be less data-demanding, give reliable estimates of stock status and provide the quantitative information necessary for designing effective management plans. The FAO (2010) further states that uncertainty and risk need to be incorporated in an assessment process that is "closely linked to fisheries management and the decision-making process", including some form of motivation to collect further data based on exploitation rate where "intensively exploited fisheries will require more intensive and frequent data collection and monitoring than moderately exploited ones".

Traditional stock assessment methods are generally not a viable option for data-poor stocks because there are rarely sufficient reliable data from which to estimate population-model parameters. In South Africa, management reference points have in the past been estimated for data-poor linefish species using spawner-biomass-per-recruit analyses (Griffiths et. al. 1999). However the reliability of these estimates is questionable as they in turn rely on estimates of natural mortality whose accuracy is debatable. Another possible management option for data-poor stocks is a simple "traffic light" framework based on qualitative information, or "expert judgment" (Caddy 2002). However, the problem with management decisions that are made in this way is that they cannot be quantified and, more importantly, they therefore cannot be simulation tested to demonstrate robustness in the presence of uncertainty (Butterworth *et al.* 2010).

The MP approach, to date used in South Africa only for the management of high-value data-rich marine resources, could lend itself well to data-poor stocks in order to better address the uncertainty and risk associated with lack of data, in a framework that is "closely linked to fisheries management and the decision making process", as stipulated by the FAO (2010). Furthermore, motivation to collect extra data is part and parcel of an MP approach in which the cost of and yield obtainable given extra data are quantified as standard management statistics. As such, the MP approach is thus perfectly positioned to be applied to the vast number of data-poor resources that are currently not under any formal assessment.

In order to manage data-poor resources better defensively from a scientific standpoint, some very simple quantitative harvesting rules are desirable where these have been shown to be robust by subjecting them to comprehensive simulation testing to ensure that management objectives are reasonably met despite uncertainties about the underlying dynamics. Rather than attempt the impossible task of developing and simulation testing numerous species-specific MPs, it seems more reasonable to try to develop generic MPs that can be applied to several similar data-poor low-value stocks. Based on available quantitative and qualitative data, different sets of operating models covering a wide range of scenarios (including different values for demographic parameters) can be specified for the different groups of similar resources. Having defined the range of operating models that would encompass the uncertainty associated with such a selected group of resources, robustness trials can then be undertaken for a candidate set of MPs depending on the data typically available. The generic MP most appropriate for a group of fisheries sharing similar characteristics can then be chosen by comparing across performance statistics.

The aim of this chapter is therefore to design and test some very simple "off-the-shelf" MPs that could be applied to a group of data-poor fisheries which share some key characteristics in terms of demographic parameters.

Building on preliminary analyses by Butterworth *et al.* (2010), this work looks at an extensive comparative testing of a selection of empirical MPs across a wide range of operating models (OMs) representing the underlying dynamics of the resource (Geromont and Butterworth 2010). In the absence of a direct index of abundance, how well can these MPs perform?

Rather than test these MPs on the data forthcoming from an existing fishery, simulated data are generated from a range of operating models encompassing the extent of uncertainty expected in reality. A generic approach is required for data-poor stocks where similar species are grouped together in "baskets" (Smith et al. 2009) according to their longevity/productivity and perceived depletion levels. Similar to the FAO (2011) categories in terms of exploitation level[8], stocks are grouped here into three broad categories depending on the perceived level of resource depletion: "depleted" or "overexploited" (current biomass B_n^{sp}/K^{sp} between 10% and 30% of the pre-exploitation level), "near target" (corresponding to a less pessimistic range for depletion of B_n^{sp}/K^{sp} of 30% to 50%) and "underexploited" (depletion in the range of 50% to 70% of the pre-exploitation level). In addition, stocks are grouped in terms of their level of productivity so that the categorisation results in nine large

[8] The Food and Agriculture Organisation of the United Nations (FAO 2011) defines the three general categories similar to those adopted here: Overexploited, fully-exploited and non-fully exploited corresponding to current biomass less than 40%, between 40% and 60%, and more than 60% of the pre-exploitation level, respectively.

"baskets" (Table 3.1). A different generic suite of operating models (OMs) need to be developed for each of the nine "baskets", with different MPs being appropriate for each. However, for this initial study whose primary purpose is illustrative, the analysis here considers only at a group of stocks of "medium productivity" deemed to be overexploited, i.e. falling in the "depleted" category.

	Low productivity	Medium productivity	High productivity
Depleted (Overexploited)	$M \sim U[0.05, 0.2]$ $B^{sp}/K^{sp} \sim U[0.1, 0.3]$	$M \sim U[0.2, 0.4]$ $B^{sp}/K^{sp} \sim U[0.1, 0.3]$	$M \sim U[0.4, 1.0]$ $B^{sp}/K^{sp} \sim U[0.1, 0.3]$
Near target	$M \sim U[0.05, 0.2]$ $B^{sp}/K^{sp} \sim U[0.3, 0.5]$	$M \sim U[0.2, 0.4]$ $B^{sp}/K^{sp} \sim U[0.3, 0.5]$	$M \sim U[0.4, 1.0]$ $B^{sp}/K^{sp} \sim U[0.3, 0.5]$
Underexploited	$M \sim U[0.05, 0.2]$ $B^{sp}/K^{sp} \sim U[0.5, 0.7]$	$M \sim U[0.2, 0.4]$ $B^{sp}/K^{sp} \sim U[0.5, 0.7]$	$M \sim U[0.4, 1.0]$ $B^{sp}/K^{sp} \sim U[0.5, 0.7]$

Table 3.1: Fish stocks grouped into nine "baskets" according to the perceived level of depletion and productivity. For the analysis that follow. Values are drawn from uniform distributions across the ranges shown.

3.2 Operating models

The technical specifications of the operating models, based on an age-structured production model (ASPM), are described in Section 2.3 of Chapter 2 of this thesis.

A Bayesian-like approach is adopted for this generic data-poor MP evaluation exercise. When dealing with extremely data-poor fish resources, there would typically not be reliable data from which to estimate population model parameters. Therefore, the operating models which describe the underlying stock structure are defined by model parameters sampled from pre-specified distributions, rather than estimating them from data.

The operating models on which the MPs are tested include model uncertainty (by effectively integrating over the ranges specified for model parameter values); this is in addition to "observation" error (taken into account by including stochastic components when generating future abundance index and length data), as well as "process" error (past and future recruitment and fishing selectivity fluctuations are included for each simulation). These three sources of uncertainty are incorporated explicitly into the generic MP approach adopted here for a group of similar data-poor resources: simulated trajectories are generated by sampling from pre-specified distributions for key model variables such as the current depletion B_n^{sp} / K^{sp} (from which the pre-exploitation equilibrium spawning biomass, K^{sp}, is back-calculated), the "steepness" of the stock-recruit relationship, h, and an age-independent natural mortality rate M, as well as for selectivity and stock-recruit residuals. The distributions chosen are intended to reflect some of the qualitative information which would typically be available for a resource, or a group of resources, while still allowing for sufficient model uncertainty which would be expected in an application for an actual resource. The range assumed here for current depletion of 10% to 30% of the pre-exploitation level corresponds to the category of resources collectively termed "depleted".

3.2.1 Pre-specified distributions

For the generic approach being pursued here, the pre-specified distributions used for model variables/parameters are based on typical ranges expected for other similar stocks of intermediate size and longevity for which data and assessments are readily available, in this case South African hake and horse mackerel (Johnston and Butterworth 2007):

- Steepness of the Beverton-Holt stock-recruitment relationship (equations 2.8 and 2.9), is sampled from a wide uniform distribution:
  $h \sim U[0.5, 0.9]$

- Natural mortality (age-independent) is sampled from a uniform distribution:
  $M_a \sim U[0.2, 0.4]$ yr^{-1}

- Selectivity residuals: generated from log-normal fluctuations about the expected fishing selectivity-at-age vector, with a standard deviation of the log-residuals of 0.4 (equation A.3 in Appendix A):
  $\tau_{y,a} \sim N(0, 0.4^2)$ where a is age and y is year

- Stock-recruit residuals: generated from log-normal fluctuations about the recruitment expected in terms of the stock-recruitment relationship (equation 2.6), with a standard deviation of the log-residuals of 0.5:
  $\zeta_y \sim N(0, 0.5^2)$

- Data for use in MPs: pseudo mean length (L) and catch-per-unit-effort (CPUE) data are generated from log-normal fluctuations about the expected indices, with standard deviations of the log-residuals of $\sigma_L = 0.25$ (equation A.1) and $\sigma_{CPUE} = 0.2$ (equation A.2) respectively.

Furthermore, as the focus here is on "very depleted" stocks, the current intended depletion may lie between 10% and 30% of its pre-exploitation level and is sampled from a corresponding to a uniform distribution $B_n^{sp} / K^{sp} \sim U[0.1, 0.3]$.

A large set of biomass trajectories is generated by sampling from these distributions, with each population biomass trajectory, or simulation, corresponding to a plausible reality. In order to ensure comprehensive sampling from these distributions, 8000 simulations are generated. Data required for the projections are generated by the operating model for each simulation, i.e. each pseudo data set generated corresponds to a different set of parameter values sampled from the input distributions defined above. Technical specifications for generating the pseudo data are given in Appendix A.

The pre-management period is taken to span $n = 40$ years, followed by a projection period of 10 years. Annual historical catches are assumed to be known exactly (Table A.1 in Appendix A).

3.3 Candidate Management Procedures

A variety of very simple MPs, suitable for data-poor resource management, are simulation tested. These empirical-type MPs are easy to code and would be readily understood by all parties typically involved in the management of the resource. Limited data are used in the formulae, with TACs increased/decreased in proportion to the trend in the resource index, or the extent to which the resource index is above or below some target value.

An unavoidable disadvantage of these simple empirical MPs is the lack of estimates of resource abundance and other management quantities such as MSY on which to base TACs. While not problematic for a data-rich scenario for which estimates of resource depletion are readily available, this poses an obvious problem for the very data-poor case for which there are not sufficient data to obtain reliable estimates of current resource status, rendering optimum resource management difficult if not impossible. In the absence of a formal assessment to provide an estimate of stock status, the

FAO (2011) suggests that data/information be collected from "grey literature" or "black literature"[9] to assist with classification of data-poor stocks. If little is known about the resource status particular caution needs to be taken to avoid undue (and undetected) resource depletion as a result of unsustainable use of the stock.

For illustrative purposes, these empirical MPs are divided into two classes appropriate to the different levels of quantitative data availability. The "extreme data-poor" scenario is typified by the lack of any direct index of abundance (such as catch-per-unit-effort, CPUE, or survey), with only mean length of catch data available as a quantitative though indirect indicator of the trend in resource abundance. By contrast, the "moderately data-poor" scenario, corresponding to a fishery for which a direct index of abundance is available, is also considered in order to quantify what the benefit, in terms of potential yield, these additional data bring.

1. Extremely data-poor (no direct index of abundance):

   A constant catch rule (Section 2.4.1) is tested to give some idea of what level of TAC can be supported by the resource in the absence of quantitative data (other than the historic catches). This provides a benchmark against which to compare feedback-control MPs[10]. 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 in Section 2.3.2). Constant catch strategies, where future TAC is fixed to some percentage (100%, 90%, 80%, etc.) of the average historic TAC (taken over the last 5 years), are 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 to adjust the TAC upwards or downwards in accordance with perceived trends in population abundance.

   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, on the condition that there has been no systematic changes in selectivity over time (for example as a result of size related regulations). This class of MPs 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 crossed (Section 2.4.2). The idea is that unless there is a strong quantitative signal from the length data, the TAC is better left where it is so as to avoid the possibility of tracking noise rather than signal in a data-poor situation. Target-based MPs, similar in form to those

[9] "Grey literature" refers to working papers, local government reports, regional fisheries management reports and projects. "Black literature" refers to personal communications, reports of local meetings, newspaper articles, and so forth.
[10] MPs that adjust management measures in response to perceived changes in resource abundance.

investigated in Wayte (2009) Tier 4 stocks[11], 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 a target mean length (Section 2.4.3).

2. Moderately data-poor (one or more indices of abundance):

   For the moderately data-poor case where CPUE data are available, some simple empirical MPs based on the recent slope of the CPUE series and on the difference of the recent CPUE from some target level are considered (Sections 2.4.4 and 2.4.5 respectively). While these MPs would normally not be applicable to very data-poor resources because such data are typically absent, they are included here in an attempt to illustrate the possible benefit of the availability of a direct index of abundance for management purposes.

These two classes of harvest control rules are compared to ascertain whether the use of more data in the control rule leads to improved performance in terms of the summary statistics described in Section 2.3.2, and by how much. Of particular importance for extremely data-poor resources is to identify, through simulation testing, which data are the most important for effective resource management. A constant catch strategy, which requires no quantitative data, acts as a baseline against which the performance of other MPs are measured.

Technical specifications of the MPs are given in Section 2.4 of this thesis. A summary of the control rules of the candidate MPs tested in this chapter are given in Table 3.2.

3.4 Management objectives and trade-offs

The first step when adopting a Management Procedure Approach is to specify the strategic objectives for the resource/fishery, as described in Chapter 2. One of the key questions that need to be answered is: “where do we want to be?”,

Consider a depleted data-poor stock whose current spawning biomass depletion lies between 10% and 30% of the pre-exploitation level, as defined in Section 3.1. Ideally, MPs are sought to rebuild the stock (or group of stocks) to a level of abundance that would maximise biological and economic yield, while also taking social issues into consideration.

[11] Tier 4 harvest control rules (HCRs) apply to species with no reliable information on either current biomass or current exploitation rate.

Given that static maximum economic yield (MEY) is achieved at a higher level of abundance than maximum sustainable biological yield (MSY), and assuming little difference between the static and dynamic optimum biomass levels as suggested by Grafton *et al.* (2007) and Anderson and Seijo (2010), the simple answer to the "where do we want to be" question is therefore "somewhere above MSY level". In addition, a suitable time period to reach the desired abundance level must also be specified: decreasing the total allowable catch (TAC) to zero in an attempt to fast-track the rebuilding process is hardly acceptable from a social point of view.

For the overexploited ("depleted") pseudo stock (or group of stocks) considered here, the spawning biomass target and limit reference points described in Section 2.3.2 are adopted. Specifically, the MP sought is one which would move the resource biomass to 20% above the MSY level (target: $B_{target} = 1.2 B^{sp}_{MSY}$) 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^{sp}_{MSY} for 90% of the time (limit reference point: $B_{\lim} = 0.5 B^{sp}_{MSY}$). Therefore, assuming that B^{sp}_{MSY} is achieved when the resource biomass is at approximately 40% of its pre-exploitation biomass level, K^{sp}, the target biomass (in median terms) to be achieved by the end of the projection period is about $50\%K$, with a 10%-ile of $20\%K^{sp}$ to meet the risk threshold.

However, deciding "where we want to be?" is generally not the tricky question. While it is fairly straightforward to choose biological and economic targets (fisheries with high discount rates excluded), the challenge lies in finding appropriate management strategies to reach goals in a manner that balances the biological, economic and social concerns. For example, for the overexploited (termed "depleted") data-poor stock investigated in this chapter, harvesting strategies are sought that would:

i. re-build resources to maximum sustainable yield levels, or above,
ii. avoid unacceptably large cuts in TAC,
iii. keep inter-annual fluctuations in TAC to an acceptable level, and
iv. achieve this within a 10 year time-frame.

Expecting to achieve all objectives and targets is somewhat unrealistic and trade-offs are generally required: in order for a depleted stock to reach the target biomass within 10 years would likely require a large drop in TAC. However, to maintain a stable fishery and avoid unacceptably large TAC cuts, something else will have to give, either in the form of a longer rebuilding time-frame or some flexibility regarding the biological target. The purpose of the management procedure approach is to present such trade-offs in a simple quantitative format to enable decision makers to select the most appropriate management strategy given the long-term objectives for the resource.

3.5 Results

The five harvesting strategies defined in Chapter 2 (summarised in Table 3.2) are considered for stock rebuilding purposes. Comprehensive robustness trials are performed for each of the candidates. The values of the control parameters used to tune the five MPs are chosen to achieve adequate biomass recovery for a depleted stock within the 10 year projection period. Tables 3.3 to 3.7 of results show medians and 90% probability intervals for pertinent performance statistics. Lower 10%-iles corresponding to the limit reference points are also given. Management quantities that are equal or above the target and limit reference points are printed in bold.

To assist realism, the results are shown as if the pre-management period of $n = 40$ years corresponded to starting in 1970 and ending in 2009. This is followed by a rebuilding period under the MP which allows only 10 years to reach management targets, i.e. from 2010 to 2019.

3.5.1 Constant catch MP

At the one extreme where no quantitative data (other than the historic total catches) are available, constant catch strategies are tested to ascertain what level of catch is required to ensure recovery in median terms of the resource to 20% above B_{MSY} level given the uncertainty inherent in a data-poor fishery, particularly one termed "depleted". When the current level of TAC is maintained for future years the spawning biomass is estimated to increase in median terms. Also on the positive side, there is no change in TAC over the projection period for this strategy. However, considering the lower 90% probability interval in Table 3.3 (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 pre-exploitation level). 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^{sp} / B^{sp}_{MSY} 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^{sp} for this MP, the target of $0.5K^{sp}$ 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^{sp} in median terms and a much improved 5%-ile value for depletion of $B^{sp} / K^{sp} = 0.18$ at the end of the 10 year projection period.

However, to achieve all the biological management targets set in Section 3.4, 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^{sp} 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 average past catch (300 tons) ensures adequate resource recovery. However, this low level of catch may be wasteful in terms of the maximum sustainable yield statistics of Table 3.3 (biomass well above 50% of B^{sp}_{MSY} at the 5%-ile level, with the median biomass estimated to be 60% above B^{sp}_{MSY}). Furthermore, the sudden large drop in TAC of 40% under this strategy would not be acceptable in terms of economic and social objectives. Therefore, of the MPs shown in Table 3.3, 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.

3.5.2 Step-wise constant catch MP

For the scenario where some catch-at-length data are available to manage the fishery, simple empirical MPs are tested which attempt to react to trend information while not responding to noise. In contrast to the previous constant catch MPs, a new difficulty introduced here is to restrict the average variation in TAC from year to year, but still to 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 3.4). Here a 5% increase and 2% decrease thresholds are 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 reduced by a further step if a second negative threshold is reached. The latter is necessary in cases of severe current resource depletion near 10% of the pre-exploitation level, corresponding to the lower bound of the pre-specified distribution for current depletion.

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 unacceptably low (4% of K^{sp}) for this option. While B^{sp}_{MSY} is reached in median terms within the projection period, there remain concerns that the median target of 20% above B^{sp}_{MSY} is not achieved and that the 10%-ile is below the limit reference point of 0.5 of B^{sp}_{MSY}. Lowering the starting value, TAC^{*}, to 90% of the average of recent catches (450 tons) results in an increase in the median spawning biomass to well above B^{sp}_{MSY} at the end of the 10 year projection period; however the spawning biomass does not recover sufficiently in median terms and risk related limit reference points are breached.

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 of 0.12 and 0.20 respectively. To ensure that the resource biomass recovers to the target level of 50% of the pre-exploitation spawning biomass, 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 reaches only 46% of the pre-exploitation level. 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 exceeding maximum sustainable yield level targets and hence sacrificing possible catch. The main concern here is the possibly large (>15%) inter annual variations in TAC, which is unlikely to be consistent with economic and social objectives.
For this class of MPs no inter-annual TAC constraint is applied as these MPs increase/decrease in predefined step levels. In addition, large reductions in catch may be required for resources defined as "depleted" in order to ensure adequate spawning biomass recovery.

3.5.3 Target mean length MP

Performance statistics for the target-type MPs based on mean length are given in Table 3.5. The first column corresponds to a target of 5%, the second one of 10%, and the third one of 15% above an historical average (taken over the last 10 years) for mean length of fish caught. While a mean target length of only 5% above past average mean length fails to achieve all the biological objectives (column 1), increasing the target length to 10% above the past average (column 2) does succeed in ensuring that the median biomass is more than 20% above the maximum sustainable yield level at the end of the projection period, as well as ensuring that the corresponding 10%-ile is above the limit reference point of 50% of B_{MSY}. However, neither target nor limit reference points for median depletion are achieved under this MP. Increasing the mean length target to 15% above historic average leads to an improvement in median depletion, although still not reaching the target level in terms of K^{sp} at the end of the projection period (column 3). In order to increase the median spawning biomass to closer to the target of 50% of K^{sp}, a lower starting point of 80% of recent catches (400 tons) is required (last column). However, this increase in median spawning biomass from 44% to 48% of *K* comes at the cost of a decrease in median average annual catch from 403 tons to 342 tons.

A limitation of 15% on inter-annual fluctuation of TAC is imposed for this type of MP, although this safeguard is not strictly necessary for the harvest control rules reported in Table 3.5.

3.5.4 CPUE slope MP

Table 3.6 shows management statistics for a CPUE slope MP which calculates the annual TAC based on trends in the index of abundance.

The first column corresponds to a MP starting value of 80% of past catches, combined with a low value of 0.4 for λ, a control parameter which determines how fast the MP reacts to perceived changes in the trend over the most recent 5 years of CPUE data. While achieving the MSY target, this harvest control rule fails to reach the biological target and limit reference points for final depletion. Choosing a lower starting point for this MP of 70% (column 2), results in the median spawning biomass increasing from a 39% to 43% of *K*, with the 10%-ile above the limit reference point of 20% of *K* at the end of the projection period. A very conservative starting value of 60% of past catches (column 3) increases median biomass depletion to 47% of *K*, but the downside is the large drop in average annual catch from 418 tons to only 365 tons in median terms. A lower value for λ of 0.2 (column 4) reduces inter-annual fluctuations in future TACs, with the added benefit of increasing the median estimate for final depletion to 49% of *K*. However, this increase in resource biomass also means less yield, with a median estimate for average yearly catch of only 332 tons for this harvest control rule.

Except for the rather severe drop in TAC in the first year of the projection period to ensure spawning biomass recovery in median terms to about 50% of *K* after 10 years, the inter-annual variations in TAC for the remainder of the projection period are sufficiently low not to require additional TAC smoothing.

3.5.5 CPUE target MP

Performance statistics for a CPUE target MP are given in Table 3.7. The first column lists summary statistics corresponding to a target of only 50% higher than the average historical CPUE. This results in median spawning biomass estimates well below the target reference points. Increasing the target to double the average historical CPUE (column 2) results in an average future catch of 453 tons and median estimates of spawning biomass in excess of 20% above the maximum sustainable yield level.

However, for these catches the median biomass does not come close to 50% of the pre-exploitation level ($B^{sp}/K^{sp} = 0.39$), although the limit reference point for the 10%-ile, to be above 20% K^{sp}, is achieved. Increasing the CPUE target to 250% of the past average improves the risk statistics somewhat at the expense of a drop in average catch in median terms from 453 to 409 tons (column 3). In order to reach the depletion target, a lower MP starting point of 70% of recent past catches is required. However, this results in a severe drop in average future TAC from 409 to 327 tons in median terms.

The inter-annual variation in catch is restricted to remain below 15% for the CPUE target-based MPs for all the candidate MPs reported in this Table.

3.5.6 Summary statistics

Pertinent management quantities in Tables 3.3 to 3.7 are shown visually in Figure 3.1 to facilitate comparison of the different MPs. The key statistics reported are medians and 90%-iles of spawning biomass depletion B^{sp}/K^{sp}, spawning biomass in terms of MSY, B^{sp}/B^{sp}_{MSY}, the average annual future TAC, and the average inter-annual variation in TAC at the end of the 10 year projection period.

Noticeable from the top two plots in Figure 3.1 is that all five MPs can be tuned to give comparable performance in terms of the risk statistics with perhaps marginally narrower probability intervals for the moderately data-poor MPs based on CPUE data (the "Islope" and "Itarget" candidates). Summary statistics for the best-performing candidates (considered to be those that maximize catch while satisfying both target and limit abundance reference points) are compared in Figure 3.2. The difference in performance between these MPs lies mainly in the extent of fluctuation in TAC that can be tolerated by the fishery, and the total average future yield to be expected under a particular MP.

For comparative purposes, and to provide a bound on the maximum recovery possible by the stock over the period considered, summary statistics are also shown for a future catch of zero (CC0).

3.5.7 Biomass and TAC projections under different strategies

Spawning biomass and TAC trajectories corresponding to the best performing MPs in each category are shown in Figures 3.3.

Projections of spawning biomass as a function of MSY level, corresponding to a constant catch harvesting strategy of 70% of average historical catch, are shown in Figure 3.3 (top). Given the extent of uncertainty encompassed by the operating models, particularly in terms of the extent of current resource depletion, a drop in TAC to 70% of recent catches (350 tons) results in all biomass trajectories shown in the left-hand plot to increase during the projection period. It is evident from this plot that most trajectories increase from below target level in 2009 to well above it under this harvest control rule. While satisfying biological objectives in terms of reaching resource recovery targets within the 10-year projection period, this large drop in TAC from 500 to 350 tons may not be acceptable from a social and economic point of view. While long term advantages for this type of MP include no inter-annual variation in the TAC (i.e. stability in the fishery) and no data requirements except for estimates of past annual catches, a constant catch strategy cannot be implemented in practice in the absence of some sort of feedback mechanism to lower TACs if biological limit reference points, or thresholds, are not met.

Spawning biomass trajectories for MPs based on a constant catch threshold strategy show similar behaviour to the constant catch MPs for the equivalent starting point of 70% of recent catches (second row of plots). However, while there is seemingly no improvement in performance in terms of the biomass trajectories compared to those under a constant catch strategy, the future catch trajectories for this MP are widely spread from as little as 100 tons to 600 tons at the end of the projection period.

Spawning biomass and TAC trajectories corresponding to the target length-based MPs are shown in the third row of plots of Figure 3.3. Compared to the TAC trajectories under the threshold strategy, this MP results in slightly less inter-annual TAC variability in order to achieve the biological target and reference points (see also Figure 3.1).

Spawning biomass and catch trajectories corresponding to the moderately data-poor MPs, based on the trend in recent CPUE data, are shown in the fourth row of plots of Figure 3.3. The spread of the future catches seems slightly reduced for this MP because of the low value of λ, although no additional TAC change constraints were applied, with catches at the end of the projection period higher than under the preceding length-based MP. However, in order to achieve the biomass target and limit reference points, the slope-type MP requires a rather sharp drop in catch in the first year of the projection period. By comparison, the initial decrease in catch is more gradual for the target-type MP (bottom two plots), but here future TACs are more widely spread than for the slope MP, with correspondingly narrower distributions for final spawning biomass at the end of the projection period.

3.5.8 Yield-risk trade-offs: do more data give better performance?

While the summary statistics in Figures 3.1 and 3.2 give useful information regarding spread of results and the trade-offs under different strategies, Figure 3.4 provides a better visual aid when comparing risk/return performance statistics. Here the median average future TAC is plotted against the 10%-ile estimates for spawning biomass depletion under different harvesting strategies and corresponding control parameter values. If the objective is to maximize future catch while at the same time minimizing the risk of resource depletion, then one seeks points that lie furthest to the top-right of in Figure 3.4. The yield-risk trade-off choice would then be made from amongst these points.

Considering the trendlines drawn for each type of harvesting strategy, it is clear that the constant catch (CC) strategy performs worst as would be expected. In the absence of an index of abundance, the stepwise constant catch (LstepCC) strategy, based on mean length data, performs best. The best performing MPs overall are the CPUE-based MPs, which achieve a higher yield in terms of median average TAC for the same level of risk of resource depletion, when compared to the length-based ones.

These results accentuate the importance of the role of an abundance index, such as provided by 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. For the CPUE-based MP, a median future TAC of over 475 tons is achievable for only 10% chance of being below a stock depletion level of 20% of the pre-exploitation biomass, which is indicated by the black vertical line in Figure 3.4. The potential yield corresponding to the stepwise constant catch MPs is somewhat less at approximately 425 tons, with the constant catch strategy yielding only 400 tons for the same level of risk. Hence, in the absence of an index of abundance, the potential yield foregone is about 15% for the same level risk. From a strategic point of view, the management authority therefore needs to decide if the extra tonnage warrants the effort that is required to obtain the additional data.

While moderately data-poor MPs based on a direct index of abundance (CPUE) perform better than the extremely data-poor length-based strategies as might be expected, these initial results show nevertheless that the very simple empirical MPs perform surprisingly well given the wide range of uncertainty for key parameters and could well be candidates to manage some of the world's many data-poor stocks, ensuring perhaps not optimum, but at least some form of management to ensure relatively stable and sustainable future catches.

3.5.9 Robustness trials

Thus far, the results reflect the performance of MPs which have been simulation tested across a suite of base case OMs with pre-specified parameter distributions as detailed in Section 3.2.1. A major shortcoming of the work presented in the previous sections is that no allowance is made for implementation error: total allowable catch (TAC) and total removals are taken to be the same, with annual historic catches assumed to be known exactly. This section examines robustness of the best performing MPs to further uncertainties, and in particular implementation error.

OM1: Undetected fluctuations about the catch series

Total removals are generated from log-normal fluctuations about past and future reported catches with a standard deviation of the log-residuals of 0.2 (equations (A.10) and (A.11) of Appendix A):

$$\varepsilon_y^C \sim N(0, 0.2^2)$$

For this robustness test, while the "true" catches (total removals) are known to the underlying population models (OMs), the MPs are not privy to this information: future TACs generated by the MPs are based upon the catch series of Table A.1.

OM2: Detected fluctuations about the catch series

The same as OM1, but for this robustness test it is assumed that the "true" catches (total removals) are known to both OMs and MPs.

OM3: Detected fluctuations about the catch series, with bias

The same as OM2, but here the "true" catches (total removals) are more likely to be greater than the reported catches (or TACs). Log-residuals are generated about a mean of 0.1 with a standard deviation of the log-residuals of 0.1 (equations (A.10) and (A.11)):

$$\varepsilon_y^C \sim N(0.1, 0.1^2)$$

OM4: Undetected positive bias in catches in the pre-management period only

The true annual catch is 40% under the reported catch over the last 10 years of the pre-management period (2000 to 2009). After 2009 the true catch is exactly equal to the reported catch (TAC generated by the MP). The best performing "extremely data-poor" MP (Ltarget4) was selected for this robustness test and the others that follow.

OM5: Undetected negative bias in catches in the pre-management period only

The true annual catch is 40% above the reported catch over the last 10 years of the pre-management period (2000 to 2009). After 2009 the true catch is again assumed to be exactly equal to the reported catch (or TAC generated by the MP).

OM5k: Same as OM5, but here bias is known.

OM6: Extremely low depletion

Spawning biomass depletion is fixed to a value of 0.05 outside the pre-selected range of [0.1, 0.3].

OM7: Low productivity

Natural mortality is fixed to a value of 0.1 outside the pre-selected range of [0.2, 0.4].

OM8: Increased observation error

For length data, increase the standard deviation from 0.25 to 0.35.

OM9: Change in expected values of selectivity vector at the time that management commences:

Age	0	1	2	3	4	5	6	7	8	9	10
Base case	0.0	0.2	0.4	0.6	0.8	1.0	1.0	1.0	1.0	1.0	1.0
OM9a	0.0	0.1	0.5	0.9	1.0	1.0	1.0	1.0	1.0	1.0	1.0
OM9b	0.0	0.0	0.0	0.0	0.0	0.1	0.5	0.9	1.0	1.0	1.0

Figure 3.5 shows summary statistics for the best performing MPs in each of the five categories when making allowance for log-normally distributed implementation error (robustness test OM1). The performance of all five MPs are largely unaffected by these random fluctuations about the “true” catches, with risk-related limit and target reference points being met in all cases. In order to visualise the extent of variation about the reported catches (and TACs), trajectories of “true” catches are shown in Figure 3.6, along with associated spawning biomass trajectories.

Rather than submit all the MPs to all nine robustness tests listed above, a target-type MP which relies only on mean length data (the “extremely data-poor” situation) is selected for further projections; this

MP was selected based on its performance across the range of base case OMs (see Figures 3.2 and 3.3). A comparison of summary statistics when subjecting the Ltarget4 MP to all robustness tests is shown in Figure 3.7. The combined tests (OM2 plus OM4 and OM5) investigate both bias and variability in the reported catches. Of particular note is that this MP is surprisingly robust across the range of uncertainty encompassed by these trials, with the exception of robustness tests OM6 and OM7; this is not surprising as these fall outside the "basket" for which the MPs were designed. This suggests that the correct classification of stocks within baskets in terms of their depletion and productivity levels is key to these MPs achieving their objectives. When dealing with stocks that fall in the "depleted" and/or "low productivity" basket, different generic MPs would need to be developed which are more conservative than the Ltarget4 considered here to avoid further depletion of the stock.

The nine robustness tests are summarised in Table 3.8. Tables of summary statistics for these robustness trials are given in Appendix A.5 (Tables A.2 to A.7).

3.6 Where next?

The generic MPs developed and simulation tested in this chapter are intentionally simple in order to illustrate some fundamental principles of the approach. The purpose of these analyses is firstly to show how an MP approach could be applied to extremely data-poor resources and, secondly, to highlight the emphasis placed on forecasting, with long-term management objectives defined in terms of target and limit reference points with decision-making based on yield-risk trade-offs and, lastly, to emphasize the potential value in terms of extra yield for extra data.

These generic MPs can of course not be adopted for practical implementation in their present form. A comprehensive MP approach would necessitate the inclusion of all seven steps enumerated in Chapter 2.

In particular, before practical application might be considered, the full extent of uncertainty (model structure uncertainty, process error, observation error and implementation error) would need to be addressed for the group of stocks under consideration. While these sources of error are incorporated to some extent in the analyses reported here, a wider range of testing would be needed. For example, robustness to uncertainty regarding the somatic growth parameters and their correlation with natural mortality needs to be considered. Systematic changes (e.g. an undetected increase) in the constant of proportionality associated with the index of abundance (e.g. the mean length of catch time series) need to be simulation tested. Furthermore, different stock-recruitment relationships, such as a Ricker model, also need to be considered. Lastly, the extent of uncertainty, as reflected by the pre-specified distributions, needs to be closely examined and accepted by all stakeholders before these simple MPs could be considered for application in practice.

The range of operating models used for trials in this chapter corresponds only to “depleted” resources of medium productivity. Ideally, these generic analyses need to be repeated, for MPs with different control parameter choices, for groups of stocks that fall in the other eight “baskets” depicted in Table 3.1, together with associated alternative historic catch series and CPUE/length data availability scenarios. An unavoidable difficulty for extremely data-poor stocks is the need to categorise stocks into “baskets” according to productivity levels and depletion. The former may not be too problematic, given results from research on similar stocks and species, but the latter presents greater challenges. A possible approach would be to follow a procedure similar to the FAO (2011) classification system which relies on “grey” and “black” literature. With few data (and an absence of quantitative assessments) to inform reliable categorisation of stocks, a more precautionary approach is required, particularly for low productive longer-lived species that have been under severe fishing pressure (stocks that fall broadly in the baskets to the top and left of Table 3.1).

Summary of candidate MPs:	
Constant catch: CC0: $TAC^{*}=0$ CC1: $TAC^{*}=C^{ave}$ CC2: $TAC^{*}=0.9C^{ave}$ CC3: $TAC^{*}=0.8C^{ave}$ CC4: $TAC^{*}=0.7C^{ave}$ CC5: $TAC^{*}=0.6C^{ave}$	$TAC_{y+1}=TAC^{*}=(1-x)C^{ave}$ where $C^{ave}=1/5\sum_{y=n-4}^{n}C_{y}$ (see section 2.4.1 for full specifications)
Step-wise constant catch (length data): LstepCC1: $TAC^{*}=C^{ave}$ LstepCC2: $TAC^{*}=0.9C^{ave}$ LstepCC3: $TAC^{*}=0.8C^{ave}$ LstepCC4: $TAC^{*}=0.7C^{ave}$ LstepCC5: $TAC^{*}=0.6C^{ave}$	$TAC_{y+1}=TAC_{y}\pm step$ where $step=5\%C^{ave}$, and TAC^{*} is the starting point.
Length target (length data): Ltarget1: $L_{target}=1.05L^{ave}, TAC^{*}=C^{ave}$ Ltarget2: $L_{target}=1.1L^{ave}, TAC^{*}=C^{ave}$ Ltarget3: $L_{target}=1.15L^{ave}, TAC^{*}=C^{ave}$ Ltarget4: $L_{target}=1.15L^{ave}, TAC^{*}=0.8C^{ave}$	$TAC_{y+1}=0.5TAC^{*}[1+(\frac{L_{y}^{recent}-L^{0}}{L^{target}-L^{0}})]$ if $L_{y}^{recent}\geq L^{0}$ $TAC_{y+1}=0.5TAC^{*}\left[\frac{L_{y}^{recent}}{L^{0}}\right]^{2}$ if $L_{y}^{recent}<L^{0}$ $L^{0}=0.9L^{ave}$, L_{y}^{recent} is the average length for the most recent 5 years, L_{ave} is the average length over the 10 years immediately preceding management.
Index slope (CPUE index of abundance): Islope1: $\lambda=0.4$, $TAC^{*}=0.8C^{ave}$ Islope2: $\lambda=0.4$, $TAC^{*}=0.7C^{ave}$ Islope3: $\lambda=0.4$, $TAC^{*}=0.6C^{ave}$ Islope4: $\lambda=0.2$, $TAC^{*}=0.6C^{ave}$	$TAC_{y+1}^{slope}=TAC_{y}(1+\lambda s_{y})$ where s_{y} is the CPUE slope (gradient of a log-linear regression) for the most recent 5 years.
Index target (CPUE index of abundance): Itarget1: $I_{target}=1.5I^{ave}, TAC^{*}=C^{ave}$ Itarget2: $I_{target}=2I^{ave}, TAC^{*}=C^{ave}$ Itarget3: $I_{target}=2.5I^{ave}, TAC^{*}=C^{ave}$ Itarget4: $I_{target}=2.5I^{ave}$, $TAC^{*}=0.7C^{ave}$	$TAC_{y+1}=0.5TAC^{*}[1+(\frac{I_{y}^{recent}-I^{0}}{I^{target}-I^{0}})]$ if $I_{y}^{recent}\geq I^{0}$ $TAC_{y+1}=0.5TAC^{*}\left[\frac{I_{y}^{recent}}{I^{0}}\right]^{2}$ if $I_{y}^{recent}<I^{0}$ $I^{0}=0.8I^{ave}$, I_{y}^{recent} is the average CPUE for the most recent 5 years, I^{ave} is the average CPUE over the 10 years immediately preceding management.

Table 3.2: The five candidate MPs considered for data-poor stocks. Full specifications for MPs are given in Section 2.4 of Chapter 2.

	MP: CC1 $TAC^* = 1.0C^{ave}$	**MP: CC2** $TAC^* = 0.9C^{ave}$	**MP: CC3** $TAC^* = 0.8C^{ave}$	**MP: CC4** $TAC^* = 0.7C^{ave}$	**MP: CC5** $TAC^* = 0.6C^{ave}$
$B^{sp}_{current} / K^{sp}$	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)
B^{sp}_{final} / K^{sp}	0.36 (0.03,0.71)	0.40 (0.07,0.75)	0.44 (0.12,0.76)	0.48 (0.18,0.82)	**0.52** (0.24,0.86)
10%-ile B^{sp}_{final} / K^{sp}	0.09	0.15	**0.20**	**0.25**	**0.30**
$B^{sp}_{current} / B^{sp}_{MSY}$	0.62 (0.33,0.95)	0.61 (0.33,0.95)	0.62 (0.33, 0.95)	0.61 (0.33,0.95)	0.62 (0.33, 0.95)
$B^{sp}_{final} / B^{sp}_{MSY}$	1.13 (0.08,2.35)	**1.24** (0.22,2.48)	**1.37** (0.35,2.56)	**1.48** (0.52,2.74)	**1.60** (0.66,2.89)
10%-ile $B^{sp}_{final} / B^{sp}_{MSY}$	0.26	0.45	**0.58**	**0.72**	**0.86**
$\overline{TAC}$	500	450	400	350	300
AAV	0.00	0.01	0.02	0.03	0.04

Table 3.3: Medians (with 5% and 95%-iles in parenthesis) shown for pertinent management quantities for the case where no resource monitoring data are taken into account in the MP. The 10%-iles for biomass depletion estimates are also shown to compare with limit reference points for these quantities. Constant catch MPs are used, the first keeping the TAC at a 100% of the recent (last 5 years) average catch C^{ave} of 500 tons, and then more conservative options of reducing the TAC to 90%, 80% , 70% and 60% of recent levels (450, 400, 350 and 300 metric tons). The average inter-annual variation in TAC statistic is included here for consistency (non-zero values arise from the drop in TAC in the first year of the projection period). 8000 simulations were performed. Units, where pertinent, are tons. Quantities are printed in bold if management's conservation targets are achieved.

Data-poor: Mean length of catch data					
	MP: LstepCC1 $TAC^* = 1.0C^{ave}$	**MP: LstepCC2** $TAC^* = 0.9C^{ave}$	**MP: LstepCC3** $TAC^* = 0.8C^{ave}$	**MP: LstepCC4** $TAC^* = 0.7C^{ave}$	**MP: LstepCC5** $TAC^* = 0.6C^{ave}$
$B^{sp}_{current} / K^{sp}$	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)
B^{sp}_{final} / K^{sp}	0.35 (0.04,0.70)	0.38 (0.07,0.72)	0.42 (0.12,0.75)	0.46 (0.18,0.80)	0.49 (0.22,0.82)
10%-ile B^{sp}_{final} / K^{sp}	0.10	0.14	**0.20**	**0.24**	**0.28**
$B^{sp}_{current} / B^{sp}_{msy}$	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)
$B^{sp}_{final} / B^{sp}_{msy}$	1.08 (0.12,2.28)	1.19 (0.22,2.35)	**1.31** (0.37,2.47)	**1.44** (0.52,2.65)	**1.53** (0.62,2.72)
10%-ile $B^{sp}_{final} / B^{sp}_{msy}$	0.30	0.42	**0.58**	**0.71**	**0.81**
$\overline{TAC}$	520 (335,638)	475 (293,588)	435 (250,538)	388 (210,488)	338 (163,438)
AAV	0.03 (0.01,0.09)	0.04 (0.02,0.11)	0.05 (0.03,0.12)	0.07 (0.04,0.15)	0.09 (0.05,0.19)

Table 3.4: As for Table 3.2, but here for the stepwise constant catch MP where only the mean length of catch data is taken into account. *TAC is the TAC in the first year under management, expressed in terms of the recent average catch C^{ave}. No TAC change constraints are applied. 8000 simulations were performed. Units, where pertinent, are tons.**

Data-poor: Mean length of catch data				
	MP: Ltarget1 $L^0 = 0.9L^{ave}$ $L^{target} = 1.05L^{ave}$ $TAC^{target} = 1.0C^{ave}$ $w = 0.5$ $\overline{\Delta TAC} \le 15\%$	**MP: Ltarget2** $L^0 = 0.9L^{ave}$ $L^{target} = 1.10L^{ave}$ $TAC^{target} = 1.0C^{ave}$ $w = 0.5$ $\overline{\Delta TAC} \le 15\%$	**MP: Ltarget3** $L^0 = 0.9L^{ave}$ $L^{target} = 1.15L^{ave}$ $TAC^{target} = 1.0C^{ave}$ $w = 0.5$ $\overline{\Delta TAC} \le 15\%$	**MP: Ltarget4** $L^0 = 0.9L^{ave}$ $L^{target} = 1.15L^{ave}$ $TAC^{target} = 0.8C^{ave}$ $w = 0.5$ $\overline{\Delta TAC} \le 15\%$
$B^{sp}_{current} / K^{sp}$	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)
B^{sp}_{final} / K^{sp}	0.37 (0.07,0.70)	0.41 (0.12,0.73)	0.44 (0.14, 0.76)	0.48 (0.19,0.80)
10%-ile B^{sp}_{final} / K^{sp}	0.13	0.19	**0.21**	**0.26**
$B^{sp}_{current} / B^{sp}_{msy}$	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)
$B^{sp}_{final} / B^{sp}_{msy}$	1.14 (0.22,2.32)	**1.28** (0.37,2.41)	**1.35** (0.42,2.52)	**1.50** (0.59,2.68)
10%-ile $B^{sp}_{final} / B^{sp}_{msy}$	0.40	**0.56**	**0.61**	**0.79**
$\overline{TAC}$	483 (363,626)	432 (344,543)	403 (332,491)	342 (289,408)
AAV	0.07 (0.05,0.11)	0.07 (0.05,0.11)	0.06 (0.05,0.10)	0.08 (0.06,0.11)

Table 3.5: As for Table 3.2, but here for the target length MP where only the mean length of catch data is taken into account. 10%-iles are shown for the risk statistics. A 15% inter-annual TAC change constraint is applied for all the target MPs considered here. See section 2.4.3 for a full definition of this MP and the parameters in the column headings. 8000 simulations were performed. Units, where pertinent, are tons.

Data-poor: CPUE index of abundance				
	MP: Islope1 $TAC^* = 0.8C^{ave}$ $\lambda = 0.4$ $p = 5$	**MP: Islope2** $TAC^* = 0.7C^{ave}$ $\lambda = 0.4$ $p = 5$	**MP: Islope3** $TAC^* = 0.6C^{ave}$ $\lambda = 0.4$ $p = 5$	**MP: Islope4** $TAC^* = 0.6C^{ave}$ $\lambda = 0.2$ $p = 5$
$B^{sp}_{current} / K^{sp}$	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)
B^{sp}_{final} / K^{sp}	0.39 (0.13, 0.69)	0.43 (0.17,0.72)	0.47 (0.21,0.78)	0.49 (0.22,0.80)
10%-ile B^{sp}_{final} / K^{sp}	0.18	**0.22**	**0.27**	**0.28**
$B^{sp}_{current} / B^{sp}_{msy}$	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)
$B^{sp}_{final} / B^{sp}_{msy}$	**1.21** (0.37, 2.28)	**1.33** (0.48,2.40)	**1.45** (0.62,2.60)	**1.54** (0.62,2.70)
10%-ile $B^{sp}_{final} / B^{sp}_{msy}$	**0.52**	**0.65**	**0.78**	**0.81**
$\overline{TAC}$	467 (374, 587)	418 (337,523)	365 (297,455)	332 (298,374)
AAV	0.06 (0.04, 0.09)	0.07 (0.05,0.10)	0.08 (0.06,0.11)	0.06 (0.05,0.07)

Table 3.6: As for Table 3.2, but here for the MP where the CPUE index of abundance is used in the slope-based harvest control rule. No TAC change constraints are applied. See section 2.4.4 for a full definition of this MP and parameters in the column headings. 8000 simulations were performed. Units, where pertinent, are tons.

Data-poor: CPUE index of abundance				
	MP: Itarget1 $I^0 = 0.8I^{ave}$ $I^{target} = 1.5I^{ave}$ $TAC^{target} = 1.0C^{ave}$ $w = 0.5$ $\overline{\Delta TAC} \leq 15\%$	**MP: Itarget2** $I^0 = 0.8I^{ave}$ $I^{target} = 2I^{ave}$ $TAC^{target} = 1.0C^{ave}$ $w = 0.5$ $\overline{\Delta TAC} \leq 15\%$	**MP: Itarget3** $I^0 = 0.8I^{ave}$ $I^{target} = 2.5I^{ave}$ $TAC^{target} = 1.0C^{ave}$ $w = 0.5$ $\overline{\Delta TAC} \leq 15\%$	**MP: Itarget4** $I^0 = 0.8I^{ave}$ $I^{target} = 2.5I^{ave}$ $TAC^{target} = 0.7C^{ave}$ $w = 0.5$ $\overline{\Delta TAC} \leq 15\%$
$B^{sp}_{current} / K^{sp}$	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)
B^{sp}_{final} / K^{sp}	0.33 (0.11,0.61)	0.39 (0.17,0.68)	0.43 (0.19,0.72)	0.49 (0.24,0.79)
10%-ile B^{sp}_{final} / K^{sp}	0.15	**0.21**	**0.25**	**0.29**
$B^{sp}_{current} / B^{sp}_{msy}$	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)
$B^{sp}_{final} / B^{sp}_{msy}$	1.01 (0.35,1.95)	**1.20** (0.50,2.20)	**1.32** (0.57,2.32)	**1.51** (0.69,2.63)
10%-ile $B^{sp}_{final} / B^{sp}_{msy}$	0.47	**0.64**	**0.72**	**0.85**
$\overline{TAC}$	537 (315,860)	453 (307,696)	409 (298,612)	327 (257,473)
AAV	0.11 (0.07,0.14)	0.10 (0.06,0.14)	0.09 (0.06,0.14)	0.10 (0.08,0.14)

Table 3.7: As for Table 3.2, but here for the MP where the CPUE index of abundance is used in the target-based harvest control rule. A 15% inter-annual TAC change constraint is applied. See section 2.4.5 for a full definition of this MP and the parameters in the column headings. 8000 simulations were performed. Units, where pertinent, are tons.

Robustness test:	Notable performance difference from base case OMs	
	Risk	**Yield**
OM1: Implementation error (undetected)	No	No
OM2: Implementation error (detected)	No	No
OM3: Implementation error (biased – detected)	Marginal –	Yes +
OM4: Undetected 40% positive bias in reported catches	Marginal –	Marginal +
OM5: Undetected 40% negative bias in reported catches	Marginal +	Marginal –
OM6: $B^{sp}/K^{sp}=0.05$ (outside base case basket)	Yes –	Yes –
OM7: $M=0.1$ (outside base case basket)	Yes –	Yes –
OM8: $\sigma_{CPUE}=0.3$; $\sigma_L=0.35$	No	No
OM9a: Shift in selectivity (S_a=1 from a=4)	No	No
OM9b: Shift in selectivity (S_a=1 from a=8)	Yes –	Yes +
OM2+OM4: Detected variations and undetected negative bias	Marginal –	Marginal +
OM2+OM5: Detected variations and undetected negative bias	Marginal +	Marginal –
OM2+OM5k: Detected variations and detected negative bias	Yes –	Yes +

Table 3.8: Summary of robustness tests.

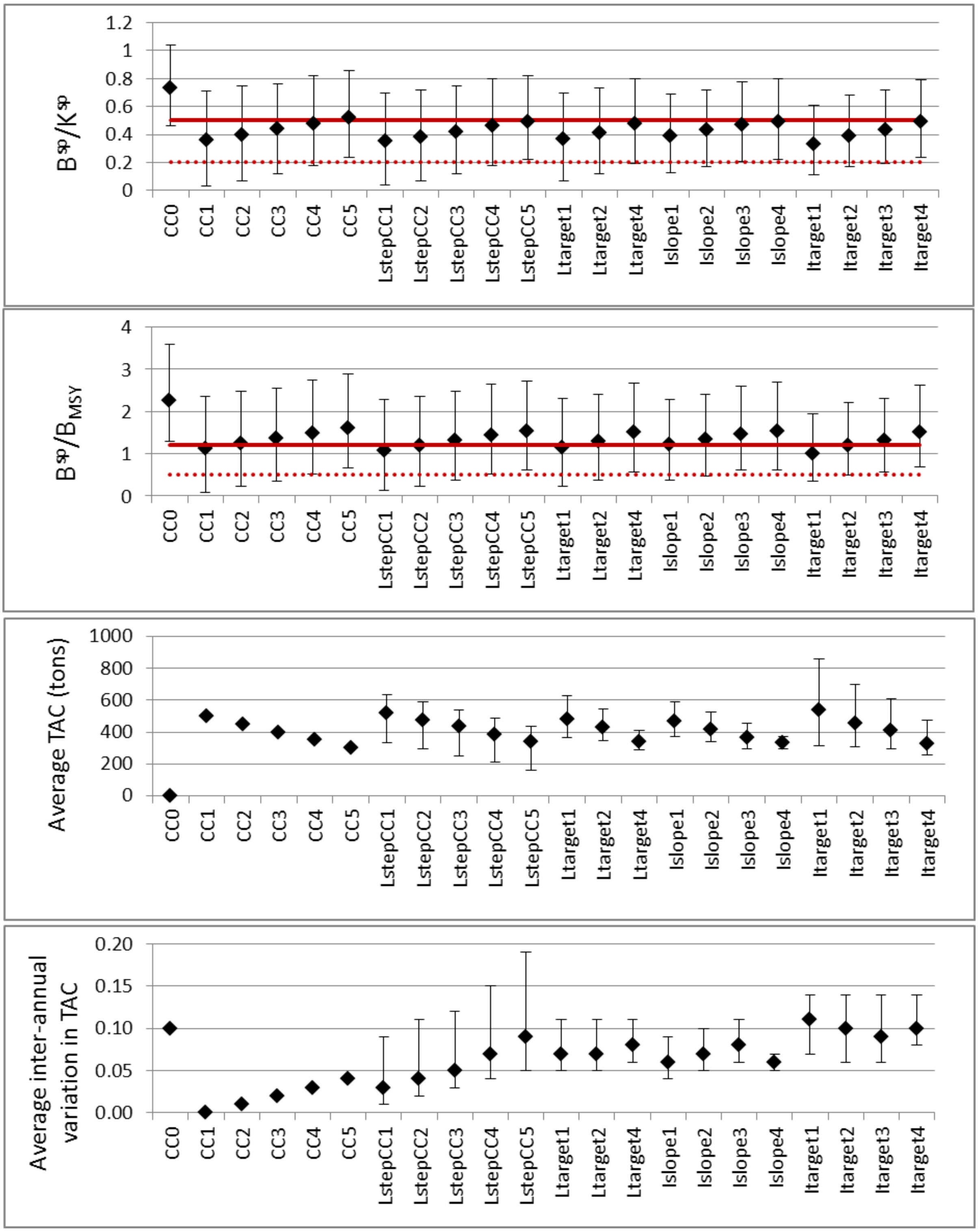

Figure 3.1: Medians and 90% probability intervals for final spawning biomass depletions (top), final spawning biomasses in terms of the MSY level (second), average future TACs (third) and average inter-annual variation in TAC (bottom) for various candidate MPs tested (see text for definitions). The solid horizontal lines correspond to the target reference points ($0.5K^{sp}$ and $1.2B_{MSY}$), while the dotted horizontal lines correspond to the limit reference points ($0.2K^{sp}$ and $0.5B_{MSY}$). Note that AAV is non-zero for the CC0 (zero future catch) scenario because of the catch reduction in the first year of management.

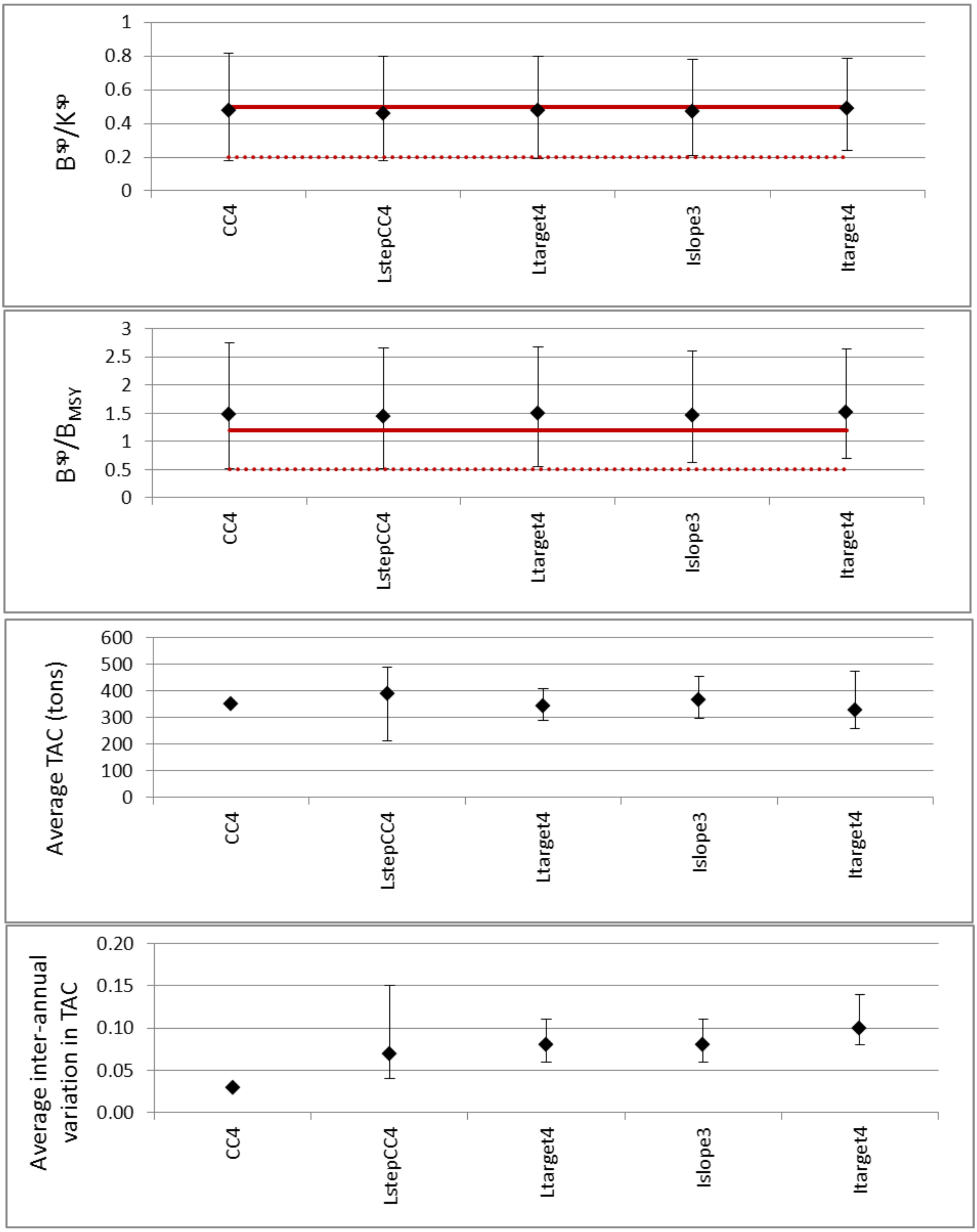

Figure 3.2: As for Figure 3.1, but here comparing the best performing MPs in each category ("best" is defined here as maximising catch subject to satisfying the spawning biomass limit reference point at the 10%-ile).

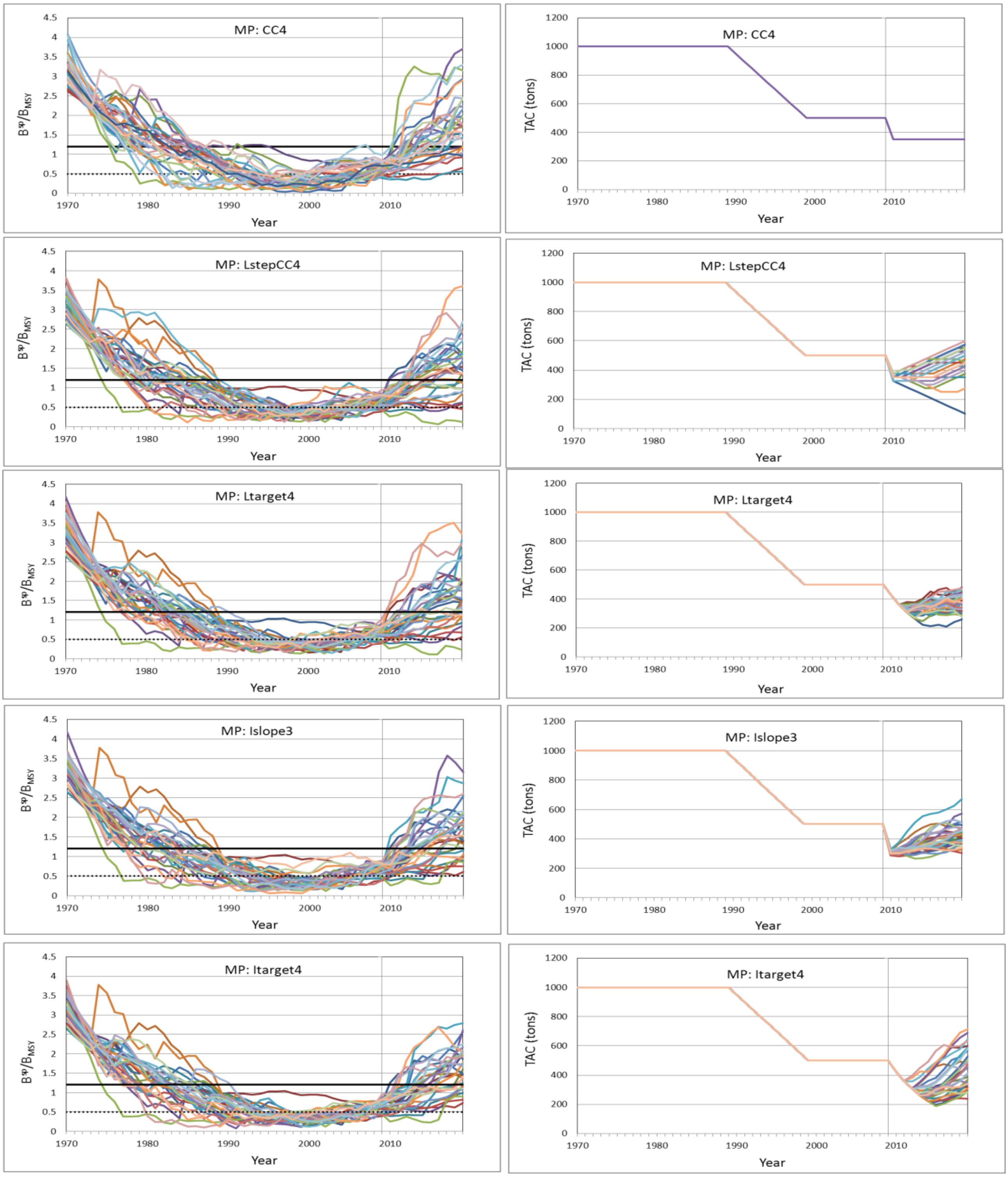

Figure 3.3: Spawning biomass in terms of the MSY level (left), and TAC (right) trajectories for 30 from a total of 8000 simulations are shown for each of the best performing MPs: constant catch (CC4- top row), stepwise constant catch (LstepCC4 – second row), length-based target (Ltarget4 – third row) , slope (Islope3 – fourth row) and target (Itarget4 – bottom row) MPs. The horizontal lines on the left-hand plots correspond to the spawning biomass target (solid) and limit (dotted) reference points. A subset of 30 simulations from a total of 8000 performed are shown so as to clearly reflect the extent of variation and uncertainty incorporated into the population models.

