A Decade of Namibian Fisheries Science
Payne, A. I. L., Pillar, S. C. and R. J. M. Crawford (Eds). *S. Afr. J. mar. Sci. 23: 241–264*
2001

DEVELOPMENT OF BAYESIAN STOCK ASSESSMENT METHODS FOR NAMIBIAN ORANGE ROUGHY *HOPLOSTETHUS ATLANTICUS*

M. K. McALLISTER and C. H. KIRCHNER†*

Bayesian methods are useful in fisheries stock assessment because they provide a conceptually elegant and statistically rigorous approach to making decisions under uncertainty. The application of Bayesian stock assessment methods in the management of Namibian orange roughy *Hoplosthethus atlanticus* within the 200 mile EEZ of Namibia is reviewed. Time-series of relative abundance are short and their reliability in indicating abundance trends is uncertain. The development of informative prior probability density functions (pdfs) for the constants of proportionality (q) for hydro-acoustic, commercial trawl swept area, and research trawl swept area indices produced statistically consistent prior estimates of absolute abundance for each of the three grounds where more than one index of abundance was available. The posterior pdfs for stock assessment model parameters were used to account for uncertainty in evaluations of the potential consequences of alternative harvesting policies under a stock reduction model in which catch removals were assumed to account for any declines. It appears that all orange roughy stocks off Namibia have been depleted below the limit reference point (50% of long-term unfished biomass). However, the stock reduction model could not easily account for the large declines in indices on the four fishing grounds over the period from 1995 until 1999 when the informative priors for q were applied. In the 2000 stock assessment, the Bayesian procedure was updated to account formally for uncertainty in model structures that could explain the decline in abundance. The possibility of very low stock abundance could still not be discounted when these uncertainties were accounted for. Although this most recent methodology applies more statistical rigour, its complexity has hindered its acceptance in Namibia. However, if it is worth quantifying risks and uncertainties in future stock assessments for the provision of precautionary management advice, it is proposed that the assessment protocols adopted be probabilistic to account for uncertainty in model parameters, that careful attention be given to subjective judgements about their inputs and the representation of uncertainty within them, and that, where appropriate, alternative hypotheses about stock abundance and mechanisms for catchability and stock decline be taken into account.

Key words: Bayesian, orange roughy, stock assessment, structural uncertainty

In developing fisheries, the abundance of a newly exploited resource is always highly uncertain and time-series of abundance indices too short for conventional stock assessment methods that use them to work with any reliability (Clark *et al*. 1985, Smith 1993, McAllister and Kirkwood 1998a, Walters 1998). Some have advocated Bayesian stock assessment methods for such situations (Clark *et al*. 1985, McAllister *et al*. 1994, McAllister and Kirkwood 1998a). These methods are useful for such fisheries because they can unify diverse but sparse sources of data and expert judgement to provide probabilistic estimates of such management quantities as stock biomass. They also permit application of a formal decision-analysis approach to fishery management (Punt and Hilborn 1997, McAllister and Kirkwood 1998b). This enables uncertainty in the potential consequences of alternative management actions to be accounted for and communicated in a probabilistic framework and can help to facilitate a precautionary approach to fishery management (McAllister and Kirkwood 1998a).

The Bayesian stock assessment approach has more often been applied to developing pelagic and gadoid fisheries (Bergh and Butterworth 1987, McAllister *et al*. 1994) than to developing deep-water fisheries, that present equally difficult management and stock assessment problems (Boyer *et al*. 2001). Of the deep-water fisheries, the approach has been applied to newly developing fisheries for orange roughy *Hoplostethus atlanticus* off New Zealand and Australia (Punt 1993). In this paper, the application of Bayesian stock assessment methods to the management of Namibian orange roughy is reviewed. Focus is given to the evolution of the stock assessment protocol and the linkage between the assessment results and decision-making over Total Allowable Catch (*TAC*) policies during the development of the fishery, from 1997 until 2000. The paper begins with a brief description of the biology of orange roughy and the characteristics of its fisheries. The problems in estimating orange roughy biomass are summarized along with some recent

* Renewable Resources Assessment Group, Department of Environmental Sciences and Technology, Imperial College, RSM Building, Prince Consort Road, South Kensington, London, SW7 2BP, UK. E-mail: m.mcallister@ic.ac.uk
† National Marine Information and Research Centre, Ministry of Fisheries and Marine Resources, P. O. Box 912, Swakopmund, Namibia

Manuscript received November 2000; accepted July 2001

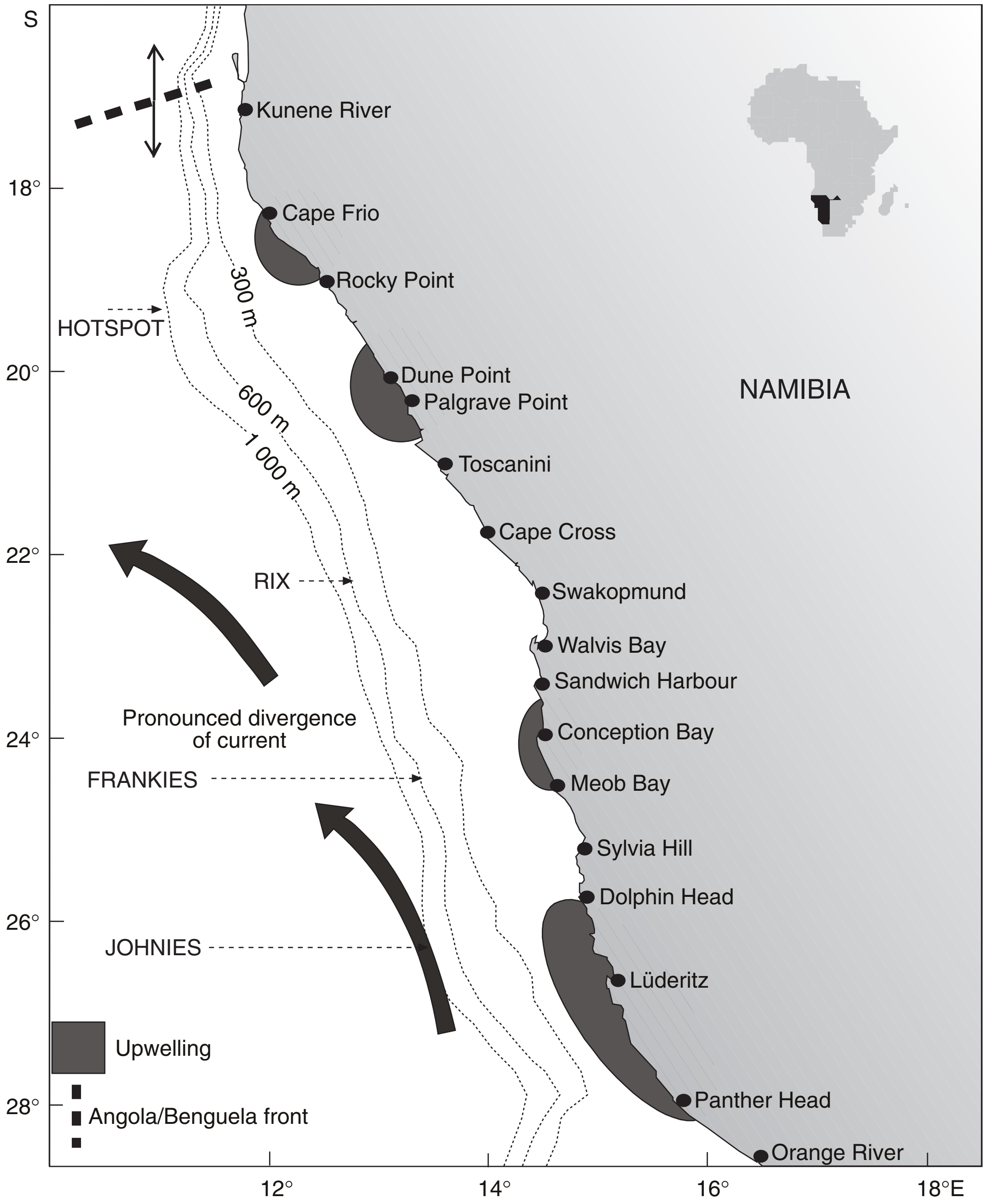

Fig. 1: Map of Namibia showing the four orange roughy fishing grounds within the 200 mile EEZ

approaches to its stock assessment. The prototypical Bayesian stock assessment approach taken in the first few years of management is outlined briefly, and the more fully Bayesian approach taken in 1999 and subsequent years is outlined and illustrated in more detail. The discussion evaluates whether the Bayesian methods applied helped to achieve good fishery management outcomes as well as some considerations

Table I: Orange roughy catches from each fishing ground, total catch and *TAC* from 1995 to 1999

Year	Catch (tons)					*TAC* (tons)
	Johnies	Frankies	Rix	Hotspot	Total	
1995	4 111		12	2 620	6 743	
1996	1 905	7 757	1 445	785	11 892	
1997	2 825	8 773	3 307	612	15 517	12 000
1998	5 954	1 244	4 249	345	11 792	12 000
1999	1 495	80	721	202	3 993	9 000

for the choice of a stock assessment methodology in developing countries.

Orange roughy are found at depths of 500–1 500 m. They have a worldwide distribution in temperate and subtropical waters. Fish are believed to be long-lived, some attaining more than 100 years, although age determination of the species remains a controversial topic (Tracey and Horn 1999, Boyer *et al*. 2001, Branch 2001). The age at maturity of Namibian orange roughy has been estimated at 20–30 years. Growth is very slow, and fish reach a maximum weight of 1–4 kg. Fecundity is also low, at 20 000–60 000 eggs per year. Mature fish form dense spawning aggregations often over pinnacles and gullies in the austral winter.

Orange roughy are harvested by large trawlers that use specialized deep-water trawl gear and sophisticated navigational equipment. Hauls of up to 70 tons are possible. Fish are headed and gutted and iced or frozen at sea. Onshore processing plants in Namibia produce fillets that are currently mainly exported to the USA. The resource has a very high landed value of US$2 750 per green-weight ton (Branch 1998).

Biomass estimation of orange roughy based on data drawn from trawl surveys, hydro-acoustic surveys and commercial catch rates is particularly difficult for the following reasons. Deep-water fisheries resources such as orange roughy are physically less accessible than other fisheries resources. They are more difficult to locate and map spatially because of their often highly patchy distribution and great distance from land. Their biological characteristics, abundance and changes in abundance are more difficult to assess because of their low hydro-acoustic target strength and highly aggregating behaviour, the difficulties in age determination, and the inability to apply mark-and-recapture tagging methods (Clark 1996). Mature fish migrate to and from spawning grounds and aggregations can form and break up rapidly (Kirchner and McAllister in press).

Off New Zealand, where the orange roughy resource has been assessed since the late 1980s, an age-structured stock assessment model has been fitted to research trawl survey indices of abundance, mean lengths and length frequencies of fish from the surveys (Francis 1992, Francis *et al*. 1992). In other instances, models have also been fitted to commercial catch rate data and biomass indices from pelagic egg surveys. The two procedures cited allow for deviates from the Beverton-Holt stock recruit function and assume that these are lognormally distributed with a standard deviation (*SD*) in the natural logarithm of the deviates >1. The procedures also treat the constant of proportionality between the abundance indices and stock size as a freely estimated parameter. The models therefore rely entirely on historical declines in the abundance indices and the observed catch removals to make inferences about stock biomass and trends in stock biomass. A time-series of six years showing a consistently decreasing trend provides fairly precise estimates of stock biomass (Francis 1992, Francis *et al*. 1992).

THE FISHERY FOR AND INITIAL STOCK ASSESSMENTS OF NAMIBIAN ORANGE ROUGHY

An exploratory orange roughy fishery off Namibia started in 1994. Catches rose from 29 tons the first year to about 12 000 tons in 1996 (Table I), by which time four major fishing grounds, Johnies, Rix, Frankies and Hotspot, had been discovered (Fig. 1). From 1997 onwards the fishery was managed by a *TAC*. The fishery management objectives for Namibian orange roughy were to maximize the net economic yield for Namibia and not to deplete the resource below B_{MSY}, the biomass at which maximum sustainable yield (*MSY*) is achieved. The management strategy adopted was to fish down the accumulated biomass for seven years with *TAC*s set larger than the *MSY*, to be followed by a seven-year transition in *TAC*s to the *MSY*.

