Evaluating the costs and benefits of research on stock structure for management of the orange roughy fishery

Dr A. David McDonald, Dr Anthony D. M. Smith and Adam J. Davidson

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NON-TECHNICAL SUMMARY

FRDC 96/109 **Evaluating the costs and benefits of research on**

Address: CSIRO Division of Marine Research
GPO Box 1538
Hobart Tas 7001
Ph: 03 6232 5201 Fax: 03 6232 5000

This report describes a procedure for objectively comparing the likely returns from research programs, particularly those designed for fisheries management purposes. This procedure requires that the management objectives for the fishery are well defined, and that the research is directed at achieving them.

The example used is for Tasmanian orange roughy. The objective of the fishery managers is *to maximise the value of the harvest, without threatening the sustainability of the fishery.* This has been interpreted as *to allow the greatest $ value of catch to be taken over the long term, so long as the breeding stock left in the water is likely to be at least 30% of its original level.*

Central to estimating the value of research for management purposes is a stock-assessment model of the fish population. The model mimics the growth and reproduction of the fish according to the best biological information available. Allowing for losses from fishing and gains from growth and reproduction, the model is used to predict the numbers of fish of each age present in each year. From those numbers at age, it calculates the total tonnage of fish in the water in each year. This is how the model estimates biomass or 'stock size' and it depends on a known pattern of fishing being provided.

Scientists are uncertain whether the population is one stock or two, however. This hampers their ability to understand the fishery fully and to assess the state of the stocks. Without reliable estimates of the current and initial size of the population, managers find it difficult to set total allowable catches (TAC) which will achieve management objectives. At present the population is managed as if it were made up of two biologically independent stocks, with an unknown degree of mixing between them. The TACs are currently set at approximately 1500 tonnes per year for the southern zone and 2000 tonnes for the eastern zone.

Research into stock structure should give scientists more information about the original stock levels and the degree of mixing. The research referred to here includes both future stock surveys, and assessment of the impacts of future TAC levels on orange roughy stocks.

If this leads to management decisions which increase the value of the catch taken over time, while still meeting sustainability criteria, then that increase might be considered to be the value of the research.

The *research - stock assessment - decision making* process was examined using three different levels of knowledge about the stock; the *prior*, using only fishery data, the *posterior*, which used the results from research completed so far, and *the pseudo-posterior*, which predicted the results of future or planned research.

In each case, thousands of stock assessments were simulated, taking into account the likely range of values for the unknown starting stock sizes and the degree of mixing, as well as the likelihood assigned to each. The likelihoods differed in each situation as a direct result of the information available. With the prior, there was no stock structure information and every value was deemed equally possible. The posterior incorporated the results of research and included indications of which values are more likely, and which are less likely. The pseudo-posterior was constructed under the assumption that proposed research would further narrow the range of likely values for starting stock sizes and degree of mixing, and give higher likelihoods to some of them. Evaluation of the fishery using the pseudo-posterior also included the possibility of an adjustment to the TACs, as a result of the research, after ten years of fishing at some initial level.

A range of catch strategies across the two areas was applied to the model for every combination of likely values of the unknown stock sizes and degree of mixing. In each case, the relative value of the catches was found. The stream of catches over time has a net present value (NPV) to industry depending on the discount rate used, and in this report the NPV was expressed comparatively (as $R), or relative to the present day value of 1 tonne of fish.

The catch strategies were simple ones. They were set as TACs in each of the two management zones: some were unchanged for 100 years and others were allowed to be revised. In each case the optimal strategy was found; that is, the one that yielded the greatest NPV without depressing the breeding stock too far. These were averaged for each of the three situations, giving the chosen indicator "average likely return", and comparisons were made to value the information used.

The results, based on historical data and the model used, show a positive likely return (on average) from both past and proposed stock structure research. This was true for all chosen discount rates. The average likely return for the posterior, using results from completed research, suggested optimum TACs that are quite similar to those currently set in the fishery. When the catch strategy allowed freedom to revise TACs, the optimum solution was very heavy fishing for a short period followed by closure of the fishery for a very long period to allow the stock to recover. This turns out to be the most "informative" strategy, but is not seriously considered as a realistic option.