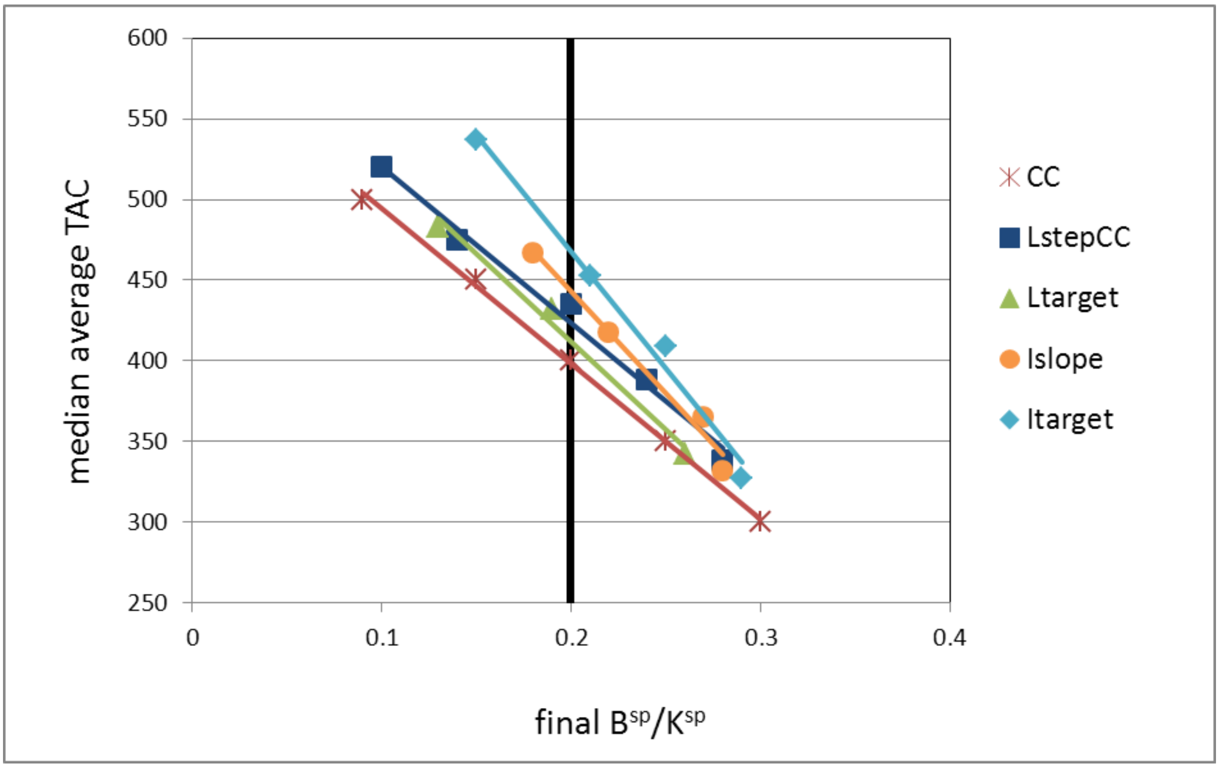

Figure 3.4: Median average future TAC plotted here against the lower 10%-ile of the probability interval for final spawning biomass depletion for the five MPs tested across a selection of tuning parameters for each: five constant catch strategies (stars), five step-wise constant catch strategies (squares), three length-based target strategies (triangles), four CPUE slope strategies (dots) and four CPUE target strategies (diamonds). Linear trend-lines are shown for each MP type to facilitate comparison. The vertical solid black line indicates the limit reference point used in selecting the best performing MPs.

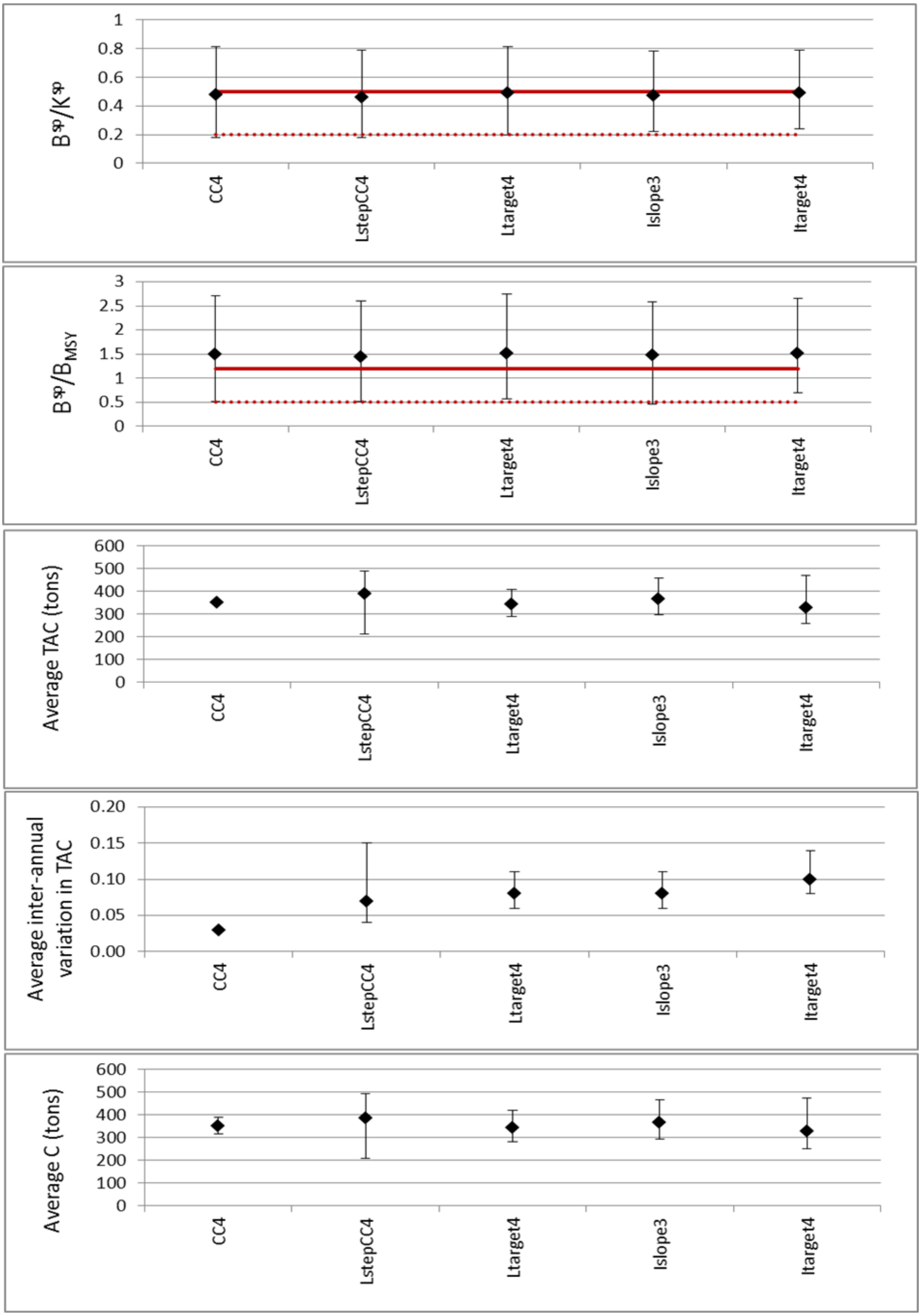

Figure 3.5: As for Figure 3.2, but here allowing for implementation error which is random and unbiased (OM1).

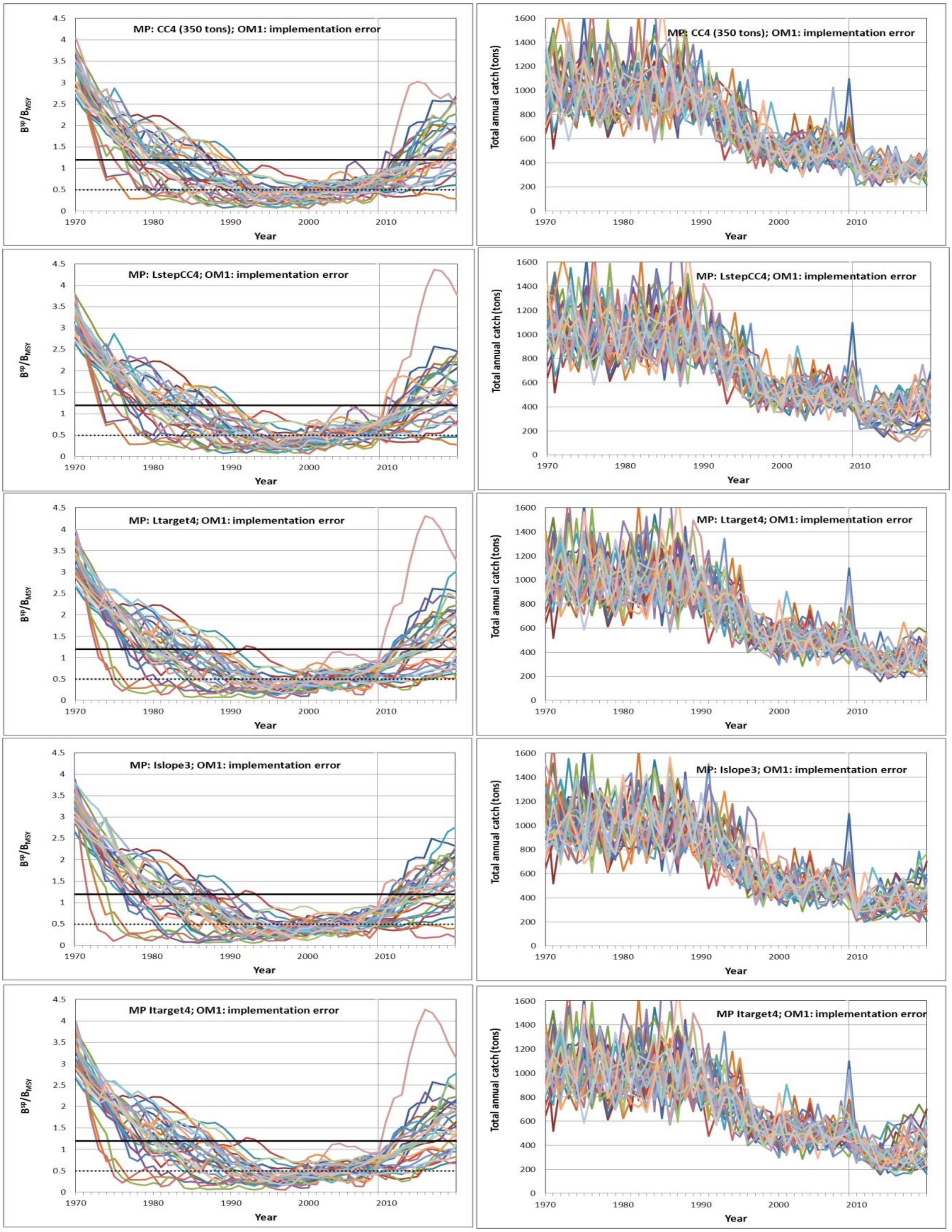

Figure 3.6 As for Figure 3.3, but here making allowance for implementation error which is random and unbiased (OM1).

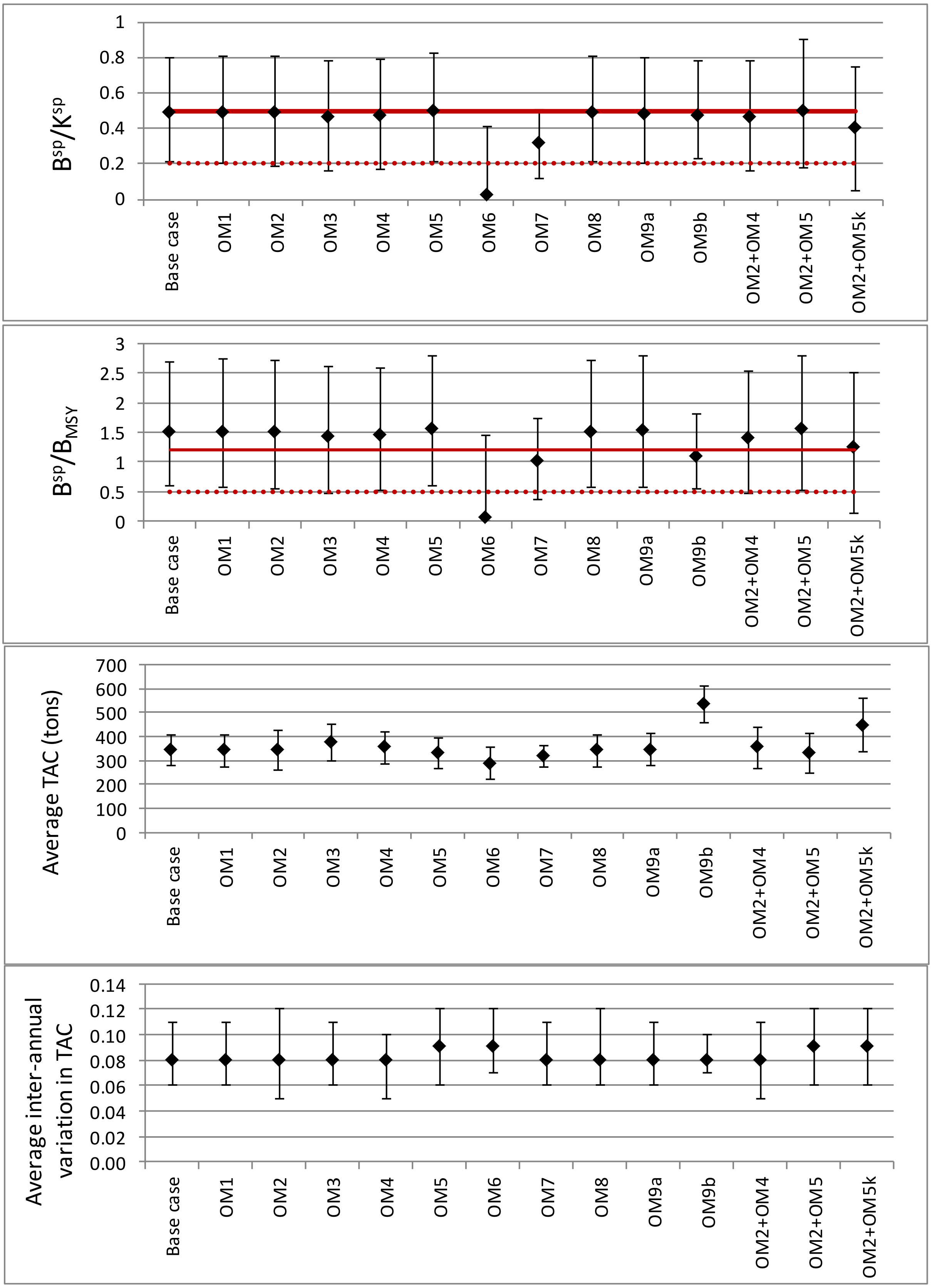

Figure 3.7: Summary statistics of various robustness tests when projecting with the length based MP: Ltarget4.

Chapter 4 Data-rich stocks: more data, better management?

4.1 Introduction

For the majority of low-value data-poor resources, traditional stock assessment methods (ICES 2012a) fail due to insufficient, or absence of, data from which to estimate pertinent resource management quantities. For these cases, the management procedure (MP) paradigm can provide an alternative approach for the provision of robust, if not optimal, scientific management advice, as discussed in the previous chapter. But which of the two management paradigms is more suitable for high-value data-rich marine resources where sufficient data for annual stock assessments are readily available? The answer depends on what the objective is.

With the thrust of current fisheries management primarily focussed on rebuilding of overfished stocks, the three key questions that need to be addressed are: "where are we now?", "where do we want to go?" and "how do we get there?" For data-rich stocks, given adequate reliable data, the first question can be answered by performing a traditional stock assessment to estimate current resource status. The second question, which relates to the choice of target stock size and the time-period over which to achieve it, is really a policy decision[12], partly informed by the stock assessment (Brodziak *et al.* 2008). However, it is the third, sometimes neglected, question of "how to get there" that is the focus of this chapter.

The traditional route for high-value stocks is to perform data-hungry complex statistical assessments annually, in this manner answering all three questions every year. While this "three birds, one stone" approach is currently used to manage most high-value marine resources worldwide, it may not be the most effective, nor the most efficient, way to address the "how to get there" question.

An alternative approach is to distinguish between these three key questions and separate the processes required to answer them. Once the first two questions are answered, the "how to get there" question can be addressed more simply, and quite possibly more effectively, by adopting a management procedure approach where annual TAC (or TAE) recommendations are based on a simple harvest control rule that relies on relatively few data.

[12] In the USA, the Magnuson–Stevens Fishery Conservation and Management Act (MSA) was amended in 1996 to include specifications in terms of maximum sustainable yield (MSY) targets and thresholds for purposes of stock rebuilding. The International Council for the Exploration of the Sea (ICES) base management advice on setting biological limit and target fishing mortality rates.

This chapter aims to compare the fishery and resource consequences of management recommendations based on complex annual resource assessments to those based on simple empirical management procedures, or harvest control rules. If we know "where are we" and "where we want to go", how much data do we need to get there?

4.2 Complex assessment or simple harvest control rule?

Scientific management advice for more valuable fish resources has generally been based on regular (often yearly) assessments. These stock assessments are usually based on age-structured population models such as Virtual Population Analysis (VPA), Statistical Catch-At-Age (SCAA) or Integrated Analyses Models (IA) which rely heavily on annual updates of fishery catch-at-age or catch-at-length data. These models are often complex, requiring a substantial amount of scientific expertise to implement (ICES 2012a). The assessment process is further complicated by decisions regarding which data to include in the analyses, and how these data are to be incorporated in the objective function being minimized to fit the population model. To review these and other stock assessment issues, ICES organised a World Conference on Stock Assessment Methods for Sustainable Fisheries (WCSAM 2013) in Boston in July 2013 with an aim to explore the merits and performance of the assessment methods currently available for providing fisheries management advice, so as to highlight typical problem areas and to initiate the development of the next generation of state-of-the-science assessment models.

While complex age-structured assessments are necessary in order to obtain the estimates of current stock status (in answer to the "where are we now" question), they may not provide the best basis for optimal long-term fisheries management advice. Indeed, detailed annual stock assessments may not be necessary to achieve management goals and may constitute an inappropriate use of limited resources. Are there simpler, more efficient ways of providing reliable management advice? More specifically: does use of more data provide better performance? These questions are all the more relevant at this time, with diminishing resources raising questions over whether the annual ageing of catches required for assessment methods such as VPA can be sustained.

The management procedure (MP) approach has established itself as a powerful fisheries management tool to assist meeting multiple management objectives in a manner that checks robustness to uncertainty for compatibility with the Precautionary Approach (e.g. De Oliveira *et al.* 2009). For this reason, *inter alia*, this approach has been, and still is, favoured over that of annual stock assessments as the basis for the provision of management advice for the most valuable data-rich fish stocks in

South Africa (Geromont *et al.* 1999). For these data-rich stocks, complex statistical assessments are typically performed only at multiyear intervals to answer the "where are we now" question, while simple empirical MPs (harvest control rules based on relatively few data) are employed to move high-value stocks towards pre-selected target levels in answer to the "how do we get there" question posed in the previous section. Both approaches are therefore important in their own right, but they answer different questions and fulfil different roles: the goal of the MP approach is to simplify and automate annual fisheries management advice (for example TAC recommendations) in order to achieve management goals, such as a target stock size, over a time-period judged optimal by the stakeholders.

Unfortunately, the MP approach is frequently misunderstood and criticised for the simplicity of its harvest control rules (and the relatively few data required by these rules) by scientists who advocate that all available data should be used in conjunction with the "best" current assessment model in order to best inform on-going management of a resource. This aim of this chapter is to show that simple harvest control rules might perform as well as, or perhaps better than, complex assessments in achieving long-term management goals, even when confronted with typical assessment problems such as retrospective patterns.

4.3 Retrospective comparison

The performances of the two management paradigms are compared in a self-consistent manner by conducting a retrospective study of four data-rich flatfish fisheries in the North Atlantic, specifically North Sea sole and plaice and New England witch flounder and plaice. The two North Sea stocks were selected for this retrospective comparative study because of the data-intensive nature of the age-structured models currently applied to provide annual TAC advice (ICES 2010). The two New England stocks have been included because of the persistent retrospective patterns[13] present in the VPA assessments on which catch advice has been based (NEFSC 2012); the advice provided for these stocks has had to adjust for these patterns to avoid TAC recommendations being too high.

Recent assessments[14] of these stocks are used as the basis to compare the two management approaches. The MPs are selected from simulation results based on resource information available up to 1989/1990 (depending on the stock investigated). Their performances are then compared to what actually transpired over the subsequent 20-year period under advice arising from regular (in some

[13] In these instances, systematic overestimation of recent spawning biomass and under-estimation of recent fishing mortality.
[14] 2010 ICES assessments for North Sea sole and plaice, and the 2012 assessments for Gulf of Maine witch flounder and plaice (see Section 4.6 for details).

cases annual) "best" assessments[15]. In all cases considered, the empirical MPs simulation tested here rely on the annual survey abundance estimates only, compared to annual assessments of the resources which were typically based on a full set of age data, as well as on one or more indices of abundance.

The comparison consists of four steps:

1) Deterministic projections of "hindsight" MPs

To start, deterministic, or hindsight, projections are performed where perfect knowledge of parameter values and residuals over the projection period from 1990/91 to 2009/10 is assumed. Three simple empirical MPs are each tuned to achieve over the last 20 years the same final (2009/10) spawning biomass as estimated by the recent assessment in question.

These MPs with their associated tunings are referred to as "hindsight" MPs, as they have the benefit of hindsight in "knowing" what will happen in the next 20 years in terms of uncertainties (i.e., "knowing" the values of the residuals related to recruitments and survey sampling errors, as well as to future selectivity- and weight-at-age vectors).

2) Stochastic projections of "hindsight" MPs.

If one had been choosing an MP 20 years ago, one would not have had the benefit of the "hindsight" above at that time, and projections would have been based on information available up to 1989/90 only. For these stochastic projections, 1000 simulations are performed in order to incorporate the key sources of future uncertainty: process error and observation error.

When the "hindsight" MPs of step 1) are applied under these stochastic "forecast" conditions, their performance deteriorates in the absence of exact knowledge about the future. In particular, this often yields final biomasses after 20 years which are considerably below those which actually eventuated. The purpose of this step is to check whether the performance of these "hindsight" MPs would have been considered sufficiently acceptable to have led to their implementation some 20 years ago.

[15] This is an admitted simplification in the interests of drawing the overall comparison. In reality TACs were hardly ever exactly equal to the output from the assessments, but they were nevertheless closely informed by them (see also Section 4.7.1. which highlights changes in management policy for North Sea sole).

3) Use of stochastic projections to tune "forecast" MPs

This step involves selecting alternative tunings of the empirical MPs considered in step 1) that might have led to their being considered acceptable some 20 years ago. The stochastic projections are used to select control parameters for these MPs that achieve a spawning biomass distribution 20 years later which at the lower 2.5% level is at least as large as the biomass estimated by the most recent assessment under the actual catches that subsequently transpired. These MPs are thus deliberately more conservative in making allowance for uncertainty in the spirit of the Precautionary Principle, and are termed "forecast" MPs.

4) Deterministic projections of "forecast" MPs

In this final step, deterministic projections are again performed, but this time with the more conservative "forecast" MPs selected at step 3). This provides a self-consistent basis to determine how well simple MPs would have managed the stocks under consideration compared to complex assessments. In particular, the resultant average catches[16] and fishing mortalities, their inter-annual variability, and the final spawning biomass at the end of the projection period are compared with what actually occurred (or strictly, is estimated to have occurred by the most recent assessment in question) under management based on the use of advice arising primarily from regularly, sometimes annually, updated assessments.

The fundamental question to be addressed is: could simple empirical MPs, based solely on a survey index of abundance, have been used to generate appropriate annual TACs for the data-rich resources under consideration?

4.4 Input to projections

Recent assessment results for North Sea sole and plaice (ICES 2010), and New England witch flounder and plaice (NEFSC 2012) are used as the basis for this retrospective study.

For purposes of this exercise, the management period for each stock is split into an "historic" and a "future" period. For the "historic" pre-1990/91 period, population numbers, fishing mortalities-at-age, natural mortality rate and number of recruits are taken directly from the corresponding Virtual Population Analysis (VPA) assessments. These are assumed to be known exactly, and are used to

[16] For the sake of simplicity, annual TACs generated by the MPs are assumed to be caught exactly with no allowance made for implementation error.

parameterize the operating model (OM) on which the harvesting strategies are tested for each stock. Deterministic and stochastic projections are then performed over a 20-year post-1990/91 projection period under various harvesting strategies. In order to ensure that deterministic results are fully compatible with VPA assessment output, the OMs are calibrated so that the same "future" population numbers and associated biomass trajectories are obtained when projecting under the catches that actually occurred (see Appendix C for technical details).

Input data (observed annual catches, estimated number of recruits and associated spawning biomasses as estimated by the VPA assessments) and pertinent parameter values are given in Appendix B for each of the stocks investigated. Tables and plots of input data and model parameters for each stock are also given in Appendix B.

4.5 Operating models

The operating models (OMs) that form the basis of the retrospective comparisons are age-structured production models (ASPMs). Fishing is assumed to be continuous throughout the year, so that the population dynamics are as described by equations (2.1) to (2.14) in Chapter 2.

The projection period spans the last 20 years of recent assessments for each of the stocks considered, i.e. from 1990 to 2009, or 1991 to 2010, depending on the stock under investigation. Therefore, projections commence in 1990/91, and are moved forward year by year by first obtaining the TAC according to a particular MP based on the latest survey abundance index, from which the corresponding fishing mortality rate, F_y, can be computed for that year given the selectivity- and natural mortality-at-age vectors selected. The population numbers and spawning biomass for the start of the next year can then be computed. The number of recruits for the following year is generated using a stock–recruit relationship. In addition, the next year's survey abundance index, which is required input to the MP, is generated. By repeating this cycle, population numbers-at-age are projected forward from 1990 to 2009, or 1991 to 2010, depending on the stock under consideration.

Perfect knowledge of the past (pre-1990) is assumed as provided by the VPA assessment that is used to parameterise the OM. While this might appear to be a gross over-simplification of an MP approach, where alternative catch control rules are typically simulation tested over a suite of operating models, the use here of a single OM achieves the primary intent which is to compare the outputs from different simple control rules with the catches which actually occurred in a clear-cut and self-consistent manner.

For the deterministic projections, perfect knowledge of the "future" (post-1989/1990) is assumed: exactly the same model parameters and residuals as implied by the VPA assessments are used by the OM so that exactly the same final biomass is achieved at the end of the projection period when projecting with actual catches, as indicated in the previous section.

For the stochastic projections, process and observation error are incorporated by generating stock–recruitment and survey residuals and sampling "future" (post-1989/1990) model parameters/variables from "past" (pre-1989/1990) values.

4.5.1 Stock-recruitment relationship

A stock–recruitment function is needed for the projections. A simple two-line "hockey-stick" stock–recruitment function (equation (2.11) in Chapter 2) has been used for these retrospective studies:

$$\begin{aligned} B^{sp}_{y-a\min} \geq B^0: &\quad R_y = \alpha e^{\zeta_y} \\ B^{sp}_{y-a\min} < B^0: &\quad R_y = (\alpha B^{sp}_{y-a\min} / B^0) e^{\zeta_y} \end{aligned} \tag{4.1}$$

where

α and B^0 are the stock–recruitment parameters estimated by fitting a two-line function to the number of recruits as per the VPA assessment for each stock (equation C.13 in Appendix C),

ς_y are the corresponding recruitment residuals which are input for the deterministic projections, or

$\varsigma_y \sim N(0,(\sigma^R)^2)$ for the stochastic projections with standard deviation of $\sigma^R = 0.8$ for North Sea sole, and $\sigma^R = 0.5$ for the other stocks (these values were used because they were close to the estimated standard deviations and for the sake of simplicity).

The stock–recruitment parameters estimated from the VPA assessment for each stock are given in Tables B1.2, B2.2, B3.2 and B4.2 in Appendix B.

4.5.2 Projected fishing selectivity-at-age

The same fishing selectivity-at-age vectors are assumed as implied by the assessment for deterministic "hindsight" projections. For the stochastic "forecast" projections, the selectivity-at-age vectors for

$$\hat{I}^i_y = q^i$$

future years (1990 onwards) are sampled randomly from past (pre-1989/1990) VPA assessment estimates.

Plots of the annual fishing selectivity-at-age vectors are given in Appendix B for each stock.

4.5.3 Projected weights

The same population and catch weight-at-age vectors used in the recent assessments for each of the stocks considered are used for the deterministic projections. For the stochastic "forecast" projections, the population and catch weight-at-age vectors for future years (1990 onwards) are set equal to the corresponding average weight for each age over the last three years prior to the projection period, i.e., the future stock weight-at-age vectors are given by:

$$w^S_{y,a} = 1/3 \sum_{y'=1987}^{1989} w^S_{y',a} \quad \text{for } y \geq 1990,$$

and the future catch weight-at-age vectors are given by:

$$w^C_{y,a} = 1/3 \sum_{y'=1987}^{1989} w^C_{y',a} \quad \text{for } y \geq 1990.$$

Weight-at-age vectors used for the projections are reported in Appendix B for each stock.

4.5.4 Generating pseudo data

For the purposes of this retrospective study, age-aggregated indices of abundance need to be generated for use in the empirical management procedures. For the simulations, for which catches will differ from simulation to simulation, underlying biomasses will differ too, and so too will the survey abundance indices, given by:

$$\hat{I}^i_y = q^i \sum_{a=a\min}^{m} w^s_{y,a} S^i_a N_{y,a} \tag{4.2}$$

where $N_{y,a}$ are the projected number of fish of age *a* at the start of year *y*,

S_a^i is the selectivity vector associated with the observed abundance index *i* (defined in Section C.2 of Appendix C),

q^i is the catchability coefficient associated with observed index i (defined in Section C.3 of Appendix C), and

$w_{y,a}^S$ denote the population weights-at-age.

Future survey data are generated assuming a log-normal error distribution such that:

$$I_y^i = \hat{I}_y^i e^{\varepsilon_y^i} \tag{4.3}$$

For the deterministic projections, the same residuals ε_y^i are used as inferred from the VPA assessment (equation C.17 in Appendix C). For the stochastic projections, the residuals are drawn from a normal distribution:

$$\varepsilon_y^i \sim N(0,(\sigma^i)^2) \tag{4.4}$$

where σ^i is the coefficient of variation (CV) associated with survey abundance index *i*. For simplicity, a value of $\sigma^i = 0.2$, consistent with what might be expected in practice, is assumed for all survey indices and stocks considered in this chapter.

4.6 Candidate Management Procedures

Three types of MPs with different harvest control rules are simulated to compare performance with assessment-based management: a constant catch rule (intended to provide a useful comparative benchmark only) and two very simple empirical MPs, based on changes in survey indices of abundance. These simple MPs are particularly useful in data-poor situations where data limitations render model-based MPs unsuitable, as shown in the previous chapter, or where there is considerable variability in the data, in which case a more complex model-based MP may well follow noise rather than trend. Furthermore, the very simple empirical rules are easy to understand, test and apply, and have shown performance and robustness to uncertainty that are comparable with their model-based counterparts (for example, model-based MPs used in the 1990s (Geromont *et al.* 1999) have been replaced in the 2000s by empirical rules (Rademeyer 2012) to manage the South African hake resource). More specifically, these simple empirical MPs have been chosen for this retrospective study to better compare the data-hungry assessment approach with a data-sparse MP approach.

Note that in implementation for relatively data-rich stocks, such as the four cases considered here, a simple MP approach like this would remain underpinned by a full resource assessment: the former provides on-going yearly management advice to move the resource towards some target stock size ("how to get there?"), while the latter is reconsidered at multiyear intervals to check the appropriateness of the MP and if necessary to adjust some of its control parameters by determining whether resource behaviour has remained within the range assumed when last testing the MP (to address "where are we now?").

- Constant catch harvesting strategy

This is an extreme and the simplest of all empirical MPs; it requires no data to set the annual TAC. The future TAC is given by

$$TAC_{y+1} = TAC^{target} \tag{4.5}$$

where TAC^{target} is chosen so that the projected population spawning biomass in the final year reaches some target level B^{target}. For the deterministic projections, the target spawning biomass is chosen to be equal to the final spawning biomass estimated in the recent assessment, $B^{target} = B^{VPA}_{2009/10}$, to facilitate comparison between the MP and the actual assessment-based management approaches.

For the stochastic projections, a search routine is used to find the constant catch that achieves the target for each simulation. The desired constant level for future catches is selected from the resulting distribution as the one that will provide adequately risk-averse performance under the uncertainty incorporated in the projections (the 2.5%-ile value is chosen for these projections).

Note: A constant catch harvesting strategy is not recommended in practice as there is no self-correcting feedback-control mechanism built into this type of MP. It does, however, give a ball-park indication of the average yield that can be expected during the projection period given a chosen target biomass, which is useful for later comparisons amongst the different candidate MPs.

- Survey slope-based harvesting strategy

  Slope-based MPs utilise the trend in a limited subset of data (typically the most recent four or five years of some abundance index) for input. The annual TAC is simply increased or decreased from where it was the previous year depending on whether the estimated trend is positive or negative. The TAC for the next year is given by equation (2.21) in Section 2.4.4.

- Survey target-based harvesting strategy

  A target-type MP moves the resource abundance towards a pre-specified target level for some abundance index. The future TAC is adjusted up or down each year depending on whether the average of the most recent index values (survey results) is above or below the target level. The TAC for the next year is given by equations (2.25) and (2.26) in Section 2.4.5.

A summary of the three MPs are given in Table 4.1. While the constant catch MP has only a single control parameter, the slope and target MPs have a number of tuneable parameters. Control parameters corresponding to the best-performing "hindsight" and "forecast" MPs for each stock are given in Tables 4.2 to 4.17 of the results section for each of the stocks considered. The choices for MP tuning parameters were based on simulation trials. For the deterministic projections, the tuning was automated by performing projections over a range of MP parameter combinations. The "best" combination of tuning parameters was chosen by inspecting the resulting biomass and catch trajectories for those combinations that "hit" the target biomass and choosing the one that gave the desired yield/risk trade-offs. For the stochastic projections, the tuning parameters were adjusted manually from those selected for the deterministic projections to obtain the desired performance.

In line with the objective of industrial stability, to avoid excessively large inter-annual increases/decreases in TAC, particularly in the first year of MP application, a limitation on the extent of inter-annual change in TAC of 20% has been imposed for most cases, although this was rarely activated in the simulations performed here.

4.7 Results

To aid comparisons amongst the MP and assessment-based performances, the MPs are first tuned to reach the same final spawning biomass as indicated by the assessment under the actual catches for the deterministic projections of step 1. For the stochastic projections of step 3, the MPs are tuned so that the 2.5%-ile of the simulated final spawning biomass distribution is the same as the final biomass estimated by that assessment.

The statistics reported for comparison of performance of the MPs over the projection period are:

- average annual total catch over the 20-year projection period, $\overline{TAC}$,
- average annual variation of the catch, given by the absolute value of annual change in catch as a proportion of previous catch which is averaged over the projection period, AAV,
- average annual fishing mortality rate over the projection period, $\overline{F}$,
- average annual variation (given by the absolute value of the proportional change between successive years) in fishing mortality, $\overline{\Delta F}$,
- final spawning biomass at the end of the projection period as a fraction of the target biomass, $B_{final}^{sp} / B^{target}$, where B^{target} corresponds to the final (2009 or 2010) spawning biomass as estimated by the original assessment, and
- minimum spawning biomass over the projection period, expressed as a fraction of the target biomass, $\min B_y^{sp} / B^{target}$.

In most cases the reasons for choosing the statistics are self-evident. The last is included because, given the uncertainty always associated with a stock–recruitment relationship, one wants to avoid decreases in abundance to levels where recruitment success could be compromised. Thus, biological risk here is defined in terms of a lower percentile of the spawning biomass distributions where recruitment success may be impaired for biomasses below that level.

Deterministic and stochastic projections are performed starting in year 1990 until 2009 for North Sea sole and plaice and in year 1991 until 2010 for New England witch flounder and plaice. For the deterministic projections, the same stock–recruitment and survey residuals are used as derived from the VPA assessment associated with each stock (see Appendix C for details).

Future (post-1989/1990) uncertainty is incorporated in the projections (steps 2 and 3 in Section 2.2 of Chapter 2) by including stochastic components when generating future abundance index data, as well as incorporating recruitment and fishing selectivity fluctuations in the simulations. In particular:

- process error: stock–recruitment residuals log-normally distributed about the stock–recruitment function with a standard deviation of $\sigma^R = 0.8$ for North Sea sole and $\sigma^R = 0.5$ for the other stocks (see equation (4.1));

- observation error: log-normal error distribution about the generated survey abundance values with a standard deviation of $\sigma = 0.2$ (see equation (4.3));
- process error: random resampling of "future" fishing selectivity vectors from past vectors; and "future" population and catch weights-at-age averaged over historic weight-at-age vectors;

For the stochastic projections, 1000 simulations are performed to ensure adequate representation.

Four sets of results, corresponding to the four steps described in Section 4.3, are shown for each stock:

1. Deterministic projections with MPs that show the best performance and are tuned to hit the target spawning biomass exactly, termed "hindsight" MPs.
2. Stochastic projections of "hindsight" MPs: Projections are performed with the same MPs (with identical control parameters) as in the previous step, but making allowance for observation and process error.
3. Stochastic projections (incorporating uncertainty) are used to tune MPs: those MPs that show the best performance while tuned to achieve, at the lower 2.5%-ile, a final spawning biomass which is equal to or greater than that indicated by the assessment for the actual catches, are selected and are termed "forecast" MPs.
4. Deterministic projections, but here under the "forecast" MPs of the previous step.

Results corresponding to projections performed with a two-line ("hockey-stick") stock–recruitment relationship are given in the following Tables and Figures for the stocks considered:

i. North Sea sole: Section 4.6.1 Tables 4.2 to 4.5 and Figures 4.1 to 4.4
ii. North Sea plaice: Section 4.6.2 Tables 4.6 to 4.9 and Figures 4.5 to 4.8
iii. New England witch flounder: Section 4.6.3 Tables 4.10 to 4.13 and Figures 4.9 to 4.12
iv. New England plaice: Section 4.6.4 Tables 4.14 to 4.17 and Figures 4.13 to 4.16.

Throughout, the tables contrast values of the performance statistics under the catches that actually occurred to those for the three types of MP. Deterministic and stochastic spawning biomass and catch trajectories are also plotted to better illustrate the effects on the population dynamics under different MP harvesting strategies. Graphical summaries of performance statistics for "hindsight" and "forecast" MPs are shown to facilitate comparisons among the different harvesting strategies and the actual catches.

Type MP	Description	Control parameters
MP constant catch (Section 2.3.1)	Future catch set at a percentage of recent average catch.	$TAC_{y+1} = TAC^{target}$ where TAC^{target} is the level of catch required to reach the target spawning biomass.
MP slope: (Section 2.3.4)	TAC adjusted up or down if the trend in recent indices is positive or negative.	$TAC_{y+1} = TAC_y(1+\lambda s_y)$ where λ is smoothing parameter, s_y is the average index slope over the most recent p years.
MP target: (Section 2.3.5)	TAC adjusted up or down if recent indices are above or below the target index level.	$TAC_{y+1} = TAC^{target}\left[w+(1-w)\frac{I^{recent}-I^0}{I^{target}-I^0}\right]$ if $I_y^{recent} \geq I^0$ or $TAC_{y+1} = wTAC^{target}\left[\frac{I_y^{recent}}{I^0}\right]^2$ if $I_y^{recent} < I^0$ where I^{target} is the target reference point for the index, $I^0 = 0.2I^{ave}$ is the limit reference point for the index, I^{ave} is the average index over the past 5 years, I_y^{recent} is the average index over the most recent 4 years, TAC^{target} is the equilibrium catch, and w is a smoothing parameter.

Table 4.1: The three candidate MPs considered for retrospective study for the four data-rich stocks. Full specifications for these MPs are given in Section 2.4 of Chapter 2.

4.7.1 North Sea sole (subarea IV)

4.7.1.1 Introduction

North Sea sole is caught together with North Sea plaice in the demersal flatfish fishery in ICES subarea IV. Annual TAC advice is based on harvest rules that depend on the state of the stock relative to a spawning biomass reference point and a target fishing mortality. However, in order to satisfy socio-economic objectives and maintain high employment levels, annual TAC advice has been aligned with limit (precautionary), rather than targets reference points, resulting in annual fishing mortality exceeding F_{MSY} over the projection period considered here (J.J. Poos, pers. comm.).

With the aim to rebuild overfished stocks by gradually reducing fishing mortality, the European Union (EU) adopted a multi-annual management plan in 2007, based on maximum sustainable yield (MSY) to ensure economic, environmental and social sustainability (Miller and Poos 2010), leading to a more conservative approach than before. The current ICES precautionary reference points for North Sea sole in terms of spawning biomass and fishing mortality rate are 35000 tons and 0.4 yr^{-1} respectively, with F_{MSY} estimated to be 0.22 yr^{-1} (ICES 2010).

Projections under three simple empirical MPs are compared to actual catches from 1990 to 2009. For purposes of this exercise, the VPA/XSA (Extended Survivor Analysis) assessment results reported in the 2010 ICES WGNSSK Report (ICES 2010) are used to parameterize the operating model from which projections are performed. The survey slope- and target-based MPs are based on the BTS Isis survey index of abundance.

Input data and parameter values used for the projections for North Sea sole are given in Tables B1.1 to B1.6 of Appendix B. Plots of input data and pertinent parameter values are given in Figures B1.1 to B1.12 of Appendix B.

4.7.1.2 Projection results

Step 1:

Pertinent management statistics for deterministic "hindsight" projections are given in Table 4.2 for three candidate MPs, each tuned so that the spawning biomass in 2009 hits the same final spawning biomass for that year as estimated by the 2010 XSA assessment.

All three MPs lead to slightly more average annual catch over the projection period compared to the actual average of 22364 tons. Furthermore, for the slope and target MPs, the same final spawning biomass is achieved with much less inter-annual fluctuation in the TAC: about 7% on average compared to the actual annual variation of approximately 15%[17]. In addition, the minimum spawning biomass over the projection period is kept above that achieved under the actual catches.

Figure 4.1 shows catch (top), spawning biomass (middle) and fishing mortality rate projections (bottom) for the three candidate MPs: each plot includes results for the three MPs (constant catch, slope-based and target-based) together with the actual (VPA/XSA) trends.

The assessment-based approach shows very high catches in the first half of the projection period followed by a rather large drop in annual catches later. The slope and target MPs achieve the same biomass in 2009 by keeping the initial increase in catch smaller than actually occurred, which allows for larger catches later. The constant catch MP achieves the same final spawning biomass in 2009 by leaving the TAC unchanged at the pre-management level.

In terms of the deterministic projection results reported in Table 4.2, all three MPs outperform the assessment-based management over the 20-year period considered, with the constant catch strategy performing the best. Despite this good performance, these "hindsight" MPs would not have been viable candidates for implementation in 1990. The reasons are readily evident from Table 4.3 which is described below.

Step 2:

Table 4.3 shows results when incorporating uncertainty (observation and process error): medians and 95% probability intervals for 1000 simulations are given. For these stochastic projections, the "hindsight" MPs of Table 4.2 are unable to achieve the 2009 target biomass at the lower 2.5%-ile,

[17] In the absence of implementation error, the comparison is not entirely fair: frequent EU policy changes typically led to large inter-annual variation in actual TAC advice over the projection period.

which is the minimum requirement adopted here to show adequate precaution. The previous "best" constant catch strategy is now the worst performing in terms of the resource risk statistics, with the median spawning biomass unable to reach the target spawning biomass at the end of the 20-year projection period. While performing slightly better than the constant catch strategy, the slope- and target-based MPs also allow the possibility of unacceptably low levels of spawning biomass and must therefore be rejected.

Step 3:

In Table 4.4, the "hindsight" MPs of the previous table are retuned to yield final spawning biomass distributions whose lower 2.5%-iles are at least as large as occurred under the actual catches. These "forecast" MPs need to be more conservative than the "hindsight" MPs as they must be robust to realistic levels of uncertainty which are high in this case, particularly as regards recruitment variability. This means that in median terms less catch is taken on average than that which actually transpired, though this comes with the advantage of a final spawning biomass improvement by a factor of more than double.

Stochastic catch and spawning biomass projections are shown in Figure 4.2 for each of the three "forecast" MPs. The first 30 simulations of the 1000 conducted are shown to illustrate the extent of variability. In order to ensure this level of safety, the constant catch strategy requires an immediate large drop in catch in 1990, followed by an additional decrease in 1991 to reach the level of catch which would ensure adequate spawning biomass recovery at the 2.5%-ile level. To achieve comparable spawning biomass levels at the end of the 20-year projection period, the slope and target MPs result in greater potential yield, with median future catch (indicated by solid black lines in the plots on the left) under these harvesting strategies greater than the constant catch required to achieve the same level of biological risk. High median catches in the first few years of the projection period under the slope and target harvesting strategies are caused by the relatively high BTS-Isis survey results for the immediate pre-management period (see Figure B1.4 in Appendix B). However, both MPs are able to self-correct, showing subsequent decreases in median catch as necessary to achieve the spawning biomass target in 2009 at the 2.5%-ile level.

Step 4:

Performance of the "forecast" MPs of Table 4.4 are compared to actual catches in Table 4.5: the same recruitment and index of abundance residuals are used as implied by the 2010 assessment.

The slope- and target-type MPs lead to slightly less average annual yield than was taken in reality, with final spawning biomass almost twice that achieved under actual catches. The constant catch strategy needs to be overly conservative (more than 25% less yield on average) as it lacks feedback control. As a consequence of the tuning parameters chosen, yearly fluctuations in TAC are kept low under MP management: 7% for the target MP compared to 15% inter-annual fluctuations in actual catch (14% inter-annual fluctuation in actual TACs set over this time period — see Figure B1.1 in Appendix B for a plot of the actual TACs).

Deterministic catch (top), spawning biomass (middle) and fishing mortality rate projections (bottom) for the three "forecast" MPs are compared in Figure 4.3. Of note is that annual fishing mortality rates for the three "forecast" MPs are much lower than those associated with actual catches, with values in the region of (and sometimes below) the current precautionary reference point of 0.4 yr^{-1}, compared to much higher values when projecting under actual catches.

4.7.1.3 Summary statistics

Figure 4.4 provides summaries of performance statistics for both the stochastic and deterministic "forecast MP" in a graphical form that is helpful when making comparisons. While not a realistic candidate, results for the constant catch MP are included for comparative purposes.

For the stochastic projections, the "forecast" MPs are tuned so that the lower 2.5%-iles reach the target biomass in 2009 with medians well above this level, as is evident in Figure 4.4 (left). Due to future uncertainty, these MPs need to be rather conservative and take about 20% less catch in median terms. This has the advantage of keeping spawning biomass well above the 2009 target over the projection period compared to a drop of 50% below this under the catches which actually occurred. Furthermore, and in the absence of realistic levels of implementation error in the simulation trials, these MPs result in less inter-annual fluctuation in catch compared to what was achieved in practice.

Given hindsight information, the "forecast" MPs are seen to overshoot the 2009 target biomass, with the final spawning biomass about double the target biomass (Figure 4.4 right). This is at the cost of about 10% less overall catch for the target and slope MPs. The constant catch strategy reflects the smallest total catches on average and would not be a candidate in reality because of its lack of feedback features to provide robustness to other uncertainties which have not been considered here.

North Sea sole (Subarea IV)	2010 VPA/XSA assessment	No data	Data: age-aggregated BTS-Isis survey index	
	Actual catches	**Constant catch** $TAC^{target} = 22465$ $\Delta TAC \leq 20\%$	**MP slope** $TAC^{*} = 1.1C_{1989}$ $\lambda = 0.29$ $p = 3$ $\Delta TAC \leq 20\%$	**MP target** $I^{0} = 0.2I^{ave}$ $I^{target} = 1.5I^{ave}$ $TAC^{target} = 25600$ $w = 0.5$ $\Delta TAC \leq 20\%$
$\overline{TAC}$	22364	22465	22703	22504
AAV	0.152	0.001	0.072	0.062
$\overline{F}$	0.908	0.525	0.684	0.749
$\overline{\Delta F}$	0.274	0.291	0.307	0.285
$B^{sp}_{1990} / B^{target}$	2.596	2.596	2.596	2.596
$B^{sp}_{2009} / B^{target}$	1.000	1.001	1.012	1.015
$\min B^{sp}_{y} / B^{target}$	0.519	0.982	0.683	0.571

Table 4.2: Comparison of results for *deterministic "hindsight" projections* for North Sea sole in Subarea IV with a two-line stock–recruit relationship when using only the BTS-Isis aggregated index in the slope and target MPs selected with hindsight (see Section 2.4 in Chapter 2 for details of the MP control parameters). Units are tons where applicable.

North Sea sole (Subarea IV)	2010 VPA/XSA assessment	No data	Data: Age-aggregated BTS-Isis survey index	
	Actual catches	**Constant catch** $TAC^{target} = 22465$ $\Delta TAC \leq 20\%$	**MP slope** $TAC^* = 1.1C_{1989}$ $\lambda = 0.29$ $p = 3$ $\Delta TAC \leq 20\%$	**MP target** $I^0 = 0.2I^{ave}$ $I^{target} = 1.5I^{ave}$ $TAC^{target} = 25600$ $w = 0.5$ $\Delta TAC \leq 20\%$
$\overline{TAC}$	22364	22465 (22465, 22465)	21131 (16123, 24213)	20135 (16780, 24592)
AAV	0.152	0.001 (0.001, 0.001)	0.060 (0.043, 0.099)	0.045 (0.032, 0.074)
$\overline{F}$	0.908	0.778 (0.179, 5.309)	0.442 (0.219, 4.466)	0.331 (0.214, 3.059)
$\overline{\Delta F}$	0.274	0.300 (0.140, 0.547)	0.183 (0.123, 0.472)	0.166 (0.118, 0.422)
$B_{2009}^{sp} / B^{target}$	1.000	0.406 (0.000, 6.088)	1.129 (0.000, 5.365)	1.981 (0.002, 5.599)
$\min B_y^{sp} / B^{target}$	0.519	0.287 (0.000, 2.456)	0.879 (0.000, 2.456)	1.401 (0.000, 2.456)

Table 4.3: Comparison of results for *stochastic projections* with *"hindsight" MPs* for North Sea sole in Subarea IV under a two-line stock–recruit relationship with $\sigma^R = 0.8$. Management quantities shown are medians with associated 95% probability intervals in parenthesis. 1000 simulations were performed. Units are tons where applicable.

North Sea sole (Subarea IV)	2010 VPA/XSA assessment	No data	Data: Age-aggregated BTS-Isis survey index	
	Actual catches	**Constant catch** $TAC^{target}=16192$ $\Delta TAC \leq 20\%$	**MP slope** $TAC^{*}=1.1C_{1989}$ $\lambda=0.5$ $p=3$ $\Delta TAC \leq 20\%$	**MP target** $I^{0}=0.2I^{ave}$ $I^{target}=1.5I^{ave}$ $TAC^{target}=22200$ $w=0.5$ $\Delta TAC \leq 20\%$
$\overline{TAC}$	22364	16265 (16265, 16265)	18840 (15855, 22527)	18126 (15909, 22033)
AAV	0.152	0.014 (0.014, 0.014)	0.086 (0.063, 0.112)	0.051 (0.038, 0.073)
$\overline{F}$	0.908	0.164 (0.102, 0.332)	0.272 (0.189, 0.395)	0.222 (0.162, 0.344)
$\overline{\Delta F}$	0.274	0.171 (0.128, 0.235)	0.153 (0.111, 0.208)	0.157 (0.114, 0.210)
B^{sp}_{2009}/B^{target}	1.000	3.965 (0.946, 8.864)	2.668 (0.937, 6.303)	3.079 (1.027, 6.870)
$\min B^{sp}_{y}/B^{target}$	0.519	2.456 (0.793, 2.456)	1.857 (0.750, 2.456)	2.289 (0.871, 2.456)

Table 4.4: Comparison of results for *stochastic projections* with *"forecast" MPs* for North Sea sole in Subarea IV under a two-line stock–recruit relationship with $\sigma^{R}=0.8$. Management quantities shown are medians with associated 95% probability intervals in parenthesis. 1000 simulations were performed. Units are tons where applicable.

North Sea sole (Subarea IV)	2010 VPA/XSA assessment	No data	Data: Age-aggregated BTS-Isis survey index	
	Actual catches	**Constant catch** $TAC^{target} = 16192$ $\Delta TAC \leq 20\%$	**MP slope** $TAC^{*} = 1.1C_{1989}$ $\lambda = 0.5$ $p = 3$ $\Delta TAC \leq 20\%$	**MP target:** $I^{0} = 0.2I^{ave}$ $I^{target} = 1.5I^{ave}$ $TAC^{target} = 22200$ $w = 0.5$ $\Delta TAC \leq 20\%$
$\overline{TAC}$	22364	16265	20722	20553
AAV	0.152	0.014	0.108	0.069
$\overline{F}$	0.908	0.197	0.491	0.420
$\overline{\Delta F}$	0.274	0.224	0.301	0.264
$B_{1990}^{sp} / B^{target}$	2.596	2.596	2.596	2.596
$B_{2009}^{sp} / B^{target}$	1.000	3.321	1.960	1.944
$\min B_{y}^{sp} / B^{target}$	0.519	2.596	1.371	1.397

Table 4.5: Comparison of results for *deterministic projections* for North Sea sole in Subarea IV under a two-line stock–recruit relationship for the best performing *”forecast” MPs* when using only the BTS-Isis aggregated index in the slope and target MPs. Units are tons where applicable.

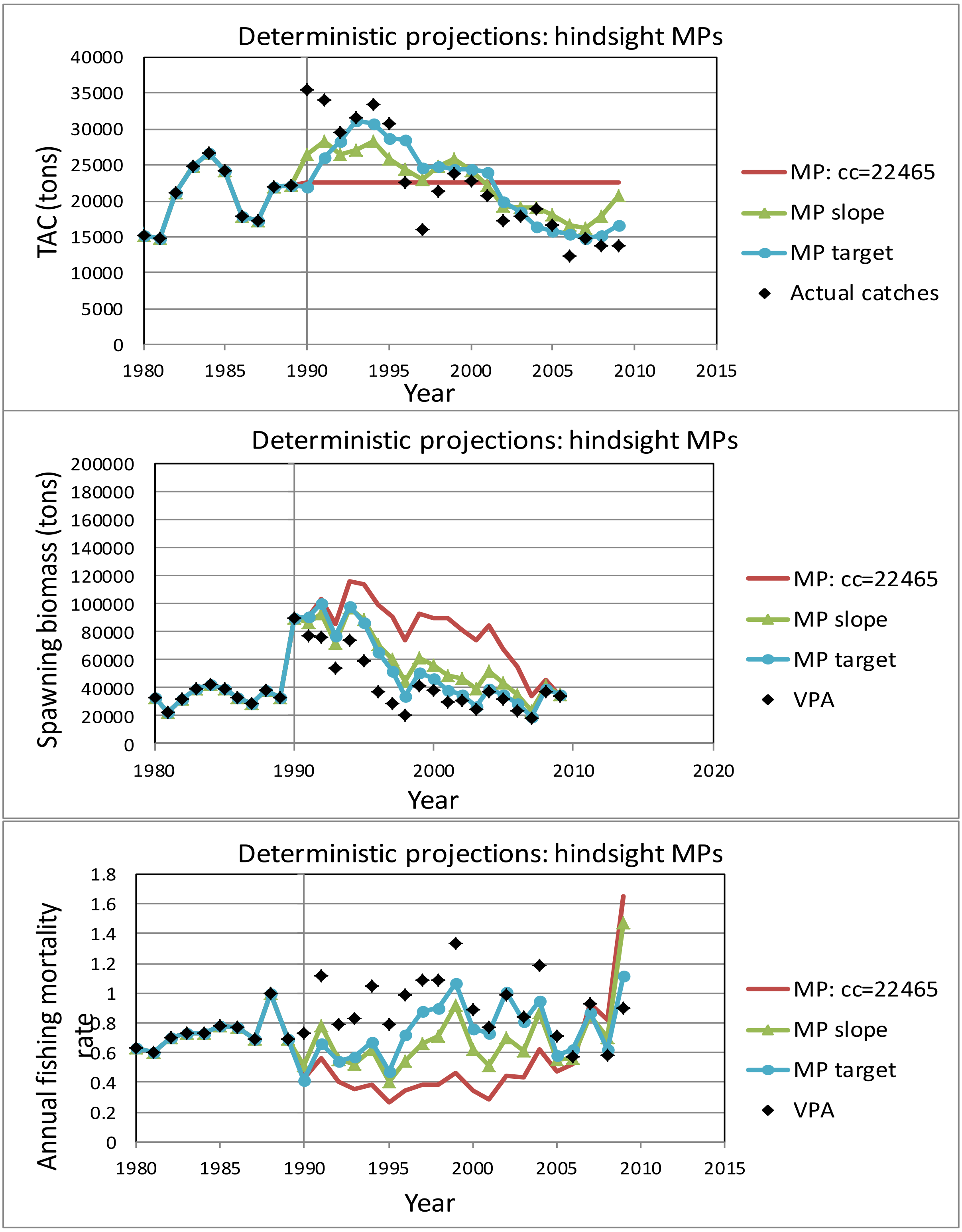

Figure 4.1: ***Deterministic projections*** **of a constant catch (red[18] line), slope (green triangles) and target (blue dots*)* *"hindsight" MPs*, tuned to hit the target biomass in 2009 exactly. TAC (top), spawning biomass (middle) and fishing mortality rate (bottom) trajectories under the three different "hindsight" MPs are compared to spawning biomass and fishing mortality rates under actual catches (black diamonds) for North Sea sole.**

[18] Colours, though perhaps not visible in the printed format, may be seen in the electronic version.

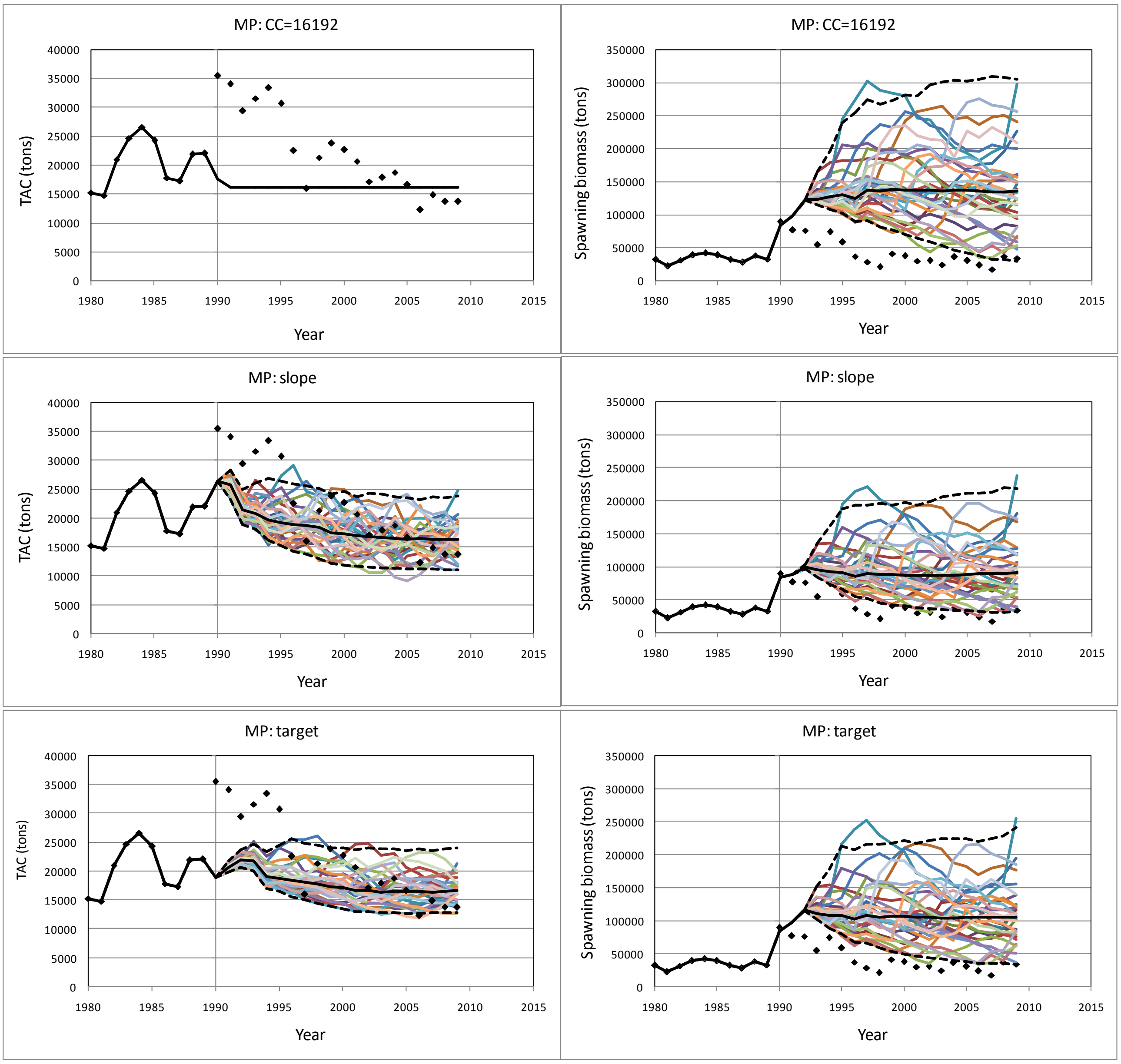

Figure 4.2: *Stochastic* TAC (left) and spawning biomass (right) trajectories for the three candidate *"forecast" MPs* tuned so that the lower 2.5%-ile reaches the target biomass in 2009 (30 of 1000 simulations are shown here). Top: constant catch MP, middle: slope-type MP and bottom: target-type MP. Spawning biomass trajectories corresponding to actual catches of North Sea sole are indicated by the black diamonds. Medians and 95% probability intervals are indicated by the solid and dashed lines.