The *TAC*s from 1997 were based on assessments using data from inside and outside the four major fishing grounds listed above. In 1997, the virgin biomass was estimated using commercial catch per unit effort (*cpue*) data because these were the only data available (Branch 1998). Branch (1998) developed a

Table II: Key features of the stock assessments for Namibian orange roughy from 1997 to 2000. The letters c, r and a refer to commercial and research swept area and acoustic estimates of biomass respectively, and *d* refers to the additional estimated parameters in the four different models for stock decline evaluated in 2000. The value in parenthesis is the input coefficient of variation in the swept area bias factor, *q*

Year	Data	Stocks modelled	Uncertain parameters	Other uncertainty evaluated
1997	c only	Total Namibian	B_0 (0.32)	Different input pdfs for q'
1998	c and a, separately	Total Namibian	B_0 (0.32)	Results using data from c v. data from a
1999	c, a and r, combined	Four stocks separately	B_0, q (0.6), M, ε_y	Stochastic recruitment
2000	c, a and r, combined	Four stocks separately	B_0, q (0.6), M, ε_y, d	Four different models for decline

swept area methodology to convert the tow-by-tow *cpue* data to a single swept area estimate of biomass. With only a single abundance estimate, other methodologies such as that of Francis (1992), that require a time-series of relative abundance indices, could not be applied. The only way to use this swept area estimate was to use expert judgement to construct a constant of proportionality (q') that could rescale the swept area estimate (I) to absolute biomass (B), such that $B = q'I$ (a more common formulation is $I = qB$). Branch (1998) adopted a Bayesian-like approach to construct a probability density function for q'. It was assumed that q' was a function of nine different "bias" factors that could affect the relationship between the commercial swept area estimate and the total biomass of mature fish (Boyer *et al*. 2001). These included factors such as the catchability of orange roughy by commercial trawl gear inside aggregations, and the extent to which trawls were directed at known aggregations. Density functions were constructed for each of these factors based on consultation with experts (Branch 1998, Boyer *et al*. 2001).

A Monte Carlo approach was applied using the nine individual density functions for the bias factors to develop a probability distribution or "density function" (pdf) for the average unfished biomass, B_0. The stock assessment procedure applied then took draws from this pdf for B_0 and projected a deterministic age-structured model (Appendix 1) 14 years forward to the year 2010 to evaluate the potential consequences of alternative fishing-down policies. The population dynamics models were similar to those applied in New Zealand, including that described in Francis (1992), except that recruitment and maturity were assumed to be knife-edged functions of age, and the values for its input parameters, except B_0, were fixed at the same values as those used in New Zealand, because of lack of biological knowledge of Namibian orange roughy (Francis 1992). Additionally, in the 1997 and 1998 assessments, recruitment was modelled as a deterministic function of the Beverton-Holt stock recruit function.

The 1997 stock assessment procedure therefore did not require a time-series of relative abundance to estimate B_0 and stock biomass. In retrospect, it could have provided valid results if the following three conditions, among others, had held:

1. If the spatial positions of individual trawls within each spatial stratum were determined on a random or systematic basis during the first few years of the fishery. This condition is highly unlikely in any commercial fishery because fishers use their knowledge to fish in what they believe to be the most likely spots. In some exploratory fisheries, it could be approached when fishers have relatively little knowledge and are starting to search for fish. However, once fish are located, fishers generally target these locations and abandon any random or systematic search pattern with which they might have started. Bias factors to correct for this problem were identified in the first assessment (Boyer *et al*. 2001).
2. If the positions of aggregations were stationary over time, i.e. from 1994 to 1996. Later analysis found this not to be the case. For those years, large catch rates were extrapolated to large scarcely sampled areas giving positively biased swept area estimates. In 2001, a recalculation allowing for non-stationarity in aggregation positions and stratum definition produced much lower swept area estimates (Boyer *et al*. 2001, Kirchner and McAllister in press). The revised swept area estimate of total unfished abundance was four times lower than that derived from the original swept area methodology.
3. If the pdf for the constant of proportionality, q', is not seriously biased in central tendency and not too narrow (Walters and Ludwig 1994, Adkison and Peterman 1996, McAllister and Kirkwood 1998a). If the central tendency was seriously biased, a pdf that was too narrow could exclude the true q'. This could then result in seriously biased estimates of B_0 and stock biomass. In retrospect, it appears that the pdf for the original bias correction was too narrow. The initial *CV* for q' was about 0.25, but this

Table III: The history of scientific advice for the management of Namibian orange roughy until 1999. The biomass estimates are the median values given by the hydro-acoustic (a) and commercial swept area (c) estimates. The % risk for the *TAC* policies shown are computed in terms of the probability that the biomass in the final projection year shown drops below 20% of virgin stock size

Year	Biomass estimate (tons)	Risk criterion	Management decision adopted
1997	300 000 (c)	20 000 ton *TAC*, <10% in 2010	12 000 ton *TAC* plus two companies
1998	230 000 (c) 150 000 (a)	12 000 ton *TAC*, <10% in 2001	12 000 ton *TAC* for 1998 only
1999	75 000 (c) 25 000 (a)	9 000 ton *TAC*, <10% in 2000	9 000 ton *TAC* for 1999 only plus closure of Frankies

was updated to about 0.3 at the 1997 stock assessment meeting. However, this value was later changed to about 0.6 for the 1999 assessment meeting (Table II).

The apparent result of applying a positively biased swept area estimate of biomass and a pdf for q' that was too narrow was a strongly positively biased commercial swept area estimate of B_0 for Namibian orange roughy in the first two stock assessments in 1997 and 1998 (Table III). During 1997, hydro-acoustic and research trawl surveys were conducted on the three southernmost fishing grounds. The estimates of biomass obtained from these were about half the values obtained from the commercial swept area time-series. In 1998, the stock assessment procedure was run separately, also using a pdf for B_0 based on the acoustic estimate and pdfs for bias factors for it (Tables II, III). Estimates of risk of different *TAC* policies were much higher using this latter estimate and alarm was raised in 1998 over the possibility that the initial assessment with the commercial swept area estimate had been too optimistic. The B_0 estimates obtained, and the estimated risks and management decisions based on the risks in each year from 1997 to 1999, are summarized in Table III.

THE REVISED BAYESIAN STOCK ASSESSMENT PROCEDURE FOR NAMIBIAN ORANGE ROUGHY

By 1999, the fishery and scientific research programme for orange roughy had operated for four years (Boyer *et al*. 2001). This permitted the construction of commercial swept area, hydro-acoustic and research trawl swept area time-series for each of the four fishing grounds. All time-series from 1995 to 1998 showed a decline, especially after 1997 on the three southern grounds (Table IV). The existence of a four-year time-series of catch and *cpue* indices and a two-year series for hydro-acoustic and research trawl swept area indices opened up the possibility of fitting a stock assessment model to these data for model parameter and biomass estimation. However, the time-series were still relatively short. Fitting a time-series model to such data and treating them as relative abundance indices with the value for q allowed to vary freely from 0 to infinity could be expected to produce highly imprecise estimates (Smith 1993, McAllister *et al*. 1994). Other studies have indicated

Table IV: Orange roughy relative abundance indices (tons) to which the 2000 stock assessment model was fitted. Model input *CV*s are given in parenthesis

Year	Hydro-acoustic	Research swept area	Commercial swept area
Johnies			
1995			17 417 (0.40)
1996			16 177 (0.42)
1997	32 171 (0.29)	57 650 (0.32)	25 471 (0.41)
1998	4 733 (0.31)	6 980 (0.30)	17 210 (0.38)
1999	–	2 137 (0.42)	6 924 (0.38)
Frankies			
1996	–	–	21 893 (0.39)
1997	19 804 (0.25)	30 995 (0.37)	36 319 (0.38)
1998	6 551 (0.34)	2 400 (0.60)	12 509 (0.38)
1999	1 751 (0.30)	3 055 (0.35)	4 143 (0.42)
Rix			
1996	–	–	12 339 (0.41)
1997	17 500 (0.29)	–	16 254 (0.42)
1998	10 041 (0.31)	–	13 697 (0.38)
1999	–	1 006 (0.59)	5 902 (0.40)
Hotspot			
1995	19 838(0.39)		
1996	3 892(0.39)		
1997	2 939(0.42)		
1998	2 112(0.39)		
1999	2 364(0.42)		

that constructing informative prior probability distributions for the constant of proportionality for abundance indices with the use of expert judgement could help to improve the precision in biomass estimates (McAllister *et al.* 1994, McAllister and Ianelli 1997). This would occur because the informative priors restrict the range of possible values for q so that they no longer range freely between 0 and infinity. Moreover, the initial assessments had already produced a pdf for q' for the commercial swept area and hydroacoustic estimates of biomass, albeit too narrow. Other work had constructed prior pdfs for q for research trawl survey swept area estimates (McAllister and Ianelli 1997), and it was therefore possible to do so for the same estimates for Namibian orange roughy. As mentioned above, the principle of using expert and technical knowledge to construct priors for q was retained in 1999. However, the narrow width of the previous priors applied was updated.

The revised stock assessment approach fitted the same age-structured stock assessment model used in the previous two assessments to the available relative abundance time-series (Table IV), but it also used informative prior pdfs for their constants of proportionality and incorporated process error in the stock-recruit function. The general steps for the revised Bayesian stock assessment procedure are set out in the following paragraphs.

1) *Formulate prior probability distributions for the estimated model parameters* (Table V). The prior distribution for a set of parameters summarizes the information about those parameters from all knowledge except data used in the likelihood calculations of the stock assessment (Punt and Hilborn 1997). The prior used assumes that the parameters are all independent of each other *a priori*, and therefore prior pdfs were constructed individually for each parameter and the joint prior is the product of the priors for each parameter. Priors were applied for the long-term average value for unexploited biomass, B_0, the rate of natural mortality, M, and the annual deviates from the Beverton-Holt stock-recruit function, ε_y (Table V). For each trial, the prior for B_0 was uniform over the interval [1 000 tons, 2 000 000 tons]. The prior for M was lognormal with a median of 0.055, and the *SD* for the logarithm of M was 0.3 (Clark *et al.* 1999). The assumed value for the prior *SD* in ε_y, σ_r, was set at 1.1.

Informative prior pdfs were also constructed for the constants of proportionality, q, for each relative abundance index based on the same pdfs for "bias factors" identified in the previous assessments and the relationship $I = qB$. An additional lognormally distributed prior uncertainty factor with a prior *CV* of 0.5 and a median of 1 was also incorporated into the priors for q. This was because recent work (McAllister and Kirkwood 1998a) had shown that the risks of overfishing could be increased substantially if the prior *CV* for parameters such as q in developing fisheries was set too low, e.g. <0.5, as in the 1997 and 1998 assessments (Table II). The values for the other model parameters (e.g. the age at maturity and the growth parameters) were fixed at values assumed known without error (see Appendix 1, Table App. 1.I). These values were obtained from age and growth studies of Namibian orange roughy (Clark *et al.* 1999). The constants for the length-weight relationship were estimated from research samples taken in 1998 and assumed to be the same for the three grounds, Johnies, Frankies and Rix, but different for the Hotspot ground (see below; Dalen *et al.* 1998). The Beverton-Holt steepness parameter was taken from Francis (1992).

Table V: "Base case" priors of some population dynamics model parameters (Appendix 1) used in the 1999 assessment of Namibian orange roughy

Parameter	Prior
B_0	U[1 000, 2 000 000]
M (year^{-1})	Log-normal: median = 0.055; *SD* = 0.3 [LogN(0.055; 0.3^2)]
ε_y	Normal(0, σ_r^2)
q(acoustic)	LogN(0.2; 0.64^2) – Johnies, LogN(0.26, 0.63^2) – Frankies, Rix
q(research swept area)	LogN(0.62; 0.55^2)
q(commercial swept area)	LogN(0.54; 0.60^2)

Individual stock assessments were done on the orange roughy stock on the four grounds separately. It was shown by analysis of age that orange roughy at Hotspot are more similar to New Zealand orange roughy, so biological parameters for New Zealand orange roughy were used (L_∞ = 37,2; K = 0.065; t_0 = -0.5; $a_r = a_m$ = 29 years; prior median M = 0.045 year^{-1}; a = 0.0921; b = 2.71).