The simulations under the posterior suggest the likely range for initial biomass in the southern zone to be between 75,000 and 160,000 tonnes and the eastern zone to be between 30,000 and 135,000 tonnes. Both with and without the benefit of research information, the optimal TAC for the southern zone was lower than that for the eastern zone, a pattern that could be produced by the southern zone being a source of recruitment to the eastern zone via spawning migration.

There was very little information about the mixing parameter from the research carried out so far. Future research needs to be of a different design to yield information on the true level of mixing. The assumption of completely separate stocks is not, however, supported by the evidence.

The procedure has now been developed conceptually and applied to a fishery by way of example. The example has demonstrated the ability of the procedure to consider and evaluate the benefits of research not yet undertaken, without presupposing the specific outcomes of that research. This can be achieved by carefully specifying the current range of uncertainty in a particular parameter (or model), by simulating the effect of future information on that uncertainty, and by evaluating the consequences of reducing that uncertainty for future management. The results from the simulations correlate well with what has actually happened in the management of that fishery, and suggest a basis for comparing returns from proposed research in a standardised way.

Future development would see this framework applied to other fisheries, perhaps with different management objectives, and its further refinement would make it more generally useable.

BACKGROUND

The development and implementation of management plans for major Australian fisheries is fundamental to the role of the Australian Fisheries Management Authority (AFMA). This work is hampered by imperfect knowledge about fish biology and population size, and also constrained by many ecological, economic and social considerations.

Inputs into, and influences on, the management process come from the fishing industry, other industries (such as tourism, mining, waste disposal, aquaculture, fish ranching and marine plant harvesting), conservation groups, recreational users of marine resources and scientific research organisations. Priorities for research are generally established by consensus in meetings of representatives of industry, management and other groups, including scientific research bodies. The process of setting research priorities for fisheries management works well but it is subjective and it is not always clear which projects might return the greatest benefit from limited resources.

Increasing pressure on research funding bodies to judge the value of research proposals and the consequent pressure on scientists to justify their work, has given rise to the present project. Tasmanian orange roughy is the chosen case study because it is a relatively new fishery, confined geographically and managed by zone using total allowable catch (TAC) quotas. It is an interesting fishery because of the uncertainty surrounding stock structure and it has already been the subject of both biological and model-based research.

The present research involves a multi-disciplinary approach for objectively assessing as-yet-unknown returns from both completed and proposed research. It incorporates economic, fish population dynamics and management considerations in an integrated framework, as put forward by McDonald and Smith (1997) [attached as Appendix A]. This framework incorporates stock assessment methods and allows for important sources of uncertainty.

It includes an example intended for demonstrating to managers and research planners how to value the collection of additional information even when a complete understanding of the fishery system may never be reached. It demonstrates the worth of reducing uncertainty when it may result in management action.

Obtaining cost estimates for the Tasmanian orange roughy fishery proved to be difficult so the research reported here focuses on providing a relative measure of how well management objectives are achieved.

Commercial fishing for orange roughy began off western Tasmania in 1986. The fishery expanded to eastern and southern waters with the discovery of a large spawning aggregation in 1989. There are currently about 20 fishing vessels operating in the fishery, having declined from 50 vessels in the early 1990's. The fishery is now based primarily in the eastern and southern management zones which are treated as separate fisheries with independent stocks. At present the annual TAC is 1500 tonnes for the southern zone and 2000 tonnes for the eastern zone. It is thought that current stocks are at about 30% of virgin biomass. There is considerable doubt, however, about whether the two zones have separate stocks.

Management objectives for the Tasmanian orange roughy fishery are set by AFMA and are detailed by Chesson (1996). The primary objective is to ensure that the orange roughy resource is exploited in an ecologically-sustainable manner. This has been interpreted, for simulation purposes, as attempting to maintain the spawning biomass of each stock above 30% of the virgin biomass (that is, 30% of the pre-1986 biomass). In the event that the stock is below this level with a probability of at least 0.5, the management strategy is to restore the stock over a 5-10 year period.

The second management objective stated is to maximise the economic efficiency of the fishery. It is assumed that what is meant by this statement is that managers, having satisfied the first objective, will attempt to allow fishers to catch their allocation in an economically-efficient manner. In the process of achieving the first objective, therefore, the second objective ensures that managers attempt to use policies that are consistent with maximisation of the present value of the flow of harvests. The third objective stated, which will not impact directly on what is discussed in the present paper, is to provide efficient management services to, and on behalf of, the Australian government.