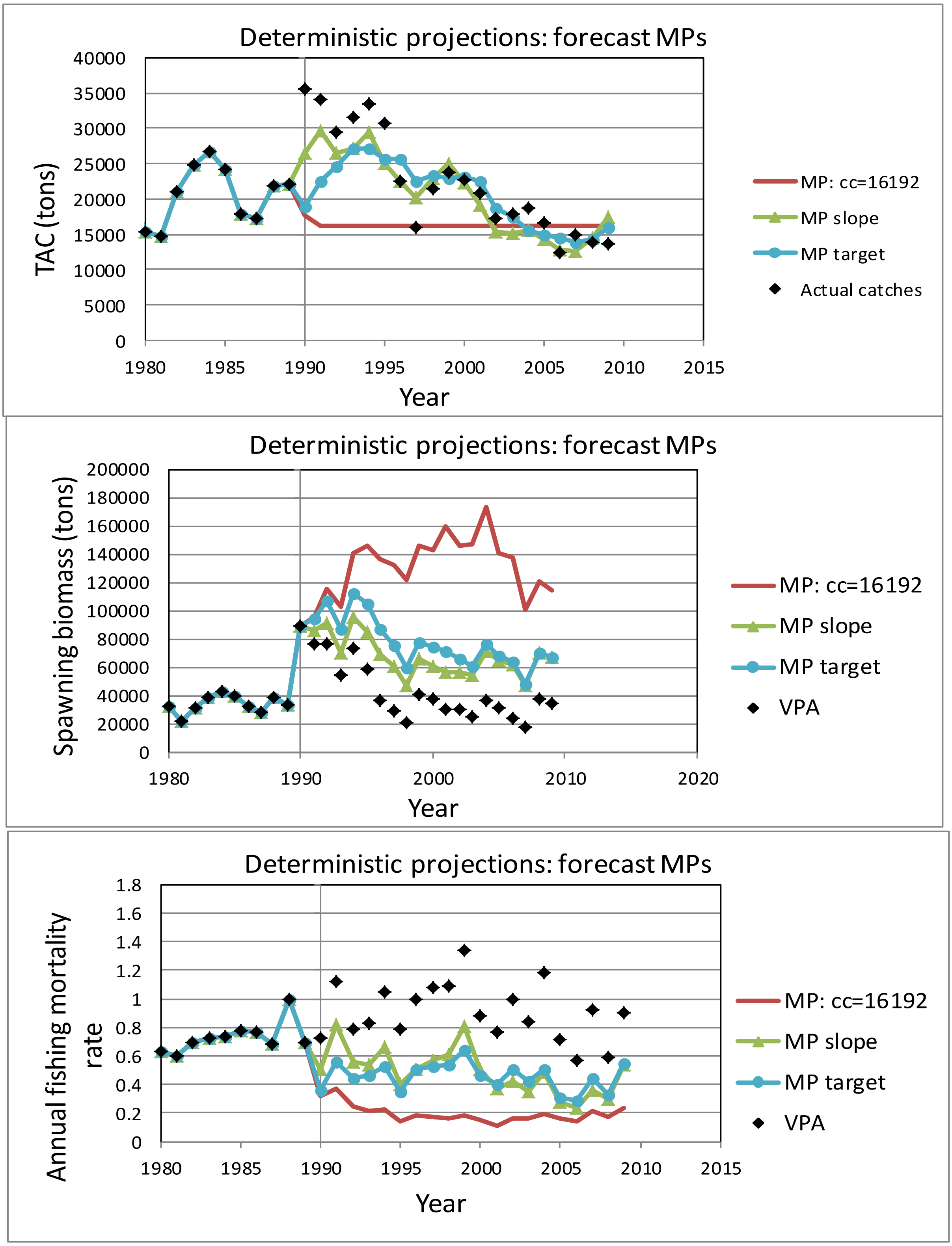

Figure 4.3: ***Deterministic projections*** **of a constant catch (red line), slope (green triangles) and target (blue dots)** ***"forecast" MPs*****. TAC (top), spawning biomass (middle) and fishing mortality rate (bottom) trajectories under the three different "hindsight" MPs are compared to spawning biomass and fishing mortality rates under actual catches (black diamonds) for North Sea sole.**

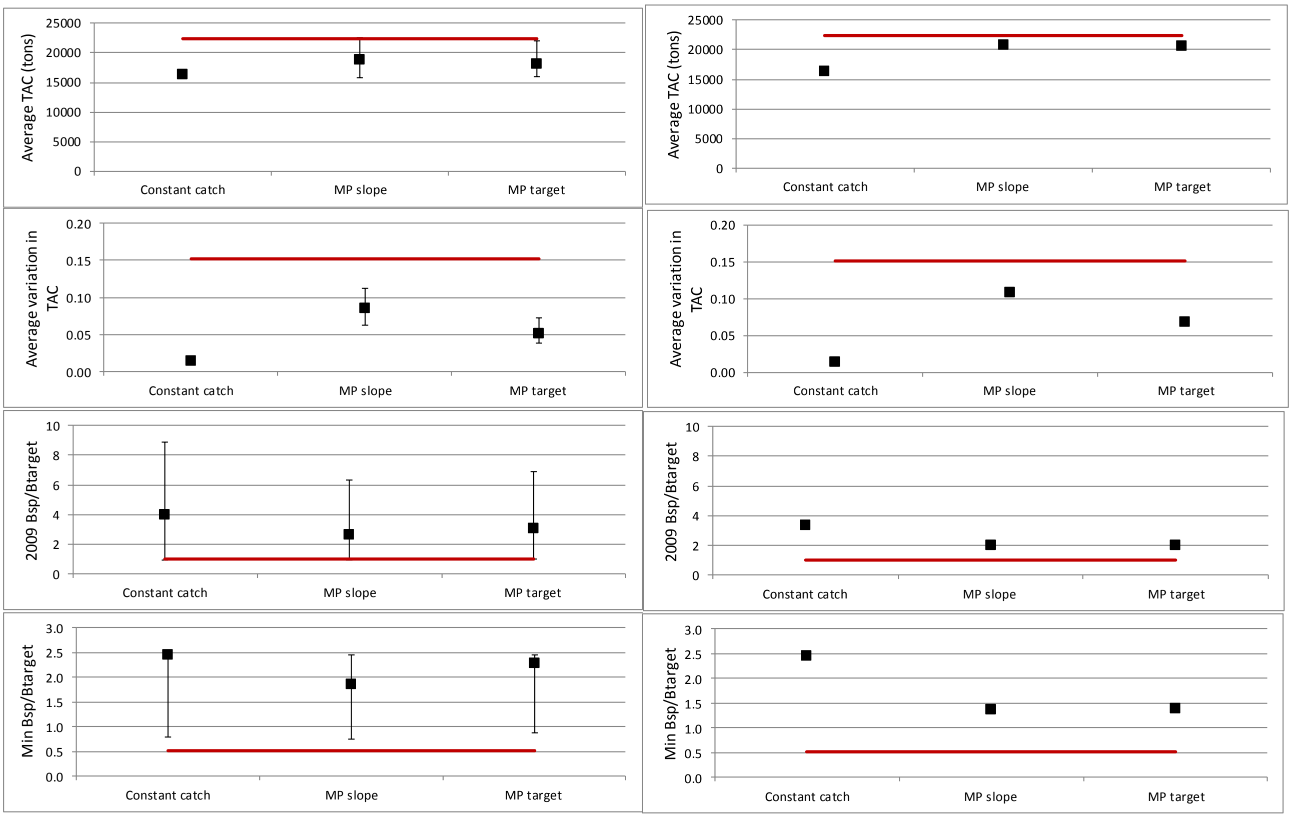

Figure 4.4: Summary statistics of *stochastic* (left) and *deterministic* (right) projections of the three candidate *forecast MPs* for North Sea sole. The medians and 95% probability intervals for 1000 simulations are shown on the plots on the left. From top to bottom: average annual TAC, average inter-annual variation in TAC, final spawning biomass as a fraction of the target level and minimum future spawning biomass as a fraction of the target level. The thick horizontal lines indicate quantities when projecting under actual catches.

4.7.2 North Sea plaice (subarea IV)

4.7.2.1 Introduction

North Sea plaice forms one component of the demersal flatfish fishery in ICES subarea IV, with North Sea sole the other. Management of the two species are closely linked, with both species targeted by beam-trawl fisheries. However, when sole is the primary target, discarding of undersized and less marketable small plaice becomes appreciable (discards constitute roughly half the total removals of plaice from subarea IV).

Both stocks are currently managed according to the multi-annual European Union (EU) management plan: annual TAC advice is based on harvest rules that depend on the state of the stock relative to a spawning biomass reference point and a target fishing mortality. The 2010 precautionary target spawning biomass and fishing mortality rate for North Sea plaice are 230000 tons and $0.6yr^{-1}$ respectively (ICES 2010).

This assessment-based management for North Sea plaice is compared to the MP approach by performing projections from 1990 to 2009 under three simple harvest control rules. For purposes of this exercise, the VPA/XSA (Extended Survivor Analysis) stock assessment outputs reported in the 2010 ICES WGNSSK Report (ICES 2010) are used to parameterise the operating model so that the pre-1990 population numbers-at-age and fishing mortality rates are the same as those for the VPA assessments. Therefore, when performing a deterministic projection under actual catches, the spawning biomass in 2009 will be the same as that estimated in the VPA assessment for the same year. The survey slope- and target-based MPs are based on the BTS Isis survey index of abundance[19].

Input data and parameter values used for the projections for North Sea plaice are given in Tables B2.1 to B2.6 of Appendix B. Plots of input data and pertinent parameter values are given in Figures B2.1 to B2.12 of the same Appendix

[19] This survey may be biased (J.J. Poos, pers. comm.), but this complication is overlooked here in the interest of keeping the MPs implemented as simple as possible.

4.7.2.2 Projection results

Step 1:

Performance statistics for deterministic “hindsight” projections are given in Table 4.6 for the three candidate MPs, each tuned so that the spawning biomass in 2009 hits the same final spawning biomass estimated for that year by the 2010 XSA assessment for North Sea plaice under catches that actually occurred.

The slope- and target-based MPs lead to about the same average annual catches over the projection period compared to the actual average of 145702 tons, with the same final spawning biomass achieved with less inter-annual fluctuation in TAC. The constant catch results have pertinence only in comparing to TAC achievements under the slope and target strategies.

Figure 4.5 shows the corresponding catch (top), spawning biomass (middle) and fishing mortality rate projections (bottom) for the three candidate MPs. The slope and target MPs reach the target biomass in 2009 by moderating a decrease in catch over a longish time period rather similar to what occurred in practice, but with less inter-annual change in catch.

Step 2:

Table 4.7 shows results when incorporating uncertainty (observation error and process error): medians and 95% probability interval envelopes for 1000 simulations are given. For these stochastic projections, only the slope MP leads to abundance levels close to the 2009 target biomass at the lower 2.5%-ile. The previous “better” constant catch and target MPs are now the worst performing in terms of the resource risk statistics, leading to unacceptably low levels of spawning biomass in 2009 at this lower percentile.

Step 3:

Table 4.8 shows results for the “forecast” MPs: “hindsight” MPs of the previous table are retuned so that the lower 2.5%-iles of the final spawning biomass distributions reach the 2009 target biomass. Of the three “forecast” MPs, the constant catch strategy is the most conservative and yields less catch in median terms. The slope MP performs the best in terms of median average annual catch; however it also performs worst in terms of leading to largest average inter-annual fluctuation in TAC, although still much lower than that which occurred in reality (8.2% compared to 16.6%).

Stochastic catch and spawning biomass projections are shown in Figure 4.6 for each of the three "forecast" MPs. In order to ensure adequate robustness to uncertainty, in particular as arises from recruitment variability, the constant catch strategy requires a more severe decrease in catch than actually occurred at the start of the projection period. The slope and target MPs require the same steep drop in catch at the lower 2.5%-ile. Note that although a lower percentile was chosen to show adequate robustness at the 2.5% level, this precautionary approach does not exclude the possibility of some trajectories (25 of the 1000 simulations performed) ending below this lower bound in 2009. One such outlier is shown in Figure 4.6: in this case the initial decrease in catch is not adequate to compensate for further low recruitment over the time-period, leading to overfishing and unacceptably low levels of spawning biomass which in turn impair subsequent recruitment (see the North Sea plaice stock–recruitment curve in Appendix B.2 where the two-line inflection point is estimated to occur at a relatively high spawning biomass).

Step 4:

Performance statistics for the deterministic projections of the "forecast" MPs of Table 4.8 are compared to results for projections under actual catches in Table 4.9.

The slope- and target-type MPs achieve approximately the same average annual catch in median terms as occurred in practice, compared to the constant catch strategy which would have been more conservative by about 10%. Of the three harvest control rules, the target MP leads to the highest average annual catch with a final spawning biomass almost twice that achieved under actual catches, while keeping fishing mortality rates below the current precautionary target for most of the projection period, as is evident in Figure 4.7.

4.7.2.3 Summary statistics

Figure 4.8 gives a summary of performance statistics for the stochastic and deterministic projections under the three candidate "forecast" MPs for North Sea plaice.

While taking roughly the same average median catch, the MPs lead to much improved median biomass estimates, as is clearly evident from Figure 4.8 (left). However, in order to compare pertinent management statistics with what happened in reality, the deterministic plots in Figure 4.8 (right) are more helpful: taking the same total catch on average leads to the same or somewhat higher final spawning biomasses than estimated to have occurred under the actual catches. This outcome is achieved with far less inter-annual variation in catch (below 10% compared to the almost 17% that occurred in reality), although these values are not exactly comparable as no allowance has been made for implementation error[20].

In terms of the summary statistics shown in these plots, the performance of the target MP dominates that of the slope MP in terms of every performance statistic. Furthermore, the target MP outperforms the data-hungry assessment-based approach, ensuring less inter-annual fluctuation in total catch (and indeed actual TAC) than occurred, while ensuring higher spawning biomass levels.

[20] The inter-annual variation in actual TACs (based on annual assessments) over the projection period is roughly 10% compared to the 17% in actual catches (landings plus discards). This difference is mainly due to the large fluctuations in discards (see Figure B2.1 in Appendix B).

North Sea plaice (Subarea IV)	2010 VPA/XSA assessment	No data	Data: age-aggregated BTS-Isis survey index	
	Actual catches	**Constant catch** $TAC^{target} = 157502$ $\Delta TAC \leq 20\%$	**MP slope** $TAC^* = 0.8C_{1989}$ $\lambda = 0.58$ $p = 4$ $\Delta TAC \leq 20\%$	**MP target** $I^0 = 0.2I^{ave}$ $I^{target} = 1.1I^{ave}$ $TAC^{target} = 206700$ $w = 0.455$ $\Delta TAC \leq 20\%$
$\overline{TAC}$	145702	161678	145670	149654
AAV	0.166	0.026	0.083	0.057
$\overline{F}$	0.735	0.602	0.736	0.693
$\overline{\Delta F}$	0.202	0.174	0.215	0.167
$B^{sp}_{1990} / B^{target}$	0.921	0.921	0.921	0.921
$B^{sp}_{2009} / B^{target}$	1.000	1.000	0.975	1.007
$\min B^{sp}_{y} / B^{target}$	0.491	0.689	0.410	0.449

Table 4.6: Comparison of results for *deterministic "hindsight" projections* for North Sea Plaice with a two-line stock–recruit relationship when using only the BTS-Isis aggregated index in slope and target MPs, selected with hindsight (see Section 2.4 in Chapter 2 for details of the MP control parameters). Units are tons where applicable.

North Sea plaice (Subarea IV)	2010 VPA/XSA assessment	No data	Data: age-aggregated BTS-Isis survey index	
	Actual catches	**Constant catch** $TAC^{target} = 157502$ $\Delta TAC \le 20\%$	**MP slope** $TAC^* = 0.8C_{1989}$ $\lambda = 0.58$ $p = 4$ $\Delta TAC \le 20\%$	**MP target** $I^0 = 0.2I^{ave}$ $I^{target} = 1.1I^{ave}$ $TAC^{target} = 206700$ $w = 0.465$ $\Delta TAC \le 20\%$
$\overline{TAC}$	145702	161677 (161677, 161677)	146404 (120608, 170769)	146454 (86996, 170350)
AAV	0.166	0.026 (0.026, 0.026)	0.081 (0.059, 0.114)	0.064 (0.049, 0.148)
$\overline{F}$	0.735	1.672 (0.230, 6.950)	0.315 (0.231, 0.515)	0.352 (0.244, 5.978)
$\overline{\Delta F}$	0.202	0.228 (0.138, 0.502)	0.179 (0.121, 0.279)	0.197 (0.119, 0.434)
$B_{2009}^{sp} / B^{target}$	1.000	0.002 (0.000, 5.507)	3.183 (0.933, 5.230)	2.881 (0.000, 5.159)
$\min B_y^{sp} / B^{target}$	0.491	0.002 (0.000, 0.955)	0.838 (0.450, 0.948)	0.764 (0.000, 0.954)

Table 4.7: Comparison of results for *stochastic projections* with *"hindsight" MPs* for North Sea Plaice under a two-line stock–recruit relationship with $\sigma^R = 0.5$. Management quantities shown are medians with associated 95% probability intervals in parenthesis. 1000 simulations were performed. Units are tons where applicable.

North Sea plaice (Subarea IV)	2010 VPA/XSA assessment	No data	Data: age-aggregated BTS-Isis survey index	
	Actual catches	**Constant catch** $TAC^{target}=122000$ $\Delta TAC \le 20\%$	**MP slope** $TAC^{*}=0.8C_{1989}$ $\lambda=0.585$ $p=4$ $\Delta TAC \le 20\%$	**MP target** $I^{0}=0.2I^{ave}$ $I^{target}=1.1I^{ave}$ $TAC^{target}=206700$ $w=0.385$ $\Delta TAC \le 20\%$
$\overline{TAC}$	145702	130710 (130710, 130710)	146440 (120378, 171214)	142675 (118093, 167207)
AAV	0.166	0.037 (0.037, 0.037)	0.082 (0.060, 0.114)	0.075 (0.056, 0.105)
$\overline{F}$	0.735	0.241 (0.166, 0.469)	0.312 (0.230, 0.506)	0.302 (0.227, 0.512)
$\overline{\Delta F}$	0.202	0.180 (0.130, 0.255)	0.178 (0.122, 0.279)	0.179 (0.125, 0.270)
B^{sp}_{2009}/B^{target}	1.000	4.689 (1.020, 7.954)	3.217 (0.999, 5.273)	3.573 (1.019, 5.530)
$\min B^{sp}_{y}/B^{target}$	0.491	0.907 (0.564, 0.955)	0.840 (0.465, 0.948)	0.811 (0.424, 0.954)

Table 4.8: Comparison of results for *stochastic projections* with *"forecast" MPs* for North Sea Plaice under a two-line stock–recruit relationship with $\sigma^{R}=0.5$. Management quantities shown are medians with associated 95% probability intervals in parenthesis. 1000 simulations were performed. Units are tons where applicable.

North Sea plaice (Subarea IV)	**2010 VPA/XSA assessment**	**No data**	**Data: age-aggregated BTS-Isis survey index**	
	Actual catches	**Constant catch** $TAC^{target} = 122000$ $\Delta TAC \leq 20\%$	**MP slope** $TAC^* = 0.8C_{1989}$ $\lambda = 0.585$ $p = 4$ $\Delta TAC \leq 20\%$	**MP target** $I^0 = 0.2I^{ave}$ $I^{target} = 1.1I^{ave}$ $TAC^{target} = 206700$ $w = 0.385$ $\Delta TAC \leq 20\%$
$\overline{TAC}$	145702	130710	145909	148002
AAV	0.166	0.037	0.084	0.066
$\overline{F}$	0.735	0.299	0.712	0.545
$\overline{\Delta F}$	0.202	0.179	0.213	0.164
$B^{sp}_{1990} / B^{target}$	0.921	0.921	0.921	0.921
$B^{sp}_{2009} / B^{target}$	1.000	3.560	1.057	1.738
$\min B^{sp}_y / B^{target}$	0.491	0.833	0.416	0.521

Table 4.9: Comparison of results for *deterministic projections* for North Sea plaice under a two-line stock–recruit relationship for the best performing *"forecast" MPs.* Units are tons where applicable.

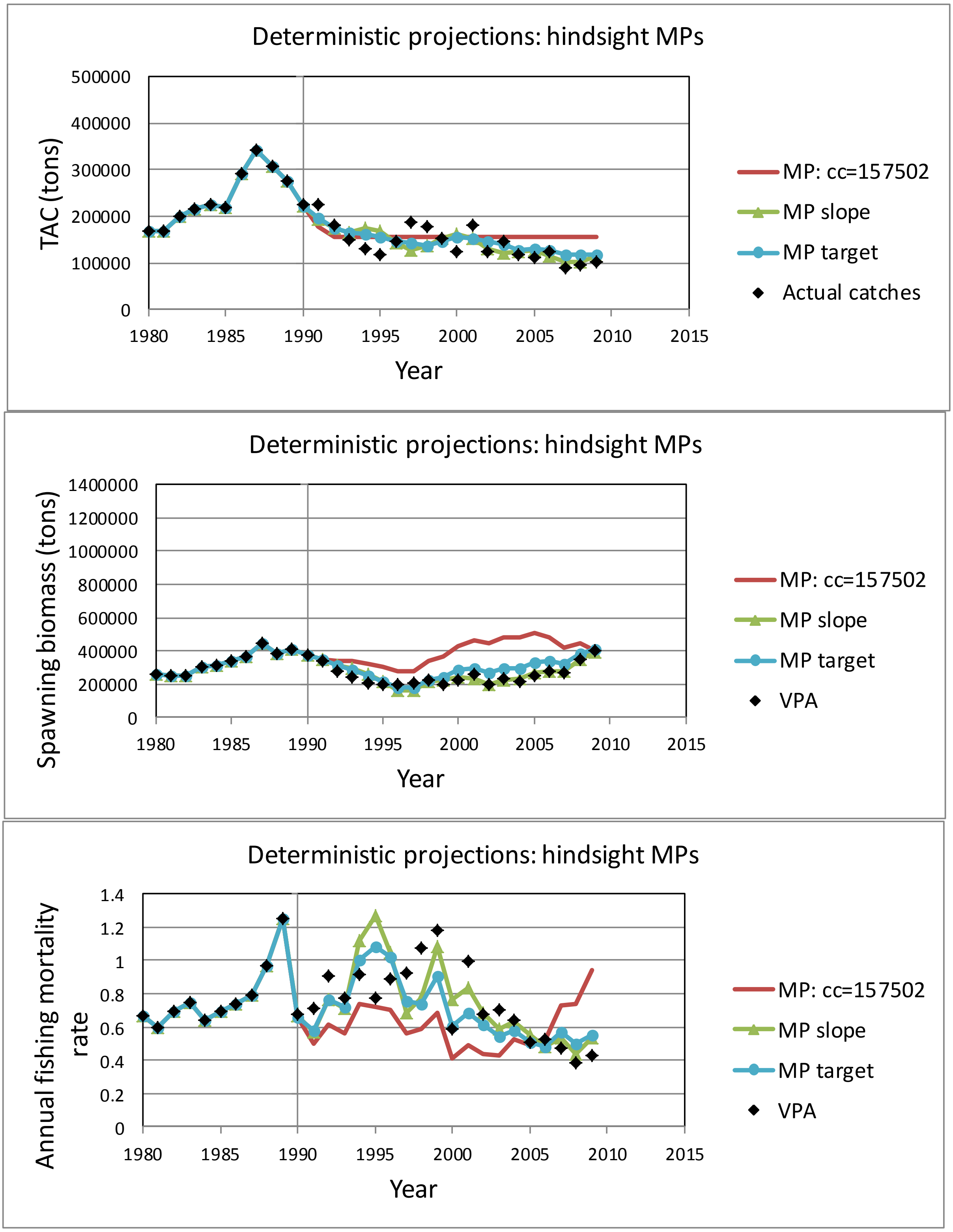

Figure 4.5: ***Deterministic projections*** **of a constant catch (red line), slope (green triangles) and target (blue dots)** ***"hindsight" MPs*****, tuned to hit the target biomass in 2009 exactly. TAC (top), spawning biomass (middle) and fishing mortality rate (bottom) trajectories under the three different "hindsight" MPs are compared to spawning biomass and fishing mortality rates under actual catches (black diamonds) for North Sea plaice.**

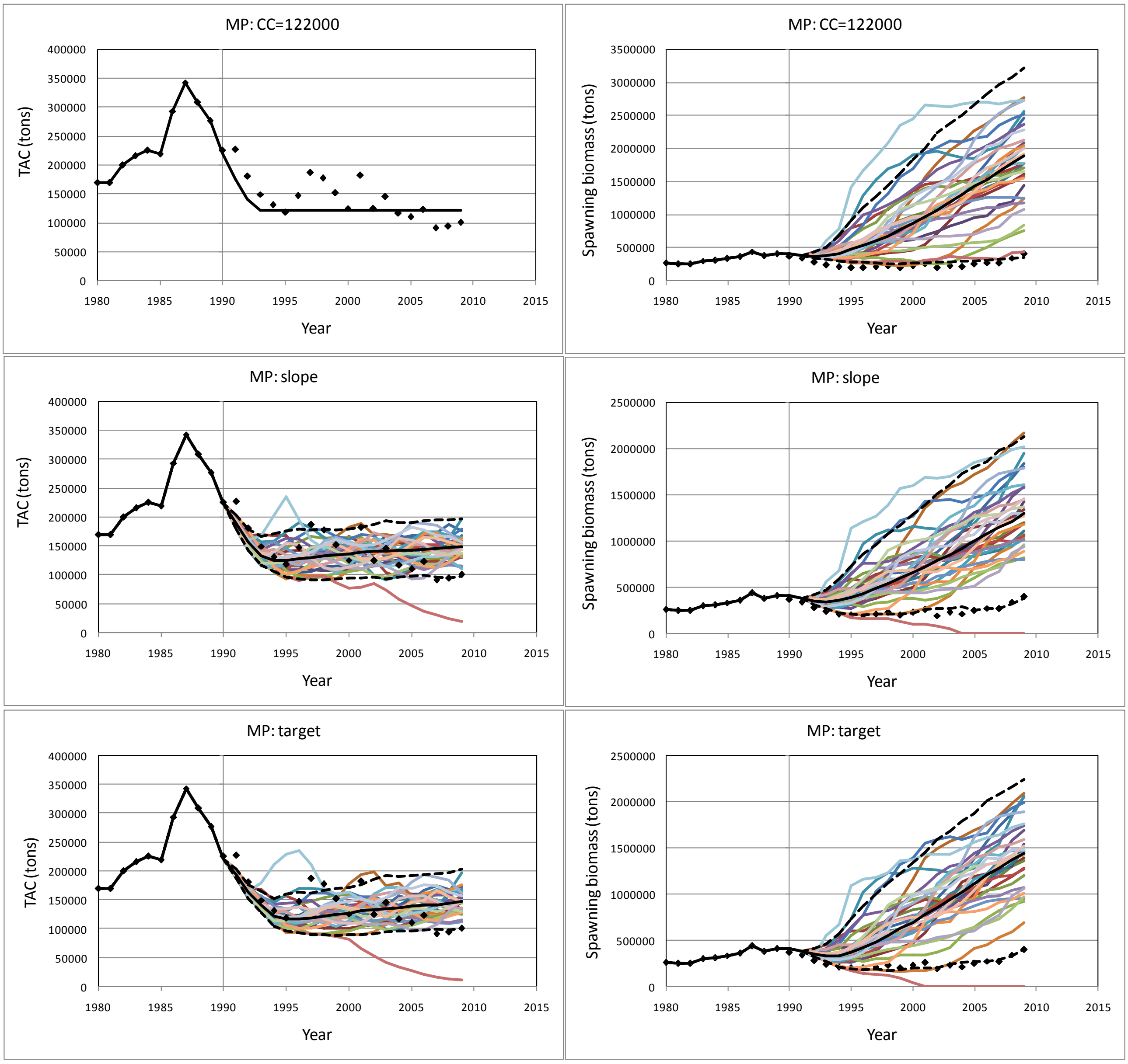

Figure 4.6: ***Stochastic*** **TAC (left) and spawning biomass (right) trajectories for the three candidate *"forecast" MPs* tuned so that the lower 2.5%-ile reaches the target biomass in 2009 (30 of 1000 simulations shown here). Top: constant catch MP, middle: slope-type MP and bottom: target-type MP. Spawning biomass trajectories corresponding to actual catches of North Sea plaice are indicated by the black diamonds. Medians and 95% probability intervals are indicated by the solid and dashed lines.**

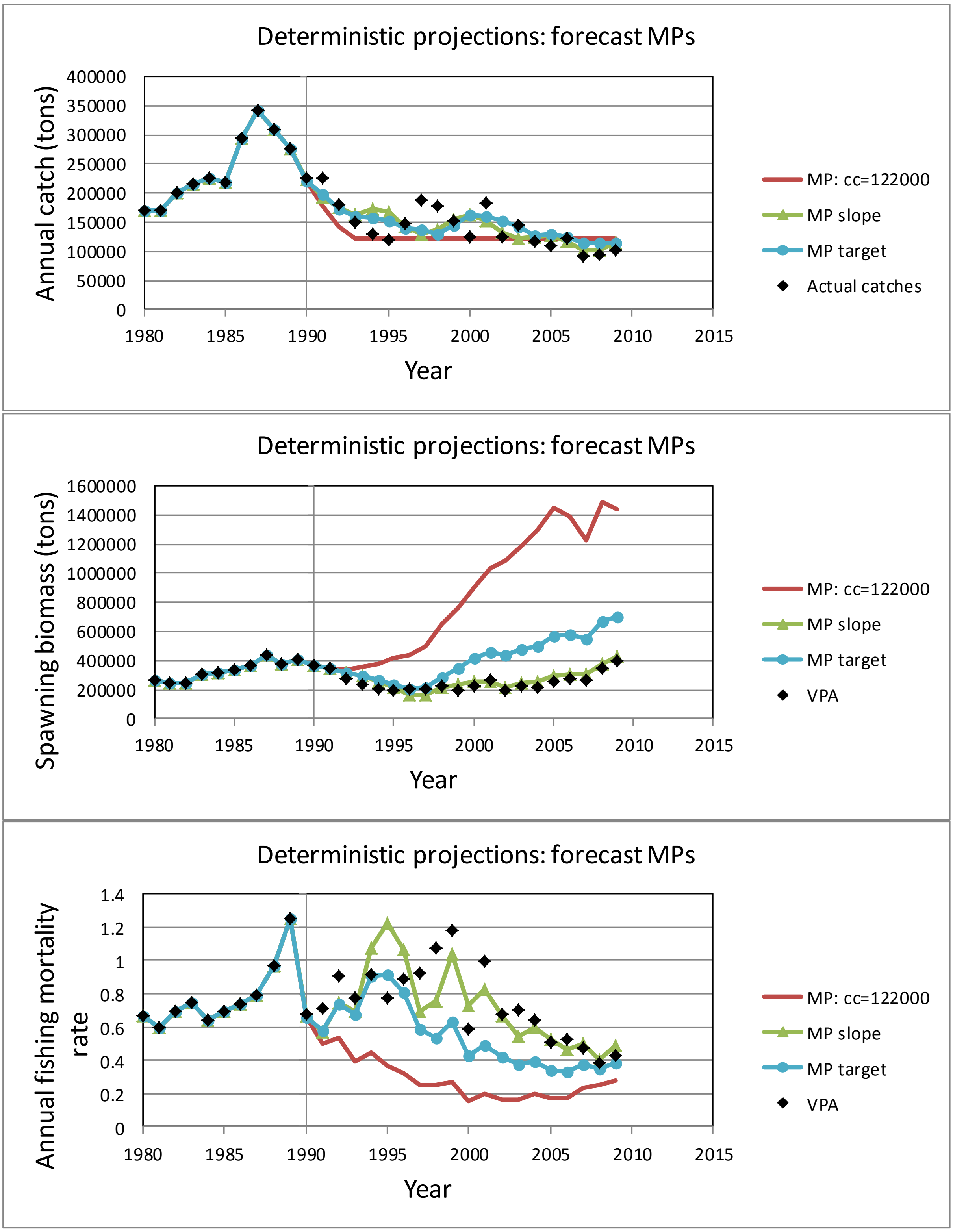

Figure 4.7: ***Deterministic projections* of a constant catch (red line), slope (green triangles) and target (blue dots) *"forecast" MPs*. TAC (top), spawning biomass (middle) and fishing mortality rate (bottom) trajectories under the three different "hindsight" MPs are compared to spawning biomass and fishing mortality rates under actual catches (black diamonds) for North Sea plaice.**

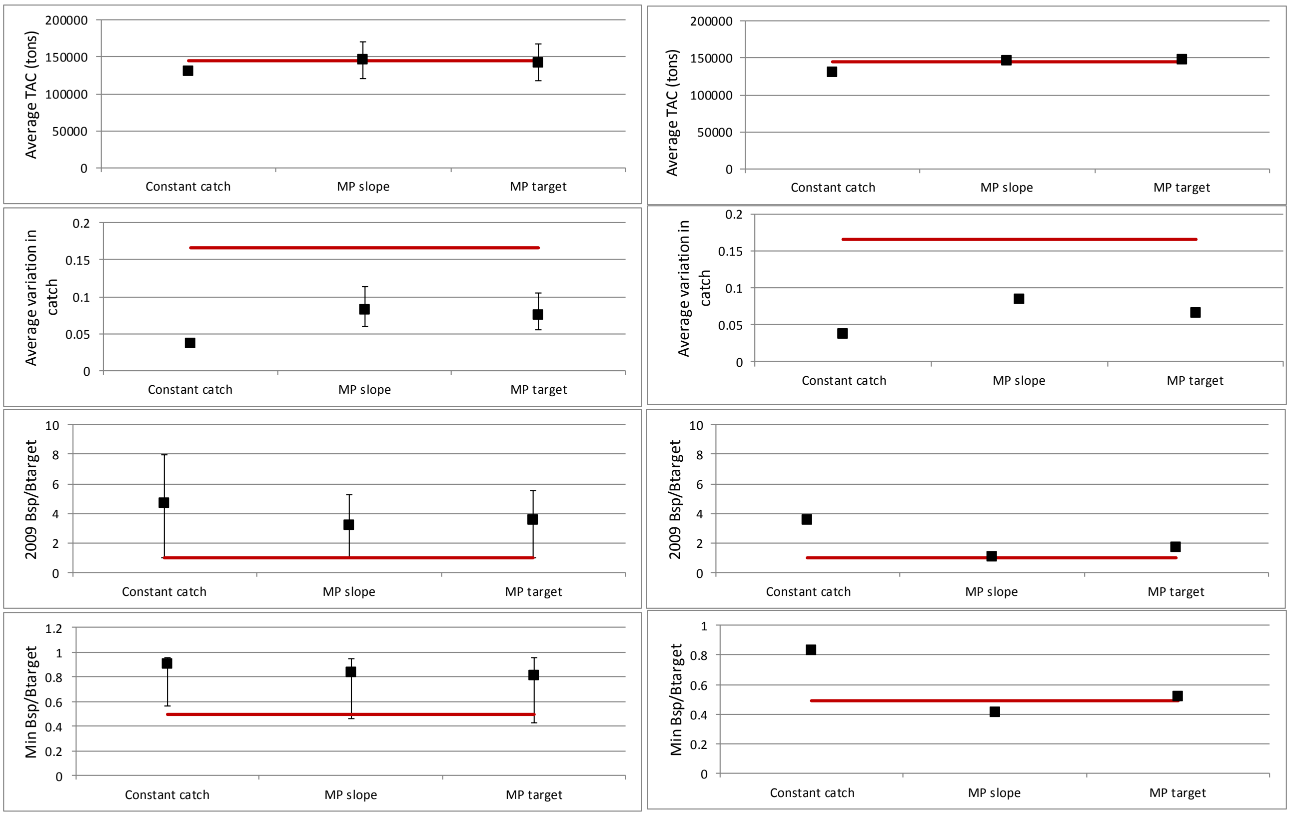

Figure 4.8: Summary statistics of *stochastic* (left) and *deterministic* (right) projections of the three candidate *forecast MPs* for North Sea plaice. The medians and 95% probability intervals for 1000 simulations are shown on the plots on the left. From top to bottom: average annual TAC, average inter-annual variation in TAC, final spawning biomass as a fraction of the target level and minimum future spawning biomass as a fraction of the target level. The thick horizontal lines indicate results when projecting under actual catches

4.7.3 New England Witch Flounder

4.7.3.1 Introduction

Witch flounder (Gulf of Maine southward) is collectively managed with 14 other New England groundfish species under the New England Fishery Management Council's Northeast Multispecies Fishery Management Plan (FPM), by means of a complex system of time/area closures, gear restrictions, minimum size limits and, more recently, direct effort controls (Table 1 in Wigley *et al.* 2003 lists almost annual changes to management regulations since the 1970s). Under the Sustainable Fisheries Act (SFA)[21], a stock rebuilding plan commenced in 2004 to achieve a target biomass within a 10-year rebuilding period (GARM 2008a). However, based on the 2012 estimates of biological reference points in terms of maximum sustainable yield, this stock is currently "overfished" $(B < 0.5B_{MSY})$, with spawning biomass estimated to be 41% below MSY level, and "overfishing" $(F > F_{MSY})$ continues, with fishing mortality estimated to be 173% above MSY level (current estimates of reference points are: $B_{MSY} = 10051$ tons, MSY=2075 tons and F_{MSY}=0.27 (NEFSC 2012)).

This lack of recovery is partly due to the persistent retrospective patterns in VPA assessments: systematic bias in estimates of abundance, with spawning biomass overestimated and fishing mortality rates underestimated in the terminal years of the assessment (see Figure F15, p468 in NEFSC 2012). This bias is carried forward into stock projections, with subsequent management advice based on the mis-specified population numbers-at-age and management targets achieved on paper rather than in reality.

Numerous reasons for these retrospective patterns have been proposed, including unrecorded catches, changes in natural mortality, changes in the abundance index catchability, and changes in fishery selectivity. In an attempt to correct for the overestimation of spawning biomass by the assessment model, the survey time series has been split in the mid-1990s; this allows for different catchability coefficients to be estimated over the two periods (GARM 2008b). In effect, this change in catchability

[21] The 1996 amendment of the Magnuson–Stevens Fishery Conservation and Management Act (MSA) which includes requirements to end overfishing, rebuild overfished stocks, and establish sustainable management practices, collectively known as the Sustainable Fisheries Act (SFA).

serves as a surrogate for any number of possible effects (as listed above) that may be the cause of these retrospective patterns (NEFSC 2012).

This retrospective study is based on the 2012 Gulf of Maine witch flounder assessment by Wigley and Emery (NEFSC 2012). VPA assessment results from 1982 to 2010 are considered for this retrospective study, with the historical "past" period running from 1982 to 1990, followed by a 20-year projection period from 1991 to 2010.

These 2012 "split run" assessment results are used for this retrospective study in an attempt to compare management actions, in terms of annual catches, which were based on past assessments with those based on the MP approach. As for the North Sea stocks considered, a 20-year projection period is adopted, from 1991 until 2010. The proposed discontinuity in the spring and autumn NEFSC survey indices therefore occurs within the time period over which the two approaches are compared. Importantly, no changes in catchability coefficients are incorporated for projections under candidate MPs, as these would not have been "known" during the period considered.

As before, three types of MPs are considered for this retrospective study: a constant catch MP (which serves as a base line), a slope-type and a target-type MPs based on the spring and autumn NEFSC survey indices (Table B3.6 and Figure B3.4 in Appendix B).

Input data and parameter values used for the projections for witch flounder are given in Tables B3.1 to B3.6 of Appendix B. Plots of input data and pertinent parameter values are given in Figures B3.1 to B3.12.

4.7.3.2 Results

Step 1:

Performance statistics for deterministic "hindsight" projections are given in Table 4.10 for the three candidate MPs, each tuned so that the spawning biomass in 2010 hits the same final spawning biomass estimated by the 2012 VPA assessment for New England witch flounder under actual catches.

To reach the target biomass in 2010, future average catches in terms of the three MPs are approximately the same as the actual average. However, as can be expected, simulated catches generated by the MPs fluctuate far less from year to year than the observed catches, with the simulated average inter-annual variation in catch approximately 5% compared to the 16% that actually occurred.

Plots of annual future catches (top), spawning biomasses (middle) and fishing mortality rates (bottom) are shown in Figure 4.9 for the three candidate MPs, chosen with hindsight, compared to the projections under the catches which actually occurred (black diamonds). These catches increased rapidly in the early 1990s with a large drop at the end of the projection period. The slope and target MPs reach the target biomass in 2009 by increasing the annual catch slowly from 1991 onwards, peaking in about 2005 with a decrease thereafter, following the overall trend in the spring and autumn NEFSC survey indices. However, with the benefit of hindsight, the constant catch MP outperforms the other strategies, by simply keeping the TAC unchanged after the initial increase in 1991. All three MPs ensure that future spawning biomass levels are kept above those achieved under actual catches. Fishing mortality rates under the three MPs are kept below those estimated to have occurred, except over the last three years of the projection period.

Step 2:

Table 4.11 shows results for these "hindsight" MPs when incorporating uncertainty (observation error and process error). The constant catch strategy is now the worst performing and fails to reach the target biomass even in median terms. The slope MP does slightly better, but still misses the mark at the lower 2.5%-ile. Surprisingly, the "hindsight" target MP seems to be robust to uncertainty, with the spawning biomass target in 2010 achieved at the lower 2.5%ile, but this comes at the price of less yield on average (2083 tons compared to an average of 2341 tons caught in reality).

Step 3:

Table 4.12 shows results for the "forecast" MPs, retuned so that the lower 2.5%-iles of the final spawning biomass distributions reach the 2010 target biomass. The target-based MP of the previous table remains unchanged due to adequate robustness to uncertainty incorporated in simulation trials. Having retuned the constant catch MP to satisfy the resource biomass target at the lower 2.5%-ile, it is now the most conservative and results in 20% less catch being taken on average in median terms. The slope and target MPs perform better, but also lead to less yield in median terms than that which occurred in reality.

Stochastic catch and spawning biomass projections are shown in Figure 4.10. To get to the target biomass by 2010, the constant catch strategy leads to an increase in catch from 1470 tons observed in 1990 to 1890 tons in 1992 and then maintains the catch at this level until 2010. Particularly noticeable in the top plot are the two “camel humps” of high fishing intensity where the actual catches exceed this constant catch. While not perhaps a plausible contender in reality, the constant catch MP serves as a baseline against which the performance of other MPs can be measured. Figure 4.10 shows that the slope and target “forecast” MPs lead to potentially higher catches than the constant catch strategy, with lower percentiles of the distributions close to the fixed catch advocated by the constant catch MP. The obvious advantage of the slope and target MPs, however, is that they rely on information forthcoming from the spring and autumn NEFSC survey indices of abundance to adjust future TACs, thus incorporating some feedback control mechanism into the TAC harvest control rule.

Step 4:

Performance statistics for the deterministic projections of the “forecast” MPs of Table 4.12 are compared to management quantities when projecting with actual catches in Table 4.13. The slope- and target-type MPs lead to approximately the same total catch as occurred in reality, while the constant catch strategy needs to be overly conservative given the “true” residuals for stochastic factors. All three candidate MPs keep the spawning biomass above the target level throughout the projection period compared to a drop by about 34% when projecting with the catches that actually occurred.

The top plot in Figure 4.11 shows clearly how the slope and target MPs track the trend in the spring and autumn NEFSC indices of abundance shown in Figure B3.4 in Appendix B, unlike the actual catches indicated by the black diamonds: large catches that occurred at the start of the projection period (top plot), resulted in a drop in spawning biomass in the early 1990s (middle plot) due to overfishing well above F_{MSY} of 0.27 (bottom plot), compared to lower initial catches and associated spawning biomass recovery under the MP approach. The “forecast” constant catch (solid red line) is almost equal to the 2012 estimate of maximum sustainable yield of 2075 tons, with associated fishing mortality rates fluctuating about the 2012 estimate of F_{MSY}=0.27 reported in NEFSC (2012), except for the most recent three years. Fishing mortality rates reach undesirable large values over this period for the slope and target MPs, though it should be kept in mind that in practical implementation such MPs would be reviewed rather more frequently than every 20 years.

4.7.3.3 Summary statistics

A comparison of summary statistics for different MPs applied to New England witch flounder is given in Figure 4.12.

In terms of the stochastic projections of Figure 4.12 (left), given the range of uncertainty considered here, taking slightly less catch than actually occurred on average (top plot), and doing so in a less variable manner (second plot), would ensure resource recovery in median terms (third plot) while at the same time keeping the spawning biomass levels healthy throughout the projection period (bottom plot).

For the deterministic projections on the right side of Figure 4.12, these MPs result in approximately the same average catch over the projection period as actually occurred, and also achieve the same final spawning biomass. The advantages of going the MP route are the likely lower inter-annual fluctuation in catches (5% compared to the more than 15% that occurred in reality) and maintaining higher spawning biomass levels throughout the management period.

The main conclusion to be drawn from these results is that these simple harvest control rules are able to achieve almost the same catch and risk performance even in the presence of fairly strong retrospective patterns: the slope and target MPs are able to adjust for the retrospective patterns through their feedback mechanisms.

Witch Flounder (1982-2010)	**2012 VPA assessment (Split run)**	**No data**	**Data: Spring and autumn NEFSC survey indices**	
	Actual catches	**Constant catch** $TAC^{target} = 2460$ $\Delta TAC \leq 20\%$	**MP slope** $TAC^{*} = 1.5TAC_{1990}$ $\lambda = 0.25$ $p = 5$ $\Delta TAC \leq 20\%$	**MP target** $I^{0} = 0.2I^{ave}$ $I^{target} = 2.5I^{ave}$ $TAC^{target} = 2700$ $w = 0.5$ $\Delta TAC \leq 20\%$
$\overline{TAC}$	2341	2409	2365	2300
AAV	0.157	0.028	0.045	0.056
$\overline{F}$	0.801	0.650	0.551	0.465
$\overline{\Delta F}$	0.275	0.302	0.294	0.289
$B^{sp}_{1991} / B^{target}$	1.424	1.424	1.424	1.424
$B^{sp}_{2010} / B^{target}$	1.000	1.011	1.041	1.074
$\min B^{sp}_{y} / B^{target}$	0.659	1.011	1.041	1.074

Table 4.10: Comparison of results for *deterministic "hindsight" projections* for New England witch flounder for a two-line stock–recruit relationship when using the NEFSC spring and autumn survey indices in the slope and target MPs selected with hindsight (see Section 2.4 in Chapter 2 for details of the MP control parameters). Units are tons where applicable.

Witch Flounder (1982-2010)	**2012 VPA assessment (Split run)**	**No data**	**Data: Spring and autumn NEFSC surveys**	
	Actual catches	**Constant catch** $TAC^{target} = 2460$ $\Delta TAC \leq 20\%$	**MP slope** $TAC^{*} = 1.5TAC_{1990}$ $\lambda = 0.25$ $p = 5$ $\Delta TAC \leq 20\%$	**MP target** $I^{0} = 0.2I^{ave}$ $I^{target} = 2.5I^{ave}$ $TAC^{target} = 2700$ $w = 0.5$ $\Delta TAC \leq 20\%$
$\overline{TAC}$	2341	2409 (2409, 2409)	2167 (1720, 2422)	2083 (1804, 2449)
AAV	0.157	0.028 (0.028, 0.028)	0.045 (0.036, 0.079)	0.052 (0.034, 0.073)
$\overline{F}$	0.801	3.080 (0.337, 6.334)	0.453 (0.302, 4.093)	0.318 (0.255, 0.498)
$\overline{\Delta F}$	0.275	0.315 (0.162, 0.496)	0.234 (0.142, 0.457)	0.199 (0.121, 0.287)
$B_{2010}^{sp} / B^{target}$	1.000	0.024 (0.000, 3.457)	1.702 (0.004, 3.831)	2.404 (0.996, 4.239)
$\min B_{y}^{sp} / B^{target}$	0.659	0.020 (0.000, 1.564)	1.332 (0.004, 1.564)	1.564 (0.884, 1.564)

Table 4.11: Comparison of results for *stochastic projections* with *"hindsight" MPs* for New England witch flounder under a two-line stock–recruit relationship with $\sigma^{R} = 0.5$. Management quantities shown are medians with associated 95% probability intervals in parenthesis. 1000 simulations were performed. Units are tons where applicable.

Witch Flounder (1982-2010)	2012 VPA assessment (Split run)	No data	Data: Spring and autumn NEFSC surveys	
	Actual catches	**Constant catch** $TAC^{target}=1890$ $\Delta TAC \leq 20\%$	**MP slope** $\lambda = 0.4$ $TAC^{*}=1.34TAC_{1990}$ $p=5$ $\Delta TAC \leq 20\%$	**MP target** $I^{0}=0.2I^{ave}$ $I^{target}=2.5I^{ave}$ $TAC^{target}=2700$ $w=0.5$ $\Delta TAC \leq 20\%$
$\overline{TAC}$	2341	1884 (1884, 1884)	2087 (1780, 2384)	2083 (1804, 2449)
AAV	0.157	0.014 (0.014, 0.014)	0.050 (0.035, 0.069)	0.052 (0.034, 0.073)
$\overline{F}$	0.801	0.276 (0.196, 0.497)	0.327 (0.252, 0.489)	0.318 (0.255, 0.498)
$\overline{\Delta F}$	0.275	0.187 (0.116, 0.290)	0.199 (0.122, 0.286)	0.199 (0.121, 0.287)
B^{sp}_{2010}/B^{target}	1.000	3.190 (1.059, 5.389)	2.400 (1.019, 4.255)	2.404 (0.996, 4.239)
$\min B^{sp}_{y}/B^{target}$	0.659	1.564 (0.953, 1.564)	1.564 (0.847, 1.564)	1.564 (0.884, 1.564)

Table 4.12: Comparison of results for *stochastic projections with "forecast" MPs* for New England witch flounder under a two-line stock–recruit relationship with $\sigma^{R}=0.5$. Management quantities shown are medians with associated 95% probability intervals in parenthesis. 1000 simulations were performed. Units are tons where applicable.

Witch Flounder **(1982-2010)**	**2012 VPA assessment** **(Split run)**	**No data**	**Data: Spring and autumn NEFSC surveys**	
	Actual catches	**Constant catch** $TAC^{target}=1890$ $\Delta TAC \leq 20\%$	**MP slope** $\lambda = 0.4$ $TAC^{*}=1.34TAC_{1989}$ $p=5$ $\Delta TAC \leq 20\%$	**MP target** $I^{0}=0.2I^{ave}$ $I^{target}=2.5I^{ave}$ $TAC^{target}=2700$ $w=0.5$ $\Delta TAC \leq 20\%$
$\overline{TAC}$	2341	1884	2295	2300
AAV	0.157	0.014	0.053	0.056
$\overline{F}$	0.801	0.284	0.461	0.465
$\overline{\Delta F}$	0.275	0.213	0.285	0.289
B^{sp}_{1991}/B^{target}	1.424	1.424	1.424	1.424
B^{sp}_{2010}/B^{target}	1.000	2.324	1.109	1.074
$\min B^{sp}_{y}/B^{target}$	0.659	1.424	1.109	1.074

Table 4.13: Comparison of results for *deterministic projections* for New England witch flounder under a two-line stock–recruit relationship for the best performing *"forecast" MPs*. Units are tons where applicable.

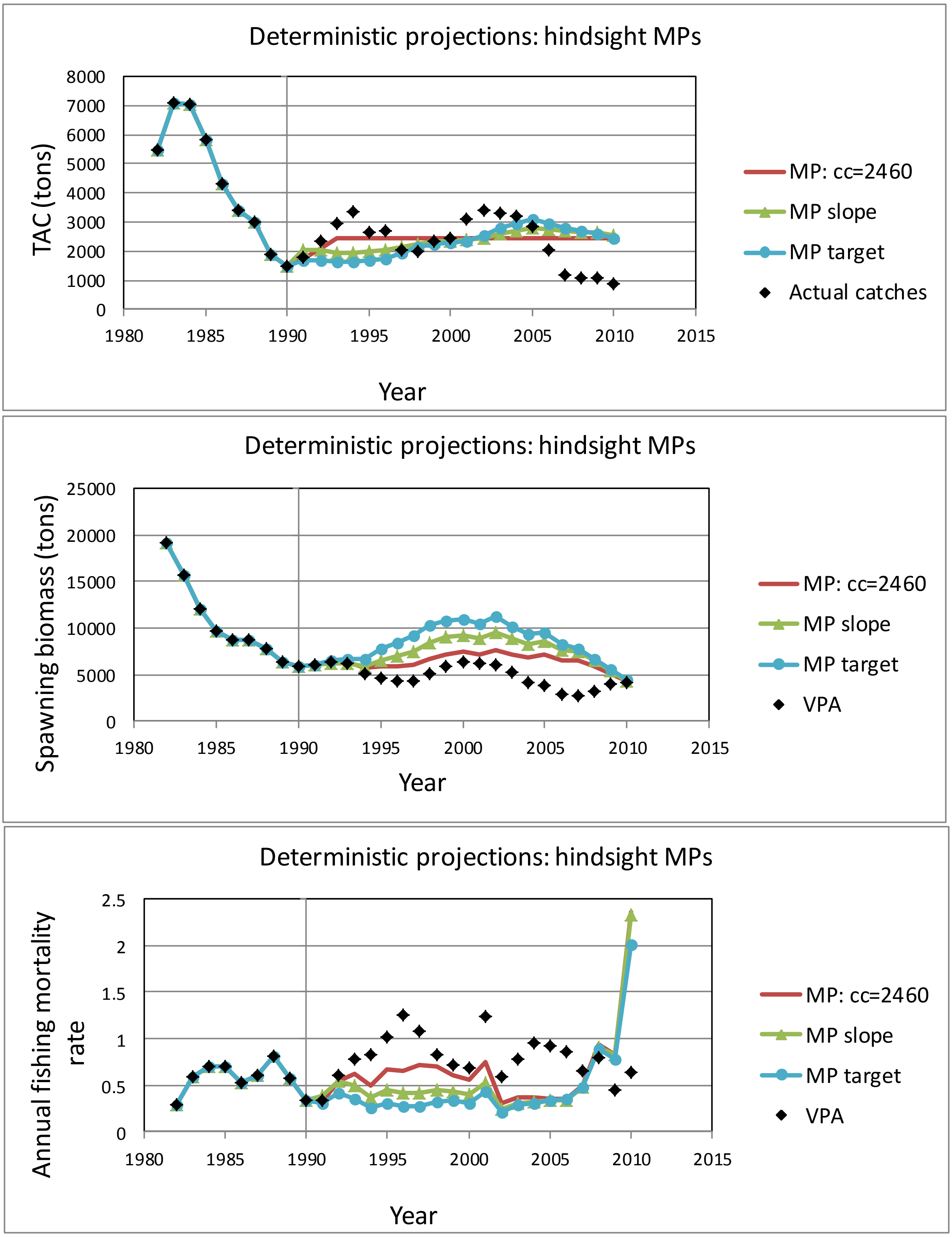

Figure 4.9: *Deterministic projections* of a constant catch (red line), slope (green triangles) and target (blue dots*)* *"hindsight" MPs*, tuned to hit the target biomass in 2009 exactly. TAC (top), spawning biomass (middle) and fishing mortality rate (bottom) trajectories under the three different "hindsight" MPs are compared to spawning biomass and fishing mortality rates under actual catches (black diamonds) for New England witch flounder.

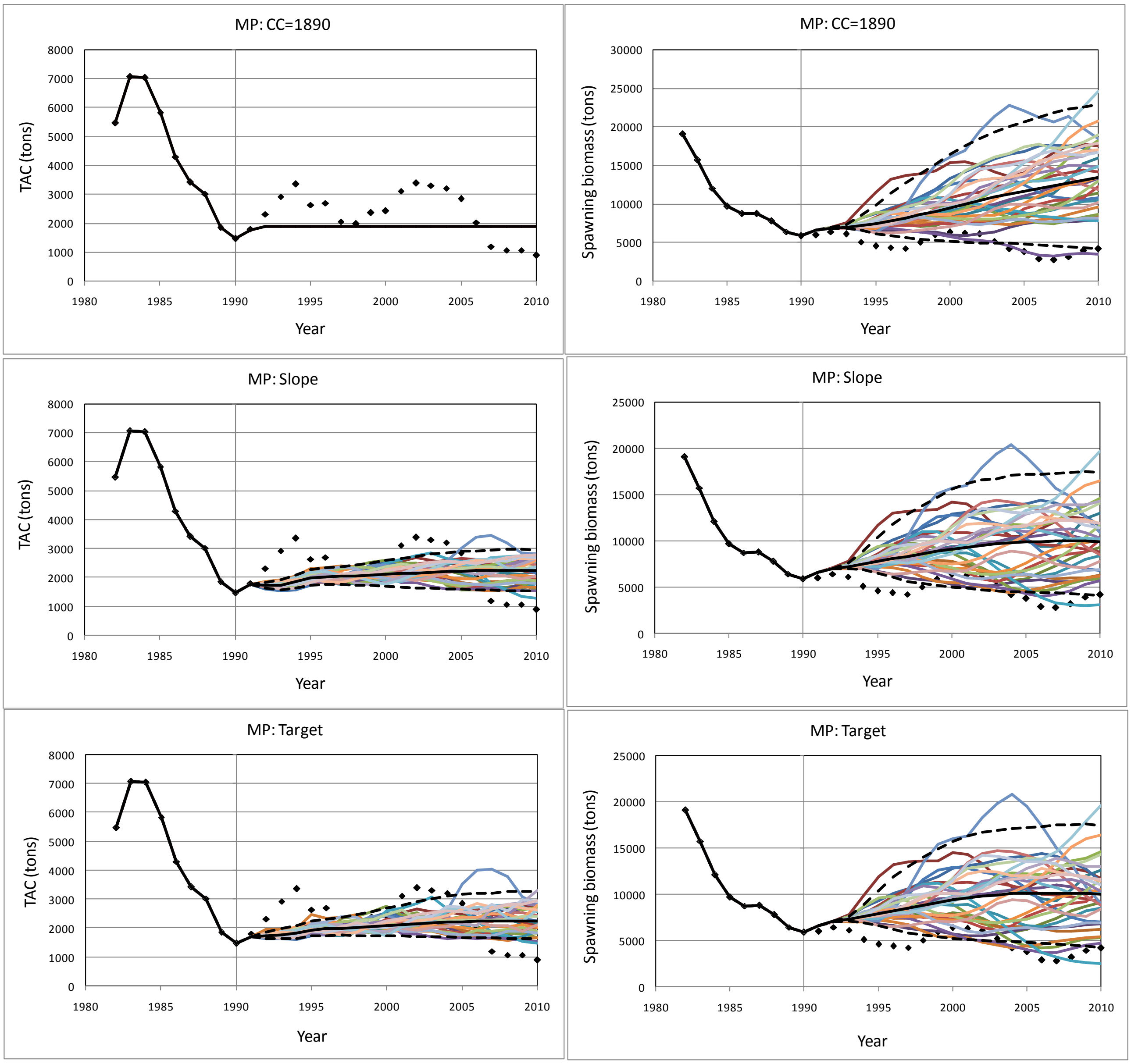

Figure 4.10: *Stochastic* TAC (left) and spawning biomass (right) trajectories for the three candidate *"forecast" MPs* tuned so that the lower 2.5%-ile reaches the target biomass in 2009 (30 of 1000 simulations are shown here). Top: constant catch MP, middle: slope-type MP and bottom: target-type MP. Spawning biomass trajectories corresponding to actual catches of New England witch flounder are indicated by the black diamonds. Medians and 95% probability intervals are indicated by the solid and dashed lines.

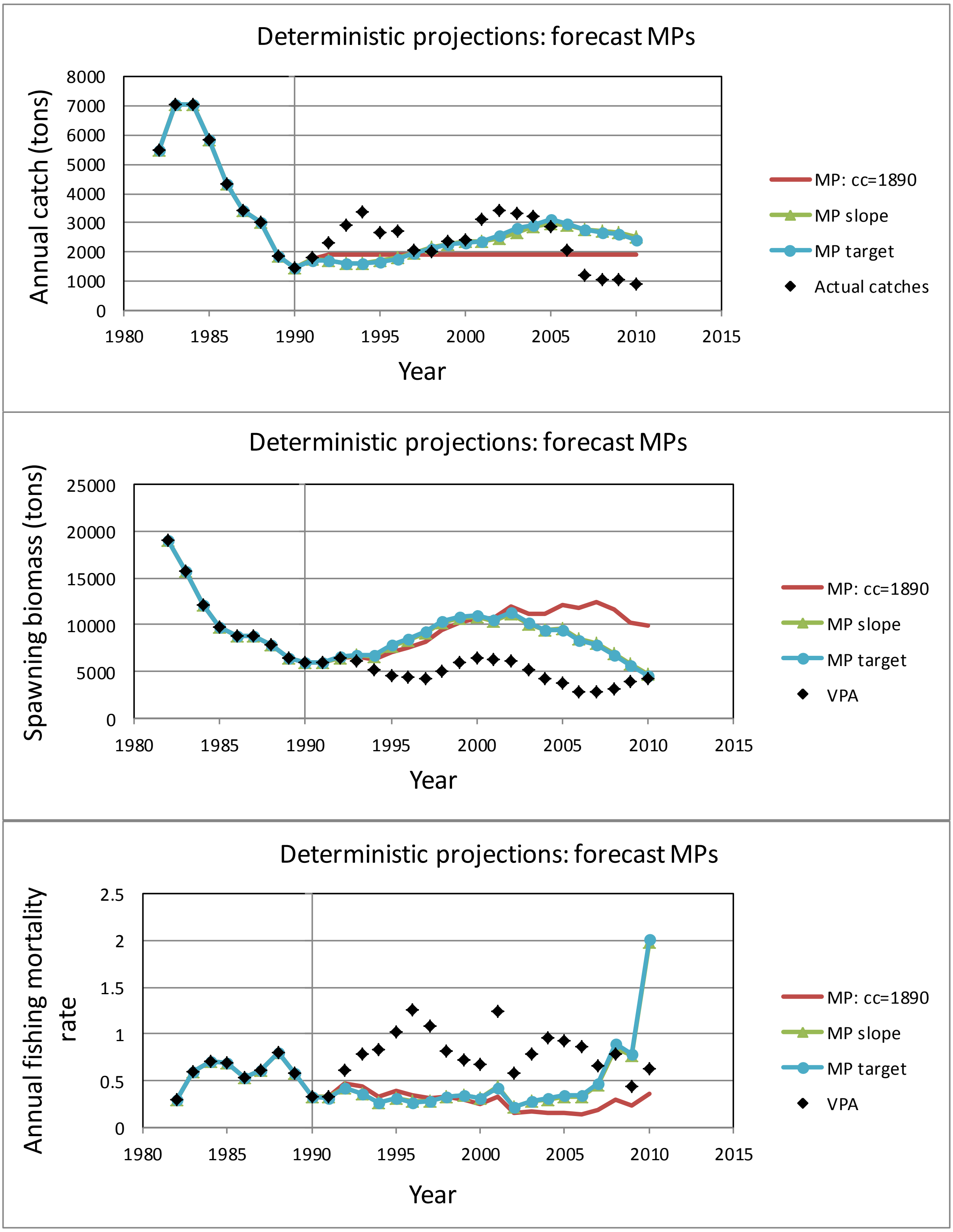

Figure 4.11: *Deterministic projections* of a constant catch (red line), slope (green triangles) and target (blue dots) *"forecast" MPs*. TAC (top), spawning biomass (middle) and fishing mortality rate (bottom) trajectories under the three different "hindsight" MPs are compared to spawning biomass and fishing mortality rates under actual catches (black diamonds) for New England witch flounder.