2) *Formulate the likelihood function of the data for each relative abundance time-series*. This function provides a formalized probabilistic measure of the goodness of fit of the model to the available stock assessment data. It gives the probability of obtaining the observed data for each possible combination of values for the estimated model parameters. A set of parameter values that provides a very close fit of the model to the data will yield a very high likelihood of the data, and vice versa. The likelihood function chosen was a lognormal density function indicating that the deviate between each observation and the value predicted for it by the model and its parameters is lognormally distributed (Appendix 1). In stock assessment, this is a commonly applied likelihood function

for relative abundance data. The product of the prior probability and the likelihood function for a given set of values for the estimated model parameters is directly proportional to the posterior probability for these values.

3) *Calculate the joint and marginal posterior probability distributions for model parameters and stock biomass in each year, as well as other management quantities such as the ratio of stock biomass in each year to* B_0. The statistical method applied for these calculations was importance sampling (Berger 1985, Rubin 1988, Gelfand and Smith 1990, West 1993), a commonly applied algorithm for Bayesian stock assessment (Francis *et al*. 1992, Punt 1993, McAllister *et al*. 1994, Raftery *et al*. 1995, Kinas 1996, McAllister and Ianelli 1997).

4) *Evaluate the potential consequences of alternative management actions*. This was achieved by randomly sampling values for model parameters from the joint posterior probability distribution obtained in the previous step and using these values to project the model into future years. The combined steps of 3) and 4) are typically called the sampling importance resampling (SIR) algorithm (Rubin 1988).

(5) *Present the results*. The posterior probability distributions for B_0, B_{cur}, and B_{cur}/B_0 were plotted for each fishing ground. Also plotted were 95% probability intervals for stock biomass over time. For the 2000 stock assessment, the potential consequences of alternative constant *TAC* policies were projected for the period 2001–2010 and presented in decision tables.

Key features of this application

One key feature of this application of Bayesian stock assessment is its use of an informative prior probability distribution for q for each of the three different indices of abundance to deal with the very short time-series of relative abundance. Independent construction of each prior allows comparison of the resulting prior biomass estimates from three different sources to check for overlap in probability intervals and to ground-truth each individual prior for q. The effect of implementing these informative priors is illustrated below by producing results with non-informative prior probability distributions for q that are uniform over its natural logarithm (McAllister *et al*. 1994).

A second feature of this assessment is its advocacy of Bayesian probability analysis to identify precautionary reference points for fishery management. An important management reference point for many species, including orange roughy, is the ratio of population biomass at *MSY* to the long-term average unexploited biomass (B_{MSY}/B_0). This can be used either as a target reference point (a system state to achieve and maintain) or a limit (threshold) reference point (not to be dropped below), depending on the situation. In past studies of orange roughy, *MSY*-based reference points were computed using an age-structured model with all parameters except B_0 and recruitment deviates fixed and uncertainty from data analysis accounted for (Francis 1992, Francis *et al*. 1992). The stochastically derived reference point was the average of 0.3 B_0, which was obtained by finding the value for F that maximized long-term catch (F_{CAY}).

Although the method of Francis *et al*. (1992) was rigorous in its treatment of uncertainty, it still assumed that parameters such as M were known without error. Methods that even more rigorously account for uncertainty can allow more thorough assessments of the reliability of estimates and the potential for error therein. Bayesian estimation of a pdf for B_{MSY}/B_0 would permit managers to be more rigorously precautionary because more parameters could be treated as uncertain. Using the mean value for B_{MSY}/B_0 as the reference point also ignores uncertainty in the estimate of B_{MSY}/B_0. Uncertainty in B_{MSY}/B_0 could be more rigorously taken into account and a more precautionary reference point could be formulated by the use of values higher than average. For example, a pre-specified percentile for B_{MSY}/B_0 that was acceptably high could be applied to set a management reference point based on B_{MSY}/B_0.

Bayesian probability distributions for B_{MSY}/B_0 were computed to identify such a reference point using a short-cut approximation. The pdfs for B_{MSY}/B_0 for the two Namibian orange roughy stocks, north and south, were computed. Probability distributions for *MSY*s for the quota management grounds of Namibia were also investigated. Stochastic and auto-correlated recruitment (assuming autocorrelation coefficient of 0.5) about the Beverton-Holt stock-recruitment function was assumed with σ_r =1.1. A posterior for *MSY* could be obtained by finding the *MSY* and other *MSY*-related parameters for each possible set of values for the uncertain population dynamics model parameters. However, with the stochastic age-structured model used and autocorrelation in recruitment residuals, this task could be quite time-consuming computationally. An approximation of the posterior mean *MSY* was instead found by first finding the harvest rate (on a grid from 0.01 to 0.99 at steps of 0.01) that gave the largest posterior mean annual catch biomass at the end of a 400-year simulation. For each candidate value for the harvest rate, a thousand 400-year simulations were performed. For each simulation, a draw was taken from the joint posterior distribution to obtain values for B_0, M, q and the stock-recruit deviates, and the model was projected from the year 2000 for 400 years. Using the harvest rate yielding the largest

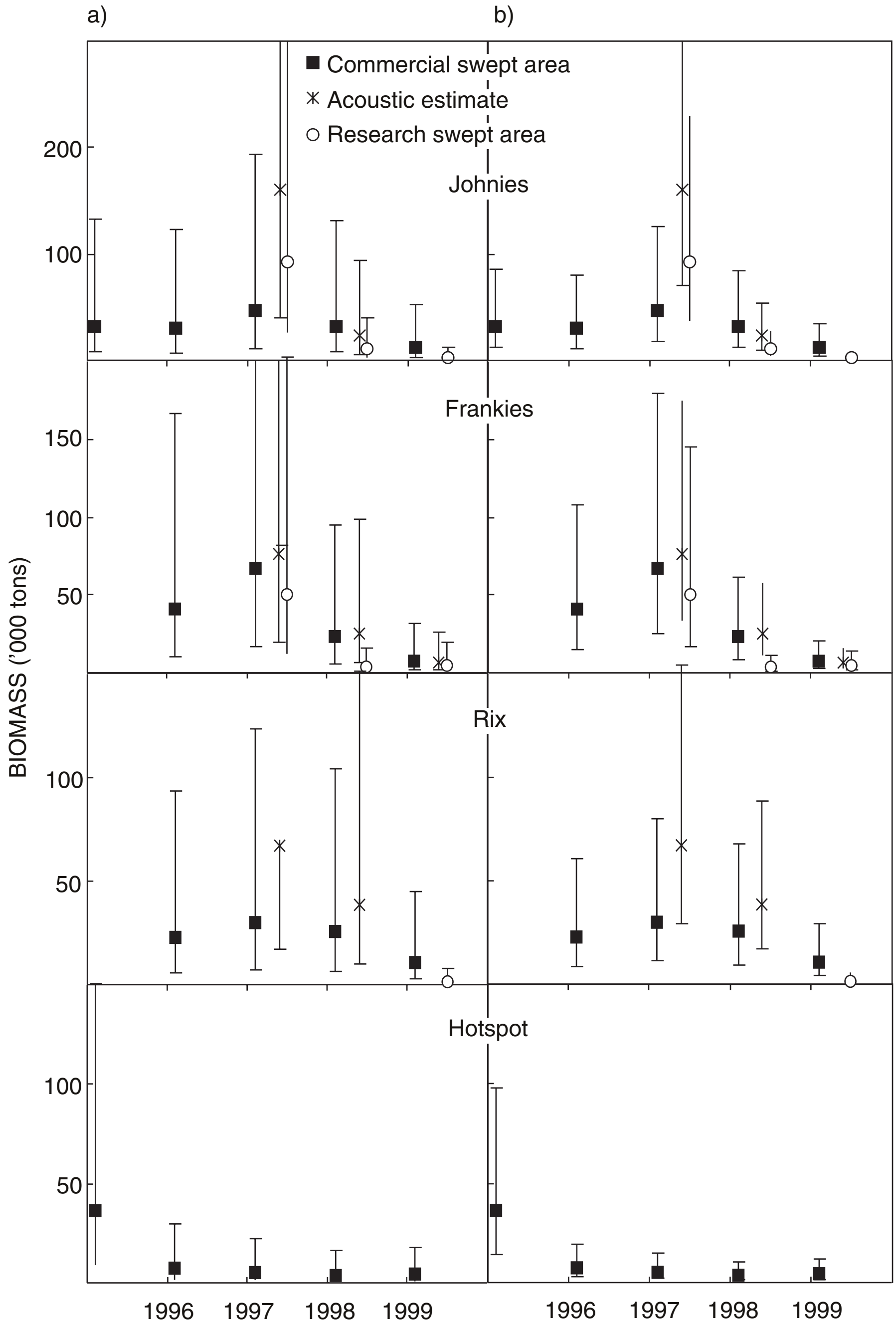

Fig. 2: Prior medians and 95% prior probability intervals for stock biomass given by dividing the abundance indices by the prior median q, and the prior 2.5th and 97.5th percentiles for q with the *CV*s in the abundance indices also incorporated. Results are shown for the Johnies, Frankies, Rix, and Hotspot fishing grounds. (a) Intervals produced using prior *CV*s for q of about 0.6 (used in 1999 and 2000); (b) intervals produced using prior *CV*s for q set at 0.3 (similar to values used in the 1997 and 1998 assessments)

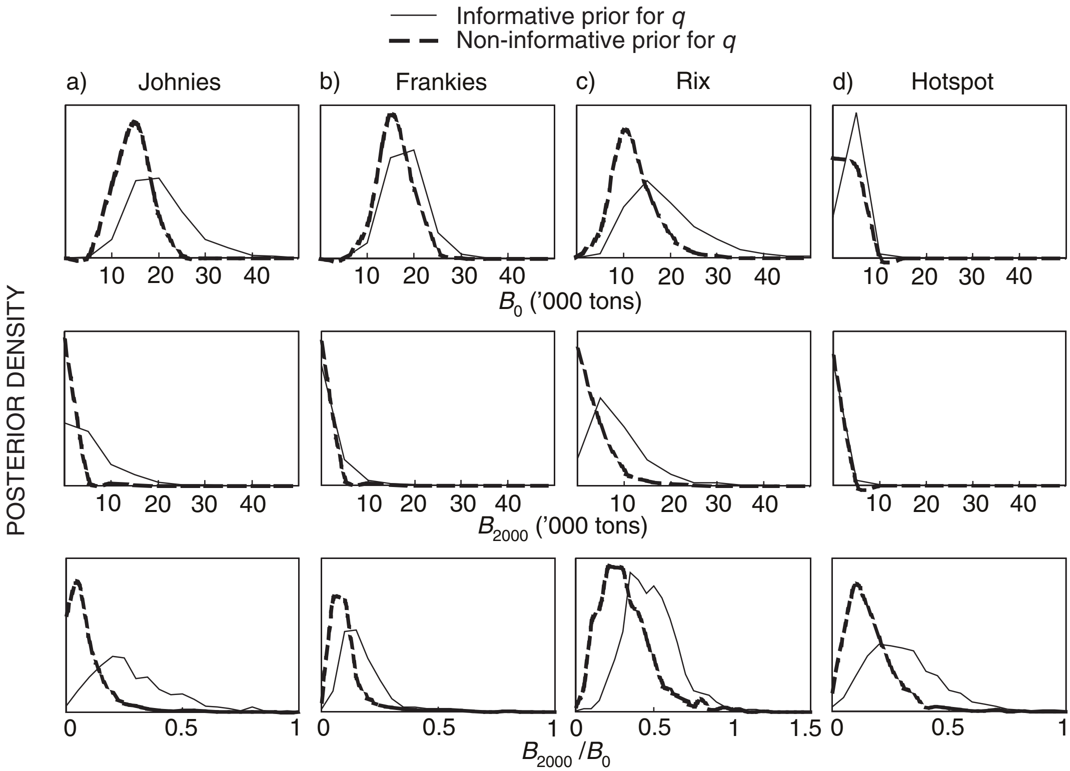

Fig. 3: Marginal posterior probability distributions for the average unfished mature biomass (B_0), mature biomass in 2000 (B_{2000}) and depletion (B_0/B_{2000}) for the (a) Johnies, (b), Frankies, (c) Rix, and (d) Hotspot fishing grounds. Results are shown with non-informative priors for q and informative priors for *q*

posterior mean catch, the ratio of B_y to B_0 in the 400th year of each simulation was assumed to be the potential B_{MSY}/B_0.