Achievement of the two main management objectives is heavily dependent on the stock structure in the fishery. Management strategies may differ markedly for the single stock and dual stock cases and so research directed at resolving which is most likely will potentially have a significant impact on the fishery. Clearly a reduction in uncertainty about stock structure that results from research will have an effect on management policies and strategies, and so affect fisher activity and the dynamics of the resource.

NEED

Stock structure is a major source of uncertainty in managing orange roughy in the South East Fishery (Staples *et al.*, 1994). Scientists are uncertain whether the population in southern and eastern Tasmania comprises one stock or two, and the two hypotheses have different implications for the status of the resource and the future management of the fishery.

Management based on the assumption of a single stock might, for example, lead to a TAC being allocated with no restriction on spatial concentration of effort. If management is based on a false assumption of separate stocks then fishing costs are likely to be higher than they would be otherwise. Whereas, if in fact two stocks do exist, then current fishing pressure on each of the two stocks might be suboptimal.

Current management of the resource hedges against this uncertainty and resolving the issue is likely to prompt modification of present management strategies. The present research addresses the issue of evaluating the expected returns to the fishery from stock-structure research.

OBJECTIVES

To evaluate the returns from research on stock structure in the SEF orange roughy fishery: this required tailoring the general framework to the specific characteristics of the orange roughy fishery and the associated stock-structure research. Achievement of this objective is indicated by the production of this report and the attached papers.

To assist in the further development of the research plan for the SEF: this has been achieved by demonstrating a practical application of the methods in the case of stock-structure research for orange roughy. Research planners now have the opportunity to clearly define the most appropriate management objective for the fishery, and then to make use of these methods in prioritising research projects, should they wish to do so.

To develop and test the Bayesian framework for evaluating research and to determine its suitability for application to other species and fisheries: this was achieved by examining appropriate data and assessments, and compiling a list of possible applications for further research. Discussions related to gathering this information have been undertaken with the staff of AFMA as well as with research subcommittee representatives from Commonwealth MACs.

METHODS

Evaluation of returns from research for fishery management is difficult because of uncertainty surrounding both the fish population and the correctness of the model in capturing the salient features of the fishery. For this reason developing an indicator of returns is the best that one can hope to achieve. Our choice of indicator is the 'average likely return' (more formally referred to as 'expected return' in the attached papers[1]) which is the average of returns to the fishery obtained for various values of the uncertain initial biomasses and degree of population mixing.

The method combines modelling techniques for making management decisions (setting TACs in particular), for tracing fish population dynamics, and for making use of new information to adjust initial estimates. We begin with an objective function derived from fishery management objectives: *to maximise the value of the harvest without threatening*

[1] The notion of expected return often directs attention to the future because of the obvious uncertainties involved. Information about the fishery's past is also uncertain however. The term expected return is therefore equally applicable to both the past and future, when it comes to evaluating the benefits of research. To avoid confusion, we will use the term 'average likely return' to reflect assessed expected return, whether that be for past or future research.

the sustainability of the fishery. This suggests a measure of the returns to the fishery: *the net present value (NPV) of 100 years of catches* (under the assumption of constant real prices and costs), which is recalculated for, and averaged over, the whole family of likely scenarios (recalling that some parameters are unknown) giving us our chosen indicator; the *'average likely' NPV*.

We use a population dynamics model and Bayesian decision analysis to determine the catch strategy that gives maximum average likely NPV and we repeat this using alternative sets of data, some of which are obtained from orange roughy egg and acoustic survey research. As the catch strategy for maximising returns changes in response to the accumulation of information, it is possible, by comparison, to determine a measure of value for collecting that information.

We consider both constant-catch, and feedback (where catch is set at some percentage of expected biomass) management strategies. Of particular importance is the way we deal with uncertainty about stock structure and initial biomass. We assign equal probabilities to all feasible pre-fishery biomass levels and for a range of possible values of a mixing parameter that describes the degree of separation of the populations in the two zones of the fishery. Fishery and research data, along with Bayes theorem, are used to modify these probabilities, giving an indication of how uncertainty changes as information is received

Details of the approach we have taken and of the methods can be found in McDonald and Smith (1997) and McDonald et al. (1997) [attached as Appendices A and B]. In summary this requires identifying a model that captures: (i) quantitative indicators for assessing achievement of fishery management objectives; (ii) the dynamics of the fishery; (iii) the management response to scientific information and uncertainty, and (iv) how research can reduce uncertainty. Given these elements, the improvement in achieving management objectives from collecting information through research can be evaluated.