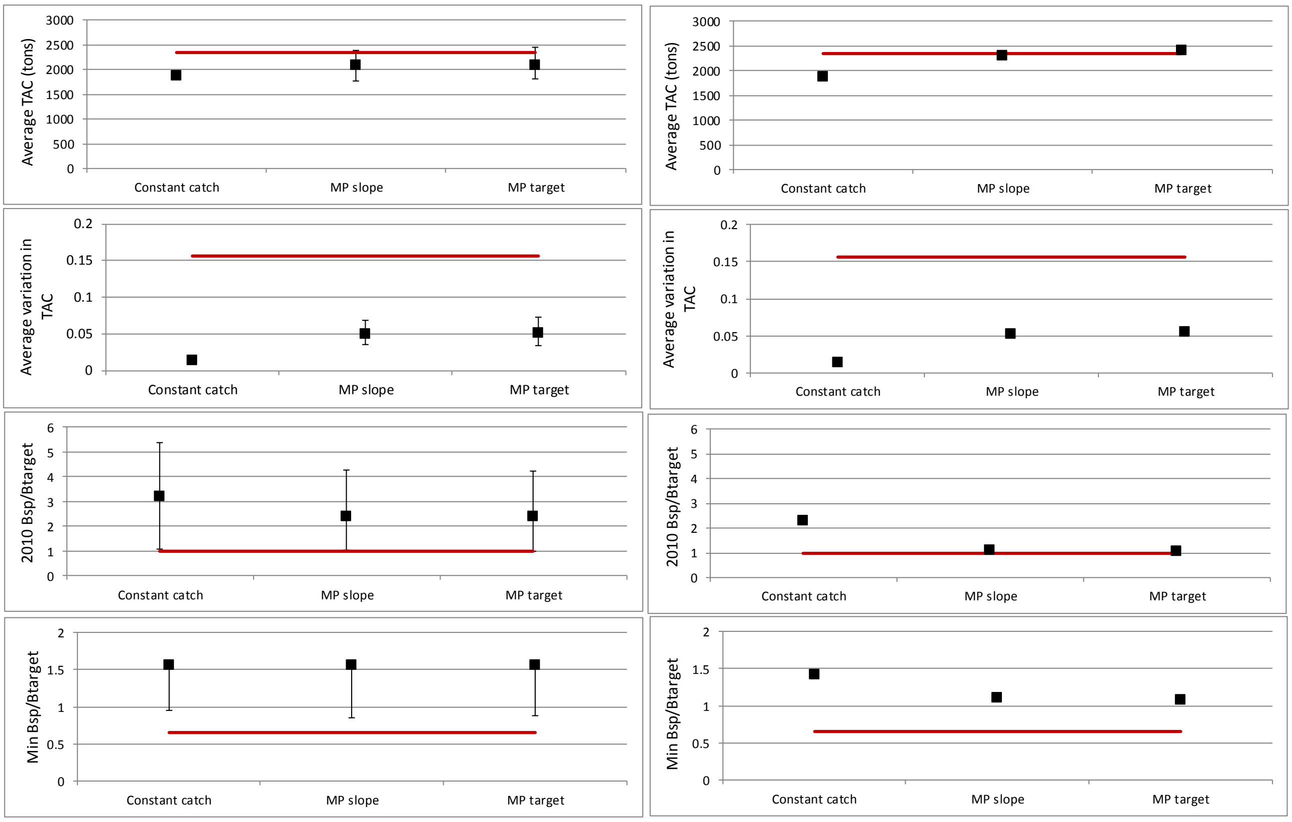

Figure 4.12: Summary statistics of *stochastic* (left) and *deterministic* (right) projections of the three candidate *forecast MPs* for New England witch flounder. The medians and 95% probability intervals for 1000 simulations are shown on the plots on the left. From top to bottom: average annual TAC, average inter-annual variation in TAC, final spawning biomass as a fraction of the target level, and minimum future spawning biomass as a fraction of the target level. The thick horizontal lines indicate quantities when projecting under actual catches.

4.7.4 American Plaice

4.7.4.1 Introduction

This retrospective study is based on the American plaice assessment for 2012 by O'Brien and Dayton (NEFSC 2012). VPA assessment results from 1980 to 2010 are used: the "historic" period corresponds to the years 1980 to 1990, with projections performed from 1991 to 2010.

While the New England plaice stock has not been managed in terms of TAC advice forthcoming from annual assessments, management advice (in terms of size, gear and area restrictions and, lately, effort controls) has nevertheless been based on VPA assessments. According to stochastic per-recruit analysis reported in NEFSC (2012), the current estimates for the biological reference points for spawning biomass and fishing mortality rate are 18398 tons and 0.18 yr^{-1}, with a maximum sustainable yield of 3385 tons.

Similarly to other New England stocks such as witch flounder (Section 4.6.3), retrospective patterns are visible in the plaice assessments, although to a lesser degree. Three MPs are tested here: the constant catch strategy and a slope- and target-type MP that rely on the most recent 5 years of spring and autumn NEFSC survey data (see Appendix B.3). In addition, in order to deal with systematic changes in model parameters over the projection period, the effect of a possible mid-cycle (2000) MP update is also investigated for this stock.

Input data and parameter values used for the projections for American plaice are given in Tables B4.1 to B4.6 of Appendix B.4. Plots of input data and pertinent parameter values are given in Figures B4.1 to B4.12.

4.7.4.2 Results

Step 1:

Performance statistics for deterministic "hindsight" projections are given in Table 4.14. In order to reach the same final spawning biomass as achieved under actual catches in 2010, the three MPs give about 10% less annual yield on average. On the plus side, the average inter-annual fluctuations in catch are much lower: approximately 5% compared to the 17% that occurred in practice, the latter mainly due to the sharp decrease in actual catches from over 7000 tons in 1992 to less than 2000 tons by 2005, as is evident in the top plot of Figure 4.13. All three MPs lead to much lower catches than actually occurred during the first half of the projection period which causes the spawning biomass trajectories corresponding to the three MPs to increase sharply from 1991 to 2000 (middle plot). Fishing mortality rates under the three harvesting strategies are compared to rates associated with the catches that occurred in reality in the bottom plot of Figure 4.13. Of particular concern are the high fishing mortality rates from 1992 to 2004 which correspond to actual catches.

Step 2:

Table 4.15 shows results for these "hindsight" MPs when incorporating uncertainty. Surprisingly all MPs overshoot the target biomass in 2010, even at the lower 2.5%-ile. The reason for this unusual result is rooted in the difference between the "forecast" and "hindsight" model parameter/variable values assumed for the projections, notably the systematic decrease in population weights-at-age for older fish over the projection period (see Figure B4.12 in Appendix B): the much higher population weights-at-age associated with the "forecast" projections results in a systematic overestimation of future spawning biomass and survey abundance index values.

Step 3:

Table 4.16 shows results for the "forecast" MPs: the overly conservative MPs of the previous table are retuned so that the lower 2.5%-iles of the final spawning biomass distributions hit the target biomass in 2010.

In order to better incorporate the systematic changes in model parameters/variables over the 20-year projection period (in particular the systematic decrease in population weights-at-age), the target MP was also re-tuned to allow for a mid-cycle update in 2000 (last column in Table 4.16). Updating the pertinent model parameters halfway through the projection period leads to a more conservative harvest control rule, with a 10% decrease in median average annual catch and fishing mortality rates compared to the target MP reported in the last but one column in Table 4.16.

An additional safeguard against such temporal changes in population weights may be necessary: the MP can readily be modified to accommodate any potential decrease by simply scaling the annual TAC by a factor $(\bar{w}_y^S / \bar{w}^S)$, where $\bar{w}_y^S$ is the average weight for year y and $\bar{w}^S$ is the average stock weight over the pre-management period.

Stochastic catch and spawning biomass projections are shown in Figure 4.14. No inter-annual variation constraints were imposed on the constant catch and slope MPs: a sharp drop in catch in 1991 of more than 20% is required to maximise the average annual catch over the projection period and to achieve the target biomass at the lower 2.5%-ile by 2010. In contrast, a 15% restriction was imposed on the target-based MP to minimise the disruption in catch at the start of the projection period and to maintain catch levels throughout with moderate inter-annual fluctuations. Noticeable in all three plots is that spawning biomass trajectories under the three MPs are substantially higher than those corresponding to the catches that actually occurred.

Step 4:

Performance statistics for the deterministic projections of the "forecast" MPs are compared to management quantities when projecting with actual catches in Table 4.17 with associated trajectories shown in Figure 4.15. None of the "forecast" MPs quite achieve the target biomass by 2010. The least conservative (the target MP of the last but one column of Table 4.17) leads to the highest yield on average (4069 tons compared to 3848 tons which actually occurred), but misses the target biomass by almost 30%. The mid-cycle updated target MP (the last column of Table 4.17) manages to move the stock closer to the target level, but at the cost of less catch on average. The only way the MPs could possibly match the performance of the assessment-based management is by taking larger catches at the beginning of the projection period when population weights are higher, with reductions in catch at the end of the projection period when weights are low, i.e., better track the catches which actually occurred. However, this type of harvesting strategy is unlikely to appeal to members of the fishing industry!

4.7.4.3 Summary statistics

Summary statistics for American plaice are given in Figure 4.16 for the stochastic and deterministic projections under candidate "forecast" MPs.

In terms of the plots shown on the left of Figure 4.16, and given the range of uncertainty considered in this retrospective study, the candidate "forecast" MPs lead to about the same average catch in median terms to that which occurred in reality (top plot) with much less inter-annual change in catch (second plot), and median estimates of final spawning biomass well above the 2010 target (third plot), with the advantage of keeping the spawning biomass levels high throughout the projection period (bottom plot).

However, summary statistics are somewhat less optimistic in terms of the deterministic comparison shown in Figure 4.16 (right). For approximately the same average annual catch as actually occurred (top plot), the MPs fail to achieve the biomass target in 2010 (third plot). The target MP performs rather poorly with the final spawning biomass approximately 25% below target. This performance is somewhat improved when performing a mid-cycle MP update which results in a final spawning biomass in 2010 close to the target level.

As before, a major advantage of the MP approach remains that large annual increases/decreases in catch are avoided (second plot) and that spawning biomass levels are maintained at healthy levels throughout the projection period (bottom plot).

American Plaice (1980-2010)	**2012 VPA assessment**	**No data**	**Data: Spring and autumn NEFSC survey indices**	
	Actual catches	**Constant catch** $TAC^{target} = 3375$ No smoothing	**MP slope** $TAC^* = 0.6TAC_{1990}$ $\lambda = 0.25$ $p = 5$ No smoothing	**MP target** $I^0 = 0.2I^{ave}$ $I^{target} = 6I^{ave}$ $TAC^{target} = 4500$ $w = 0.5$ $\Delta TAC \leq 15\%$
$\overline{TAC}$	3848	3375	3446	3496
AAV	0.167	0.013	0.053	0.042
$\overline{F}$	0.592	0.210	0.214	0.238
$\overline{\Delta F}$	0.225	0.238	0.251	0.248
$B^{sp}_{1991} / B^{target}$	0.594	0.594	0.594	0.594
$B^{sp}_{2010} / B^{target}$	1.000	0.999	0.961	0.980
$\min B^{sp}_{y} / B^{target}$	0.349	0.594	0.594	0.594

Table 4.14: Comparison of results for *deterministic "hindsight" projections* for American plaice with a two-line stock–recruit relationship when using the NEFSC spring and autumn indices in the slope and target MPs selected with hindsight (see Section 2.4 in Chapter 2 for details of the MP control parameters). Units are tons where applicable.

American Plaice (1980-2010)	**2012 VPA assessment**	**No data**	**Data: Spring and autumn NEFSC indices of abundance**	
	Observed catches	**Constant catch** $TAC^{target} = 3375$ No smoothing	**MP slope** $TAC^{*} = 0.65 TAC_{1990}$ $\lambda = 0.25$ $p = 5$ No smoothing	**MP target** $I^{0} = 0.2 I^{ave}$ $I^{target} = 6 I^{ave}$ $TAC^{target} = 4500$ $w = 0.5$ $\Delta TAC \le 15\%$
$\overline{TAC}$	3848	3375 (3375, 335)	3557 (3190, 3545)	3348 (3167, 3600)
AAV	0.167	0.013 (0.013, 0.013)	0.037 (0.033, 0.042)	0.033 (0.028, 0.041)
$\overline{F}$	0.592	0.185 (0.148, 0.242)	0.164 (0.138, 0.197)	0.208 (0.176, 0.248)
$\overline{\Delta F}$	0.225	0.145 (0.104, 0.192)	0.144 (0.105, 0.194)	0.149 (0.106, 0.200)
$B_{2010}^{sp} / B^{target}$	1.000	1.883 (1.094, 2.911)	1.857 (1.192, 2.792)	1.908 (1.243, 2.837)
$\min B_{y}^{sp} / B^{target}$	0.349	0.604 (0.604, 0.604)	0.604 (0.604, 0.604)	0.604 (0.604, 0.604)

Table 4.15: Comparison of results for *stochastic projections with "hindsight" MPs* for American plaice under a two-line stock–recruit relationship with $\sigma^{R} = 0.5$. Management quantities shown are medians with associated 95% probability intervals in parenthesis. 1000 simulations were performed. Units are tons where applicable.

American Plaice (1980-2010)	2012 VPA assessment	No data	Data: Spring and autumn NEFSC indices of abundance		
	Actual catches	**Constant catch:** $TAC^{target} = 3496$ No smoothing	**MP slope** $TAC^{*} = 0.65 TAC_{1990}$ $\lambda = 0.25$ $p = 5$ No smoothing	**MP target** $I^0 = 0.2 I^{ave}$ $I^{target} = 3I^{ave}$ $TAC^{target} = 4500$ $w = 0.5$ $\Delta TAC \le 15\%$	**MP target**+ $I^0 = 0.2 I^{ave}$ $I^{target} = 4I^{ave}$ $TAC^{target} = 4500$ $w = 0.5$ $\Delta TAC \le 15\%$ Mid-cycle MP update
$\overline{TAC}$	3848	3496 (3496, 3496)	3588 (3396, 3799)	3814 (3454, 4305)	3441 (3187, 3799)
AAV	0.167	0.011 (0.011, 0.011)	0.034 (0.030, 0.039)	0.042 (0.033, 0.056)	0.041 (0.033, 0.052)
$\overline{F}$	0.592	0.199 (0.157, 0.267)	0.189 (0.157, 0.233)	0.216 (0.189, 0.255)	0.196 (0.168, 0.231)
$\overline{\Delta F}$	0.225	0.145 (0.104, 0.195)	0.144 (0.103, 0.196)	0.147 (0.103, 0.198)	0.141 (0.098, 0.199)
$B^{sp}_{2010} / B^{target}$	1.000	1.796 (1.000, 2.843)	1.701 (1.037, 2.624)	1.518 (0.951, 2.347)	1.564 (0.986, 2.382)
$\min B^{sp}_y / B^{target}$	0.349	0.604 (0.604, 0.604)	0.604 (0.604, 0.604)	0.604 (0.604, 0.604)	0.604 (0.604, 0.604)

Table 4.16: Comparison of results for *stochastic projections with "forecast" MPs* for American plaice under a two-line stock–recruit relationship with $\sigma^R = 0.5$. Management quantities shown are medians with associated 95% probability intervals in parenthesis. 1000 simulations were performed. Units are tons where applicable.

American Plaice (1980-2010)	2012 VPA assessment	No data	Data: Spring and autumn NEFSC indices of abundance		
	Actual catches	**Constant catch** $TAC^{target}=3496$ No smoothing	**MP slope** $TAC^{*}=0.65TAC_{1990}$ $\lambda=0.25$ $p=5$ No smoothing	**MP target** $I^{0}=0.2I^{ave}$ $I^{target}=3I^{ave}$ $TAC^{target}=4500$ $w=0.5$ $\Delta TAC\leq 15\%$	**MP target**[+] $I^{0}=0.2I^{ave}$ $I^{target}=4I^{ave}$ $TAC^{target}=4500$ $w=0.5$ $\Delta TAC\leq 15\%$ Mid-cycle MP update
$\overline{TAC}$	3848	3496	3694	4069	3719
AAV	0.167	0.011	0.050	0.073	0.068
$\overline{F}$	0.592	0.225	0.250	0.339	0.339
$\overline{\Delta F}$	0.225	0.239	0.253	0.280	0.263
B_{1991}^{sp}/B^{target}	0.594	0.594	0.594	0.594	0.594
B_{2010}^{sp}/B^{target}	1.000	0.955	0.870	0.721	0.865
$\min B_{y}^{sp}/B^{target}$	0.349	0.594	0.594	0.594	0.594

Table 4.17: Comparison of results for *deterministic projections* for American plaice under a two-line stock–recruit relationship for the best performing *"forecast" MPs*. Units are tons where applicable.

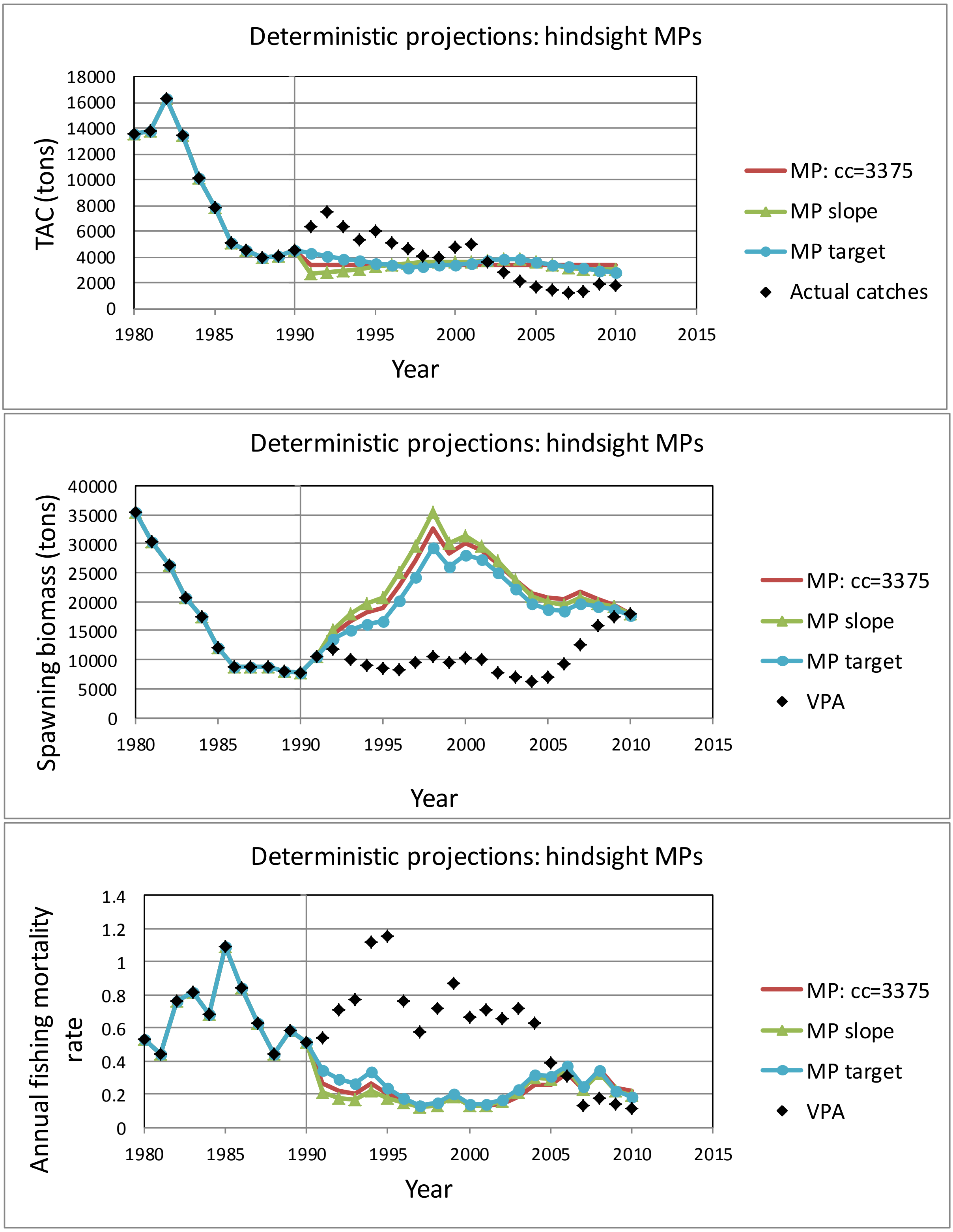

Figure 4.13: ***Deterministic projections*** **of a constant catch (red line), slope (green triangles) and target (blue dots)** ***"hindsight" MPs*****, tuned to hit the target biomass in 2009 exactly. TAC (top), spawning biomass (middle) and fishing mortality rate (bottom) trajectories under the three different "hindsight" MPs are compared to spawning biomass and fishing mortality rates under actual catches (black diamonds) for American plaice.**

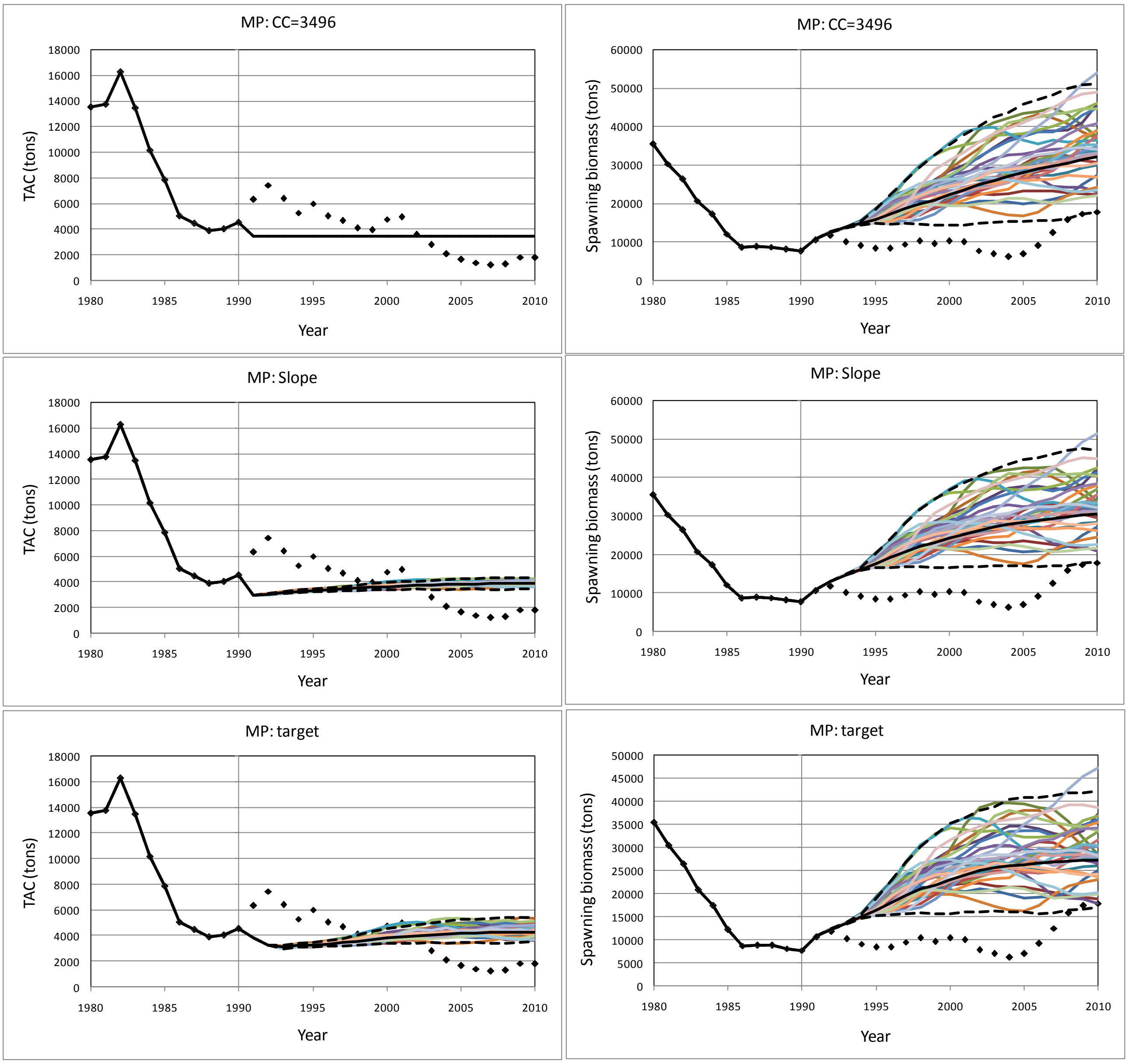

Figure 4.14: *Stochastic* TAC (left) and spawning biomass (right) trajectories for the three candidate *"forecast" MPs* tuned so that the lower 2.5%-ile reaches the target biomass in 2009 (30 of 1000 simulations are shown here). Top: constant catch MP, middle: slope-type MP and bottom: target-type MP. Spawning biomass trajectories corresponding to actual catches of American plaice are indicated by the black diamonds. Medians and 95% probability intervals are indicated by the solid and dashed lines.

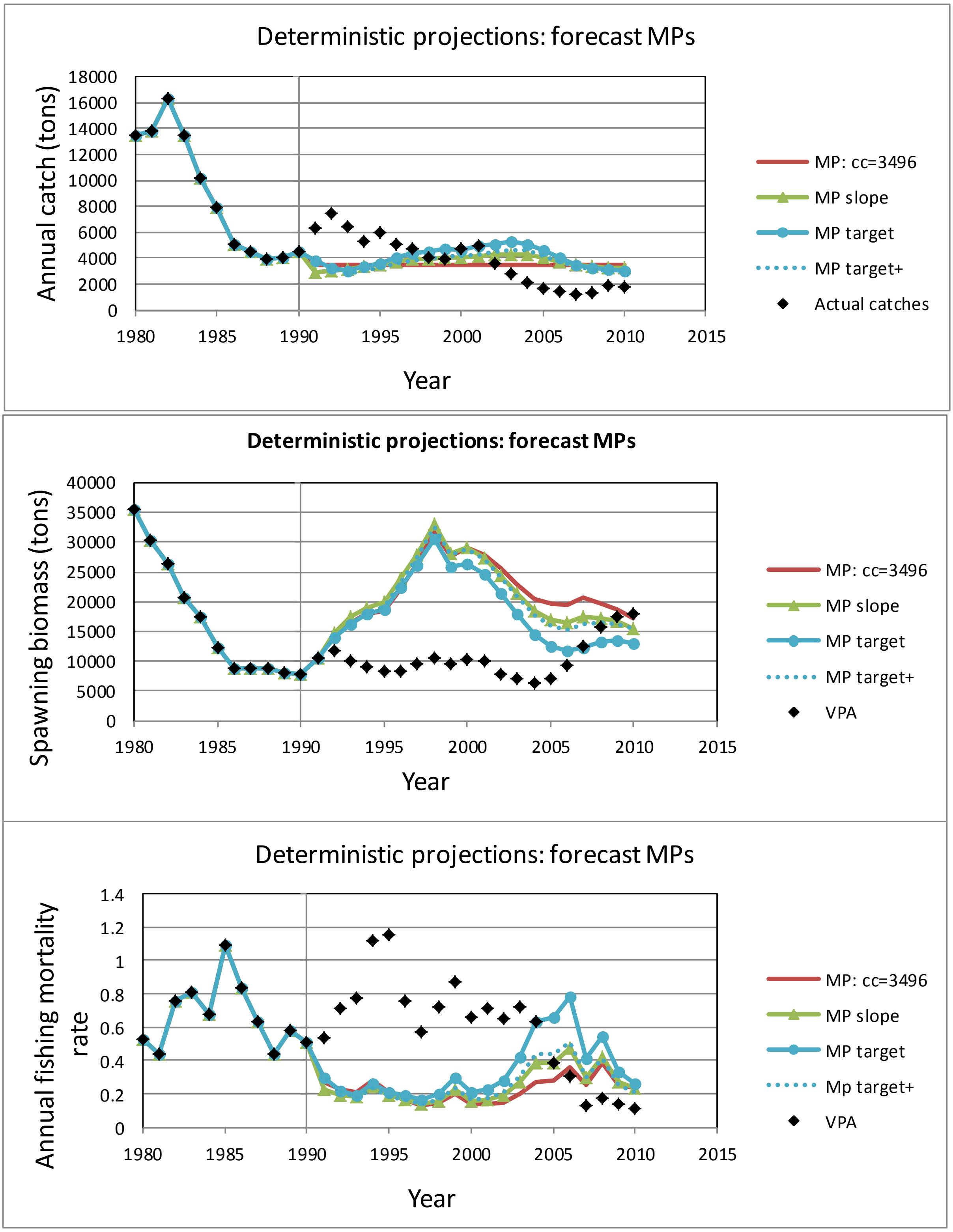

Figure 4.15: ***Deterministic projections*** **of a constant catch (red line), slope (green triangles) and target (blue dots)** ***"forecast" MPs*****. TAC (top), spawning biomass (middle) and fishing mortality rate (bottom) trajectories under the three different "hindsight" MPs are compared to spawning biomass and fishing mortality rates under actual catches (black diamonds) for American plaice.**

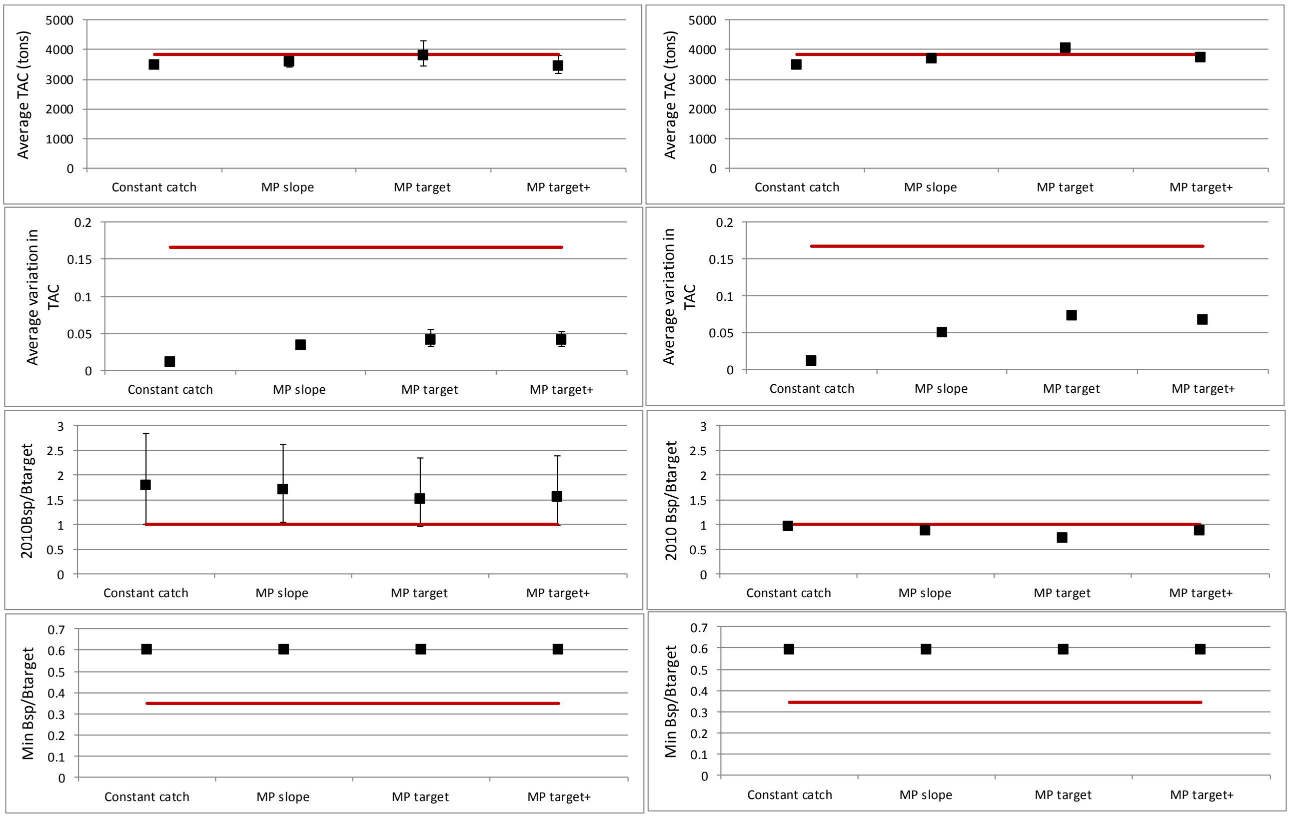

Figure 4.16: Summary statistics of *stochastic* (left) and *deterministic* (right) projections of the three candidate *forecast MPs* for American plaice. The medians and 95% probability intervals for 1000 simulations are shown on the plots on the left. From top to bottom: average annual TAC, average inter-annual variation in TAC, final spawning biomass as a fraction of the target level and minimum future spawning biomass as a fraction of the target level. The thick horizontal lines indicate quantities when projecting under actual catches.

4.8 Stock rebuilding: one MP or many assessments?

These simple retrospective comparative studies suggest that a simple empirical MP, implemented over a 20-year period, could have given comparable, or better, performance than the potentially 20 annual VPA assessments actually conducted, even in the presence of relatively strong retrospective patterns in the assessments.

For comparative purposes, the three MPs were tuned to reach the same final spawning biomass as would be achieved when projecting with the catches that actually occurred. The goal, therefore, was not to achieve the maximum sustainable yield (MSY) targets that underpin the actual management of the fishery. However, the average fishing mortality rates achieved under these simple harvest control rules seem to be better aligned with the current MSY targets quoted in ICES (2010) and NEFSC (2012). It therefore seems likely that the MP approach would also work if the actual biomass target, B_{MSY}, were selected instead of the final assessment-based biomass, B^{target}, chosen here to facilitate comparisons for the retrospective illustrations of this chapter.

These initial results highlight some of the advantages of going the MP route, which include a potential drop in unnecessary inter-annual fluctuations in catch and maintaining spawning biomass at higher levels while relying on far fewer data to do so, i.e. more efficient management than was achieved under the historical data-hungry assessment approach. These simple harvest control rules are able to achieve almost the same catch and risk performance, even in the presence of relatively strong retrospective patterns: the slope and target MPs are able to adjust for these retrospective patterns to a large (though not complete) extent through feedback. The American plaice example does, however, also point to the need for expanded analyses which include robustness tests which incorporate a wider suite of uncertainties.

Furthermore, these results suggest that a 20-year MP cycle would probably be too long, as might have been expected, given that here a more realistic MP update period of 10 years leads to improved performance. Based on the South African experience, where MPs have been implemented with some success over the past two decades, the optimal MP cycle is about 4 to 5 years: a shorter cycle will lead to more workload without associated benefits and with increased inter-annual fluctuations in TAC. The IWC Scientific Committee also uses a 5-year cycle.

This study does not include implementation error in its retrospective comparisons (in terms of the inter-annual variation statistics), and therefore does not paint the full picture in this regard. However, plots of annual catches and TACs (see Figures B1.1 and B2.1 in Appendix B) for North Sea sole and plaice highlight typical volatility, not only in annual catches, but also in annual TACs when ongoing management advice is based on annual assessments. This would suggest that the assessment-based management typically leads to large seemingly unwarranted changes in TAC, with fluctuations caused by factors that are unrelated to the trend in resource biomass.

In general these results are similar to those obtained in simulation studies by Punt (1993), which showed for South African hake that compared to simpler management procedure approaches on production models, attempts to take age-structure into account through VPA in recommending catch limits led to greater variability in those limits without any corresponding enhancement of performance in terms of reduced conservation risk.

Because of diminishing research resources, there may well be difficulties in sustaining the level of input data and expertise required for complex annual assessments. This raises the question of whether such complex assessments can continue to serve as the primary basis to provide scientific advice on catch limits, so that there is a need to explore alternative possibilities as has been done here. This is not to suggest that complex assessments must be abandoned, however. Rather, they still need to be conducted from time to time to provide reliable estimates of stocks status in answer to the “where are we now” question, as well as to provide updated operating models for the MP review processes which are typically conducted every 4 to 5 years. Nevertheless, when the goal is to aim for a target biomass within a specified time-frame, the MP approach seems best suited, particularly in terms of achieving greater stability in annual TAC advice.

To conclude, these initial results strongly suggest that simple empirical MPs, that rely only on survey index of abundance data, may provide a defensible, simpler and less costly alternative approach to the provision of long-term scientific management advice based on frequent (possibly annual) updates of complex age- or length-based assessments.

4.9 Where next?

These retrospective studies were intentionally simple to highlight some of the key features of an MP approach. A comprehensive MP evaluation approach tailored to each of the stocks considered, and which takes account of the full range of uncertainty that is present in reality, would be a complex and time-consuming exercise which is beyond the scope of this thesis. However, even without approaching such a fully comprehensive MP evaluation, there are nevertheless some aspects of this work which might be usefully extended further:

- In the calculations above, the TAC specified by the MP is assumed to be exactly equal to the total removals for the year concerned. Realistic levels of implementation error need to be incorporated into projections. In particular, a distinction between landings and discards needs to be introduced.

- Projections with model-type MPs, with exactly the same data-hungry age-structured assessment models used for current resource management, should be compared to simple empirical control rules based on an index of abundance. Such a comparison would be more effective in isolating model and data effects, without confusion of other management concerns such as implementation error.

- Projections with empirical MPs that generate Total Allowable Effort (TAE) rather than TAC need to be tested, for example using a target-type MP (Figure 2.3) based on fishing mortality with F_{MSY} as limit reference point and a target fishing mortality set at some percentage below the limit. For data-rich stocks, the target and limit reference points, $\%F_{MSY}$ and F_{MSY}, would be provided by quantitative assessment estimates and distributions.

- The stochastic projection trial exercise should be extended to incorporate more checks of robustness. Aspects to be considered for inclusion in such an extension include first estimation and then model structure uncertainty in the numbers-at-age vector that commences the projections, variability and trends in natural mortality over time, variability and systematic changes in model variables such as the population weights, and changes (undetected increases) in survey (and possibly CPUE) catchability. Furthermore, robustness of MPs to systematic low recruitment (or recruitment failure) needs to be demonstrated. Circumstances under which MPs fail due to lack of robustness need to be clearly specified, and where possible, warning signals need to be included as part of the MP monitoring process to alert to impending failure (e.g. signals in a juvenile index of abundance indicating consecutive years of low recruitment).

- In comparing performances above, “forecast” MPs were tuned to achieve the same final spawning biomass level at some low percentile (2.5%) of the distribution of this statistic. Trade-off comparisons might be more meaningful to stakeholders if instead tuning was effected to achieve the same total catch over the period.

- At a later stage, if this approach finds wider favour, then rather than relying on demonstrations of adequacy based on history, the analyses will need to move on to consider simulations projecting forward from the present time, so as to develop MPs that could be considered seriously for implementation. This could involve extension beyond the very simple types of MPs considered here, and would require a wide range of robustness testing.

Chapter 5 Discussion

This final chapter of the thesis draws some of the main conclusions, discusses shortcomings of the analyses performed, and offers suggestions for further work to be undertaken.

5.1 Management procedures

The management procedures considered in this thesis are all intentionally simple catch control rules. In addition to the constant catch rule that serves as a benchmark, four empirical MPs which rely on either an indirect (mean length of catch) or direct (survey or CPUE) indices of abundance have been simulation tested.

The main reason for focussing only on empirical rules in this study is to show that the availability of age data is not absolutely necessary for purposes of adequate forecasting. As shown, it is possible to base reliable (and robust) fisheries management advice on relatively few data, such as a short (albeit reliable) index of abundance.

5.1.1 Empirical or model-based?

Simple empirical algorithms, based on one or more indices of abundance, are generally preferred to model-based MPs in South Africa where they have been implemented successfully for some high-value data-rich resources/fisheries over the past two decades.

A frequent argument in favour of model-based MPs is that the models used smooth through the observation error in the data, thus reducing TAC variability. However, adding TAC change constraints to empirical MPs can account for this, while models can introduce bias through model-misspecification: unnecessary levels of annual adjustments to the TAC can result from lack of fit of the model to the data sets, or noisy data with no discernable trend, or data with conflicting trends, or badly specified prior distributions, or coding problems, to name a few. In addition, problems when automating large numbers of robustness trials for model-based MPs can go unnoticed (e.g. lack of convergence to the global maximum of the objective function) with resultant TACs possibly based on prior distributions rather than on information content in the data. Furthermore, once a model-type MP has been shown to be robust and is selected and eventually implemented, there is often a tendency to want to improve the model, perhaps to improve the fit to the data, similar to the "best assessment" paradigm. However, in an MP approach this may not be done as it is exactly the same model that must be applied (along with the pre-specified data set) to generate the annual TAC over the pre-specified management period, regardless of how imperfect it is deemed to be. Tinkering with the MP output is not allowed. The reason for this prohibition on model upgrade is simply because the MP model that was shown to be robust must be the same model used to generate the TAC; if a “better” model is desired, the “better” model must first undergo robustness trials prior to implementation. This process can be counter-productive, leading to annual TAC adjustments which imitate model adjustments rather than real changes in resource abundance, effectively following human behaviour rather than fish stock abundance. Typical problems associated with model-based MPs are:

- Model-based MPs, essentially resource assessment models, are complex: age- or length-structured models are not well understood by stakeholders (often not well understood by scientists either!) and undermine communication and collaboration between the different parties;
- Difficult to simulation test: lack of convergence of model-based MPs when performing robustness trials over a wide range of operating models (OMs) is common and often difficult to detect;
- Robustness trials of model-based MPs can be very time-consuming: typically thousands of simulations/minimisations are required ─ saving time by reducing the range of trials is not precautionary;
- Model-based MPs typically require a comprehensive set of data which, while available historically, may not be forthcoming in future.

A simple empirical catch control rule (MP), that has undergone extensive simulation trials to show robustness to key uncertainties about the underlying population model (OM), is far more likely to give reliable TAC advice than a complex model-based MP that, because of limitations of time for analysis, has not been shown to be robust to the range of plausible uncertainties. Besides, these complex models do not encourage stakeholder involvement as the complexity excludes and alienates all but the statisticians/mathematicians from development process, thereby losing a crucial benefit of the MP approach.

If a simple rule, understood by the layperson, is shown to perform as well as the complex model, understood only by the scientist who develops it, why then choose to go complex? Probably because most fisheries scientists are familiar with the traditional assessment paradigm, while still largely unfamiliar with the procedural paradigm based on MPs. Rather than adopt a fundamental change in approach to fisheries management, the traditional scientist typically feels more comfortable to combine the two approaches in a somewhat cumbersome manner without doing justice to either. Bentley and Stokes (2009) contrast the two paradigms by distinguishing between the roles of fisheries science and management:

- The assessment paradigm, which aims to estimate the true status of the stock, is based on science: *"the systematic creation of knowledge about the fishery through observation and experimentation"*.
- The procedural paradigm is solution orientated and distinguishes between the roles of science and engineering, with the latter (the MPs) relying on the former (the OMs): *"application of the knowledge to design and evaluate management procedures that best realise management objectives"*.

The procedural paradigm elegantly distinguishes between science and solution, with the latter simulation tested on the former, without confusing the two. From a design point of view, it would therefore seem counterproductive to use the same age- or length-based population models as operating models that describe the "truth", and the control rules that represent the "solution".

Indeed, Punt (1993) showed in a comparative study that incorporating age structure in a model-based MP did not improve performance for Cape hakes. These early indications have been put into practice: over the past two decades, management of the South African data-rich hake resource has moved away from age-aggregated model-based MPs to empirical rules given adequate performance achieved under the simpler MPs (Rademeyer 2012).

Further analyses, which look at management options for different types of species and fisheries, are nevertheless required before definitive conclusions can be drawn. In this respect, a worthwhile extension to the analyses reported in this thesis would be to compare performance of empirical and model-based catch control rules in terms of the generic operating models employed in Chapter 3. In this manner, the efficacy of simple and complex control rules could be tested across the wide range of uncertainty captured by these generic operating models which represent different groups (types) of species and fisheries.

5.2 Robustness to uncertainty

The success of an MP approach hinges on robustness to past and future uncertainties. If a candidate MP has not passed these robustness trials, it is unlikely to work well once implemented in the real world, regardless of the complexity of the control rule. Rather, it is the complexity and range of operating models that matter: these models should cover all plausible realities and incorporate uncertainty regarding the population model (model error), fluctuations about the model's dynamics (process error), uncertainty about the data (observation error), as well as uncertainty regarding the implementation of management advice (implementation error).

In terms of extensions to the analyses reported here, the generic MP study initiated in Chapter 3 provides an ideal platform for comparative robustness trials to ascertain which source of uncertainty (observation, process, model or implementation) dominates MP performance for a collective group of stocks. The outcomes of such a simulation study could inform future research and monitoring to achieve improved management.

5.2.1 Implementation error

Implementation error can be defined as variability in the implementation of a management policy. In particular, it is the inability to achieve an intended harvesting strategy exactly. It is generally not considered to fall within the scope of scientific fisheries management, but rather seen as a consequence of inadequate monitoring, control and surveillance (Caddy and Mahon 1995). Implementation error has rarely been incorporated in simulation studies of MPs.

There is another component of implementation error that is generally ignored under the assessment paradigm: policy decisions that differ in basis (sometimes radically for the stocks considered in Chapter 4) from the basis underlying the scientific advice.

Consider the three very distinct stages in traditional fisheries management: scientific, policy, and implementation. These three components frequently do not give the same weight to different objectives: while the scientist focuses on biological objectives, the policy maker concentrates on socio-political issues and the fisherman keeps his eye on economic targets. Once TAC (or TAE) advice is submitted by the scientists to the policy makers, the advice will likely be re-configured to better suit a different set of objectives. The resultant TAC (or TAE) is then repackaged into smaller units before being converted to currency by one or more fishing fleets, from one or more countries, competing for one or more resources, with catches often not being well monitored. It comes as no surprise then that the resultant catch (including discards) in any year may well be very different from the TAC advised by the scientist.

The MP approach goes a long way to repair some of the discontinuities and wastage of human resources involved in that traditional process by making sure that scientists are aware of social and economic objectives when designing harvesting strategies, and that members of industry fully understand the short- and long-term catch/catch rate trade-offs of the strategy that they themselves endorse prior to implementation. More importantly, once an MP is selected for implementation by the stakeholders in a formal MP approach, the TAC (or TAE) generated by the control rule automatically becomes the formal TAC (TAE) advice by sidestepping political interference that ultimately conflicts with the attainment of longer-term objectives.

An obvious shortcoming of the analyses reported in chapter 4 is the absence of simulated implementation error: for projections, TACs generated by the catch control rules have been assumed to be taken exactly. Furthermore, past catches were assumed to be known without error. These assumptions are not always near to reality and some allowance for implementation error will need to be incorporated into analyses intended to lead to actual application of the MPs developed.

5.3 Simulation to implementation: long road to sustainability?

While the simulation studies in the previous chapters show promising results for both data-poor and data-rich applications, the question remains: how well would they work in practice?

From this initial simulation study, it seems plausible to use simple generic MPs to generate annual TAC (or TAE) advice for "extremely data-poor" stocks, as long as the operating models encompass the high level of uncertainty which would apply for the stock/fishery under consideration. That said, such a generic approach would be precautionary by default as the distributions from which the operating model parameters are chosen would need to be sufficiently wide to include probable ranges for a collection of similar stocks, rather than be tailored to a specific stock alone, and candidate MPs would have to be robust over the entire range of operating models that encompass the group as a whole. In other words, TACs would necessarily be less than for an equivalent data-rich situation.

While hardly optimal, this would provide at least some form of quantitative management for the vast majority of exploited stocks worldwide that are not currently assessed quantitatively. A conservative estimate given by the FAO (2010) is that approximately 10% of exploited fish stocks are currently under scientific assessment, accounting for approximately 80% of total declared landings. For the remaining 90% of exploited stocks, very little information exists about stock status due to the lack of resource monitoring data, the lack of a suitable management infrastructure, the lack of local scientific expertise and the lack of appropriate methods to assist management decision making. Because these data-poor fisheries are of relatively low value compared to the high-value data-rich stocks which undergo regular assessment, there is little motivation to develop fisheries management structures due to the relatively high cost to yield/return ratio.

However, the FAO Code of Conduct for Responsible Fisheries clearly states that a precautionary approach to the management of all harvested stocks is required, regardless of data-poor they are deemed to be. In particular, The Code states that "*The absence of adequate scientific information should not be used as a reason for postponing or failure to take conservation and management* *measures*" (Article 7.5, FAO 1995). In order to implement these recommendations, with particular emphasis on data-poor stocks, a number of national fisheries management agencies have developed tier systems to better link stock assessment methods to the quality and quantity of data available (Punt *et al.* 2013). This presents a more structured approach to management where fish stocks are classified into categories, or tiers, according to their information type and availability, from data-rich to data-poor, with the level of precaution intended to increase from one tier to the next. Harvest control rules on which management advice is based, become increasingly conservative with increasing tier level, with Tier 1 typically reserved for data-rich stocks under regular assessment based on a comprehensive data set. This system has the added benefit of incentivising the collection of data to move a stock further up the tiers associated with less uncertainty and better (closer to optimal) management.

5.3.1 Data-poor management

To discuss various challenges for managing data-poor stocks, a workshop was held in California in 2008. This brought to light current approaches used around the globe. For example, in New Zealand, data required to inform management of data-poor fisheries are collected by fishers on a voluntary basis. Starr (2010) emphasises that such programmes need careful design, supervision and support to succeed, but that the benefits of such a collaborative approach are far-reaching: direct involvement of fishers in the scientific aspects of the management of the fishery fosters ownership of the data as well as the subsequent analyses of those data, thereby promoting buy-in by the fishers into the management process as a whole.

In Australia, a Harvest Strategy Policy (HSP) was introduced in 2007 to set limit and target biomass reference points to achieve risk-related sustainability objectives even in circumstances when data availability is compromised (Smith *et al.* 2009). An objective of this HSP is to ensure that harvesting strategies meet risk thresholds even when the level of uncertainty is high, as is the case for data-poor stocks. In particular, Smith *et al.* (2009) propose that information from data-rich stocks/fisheries could be used when developing harvest control rules to manage data-poor stocks/fisheries, either by using the "Robin Hood" approach of taking from the rich to benefit the poor (adopting typical ranges for parameter values developed for data-rich stocks when conducting data-poor analyses – Chapter 3), or by simply grouping similar (bycatch) species in "baskets" and basing management decisions on one member of such a group. Based on experience in Australia, Smith *et al.* (2009) summarise their recommendations as follows:

- In the absence of stock assessments due to insufficient data, objective harvest control rules can be developed to manage data-poor stocks/fisheries.

- Simulation testing of harvest control rules within a comprehensive MP approach is ideal but time-consuming and therefore not always a realistic expectation.
- Data/information available for data-rich stocks can be used to inform analyses for demographically similar data-poor stocks.
- Stakeholder knowledge and buy-in is essential when developing and choosing MPs to manage data-poor stocks/fisheries.
- Trade-offs between the cost of data collection and the value of the fishery need to be recognised. For very data-poor low-value stocks, a sufficiently precautionary approach is required.

Prince (2010) argues that data-poor fisheries can be successfully managed only by involving local fishers in all aspects of the fishery (data collection, assessment and management). Based on experiences around the world, and particularly in Oceania, he considers that certain factors are essential for the management process to succeed (Prince 2010):

- Dedicated access privileges: long-term incentives to promote stewardship.
- Change agents and "barefoot ecologists": build the skills set of members of the fishing community to monitor and manage themselves.
- Collaborative involvement of local fishers: this includes data collection, assessment and management.
- Clear management objectives: conservatively chosen levels of local spawning biomass.
- Simple transparent decision rules: empirical MPs based on resource indicators collected directly from catch data (e.g. size-based indices of abundance).

The situation is not much different in South Africa: of the more than some 500 stocks fished in South Africa, only 11 would be deemed "well-managed" in the sense of the data available allowing for detailed quantitative assessments (C. Attwood pers. comm.). These 11 well-managed[22] resources account for about 80% of the catch in terms of mass (DAFF 2011). Nevertheless, there is a need for better management of the remaining 20% in order to maintain biodiversity and to sustain the fishing communities that rely on these data-poor stocks.

At present there are as yet very few quantitative measures in place to manage the majority of those same 500 stocks, mainly due to their relative low value compared to other resources (such as Cape hakes) and to a shortage of skilled quantitative scientists to perform complex analyses, as well as a 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 high levels of uncertainty (observation, model, process and implementation error). Rather than

[22] In terms of landed value, the bulk of these high-value resources/fisheries are under MP management.

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 inshore South African resources, typically data-poor, are particularly prone to overfishing due to the low cost/yield ratio resulting in a very low bionomic equilibrium, BE (see Figure 1.4 in Chapter 1): while labour-intensive, the linefisheries require low technology and low investment for a product that is typically of high quality, potentially fetching high prices on both local and international fish markets.

No formal assessments are performed for the majority of these stocks. In the past, spawning biomass-per-recruit analyses have provided management reference points; however these estimates are unreliable as they in turn rely on estimates of natural mortality which are hard to come by (Griffiths *et al.* 1999). For those stocks for which sufficient data are available, age-structured stock assessments have typically failed due to the noise in the data (Geromont and Butterworth 2011), rendering futile any attempt to estimate model parameters directly. Given the extent of uncertainty about population model parameters and the few data available for the large number of inshore linefish species, a generic MP approach would therefore be ideal to provide on-going management advice.

While reliable total annual catch estimates are difficult to obtain due to the multi-component nature of these inshore fisheries (commercial, recreational and subsistence), fairly reliable CPUE data are generally forthcoming from the commercial sectors of these fisheries (DAFF 2012). An MP approach, which includes uncertainty about the historical total catches, as well as implementation error to be expected in future years, therefore seems desirable. Empirical MPs similar to those tested for the "moderately data-poor" stocks in Chapter 3 could be simulation tested for robustness to realistic levels of implementation error.

This approach would necessitate identifying and grouping data-poor stocks according to their demographic parameters and further pairing these groups with data-rich stocks so that typical parameter distributions can be "borrowed" from the latter to apply to the former. The next step in terms of work reported in this thesis would therefore be to extend the analyses conducted in Chapter 3 to include test cases from the South African inshore fisheries.

5.3.2 Data-rich management

Management Procedures have been successfully implemented for a select few stocks only, while management recommendations for the majority of the world's fish stocks remain based on regular (mostly annual) assessments. Compared to the management procedure paradigm, which is unfamiliar and often misunderstood[23], the assessment paradigm is well-known and familiar. There therefore seems little motivation to adopt a different management approach for high-value data-rich stocks currently under regular assessment.

The retrospective studies reported in Chapter 4 present some arguments to move to an MP approach based on relative performance when the main objective is to reach a target biomass within a pre-selected time-period. Furthermore, unlike the assessment approach, the MP simulation trials provide a basis for risk evaluation (Butterworth 2007). But are there other benefits that an MP approach could bring to on-going management of high-value stocks? This section offers a rationale as to why it may be prudent to adopt an MP approach, even in circumstances when reliable data, expertise and financial support are readily available to perform annual assessments.

A comprehensive MP approach requires substantial time, effort and expertise from scientists and other stakeholders alike. The development process is thorough, time consuming and typically takes one to two years. This evaluation process includes a full investigation of the data and population models, in consultation with experts in the field, with the aim to identify and incorporate equally plausible alternative realities in terms of the operating models, without prior knowledge of how these might influence the results. Specifically, sufficient time is apportioned to allow for thorough inspection of the following:

i) Data: all historical data need to be examined by stakeholders to highlight discrepancies, discontinuities, uncertainties, etc.
ii) Population models: A suite of operating models needs to be identified that describe alternative hypotheses identified by stakeholders.
iii) Management controls: strategies need to be simulated to ascertain which are most likely to succeed in reality; furthermore the criteria for finding that “exceptional circumstances” apply, and the associated action that then needs to be follow, need to be specified (see Chapter 2, Section 2.2).
iv) Policy: realistic and achievable goal posts need to be chosen in consultation with stakeholders.

By comparison, very little time is allocated for annual assessments (generally a few months, or in an RFMO[24] Scientific Committee perhaps no more than one week) which leaves little or no time to address the very important issues listed above in sufficient depth. Rather the same, or slightly modified, population model (the “best” assessment) is applied annually to updated data, without much

[23] Management procedures are frequently criticized as being too simple to manage complex high-value fisheries.
[24] The Regional Fisheries Management Organisation (RFMO) is an inter-governmental organization that is committed to the long-term conservation and sustainable use of the fish resources of the South Pacific Ocean.

questioning of the reliability of such data or the validity of underlying model assumptions. Usually, data and model assumptions are accepted/rejected only once assessment diagnostics become available – in effect, putting the cart before the horse. While a good fit to the data is undeniably gratifying, it does not guarantee that the model assumptions are correct, nor that the data are representative – both can be wrong. The long-term biological and economic consequences can be disastrous when management advice is based on miss-specified "best" assessments [25]. The MP approach is precautionary: a range of operating models are specified, with associated alternative data sets, to ensure that subsequent management advice is based on control rules that are robust to different interpretations.

Furthermore, the MP paradigm presents the ideal framework to combine expertise and insight from scientists, policy makers and industry representatives when seeking to improve management of high-value fisheries:

i) scientists are exposed to the realities of fisheries management and attendant uncertainties, economic objectives and social constraints;
ii) industry members are informed regarding the risk-return trade-offs and potential long-term gains associated with healthy biomass levels; and
iii) policy makers get insight into biological and economic implications of alternative strategies.

In contrast, the assessment paradigm does not present any formal structure to incorporate viewpoints and hypotheses from different interest groups. Isolating the assessment scientists from the "real" aspects of fisheries management may well be counterproductive: better and more complex mathematical/statistical assessment models do not automatically translate into improved resource management! This lack of discourse may lead to management recommendations that are not consistent with scientific advice[26], with possibly dire biological and economic consequences.

Indeed, both approaches would be beneficial to high-value data-rich resource management. A simple (but nevertheless robust) MP approach would serve as a cost-effective management option which in turn allows for savings to be better spent on the collection of key data. This allows for costly and complex assessments to be performed less regularly, serving rather as a "check and balance" every four or five years. Moreover, in conjunction, each approach could benefit from the other: complex assessment techniques are invaluable when developing operating models, while the inclusive nature of the MP approach may yield valuable insights for parameterising assessments.

[25] For example, persistent retrospective patterns in assessments of New England witch flounder have led to catch limits that are too high, resulting in the lack of recovery of the resource (Section 4.7.3).
[26] Prior to the adoption of the EU management plan in 2007, formal TAC advice exceeded scientific advice by a large margin for North Sea sole (Section 4.7.1).

5.4 Last word: how do we get there?

With so many fisheries to manage and relatively few fisheries scientists to develop the complex models on which advice is typically based, it seems unavoidable that much of fisheries management becomes simpler and more generic. Automated management advice in the form of MPs is nothing new and has been well researched within the Scientific Committee of the IWC, and implemented successfully in some parts of the world.

However, going the MP route is not a process that can be performed by fishery scientists alone in offices with fast computers. While part of the process can be delegated to the numerical scientist (that of setting up the operating models and harvest control rules), the approach requires the input of other specialists to make it work: key stakeholders and interest groups such as policy makers, representatives from industry and the fishing communities, ecologists, conservationists, biologists and economists, need to take part in the process to ensure that objectives are prioritised, realistic goals are set given the trade-offs which apply, and targets are achievable.

At the World Conference on Stock Assessment Methods held in Boston in 2013, Sidney Holt[27] stressed in his keynote address that management procedures, rather than assessment procedures, are needed. He emphasised the need to focus on forecasting rather than assessing to achieve successful fisheries management.

Perhaps the two paradigms can be compared best using a non-scientific analogy: the choice between the assessment and MP approach can be likened to choosing between an expensive supercar (the complex statistical assessment) and the humble hatchback (the empirical MP). The one is an expensive and complex piece of machinery (the likelihood maximised) that needs regular tuning and a dedicated highly qualified mechanical intervention (the mathematician/statistician). It is prone to overheating (over-parameterisation and non-convergence) and breaking (model and data errors) which are difficult to fix. It is difficult, even dangerous, to drive for an ordinary person (the non-statistician/mathematician), easy to crash (no drive-assist included), and does not handle speed bumps and potholes (noisy data and conflicting indices) well. It is great for the occasional drive on perfect tarmac (multiyear stock assessments with a full complement of reliable age data), but not designed for everyday commuting by all (on-going management for the majority of stocks). Mostly, the supercar is great as a prototype and test vehicle (operating models on which MPs can be tested). Everybody wants one, but few people can afford it!

[27] Best known as co-founder, with R. Beverton, of modern fisheries science.

On the other hand, the humble hatchback (simple empirical MP) is inexpensive, mass produced (generic) and cheap to run (low data costs). It is simple and reliable and readily understood by non-petrol-heads (members of industry, policy makers, politicians, NGOs), easy to drive (once implemented the MP runs as if on autopilot) and easy to maintain (simple control rules implemented over 4/5 year cycles). It can handle speed bumps and potholes and, while not as fast as the supercar (doesn't give as high catches), it is more likely to get to the destination on time (reach management objectives within chosen time-frames).

Ideally, every respectable garage (fishery) should have both (assessment and MP). However, that would be unrealistic. Due to financial constraints and lack of a adequate technical skills, particularly in the developing world, a more economically viable and practical solution is needed. Generic MPs designed for data-poor situations are strong candidates to provide this.

Acknowledgements

First and foremost, I would like to express my sincere thanks to my supervisor, Emeritus Professor Doug Butterworth, for his relentless efforts to stimulate international interest in this work and ensure close working relationships with global experts in the field of quantitative fisheries management. Well-respected internationally, and ever-present at scientific meetings and workshops all over the world, his contribution to the field of fisheries management is enormous. Thank you, Doug, for your undying enthusiasm for all things fishy!

Members of the Marine Resource Assessment and Management Group (MARAM) with whom I share an office at the University of Cape Town must be thanked for their general support and comments over the last four years. I am particularly grateful to Susan Holloway, William Robinson and Andrea Ross-Gillespie for volunteering for the tiresome job of proof-reading this thesis.

With regard to the work reported in Chapter 3, I would like to thank Colin Attwood and Sven Kerwath for insights into the management of the South African data-poor linefisheries. Comments and suggestions by André Punt, Ana Parma and Toshihide Kitakado regarding technical aspects of the generic data-poor study are much appreciated.

In terms of the data-rich analyses reported in Chapter 4, I would like to express my thanks to José De Oliveira, Charlie Edwards and Laurie Kell for assistance in providing assessment data for the retrospective analyses. I would particularly like to thank David Millar and Jan Jaap Poos for their insightful comments as well as deserved criticism regarding the retrospective studies.

If the final product is partly correct but wholly wrong, rather than wholly correct but partly wrong, then the author alone is to blame!