A third feature of this application is that, in the fourth year, the procedure was extended to account formally for structural uncertainties rather than just uncertainty in the values of parameters such as B_0 and *M*. The large drop in the biomass indices could not be explained easily by the relatively small catches. Therefore, four structurally different models for resource decline were developed.

1) *The catch removal model* — The observed declines were mainly attributable to catches and the priors for *q* being centred too low.
2) *The fishing disturbance model* — The observed declines resulted from successive disturbances of the orange roughy aggregations by fishing. Orange roughy have responded by failing to re-aggregate on the fishing grounds. If fishing is stopped, the fish may re-aggregate.
3) *The intermittent aggregation model* — The observed declines were caused by temporary factors unrelated to fishing. Orange roughy may aggregate on an intermittent basis depending on various environmental conditions. Fish will re-aggregate on the fishing grounds, but when they will do this remains unpredictable.
4) *The mass emigration or mortality model* — The observed declines were caused by either mass mortality or mass emigration, and the original large abundance observed on the fishing grounds is unlikely to be re-established in the near future.

The mathematical features of these models are outlined in Appendix 2. Each model was fitted to the same data (Table IV) and a marginal posterior probability computed for each. To obtain these probabilities, Bayes' factors were computed for each alternative model based on its priors and likelihood functions with the use of an importance-sampling algorithm (Kass and Raftery 1995, McAllister and Kirchner in press).

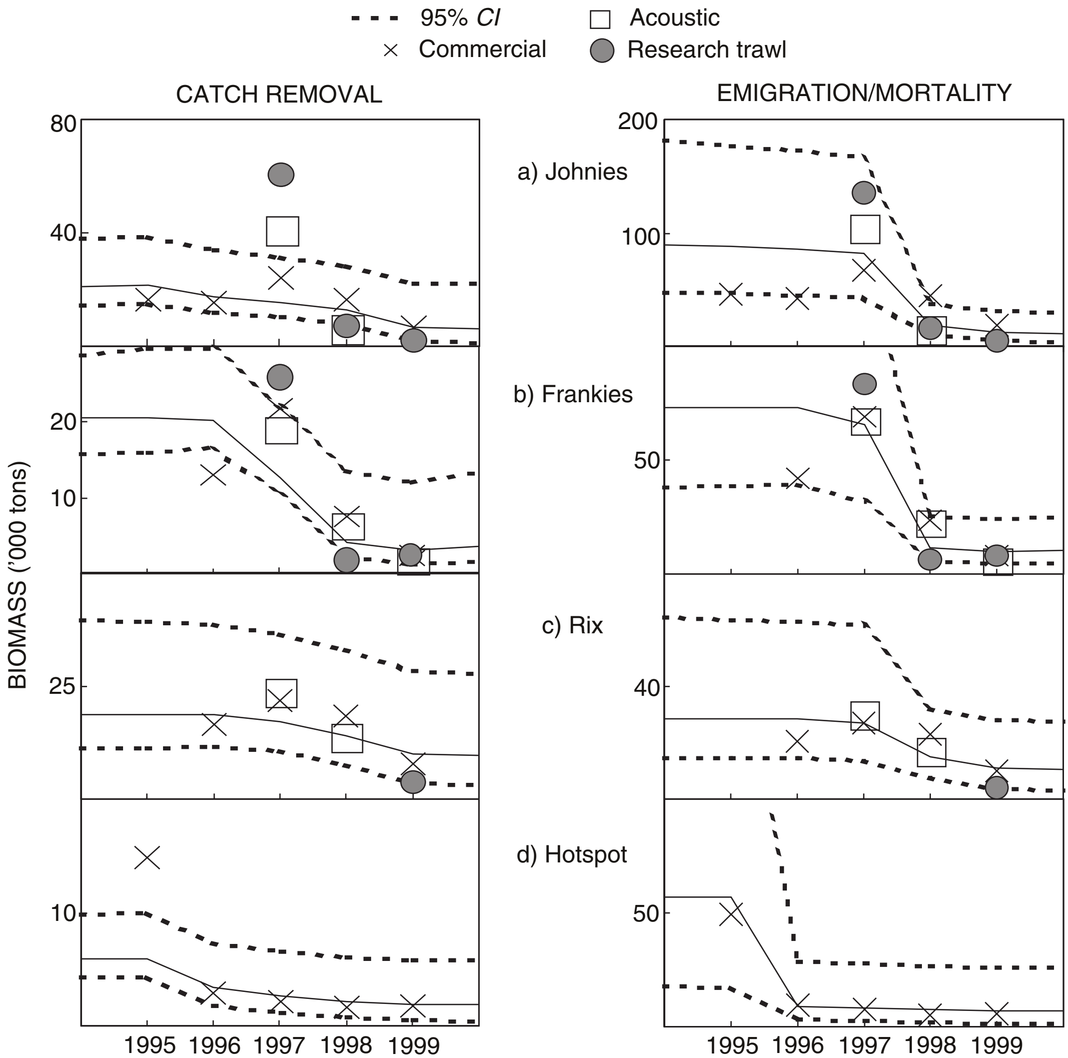

Fig. 4: Posterior medians and 95% posterior probability intervals for mature stock biomass from 1994 until 2000 for the (a) Johnies, (b), Frankies, (c) Rix, and (d) Hotspot fishing grounds. The abundance indices rescaled by the posterior median q are also plotted. Results are shown for the catch removal and mass emigration/mortality hypotheses with informative priors for q

These factors were combined with a prior probability for each model to give Bayes' marginal posterior probabilities, i.e. the total weight of evidence in support of each alternative model. Each model was assigned an equal prior probability. This was because it was believed that, before analysing the stock assessment data, there was no other rational basis that could be applied to rate the credibility of each model (Butterworth *et al*. 1996). This procedure allowed the probability distributions for management quantities such as stock biomass to be combined across models with the weighting for each distribution given by the associated model's marginal posterior probability. The resulting estimates could thereby account more formally for uncertainty in both the values of model parameters and the structure of the stock assessment models for Namibian orange roughy. Some of the results of this assessment are given in the next section.

RESULTS

Prior medians and probability intervals for abundance indices

In order to check whether the priors for q gave consistent biomass estimates, the biomass indices were rescaled by the prior median value and 95% probability intervals for q (incorporating the prior *CV* and the survey *CV* for each index, Table IV). These are shown in Figure 2. Where there is more than one abundance index per year, all the 95% probability intervals overlap considerably, indicating that there are no serious inconsistencies among the prior biomass estimates and the trends given by the indices. However, the trends in the commercial swept area estimates yield smaller declines than the other two indices on the three southern grounds where all three types of indices are available. Moreover, on each ground, the indices suggest a very large biomass in the initial years of the fishery followed by a steep decline. The prior *CV*s of about 0.3 used in 1997 and 1998 gave prior probability intervals for biomass that overlapped much less and suggested that these earlier prior *CV*s were far too small (Fig. 2b).

Use of non-informative v. informative prior distributions for *q*

If the approach of Francis *et al*. (1992), which effectively used non-informative priors for q, were to be applied, the results would suggest that considerably fewer orange roughy are left on the fishing grounds than if informative priors were applied (Fig. 3). The wide probability distributions for stock biomass in both cases indicate that uncertainty in the estimates is very large.

To evaluate whether the models applied could fit the data adequately, the posterior 95% probability intervals for stock biomass from 1994 to 1999 are plotted on Figure 4. The relative biomass indices rescaled by the posterior median value for q are also shown on these plots. Median values for the biomass indices falling outside of the posterior 95% probability intervals would indicate that the model and the prior assumptions do not fit the data very well. When both informative and non-informative priors for q are applied, some of the rescaled biomass indices fall outside the posterior 95% intervals for each of the grounds, except Rix.

When structural uncertainty was accounted for, the only model that encompassed the rescaled indices within its posterior 95% probability intervals for stock biomass on all four fishing grounds was the mass emigration/mortality model (Fig. 4). This model also suggested that the current biomass on each of the four fishing grounds was very low.

Use of decision-analysis results in decision-making

The key results (for fishery managers) were presented as the risks associated with alternative *TAC* policy options (Table III). These were given in terms of the probability of the stock biomass dropping below some level of virgin biomass in some future year. In the first stock assessment in 1997, when alternative fishing-down *TAC*s were considered, the horizon was 14 years until 2010 (Table III). *TAC* policies that began at no more than some 20 000 tons had less than a 10% chance of forcing stock biomass below 20% of B_0 in 2010. The Namibian Cabinet adopted a 12 000 ton *TAC* option, but allowed two more fishing companies into the fishery to share the same *TAC*. In the next assessment in 1998, when the much more pessimistic 1997 hydro-acoustic estimate was used to produce a pdf for B_0, only a three-year horizon until 2001 was applied to evaluate the potential consequences of alternative *TAC* options. *TAC* policies of no more than 12 000 tons had a <10% risk of forcing stock biomass below 20% of B_0 by 2001. The Cabinet approved a 12 000 ton *TAC*, but only for the 1998 fishing season. In 1999, when the revised stock assessment procedure was applied, a 9 000 ton *TAC* had a <10% risk of forcing stock biomass below 20% of B_0 with only a one-year projection to 2000. The Cabinet approved a 9 000 ton *TAC* and closed the Frankies fishing ground, where the observed decline was the most severe.

In the 2000 assessment, the declines had continued on the grounds remaining open. Only much smaller *TAC*s, e.g. 1 500 tons combined across grounds, had less than a 50% chance of causing further decline on all fishing grounds. The Cabinet followed this advice but made the provision that the *TAC* could be increased if orange roughy appeared to be re-aggregating. Although preliminary results presented from the analysis of structural uncertainty suggested that stock biomass might not be so severely depleted, these results were considered too preliminary to be given any weight in the provision of management advice.

Results from analysis of structural uncertainty

More recent updates of the methodology to account for structural uncertainty provided the following results. The probability distributions for stock biomass

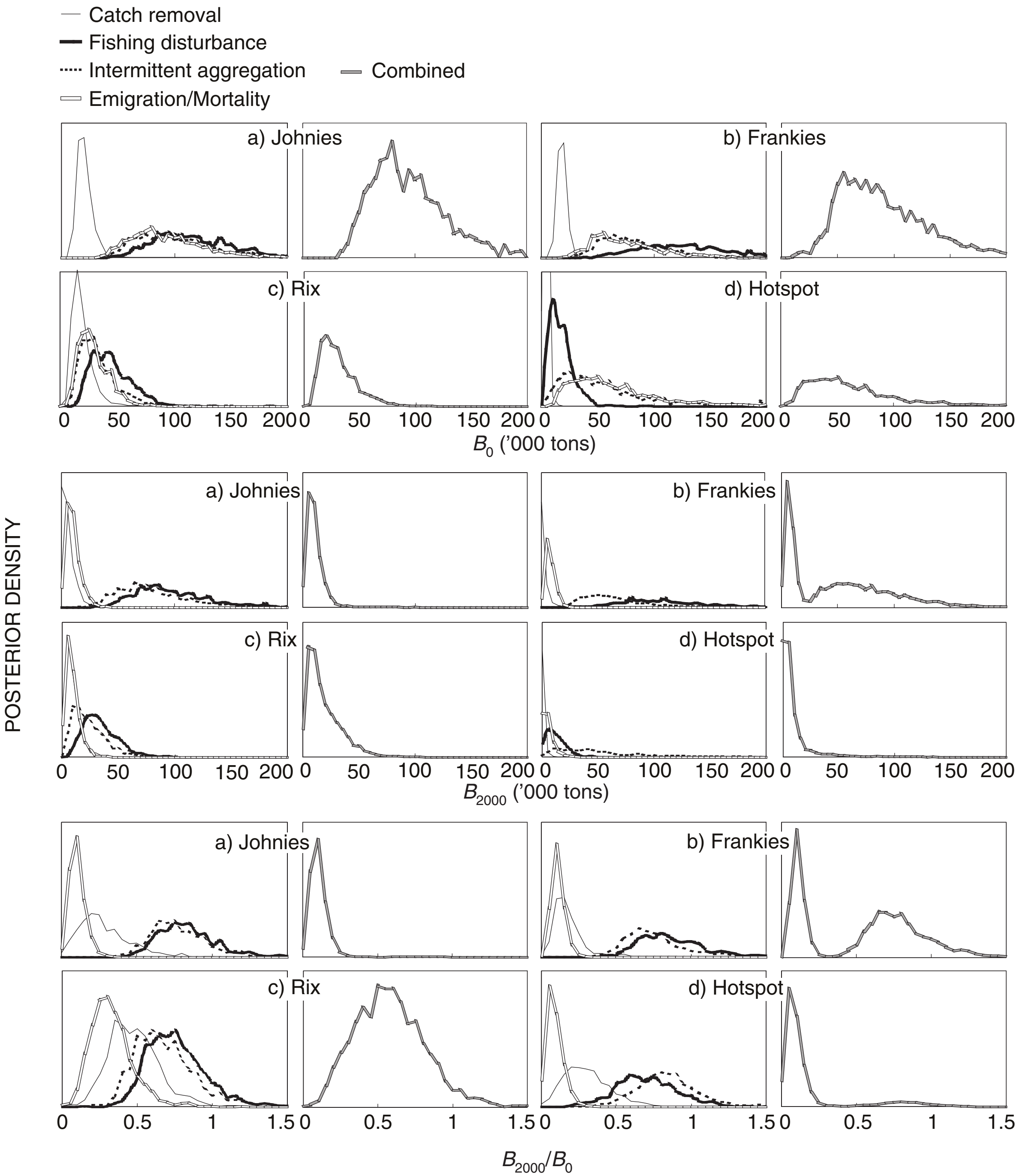

Fig. 5: Marginal posterior probability distributions of the average unfished mature biomass (B_0), mature biomass in 2000 (B_{2000}) and depletion (B_0/B_{2000}) for the (a) Johnies, (b), Frankies, (c) Rix, and (d) Hotspot fishing grounds. Results are shown separately and combined for the catch removal model, fishing disturbance model, intermittent aggregation model, and the mass emigration and mortality model (reproduced from McAllister and Kirchner in press)