RESULTS

The initial assignment of probabilities to various starting biomasses and mixing parameters is termed specifying a prior (or the prior distribution). This prior takes account of only the fishery and research data available at the time the prior is specified. As additional information comes available the probabilities are revised, giving what is termed a posterior (or posterior distribution). When one predicts the results of research before it is carried out, and adjusts the probabilities accordingly, those postulated results give a pseudo posterior (or pseudo-posterior distribution). We use these distributions to assess the average likely returns from the fishery with and without fishery and research data, and with possible future research data. By comparing the resultant NPV for the optimum management strategy in each case, the relative average likely returns from research can be obtained. In addition, differences among priors, posteriors and pseudo-posteriors as a result of additional research information, indicate the contribution of that research data to reducing the uncertainty of the biomass estimates and of the stock structure.

We considered constant-catch strategies for each zone ranging from zero to 8000 tonnes per annum in increments of 400 tonnes and evaluated the average likely NPV of the fishery with each. This was done (i) using only fishery data, (ii) using both fishery and research data, and (iii) using both fishery and research data as well as consideration of a possible future research survey. The results of this analysis are reported in McDonald et al. (1997) [Appendix B]. It should be noted that the number and complexity of strategies had, of necessity, to be limited because of the computer time required to complete the analysis. In addition, the analysis was subject to the important simplifying assumption that low stock size is penalised in the terminal year of the chosen 100-year "planning" horizon. A summary of the results follows.

For a zero discount rate[2] and under the prior, the maximum average likely NPV of R$252,591[3] is obtained, surprisingly, with TACs of zero in zone 1 (the southern zone) and 4000 tonnes in zone 2 (the eastern zone). Under the posterior, this optimal catch strategy yields an average likely NPV of R$363,178. This compares with R$421,749 from TACs of 2000 tonnes in zone 1 and 2400 tonnes in zone 2, which is optimal under the posterior. These results imply an average likely return from past experimental research of R$58,571.

Average likely returns attributable to a 10-year trial strategy which incorporates experimental research, followed by an optimal catch strategy thereafter, are reported below. The experimental research envisaged is essentially an adaptive fishing experiment with a stock survey in 2005, aimed at providing contrast in stock size to better estimate the mixing parameter. In the no-discounting case, the maximum average likely NPV of R$566,373 results from TACs of 4400 tonnes in zone 1 and 7600 tonnes in zone 2 for 1995-2005. To compare with this, the appropriate average likely return from the optimal strategy under the posterior is R$480,931. This implies an average likely return from the planned research of R$85,442. Similar results were obtained using discount rates of 3% and 6%.

Based on historical data and the model used, it is clear that for all chosen discount rates average likely returns from completed stock-structure research for the Tasmanian orange roughy fishery are positive. In particular we have found that the average likely return from previous research is approximately R$58,571, R$49,177 and R$31,852 at discount rates of 0.00, 0.03 and 0.06. For the proposed research the average likely returns are R$85,442, R$74,648 and R$69,619.

We also examined management strategies that are best described as 'simple feedback controls' for the fishery under the prior and posterior distributions (but not for the case of proposed future research). In these cases, we considered the possibility of revising the

[2] Discounting is often done to make returns in different time periods comparable.
[3] R$1 is the assumed constant real value of 1 tonne of fish. All NPVs reported below should be interpreted relative to this benchmark.

control after a period of 10 years: that is, after management authorities have had time to evaluate information from fishery and research reports. The controls considered were applied to each zone separately and were enumerated as the TAC for the next year as a percentage of the average likely biomass. The percentages of average likely biomass examined were 0, 1, 2, 3, 4, 5, 6, 8, 10, 20, 50, 75 and 100. Any one of these percentages could be chosen for the first 10 years and any one of them for the next 90 years, based on maximising the average likely NPV of the stream of fish catches.