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Appendix A: Specifications for generic data-poor simulation testing

A.1 Historic data

For purposes of this exercise, a pseudo stock has been selected that has been depleted to well below the maximum sustainable level ($MSYL = B^{sp}_{msy} / K^{sp}$), with historic catches having been high at the start of the fishery after which they are reduced later to prevent further resource depletion. The historic catches assumed for the pseudo fishery for the pre-management period ($y = 1$ to $n = 40$) are given in Table A.1.

Year	Catch (metric 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 (metric 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 historic catches in tons assumed for the generic analyses reported in Chapter 3.

A.2 Generation of resource monitoring data

In order to perform the projections, future data need to be generated from the operating models that represent possible true realities. The different candidate management procedures used in the projections rely on these data (except for the constant catch rule) to set the yearly TAC over the projection period. The MPs simulation tested in this work include two harvest control rules based on mean length of fish harvested, and two control rules based on a direct index of abundance (survey or CPUE). This is in addition to the constant catch rule that requires no data. Technical specifications for generating the mean length data and the abundance index data are given below.

A.2.1 Mean length data

The annual mean length of the catch, when allowing for observation error, is given by:

$$\bar{L}_y = \sum_{a=a_{\min}}^{m} P_{y,a} L_a \qquad \text{(A.1)}$$

where L_a is the length of fish of age a as per the von Bertalanffy growth curve given by equation (A.4) below, and

$P_{y,a} = P_{y,a} e^{\varphi_{y,a} - \sigma_l^2/(2P_{y,a})}$ is the predicted proportion of fish caught of age a in year y which is renormalized such that $\sum_{a=a_{\min}}^{m} P_{y,a} = 1$.

In the formulation above $P_{y,a}$ denotes the proportion of fish of age a caught in year y of the simulation, given by:

$$P_{y,a} = \frac{C_{y,a}}{\sum_{a'=a_{\min}}^{m} C_{y,a'}}$$

where $C_{y,a}$ is the total number of fish caught of age a in year y, given by equations (2.4), and $\varphi_{y,a} \sim N(0, \sigma_L^2 / P_{y,a})$ reflects the variability for which the variance is assumed to be greater for those ages where sample sizes are smaller, where σ_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 that for fisheries such as that for South African hake. This "Punt-Kennedy" distribution form assumption for composition data is advocated by Maunder (2011) in his comparative review of a number of such approaches.

A.2.2 CPUE data

The CPUE data are generated assuming that the abundance index is log-normally distributed about its expected value such that:

$$I_y = \hat{I}_y e^{\varepsilon_y} \tag{A.2}$$

where

I_y is the abundance index generated for year *y*,

$\hat{I}_y = \hat{q}\ B_y^{\exp}$ is the corresponding model value, where $B_y^{\exp}$ is the model value of exploitable resource biomass, given by equations (2.12) or (2.13),

$\hat{q}$ 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

$\varepsilon_y \sim N(0,\sigma_{CPUE}^2)$ where σ_{CPUE} is the coefficient of variation (CV) associated with the resource abundance index. A value of $\sigma_{CPUE} = 0.2$, consistent with what might be expected in practice, is assumed for data generation purposes.

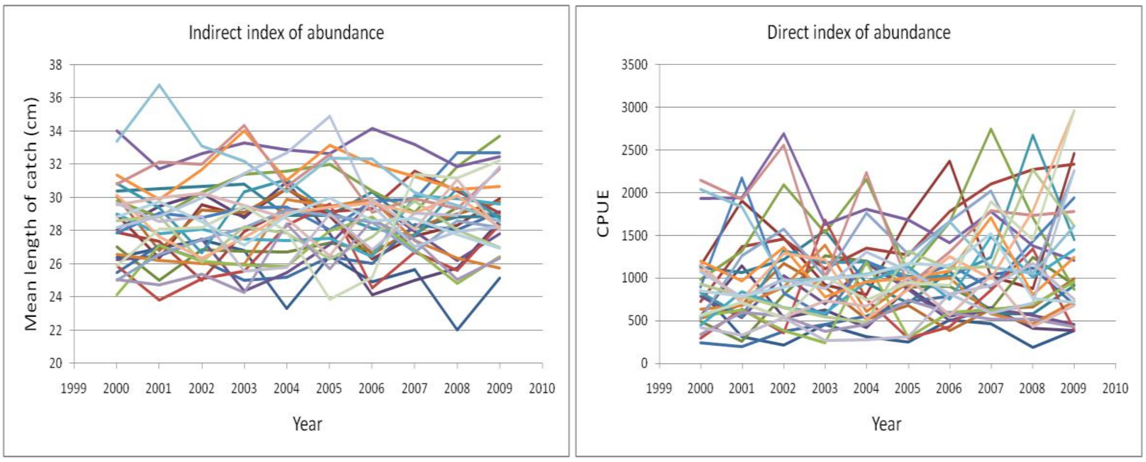


Figure A.1: Annual historic mean length (left) and CPUE (right) data generated by the operating model (30 from a total of 8000 simulations shown here).

A.3 Model parameters

Parameter values were chosen to reflect typical values for fish of intermediate size and longevity such as South African horse mackerel and hake.

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 these calculations this is approximated by a knife-edge form with $f_a = 0$ or $a < 3$ and $f_a = 1$ for $a \geq 3$.

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 South African horse mackerel or hake.

Fishing selectivity: An age-dependent fishing selectivity of the form

S_a=[0, 0.2, 0.4, 0.6, 0.8, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0] for ages $a = 0, 1, ..., 9, 10+$

is assumed. Log-normally distributed variability about these values is taken to be correlated across both ages and years (Butterworth *et al.* 2001), such that:

$$S_{y,a} = S_a e^{\tau_{y,a} - \sigma_\tau^2/2} \tag{A.3}$$

where

$\tau_{1,a_{\min}} \sim N(0, \sigma_\tau{}^2)$ 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 generated for ages $a=a_{min}+1$ 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 $a_{\min}$ and year y,

$\chi_{y,a} \sim N(0, \sigma_\tau^2)$,

σ_τ is the standard deviation of the log-residuals, which is input ($\sigma_\tau = 0.4$ is used here), and

ρ is the auto correlation coefficient, which is input ($\rho = 0.5$ is assumed for these calculations).

Mass-at-age: The mass (w) of a fish at age (a) is assumed to follow a von Bertalanffy growth equation:

$$w_a = \alpha\,[l_\infty(1-\exp(-\kappa(a-t_0)))\,]^{\beta} \tag{A.4}$$

Parameter values for the South African horse mackerel stock are chosen as typical for species of intermediate size and longevity (Butterworth *et al.* 2010):

$\alpha = 0.0078$ g,

$\beta = 3.0$,

$l_\infty = 54.56$ cm,

$\kappa = 0.183$ yr^{-1}, and

$t_0 = -0.654$ yr.

A.4 Yield-per-recruit analysis

It is increasingly becoming standard practice to evaluate the whether a resource has been overfished, or whether overfishing is taking place, by comparison of current levels of spawning stock biomass B^{sp} or of fishing mortality F to their corresponding values at MSY: B^{sp}_{MSY} and F_{MSY}. A difficulty arises in data-poor situations, however, where there is insufficient information to estimate these MSY reference points directly. This section provides a simple approach to achieve this in a data-poor situation where resource status is indexed only by information on the mean mass or mean length of the species harvested. It achieves this through an equilibrium per-recruit analysis, and uses a conventional default often adopted when applying the US Magnuson-Stevens Act: that MSY is achieved a situation where the spawning biomass per recruit (B^{sp}/R) has been reduced to 35% of its value in the absence of fishing. (Note that actually values in the range 30% to 40% are typically used, with the 35% chosen here a representative example.)

The information required for the analysis is:

- Values of the parameters of a somatic growth curve;
- A value for the natural mortality rate *M;*
- Values for selectivity-at-age and maturity-at-age;
- Values of the parameters of a weight length relationship.

Note that if some of these parameter values have not been estimated directly for the stock under consideration, then the values available for another stock of the same species or an ecologically similar species could be used.
In terms of the population model equations set out in Chapter 2, the population numbers per recruit are given by:

$$N_{a\min} = 1 \tag{A.5}$$

$$N_{a+1} = N_a e^{-(M_a + S_a F)} \qquad \textit{for} \qquad a_{\min} \le a \le m-2 \tag{A.6}$$

$$N_m = N_{m-1} e^{-(M_{m-1} + S_{m-1} F)} + N_m e^{-(M_m + S_m F)} \tag{A.7}$$

where

N_a is the number (per recruit) of fish of age *a*,

M_a denotes the natural mortality rate on fish of age *a* (assumed here to be age-independent),

S_a is the age-specific selectivity,

F is the fishing mortality,

m is the maximum age considered (taken to be a plus-group), and

$a_{\min}$ is the minimum age considered.

The spawning biomass per recruit is given by:

$$B^{sp}/R = \sum_{a=amat}^{m} w_a N_a \tag{A.8}$$

where w_a is the begin-year mass of fish of age *a.*

The yield per recruit is given by:

$$Y/R = \sum_{a=a\min}^{m} w_{a+1/2} N_a \frac{S_a F}{Z_a}(1-e^{-Z_a}) \tag{A.9}$$

Given the model parameters of Section A.3 for the pseudo stock under consideration, the equilibrium mean length and mean mass can be estimated in terms of spawning biomass for different natural mortality rates, M, as shown in the top two plots below. These are followed by spawning biomass-per-recruit relative to its pristine value and yield-per-recruit plots as a function of fishing mortality F.

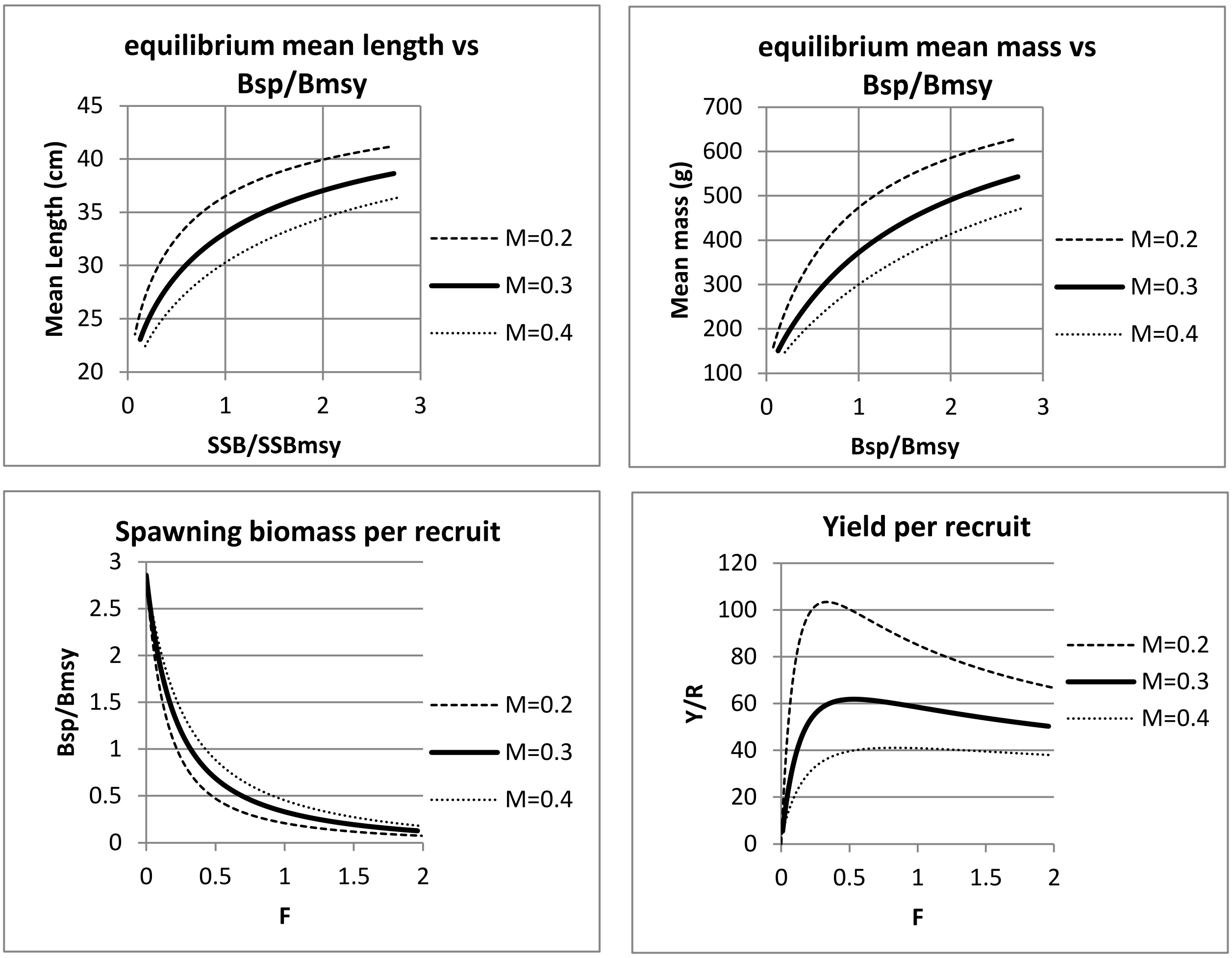


Figure A.2: Equilibrium spawning biomass and yield per recruit plots with corresponding mean length and mass targets. Model parameters (selectivity vector and growth parameters) are given in Section A.3 of this Appendix.

A.5 Robustness tests

A key uncertainty when dealing with a data-poor resource is associated with the reliability of a limited set of data, in particular the historical catch series. Rather that assume that the historical catches are known without error, simulated catch data are generated assuming that total removals are log-normally distributed about the reported historical catches, i.e.:

$$C_y = \hat{C}_y e^{\varepsilon_y^C - \sigma_C^2/2} \tag{A.10}$$

where

C_y is the true catch in year y,

$\hat{C}_y$ is the reported catch for year *y*, which is input (Table A.1), and

$\varepsilon_y^C \sim N(\mu, \sigma_C^2)$ where μ is the mean, allowing for the possibility of bias, and σ_C is the standard deviation of the log-residuals.

Uncertainty regarding future catches are incorporated in the same manner:

$$C_y = TAC_y e^{\varepsilon_y^C - \sigma_C^2/2} \tag{A.11}$$

where TAC_y is the TAC generated by the MP for year *y*.

Summary statistics for robustness trials are given in the tables that follow:

Table A.2: Robustness test OM1: implementation error (undetected fluctuations about an unbiased catch series).

Table A.3: Robustness test OM2: implementation error (detected fluctuations about an unbiased catch series).

Table A.4: Robustness test OM3: implementation error (detected fluctuations about negatively biased catch series).

Table A.5: Robustness tests OM1-OM5: MP Ltarget4 (extremely data-poor).

Table A.6: Robustness tests OM6-OM9: MP Ltarget4 (extremely data-poor).

Table A.7: Robustness tests with combined effects: MP Ltarget4 (extremely data-poor).

OM1: Implementation error (undetected fluctuations about unbiased catch series)					
	CC4: $TAC^* = 0.7C^{ave}$	**LstepCC4:** $TAC^* = 0.7C^{ave}$	**Ltarget4:** $L^0 = 0.9L^{ave}$ $L^{target} = 1.15L^{ave}$ $TAC^{target} = 0.8C^{ave}$ $w = 0.5$ $\lvert\Delta TAC_{y+1}\rvert \le 15\%$	**Islope3:** $TAC^* = 0.6C^{ave}$ $\lambda = 0.4$ $p = 5$	**Itarget4:** $L^0 = 0.8L^{ave}$ $I^{target} = 2.5I^{ave}$ $TAC^{target} = 0.7C^{ave}$ $w = 0.5$ $\lvert\Delta TAC_{y+1}\rvert \le 15\%$
$B^{sp}_{current} / K^{sp}$	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)
B^{sp}_{final} / K^{sp}	0.48 (0.18, 0.81)	0.46 (0.18, 0.79)	0.49 (0.20, 0.81)	0.47 (0.22, 0.78)	0.49 (0.24,0.79)
10%-ile B^{sp}_{final} / K^{sp}	**0.25**	**0.23**	**0.26**	**0.28**	**0.29**
$B^{sp}_{current} / B^{sp}_{MSY}$	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)
$B^{sp}_{final} / B^{sp}_{MSY}$	**1.50** (0.52, 2.71)	**1.44** (0.52, 2.61)	**1.51** (0.57, 2.74)	**1.47** (0.46, 2.58)	**1.52** (0.69, 2.66)
10%-ile $B^{sp}_{final} / B^{sp}_{MSY}$	**0.71**	**0.70**	**0.77**	**0.80**	**0.86**
$\overline{TAC}$	350	388 (210, 488)	342 (290, 409)	366 (298, 457)	326 (256, 470)
AAV	0.03 (0.03, 0.03)	0.07 (0.04, 0.15)	0.08 (0.06, 0.11)	0.08 (0.06, 0.11)	0.11 (0.08, 0.14)
$\bar{C}$	349 (314, 387)	384 (208, 492)	342 (282,418)	365 (291, 467)	327 (251,474)

Table A.2: Robustness to fluctuations about historical and future TAC (undetected fluctuations): medians (with 5% and 95%-iles in parenthesis) are shown for pertinent management quantities for the best performing MPs of previous tables in the presence of implementation error. The 10%-iles for biomass depletion estimates are also shown to compare with limit reference points for these quantities. 8000 simulations were performed. Units, where pertinent, are tons. Quantities are printed in bold if management's conservation targets are achieved.

OM2: Implementation error (detected fluctuations about unbiased catch series)					
	CC4: $TAC^{*} = 0.7C^{ave}$	**LstepCC4:** $TAC^{*} = 0.7C^{ave}$	**Ltarget4:** $L^{0} = 0.9L^{ave}$ $L^{target} = 1.15L^{ave}$ $TAC^{target} = 0.8C^{ave}$ $w = 0.5$ $\left\|\Delta TAC_{y+1}\right\| \leq 15\%$	**Islope3:** $TAC* = 0.6C^{ave}$ $\lambda = 0.4$ $p = 5$	**Itarget4:** $L^{0} = 0.8L^{ave}$ $I^{target} = 2.5I^{ave}$ $TAC^{target} = 0.7C^{ave}$ $w = 0.5$ $\left\|\Delta TAC_{y+1}\right\| \leq 15\%$
$B^{sp}_{current} / K^{sp}$	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)
B^{sp}_{final} / K^{sp}	0.49 (0.18,0.80)	0.46 (0.17, 0.80)	0.49 (0.19, 0.81)	**0.51** (0.28, 0.80)	0.49 (0.22,0.79)
10%-ile B^{sp}_{final} / K^{sp}	**0.26**	**0.25**	**0.26**	**0.33**	**0.29**
$B^{sp}_{current} / B^{sp}_{MSY}$	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)
$B^{sp}_{final} / B^{sp}_{MSY}$	**1.52** (0.51,2.72)	**1.44** (0.50, 2.66)	**1.51** (0.55, 2.71)	**1.57** (0.83, 2.64)	**1.52** (0.66, 2.64)
10%-ile $B^{sp}_{final} / B^{sp}_{MSY}$	**0.63**	**0.72**	**0.74**	**0.98**	**0.84**
$\overline{TAC}$	348 (300, 403)	382 (208, 495)	343 (276, 426)	303 (207, 486)	331 (247, 474)
AAV	0.03 (0.01, 0.5)	0.07 (0.03, 0.15)	0.08 (0.05, 0.12)	0.13 (0.09, 0.20)	0.11 (0.08, 0.14)
$\overline{C}$	348 (289, 417)	380 (207, 505)	342 (269, 434)	302 (203, 488)	331 (243,477)

Table A.3: As for Table A.2, but here the true catches are known, i.e. the MPs are tested over a range of different historical catch series.

OM3: Implementation error (detected fluctuations about negatively biased catch series)					
	CC4: $TAC^{*} = 0.7C^{ave}$	**LstepCC4:** $TAC^{*} = 0.7C^{ave}$	**Ltarget4:** $L^{0} = 0.9L^{ave}$ $L^{target} = 1.15L^{ave}$ $TAC^{target} = 0.8C^{ave}$ $w = 0.5$ $\lvert\Delta TAC_{y+1}\rvert \le 15\%$	**Islope3:** $TAC* = 0.6C^{ave}$ $\lambda = 0.4$ $p = 5$	**Itarget4:** $L^{0} = 0.8L^{ave}$ $I^{target} = 2.5I^{ave}$ $TAC^{target} = 0.7C^{ave}$ $w = 0.5$ $\lvert\Delta TAC_{y+1}\rvert \le 15\%$
$B^{sp}_{current} / K^{sp}$	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)
B^{sp}_{final} / K^{sp}	0.46 (0.15,0.78)	**0.50** (0.22, 0.82)	0.46 (0.16, 0.78)	0.45 (0.19, 0.75)	0.47 (0.22,0.76)
10%-ile B^{sp}_{final} / K^{sp}	**0.22**	**0.28**	**0.23**	**0.25**	**0.28**
$B^{sp}_{current} / B^{sp}_{MSY}$	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)
$B^{sp}_{final} / B^{sp}_{MSY}$	**1.42** (0.42,2.63)	**1.55** (0.64, 2.74)	**1.43** (0.47, 2.61)	**1.40** (0.53, 2.48)	**1.47** (0.63, 2.54)
10%-ile $B^{sp}_{final} / B^{sp}_{MSY}$	**0.65**	**0.82**	**0.69**	**0.72**	**0.80**
$\overline{TAC}$	387 (359, 315)	345 (188, 428)	375 (313, 453)	399 (323, 505)	359 (278, 509)
AAV	0.03 (0.02, 0.4)	0.08 (0.05, 0.15)	0.08 (0.06, 0.11)	0.08 (0.06, 0.11)	0.11 (0.08, 0.14)
$\bar{C}$	427 (391, 467)	381 (208, 476)	415 (344, 503)	441 (356, 562)	396 (305,565)

Table A.4: As for Table A.3, but here the log-residuals are drawn from a normal distribution with mean $\mu = 0.1$, i.e. catch series is negatively biased.

MP Ltarget4: Extremely data-poor					
	OM1: Implementation error (undetected): $\varepsilon^C \sim N(0.0, 0.2^2)$	**OM2:** Implementation error (known): $\varepsilon^C \sim N(0.0, 0.2^2)$	**OM3:** Implementation error (biased, known): $\varepsilon^C \sim N(0.1, 0.1^2)$	**OM4:** True catch 40% below reported catch from 2000-2009 (undetected)	**OM5:** True catch 40% above reported catch from 2000-2009 (undetected)
$B^{sp}_{current} / K^{sp}$	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)
B^{sp}_{final} / K^{sp}	0.49 (0.20, 0.81)	0.49 (0.19, 0.81)	0.46 (0.16, 0.78)	0.47 (0.17, 0.79)	0.50 (0.21, 0.83)
10%-ile B^{sp}_{final} / K^{sp}	**0.26**	**0.26**	**0.23**	**0.24**	**0.27**
$B^{sp}_{current} / B^{sp}_{MSY}$	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)
$B^{sp}_{final} / B^{sp}_{MSY}$	1.51 (0.57, 2.74)	1.51 (0.55, 2.71)	1.43 (0.47, 2.61)	1.44 (0.51, 2.58)	1.56 (0.60, 2.80)
10%-ile $B^{sp}_{final} / B^{sp}_{MSY}$	**0.77**	**0.74**	**0.69**	**0.72**	**0.79**
$\overline{TAC}$	342 (290, 409)	343 (276, 426)	375 (313, 453)	354 (298, 421)	327 (280, 390)
AAV	0.08 (0.06, 0.11)	0.08 (0.05, 0.12)	0.08 (0.06, 0.11)	0.08 (0.05, 0.10)	0.09 (0.06, 0.12)
$\bar{C}$	342 (282,418)	342 (269, 434)	415 (344, 503)	354 (298, 421)	327 (280, 390)

Table A.5: Robustness tests OM1 to OM5 for MP Ltarget4 (extremely data-poor).

MP Ltarget4: Extremely data-poor					
	OM6: Extreme depletion: $B^{sp}/K^{sp}=0.05$	**OM7:** Less productive: $M=0.1yr^{-1}$	**OM8:** Increase observation error: $\sigma_L=0.35$	**OM9a:** Selectivity shifted left (fully selected from age 4)	**OM9b:** Selectivity shifted right (fully selected from age 8)
$B^{sp}_{current}/K^{sp}$	0.05 (0.05,0.05)	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)
B^{sp}_{final}/K^{sp}	0.02 (0.0, 0.41)	0.32 (0.12, 0.51)	0.49 (0.21, 0.81)	0.48 (0.20, 0.80)	0.47 (0.23, 0.78)
10%-ile B^{sp}_{final}/K^{sp}	0.0	0.16	**0.27**	**0.26**	**0.28**
$B^{sp}_{current}/B^{sp}_{MSY}$	0.15 (0.13,0.18)	0.63 (0.34,0.96)	0.61 (0.33,0.95)	0.64 (0.34,0.99)	0.46 (0.24,0.76)
$B^{sp}_{final}/B^{sp}_{MSY}$	0.07 (0.0, 1.44)	1.00 (0.36, 1.74)	1.51 (0.58, 2.72)	1.54 (0.58, 2.79)	1.09 (0.56, 2.38)
10%-ile $B^{sp}_{final}/B^{sp}_{MSY}$	0.0	0.48	**0.79**	**0.78**	**0.67**
$\overline{TAC}$	287 (250, 354)	316 (280, 362)	339 (283, 407)	344 (291, 410)	534 (461, 610)
AAV	0.09 (0.07, 0.12)	0.08 (0.06, 0.11)	0.08 (0.06, 0.12)	0.08 (0.06, 0.11)	0.08 (0.07, 0.10)

Table A.6: Robustness tests OM6 and OM9 for MP Ltarget4 (extremely data-poor).

MP Ltarget4: Extremely data-poor			
	OM2 + OM4: Implementation error (known) and true catches below reported catches 2000-2009 (undetected): $\varepsilon^C \sim N(0.0, 0.2^2)$	**OM2 + OM5:** Implementation error (known) and true catches above reported catches 2000-2009 (undetected): $\varepsilon^C \sim N(0.0, 0.2^2)$	**OM2 + OM5:** Implementation error (known) and true catches above reported catches 2000-2009 (known): $\varepsilon^C \sim N(0.0, 0.2^2)$
$B^{sp}_{current} / K^{sp}$	0.20 (0.11,0.29)	0.20 (0.11,0.29)	0.20 (0.11,0.29)
B^{sp}_{final} / K^{sp}	0.46 (0.16, 0.78)	0.50 (0.18, 0.90)	0.40 (0.05, 0.75)
10%-ile B^{sp}_{final} / K^{sp}	**0.23**	**0.26**	0.13
$B^{sp}_{current} / B^{sp}_{MSY}$	0.61 (0.33,0.95)	0.61 (0.33,0.95)	0.61 (0.33,0.95)
$B^{sp}_{final} / B^{sp}_{MSY}$	1.41 (0.47, 2.54)	1.55 (0.53, 2.79)	1.24 (0.13, 2.51)
10%-ile $B^{sp}_{final} / B^{sp}_{MSY}$	**0.69**	**0.76**	0.38
$\overline{TAC}$	354 (282, 440)	328 (262, 410)	445 (359, 556)
$\overline{\Delta TAC}$	0.08 (0.05, 0.11)	0.09 (0.06, 0.12)	0.09 (0.06, 0.12)
$\bar{C}$	354 (276, 450)	228 (256, 419)	446 (349, 563)

Table A.7: Robustness tests alternatively combining the effects of OM2 with OM4 and OM5 for MP Ltarget4 (very data-poor).

Appendix B: Input to projections

B.1 North Sea Sole

The 2010 VPA/XSA stock assessment (ICES 2010) for North Sea Sole is used as basis for this retrospective comparison.The natural mortality rates and maturity ogive used in the stock assessment, and as assumed here for the retrospective projections commencing in 1990, are given in Table B1.1 of Appendix B. To take into account the effect of the severe winter during 1962 to 1963, a value of 0.9 for natural mortality rate was used for 1963.

Stock–recruitment parameters required for the deterministic and stochastic projections, estimated by fitting a two-line ("hockey-stick") and Beverton-Holt function to the 2010 XSA assessment estimates for spawning biomass and recruitment, are given in Table B1.2.

The observed annual catches, 2010 XSA estimated number of recruits (1-yr-olds) and associated spawning biomasses are given in Table B1.3. The 2010 XSA population numbers-at-age matrix, with plusgroup adjusted for consistency according to Section 4.4.2 of Chapter 4, is given in Table B1.4, with the adjusted fishing mortality-at-age matric given in Table B1.5.

The age-aggregated BTS-Isis and SNS survey indices of abundance are given in Table B1.6.

A visual representation of the data are given in Figures B1.1 to B1.12:

Figure B1.1: Annual TACs and total annual landings of Sole in Subarea IV in tons along with log residuals shown on the right axis.

Figure B1.2: Adjusted plusgroup population numbers compared to the VPA/XSA estimates for Sole in Subarea IV.

Figure B1.3: Adjusted plusgroup catch compared to observed catch for Sole in Subarea IV.

Figure B1.4: Age-aggregated survey indices of abundance for Sole in Subarea IV.

Figure B1.5: Trajectories for various biomass components from the VPA/XSA assessment for Sole in Subarea IV with plusgroup adjusted as detailed in the text.

Figure B1.6: Number of recruits (1-yr-olds) estimated in the 2010 VPA/XSA assessment for Sole in Subarea IV and number of recruits in terms of a two-line and Beverton-Holt stock-recruit functions fitted to data from 1957 to 1989 (forecast).

Figure B1.7: Annual number of recruits (1-yr-olds) estimated in the 2010 VPA/XSA assessment for Sole in Subarea IV compared to the number of recruits in terms of the two-line and Beverton-Holt stock-recruit functions.

Figure B1.8: VPA/XSA estimated fishing selectivities-at-age for Sole (Subarea IV) for the historic period from 1957 to 1989.

Figure B1.9: VPA/XSA estimated fishing selectivities for Sole in Subarea IV over the projection period from 1990 to 2009.

Figure B1.10: Age-aggregated survey indices of abundance estimated from survey numbers-at-age as a fraction of the adjusted XSA estimated population numbers-at-age for Sole in Subarea IV.

Figure B1.11 Landing weights (kg) for Sole in Subarea IV for each age group.

Figure B1.12 Population weights (kg) for Sole in Subarea IV for each age group.

Age	1	2	3	4	5	6	7	8	9	10
Natural mortality rate	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Maturity	0.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
BTS-Isis survey selectivity	1.00	0.84	0.39	0.26	0.35	0.22	0.28	0.16	0.47	

Table B1.1: Natural mortality-at-age, maturity-at-age and survey selectivity vectors.

		two-line			Beverton-Holt		
	Period	σ_R	α (thousands)	B^0 (tons)	σ_R	α (thousands)	β (tons)
Deterministic	1957-2009	0.745	93345	17857	0.750	111522	8074
Stochastic	1957-1989	0.829	91226	22280	0.835	106895	7739

Table B2.2: Stock-recruit function parameters.

Year	Number of recruits	Spawning biomass	Total catch
1957	128913	60713	12067
1958	128646	64446	14287
1959	488778	66599	13832
1960	61716	71980	18620
1961	99499	113421	23566
1962	22899	111614	26877
1963	20424	106822	26164
1964	539159	36250	11342
1965	121982	28686	17043
1966	39909	83085	33340
1967	75191	81938	33439
1968	99252	68048	33179
1969	50869	51582	27559
1970	137891	44507	19685
1971	42107	39149	23652
1972	76403	43523	21086
1973	105045	34480	19309
1974	109975	33280	17989
1975	40825	35680	20773
1976	113295	37232	17326
1977	140307	30380	18003
1978	47127	34920	20280
1979	11664	42679	22598
1980	151574	32895	15807
1981	148896	22280	15403
1982	152374	31867	21579
1983	141488	39308	24927
1984	70850	42631	26839
1985	81670	39661	24248
1986	159308	32562	18201
1987	72702	28693	17368
1988	455761	38698	21590
1989	108274	33199	21805
1990	177524	89328	35120
1991	70435	77064	33513
1992	353383	76294	29341
1993	69162	54425	31491
1994	56976	74044	33002
1995	95962	58771	30467
1996	49342	37138	22651
1997	270702	29097	14901
1998	113617	20843	20868
1999	82211	41474	23475
2000	123072	38011	22641
2001	62890	30306	19944
2002	183396	30855	16945
2003	83962	24764	17920
2004	44153	36962	18757
2005	48196	31460	16355
2006	216019	23789	12594
2007	55007	17857	14635
2008	81516	37490	14071
2009	102743	34414	13952

Table B1.3: Number of recruits and spawing biomass estimates from the 2010 XSA assessment, with total annual catches for Sole in Subarea IV.

Year	1	2	3	4	5	6	7	8	9	10
1957	128913	72455	89309	59106	17319	15058	27046	11837	2500	46183
1958	128646	116645	64214	71157	41456	12092	10843	18272	9062	34616
1959	488778	116404	103781	50075	50907	28474	7627	6950	12311	29191
1960	61716	442265	101846	82467	35416	37526	20278	5754	4362	29304
1961	99499	55843	388723	78710	58640	23192	25996	13739	3691	22703
1962	22899	90030	49617	304373	53013	41261	16519	19770	8361	18195
1963	20424	20719	79946	38988	219104	33371	27307	10356	13977	17730
1964	539159	8304	7993	27187	10396	59622	8154	6857	2666	7985
1965	121982	487799	7366	5222	19166	5784	37457	4405	4483	6525
1966	39909	110374	396576	5629	3204	12584	2872	22002	2504	6396
1967	75191	36111	88191	231736	4152	1776	7877	1891	13893	5680
1968	99252	68036	29169	55369	128708	1898	1097	5302	988	10948
1969	50869	88820	45250	13175	26344	70258	1278	760	3234	7082
1970	137891	45652	57613	20539	6855	12054	39659	841	455	5724
1971	42107	123534	35467	27405	10751	4505	7833	24508	527	3786
1972	76403	37700	80036	18370	12662	5462	2705	4874	15314	2407
1973	105045	68792	26889	37454	9892	6734	3453	1950	3238	10857
1974	109975	94380	50614	12171	18492	5122	3883	2179	1037	7712
1975	40825	99414	70768	25308	5793	10016	2806	2006	1346	4697
1976	113295	36689	68119	36890	11754	3256	5419	1788	952	3297
1977	140307	101523	29828	35034	20050	6051	2027	3088	1095	2039
1978	47127	125294	70623	15505	17141	11065	3783	1531	1736	2139
1979	11664	42617	89560	36039	8200	9194	5969	1770	804	2135
1980	151574	10546	30781	41875	17332	4570	5255	3739	825	1821
1981	148896	136544	8392	15951	20977	8742	2755	2665	2043	1275
1982	152374	134324	95758	4493	7902	11158	4428	1592	1568	1819
1983	141488	135343	96396	43130	2313	3788	5541	2410	855	1822
1984	70850	127653	89734	47855	18870	1499	2116	3159	1250	1272
1985	81670	63926	86270	39406	21847	8712	652	1103	1866	1277
1986	159308	73741	42036	36955	16359	10823	4501	391	637	1824
1987	72702	143792	57817	20440	16600	7433	4547	1913	249	1187
1988	455761	65694	102472	31344	10030	8826	3759	2624	872	855
1989	108274	412380	46868	47840	13872	4908	4293	1926	1527	575
1990	177524	97859	329012	25036	21738	8154	2869	2518	1127	1302
1991	70435	159810	77190	198343	13363	10924	4192	1604	1139	1062
1992	353383	63618	132081	45664	105355	5695	6388	2142	767	649
1993	69162	318822	51065	77298	25905	58879	2797	2888	1233	581
1994	56976	62529	240492	30255	40065	10247	30413	1114	1487	997
1995	95962	50871	49155	134466	14487	18427	3840	16760	567	792
1996	49342	82263	33885	28476	56443	7108	9723	1576	9444	557
1997	270702	44482	56528	15260	9629	25144	2762	4251	529	5718
1998	113617	243429	34497	28652	6840	3854	10582	1356	1634	1916
1999	82211	102573	166378	16812	11719	2864	1641	5040	472	1081
2000	123072	74114	77819	81610	7424	4791	1438	853	2673	369
2001	62890	109124	52724	39272	33128	3590	1979	537	358	1745
2002	183396	56064	74154	27165	16628	14061	1891	997	225	965
2003	83962	164940	40215	35848	12889	7231	6590	1071	335	629
2004	44153	74975	118490	19743	17131	6126	2828	3651	589	521
2005	48196	39460	53619	61584	8805	8408	3484	1702	2390	307
2006	216019	42510	28650	26504	27640	3913	3852	1703	954	1597
2007	55007	188980	29247	16307	15098	14889	2045	2027	871	1385
2008	81516	49471	133054	16108	8623	8200	8228	1067	1141	807
2009	102743	71932	38866	85491	8984	5072	5188	5008	548	981

Table B1.4: Population numbers-at-age for Sole in Subarea IV taken from 2010 ICES XSA assessment, but with plusgroup adjusted as described in text.

Year	1	2	3	4	5	6	7	8	9	10
1957	0.000	0.021	0.127	0.255	0.259	0.228	0.292	0.167	0.241	0.241
1958	0.000	0.017	0.149	0.235	0.276	0.361	0.345	0.295	0.303	0.303
1959	0.000	0.034	0.130	0.246	0.205	0.239	0.182	0.366	0.248	0.248
1960	0.000	0.029	0.158	0.241	0.323	0.267	0.289	0.344	0.294	0.294
1961	0.000	0.018	0.145	0.295	0.252	0.239	0.174	0.397	0.272	0.272
1962	0.000	0.019	0.141	0.229	0.363	0.313	0.367	0.247	0.304	0.304
1963	0.000	0.053	0.179	0.422	0.402	0.509	0.482	0.457	0.479	0.479
1964	0.000	0.020	0.326	0.250	0.486	0.365	0.516	0.325	0.390	0.390
1965	0.000	0.107	0.169	0.388	0.321	0.600	0.432	0.465	0.443	0.443
1966	0.000	0.124	0.437	0.204	0.490	0.368	0.318	0.360	0.349	0.349
1967	0.000	0.114	0.365	0.488	0.683	0.382	0.296	0.549	0.481	0.481
1968	0.011	0.308	0.695	0.643	0.505	0.296	0.268	0.394	0.422	0.422
1969	0.008	0.333	0.690	0.553	0.682	0.472	0.318	0.412	0.489	0.489
1970	0.010	0.152	0.643	0.547	0.320	0.331	0.381	0.367	0.390	0.390
1971	0.011	0.334	0.558	0.672	0.577	0.410	0.374	0.370	0.483	0.483
1972	0.005	0.238	0.659	0.519	0.531	0.358	0.227	0.309	0.390	0.390
1973	0.007	0.207	0.693	0.606	0.558	0.451	0.360	0.532	0.503	0.503
1974	0.001	0.188	0.593	0.642	0.513	0.502	0.561	0.382	0.522	0.522
1975	0.007	0.278	0.551	0.667	0.476	0.514	0.351	0.645	0.506	0.506
1976	0.010	0.107	0.565	0.510	0.564	0.374	0.463	0.391	0.634	0.634
1977	0.013	0.263	0.554	0.615	0.494	0.370	0.181	0.476	0.282	0.282
1978	0.001	0.236	0.573	0.537	0.523	0.517	0.660	0.544	0.496	0.496
1979	0.001	0.225	0.660	0.632	0.485	0.459	0.368	0.663	0.379	0.379
1980	0.004	0.128	0.557	0.591	0.584	0.406	0.579	0.504	0.630	0.630
1981	0.003	0.255	0.525	0.602	0.531	0.580	0.449	0.430	0.501	0.501
1982	0.019	0.232	0.698	0.564	0.635	0.600	0.508	0.521	0.520	0.520
1983	0.003	0.311	0.600	0.727	0.334	0.482	0.462	0.556	0.644	0.644
1984	0.003	0.292	0.723	0.684	0.673	0.733	0.552	0.426	0.581	0.581
1985	0.002	0.319	0.748	0.779	0.602	0.561	0.411	0.448	0.444	0.444
1986	0.002	0.143	0.621	0.700	0.689	0.767	0.756	0.351	0.629	0.629
1987	0.001	0.239	0.512	0.612	0.532	0.582	0.450	0.686	0.419	0.419
1988	0.000	0.238	0.662	0.715	0.615	0.621	0.569	0.442	0.999	0.999
1989	0.001	0.126	0.527	0.689	0.431	0.437	0.434	0.436	0.379	0.379
1990	0.005	0.137	0.406	0.528	0.588	0.565	0.482	0.694	0.727	0.727
1991	0.002	0.091	0.425	0.533	0.753	0.436	0.572	0.637	1.121	1.121
1992	0.003	0.120	0.436	0.467	0.482	0.611	0.694	0.452	0.791	0.791
1993	0.001	0.182	0.423	0.557	0.827	0.561	0.820	0.564	0.499	0.499
1994	0.013	0.141	0.481	0.636	0.677	0.882	0.496	0.576	1.043	1.043
1995	0.054	0.306	0.446	0.768	0.612	0.539	0.790	0.474	0.792	0.792
1996	0.004	0.275	0.698	0.984	0.709	0.845	0.727	0.991	0.459	0.459
1997	0.006	0.154	0.580	0.702	0.816	0.765	0.611	0.856	1.082	1.082
1998	0.002	0.281	0.619	0.794	0.771	0.754	0.642	0.955	1.089	1.089
1999	0.004	0.176	0.612	0.717	0.794	0.589	0.554	0.534	1.336	1.336
2000	0.020	0.241	0.584	0.802	0.627	0.784	0.886	0.768	0.456	0.456
2001	0.015	0.286	0.563	0.759	0.757	0.541	0.585	0.769	0.679	0.679
2002	0.006	0.232	0.627	0.646	0.733	0.658	0.469	0.992	0.537	0.537
2003	0.013	0.231	0.611	0.638	0.644	0.839	0.490	0.499	0.515	0.515
2004	0.012	0.235	0.554	0.707	0.612	0.464	0.408	0.324	1.187	1.187
2005	0.026	0.220	0.605	0.701	0.711	0.681	0.616	0.479	0.424	0.424
2006	0.034	0.274	0.464	0.463	0.519	0.549	0.542	0.570	0.511	0.511
2007	0.006	0.251	0.496	0.537	0.510	0.493	0.551	0.475	0.928	0.928
2008	0.025	0.141	0.342	0.484	0.431	0.358	0.397	0.567	0.586	0.586
2009	0.017	0.164	0.341	0.391	0.479	0.415	0.385	0.384	0.899	0.899

Table B1.5: Fishing mortality-at-age for Sole in Subarea IV taken from the 2010 ICES XSA assessment, but with plusgroup adjusted as described in text.

Year	BTS-Isis	SNS
1957		
1958		
1959		
1960		
1961		
1962		
1963		
1964		
1965		
1966		
1967		
1968		
1969		
1970		293.271
1971		326.698
1972		129.932
1973		388.106
1974		149.056
1975		188.455
1976		113.629
1977		278.598
1978		312.679
1979		151.525
1980		222.524
1981		396.531
1982		487.724
1983		323.870
1984		355.336
1985	2.709	315.860
1986	2.003	267.961
1987	3.190	260.693
1988	6.819	716.098
1989	11.912	863.145
1990	11.015	523.502
1991	7.270	667.303
1992	11.310	698.119
1993	10.028	579.423
1994	5.658	268.420
1995	6.043	226.161
1996	3.088	75.031
1997	10.290	579.225
1998	5.459	690.122
1999	6.940	297.214
2000	2.854	156.842
2001	2.810	170.643
2002	2.772	470.770
2003	3.117	
2004	1.898	247.183
2005	1.664	76.286
2006	1.637	166.041
2007	3.942	195.469
2008	5.085	167.186
2009	3.350	180.814

Table B1.6: Age-aggregated survey biomass indices for Sole in Subarea IV.

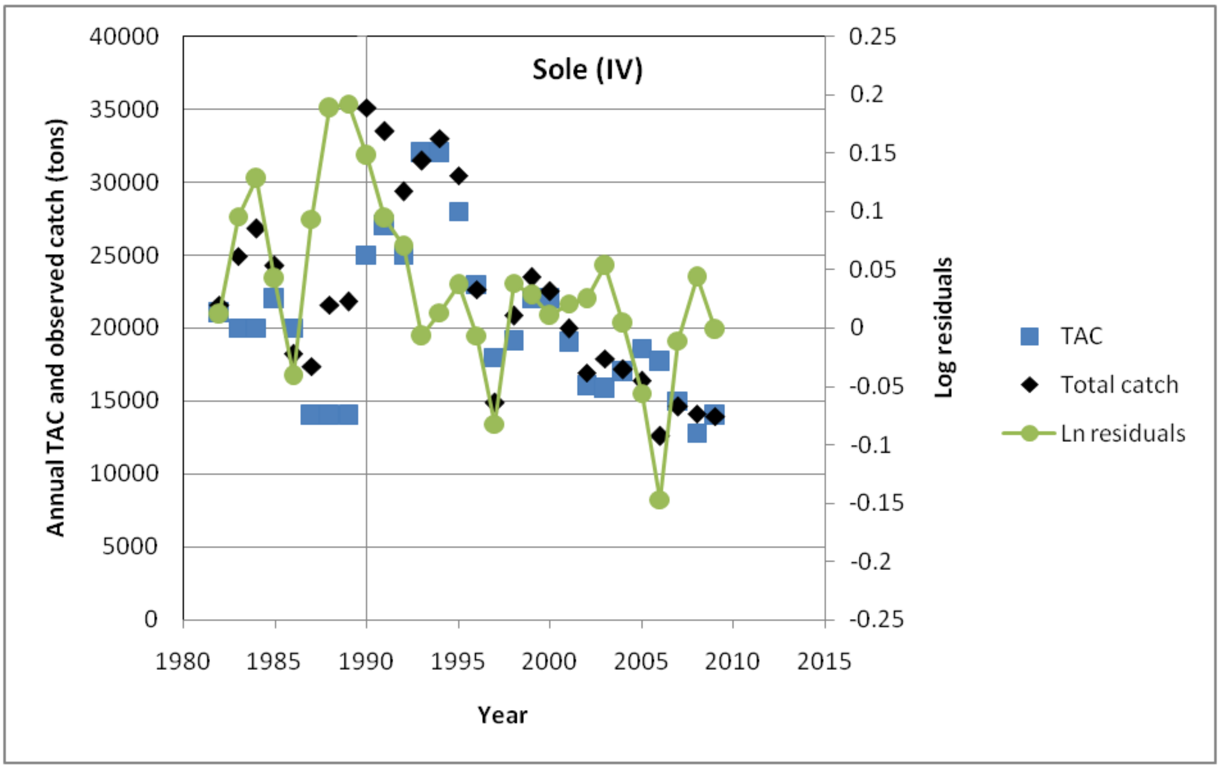


Figure B1.1: Total annual catches of Sole in Subarea IV in tons (black diamonds) with annual TACs indicated by the blue squares. The log residuals (circles) are shown on the right axis.

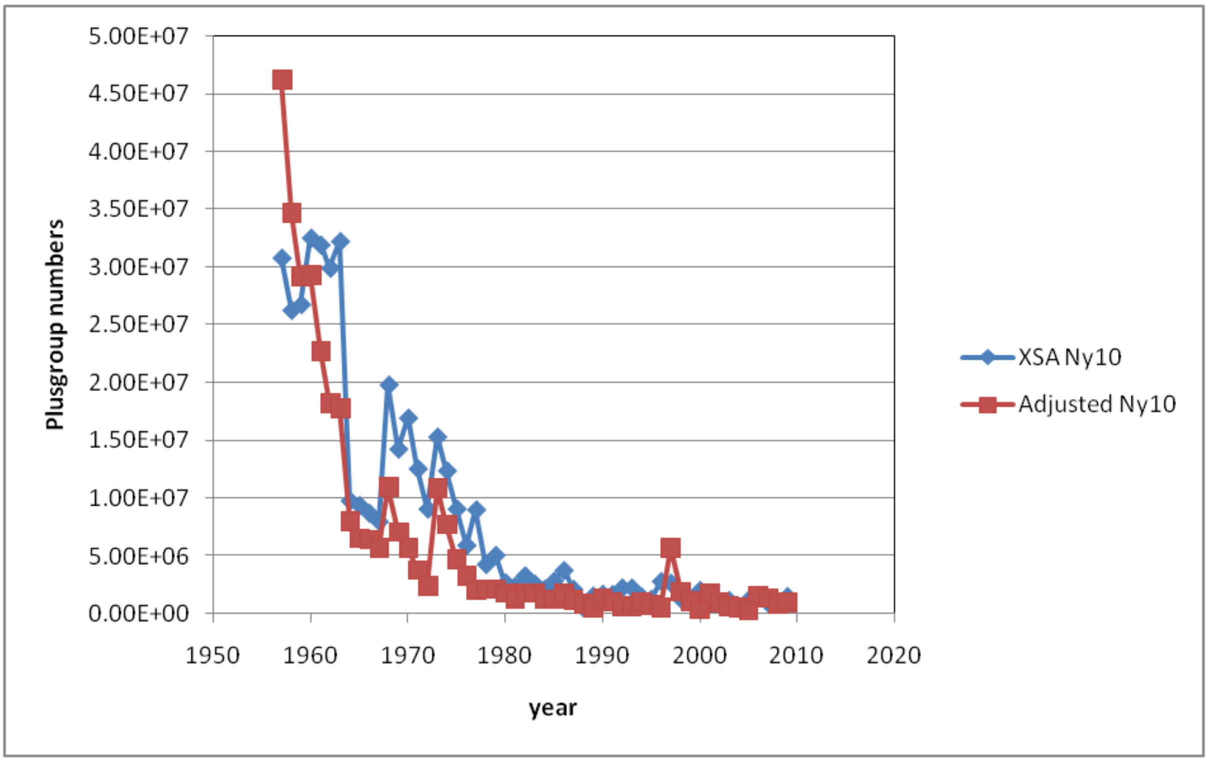


Figure B1.2: Adjusted plusgroup population numbers compared to the VPA/XSA estimates for Sole in Subarea IV.

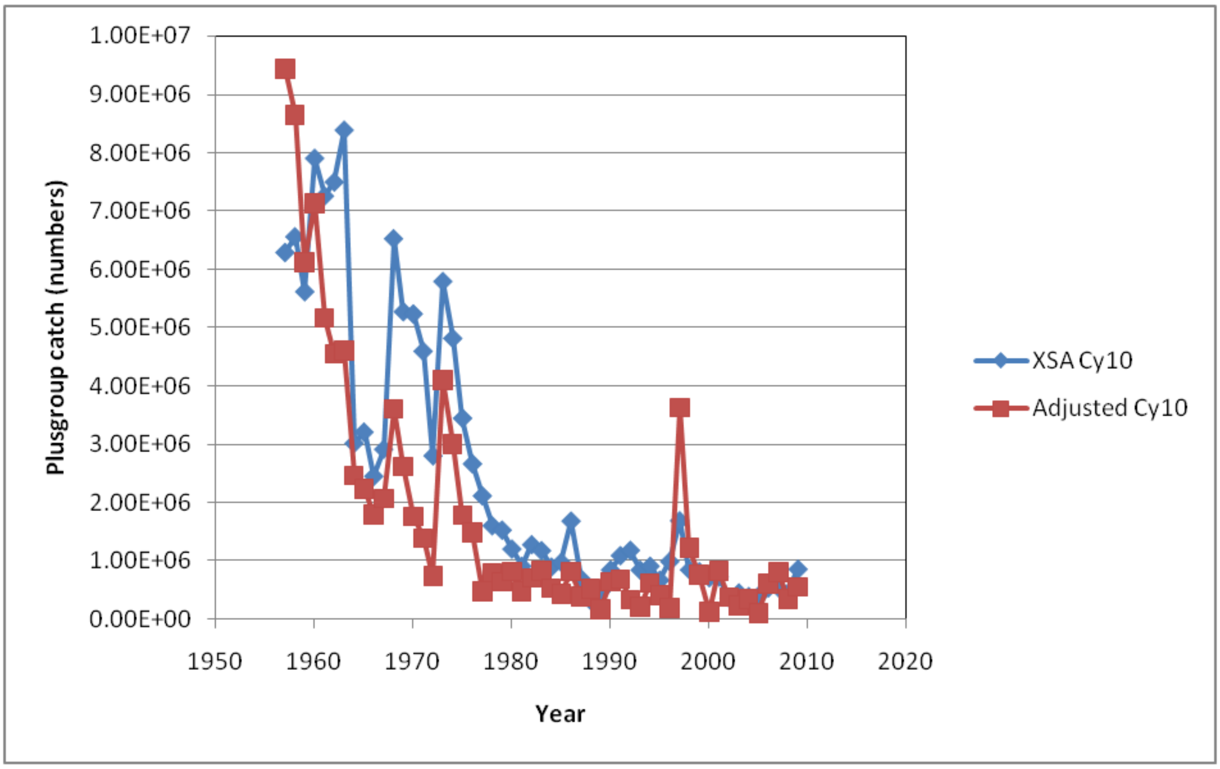


Figure B1.3: Adjusted plusgroup catch compared to observed catch for Sole in Subarea IV.

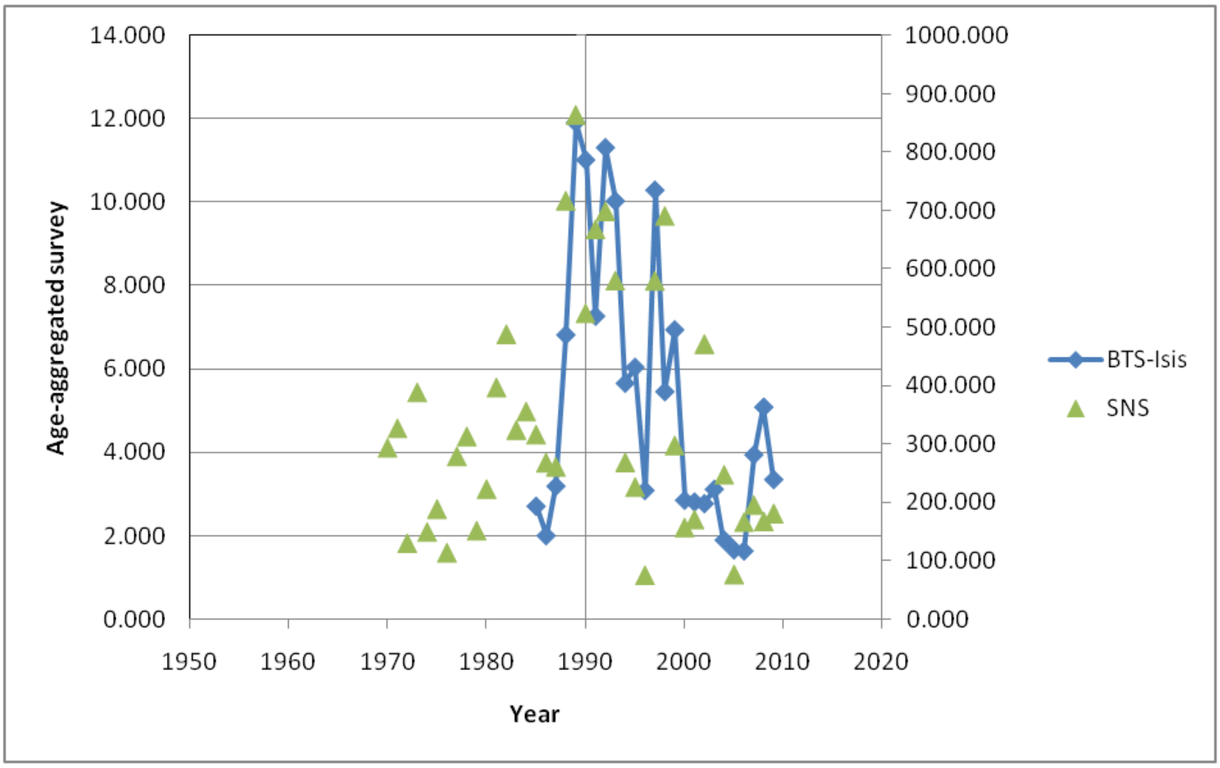


Figure B1.4: Age-aggregated survey indices of abundance for Sole in Subarea IV.

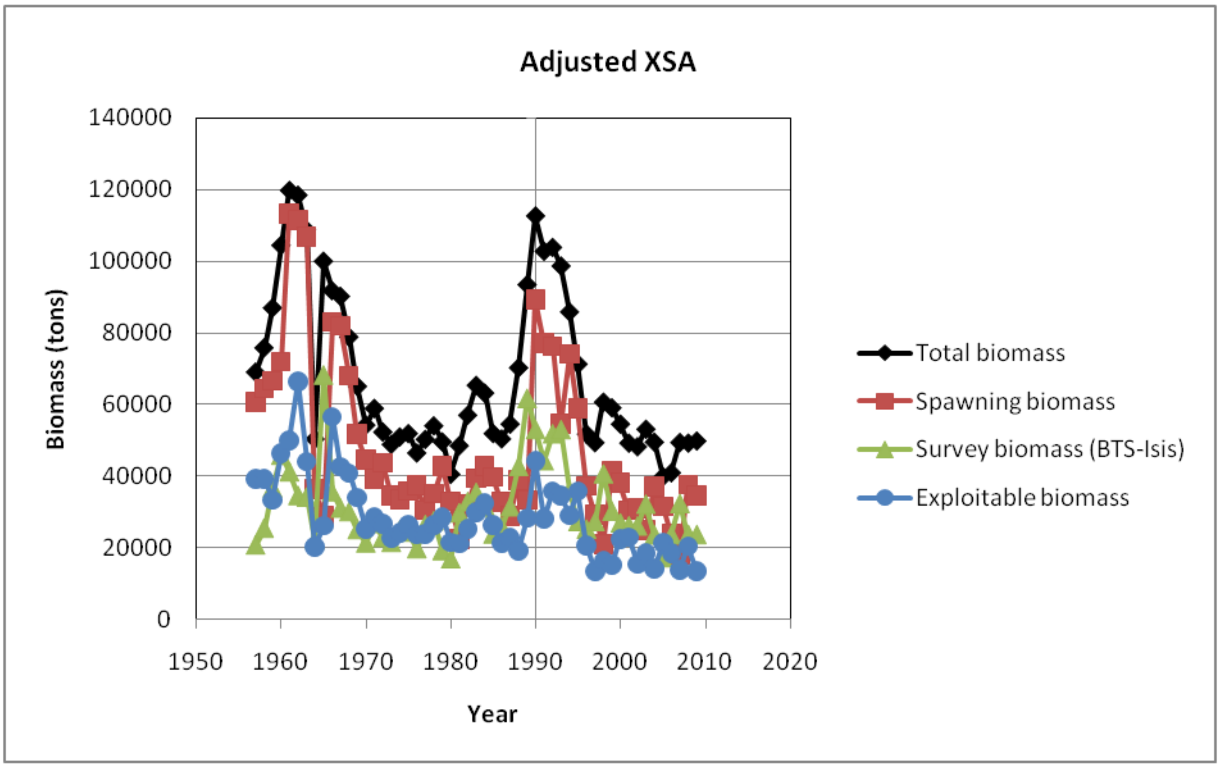


Figure B1.5: Trajectories for various biomass components from the VPA/XSA assessment for Sole in Subarea IV with plusgroup adjusted as detailed in the text.

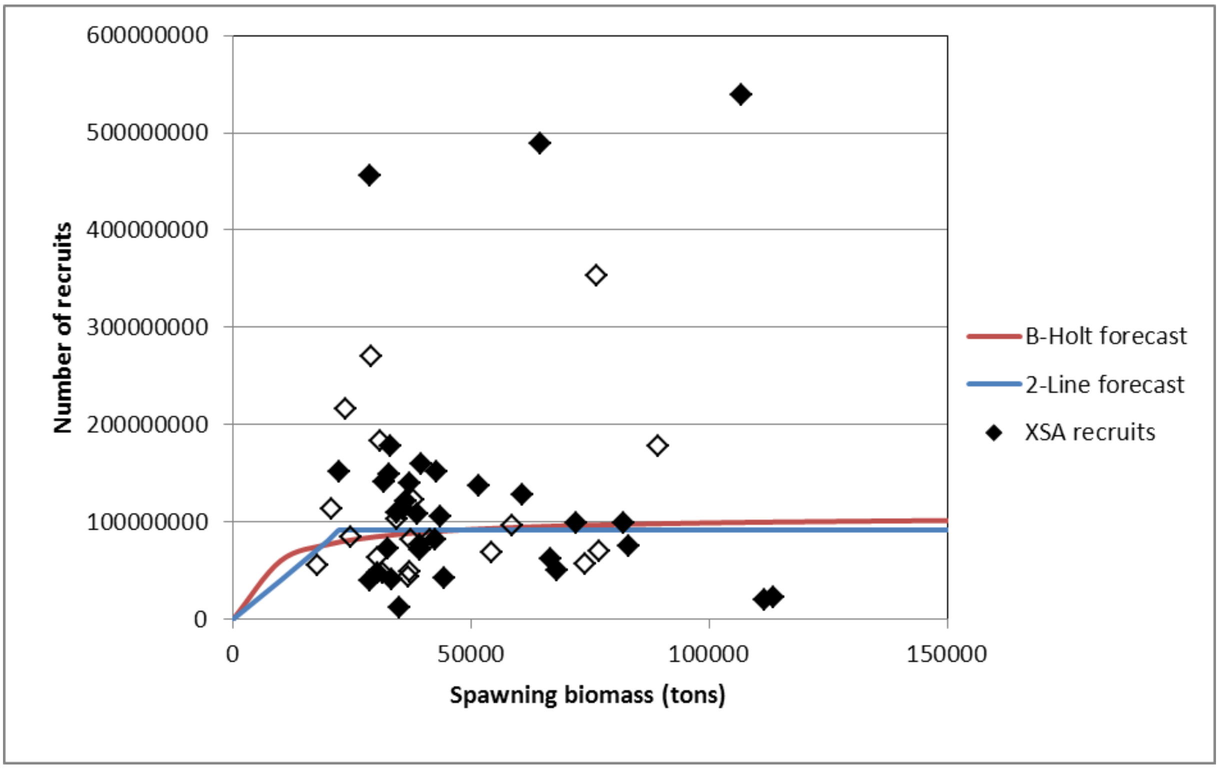


Figure B1.6: Number of recruits (1-yr-olds) estimated in the 2010 VPA/XSA assessment for Sole in Subarea IV (diamonds) compared to the number of recruits in terms of a Beverton Holt stock–recruitment curve when fixing *h* to 0.9 and a two-line stock recruit relationship fitted to data from 1957 to 1989 (forecast). Recruitments from 1990 onwards are shown by open diamonds.