Table VI: Posterior probabilities for the four different hypotheses for the four major orange roughy fishing grounds. See Appendix 2 for a description of the equations, parameters and the priors for the parameters applied for each model

Ground	Hypothesis			
	Catch removal	Fishing disturbance	Intermittent aggregation	Mass emigration/ mortality
Rix	25%	45%	13%	17%
Frankies	<1%	37%	25%	37%
Johnies	<1%	<1%	2%	98%
Hotspot	<1%	1%	12%	87%

given by the different structural models suggested far larger uncertainties in stock size than any one of the models considered alone (Fig. 5). For some grounds, e.g. Frankies and Johnies, these probability distributions were non-overlapping (Fig. 5). Given these widely differing results across structural models, the key question was how should each model be weighted? This weighting was obtained by computing a posterior probability for each structural alternative (Table VI). For Rix, none of the four alternative models had very low probability. For Frankies, only catch removal had very low probability. For Johnies and Hotspot, the catch removal and fishing disturbance models had low probability. On all four fishing grounds, only the mass emigration/mortality hypothesis retained moderate to high probability. Given that it is unlikely that different mechanisms for decline are operating on the four grounds, these combined results give most credibility to the mass emigration/mortality hypothesis, but they still convey considerable uncertainty over the mechanisms for decline. The probability distributions for stock biomass that result from use of these model probabilities to combine the distributions from the different models were much flatter for most of the fishing grounds (Fig. 5). In some cases, such as for Frankies and Hotspot, the combined distributions were bimodal, suggesting that the stock was either lightly exploited or heavily depleted.

The estimates of risk from each of the structural alternatives can be presented in a single decision table (Hilborn *et al*. 1993, McAllister and Kirkwood 1998b). For the sake of illustration, results are shown only for the Rix fishing ground (Table VII). This shows the four structural hypotheses along the top and the marginal posterior probability for each hypotheses in the next row down. In the following rows the potential consequences resulting from each *TAC* policy under each structural hypothesis are shown. In the table shown, this is in terms of the 10th percentile for mature stock biomass in the year 2010 relative to B_0. This indicates that there is about a 10% chance that stock biomass will drop below the values shown. The final column integrates the results under the different hypotheses for each *TAC* policy and thus accounts for both parameter and structural uncertainty. The table indicates that the largest *TAC* for which the risk of dropping below 20% of B_0 is <10% depends strongly on the model assumed, with the highest risks given by the catch removal and mass emigration/mortality hypotheses. When structural uncertainty is accounted for and the results integrated across different models, the lowest *TAC* evaluated, 500 tons, would have a risk of <10%.

Uncertainty in biological reference points

The following results were computed with the catch removal model. The range (80% probability intervals) of B_{MSY}/B_0 for Namibian orange roughy in the north and

Table VII: Decision table of alternative *TAC* policy options for the Rix ground for the years 2000–2010. The 10th percentiles are shown for total mature biomass in the year 2010 relative to B_0. This indicates a 10% probability that biomass will be below this level. CRH refers to the catch removal hypothesis, FDH to the fishing disturbance hypothesis, IAH to the intermittent aggregation hypothesis, and MEH to the mass emigration/mortality hypothesis

Parameter	CRH	FDH	IAH	MEH	Combined
Probability	0.25	0.45	0.13	0.17	
TAC					
500 tons	0.21	0.52	0.40	0.14	0.36
1 000 tons	0.02	0.41	0.22	0.01	0.22
1 500 tons	0.01	0.28	0.06	0.005	0.14
2 000 tons	0.01	0.16	0.02	0.004	0.08

Table VIII: Biological reference points from Bayesian analysis. 80% confidence intervals and medians (in parenthesis) are shown for long-term unfished biomass (B_0), biomass at maximum sustainable yield level (B_{MSY}), *MSY* and the depletion at *MSY* level (B_{MSY}/B_0) for the four quota management areas

Ground	B_{MSY}/B_0	B_{MSY}	*MSY*
Johnies	13% – 40% (0.23)	2 000 – 7 000 (4 000)	200 – 700 (400)
Frankies	13% – 40% (0.23)	3 000 – 8 000 (5 000)	200 – 800 (400)
Rix	13% – 40% (0.23)	2 000 – 7 000 (4 000)	200 – 700 (400)
Hotspot	13% – 40% (0.23)	700 – 2 000 (1 000)	50 – 200 (100)

the south was estimated to be 13–40%, with a median estimate of 23%. The median biomass at *MSY* ranges from 1 000 tons at Hotspot to 5 000 tons on Frankies, whereas the *MSY* ranges from 100 tons on Hotspot to 400 tons on all southern grounds (Table VIII). Fishing at the *MSY* level on Johnies, Frankies and Rix still presents an approximate 35% risk of forcing the stock below 20% of its B_0 level. In the study of Clark *et al*. (1999), the maximum constant yield was estimated to be some 300 tons for the southern grounds and 85 tons for Hotspot. The current annual yield was higher, at approximately 400 tons for the southern grounds and 100 tons on Hotspot.

Although the range of B_{MSY}/B_0 is between 13 and 40%, there is still a 20% risk that the value lies outside this range. A precautionary approach could suggest the use of a percentile higher than the median, for example the 90th percentile, as the minimum (threshold) reference point for B_{MSY}/B_0. If it were desirable to have a <10% risk of dropping below B_{MSY}/B_0, any ground for which the estimated median depletion was below this threshold should not be fished until this value was found to have increased above that threshold. This would be analogous to the use by the International Whaling Commission (IWC) of posterior percentiles for depletion for the precautionary management of aboriginal fisheries for bowhead whale stocks (Raftery *et al*. 1995).

DISCUSSION

How well have the stock assessment methodologies served fishery management?

Management of the developing fishery for Namibian orange roughy posed some onerous challenges for stock assessment. The Namibian Ministry of Fisheries, as in many other developing countries, had relatively few scientists trained in the development and application of stock assessment methods. Nevertheless, the scientists had well-developed biological expertise, though not with deep-water species, and were provided with considerable financial support to collect biological data on the resource and to bring in overseas expertise to help develop and apply a stock assessment methodology for managing it. Data on abundance were scarce at first and were initially established from the contribution by industry of detailed commercial catch rate information. Even after three different sets of indices of abundance were established, the time-series was too short to use established methods for stock assessment (e.g. Francis 1992, Francis *et al*. 1992, Smith 1993). Scientific and marketing expertise from orange roughy fisheries in New Zealand and Australia were also available to facilitate the rapid development of the resource. As the fishery developed with a single exploratory licence-holder and catch rates and profits grew quickly, other companies requested entry into the fishery.

Because one of the general guidelines for managing the fishery was to maintain a precautionary approach to its development in the face of the large uncertainty over resource potential, scientific advice was needed on both resource potential and the potential consequences of alternative harvesting policies. A long-term fishery management strategy was suggested that would fish down the resource over seven years and then allow a smooth transition to catches that might maintain the resource at or above the *MSY* level. A fundamental question for the first stock assessments was how large the initial *TAC*s should be? Even then, it was recognized that some adjustments might be necessary as estimates of abundance were updated.

Therefore, a stock assessment methodology to provide such advice was required to:

1) incorporate and integrate sparse data from diverse sources;
2) estimate resource abundance and its potential responses to exploitation as the fishery proceeded;
3) explicitly account for uncertainty in estimates of abundance and trends in abundance;
4) quantitatively evaluate the potential consequences of alternative fishing-down policies;
5) provide precautionary fishery management advice so that the *TAC* options adopted had an acceptably low risk of depleting the resource below *MSY*;

6) be sufficiently transparent, understandable and credible to the various parties to the fishery management system.

The Bayesian methodology applied addressed these various requirements to varying extents, but some difficulties in implementation led to a few undesirable outcomes. These are discussed separately for each of the listed requirements.

INCORPORATING AND INTEGRATING SPARSE DATA FROM DIVERSE SOURCES

The prototypical Bayesian methodology adopted in the first few years allowed the incorporation of biological expertise from New Zealand, including the basic population dynamics model to be applied and the values for such input parameters as growth rate and M. In 1997, a single index of resource abundance was used to produce a pdf of B_0. In the 1998 stock assessment, the assessment method was applied separately to two different indices when a second one became available. This produced very different abundance and risk estimates and helped to highlight the large uncertainty in the early estimates of these quantities. The procedure could have been updated to construct a pdf for B_0 from a sequence of swept area estimates in one or more time-series by, for example, adding the observed cumulative catches to each rescaled swept area value and taking some sort of weighted mean of these values. This was not attempted, however. Instead, a more conventional stock assessment modelling approach was adopted that fitted a population dynamics model to the available time-series of abundance indices, the latter being treated as relative rather than absolute abundance indices.

The Bayesian methodologies applied in 1999 and 2000 integrated all available abundance indices into a single estimation. The consistency of the inputs was evaluated by inspecting plots of biomass indices and their prior probability intervals before they were input into the stock assessment model. This was also done in the 1998 assessment. The different sources of data were incorporated in a statistically rigorous manner by allowing the stock assessment model to be fitted to them, so the prior estimates of model parameters could be statistically updated after analysing the data.

ESTIMATING RESOURCE ABUNDANCE AND ITS POTENTIAL RESPONSES TO EXPLOITATION AS THE FISHERY PROCEEDS

The initial stock assessment methodology permitted estimation of abundance from a single swept area estimate of abundance from commercial *cpue* data and the use of bias correction factors that accounted for biases from directed fishing rather than the random placement of trawls. The latter incorporated expert judgement on the factors determining q' in terms of what the factors were and how their values were distributed over the range of possible values. The approach used to construct them was by scientific management group consensus. In retrospect, uncertainty in the biomass estimate was under-represented, because the initial distributions adopted for the bias factors were too narrow. Although some scientists raised concerns that these distributions were too narrow and suggested wider ones, the suggestions could not be incorporated in the provision of *TAC* advice because of the requirement for consensus. The estimate of unfished biomass, B_0, in the first year's assessment was overestimated several-fold because the swept area methodology applied in 1997 extrapolated clusters of high catch rates to large, poorly sampled areas on the assumption that fish aggregations were spatially stable from year to year. This assumption was proven incorrect and, when a revised swept area procedure was applied that redefined sampling areas on the basis of clusters of similar catch rates, an estimate four times smaller than the original estimate of 305 000 tons resulted. The simulation modelling methodology used as input the resulting distribution for B_0, once the bias factors had been applied, and projected the abundance forward under different *TAC* policy options to indicate changes in abundance in response to catches.