The result of our preliminary examination of each of these control levels is that the optimal strategy might, from a fishery point of view, be to set the TAC at close to the average likely biomass for the first 10 years and then at between 0 and 3 percent of average likely biomass for the next 90 years. Such a strategy would both maximise expected economic returns and allow the stock to recover sufficiently by the end of the planning horizon. As already mentioned, in the present paper the sustainability constraint is applied at the end of 100 years only, but this would probably be unacceptable for stock-assessment purposes, given the diversity of sources of uncertainty.

Finally, it is worth examining the change in our perception of the uncertainty about the stock structure of Tasmanian orange roughy as a result of this work. This is most easily demonstrated graphically. The posterior distribution (which incorporates all historical research data) for the mixing parameter displayed in figure 3 of Appendix B, indicates little departure from the uniform prior distribution, so the historical data don't appear to have added to our knowledge about it. Under both the prior and posterior distributions, however, the optimal TAC for zone 1 is consistently lower than that for zone 2, a pattern that could be produced by zone 1 being a source of recruitment to the zone 2 fishery via spawning migration.

Consistent with this latter evidence, Figures 4 and 5 (Appendix B) display the posterior distributions for virgin biomass in zones 1 and 2. These indicate that virgin biomass in zone 1 is most likely to have been between 75,000-160,000 tonnes and that virgin biomass in zone 2 is most likely to have been between 30,000 tonnes and 135,000 tonnes.

The upshot of this graphical evidence is that the assumption, of completely separate stocks in zones 1 and 2 is not supported by the evidence, given the model and data used. The suggested catch strategy changes would result in an improved average likely NPV of the fishery and, therefore, positive average likely returns from stock-structure research for Tasmanian orange roughy. The average likely returns must obviously be compared to research costs before a decision is made on whether to proceed with the proposed research.

In terms of research that might lead to a reduction in stock-structure uncertainty, the results point to the need for adaptive management of the two zones of the fishery. Such adaptive management would involve setting TACs in the two zones different enough from each other that they produce a clearer contrast between the two current populations and their recovery, thus yielding information on the true level of mixing.

BENEFITS

The direct benefits of this research will come from the further development of the research and management plan for the SEF orange roughy fishery. Average likely returns from particular types of experimental and analytical research could be enumerated for the SEF orange roughy fishery. For practical use in evaluating competing research proposals, it is crucial that management objectives are specified clearly and that the fishery model used is identical to the one used for stock assessment.

The longer-term benefits however, are potentially much more substantial. More general application of the Bayesian framework should lead to research funding being better directed at achieving the objectives of fishery managers. Such application would come at a cost, however, because of the considerable effort (and, therefore, resources) required for conducting such analyses.

INTELLECTUAL PROPERTY

Not Applicable

FURTHER DEVELOPMENT

1. Make direct use of the stock assessment model used in the orange roughy stock assessment and consider a greater range and finer grid of catch strategies in order to make the analysis more suitable for practical management purposes (including input into evaluation of research proposals).

2. Revise the analysis to penalize depletion to low stock sizes each year, not just in the terminal year.

3. Apply these methods to fisheries where both industry and research data are used in policy formulation and the setting of management strategies and rules. Examples of fisheries that might be suitable are: eastern gemfish, southern shark and southern bluefin tuna.

STAFF

A. David McDonald (Principal Investigator)

Anthony D. M. Smith

Adam J. Davidson

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CONFERENCE AND SEMINAR PRESENTATIONS

McDonald, A.D., Smith, A.D.M., Punt, A.E., Tuck, G.N. and Davidson, A.J. (1996). "Empirical Evaluation of Expected Returns from Research on Stock Structure for Determination of Total Allowable Catch" invited presentation at the International Workshop on Assessment and the Distribution of Harvest Quotas in Fisheries, Geiranger, Norway, July 8-11.

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APPENDIX A

McDonald, A.D. and Smith, A.D. (1997). A Tutorial on Evaluating Expected Returns from Research for Fishery Management, Natural Resource Modeling, 10(3), 1-33.

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A TUTORIAL ON EVALUATING EXPECTED RETURNS FROM RESEARCH FOR FISHERY MANAGEMENT USING BAYES' THEOREM

A. DAVID MCDONALD
CSIRO Division of Marine Research
P.O. Box 1538
Hobart, Tasmania 7001
Australia

ANTHONY D.M. SMITH
CSIRO Division of Marine Research
P.O. Box 1538
Hobart, Tasmania 7001
Australia

ABSTRACT. Traditional methods for evaluating potential or actual returns from research and development include scoring methods, cost-benefit analysis and production-function approaches. The research reported in the present paper complements these traditional methods with the use of statistical decision analysis and Bayesian methods to account explicitly for risk and uncertainty and to capture some of the effects of information evolution. Measurement of the expected returns from research for fishery management is detailed. Both ex post and ex ante evaluation of expected returns are illustrated by deliberately simplified example.