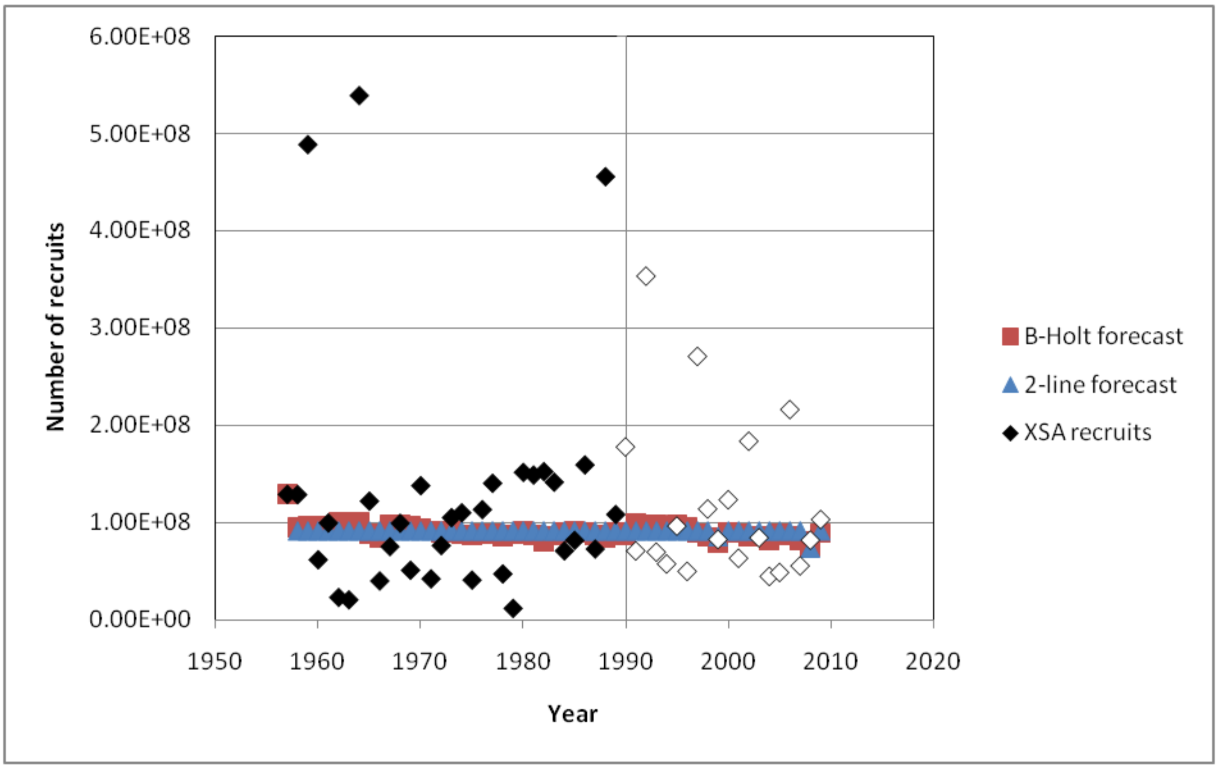


Figure B1.7: Annual number of recruits (1-yr-olds) estimated in the 2010 VPA/XSA assessment for Sole in Subarea IV (diamonds) compared to the number of recruits in terms of a Beverton Holt stock–recruitment curve fixing *h*=0.9 (squares) and a two-line stock-recruit relationship (triangles).

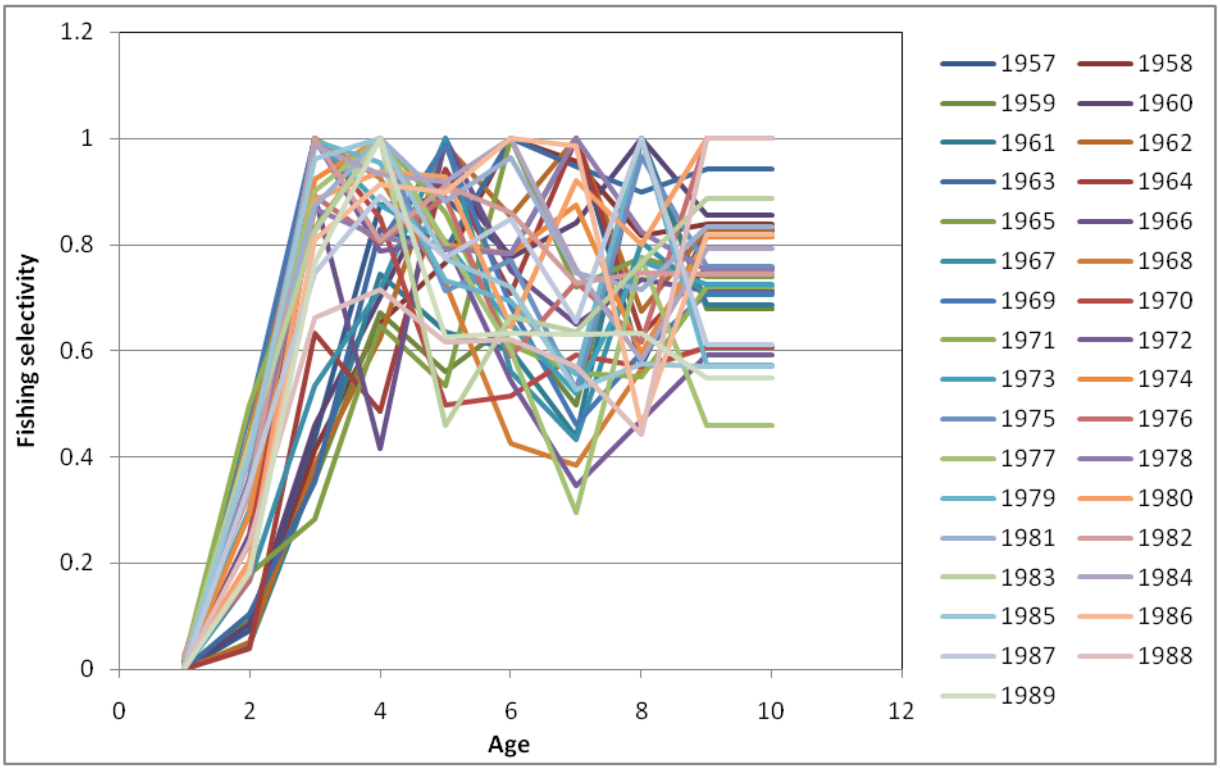


Figure B1.8: VPA/XSA estimated fishing selectivities-at-age for Sole (Subarea IV) for the historic period from 1957 to 1989. "Future" selectivity vectors for forecast projections are randomly sampled from "past" vectors from 1980 to 1989.

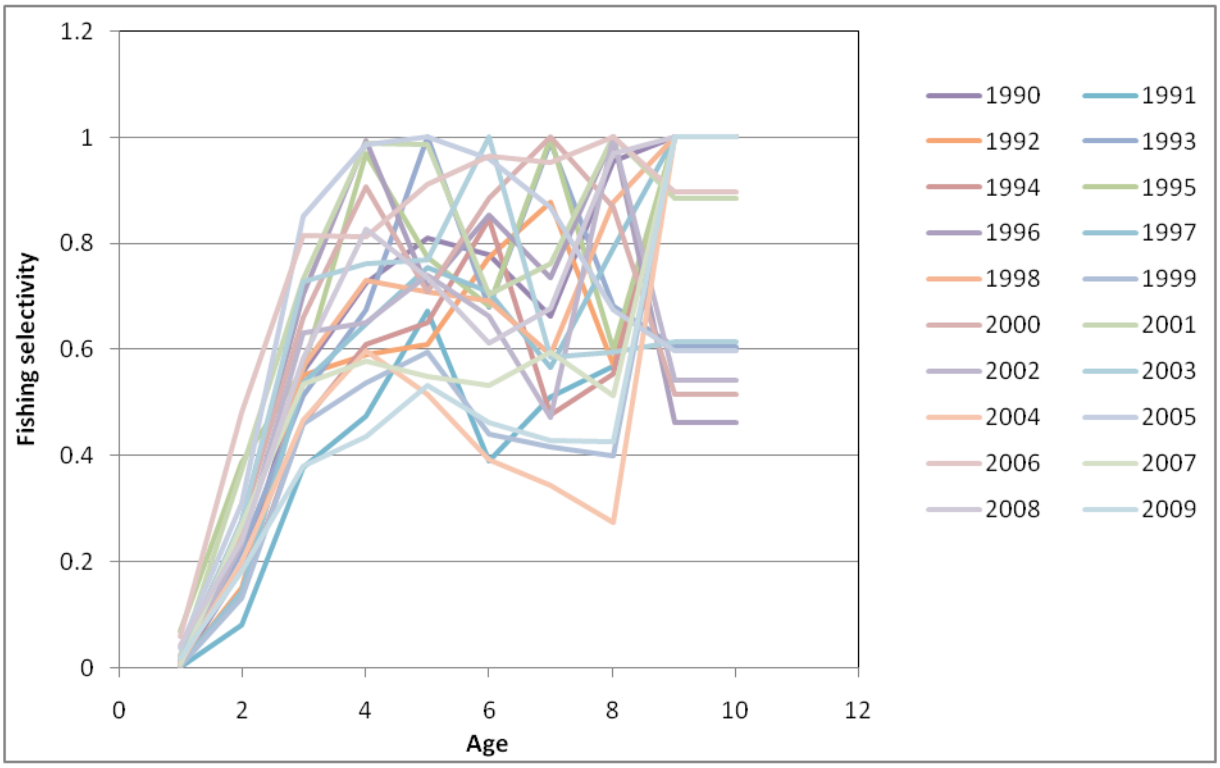


Figure B1.9: VPA/XSA estimated fishing selectivities for Sole in Subarea IV over the projection period from 1990 to 2009.

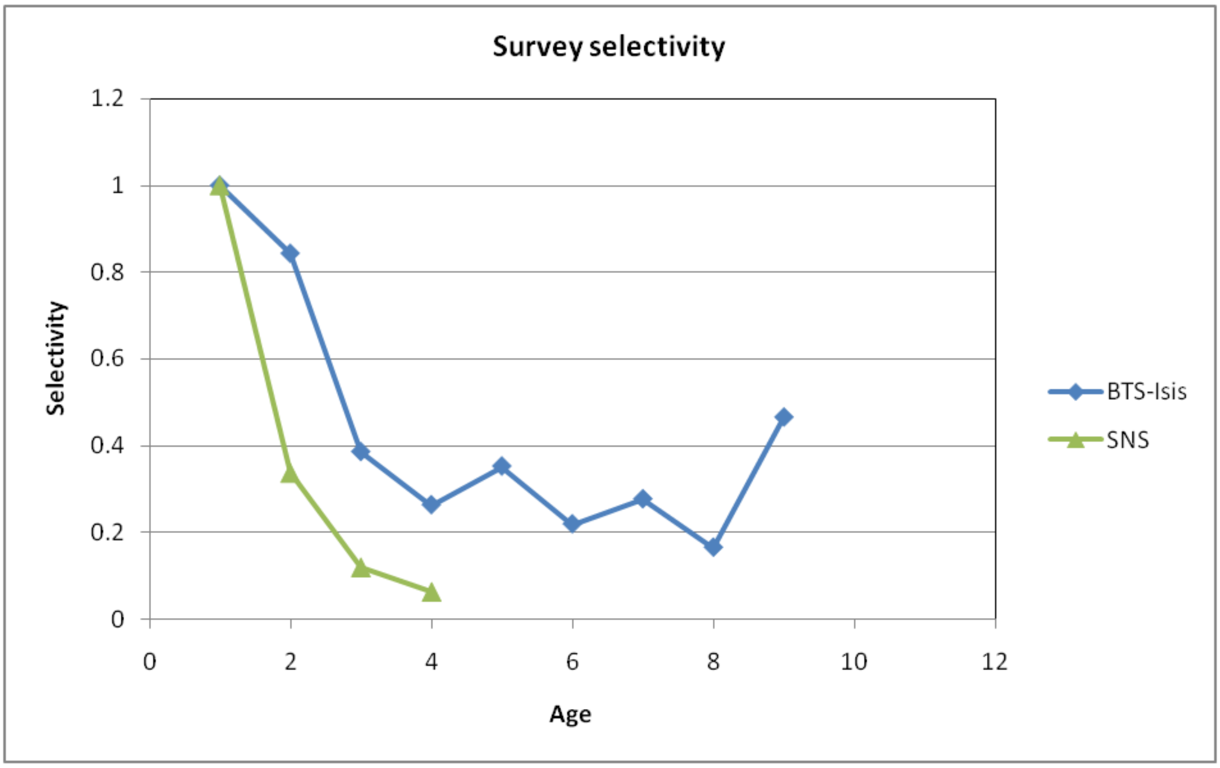


Figure B1.10: Survey selectivity vectors estimated from survey numbers-at-age as a fraction of the adjusted XSA estimated population numbers-at-age for Sole in Subarea IV.

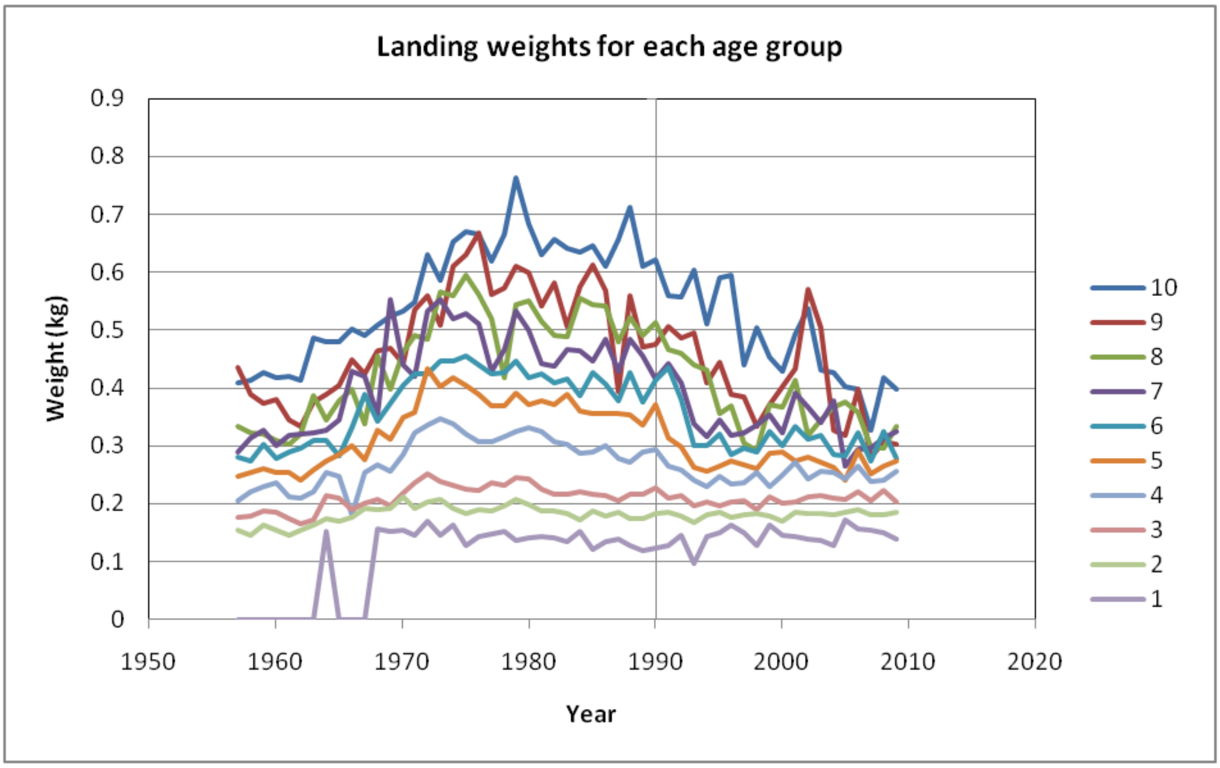


Figure B1.11 Landing weights (kg) for Sole in Subarea IV for each age group.

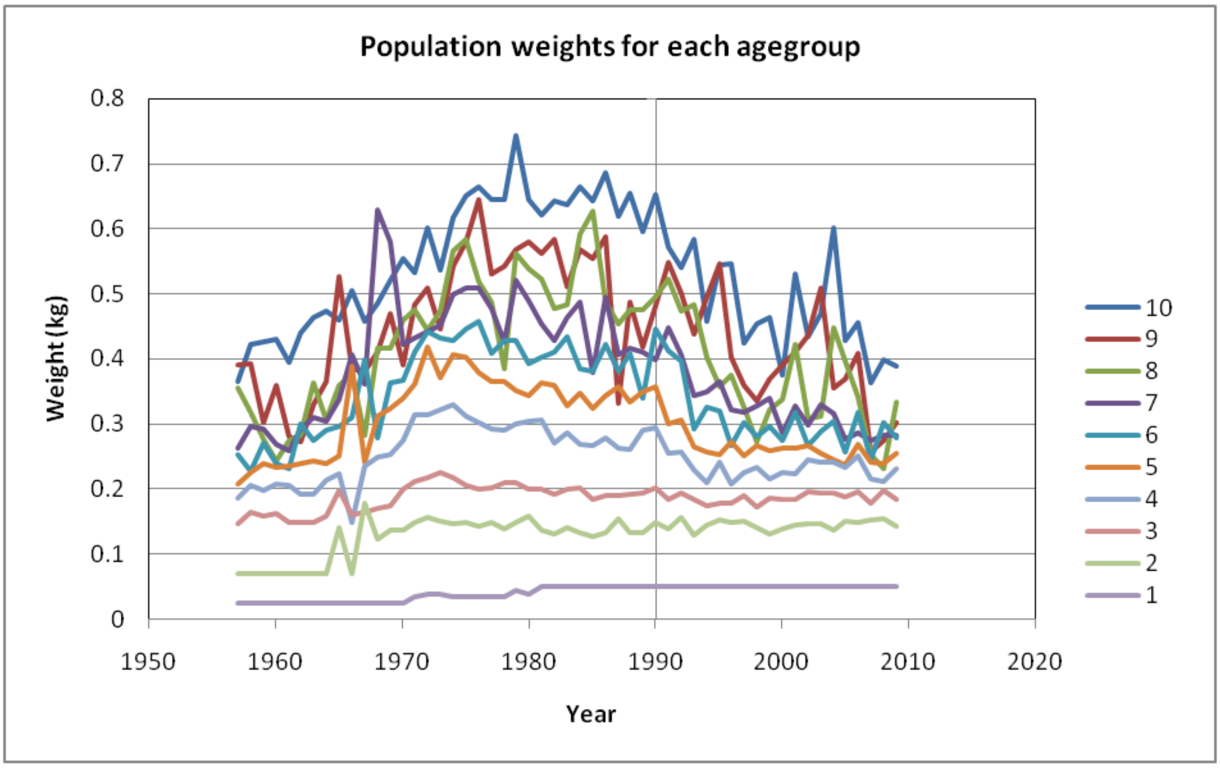


Figure B1.12 Population weights (kg) for Sole in Subarea IV for each age group.

B.2 North Sea Plaice

The 2010 VPA/XSA stock assessment (ICES 2010) for North Sea Plaice is used as basis for this retrospective comparison.The natural mortality rates and maturity ogive used in the stock assessment, and as assumed here for the retrospective projections commencing in 1990, are given in Table B2.1.

Stock–recruitment parameters required for the deterministic and stochastic projections, estimated by fitting a two-line (“hockey-stick”) and Beverton-Holt function to the 2010 XSA assessment estimates for spawning biomass and recruitment, are given in Table B2.2.

The observed annual catches, 2010 XSA estimated number of recruits (1-yr-olds) and associated spawning biomasses are given in Table B2.3. The 2010 XSA population numbers-at-age matrix, with plusgroup adjusted for consistency according to Section 4.4.2 of Chapter 4, is given in Table B2.4, with the adjusted fishing mortality-at-age matric given in Table B2.5.

The age-aggregated BTS-Isis, BTS-Tridens and SNS survey indices of abundance are given in Table B2.6.

A visual representation of the data are given in Figures B2.1 to B2.12:

Figure B2.1: Annual TACs and total annual landings of Plaice in Subarea IV in tons along with log residuals shown on the right axis.

Figure B2.2: Adjusted plusgroup population numbers compared to the VPA/XSA estimates for Plaice in Subarea IV.

Figure B2.3: Adjusted plusgroup catch compared to observed catch for Plaice in Subarea IV.

Figure B2.4: Age-aggregated survey indices of abundance for Plaice in Subarea IV.

Figure B2.5: Trajectories for various biomass components from the VPA/XSA assessment for Plaice in Subarea IV with plusgroup adjusted as detailed in the text.

Figure B2.6: Number of recruits (1-yr-olds) estimated in the 2010 VPA/XSA assessment for Plaice in Subarea IV and number of recruits in terms of a two-line and Beverton-Holt stock-recruit functions fitted to data from 1957 to 1989 (forecast).

Figure B2.7: Annual number of recruits (1-yr-olds) estimated in the 2010 VPA/XSA assessment for Plaice in Subarea IV compared to the number of recruits in terms of the two-line and Beverton-Holt stock-recruit functions.

Figure B2.8: VPA/XSA estimated fishing selectivities-at-age for Plaice (Subarea IV) for the historic period from 1957 to 1989.

Figure B2.9: VPA/XSA estimated fishing selectivities for Plaice in Subarea IV over the projection period from 1990 to 2009.

Figure B2.10: Survey selectivities-at-age for Plaice in Subarea IV.

Figure B2.11 Landing weights (kg) for Plaice in Subarea IV for each age group.

Figure B2.12 Population weights (kg) for Plaice in Subarea IV for each age group.

Age	1	2	3	4	5	6	7	8	9	10
Natural mortality rate	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Maturity	0	0.5	0.5	1.0	1.0	1.0	1.0	1.0	1.0	1.0
BTS-Isis survey selectivity	1.00	0.56	0.28	0.14	0.09	0.07	0.06	0.08	0.05	

Table B2.1: Natural mortality-at-age , maturity-at-age and survey selectivity vectors.

		two-line			Beverton-Holt		
	Period	σ_R	α (thousands)	B^0 (tons)	σ_R	α (thousands)	β (tons)
Deterministic	1957-2009	0.496	927286	198132	0.512	2301950	434656
Stochastic	1957-1989	0.555	939593	250267	0.561	2147050	405406

Table B2.2: Stock-recruit function parameters.

Year	Number of recruits	Spawning biomass	Total catch	Landings	Discards
1957	457973	288705	78443	70563	7880
1958	698110	291614	88191	73354	14837
1959	863386	291514	109164	79300	29864
1960	757298	302878	117334	87541	29793
1961	860576	309561	118474	85984	32490
1962	589154	365078	125375	87472	37903
1963	688366	348818	148376	107118	41258
1964	2231500	339871	147571	110540	37031
1965	694573	316015	140223	97143	43080
1966	586777	337571	166552	101834	64718
1967	401295	403512	163365	108819	54546
1968	434277	382406	139521	111534	27987
1969	648869	350206	142820	121651	21169
1970	650576	326437	159982	130342	29640
1971	410270	291251	136939	113944	22995
1972	366617	299224	142475	122843	19632
1973	1312009	252552	143783	130429	13354
1974	1132726	259124	157485	112540	44945
1975	864773	273132	195235	108536	86699
1976	692682	292629	166917	113670	53247
1977	988665	307704	176689	119188	57501
1978	912345	295538	159639	113984	45655
1979	891239	287895	213282	145347	67935
1980	1128156	263884	171031	139951	31080
1981	865944	252209	172778	139747	33031
1982	2031170	250267	203674	154547	49127
1983	1308491	303768	218521	144038	74483
1984	1259358	314454	226963	156147	70816
1985	1848419	337665	220387	159838	60549
1986	4760609	364215	295300	165347	129953
1987	1962845	442388	344194	153670	190524
1988	1770461	382424	310898	154475	156423
1989	1186811	411792	277611	169818	107793
1990	1036516	371947	227465	156240	71225
1991	914585	343770	228939	148004	80935
1992	776744	279797	182239	125190	57049
1993	530684	242006	152129	117113	35016
1994	442947	209421	134177	110392	23785
1995	1164164	201208	120184	98356	21828
1996	1290364	202807	133722	81673	52049
1997	2155842	211554	183193	83048	100145
1998	774928	228808	175285	71534	103751
1999	840878	201461	151638	80662	70976
2000	991191	228618	125459	81148	44311
2001	540350	262660	182272	81963	100309
2002	1726207	198132	124607	70217	54390
2003	537804	230789	144294	66502	77792
2004	1248173	215963	115902	61436	54466
2005	791655	252773	109576	55700	53876
2006	922375	275293	119789	57943	61846
2007	1046417	271502	89179	49744	39435
2008	821795	347508	94749	48874	45875
2009	1017863	403767	100198	54973	45225

Table B2.3: Number of recruits and and spawing biomass estimates from the adjusted 2010 XSA assessment, with total annual catches (landings and discards) for North Sea Plaice.

Year	1	2	3	4	5	6	7	8	9	10
1957	457973	256778	322069	182986	117504	49780	48438	35192	20763	58933
1958	698110	383614	184865	225749	122171	75186	36568	33338	23255	53959
1959	863386	568706	270362	123650	142799	76063	49331	25309	22555	50581
1960	757298	670799	377298	171551	76786	85609	46907	31440	16805	45847
1961	860576	614899	441591	239779	105744	48183	50972	28949	19875	38652
1962	589154	706789	416674	283132	151855	63044	31337	32158	16921	36179
1963	688366	484324	465009	259569	172009	89026	37245	19737	20503	32369
1964	2231500	536380	304564	276885	152215	101919	50127	21480	11359	30565
1965	694573	1956330	325547	176043	156783	80258	56631	30309	13162	23972
1966	586777	586899	1355540	198052	105458	99441	43686	33776	19288	22299
1967	401295	494319	371937	832385	116531	59210	63824	23833	20304	24356
1968	434277	343893	314556	224454	500704	65484	32351	42364	13952	26340
1969	648869	322587	233484	201830	141578	314124	42894	19435	28723	25665
1970	650576	506081	213512	152352	129908	93520	185267	28910	11797	34472
1971	410270	471051	296427	118122	83215	74030	51104	92598	20156	26245
1972	366617	305254	305838	182003	72494	50103	45122	30153	55506	27947
1973	1312010	263017	188694	185322	108922	43137	29096	27149	16912	48925
1974	1132730	1060050	160417	110708	97545	57136	25825	17876	15198	37047
1975	864773	821976	643812	88838	59831	48609	32888	15753	10162	29077
1976	692682	548525	450535	342684	46074	29718	23712	18465	8620	20423
1977	988665	449171	330275	266210	201243	28417	17430	12780	10628	16840
1978	912345	647406	253598	182219	146168	93607	16894	10147	6787	14865
1979	891239	608629	381577	144234	102938	83416	50378	9636	5993	12245
1980	1128160	526305	290915	177429	66449	47031	37199	22538	4761	8377
1981	865944	804536	297898	135126	86149	36186	25369	20569	12348	6997
1982	2031170	655698	448153	151458	67118	43539	20882	13857	10914	10242
1983	1308490	1443460	353260	202293	69838	33268	23392	11676	7335	10880
1984	1259360	934165	777188	181001	86673	34500	17757	13351	6576	9367
1985	1848420	843888	486900	392310	89506	41365	18156	9917	6807	8150
1986	4760610	1286790	475587	269456	176694	49864	22568	9893	5502	7895
1987	1962840	3243130	633464	228453	129409	78140	22104	11575	4680	5789
1988	1770460	1432170	1546360	290743	99541	54212	37434	9107	6344	4891
1989	1186810	1270380	703021	723770	134181	44160	25017	17916	3122	4841
1990	1036520	869783	642864	351602	353191	64212	21540	12585	9019	2062
1991	914585	798177	490389	328242	185828	162794	32481	11758	7377	5991
1992	776744	651967	394198	229534	147764	93483	72635	15207	5661	6678
1993	530684	567595	339205	185748	106060	60448	51973	37617	7130	4530
1994	442947	385219	315695	167606	87929	45514	26903	34212	23315	4880
1995	1164160	340377	214579	155030	74346	42117	21652	9768	24869	19340
1996	1290360	932940	194551	101746	64911	31921	20918	10296	4685	36050
1997	2155840	1060700	488817	88535	44228	27742	15018	8839	5009	15152
1998	774928	1827460	432991	175218	38011	18319	12140	7538	4543	9902
1999	840878	601558	1009900	143943	54210	18214	10426	6242	4436	7747
2000	991191	639225	337810	544968	40139	25850	9929	6787	3512	7050
2001	540350	795939	400484	219442	274990	20887	14274	6708	5002	6871
2002	1726210	455774	350797	134668	81575	111630	12252	8670	4997	9302
2003	537804	1266050	228653	189466	64328	37549	64349	6567	6143	10916
2004	1248170	421550	612659	111405	106730	28747	18390	36518	4412	13717
2005	791655	907301	200817	346915	61062	76051	15049	12051	28709	14799
2006	922375	624505	496183	115723	217144	35145	54069	8405	8417	36159
2007	1046420	624515	334116	282853	72005	153819	25328	43503	5468	34097
2008	821795	872142	352979	203537	202618	50212	116243	20417	36033	32071
2009	1017860	614491	539583	245324	143705	153734	39699	90345	16765	60403

Table B2.4: Population numbers-at-age for North Sea Plaice taken from 2010 ICES XSA assessment, but with adjusted plusgroup as discussed in text.

year	1	2	3	4	5	6	7	8	9	10
1957	0.077	0.229	0.255	0.304	0.347	0.208	0.274	0.314	0.290	0.290
1958	0.105	0.250	0.302	0.358	0.374	0.321	0.268	0.291	0.323	0.323
1959	0.152	0.310	0.355	0.376	0.412	0.383	0.350	0.309	0.367	0.367
1960	0.108	0.318	0.353	0.384	0.366	0.419	0.383	0.359	0.383	0.383
1961	0.097	0.289	0.344	0.357	0.417	0.330	0.361	0.437	0.381	0.381
1962	0.096	0.319	0.373	0.398	0.434	0.426	0.362	0.350	0.395	0.395
1963	0.149	0.364	0.418	0.434	0.423	0.474	0.450	0.452	0.448	0.448
1964	0.032	0.399	0.448	0.469	0.540	0.488	0.403	0.390	0.459	0.459
1965	0.068	0.267	0.397	0.412	0.355	0.508	0.417	0.352	0.410	0.410
1966	0.071	0.356	0.388	0.430	0.477	0.343	0.506	0.409	0.435	0.435
1967	0.054	0.352	0.405	0.408	0.476	0.504	0.310	0.435	0.428	0.428
1968	0.197	0.287	0.344	0.361	0.366	0.323	0.410	0.289	0.351	0.351
1969	0.149	0.313	0.327	0.341	0.315	0.428	0.295	0.399	0.356	0.356
1970	0.223	0.435	0.492	0.505	0.462	0.504	0.594	0.261	0.467	0.467
1971	0.196	0.332	0.388	0.388	0.407	0.395	0.428	0.412	0.407	0.407
1972	0.232	0.381	0.401	0.413	0.419	0.443	0.408	0.478	0.434	0.434
1973	0.113	0.394	0.433	0.542	0.545	0.413	0.387	0.480	0.475	0.475
1974	0.221	0.399	0.491	0.515	0.596	0.452	0.394	0.465	0.486	0.486
1975	0.355	0.501	0.531	0.557	0.600	0.618	0.477	0.503	0.553	0.553
1976	0.333	0.407	0.426	0.432	0.383	0.434	0.518	0.452	0.445	0.445
1977	0.323	0.472	0.495	0.500	0.665	0.420	0.441	0.533	0.514	0.514
1978	0.305	0.429	0.464	0.471	0.461	0.520	0.461	0.427	0.470	0.470
1979	0.427	0.638	0.666	0.675	0.683	0.708	0.704	0.605	0.678	0.678
1980	0.238	0.469	0.667	0.622	0.508	0.517	0.492	0.502	0.530	0.530
1981	0.178	0.485	0.576	0.600	0.582	0.450	0.505	0.534	0.536	0.536
1982	0.242	0.518	0.695	0.674	0.602	0.521	0.481	0.536	0.565	0.565
1983	0.237	0.519	0.569	0.748	0.605	0.528	0.461	0.474	0.565	0.565
1984	0.300	0.552	0.584	0.604	0.640	0.542	0.482	0.574	0.571	0.571
1985	0.262	0.473	0.492	0.698	0.485	0.506	0.507	0.489	0.539	0.539
1986	0.284	0.609	0.633	0.633	0.716	0.714	0.568	0.648	0.739	0.739
1987	0.215	0.641	0.679	0.731	0.770	0.636	0.787	0.501	0.661	0.661
1988	0.232	0.612	0.659	0.673	0.713	0.673	0.637	0.971	0.742	0.742
1989	0.211	0.581	0.593	0.617	0.637	0.618	0.587	0.586	1.251	1.251
1990	0.161	0.473	0.572	0.538	0.675	0.582	0.505	0.434	0.515	0.515
1991	0.238	0.605	0.659	0.698	0.587	0.707	0.659	0.631	0.594	0.594
1992	0.214	0.553	0.652	0.672	0.794	0.487	0.558	0.657	0.902	0.902
1993	0.220	0.487	0.605	0.648	0.746	0.710	0.318	0.378	0.771	0.771
1994	0.163	0.485	0.611	0.713	0.636	0.643	0.913	0.219	0.277	0.277
1995	0.121	0.459	0.646	0.771	0.745	0.600	0.643	0.635	0.104	0.104
1996	0.096	0.546	0.687	0.733	0.750	0.654	0.761	0.621	0.889	0.889
1997	0.065	0.796	0.926	0.746	0.781	0.726	0.589	0.566	0.611	0.611
1998	0.153	0.493	1.001	1.073	0.636	0.464	0.565	0.430	0.523	0.523
1999	0.174	0.477	0.517	1.177	0.641	0.507	0.329	0.475	0.447	0.447
2000	0.119	0.368	0.331	0.584	0.553	0.494	0.292	0.205	0.330	0.330
2001	0.070	0.719	0.990	0.890	0.802	0.433	0.399	0.195	0.144	0.144
2002	0.210	0.590	0.516	0.639	0.676	0.451	0.524	0.245	0.170	0.170
2003	0.144	0.626	0.619	0.474	0.705	0.614	0.467	0.298	0.118	0.118
2004	0.219	0.642	0.469	0.501	0.239	0.547	0.323	0.141	0.103	0.103
2005	0.137	0.504	0.451	0.369	0.452	0.241	0.482	0.259	0.085	0.085
2006	0.290	0.525	0.462	0.374	0.245	0.228	0.117	0.330	0.168	0.168
2007	0.082	0.471	0.396	0.234	0.260	0.180	0.116	0.088	0.110	0.110
2008	0.191	0.380	0.264	0.248	0.176	0.135	0.152	0.097	0.020	0.020
2009	0.168	0.426	0.257	0.204	0.184	0.129	0.086	0.087	0.035	0.035

Table B2.5: Fishing mortality-at-age for North Sea Plaice taken from the 2010 ICES XSA assessment with adjusted plusgroup.

	BTS-Isis	BTS-Tridens	SNS
1970			2272.52
1971			4115.48
1972			3419.04
1973			3490.6
1974			2731.37
1975			3671.22
1976			1302.31
1977			2276.69
1978			2921.2
1979			3498.43
1980			5141.19
1981			3844.22
1982			4781.09
1983			3369.44
1984			4034.47
1985	45.26		3741.39
1986	62.71		5260.06
1987	98.30		4911.93
1988	74.58		4979.08
1989	72.71		3975.19
1990	47.12		2442.32
1991	48.61		4499.28
1992	47.21		4138.53
1993	60.21		2466.78
1994	33.59		1901.9
1995	26.54		1732.16
1996	46.13	5.09	2485.38
1997	48.85	6.67	3986.73
1998	58.91	9.23	4766.81
1999	51.74	11.05	4452.05
2000	31.36	10.80	1576.88
2001	30.28	8.65	1130.47
2002	36.30	10.54	1665.43
2003	30.31	15.94	
2004	33.38	16.20	1229.38
2005	21.25	16.83	759.74
2006	18.63	20.29	909.908
2007	33.02	21.85	897.587
2008	36.64	37.93	1104.63
2009	51.01	37.52	1098.33

Table B2.6: Age-aggregated survey biomass indices for North Sea Plaice in subarea IV.

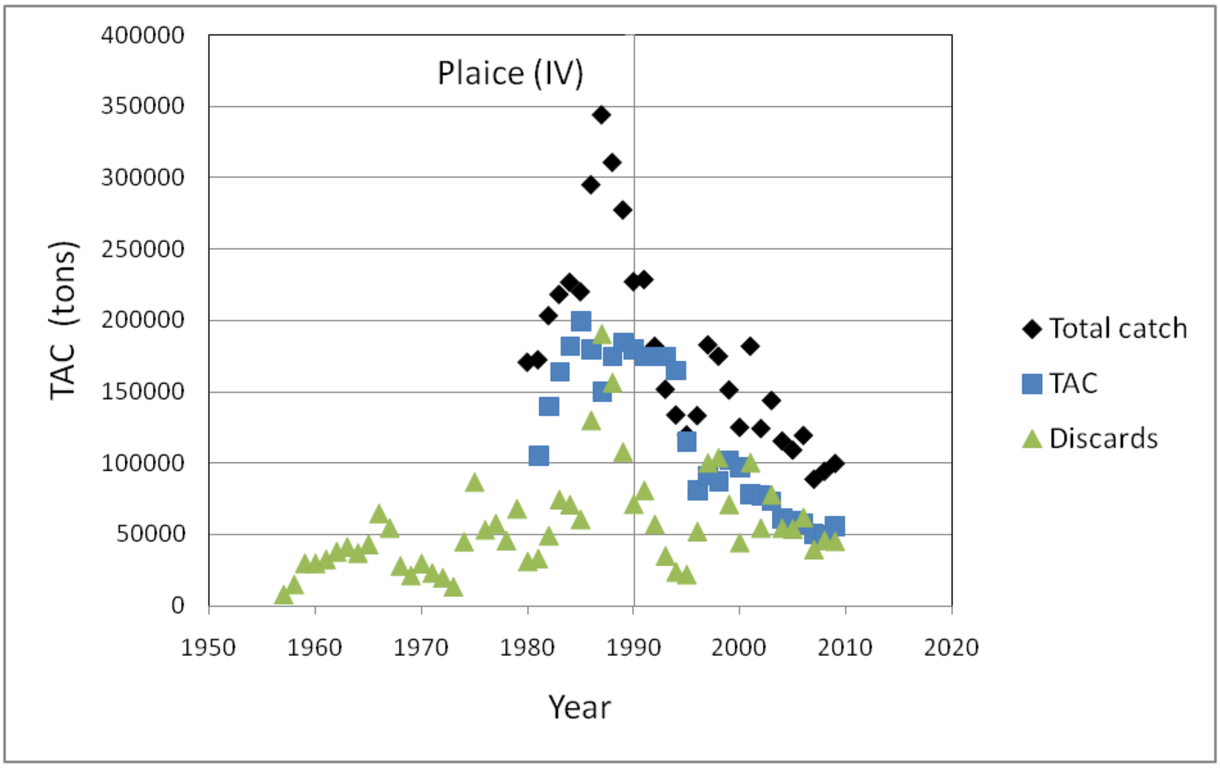


Figure B2.1: Total annual catches of Plaice in Subarea IV in tons (black diamonds) with annual TACs indicated by the blue squares and number of discards indicated by the green diamonds.

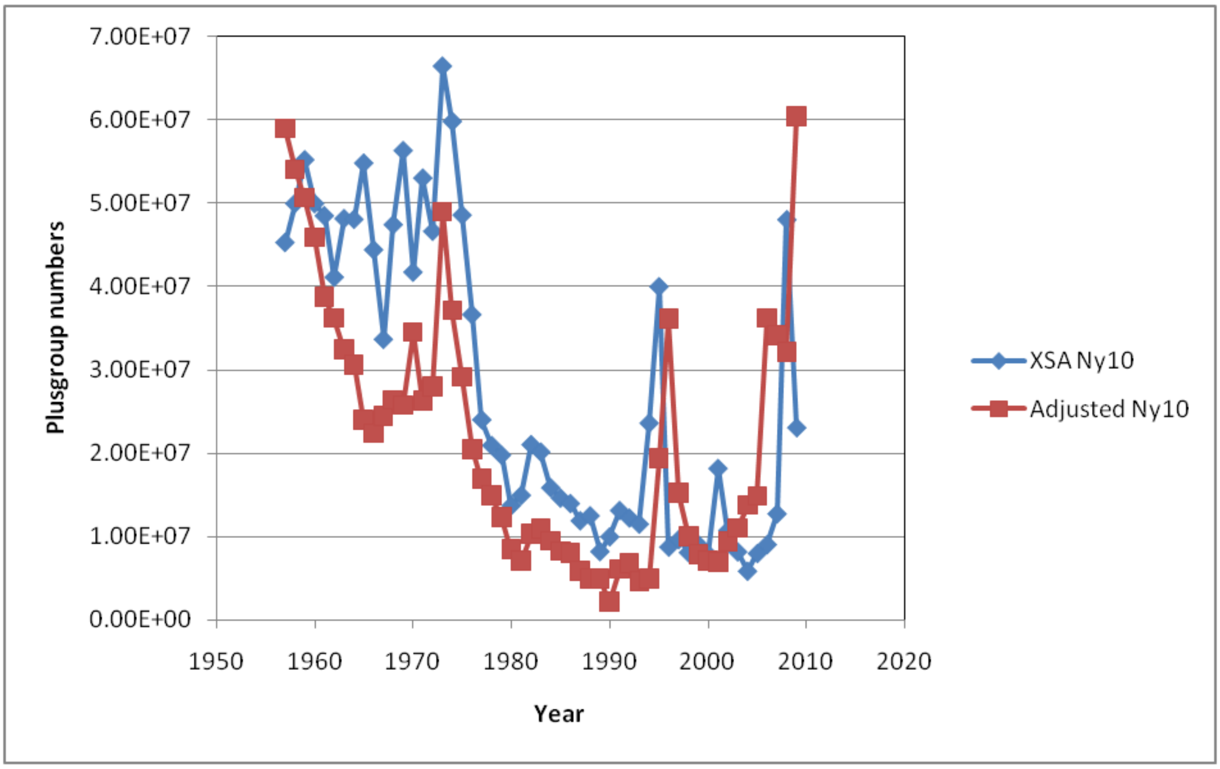


Figure B2.2: Adjusted plusgroup population numbers compared to the VPA/XSA estimates for North Sea Plaice in subarea IV.

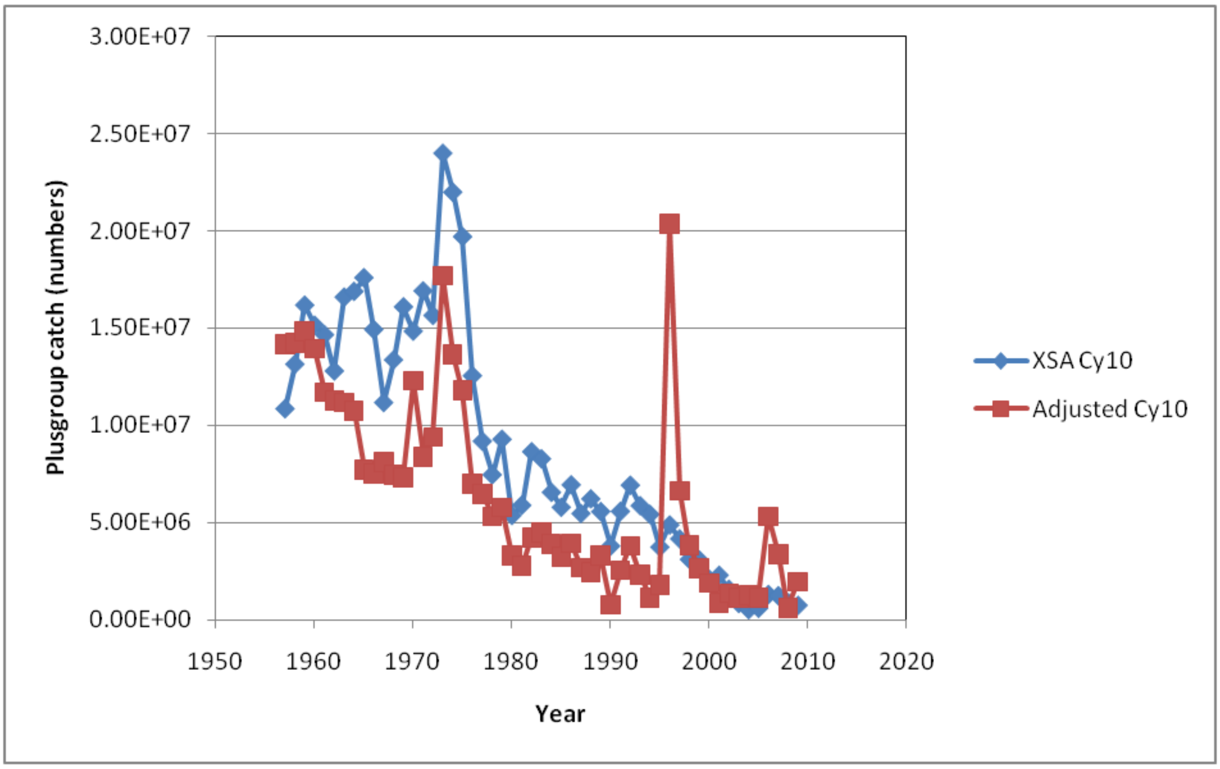


Figure B2.3: Adjusted plusgroup catch compared to observed catch for North Sea Plaice in subarea IV.

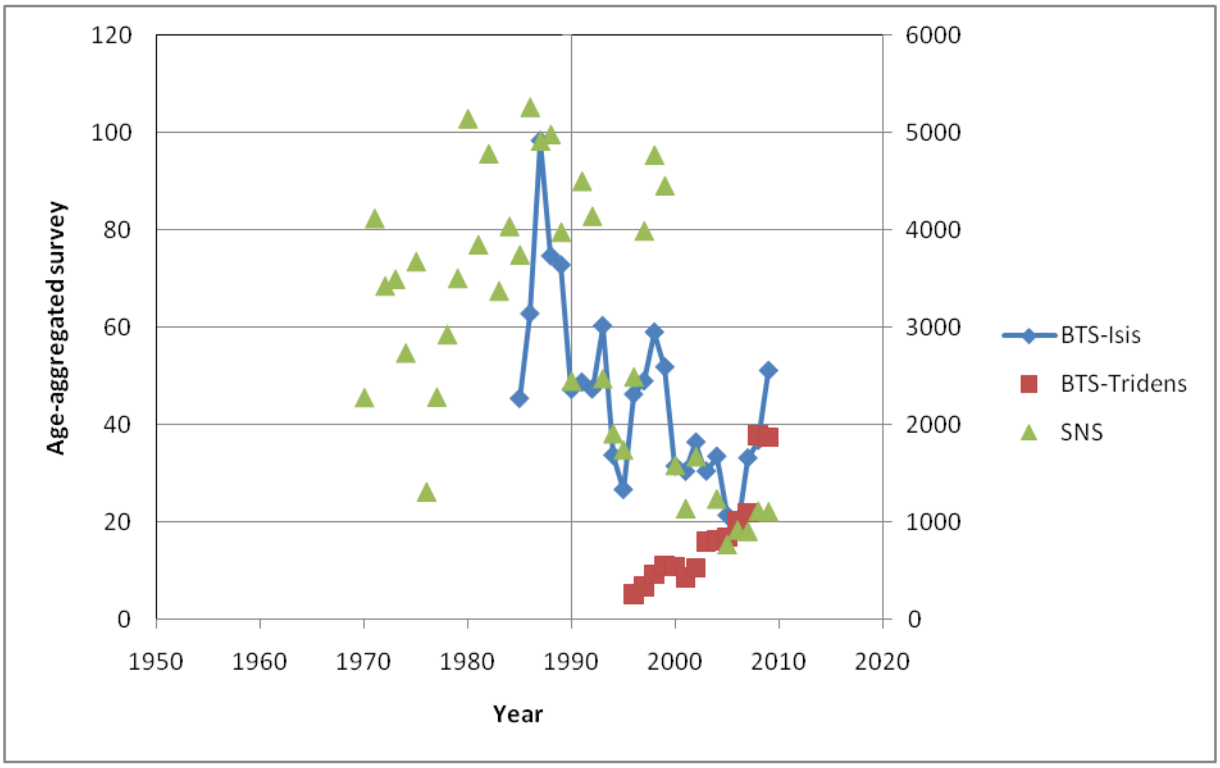


Figure B2.4: Age-aggregated survey indices for North Sea Plaice in subarea IV.

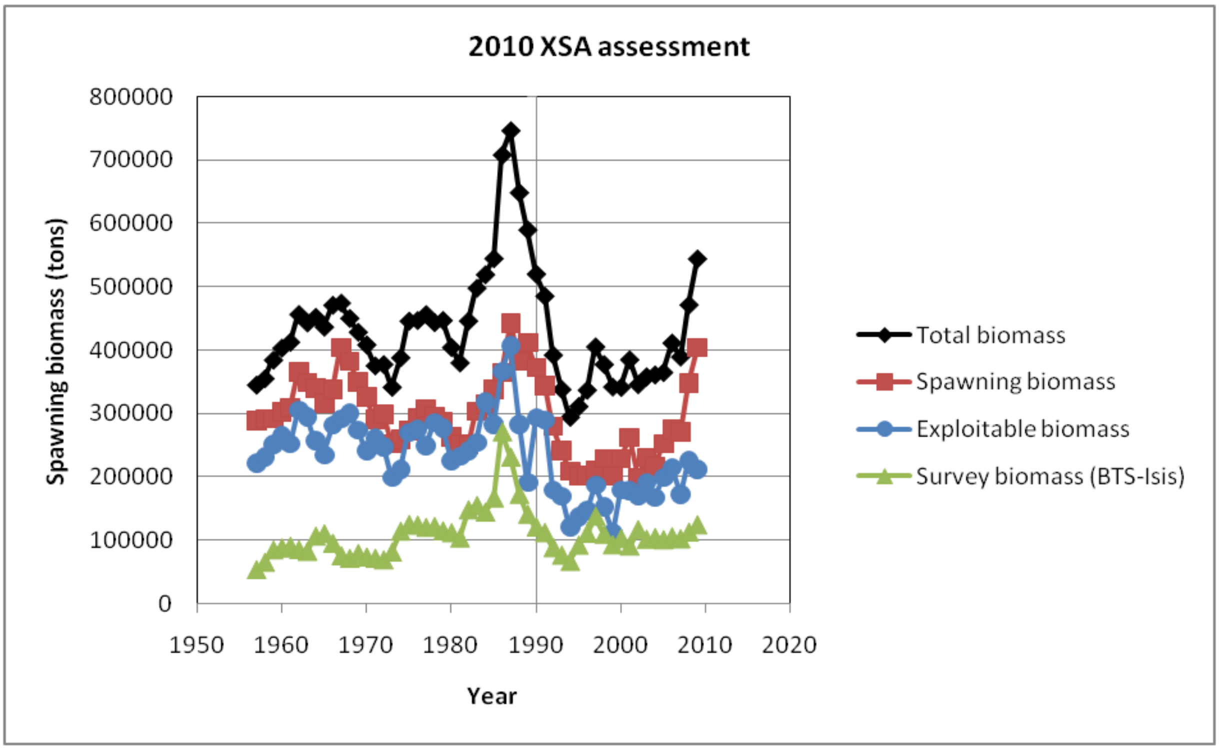


Figure B2.5: Trajectories for various biomass components from the 2010 VPA/XSA assessment for North Sea Plaice in subarea IV with the plusgroup adjusted as detailed in text.

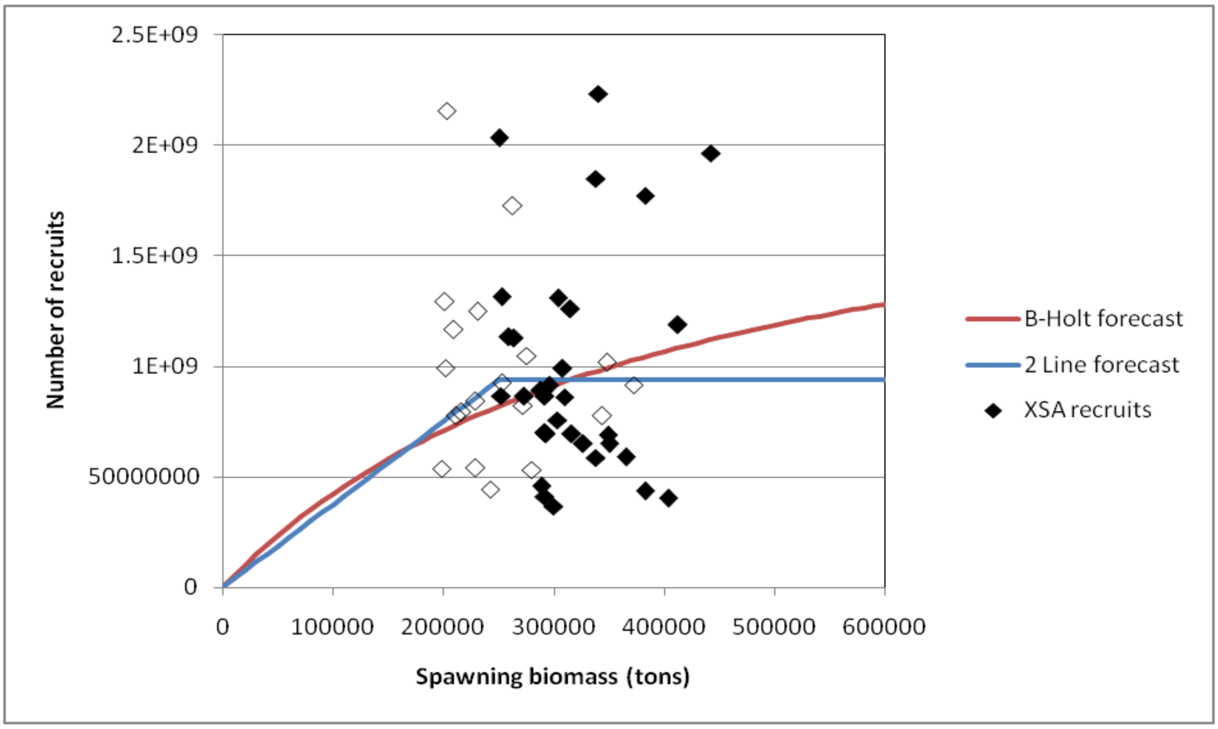


Figure B2.6: Number of recruits (1-yr-olds) estimated in the 2010 VPA/XSA assessment for North Sea Plaice (diamonds) compared to the number of recruits in terms of a Beverton Holt stock–recruitment curve when fixing *h* to 0.9 and a two-line stock recruit relationship fitted to data from 1957 to 1989 (forecast). Recruitments from 1990 onwards are shown by open diamonds.

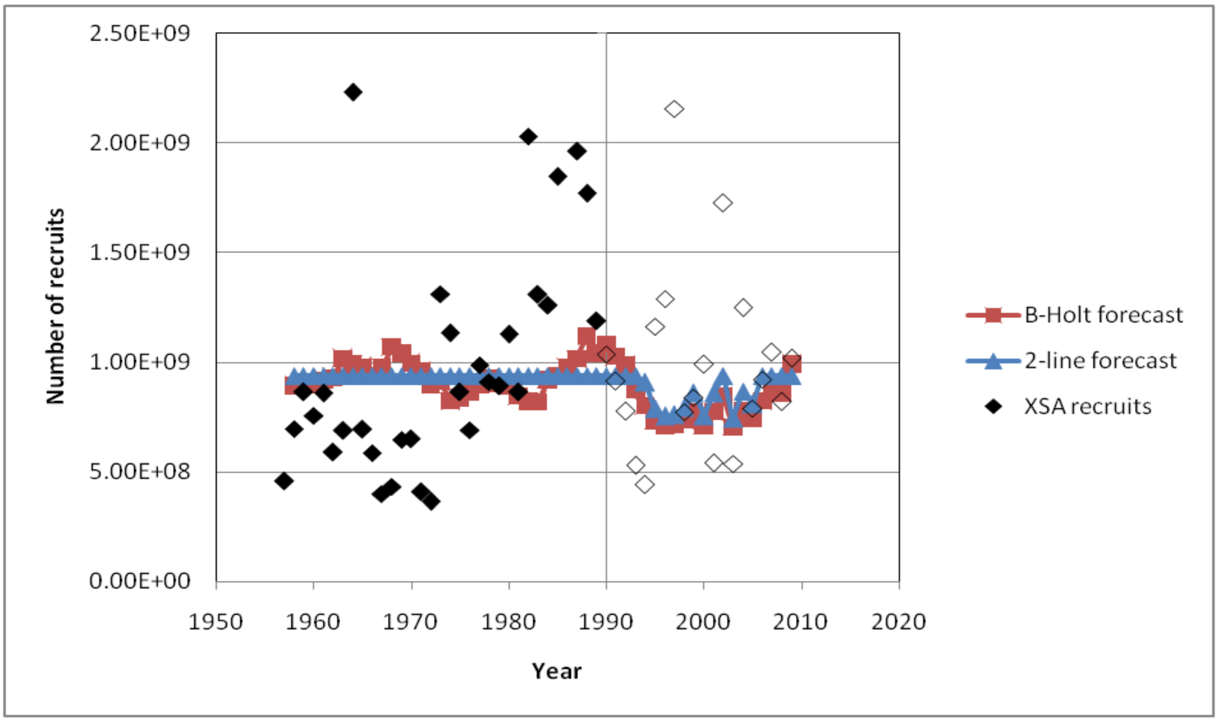


Figure B2.7: Annual number of recruits (1-yr-olds) estimated in the 2010 VPA/XSA assessment for North Sea Plaice in subarea IV (diamonds) compared to the annual number of recruits in terms of a Beverton Holt stock–recruitment curve fixing *h*=0.9 (squares) and a two-line stock-recruit relationship (triangles).Figure A1.8: Fishing selectivities-at-age over the assessment period from 1957 to 2009 for North Sea Plaice.

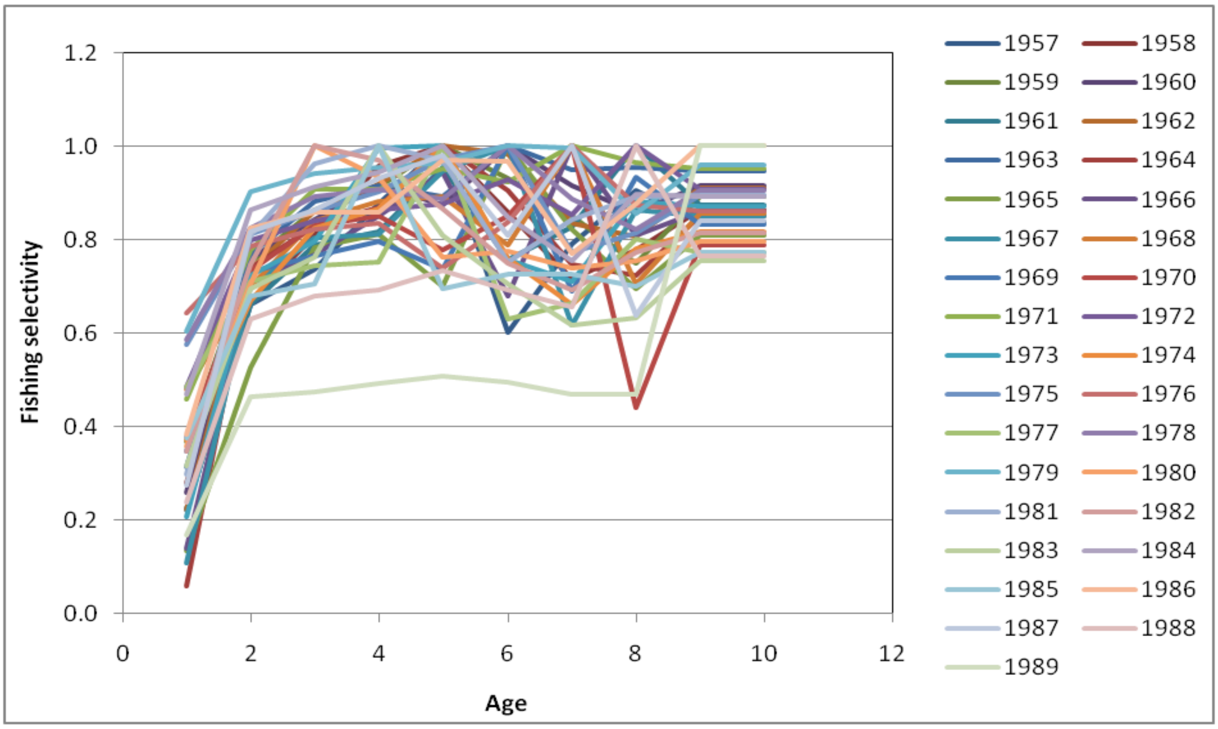


Figure B2.8: VPA/XSA estimated fishing selectivities-at-age for North Sea Plaice (Subarea IV) for the historic period from 1957 to 1989. "Future" selectivity vectors for forecast projections are randomly sampled from "past" vectors from 1980 to 1989.

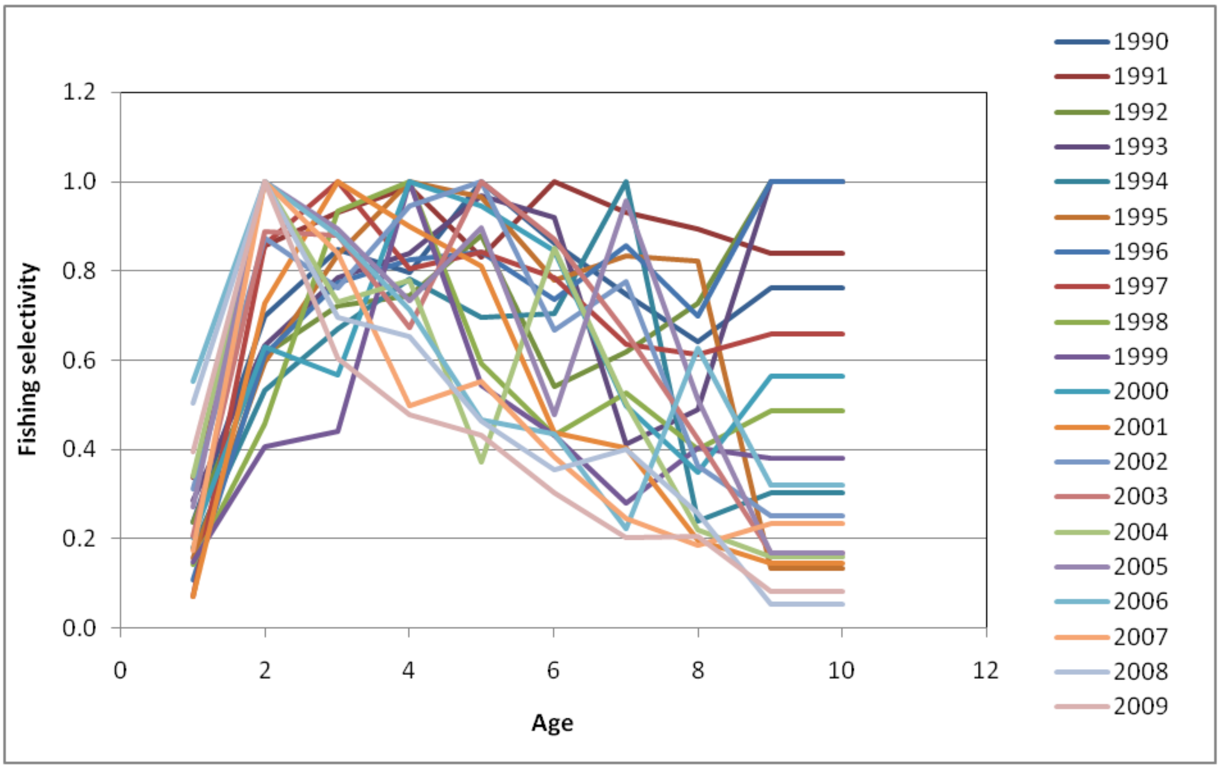


Figure B2.9: VPA/XSA estimated fishing selectivities for North Sea Plaice in subarea IV over the projection period from 1990 to 2009.