The methodologies applied in 1999 and 2000 estimated abundance and trends using more than one data series. A single short time-series might not be very informative about any possible trends in stock size unless they were catastrophic (Smith 1993, McAllister and Kirkwood 1998a). The use of data series from different sources (commercial catch rate, hydro-acoustic and research trawl surveys) that happen to show similar trends, as observed on the three southern grounds, provides more credible evidence of a real trend in abundance. Abundance estimation was possible from the very short time-series with the use of informative prior probability distributions for the constants of proportionality, q, for each abundance index. None of the methods applied, however, would be capable of dealing rigorously with data series that showed dissimilar trends in abundance (Schnute and Hilborn 1993).

EXPLICITLY ACCOUNTING FOR UNCERTAINTY IN ESTIMATES OF ABUNDANCE AND TRENDS IN ABUNDANCE

The initial methodology applied in 1997 quantified uncertainty in original abundance from the subjectively input uncertainty in q'. The method of 1999 was designed to account for uncertainty in B_0, q, abundance trends, M and deviates from the stock-recruit function. The method developed in 2000 also formally accounted for uncertainty in the structural formulation of the stock assessment model. The results from the latter method demonstrate that uncertainty in stock size and trends in abundance were underestimated with the use of a single stock assessment model that accounted for uncertainty only in the values of its parameters. Uncertainty across models was quantified by computing the marginal probability for each model that reflected the total weight of evidence in support of each model but also accounted for parameter uncertainty. The overall uncertainty in abundance was shown by combining the probability distributions from the separate stock assessment models into a single distribution that reflected both parameter and structural uncertainty. The underestimation of uncertainty continues to be a major concern where stock assessment results are used to help provide management advice.

QUANTITATIVELY EVALUATE THE POTENTIAL CONSEQUENCES OF ALTERNATIVE FISHING-DOWN POLICIES

This could be done with each of the stock assessment methodologies provided. The method developed in 2000 could broadly evaluate the potential consequences by integrating the uncertainty in potential consequences across structurally different stock assessment models. Conventional approaches to account for structural uncertainty usually involve re-running stock assessments and producing policy projections with each different structural alternative (Punt and Smith 1999). Bayesian methodologies to account more rigorously for structural uncertainty have only recently begun to be applied in fisheries stock assessment (Sainsbury 1988, Patterson 1999, Parma in press). McAllister and Kirchner (in press) review these various conventional and newer approaches.

PROVISION OF PRECAUTIONARY FISHERY MANAGEMENT ADVICE

This was achieved by accounting for either parameter uncertainty only or both parameter and structural uncertainty in estimates of management quantities and providing estimates of the risks of each alternative management action. The 1997 and 1998 assessments accounted for uncertainty in q', and this uncertainty was underestimated (as mentioned above) because it implied that, in the first stock assessments, biomass could be known with a *CV* of 0.3 or 0.4, an unlikely precision in any developing deep-water fishery. The precautionary basis for the management advice provided therefore rested mainly on the identified subjective uncertainty in potential sources of bias in the swept area estimates. The 1998 assessment went a step further by analysing separately the acoustic biomass estimate to provide risk estimates (Table II). This helped to prepare the management groups for reductions in *TAC*s earlier than had been anticipated. In 1999, parameter uncertainty was accounted for more thoroughly because uncertainty in M and stock-recruit deviates was incorporated and the prior *CV* in q was increased from about 0.3 to about 0.6. The latter is more comparable to prior *CV*s for similar parameters in other assessments (McAllister *et al*. 1994, McAllister and Ianelli 1997). Estimates of the severe declines in abundance indices were also incorporated. It was assumed that the decline was caused primarily by fishing, likely a near worst case scenario. The precautionary basis for management therefore became more rigorous in each year.

The method developed in 2000 went further in accounting for structural uncertainty, as mentioned above. The first alternative models considered prior to the 2000 assessment modelled the fishing disturbance and the intermittent aggregation hypotheses. It may appear that accounting for these additional possibilities made the advice even more precautionary. However, this is not the case because:

(i) It was known in 1998 that the large observed declines in the indices could not be easily accounted for by catch removals. This was obvious from comparing the large observed declines and the relatively small catches (Tables I, IV).
(ii) The two alternative hypotheses considered were much less conservative in their interpretation of events in that they both implied that mature stock biomass was still very large, and that fish were just not aggregating but could come back when conditions changed. Hence, based on one pessimistic alternative appearing not to fit the data very well, two alternatives were suggested that happened to be considerably more optimistic.

The question arises whether this is a reasonable protocol for selecting structural alternatives to evaluate in light of the precautionary approach? Perhaps it is not. The idea that a poor fit of a pessimistic model to data suggests that only optimistic interpretations should be considered instead is certainly not precautionary. It is still plausible that other mechanisms could have caused a more or less permanent drop in the availability of fish on the fishing grounds; until the 2000 assessment, this possibility had been ignored. A protocol more consistent with the precautionary approach would instead be to formulate other hypotheses on plausible mechanisms for a strong decline in stock abundance and require that a rigorous standard of proof be met before rejection of the hypothesis of low stock abundance, and fishery management decisions in line with this rejection, could be permitted. To provide a more balanced formulation of alternative hypotheses, a fourth model (Appendix 2), which modelled this latter possibility, was constructed and evaluated along with the other three following the 2000 assessment meeting (McAllister and Kirchner in press).

This experience has led to the conclusion that, when structural uncertainty and precautionary fishery management are to be considered, careful attention is needed in the selection of the set of alternative models to evaluate. In any assessment, an infinite variety of plausible alternatives exist that cannot all be evaluated (Punt and Hilborn 1997); decisions must be made about which ones to consider in the stock assessment. From a precautionary viewpoint, it is desirable for decision-makers to be made aware of the potential range of plausible consequences for the management options of interest and, in most instances, population dynamics can be plausibly represented, before data are evaluated, by both optimistic and pessimistic models. Therefore, for the sake of adequately informing managers about the potential outcomes of management decisions and accounting for uncertainty, it is appropriate to select for evaluation a set of models that represent the range of potential outcomes. This could be obtained by formulating a set of structural alternatives balanced with regards to both optimistic and pessimistic interpretations, e.g. the same number of each that could be plausible *a priori* and in light of the data. For Namibian orange roughy, this was done following the 2000 assessment and the more precautionary *TAC*s adopted in 2000 and 2001 were supported by this analysis (McAllister and Kirchner in press).

TRANSPARENCY AND CREDIBILITY TO THE VARIOUS PARTIES OF THE FISHERY MANAGEMENT SYSTEM

Bayesian assessments involve "expert/subjective judgements", and all management groups were kept aware of this in each of the annual assessments. As long as the assessment methods suggested the possibility of large abundance and the recommended *TAC*s were not much less than the previous year, industry groups supported use of the stock assessment results. In contrast, government scientists exhibited scepticism of the results from early on because they were cognizant of their dependence on the subjective choices leading to the model structures and inputs adopted. They were disturbed by the possibility that the models adopted might not adequately have represented hypotheses of current low total stock abundance because of the limited range of model structures and data considered.

The stock assessment method applied in 1997 and 1998 was the simplest and easiest to understand and appeared to be the most widely accepted in the stock assessment working group when it was first applied, partly because of this. However, even in the first assessment, some scientists protested about the high degree of certainty placed on some of the input distributions. The method applied in 1999 was more complex in its statistical methodology than the first, and it was met with more scepticism. Nonetheless, its results were still accepted by the group and the Minister and Cabinet still acted according to its risk-based advice. The acceptance of the results was partly facilitated because the statistical methodology had been peer-reviewed and applied in other fisheries (Punt 1993, McAllister *et al*. 1994, McAllister and Ianelli 1997). The new method to deal with structural uncertainty developed during the 2000 assessment was not used for management because it was new and had not by then been subjected to peer review.

Another controversial aspect of the assessments is that the risk criterion changed each time an assessment was conducted (Table III). This occurred because of the very large changes in data each year and the large changes in the estimates of risk from the previous year. In 1998, the estimates of risk, using the same 14-year horizon risk criterion as the year before, skyrocketed when the acoustic estimate was used. This unforeseen new data point indicated that the stocks could very soon be depleted nearly to the *MSY* level or lower. Owing to uncertainty over the level of depletion, the risk criterion was changed to include just a three-year horizon, and it was decided to wait and see what the next year's assessment brought in the way of new data. The flexibility in changing the risk criterion to one still acceptable with respect to precaution and still allowing commercial operations to continue, helped to maintain faith in the stock assessment and *TAC* recommendation process among most parties to the assessment. The change to a one-year horizon risk criterion in 1999 was brought about by the huge drop in most indices for the three southern grounds between 1997 and 1998. All realized that the criterion could be pushed no further and that a major decision was needed either that year or the next. A drop in *TAC* from 12 000 to 9 000 tons was recommended and implemented. A return to the use of the original 14-year risk horizon in the 2000 assessment and the stock assessment's support for very low *TAC*s kept conservation as a key decision variable.

Considerations in the choice of stock assessment methodology for fisheries in developing countries

Stock assessment scientists occasionally need to make choices over a stock assessment approach to be applied, as was the case for Namibian orange roughy. From a scientific perspective, it is desirable that any stock assessment method be simple enough to be fully understood and easily applied. In many cases, this could conceivably be something that could be implemented in an Excel spreadsheet or be available in easily accessible software programs purpose-built for stock assessment applications. It is also desirable that the method model the key features of the fishery's dynamics, be statistically rigorous, and be able to incorporate the various data and quantitatively account for key uncertainties. For a variety of reasons, it may sometimes be difficult to achieve each of these aspects at once in a single methodology. Some methods might be easy to understand and apply but lack statistical rigour and realism in their models of fishery dynamics. Other methods could be applied to more closely model fishery dynamics and incorporate considerable statistical rigour, but might be impossible for the scientists to apply because of the additional specialized skills and knowledge required to modify, operate and effectively apply the models. Therefore, to help develop confidence in desired stock assessment methods, ongoing skills-development programmes are required to ensure that scientists gain the necessary expertise.

SUMMARY

The stock assessment methods developed for managing the Namibian orange roughy fishery have either helped to facilitate or have hindered fishery management by achieving the following.

1) The methods have helped to integrate diverse sources of information, contributed by industry members and government scientific research, to provide estimates of stock biomass and trends in stock biomass and to predict the potential outcomes of alternative management outcomes.
2) The probabilistic modelling methods applied have taken uncertainties into account and provided fishery managers with estimates of biological risks of alternative *TAC* options. This has served as a basis for providing precautionary fishery management advice.
3) Subjective judgements about stock assessment model formulation and inputs in the 1997 and 1998 assessments led to underestimates of uncertainty in stock biomass, overestimates of stock biomass, and underestimates of the risks of alternative *TAC* management options. Two judgements in particular appear to be largely responsible for this. The first was the requirement for consensus among industry members and scientists in developing probability distributions for the bias correction factors for the commercial swept area biomass estimate. This led to the distributions applied being too narrow and conveying too much certainty. The second was the assumptions that fish aggregations are spatially stationary from year to year and that clusters of high *cpue* values can be extrapolated to large, poorly sampled areas.
4) The revised Bayesian assessment method applied in 1999 and 2000 more adequately accounted for uncertainty in bias factors for the abundance indices, stock biomass and risk, but it ignored structural uncertainty, particularly over whether the catchability of orange roughy on the fishing grounds had changed. Because of this, the methodology could not easily account for the large decline in biomass indices and lost credibility before industry.
5) A Bayesian method was developed in 2000 to account for uncertainty in the structural formulation of stock assessment models and considered a set of plausible alternative models that was balanced with respect to conjectures about catchability and the remaining stock biomass. Some of the alternatives considered more adequately accounted for declines in the biomass indices. Because this methodology accounts for both parameter and structural uncertainty in a statistically rigorous and balanced manner, it provides a more scientifically defensible basis for precautionary fishery management.
6) Bayesian posterior probability distributions for biological reference points for Namibian orange roughy, such as B_{MSY}/B_0, were computed and indicated that mean values from previous analyses could easily have been too low. This permitted the identification of more-precautionary reference points, e.g. the 90th percentile for B_{MSY}/B_0 of about 40% of B_0, instead of the previous mean estimate of 30%.

ACKNOWLEDGEMENTS

MKM's contribution to the research reported in this article was funded by the Namibian Government and the Fisheries Management Science Programme of the United Kingdom Department for International Development. The authors are indebted to Dr B. W.