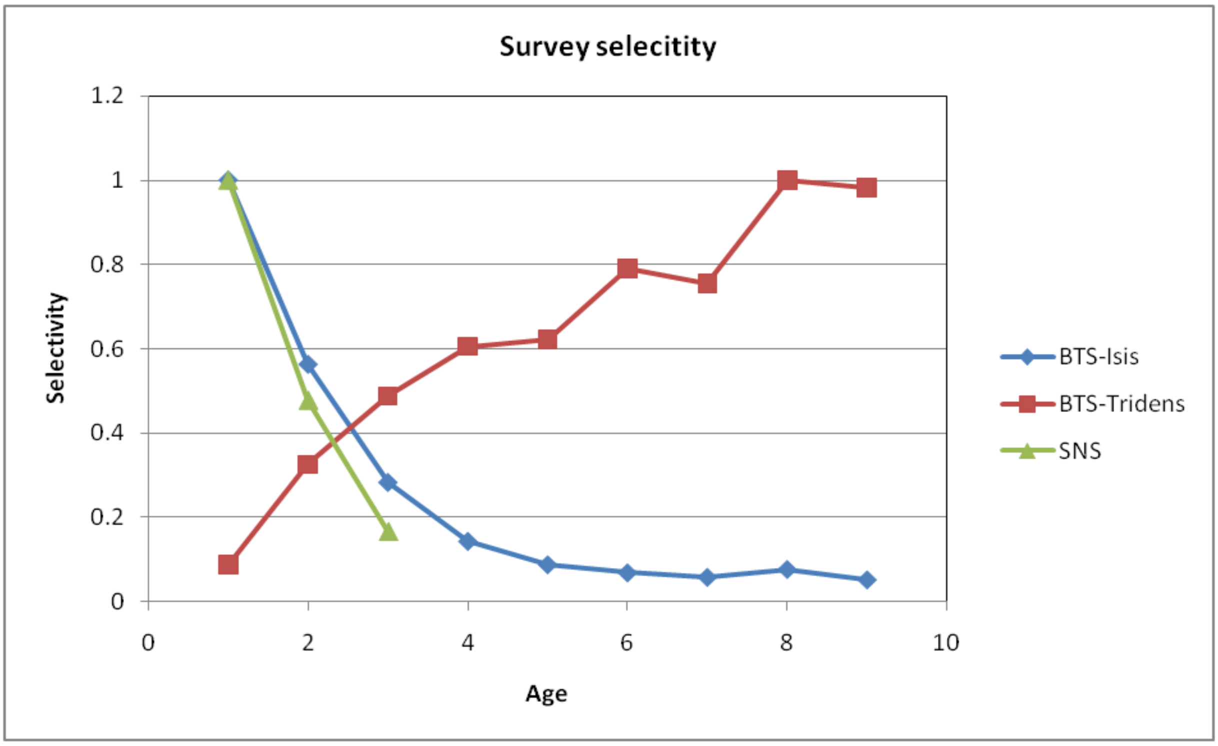


Figure B2.10: Survey selectivity vectors estimated from survey numbers-at-age as a fraction of the XSA estimated population numbers-at-age for North Sea Plaice.

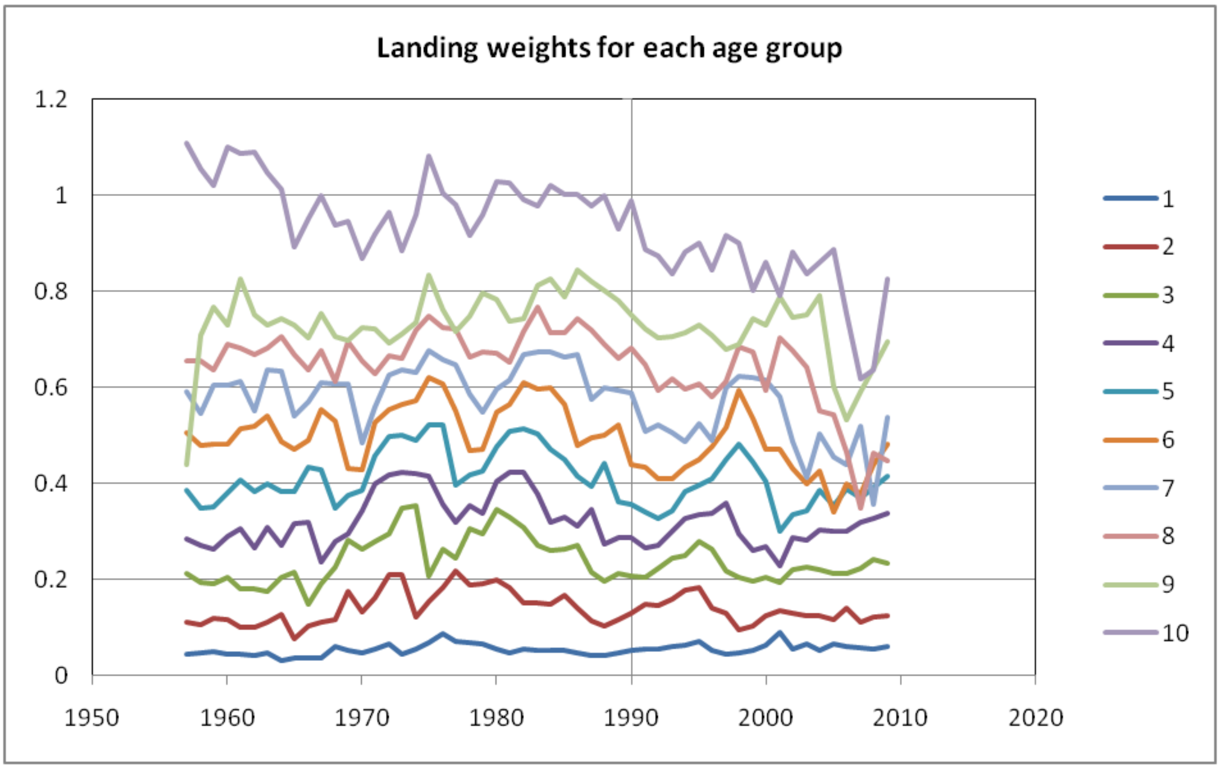


Figure B2.11 Landing weights (kg) for North Sea Plaice for each age group.

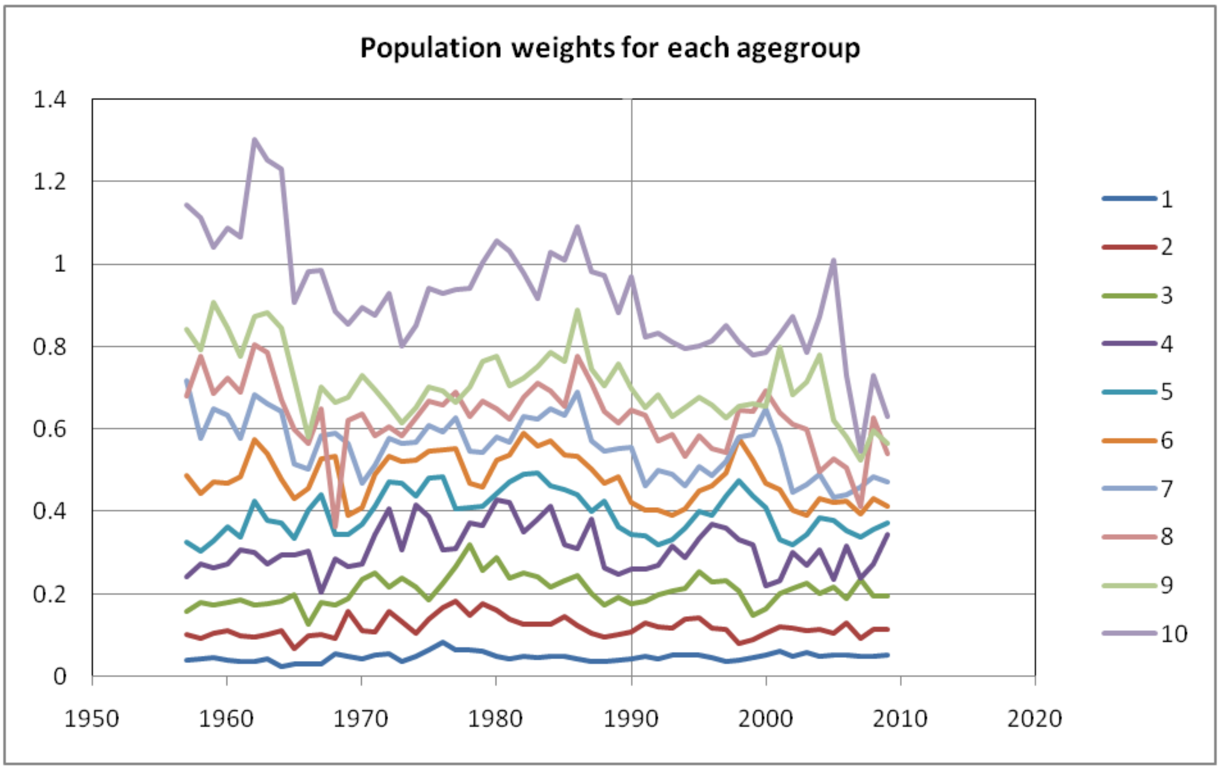


Figure B2.12 Population weights (kg) for North Sea Plaice for each age group.

B.3 New England Witch Flounder

Witch flounder is a slow growing long-lived species. An age-independent instantaneous rate of natural mortality (*M*) of 0.15 yr^{-1} is assumed for this retrospective study, the same as used for the 2012 VPA stock assessments of Wigley and Emery (2012).Furthermore, the same maturity ogive used in the 2012 witch flounder stock assessment (Gulf of Maine southward) is assumed here for the retrospective projections commencing in 1991, given in Table B3.1.

The NEFSC spring and autumn abundance indices are given in Table B3.2. Due to changes apparent in selectivity patterns over the assessment years from 1982 to 2010, in particular with regard to younger fish in the catch, different selectivity vectors are used in the "hindsight" (when averaging over all years) and "forecast" (when assuming knowledge up to 1990 only) projections.

Stock–recruitment parameters required for the deterministic and stochastic projections, estimated by fitting a two-line ("hockey-stick") and Beverton-Holt function to the 2012 VPA assessment estimates for spawning biomass and recruitment, are given in Table B3.3.

The annual number of recruits (3-yr-olds) and associated spawning biomasses from 1982 to 2010 as estimated in the 2012 VPA assessment, as well as observed total annual catches are given in Table B3.4. The population numbers-at-age matrix estimated in the 2012 VPA assessment, with plusgroup adjusted for consistency according to Section 4.4.2 of Chapter 4, is given in Table B3.5, with the adjusted fishing mortality-at-age matrix given in Table B3.6.

The age-aggregated NEFSC spring and autumn survey indices of abundance are given in Table B3.7.

A visual representation of the data are given in Figures B3.1 to B3.12:

Figure B3.1: Total annual catches (landing plus discards) of New England witch flounder in tons.

Figure B3.2: Adjusted plusgroup population numbers compared to the 2012 VPA estimates for witch flounder.

Figure B3.3: Adjusted plusgroup catch compared to observed catch for witch flounder.

Figure B3.4: Age-aggregated NEFSC spring and autumn survey indices of abundance for witch flounder.

Figure B3.5: Trajectories for various biomass components from the 2012 VPA assessment for New England witch flounder with plusgroup adjusted as detailed in the text.

Figure B3.6: Number of recruits (3-yr-olds) estimated in the 2012 VPA assessment for New England witch flounder and the number of recruits in terms of a two-line (a) and Beverton-Holt (b) stock-recruit functions fitted to data from 1982 to 2010 (hindsight) or 1982 to 1990 (forecast).

Figure B3.7: Annual number of recruits (3-yr-olds) estimated in the 2012 VPA assessment for New England witch flounder compared to the number of recruits in terms of the two-line (a) and Beverton-Holt (b) stock-recruit functions.

Figure B3.8: 2012 VPA estimated fishing selectivities for New England witch flounder over the projection period from 1991 to 2010.

Figure B3.9: 2012 VPA estimated fishing selectivities for New England witch flounder over the projection period from 1991 to 2010.

Figure B3.10: The NEFSC survey selectivities-at-age for New England witch flounder for alternative periods.

Figure B3.11 Landing weights (kg) for New England witch flounder for each age group.

Figure B3.12 Population weights (kg) for New England witch flounder for each age group.

Age:	3	4	5	6	7	8	9	10	11
Natural Mortality rate	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
Maturity	0.11	0.25	0.47	0.71	0.87	0.95	0.98	0.98	1.0
NEFSC spring survey selectivity	0.56	0.57	0.73	0.63	0.75	0.80	0.97	0.85	1.00
NEFSC autumn survey selectivity	1.00	0.62	0.53	0.50	0.60	0.52	0.50	0.48	0.89

Table B3.1: Natural mortality-at-age, maturity-at-age and survey selectivity vectors.

		two-line			Beverton-Holt		
	Period	σ_R	α (thousands)	B^0 (tons)	σ_R	α (thousands)	β (tons)
Deterministic	1982-2010	0.483	8865	2790	0.469	9768	1101
Stochastic	1982-1990	0.544	8568	5917	0.352	6574	742

Table B3.2: Stock–recruitment parameters estimated for "hindsight" and "forecast" projections. Note that recruits refer to the 3-year old age-group and that the Beverton-Holt recruitment estimates are therefore estimated from spawning biomass estimates of three years prior.

Year	Number of recruits	Spawning biomass	Total Catch (tons)
1982	15409	19105	5469
1983	17706	15757	7071
1984	16371	12087	7037
1985	7670	9726	5817
1986	5437	8767	4311
1987	3137	8806	3423
1988	9301	7787	3023
1989	6070	6448	1870
1990	7541	5917	1470
1991	8659	6031	1807
1992	12156	6453	2325
1993	8905	6176	2931
1994	13104	5131	3360
1995	11837	4590	2644
1996	15676	4403	2706
1997	13896	4261	2065
1998	14774	5061	1991
1999	12596	5979	2361
2000	11448	6397	2430
2001	12134	6310	3122
2002	11213	6140	3398
2003	8476	5246	3310
2004	5106	4216	3222
2005	3702	3847	2859
2006	4521	2898	2040
2007	12438	2790	1204
2008	7277	3202	1075
2009	3962	3948	1074
2010	5119	4236	900

Table B3.3: Number of recruits and adjusted spawning biomass estimates, taken from the 2012 VPA assessment, with total annual catches (landings plus discards) with adjusted plusgroup incorporated for witch flounder in USA subareas 3, 4, 5 and 6 and Canada.

Age	3	4	5	6	7	8	9	10	11+
1982	15409	12176	9564	7830	4290	2752	2102	1101	8938.46
1983	17706	13086	9495	7115	5376	3077	1763	1440	6624.82
1984	16371	14927	10017	6766	4669	3160	1747	839	4308.16
1985	7670	13954	11491	6771	4218	2648	1344	862	2314.16
1986	5437	6487	10922	7932	4041	2225	1132	600	1378.05
1987	3137	4659	5234	7998	4270	2036	1146	594	1025.53
1988	9301	2680	3842	4073	5700	2225	951	545	761.198
1989	6070	7449	2177	3062	2897	3629	856	449	536.72
1990	7541	5141	6123	1731	2344	1792	2308	414	598.348
1991	8659	6208	4069	4548	1252	1762	1104	1675	686.24
1992	12156	6992	4759	2502	3313	859	1290	680	1623.18
1993	8905	10313	5121	3067	1172	2178	553	946	1606.23
1994	13104	7584	7945	3099	1788	459	1334	275	1503.31
1995	11837	11216	5934	4932	1425	668	211	648	852.026
1996	15676	9592	9302	4140	2667	445	327	92	714.396
1997	13896	13358	7903	7169	2315	954	136	80	226.462
1998	14774	11845	10849	5972	5053	1052	278	40	89.4064
1999	12596	12505	9907	8642	3916	2834	553	105	64.0752
2000	11448	10698	10314	7624	6033	2212	1696	233	96.2688
2001	12134	9738	8863	8350	5483	3608	963	937	160.048
2002	11213	10382	8071	6661	6142	3096	1740	240	475.22
2003	8476	9621	8400	5907	4473	3305	1486	903	353.396
2004	5106	7266	8014	6194	3583	2092	1390	582	517.134
2005	3702	4364	5920	5806	3840	1676	736	458	377.05
2006	4521	3172	3584	4317	3266	1637	675	251	320.888
2007	12438	3847	2663	2862	3056	1371	596	249	209.002
2008	7277	10637	3229	2194	2216	1797	610	351	223.737
2009	3962	6236	8979	2618	1598	1359	1127	238	325.94
2010	5119	3385	5213	7321	1975	915	750	671	322.224

Table B3.4: Population numbers-at-age for New England witch flounder from the 2012 VPA “split run” assessment, but with adjusted plusgroup as discussed in Section 4.4.2 of Chapter 4.

Age	3	4	5	6	7	8	9	10	11+
1982	0.013	0.099	0.146	0.226	0.182	0.295	0.228	0.266	0.266
1983	0.021	0.117	0.189	0.271	0.381	0.416	0.593	0.477	0.477
1984	0.010	0.112	0.242	0.323	0.417	0.705	0.556	0.649	0.649
1985	0.018	0.095	0.221	0.366	0.489	0.700	0.657	0.685	0.685
1986	0.005	0.065	0.162	0.469	0.536	0.513	0.495	0.507	0.507
1987	0.008	0.043	0.101	0.189	0.502	0.611	0.594	0.605	0.605
1988	0.072	0.058	0.077	0.191	0.301	0.806	0.600	0.739	0.739
1989	0.016	0.046	0.079	0.117	0.331	0.303	0.575	0.349	0.349
1990	0.045	0.084	0.148	0.174	0.135	0.334	0.171	0.239	0.239
1991	0.064	0.116	0.336	0.167	0.226	0.162	0.334	0.225	0.225
1992	0.014	0.161	0.289	0.608	0.270	0.290	0.161	0.210	0.210
1993	0.011	0.111	0.352	0.390	0.788	0.340	0.550	0.379	0.379
1994	0.006	0.096	0.327	0.627	0.834	0.625	0.573	0.586	0.586
1995	0.060	0.037	0.210	0.465	1.015	0.565	0.683	0.592	0.592
1996	0.010	0.044	0.111	0.431	0.877	1.032	1.254	1.120	1.120
1997	0.010	0.058	0.130	0.200	0.638	1.084	1.067	1.082	1.082
1998	0.017	0.029	0.078	0.272	0.428	0.493	0.822	0.553	0.553
1999	0.013	0.043	0.112	0.209	0.421	0.363	0.717	0.413	0.413
2000	0.012	0.038	0.061	0.180	0.364	0.682	0.444	0.571	0.571
2001	0.006	0.038	0.136	0.157	0.422	0.579	1.239	0.687	0.687
2002	0.003	0.062	0.162	0.248	0.470	0.584	0.506	0.555	0.555
2003	0.004	0.033	0.155	0.350	0.610	0.716	0.787	0.738	0.738
2004	0.007	0.055	0.172	0.328	0.610	0.895	0.959	0.920	0.920
2005	0.005	0.047	0.166	0.425	0.703	0.759	0.924	0.806	0.806
2006	0.011	0.025	0.075	0.196	0.718	0.860	0.848	0.857	0.857
2007	0.006	0.025	0.044	0.106	0.381	0.660	0.380	0.566	0.566
2008	0.004	0.019	0.060	0.167	0.339	0.316	0.792	0.417	0.417
2009	0.007	0.029	0.054	0.132	0.408	0.445	0.369	0.410	0.410
2010	0.006	0.021	0.049	0.068	0.175	0.635	0.297	0.466	0.466

Table B3.5: Fishing mortality-at-age for New England witch flounder from the 2012 VPA “split run” assessment with adjusted plusgroup.

	NEFSC survey	
Year	Spring	Autumn
1982	1.87	0.83
1983	2.74	2.12
1984	1.66	2.33
1985	2.75	1.59
1986	1.35	1.09
1987	0.65	0.37
1988	0.85	0.57
1989	0.74	0.38
1990	0.24	0.40
1991	0.57	0.54
1992	0.48	0.24
1993	0.36	0.54
1994	0.53	0.42
1995	0.47	0.62
1996	0.28	1.02
1997	0.43	0.77
1998	0.77	0.47
1999	0.48	0.88
2000	0.52	1.11
2001	0.75	1.71
2002	1.61	1.06
2003	1.30	0.79
2004	1.08	1.03
2005	0.89	0.38
2006	0.72	0.46
2007	0.58	0.57
2008	1.40	0.64
2009	0.50	0.45
2010	0.54	0.36

Table B3.6: Age-aggregated spring and autumn survey biomass indices for New England witch flounder.

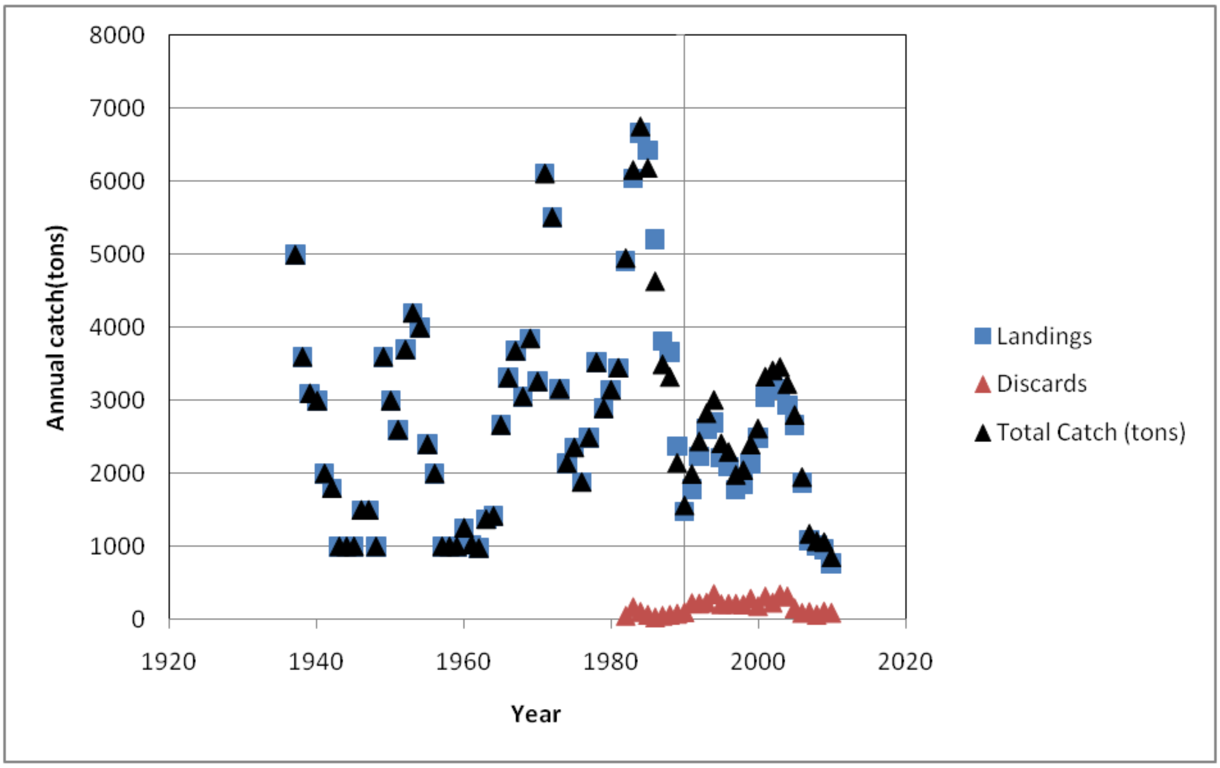


Figure B3.1: Total annual catches (landings and discards) of Witch Flounder in US subareas 3, 4, 5 and 6 and Canada.

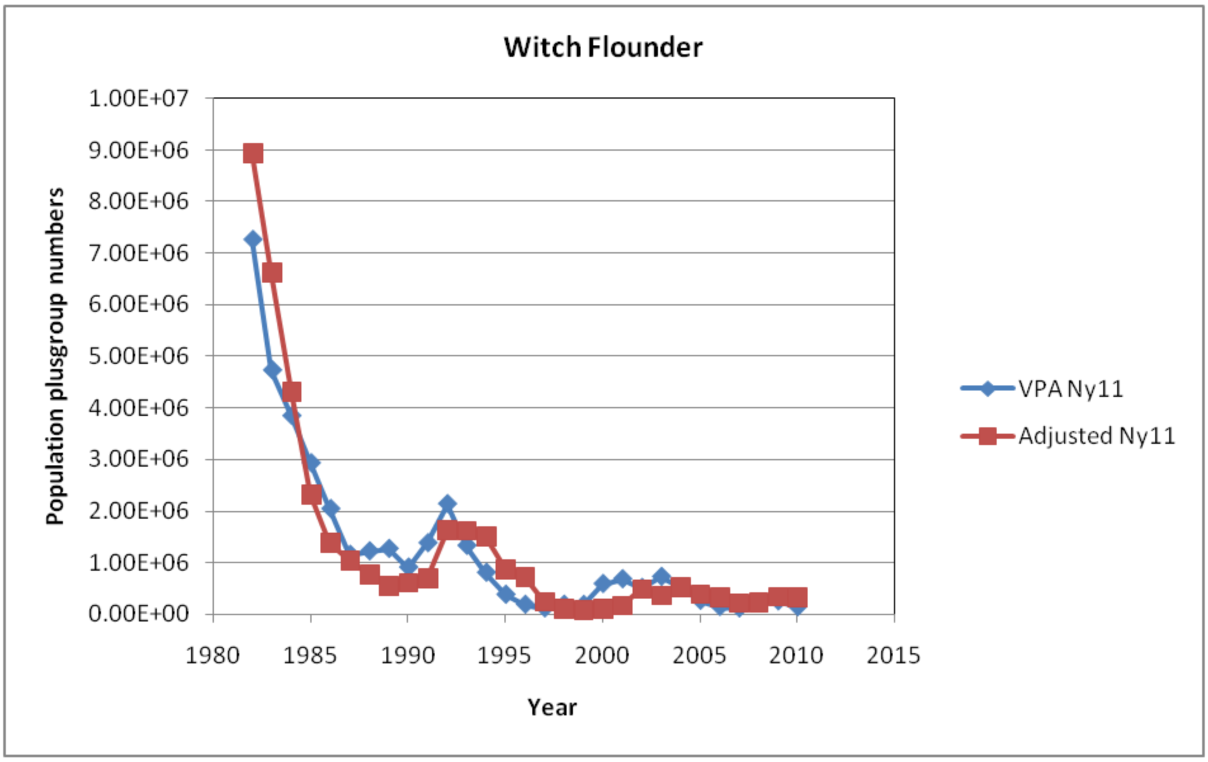


Figure B3.2: Adjusted plusgroup population numbers compared to the 2012 VPA estimates for Gulf of Maine/Georges Bank Witch Flounder.

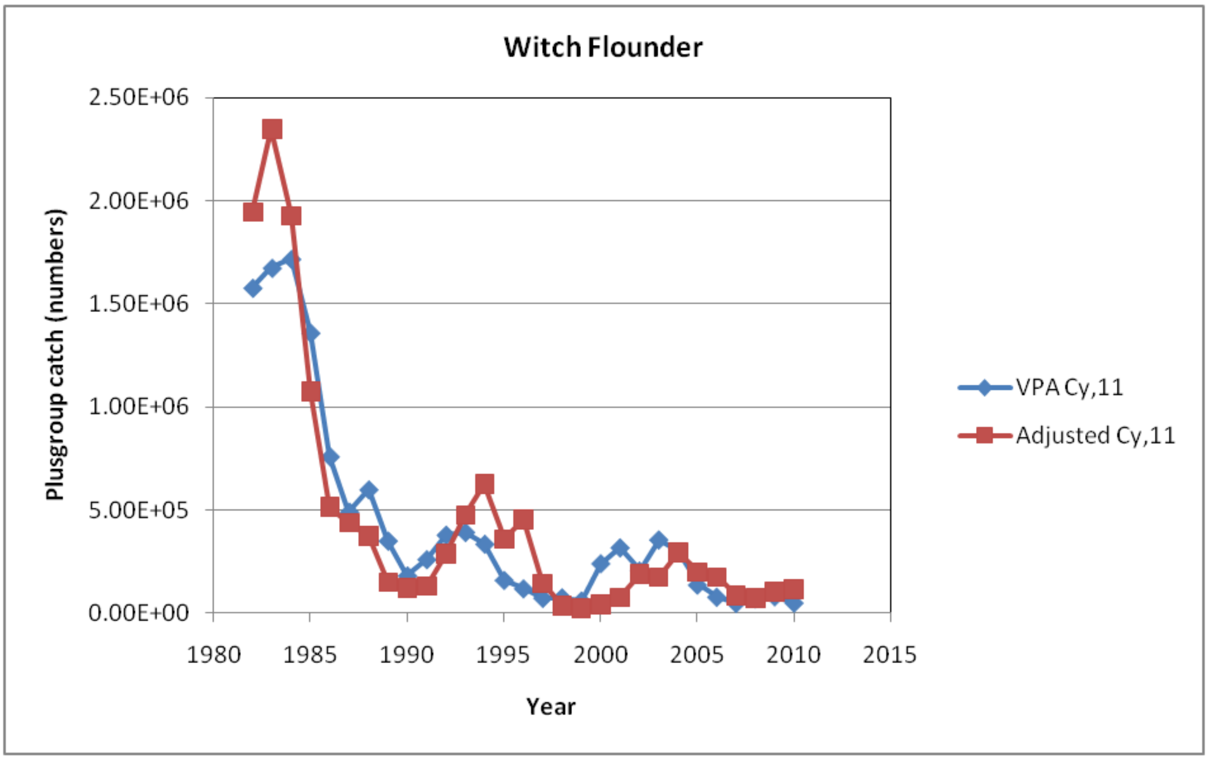


Figure B3.3: Adjusted plusgroup catch (in numbers) compared to the observed catch for New England witch flounder.

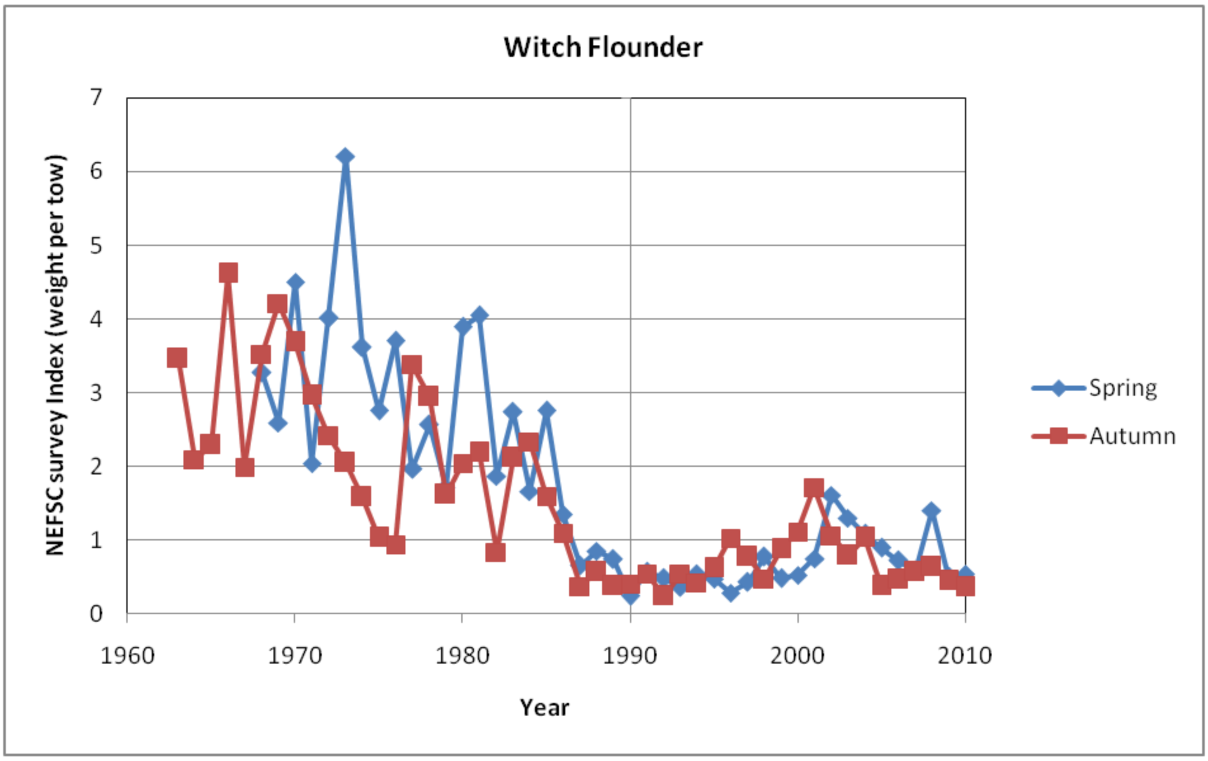


Figure B3.4: Stratified mean weight (kg) per tow of witch flounder in NEFSC spring and autumn bottom trawl surveys in the Gulf of Maine region.

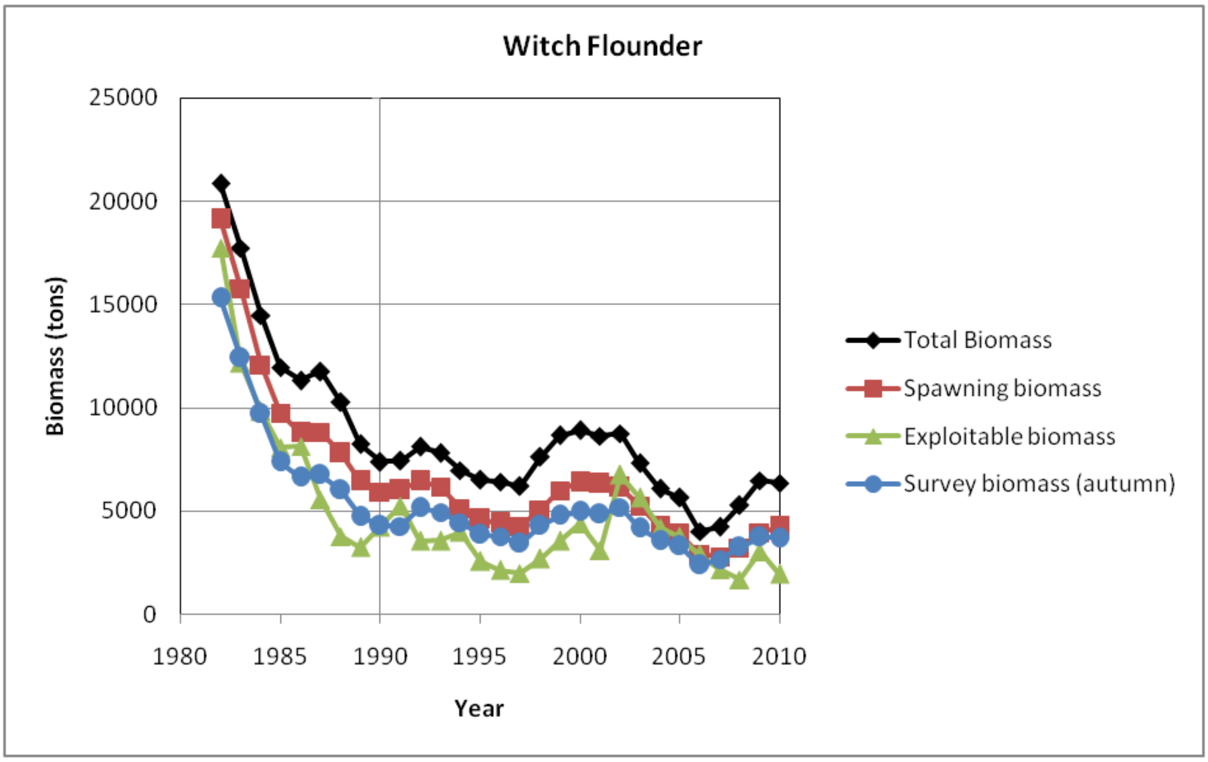
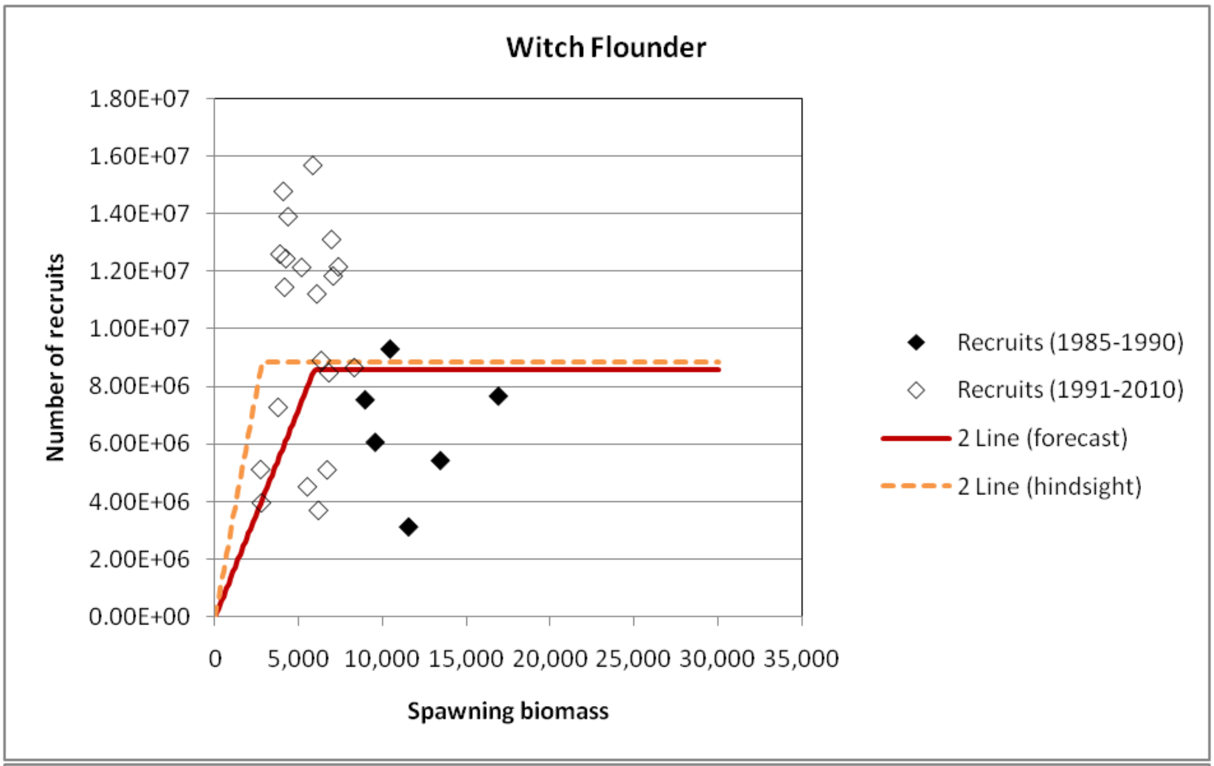


Figure B3.5: Trajectories for various biomass components from the 2012 VPA assessment for New England witch flounder, as well as derived biomass estimates corresponding to the NEFSC autumn index.



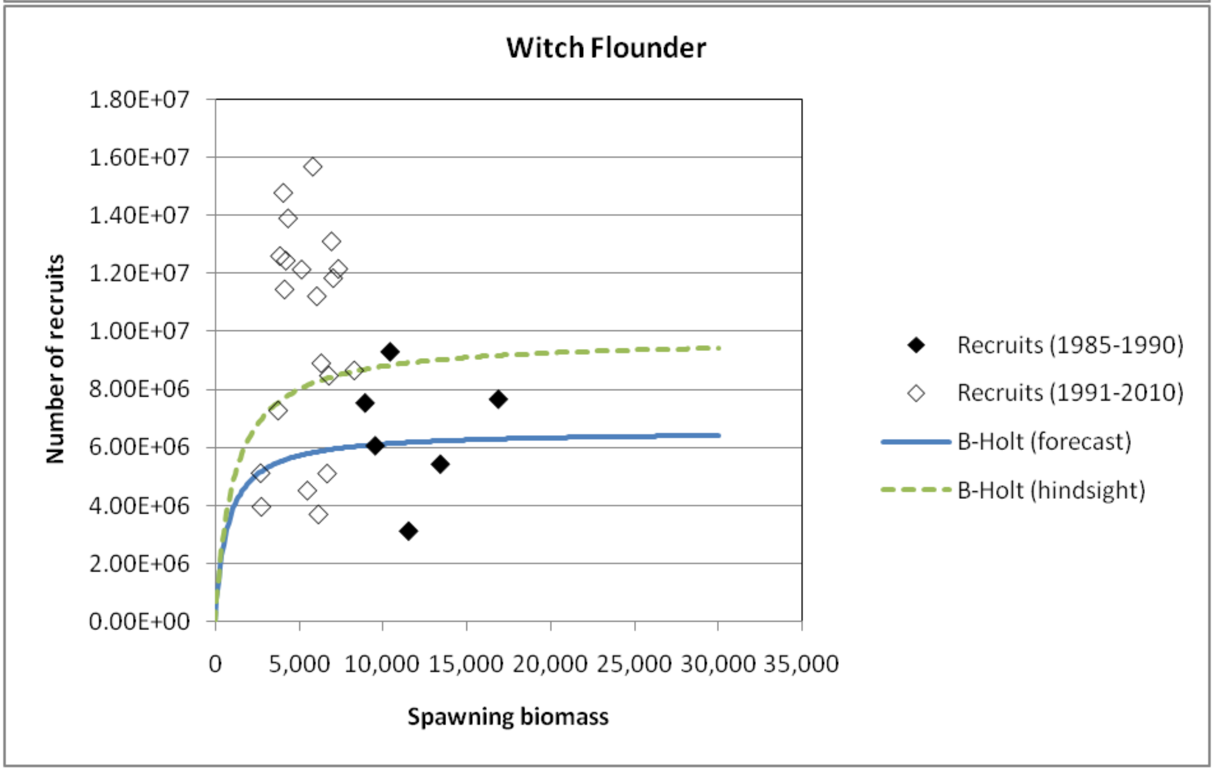
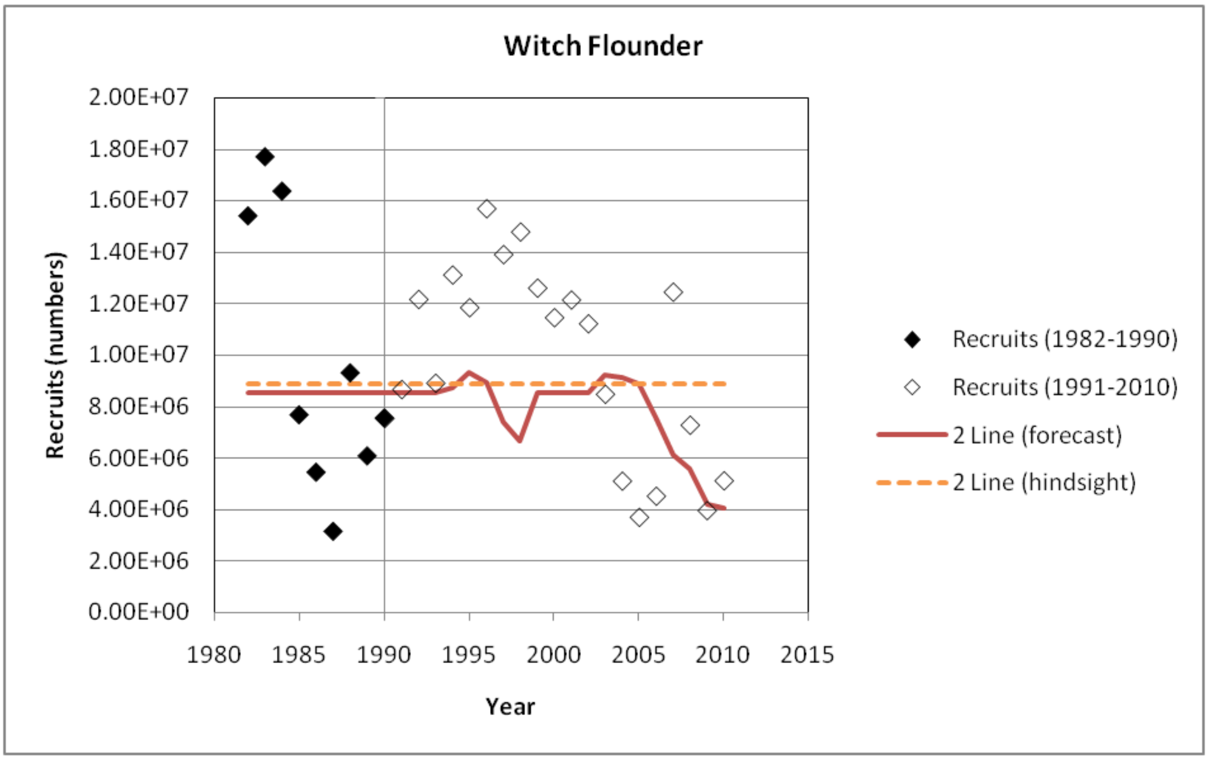


Figure B3.6a and b: Number of recruits (3 year olds) as a function of spawning biomass. Solid diamonds correspond to the 2012 VPA "split run" assessment recruitment estimates from 1985 to 1990 (the "past"), while empty diamonds correspond to the projection period from 1991 to 2010 (the "future"). The two stock–recruitment functions shown are based on "past" (pre-1991) recruitment and biomass estimates (solid lines) and recruitment and biomass estimates over the entire period (dotted lines). Note that for the Beverton-Holt function only recruitment estimates from 1985 onwards are used, while for the two-line function recruits from 1982 are included in the fit.



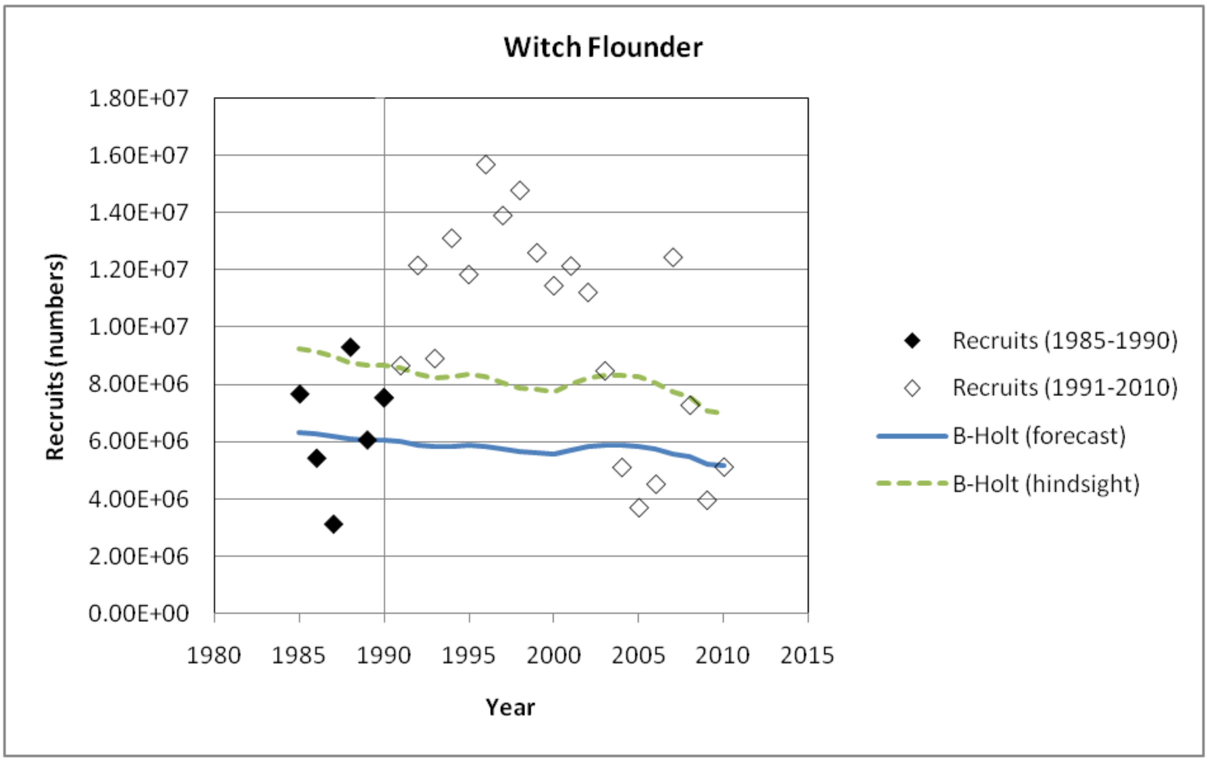


Figure B3.7a and b: Annual number of recruits (3 year olds) estimated in the 2012 VPA "split run" assessment of New England witch flounder (diamonds) compared to the annual number of recruits in terms of two-line stock-recruit relationship (top plot) when using parameters corresponding to the forecast and hindsight scenarios. The bottom plot shows the corresponding Beverton-Holt stock–recruitment function when fixing h=0.9. Note that three additional recruitment data points are available for the fit to the two-line SR function. See Table B3.3 for stock–recruitment parameter values.

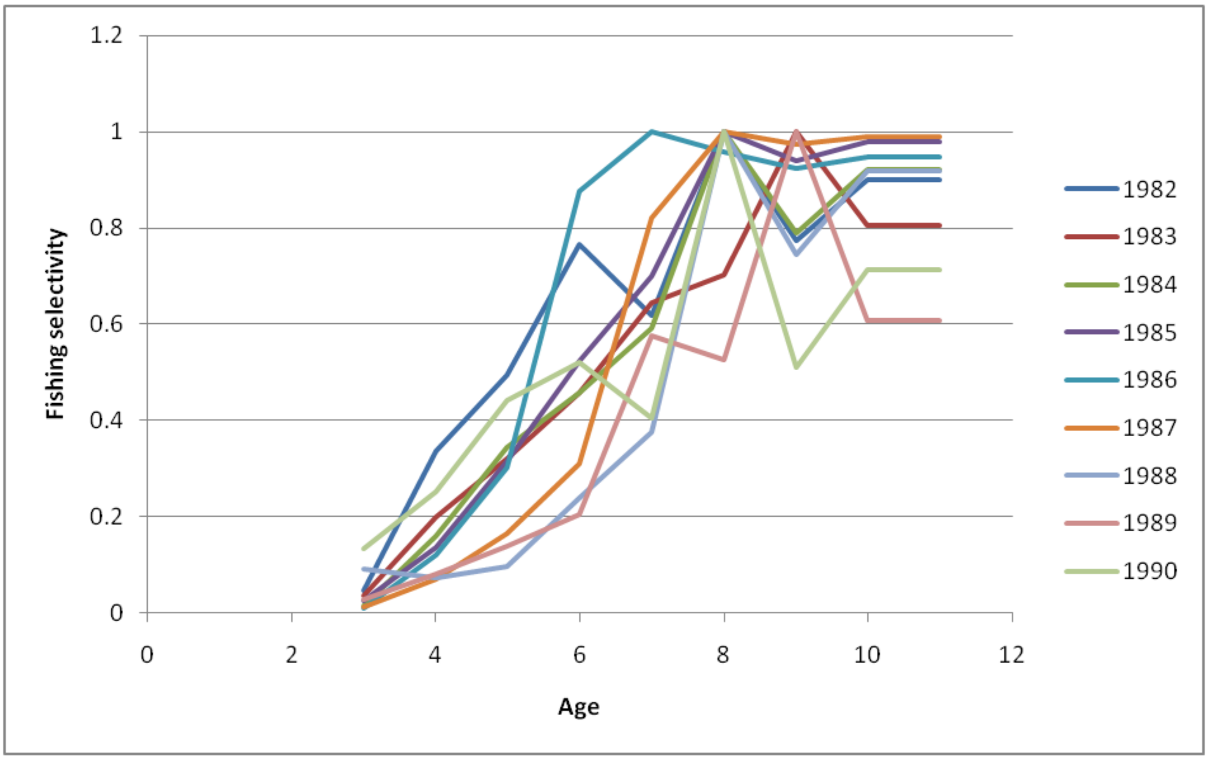


Figure B3.8: VPA estimated fishing selectivities for New England witch flounder over the historic period from 1982 to 1990. Selectivity vectors for stochastic "forecast" projections are randomly sampled from these past vectors.

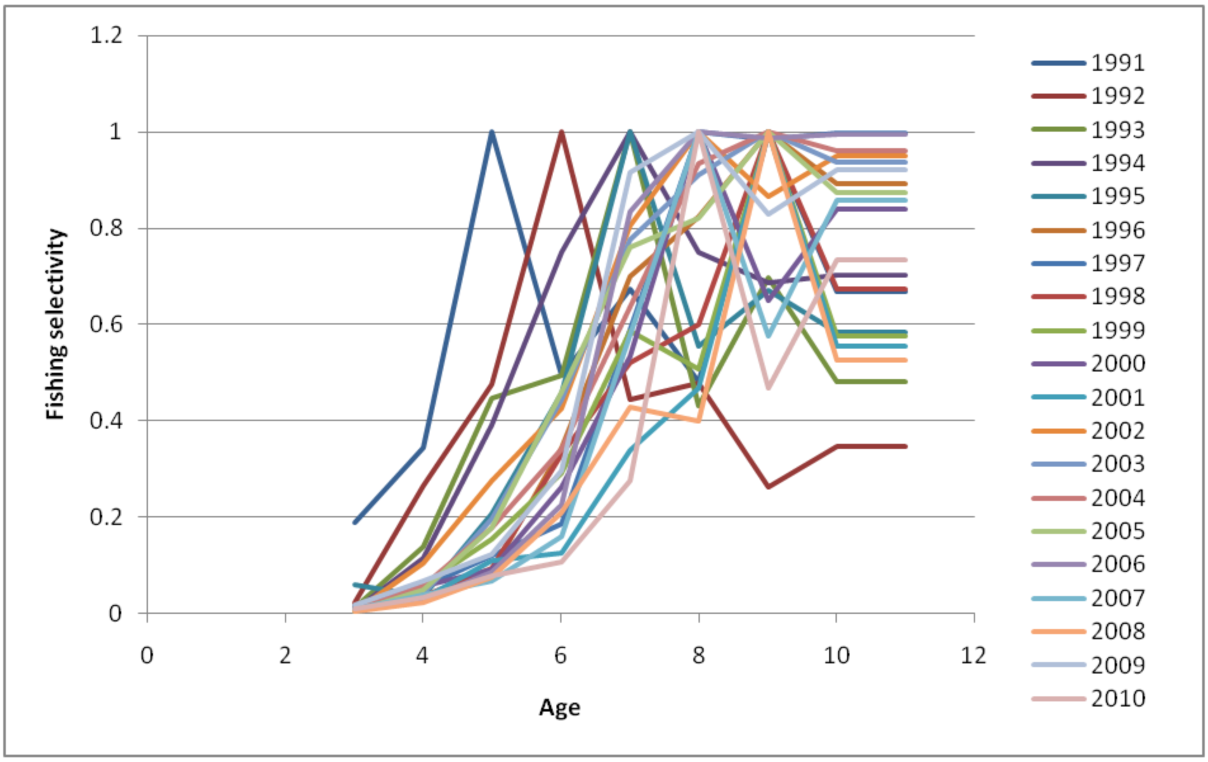


Figure B3.9: VPA estimated fishing selectivities used for the deterministic projection for New England witch flounder over the projection period from 1991 to 2010.

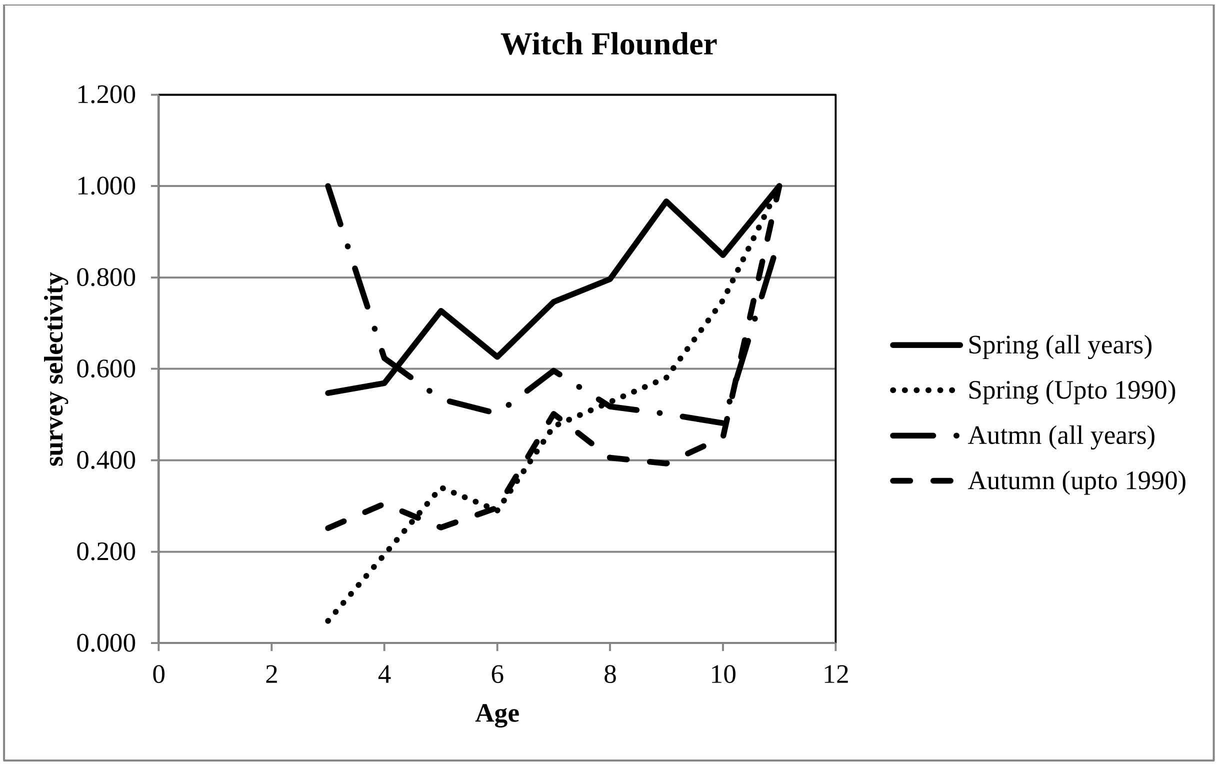


Figure B3.10: NEFSC spring and autumn selectivity vectors estimated from survey numbers-at-age as a fraction of the adjusted VPA estimated population numbers-at-age for witch flounder over alternative periods.

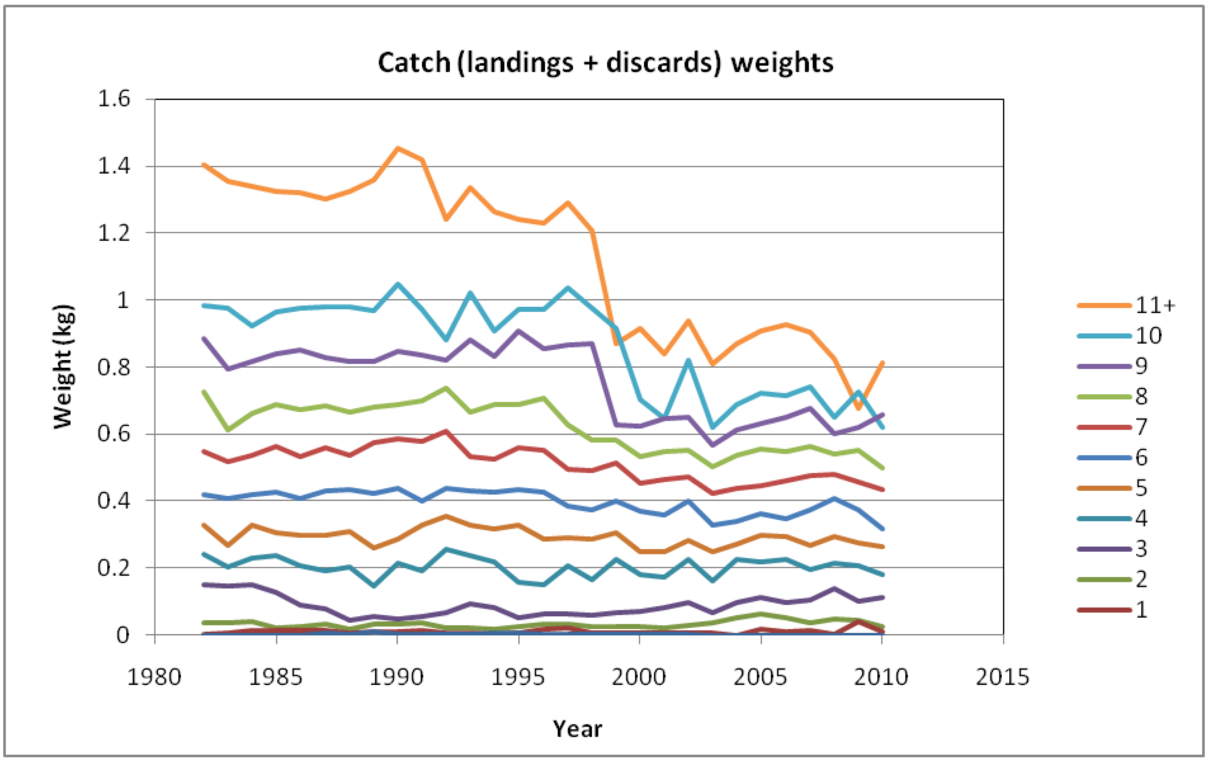


Figure B3.11 Catch (landings and discards) weights (kg) for New England witch flounder for each age group.