Oelofson (Namibian Ministry of Fisheries and Marine Resources), Messrs D. C. Boyer, A. Staby and B. Vaske (all National Marine Information and Research Centre, NatMIRC) and T. A. Branch (University of Cape Town, UCT), Prof. D. S. Butterworth (UCT), and Drs A. G. James (Gendor, Namibia) and M. R. Clarke (National Institute of Water and Atmosphere Ltd., Wellington, New Zealand), as well as many others for their frankness and willingness to express their opinions and to contribute to the material presented in this paper. Drs A. E. Punt (University of Washington, Seattle) and A. D. M. Smith (CSIRO, Australia) are thanked for their detailed and helpful comments on the manuscript.

LITERATURE CITED

ADKISON, M. D. and R. M. PETERMAN 1996 — Results of Bayesian methods depend on details of implementation: an example of estimating salmon escapement goals. *Fish. Res.* **25**: 155–170.

BERGER, J. O. 1985 — *Statistical Decision Theory and Bayesian Analysis*. New York; Springer: 617 pp.

BERGH, M. O. and D. S. BUTTERWORTH 1987 — Towards rational harvesting of the South African anchovy considering survey imprecision and recruitment variability. In *The Benguela and Comparable Ecosystems*. Payne, A. I. L., Gulland, J. A. and K. H. Brink (Eds). *S. Afr. J. mar. Sci.* **5**: 937–951.

BOYER, D. C., KIRCHNER, C. H., McALLISTER, M. K., STABY, A. and B. I. STAALESEN 2001 — The orange roughy fishery of Namibia: lessons to be learned about managing a developing fishery. In *A Decade of Namibian Fisheries Science*. Payne, A. I. L., Pillar, S. C. and R. J. M. Crawford (Eds). *S. Afr. J. mar. Sci.* **23**: 205–221.

BRANCH, T. A. 1998 — Assessment and adaptive management of orange roughy off southern Africa. M.Sc. thesis, University of Cape Town: 204 pp.

BRANCH, T. A. 2001 — A review of orange roughy *Hoplostethus atlanticus* fisheries, estimation methods, biology and stock structure. In *A Decade of Namibian Fisheries Science*. Payne, A. I. L., Pillar, S. C. and R. J. M. Crawford (Eds). *S. Afr. J. mar. Sci.* **23**: 181–203.

BUTTERWORTH, D. S., PUNT, A. E. and A. D. M. SMITH 1996 — On plausible hypotheses and their weighting, with implications for selection between variants of the Revised Management Procedure. *Rep. int. Whalg Commn* **46**: 637–640.

CLARK, C. W., CHARLES, A. T., BEDDINGTON, J. R. and M. MANGEL 1985 — Optimal capacity decisions in a developing fishery. *Mar. Resour. Econ*. **2**: 25–54.

CLARK, M. R. 1996 — Biomass estimation of orange roughy: a summary and evaluation of techniques for measuring stock size of a deep-water fish species in New Zealand. *J. Fish Biol.* **49**(Suppl. A): 114–131.

CLARK, M. R., TRACEY, D., STEVENS, D. and R. COBURN 1999 — Age and growth of orange roughy from Namibian waters. Unpublished report, Ministry of Fisheries and Marine Resources, Namibia: 11 pp. (mimeo).

DALEN, J., BOYER, D., STAALESEN, B., STABY, A., KIRCHNER, C., CLARKE, M., HAMPTON, I., KVINGE, B. and J. JOHANNSON 1998 — Orange roughy survey, 1 – 25 July 1998. Cruise report 4/98, NORAD-FAO/UNDP Project GLO 92/013. Unpublished report Ministry of Fisheries and Marine Resources, Namibia: 92 pp. + 32 Appendices (mimeo).

FRANCIS, R. I. C. C. 1992 — Use of risk analysis to assess fishery management strategies: a case study using orange roughy (*Hoplostethus atlanticus*) on the Chatham Rise, New Zealand. *Can. J. Fish. aquat. Sci*. **49**: 922–930.

FRANCIS, R. I. C. C., ROBERTSON, D. A., CLARK, M. R. and R. P. COBURN 1992 — Assessment of the QMA 3B orange roughy fishery for the 1992/93 fishing year. N.Z. Fisheries Assess-ment Research Document **92/4**: 26 pp. (mimeo).

GELFAND, A. E. and A. F. M. SMITH 1990 — Sampling-based approaches to calculating marginal densities. *J. Am. Stat. Assoc*. **85**: 398–409.

HILBORN, R., PIKITCH, E. K. and R. I. C. C. FRANCIS 1993 — Current trends in including risks and uncertainty in stock assessment and harvest decisions. *Can. J. Fish. aquat. Sci*. **50**: 874–880.

KASS, R. E. and A. E. RAFTERY 1995 — Bayes factors. *J. Am. Stat. Assoc*. **90**: 773–795.

KINAS, P. G. 1996 — Bayesian fishery stock assessment and decision making using adaptive importance sampling. *Can. J. Fish. aquat. Sci*. **53**: 414–423.

KIRCHNER, C. H. and M. K. McALLISTER (in press) — A new improved method to compute swept area estimates of biomass from commercial catch rate data: application to Namibian orange roughy (*Hoplostethus atlanticus*). *Fish. Res.*

McALLISTER, M. K. and J. N. IANELLI 1997 — Bayesian stock assessment using catch-age data and the sampling/importance resampling algorithm. *Can. J. Fish. aquat. Sci*. **54**: 284–300.

McALLISTER, M. K. and C. H. KIRCHNER (in press) — Accounting for structural uncertainty to facilitate precautionary fishery management: illustration with Namibian orange roughy. In *Targets, Thresholds, and the Burden of Proof in Fisheries Management*. Mangel, M. (Ed.). *Bull. mar. Sci*.

McALLISTER, M. K. and G. P. KIRKWOOD 1998a — Using Bayesian decision analysis to help achieve a precautionary approach for managing developing fisheries. *Can. J. Fish. aquat. Sci*. **55**: 2642–2661.

McALLISTER, M. K. and G. P. KIRKWOOD 1998b — Bayesian stock assessment: a review and example application using the logistic model. *ICES J. mar. Sci*. **55**: 1031–1060.

McALLISTER, M. K., PIKITCH, E. K., PUNT, A. E. and R. HILBORN 1994 — A Bayesian approach to stock assessment and harvest decisions using the sampling/importance resampling algorithm. *Can. J. Fish. aquat. Sci*. **51**: 2673–2687.

PARMA, A. M. (in press) — Bayesian approaches to the analysis of uncertainty in the stock assessment of Pacific halibut. In *Incorporating Uncertainty into Fisheries Models*. Berkson, J. M., Kline, L. L. and D. J. Orth (Eds). Bethesda, Maryland; American Fisheries Society.

PATTERSON, K. R. 1999 — Evaluating uncertainty in harvest control law catches using Bayesian Markov Chain Monte Carlo virtual population analysis with adaptive rejection sampling and including structural uncertainty. *Can. J. Fish. aquat. Sci*. **56**: 208–221.

PUNT, A. E. 1993 — The implications of some multiple stock hypotheses for Chatham Rise orange roughy. N.Z. Fisheries Assessment Research Document **93/16**: 28 pp. (mimeo).

PUNT, A. E. and R. HILBORN 1997 — Fisheries stock assessment and decision analysis: the Bayesian approach. *Revs Fish Biol. Fish*. **7**: 35–63.

PUNT, A. E. and A. D. M. SMITH 1999 — Harvest strategy evaluation for the eastern stock of gemfish (*Rexea solandri*). *ICES J. mar. Sci*. **56**: 860–875.

RAFTERY, A. E., GIVENS, G. H. and J. E. ZEH 1995 — Inference from a deterministic population dynamics model for bowhead whales. *J. Am. Stat. Assoc*. **90**: 402–416.

RUBIN, D. B. 1988 — Using the SIR algorithm to simulate posterior

distributions. In *Bayesian Statistics*. **3**. *Proceedings of the Third Valencia International Meeting, June 1987*. Bernardo, J. M., Degroot, M. A., Lindley, D. V. and A. M. Smith (Eds). Oxford; Clarendon: 385–402.
SAINSBURY, K. J. 1988 — The ecological basis of multispecies fisheries, and management of a demersal fishery in tropical Australia. In *Fish Population Dynamics*, 2nd ed. Gulland, J. A. (Ed.). Chichester; Wiley: 349–382.
SCHNUTE, J. T. and R. HILBORN 1993 — Analysis of contradictory data sources in fish stock assessment. *Can. J. Fish. aquat. Sci*. **50**: 1916–1923.
SMITH, A. D. M. 1993 — Risks of over- and under-fishing new resources. In *Risk Evaluation and Biological Reference Points for Fisheries Management*. Smith, S. J., Hunt, J. J. and D. Rivard (Eds). *Can. Spec. Publ. Fish. aquat. Sci*. **120**: 261–267.
STAALESEN, B., BOYER, D., STABY, A., KAINGE, P., GAMATHAM, J., SHIMHANDA, M., WELLS, S., BARANGE, M., HAMPTON, I., REES, A., OLSEN, M., MØRK, T. and T. JOHANSSON 1999 — Orange roughy survey 6 July – 29 July 1999. Cruise report No 5/99. NORAD-FAO/UNDP Project GLO 92/013. Unpublished report, Ministry of Fisheries and Marine Resources, Namibia: 72 pp. + 12 Appendices (mimeo).
TRACEY, D. M. and P. L. HORN 1999 — Background and review of ageing orange roughy (*Hoplostethus atlanticus*, Trachichthyidae) from New Zealand and elsewhere. *N.Z. Jl mar. Freshwat. Res*. **33**: 67–86.
WALTERS, C. J. 1998 — Evaluation of quota management policies for developing fisheries. *Can. J. Fish. aquat. Sci*. **55**: 2691–2705.
WALTERS, C. J. and D. LUDWIG 1994 — Calculation of Bayes posterior probability distributions for key population parameters: a simplified approach. *Can. J. Fish. aquat. Sci*. **51**: 713–722.
WEST, M. 1993 — Approximating posterior distributions by mixtures. *J. R. statist. Soc., Ser. B* **55**: 409–422.

APPENDIX 1

The population dynamics model for Namibian orange roughy

The population dynamics model applied in 1999 and 2000 is described below. It is age-structured, relates recruitment to spawner-biomass by means of the Beverton-Holt stock-recruitment relationship, applies knife-edge selection and maturity, and allows for stochastic recruitment. The values for model parameters that were fixed are given in Table App. 1.I. The population dynamics model applied in 1997 and 1998 is the same, except that recruitment was deterministic.

Table App.1.I: Values of the model parameters used in the assessment of Namibian orange roughy

Parameter	Value
L_∞ (cm)	29.5
κ (year^{-1})	0.069
t_0 (years)	-2.0
a (g cm^{-3})	0.1354
B	2.565
Plus-group – m (years)	70
a_r (years)	23
Steepness h	0.75
σ_r	1.1

RESOURCE DYNAMICS

The dynamics of animals aged 2 years and above are governed by the equation

$$\begin{aligned} N_{y+1,a} &= \mathrm{e}^{-M}\, N_{y,a-1} && 2 \le a < a_r \\ N_{y+1,a} &= \mathrm{e}^{-M}\, N_{y,a-1}\left(1-H_y\right) && a_r \le a < m \\ N_{y+1,m} &= \mathrm{e}^{-M}\left(N_{y,m}+N_{y,m-1}\right)\left(1-H_y\right) && a = m \quad , \end{aligned} \tag{App.1.1}$$

where $N_{y,a}$ is the number of animals of age a at the start of year y, a_r the age at recruitment to the fishery and the age at maturity, M the instantaneous rate of natural mortality on animals, H_y the exploitation rate during year y, and m is the maximum (lumped) age-class (all animals in this and the previous age-class are recruited and mature).

BIRTHS

$$N_{y,1} = \left[B_{y-1} / \left(\alpha + \beta B_{y-1}\right)\right] \mathrm{e}^{\varepsilon_y - \sigma_r^2/2} \; , \tag{App.1.2}$$

where B_y is the biomass of mature animals during year y at the time of spawning:

$$B_y = \sum_{a=a_r}^{m} w_a\, N_{y,a} \quad , \tag{App.1.3}$$

w_a is the mass of a fish of age a (assumed to be constant throughout the year):

$$w_a = \delta_1 \left(L_a\right)^{\delta_2} \tag{App.1.4}$$

$$,$$

$$L_a = L_\infty\left(1-\mathrm{e}^{-\kappa\left(a-t_0\right)}\right) \tag{App.1.5}$$

ε_y is the recruitment residual for year y, $\varepsilon_y \sim N(0, \sigma_r^2)$, σ_r is the standard deviation of the log of the multiplicaive fluctuations in births, and α, β are stock-recruitment function parameters.

INITIAL CONDITIONS

Were there no fluctuations in recruitment, the resource would be assumed to be at its unexploited equilibrium level, with the corresponding age-structure, at the start of exploitation (year y_1). Instead, because of historic recruitment fluctuations, the sizes of the cohorts at the start of year y_1 are uncertain with a lognormal prior pdf for the deviations from the stock-recruit function, $\varepsilon_a \sim N(0, \sigma_r^2)$, and the initial biomass is therefore similarly distributed about the corresponding deterministic equilibrium level. The initial numbers-at-age are given by the corrected equation

$$\begin{aligned} N_{y1,a} &= R_1 \exp\left\{-(a-1)M\right\} \mathrm{e}^{\varepsilon_a - \sigma_{\varepsilon_a}^2/2} && 1 \le a \le m-1 \\ & && a = m \\ N_{y1,m} &= R_1 \exp\left\{-(m-1)M\right\} / \left(1-\exp(-M)\right) && 1 \le a \le m-1 \; , \end{aligned} \tag{App.1.6}$$

where R_1 is the number of 1-year-olds at the deterministic equilibrium that corresponds to an absence of harvesting and ε_a is a random variable with prior $N(0,\sigma_r^2)$. A value for R_1 is calculated from the value for the virgin biomass at the end of the year, B_0, using the equation:

$$R_1 = B_0 / \left\{ \sum_{a=1}^{m-1} w_a \exp(-aM) + w_m \exp(-mM) / \left(1-\exp(-M)\right) \right\} \; . \tag{App.1.7}$$

Note that the equation for the plus-group does not incorporate a recruitment variability term because this group consists of a large number of age-classes which will largely damp out this effect. Values for the stock-recruit parameters α and β are calculated from the values of R_1 and the "steepness" of the stock-recruit relationship, h. The "steepness" is the fraction of R_1 to be expected (in the absence of recruitment variability) when the mature biomass is reduced to 20% of its pristine level (Francis 1992), so that:

$$\alpha = \tilde{B}_0^S \frac{1-h}{4hR_1}$$

$$\beta = \frac{5h-1}{4hR_1}$$

$$\tilde{B} = \left\{ \sum_{a-a_r}^{m-1} w_a \exp(-aM) + w_m \exp(-mM) / \left(1-\exp(-M)\right) \right\} \quad \text{(App.1.8)}$$

CATCHES

The exploitation rate during year y, H_y, is calculated using the equation

$$H_y = C_y / B_y \quad , \quad \text{(App.1.9)}$$

where C_y is the catch during year y.

DATA AND LIKELIHOOD FUNCTION

Targeted hydro-acoustic estimates were used for the acoustic index, i.e. only the aggregations were included in this index (Huse *et al*. 1997, Dalen *et al*. 1998, Staalesen *et al*. 1999). The second index is the commercial swept area estimate, calculated by using non-stationary stratification (Kirchner and McAllister in press), and the *cpue* was corrected for vessel effect for the three quota management areas. The third index is a research index of swept area biomass, which is obtained during July each year by using an industry vessel to make stratified hauls in the quota management areas.

The log likelihood function for the combined relative abundance series for each stock is given by

$$\lambda = \sum_{j=1}^{N_g} \sum_{i=1}^{n_j} -\frac{0.5}{\sigma_j^2} \log\left(\frac{O_{i,j}}{q_j B_{i,j}}\right)^2 - \text{const}_j \quad , \quad \text{(App.1.10)}$$

where N_g is the number of indices on ground g, n_j the number of observations in series j, $O_{i,j}$ the ith observation in series j, q_j the constant of proportionality for series j (on ground g), $B_{i,j}$ the annual stock biomass corresponding to observation $O_{i,j}$, σ_j the lognormal *SD* for residual errors between observed values and model-predicted values for each annual index of abundance in series j, and $const_j$ is a constant for series j.

The parameter σ_j typically reflects the relative goodness of fit between the model predicted trend in biomass and the trend in the observed values and is approximately equal to the *CV*, roughly the *SD* of the observations from the predicted values divided by the mean predicted value. Values for σ_j that indicate a reasonably satisfactory goodness of fit between model-predicted and observed indices are usually <0.4. Values >0.4 usually indicate that the series is not a reliable indicator of trends in abundance unless they are extreme, e.g. catastrophic.

The parameter σ_j is typically estimated when there are at least 20 years of observations. When the number of years in a series is relatively few, the value for σ_j or the *CV* is usually fixed beforehand; this is done based on previous experience in other fisheries (McAllister *et al*. 1994). The higher the *CV*, the less the weighting of the series relative to the others. Furthermore, the higher the *CV*, the lower the weighting of the relative trend in the series. Because informative priors for q are applied, increasing the *CV*s on the priors results in higher weighting on the indices as absolute estimates of biomass.

Because the number of years in each series was few, the value for each σ_j was fixed based on previous experience and the understanding that each series is new, and there is therefore uncertainty over whether each can actually track trends in abundance. Consequently, the values for σ_j chosen are on the higher end of the range of values typically applied and reflect a small degree of scepticism about the potential of each series to track relative trends in abundance closely. For the baseline run, the acoustic index was given a mean *CV* of 0.30, research swept area a mean *CV* of 0.35, and the non-stationary commercial swept area index (Kirchner and McAllister in press) was used with a weighted mean *CV* of 0.4. Deviations in *CV* from the mean were obtained by incorporating sampling error estimates from the data for each year. The commercial swept area index was used together with the acoustic and research swept area indices for the baseline run (Table IV). Commercial catches are available from the beginning of the fishery in 1994, and they are totalled over the calendar year, given in Table I.

APPENDIX 2

Four alternative models for stock decline

The new 2000 stock assessment methodology for Namibian orange roughy (McAllister and Kirchner in press) considered four alternative hypotheses to account for the sharp decline in aggregating biomass.

CATCH REMOVAL HYPOTHESIS (CRH)

Under this hypothesis, catch removals are the main cause of declines in aggregating biomass. Annual deviates from the Beverton-Holt stock-recruitment function are also modelled under this and the other hypotheses and can also help to account for the drop in aggregating biomass. The term aggregating biomass refers to the mature portion of the stock that aggregates and becomes vulnerable to fishing so making it accessible to commercial swept-area biomass estimates or indices. It is assumed that this portion of the stock is the same as that detected by acoustic and research trawl surveys of abundance. Although this assumption probably does not hold perfectly in reality, it is likely a very good approximation because the research trawl and acoustic surveys occur at approximately the same time and in the same areas and tend to focus at the times and places where most of the commercial catch is taken on each fishing ground. Under this hypothesis, catchability for each abundance index remains constant over time, as was assumed in the 1999 assessment.

$$q_{j,y} = q_j \quad . \qquad \text{(App.2.1)}$$

The baseline prior probability distributions for each q_j are shown in Table V. The large decline can be accounted for only if the posterior supports a much larger value for q than the prior (i.e. the prior for q is overruled by the data).

INTERMITTENT AGGREGATION HYPOTHESIS (IAH)

$$q_{y,j} = q_j \times E_y \quad , \qquad \text{(App.2.2)}$$

where E_y is a random variable that reflects the annual deviate from the average fraction of the adult population that aggregates in a given year. Note that E_y is constant across the different abundance indices. If E_y showed a sequential pattern of decrease, the IAH would be indistinguishable from the fishing-disturbance hypothesis, but a strong increase in E_y in any of the years after the initiation of fishing would tend to refute the fishing-disturbance hypothesis and so support the IAH. Because of the paucity of data, E_y was estimated only for the years 1998 and 1999 for the three southern grounds because the large decline occurred after 1997 (Fig. 2). On one of the grounds, Hotspot, the drop occurred after 1995 (Fig. 2). Therefore, for Hotspot, a single mean deviate in the proportion aggregating was estimated for the years 1996–1999. For all earlier years, E_y was fixed at 1, implying that the long-term average proportion of mature fish aggregating applied.

A relatively uninformative prior distribution for E_y was used: E_y ~ Uniform(0, 3). The upper bound of 3 was chosen because the mean annual proportion of aggregating mature fish on each of the fishing grounds could conceivably be as low as 1/3. In addition, for the comparison of structurally different models, it is desirable for the ranges of plausible parameter values for analogous parameters, e.g. E_y and M_{97} (see next hypothesis), to be as similar as possible. A short range for one parameter would give it more posterior credibility than the other if the data were relatively uninformative, because the normalizing constant for the prior for the parameter with a very short range would be much larger, e.g. equal to 1 over the range of the parameter if the prior had a uniform density function.

FISHING DISTURBANCE HYPOTHESIS (FDH)

A simple model suggesting fishing-disturbance models $q_{j,y}$, the catchability in a given year, as a function of the average catch rate in the last L years, is

$$q_{j,y} = q_j\left(1 - \frac{a}{L}\left(\sum_{i=1}^{L} u_{y-i}\right)\right) \quad , \qquad \text{(App.2.3)}$$

where q_j is the catchability coefficient for the commercial swept-area series j, a a parameter that determines the amount of impact of the previous year's catch on year y's catchability, L the number of recent years affecting this year's catchability, and u_y is the catch fraction, C_y/B_y, in year y.

If only the last year affects this year's catch rate, catchability in this year y is given by

$$q_{j,y} = q_j\,(1 - a\,u_{y-1}) \quad .$$

If the last two years' catch rate affect this year's catchability, then

$$q_{j,y} = q_j\,(1 - a\,(u_{y-1} + u_{y-2})\,/\,2) \quad .$$

A marginal posterior was computed for submodels with 1-, 2-, and 3-year lags, and the one with the highest marginal posterior was selected to represent the FDH.

The parameter a can take on values from 0 to

$$1\,/\,\mathrm{MAX}\left(\frac{1}{L}\left(\sum_{i=1}^{L} u_{y-i}\right)\right) \quad , \qquad \text{(App.2.4)}$$

where MAX reflects the maximum value in the time-series. If $a = 0$, fishing has no disturbance effect. Values of $a > 0$ up to the maximum suggest increasing levels of disturbance by fishing of the formation of subsequent aggregations. With a 2-year lag, L, the first year of fishing imposes only an intermediate disturbance on the subsequent aggregations. Only after a second year of fishing is the full disturbance effect realized. Furthermore, if fishing is stopped, then it will take a full 2 years before the effect of the disturbance disappears. The parameter a was assumed constant across the different abundance indices.

A relatively uninformative prior for a was used: $a \sim$ Normal(0, 20^2), with truncation below 0. Therefore, the Normal(0, 20^2) density function had to be multiplied by 2 to make it a proper density function. Unlike E_y and M_y (below), a was Normal and not uniform because an upper maximum value could not be identified on the basis of prior knowledge. The value for the standard deviation (*SD*) was chosen by selection of a value that was large enough to be relatively uninformative, but not so large as to result in a very small normalizing constant that would discredit the FDH model relative to the others. This was accomplished by running the FDH model for the different grounds to find the maximum possible value for a (Equation App.2.4), approximately 20, and setting the *SD* equal to it. Values much larger than 20 changed the FDH model results negligibly.

MASS EMIGRATION OR MORTALITY (MEH)

This hypothesis was introduced after the first three had been put forward. A sudden drop in abundance of a demersal species could very well be consistent with mass emigration or a mortality event, an explanation that, without considerable data, cannot easily be refuted. This possibility was modelled by estimating the rate of natural mortality in the year before the known drop in abundance. For the three southern fishing grounds, the natural mortality rate, M_y, was estimated separately for the year 1997, because the main drop on these grounds occurred after 1997. The winter acoustic survey in that year suggested one potential anomaly: the presence of large numbers of feeding sperm whales in association with the spawning aggregations in that winter only. It is not known whether those whales fed on orange roughy. For the Hotspot fishing ground, the northernmost, the main decline occurred after 1995, and M_y was estimated separately for that year.

A relatively uninformative prior for M_y was used: $M_y \sim$ Uniform(0.001, 3). The lower bound was set close to 0, and the upper bound was set to a conceivably extremely high value for the rate of natural mortality or emigration that could be consistent with mass mortality or an emigration event. These bounds were also chosen to give a value for the normalizing constant for the prior for this parameter as similar as possible to that for E_y.