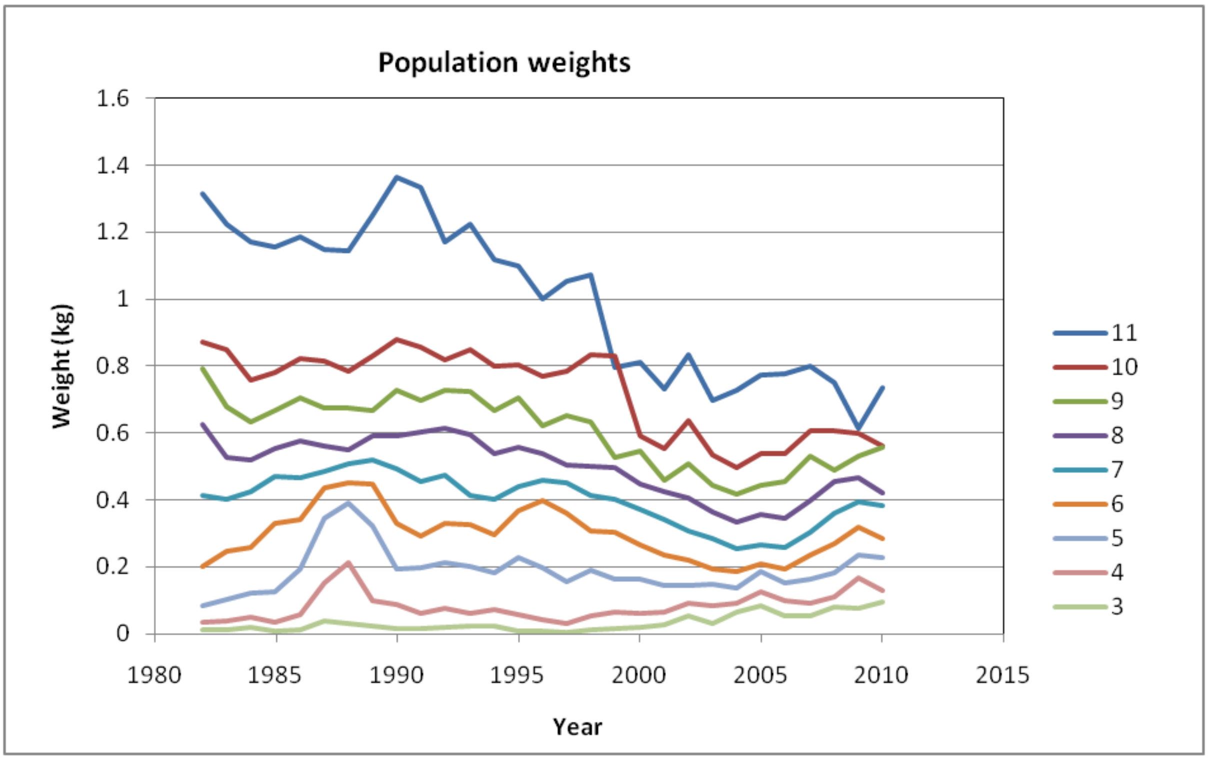


Figure B3.12 Population weights (kg) for New England witch flounder for each age group.

B.4 American Plaice

The latest VPA assessment for the American Plaice stock by O'Brien and Dayton (2012) is used as basis for this retrospective study. An age-independent instantaneous rate of natural mortality (*M*) of 0.2 yr^{-1} is assumed, the same as used for the 2012 stock assessment. Furthermore, the same maturity ogive used in the 2012 American Plaice stock assessment is assumed here for the retrospective projections commencing in 1991, given in Table B4.1.

The selectivity vectors associated with the NEFSC spring and autumn abundance indices are given in Table B4.2. Due to changes apparent in selectivity patterns over the assessment years from 1982 to 2010, different selectivity vectors are used for the "hindsight" (when averaging over all years) and "forecast" (when assuming knowledge up to 1990 only) projections.

Stock–recruitment parameters required for the deterministic and stochastic projections, estimated by fitting a two-line ("hockey-stick") and Beverton-Holt function to the 2012 VPA assessment estimates for spawning biomass and recruitment, are given in Table B4.3.

The annual number of recruits (1-yr-olds) and associated spawning biomasses from 1982 to 2010 as estimated in the 2012 VPA assessment, as well as observed total annual catches are given in Table B4.4. The population numbers-at-age matrix estimated in the 2012 VPA assessment, with plusgroup adjusted for consistency according to Section 4.4.2 of Chapter 4, is given in Table B4.5, with the adjusted fishing mortality-at-age matrix given in Table B4.6.

The age-aggregated NEFSC spring and autumn survey indices of abundance are given in Table B4.7.

A visual representation of the data are given in Figures B4.1 to B4.12:

Figure B4.1: Total annual catches (landings plus discards) of American Plaice in tons.

Figure B4.2: Adjusted plusgroup population numbers compared to the 2012 VPA estimates for American Plaice.

Figure B4.3: Adjusted plusgroup catch compared to observed catch for American Plaice.

Figure B4.4: Age-aggregated NEFSC spring and autumn survey indices of abundance for American Plaice.

Figure B4.5: Trajectories for various biomass components from the 2012 VPA assessment for Gulf of Maine/Georges Bank American Plaice with plusgroup adjusted as detailed in the text.

Figure B4.6: Number of recruits (1-yr-olds) estimated in the 2012 VPA assessment for American Plaice and the number of recruits in terms of a two-line (a) and Beverton-Holt (b) stock-recruit functions fitted to data from 1980 to 2010 (hindsight) or 1980 to 1990 (forecast).

Figure B4.7: Annual number of recruits (1-yr-olds) estimated in the 2012 VPA assessment for American Plaice compared to the number of recruits in terms of the two-line (a) and Beverton-Holt (b) stock-recruit functions.

Figure B4.8: 2012 VPA estimated fishing selectivities for American Plaice for the "historic" period from 1980 to 1990.

Figure B4.9: 2012 VPA estimated fishing selectivities for American Plaice over the projection period from 1991 to 2010.

Figure B4.10: Alternative NEFSC spring and autumn survey selectivities-at-age for American Plaice.

Figure B4.11: Catch weights (kg) for American Plaice for each age group.

Figure B4.12 Population weights (kg) for American Plaice for each age group.

Age:	1	2	3	4	5	6	7	8	9	10	11
Natural Mortality rate	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Maturity	0.03	0.08	0.24	0.51	0.77	0.92	0.97	0.99	1.0	1.0	1.0
NEFSC spring survey selectivity	0.35	0.72	0.97	1.00	0.81	0.67	0.48	0.46	0.44	0.46	0.53
NEFSC autumn survey selectivity	0.05	0.46	0.76	1.00	0.99	0.83	0.74	0.62	0.64	0.60	0.59

Table B4.1 Natural mortality rate, maturity-at-age and survey selectivity vectors.

		two-line			Beverton-Holt		
	Period	σ_R	α (thousands)	B^0 (tons)	σ_R	α (thousands)	β (tons)
Deterministic	1982-2010	0.444	24713	6251	0.453	28044	30413
Stochastic	1982-1990	0.412	28567	7727	0.428	1829	1984

Table B4.2: Stock–recruitment parameters estimated for “hindsight” and “forecast” projections.

Year	Number of recruits	Spawning biomass	Total catch (tons)
1980	50232	37995	13597
1981	25903	28898	12901
1982	20906	25109	15156
1983	24864	21148	13178
1984	15983	18621	10142
1985	19961	11282	7070
1986	26410	8203	4506
1987	47524	8449	3849
1988	63586	8639	3490
1989	24530	8117	3621
1990	24478	8093	4129
1991	24216	10661	6150
1992	27203	11596	7231
1993	44903	10100	6329
1994	44324	9836	5688
1995	28017	8184	5683
1996	24976	8464	4957
1997	21205	9954	4852
1998	16448	11103	4405
1999	19906	9728	3989
2000	10803	10246	4673
2001	14785	10036	4935
2002	27477	8216	3795
2003	21577	7028	2806
2004	33402	6210	2069
2005	36719	6875	1641
2006	38879	9194	1391
2007	16890	12271	1237
2008	21564	15963	1358
2009	18368	16919	1771
2010	7623	17642	1798

Table B4.4: Number of recruits and adjusted spawning biomass estimates, taken from the 2012 VPA assessment, with total annual catches (landings plus discards) with adjusted plusgroup incorporated for American Plaice.

Age	1	2	3	4	5	6	7	8	9	10	11
1980	50232	39485	32630	24058	19252	13956	9946	4677	3005	2776	2947.2
1981	25903	41122	32238	25748	17289	12219	7895	4890	2764	1441	3109.71
1982	20906	21203	32781	24417	16531	9366	6729	4309	2585	1683	2472.63
1983	24864	17108	16815	23820	15874	9490	4446	2568	1709	995	1776.18
1984	15983	20344	13409	12434	14849	8587	4272	1618	969	772	1149.44
1985	19961	13084	16322	10084	8001	6762	4125	1769	805	547	889.651
1986	26410	16284	10570	12265	7052	4393	2968	1394	488	269	550.083
1987	47524	21570	12756	7988	7986	4246	2273	1262	577	173	383.058
1988	63586	38875	17127	8786	5245	4490	2277	1060	548	304	278.905
1989	24530	51776	31119	12364	5544	2861	2381	1368	625	290	326.368
1990	24478	20056	38857	21770	7074	2911	1490	1175	630	336	306.079
1991	24216	20039	14642	24755	13338	3679	1690	863	580	342	359.499
1992	27203	19824	16000	10566	14199	6355	1863	1088	556	293	396.716
1993	44903	22254	15782	11662	6785	6051	2802	752	719	338	316.17
1994	44324	36724	17720	12322	7561	3248	2585	1058	378	332	274.065
1995	28017	36185	28496	14050	8466	3555	1451	1079	334	101	251.386
1996	24976	22859	25439	21113	8995	3814	1204	597	354	87	124.552
1997	21205	20426	16844	18950	13132	4765	1721	460	271	176	92.2472
1998	16448	17335	15582	13323	13052	7137	2294	835	214	146	129.271
1999	19906	13433	14111	12433	10062	8046	3506	915	399	121	128.735
2000	10803	16294	10802	11384	9055	6689	4368	1623	313	192	126.52
2001	14785	8843	13061	8379	8446	5841	3437	1988	820	133	156.598
2002	27477	12104	7156	10272	5832	4728	2737	1377	805	405	126.279
2003	21577	22494	9898	5757	7697	3453	2235	1169	662	403	243.542
2004	33402	17645	17193	8049	4406	5102	1668	1173	467	297	311.574
2005	36719	27338	14223	13840	6184	2760	3074	899	626	204	351.117
2006	38879	30001	21882	11515	10909	4114	1534	2103	570	422	346.949
2007	16890	31783	24434	17780	8940	8186	2859	925	1545	376	531.14
2008	21564	13538	25616	19769	13965	6581	6245	2134	666	1212	685.601
2009	18368	17629	10990	20801	15668	10613	4859	4800	1588	461	1419.91
2010	7623	15037	14355	8873	16565	11900	7773	3444	3538	1166	1365.82

Table B4.5: Population numbers-at-age for American Plaice from the 2012 VPA assessment, but with adjusted plusgroup as discussed in Appendix Section 4.4.2 of Chapter 4.

Age	1	2	3	4	5	6	7	8	9	10	11
1980	0	0	0.04	0.13	0.25	0.37	0.51	0.33	0.53	0.41	0.41
1981	0	0.03	0.08	0.24	0.41	0.4	0.41	0.44	0.3	0.41	0.41
1982	0	0.03	0.12	0.23	0.36	0.55	0.76	0.72	0.75	0.65	0.65
1983	0	0.04	0.1	0.27	0.41	0.6	0.81	0.78	0.59	0.68	0.68
1984	0	0.02	0.08	0.24	0.59	0.53	0.68	0.5	0.37	0.57	0.57
1985	0	0.01	0.09	0.16	0.4	0.62	0.89	1.09	0.9	0.76	0.76
1986	0	0.04	0.08	0.23	0.31	0.46	0.66	0.68	0.84	0.56	0.56
1987	0	0.03	0.17	0.22	0.38	0.42	0.56	0.63	0.44	0.49	0.49
1988	0.01	0.02	0.13	0.26	0.41	0.43	0.31	0.33	0.44	0.38	0.38
1989	0	0.09	0.16	0.36	0.44	0.45	0.51	0.58	0.42	0.5	0.5
1990	0	0.11	0.25	0.29	0.45	0.34	0.35	0.51	0.41	0.38	0.38
1991	0	0.03	0.13	0.36	0.54	0.48	0.24	0.24	0.48	0.37	0.37
1992	0	0.03	0.12	0.24	0.65	0.62	0.71	0.21	0.3	0.58	0.58
1993	0	0.03	0.05	0.23	0.54	0.65	0.77	0.49	0.57	0.67	0.67
1994	0	0.05	0.03	0.18	0.55	0.61	0.67	0.95	1.12	0.68	0.68
1995	0	0.15	0.1	0.25	0.6	0.88	0.69	0.91	1.15	0.84	0.84
1996	0	0.11	0.09	0.27	0.44	0.6	0.76	0.59	0.5	0.63	0.63
1997	0	0.07	0.03	0.17	0.41	0.53	0.52	0.57	0.42	0.53	0.53
1998	0	0.01	0.03	0.08	0.28	0.51	0.72	0.54	0.37	0.56	0.56
1999	0	0.02	0.01	0.12	0.21	0.41	0.57	0.87	0.53	0.48	0.48
2000	0	0.02	0.05	0.1	0.24	0.47	0.59	0.48	0.66	0.51	0.51
2001	0	0.01	0.04	0.16	0.38	0.56	0.71	0.7	0.5	0.63	0.63
2002	0	0	0.02	0.09	0.32	0.55	0.65	0.53	0.49	0.58	0.58
2003	0	0.07	0.01	0.07	0.21	0.53	0.44	0.72	0.6	0.53	0.53
2004	0	0.02	0.02	0.06	0.27	0.31	0.42	0.43	0.63	0.35	0.35
2005	0	0.02	0.01	0.04	0.21	0.39	0.18	0.25	0.19	0.27	0.27
2006	0	0.01	0.01	0.05	0.09	0.16	0.31	0.11	0.22	0.17	0.17
2007	0.02	0.02	0.01	0.04	0.11	0.07	0.09	0.13	0.04	0.08	0.08
2008	0	0.01	0.01	0.03	0.07	0.1	0.06	0.1	0.17	0.09	0.09
2009	0	0.01	0.01	0.03	0.08	0.11	0.14	0.1	0.11	0.12	0.12
2010	0	0.07	0.06	0.07	0.05	0.11	0.1	0.08	0.04	0.09	0.09

Table B4.6: Fishing mortality-at-age for American Plaice from the 2012 VPA assessment with adjusted plusgroup.

	NEFSC survey (weight/tow)	
Year	Spring	Autumn
1980	4.8	5.1
1981	5.9	5.6
1982	3.8	2.5
1983	4.6	3.4
1984	1.4	2.0
1985	1.9	2.0
1986	0.9	1.6
1987	0.8	1.1
1988	0.8	1.5
1989	0.7	1.2
1990	0.8	2.9
1991	1.0	1.6
1992	1.4	1.8
1993	1.4	2.4
1994	0.9	2.7
1995	1.9	2.6
1996	1.7	2.2
1997	1.6	1.9
1998	1.1	2.2
1999	1.2	2.6
2000	2.3	2.8
2001	2.2	2.6
2002	1.8	2.2
2003	0.9	2.3
2004	1.4	1.0
2005	0.8	1.0
2006	1.0	1.7
2007	1.3	1.4
2008	1.5	2.1
2009	1.0	1.4
2010	1.2	1.5

Table B4.7: Age-aggregated spring and autumn survey biomass indices for American Plaice.

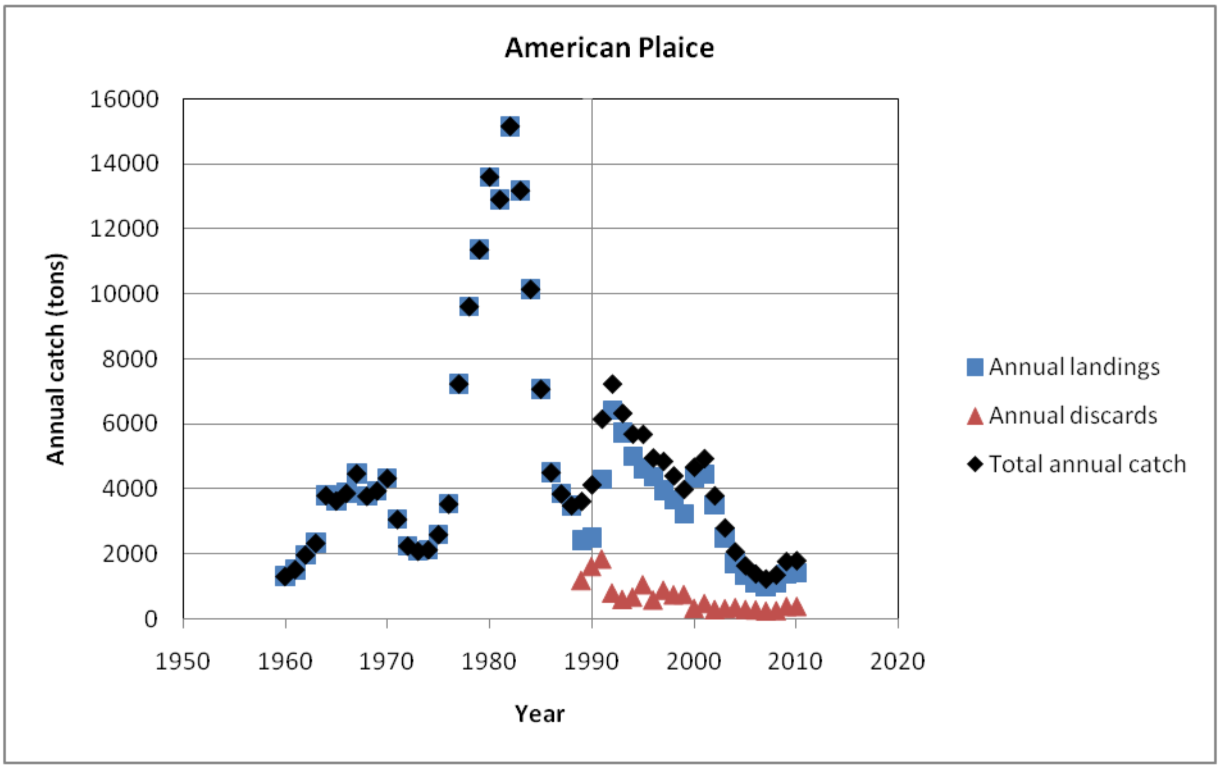


Figure B4.1: Total annual catches (landings plus discards) of Gulf of Maine/Georges Bank American Plaice.

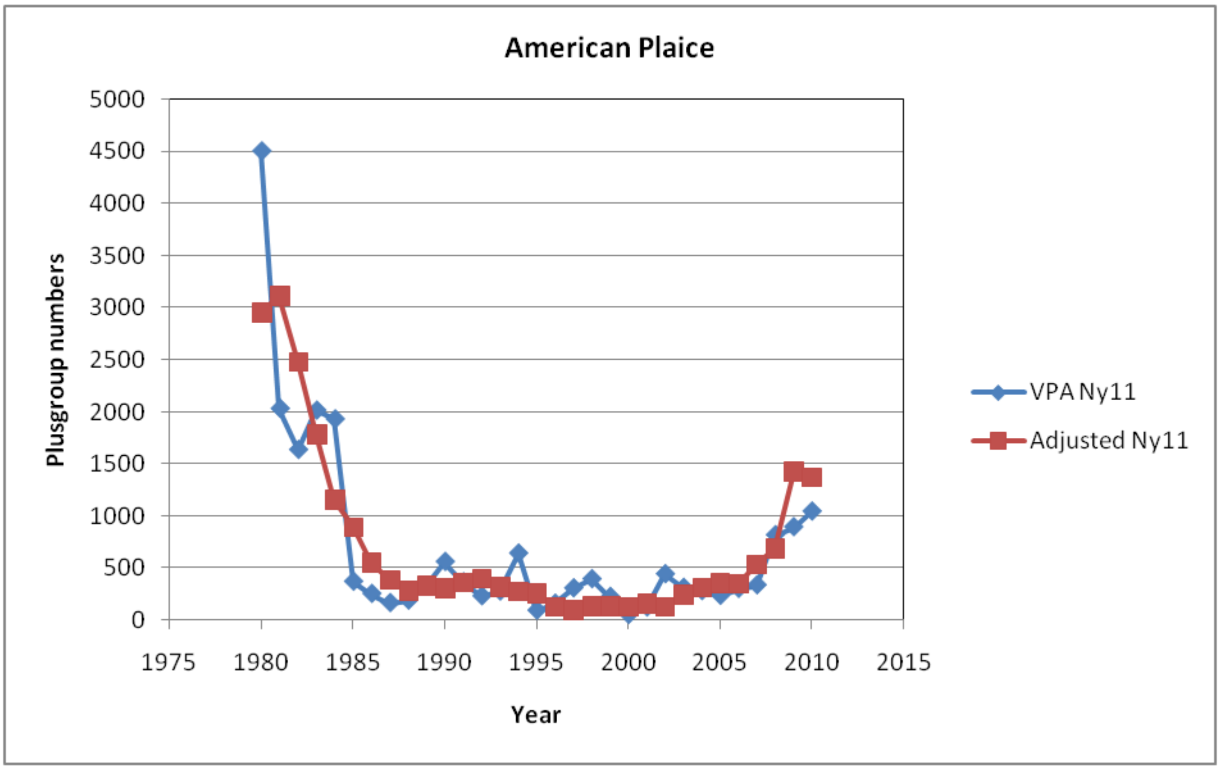


Figure B4.2: Adjusted plusgroup population numbers compared to the 2012 VPA estimates for Gulf of Maine/Georges Bank American Plaice.

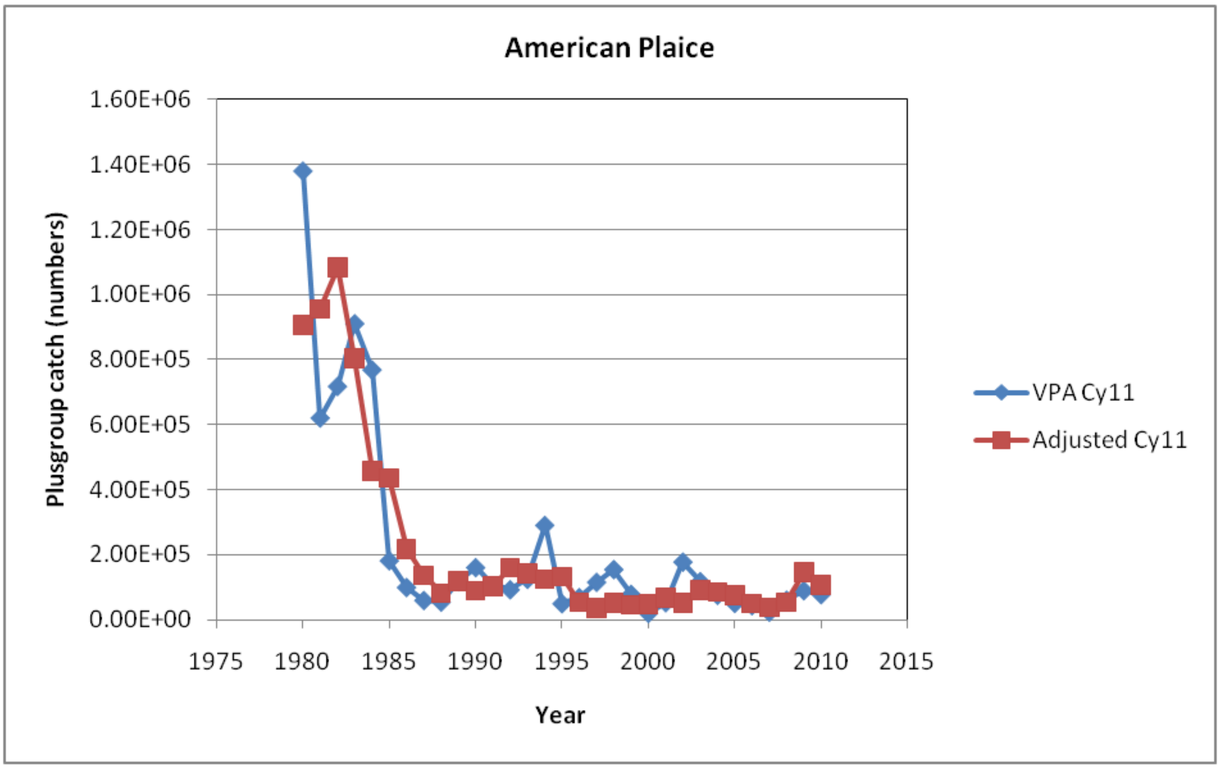


Figure B4.3: Adjusted plusgroup catch (numbers) compared to the observed catch for American Plaice.

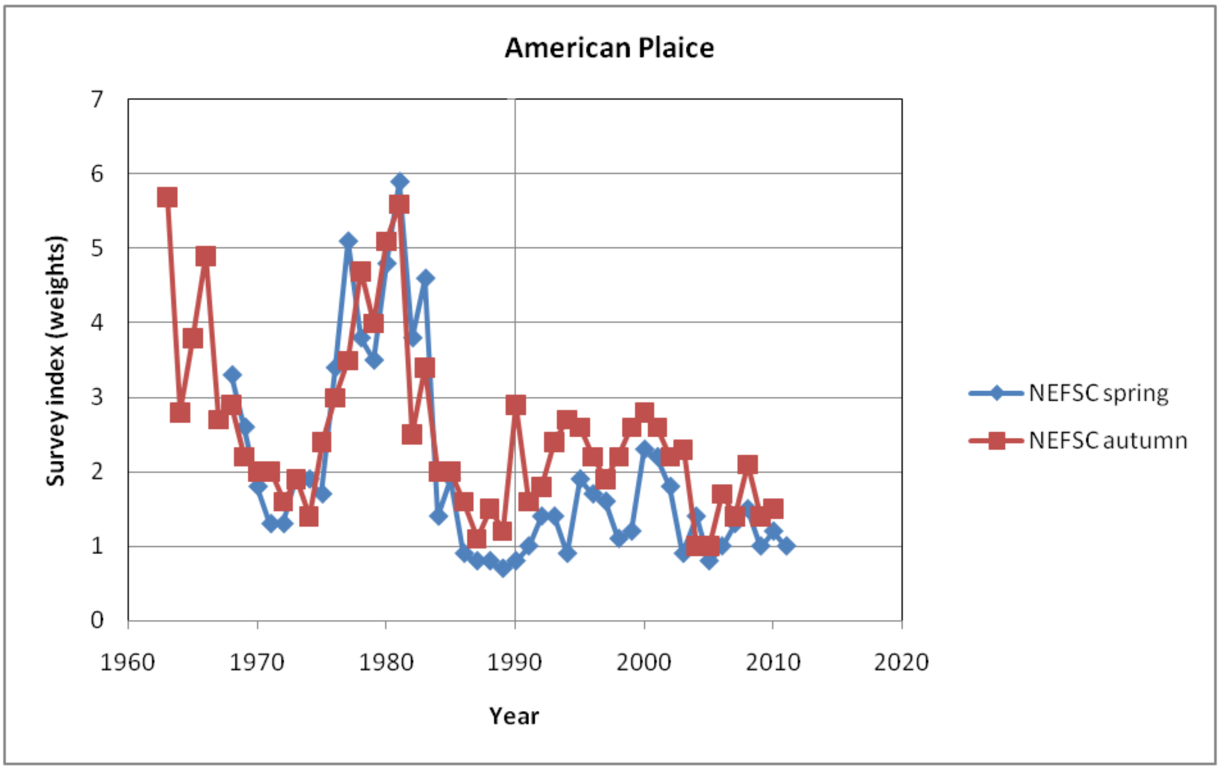


Figure B4.4: Stratified mean weight (kg) per tow of American Plaice in NEFSC spring and autumn bottom trawl surveys in the Gulf of Maine/Georges Bank region.

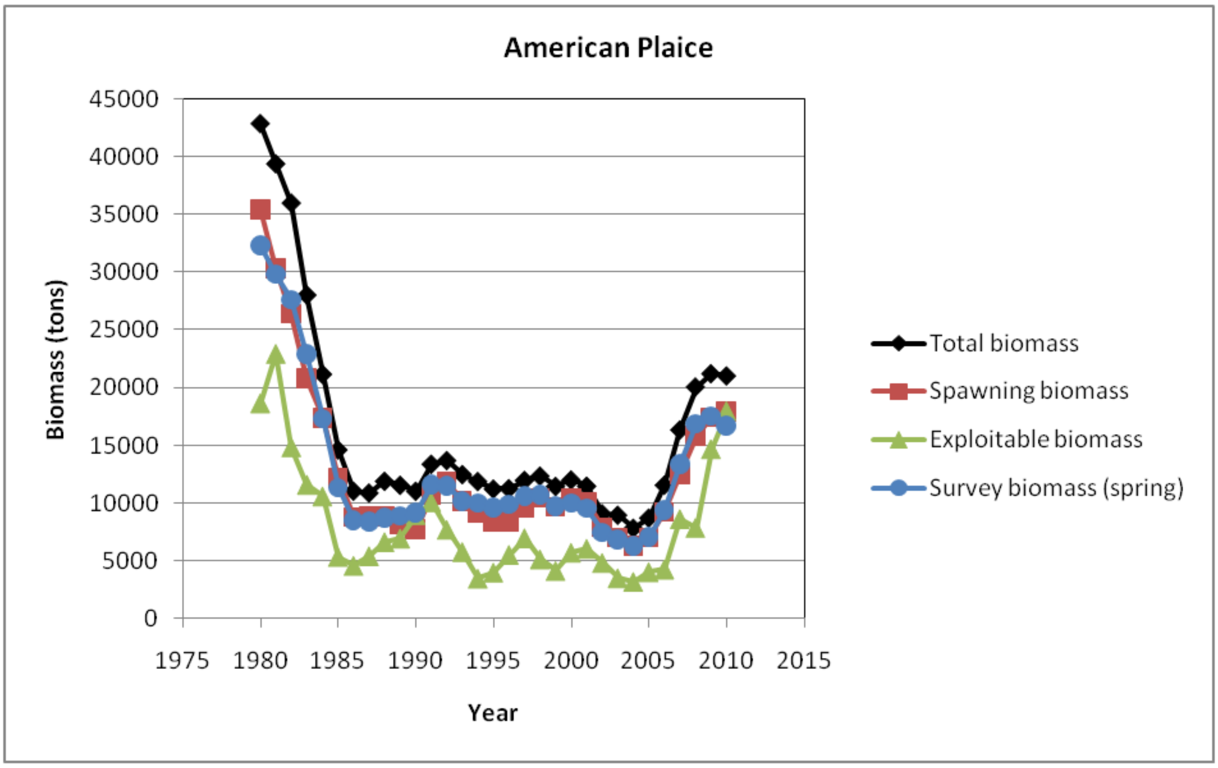
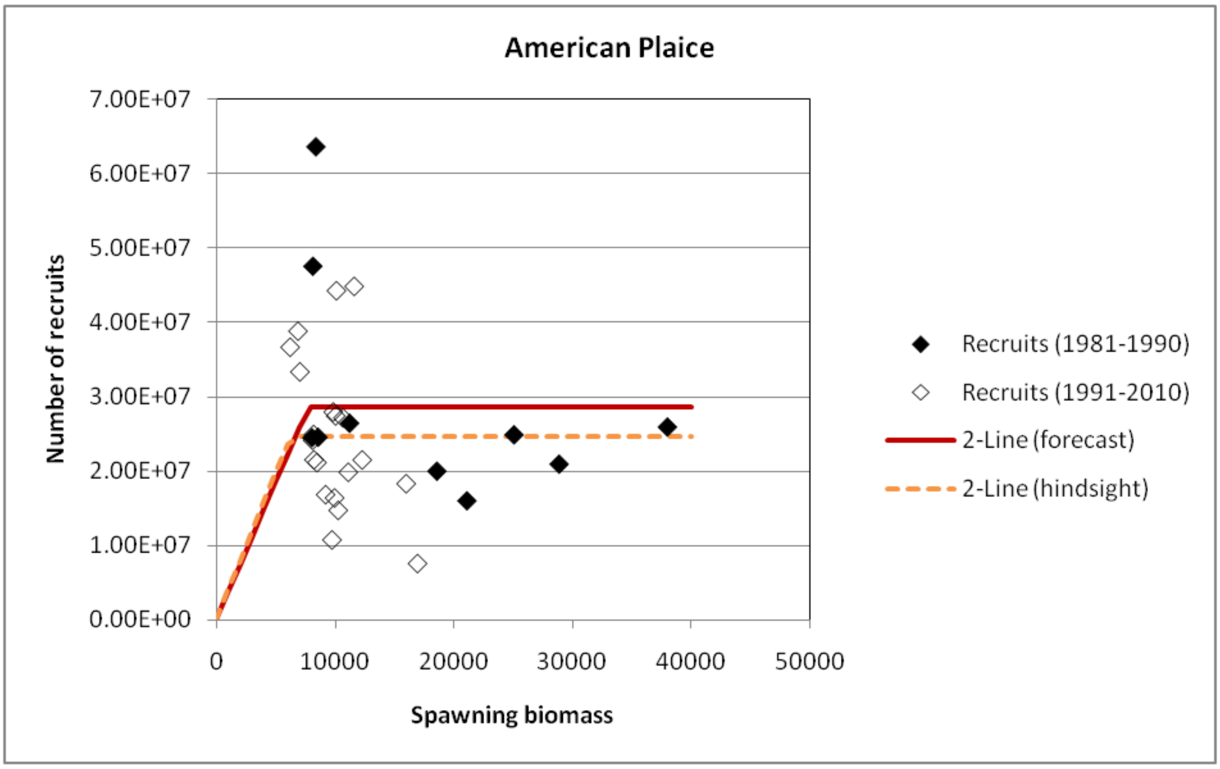


Figure B4.5: Trajectories for various biomass components from the 2012 VPA assessment for Gulf of Maine American Plaice, as well as derived biomass estimates corresponding to the NEFSC spring index.



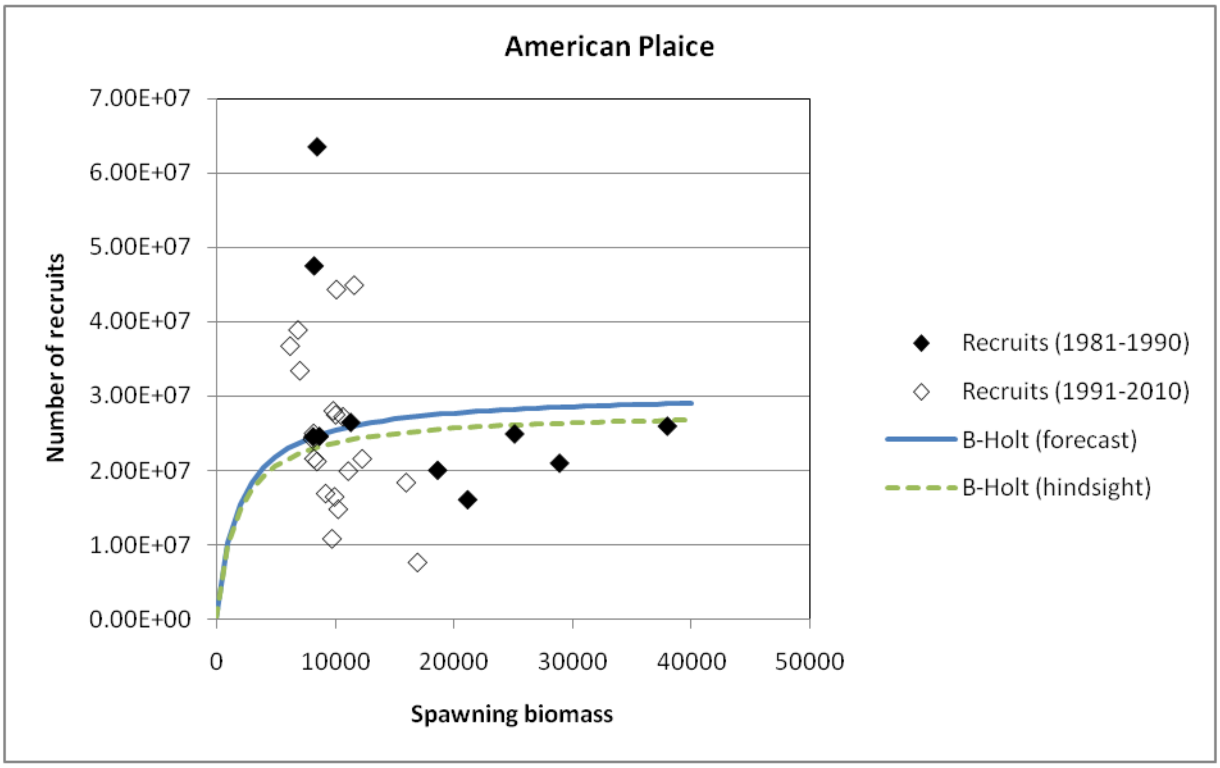
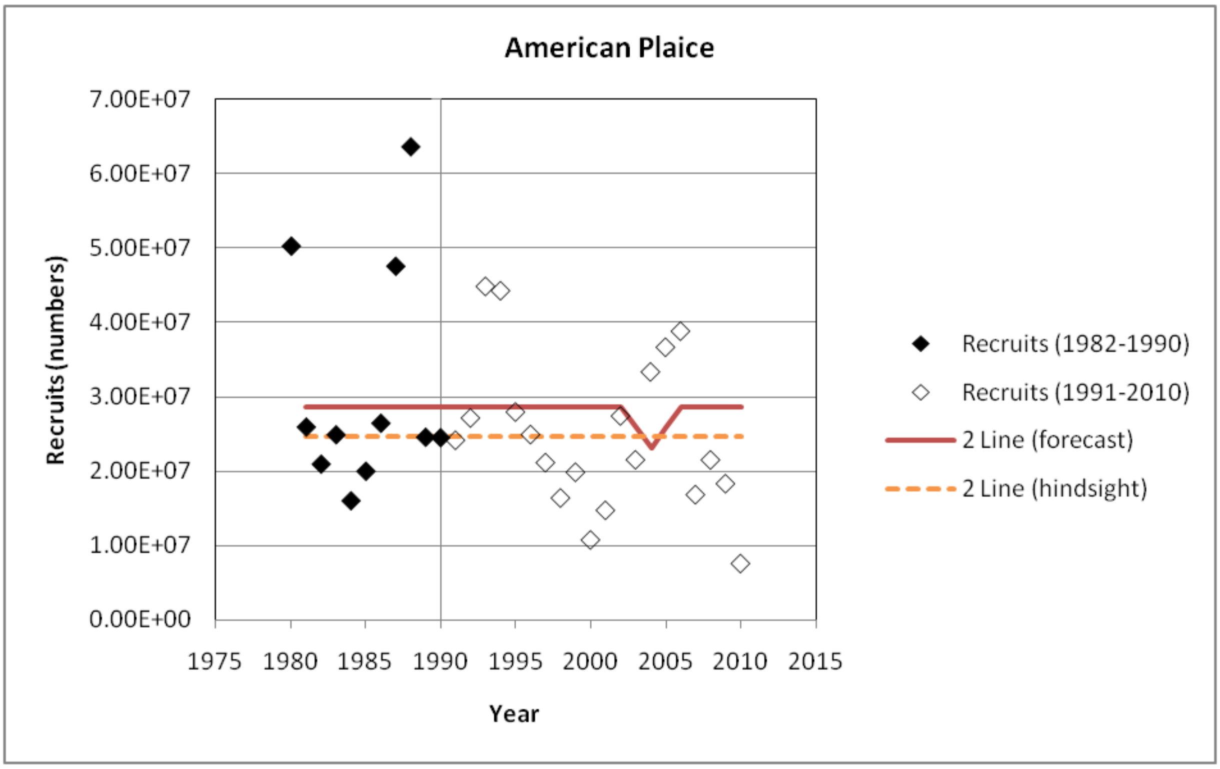


Figure B4.6a and b: Number of recruits as a function of spawning biomass. Solid diamonds correspond to the 2012 VPA assessment recruitment estimates from 1981 to 1990 (the "past"), while empty diamonds correspond to the projection period from 1991 to 2010 (the "future"). The two stock–recruitment functions shown are based on "past" (pre-1991) recruitment and biomass estimates (solid lines) and recruitment and biomass estimates over the entire period (dotted lines).



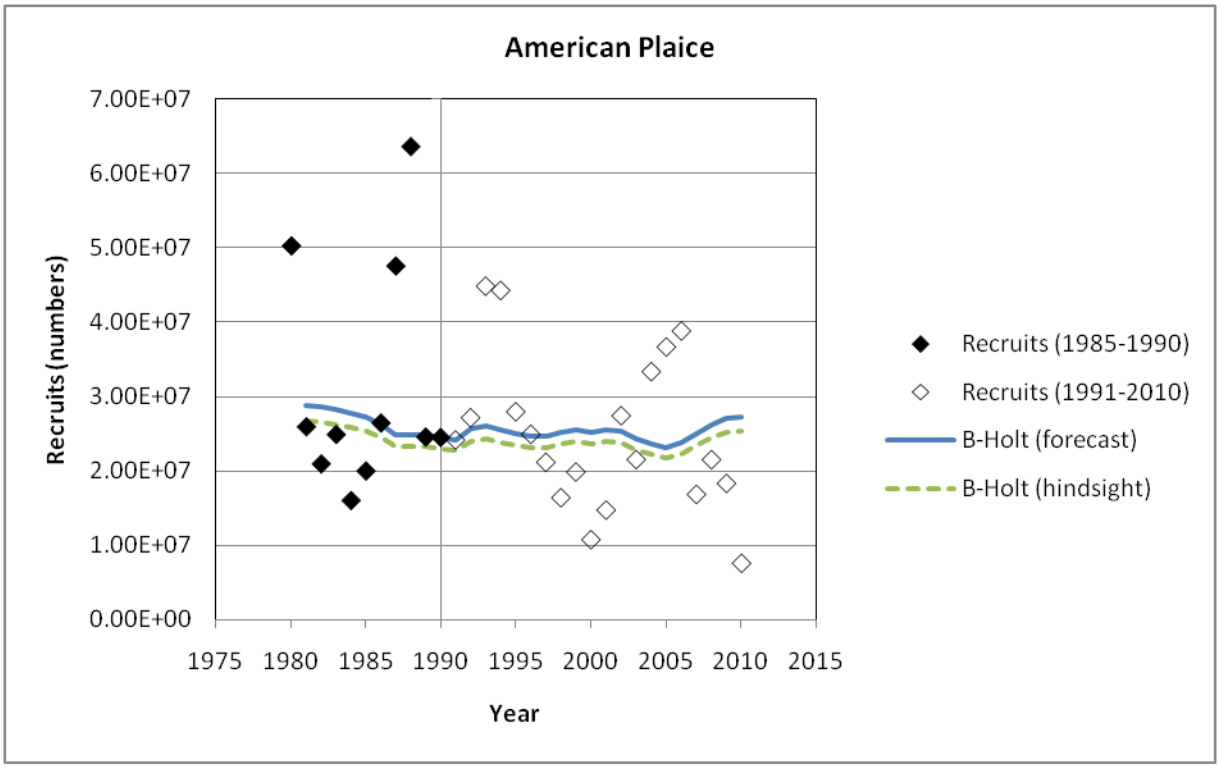


Figure B4.7a and b: Annual number of recruits estimated in the 2012 VPA assessment of American Plaice (diamonds) compared to the annual number of recruits in terms of two-line stock-recruit relationship (top plot) when using parameters corresponding to the forecast and hindsight scenarios. The bottom plot shows the corresponding Beverton-Holt stock–recruitment function when fixing h=0.9. See Table B4.3 for stock–recruitment parameter values.

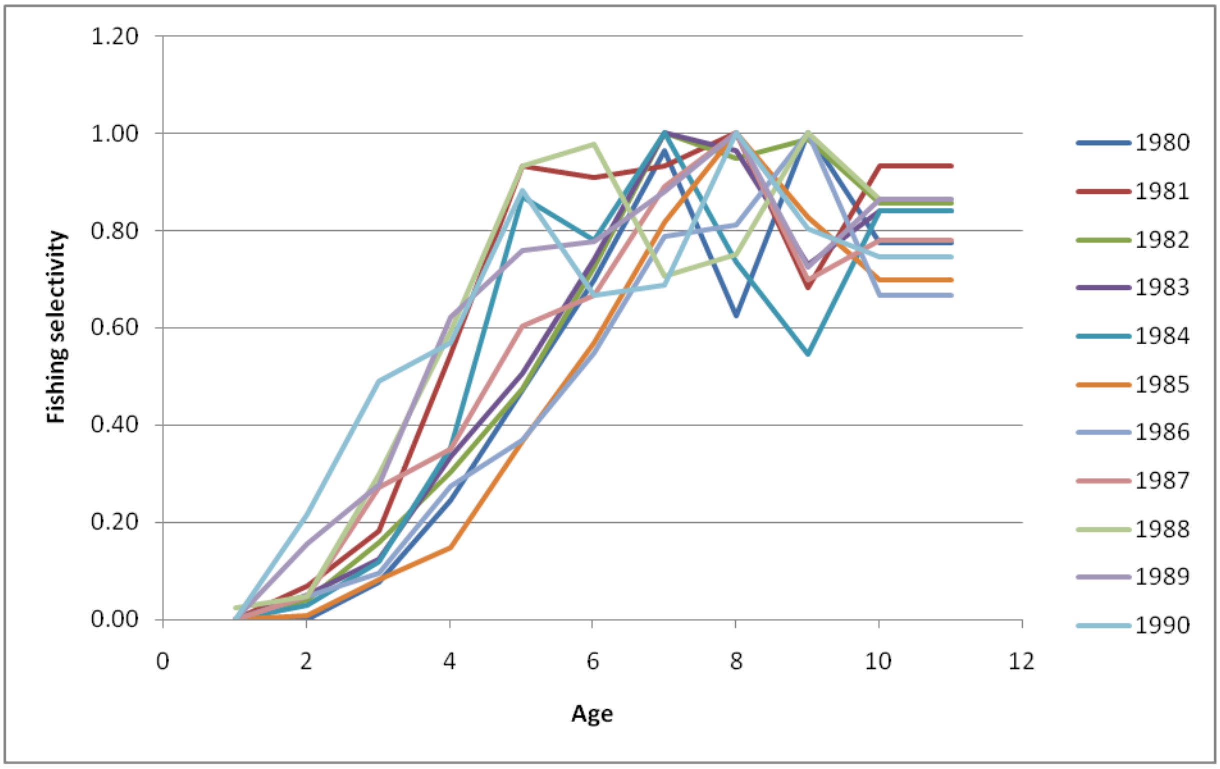


Figure B4.8: VPA estimated fishing selectivities for American Plaice over the historic period from 1980 to 1990. Selectivity vectors for stochastic "forecast" projections are randomly sampled from these past vectors.

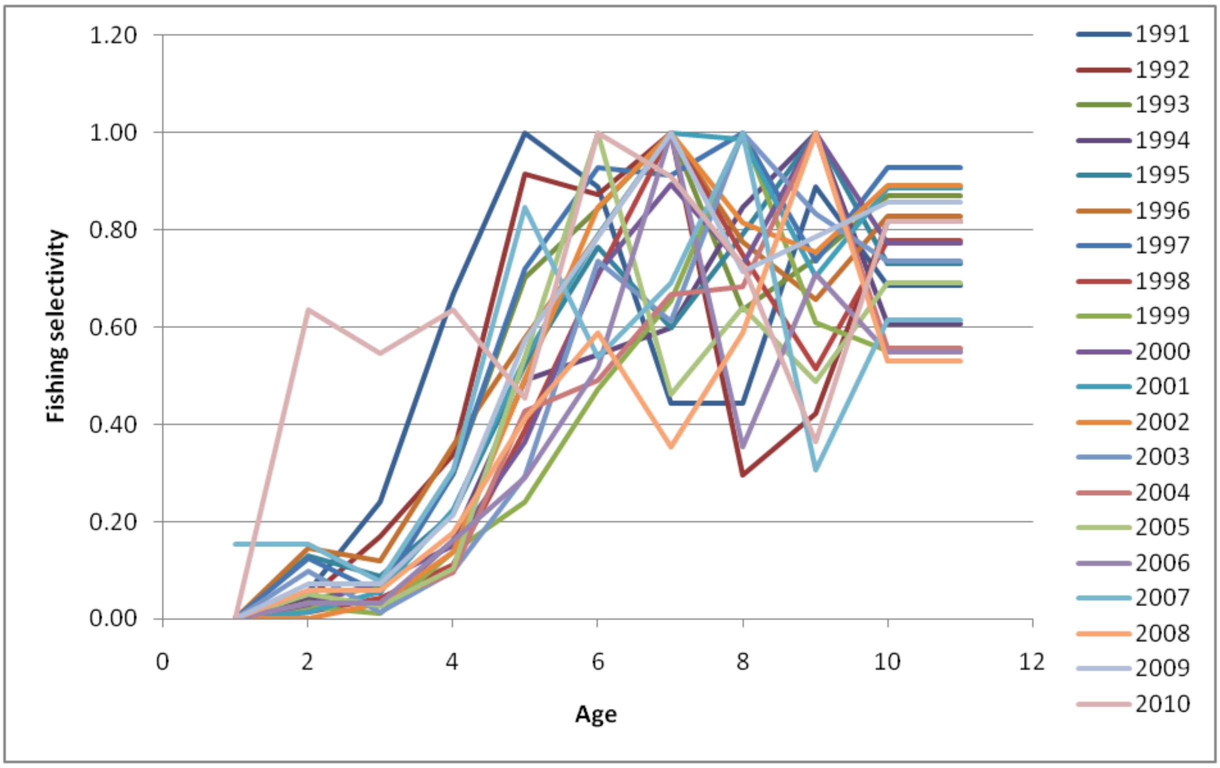


Figure B4.9: VPA estimated fishing selectivities used for the deterministic projections for American Plaice over the projection period from 1991 to 2010.

Figure B4.10: NEFSC spring and autumn selectivity-at-age vectors for the hindsight (1980 to 2010) and forecast (1980-1990) projections.

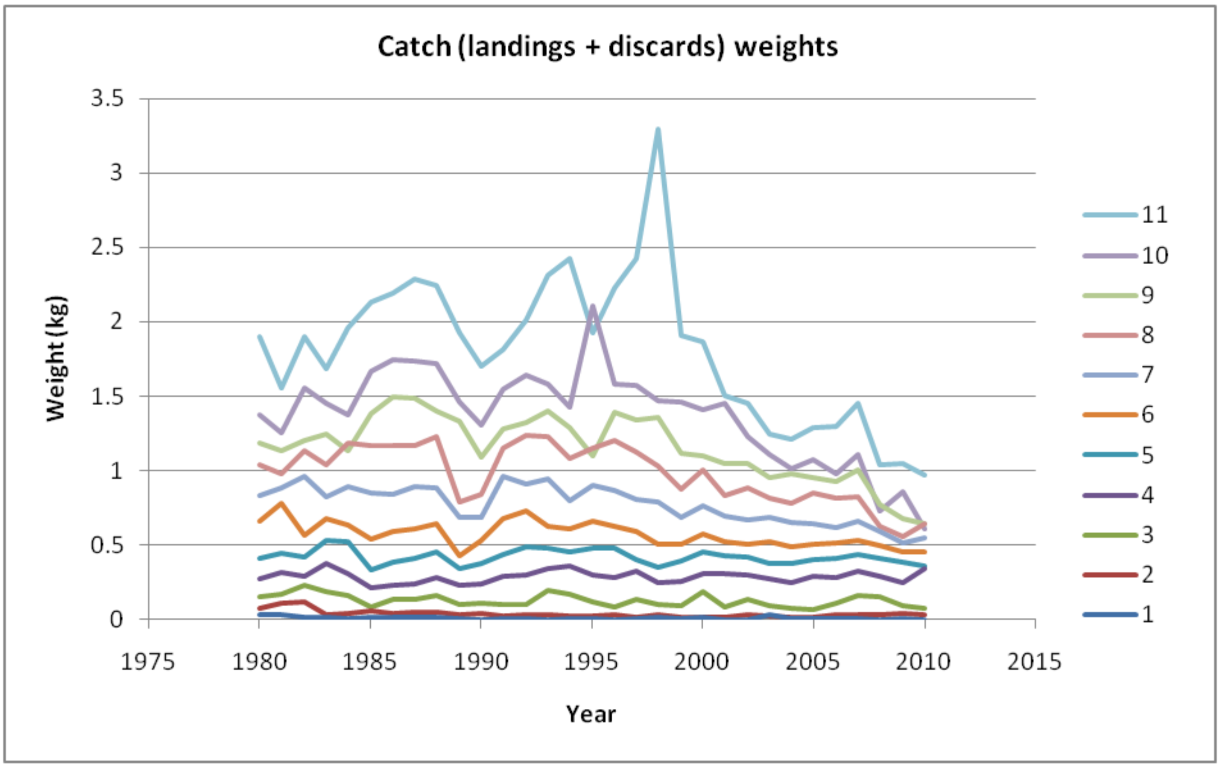


Figure B4.11 Catch (landings plus discards) weights (kg) for America Plaice for each age group.

Figure B4.12 Population weights (kg) for American Plaice for each age group.

Appendix C: Data preparation and fitting prior to projections

The most recent assessment outputs for North Sea sole and plaice (ICES 2010) and New England witch flounder and plaice (NEFSC 2012) are used as basis for the retrospective analysis.
Input data (observed annual catches, estimated number of recruits and associated spawning biomasses as estimated by the most recent stock assessments) and pertinent parameter values are given Appendix B for each of the four stocks investigated in this retrospective study. Tables and plots of input data and model parameters for each stock are also shown in the Appendix B.

C.1 Plusgroup adjustment

An age-structured production model (ASPM) is used to model the resource dynamics, as described in Chapter 2. Continuous fishing throughout year is assumed so that the population dynamics are described by the Baranov equations (2.1) to (2.4).

Difficulties arise from the manner in which the plusgroup has been treated in Virtual Population Analysis (VPA) assessments for the four stocks considered which, although this makes little difference to the overall assessment results, is mathematically inconsistent in not respecting equation (2.3) for the dynamics. Because of the need for comparable and consistent reflections of the dynamics in the alternative projections considered in this analysis, the plusgroup numbers and fishing mortalities from the assessments needed to be re-estimated in a way that avoids this inconsistency. To this end, for both the assessments and the projections, the plusgroup numbers, $N_{y,m}$, have been re-estimated such that:

$$N_{y+1,m} = \sum_{a=m-1}^{m} N_{y,a} e^{-Z_{y,a}} \qquad \text{(C.1)}$$

where

$N_{y+1,m}$ is the plusgroup number of fish at the start of year *y+1*,

m is the maximum age considered (taken to be a plusgroup),

$Z_{y,a} = M_{y,a} + F'_{y,a}$ is the total mortality on fish in year *y*, where

$M_{y,a}$ is the natural mortality rate, assumed to be age and year-independent, and

$F'_{y,a} = S_{y,a} F_y$ are the fishing mortalities-at-age in year *y*.

In the equation above both $N_{y,m-1}$ and $Z_{y,m-1}$ are known from the VPA assessment. In order to re-compute the plusgroup number for the next year $y+1$, the plusgroup number for year y needs to be known, which in turn is computed from the previous year's plusgroup number, etc. Therefore, only an estimate of the first plusgroup, $N_{1,m}$, is required to be able to compute all subsequent plusgroup numbers.

The plusgroup fishing mortality rates, $F_{y,10}$, are re-estimated using the Baranov catch equation:

$$C_{y,m} = F'_{y,m} N_{y,m} (1 - e^{-Z_{y,m}}) / Z_{y,m} \tag{C.2}$$

In addition, flat fishing selectivity is assumed at older ages so that:

$$F'_{y,m} = F'_{y,m-1} \tag{C.3}$$

Since the three equations above cannot be satisfied simultaneously, $N_{1,m}$ and $F_{y,m}$ need to be estimated in some manner that satisfies the last two equations as closely as possible without being exact for both. This has been effected by setting up the problem in a likelihood context, and estimating maximum likelihood values. The likelihood is calculated assuming that the observed plusgroup catches defined by equation (C.2) are log-normally distributed about their expected values:

$$C_{y,m} = \hat{C}_{y,m} e^{\zeta_y} \tag{C.4}$$

where $\zeta_y \sim N(0, (\sigma^C)^2)$. Similarly, the plusgroup fishing mortalities are assumed to be log-normally distributed about their expected values:

$$F'_{y,m} = F'_{y,m-1} e^{\tau_y} \tag{C.5}$$

where $\tau_y \sim N(0, (\sigma^F)^2)$.

The contributions to the negative of the (penalised) log-likelihood function are given by:

$$-\ln L = -\ln L^F - \ln L^C \tag{C.6}$$

where

$$-\ln L^F = \sum_y [\ln \sigma^F + (\ln F'_{y,m-1} - \ln F'_{y,m})^2 / 2(\sigma^F)^2] \qquad \text{(C.7)}$$

and

$$-\ln L^C = \sum_y [\ln\sigma^C + (\ln C_{y,m} - \ln \hat{C}_{y,m})^2 / 2(\sigma^C)^2] \qquad \text{(C.8)}$$

where σ^F and σ^C are the standard deviation of the residuals, estimated in the fitting procedure by their maximum likelihood values:

$$\sigma^F = \sqrt{1/n \sum_y (\ln F'_{y,m} - \ln F'_{y,m-1})^2} \qquad \text{(C.9)}$$

and

$$\sigma^C = \sqrt{1/n \sum_y (\ln C_{y,m} - \ln \hat{C}_{y,m})^2} \qquad \text{(C.10)}$$

where n is the number of years over which the summation is taken.

The population numbers and fishing mortality matrices, $N_{y,a}$ and $F'_{y,a}$ which incorporate these adjustments are given in Appendix B for each stock investigated. Due to the near-zero estimates of σ^F, the $F'_{y,a}$ matrices are effectively unchanged from those estimated in the VPA assessments. The plots of the adjusted plusgroup population numbers, $N_{y,m}$, and annual plusgroup catches (landings and discards), $C_{y,m}$, are also shown in Appendix B for each stock.

The age-specific fishing selectivity vectors for each year are derived from the adjusted $F'_{y,a}$ matrix such that:

$$S_{y,a} = F'_{y,a} / F_y \qquad \text{(C.11)}$$

where $F_y = \max_a (F'_{y,a})$.

These annual fishing selectivity-at-age vectors are shown in Appendix B for each of the stocks considered.

C.2 Stock–recruitment relationship

A stock–recruitment function is required for the projections. The number of recruits is assumed to be log-normally distributed about a stock–recruitment relationship such that:

$$R_y^{VPA} = \hat{R}_y e^{\varsigma_y} \tag{C.12}$$

where

R_y^{VPA} are the number of recruits in year *y*, input from the most recent VPA assessment,

$\hat{R}_y$ is the number of recruits according to some stock-recruit relationship, and

ς_y are the corresponding recruitment residuals.

The objective function minimized to estimate the parameters of the relationship is given by:

$$-\ln L = \sum_y [\ln \sigma^R + (\ln R_y^{VPA} - \ln \hat{R}_y)^2 / 2(\sigma^R)^2] \tag{C.13}$$

where $\sigma^R = \sqrt{1/n \sum_y (\ln R_y^{VPA} - \ln \hat{R}_y)^2}$ is the standard deviation of the residuals estimated in the fitting procedure by its maximum likelihood value and *y* runs over the "historic" pre-1990 years for the stochastic projections, and over the entire assessment period for the deterministic projections. These recruitment residuals are then either input for the deterministic "hindsight" projections, or re-sampled from a normal distribution with associated standard deviation, σ^R , for the stochastic "forecast" simulations. For the sake of simplicity, the estimated standard deviation for each stock for both the historic and the entire periods considered is rounded to a single decimal place for the projections: $\sigma^R = 0.8$ for North Sea sole and $\sigma^R = 0.5$ for North Sea plaice and New England witch flounder and plaice.

Two forms of relationships are considered: a Beverton-Holt stock–recruitment function and a simple two-line ("hockey-stick") function. The estimated stock–recruitment parameters and associated standard deviation of the residuals are given in the supplementary material for each stock under consideration (see Tables B1.2, B2.2, B3.2 and B4.2).

C.3 Survey abundance data

A variety of age-disaggregated survey data were used in the VPA assessments that form the basis of study. However, for purposes of this retrospective study, an age-aggregated index of abundance is required for use in the management procedures. The observed age-aggregated survey index, I_y^i, is computed from the survey age data, such that:

$$I_y^i = \sum_a w_{y,a}^S I_{y,a}^i \qquad \text{(C.14)}$$

where $I_{y,a}^i$ are the age-disaggregated survey indices used in the respective stock assessments and the $w_{y,a}^S$ denote the population weights-at-age.

For each observed index of abundance, a catchability coefficient, q^i, needs to be computed for use in the projections. The observed abundance indices, I_y^i, are assumed to be log-normally distributed about their expected values such that:

$$I_y^i = \hat{I}_y e^{\varepsilon_y^i} \qquad \text{(C.15)}$$

where

I_y^i is the actual age-aggregated survey abundance index *i* for year *y* given by equation (C.14),

$\hat{I}_y^i = q^i \sum_{a=a\min}^{m} w_{y,a}^S S_a^i N_{y,a}$ is the corresponding VPA assessment model estimate,

$N_{y,a}$ are the population numbers-at-age at the start of the year according to the VPA assessment,

$S_a^i = 1/n \sum_y I_{y,a}^i / N_{y,a}$ is the survey selectivity vector associated with abundance index *i*, expressed as the average observed survey catch-at-age as a fraction of the total numbers-at-age according to the VPA assessment, and

q^i is the constant of proportionality for abundance series *i* given by:

$$\ln q^i = 1/n \sum_y (\ln I_y^i - \ln \sum_{a=a\min}^{m} w_{y,a} S_a^i N_{y,a}) \qquad \text{(C.16)}$$

and ε_y^i are the residuals:

$$\varepsilon_y^i = \ln I_y^i - \ln(q^i \sum_{a=a\min}^{m} w_{y,a} S_a^i N_{y,a}) \tag{C.17}$$

where n is the number of years of survey data for index i.

The age-aggregated survey indices, with corresponding plots, are given in Appendix B of the supplementary material for the respective stocks. The catch and population weights-at-age matrices, $w_{y,a}^C$ and $w_{y,a}^S$, taken directly from those used in the respective assessments, are also given in Appendix B.