KEY WORDS: Bayesian methods, expected returns from research, risk and uncertainty.

1. Introduction. The value of research for fisheries management has long been of interest to funding bodies, fishery managers, the fishing industry and environmental groups, as well as the community at large. A major component of research for fisheries management is the treatment of risk and uncertainty, both of which have their roots in complex interactions among ecological, economic and social systems. The work presented in this paper has been conducted so as to draw upon and augment the quantitative literature on evaluation of research, with particular regard to fisheries management.

A broad range of methods has been used for evaluation of anticipated or realized research. These include scoring methods, cost-benefit analysis, the use of economic surplus measures of social welfare and production-function and cost-function approaches.

Scoring methods of project evaluation involve allocating numerical scores to reflect the intensity or level of various attributes (both desirable and undesirable) of a particular research project or management policy.[1] These scores are then aggregated to arrive at a performance index for ranking different projects. In essence, the scoring method rests on the premise that scientific research teams can confidently predict the outcome of scientific inquiry and so can choose projects that offer the highest returns. By necessity, the required procedures tend to be specific to particular research or policy projects and the teams carrying them out.

Cost-benefit analysis (CBA)[2] provides a structured framework for evaluating the net benefit to society of a particular project or policy. It extends the financial evaluation of a project using discounted cash flow techniques. It is a procedure that involves evaluation of both costs and benefits, whether these are measured directly via market data or indirectly by some other means, and the calculation of summary statistics that are expressed as monetary values and interpreted as indices of desirability from society's point of view. Naturally the summary statistics are designed to capture direct influences on individual's welfare as well as indirect spillover effects or externalities that are not captured in market data. Some externalities and, indeed, some direct effects, may not be quantifiable, although in a thorough CBA, they will be discussed and evaluated qualitatively.

The production-function approach to measurement of gains to research involves estimation of output as a function of various inputs, including research.[3] Variation of production through time can then be decomposed into a research component and a component due to other inputs. The value of increased production due to research may then be estimated. The cost function approach is similar except that, obviously, a cost function is estimated. Enumeration of a downward shift in the marginal cost curve due to research facilitates estimation of industry cost savings. Estimation of the cost function is equivalent to identifying the supply curve, under appropriate assumptions, and therefore also forms part of the measurement of changes in economic surplus for particular demand conditions.

The approaches mentioned above have been used for assessing returns from research and development in a variety of organization, industrial and market settings. For the purpose of evaluating returns from research for fishery management, however, these methods suffer from a number of shortcomings. First, temporal dynamics have not been a primary focus of attention in applied studies; instead, comparative statics and the steady state have dominated the literature to date. Second, explicit modelling of learning and information processing has received little attention. Third, there is a largely unfilled need to incorporate the effects of risk and uncertainty. Fourth, attention has been focused on direct technological advances as outputs from research, without explicit evaluation of information-processing research, which may yield only indirect benefits to firms and organizations.

By contrast, research for fishery management is vitally concerned with fishery dynamics, learning and information-processing, the effects of risk and uncertainty, and the indirect effects of the research itself on the fishery and its management. In what follows, an attempt is made to augment the existing methods by incorporating statistical decision analysis and Bayesian methods and so take explicit account of these important aspects of fishery management.

The modelling of research inputs and impacts must account for direct effects on the objective function as well as indirect effects that may have a significant impact on management. Direct effects on the objective function will be felt via the state variables (that include research variables) and/or via the introduction of exogenous research variables into the objective function. Taking account of direct effects involves the above-mentioned production and cost function approaches. Direct effects include those resulting from invention and the adoption of new production technology. The indirect effects of research have their impact on the objective function as evidence is gathered on stochastic or random components of the system. For example, degrees of belief about alternative feasible models, including the prior densities of their random coefficients, can be revised via Bayes theorem, and this revision will change the value of the objective function (or its moments). Such revision and similar information-processing tasks of research might lead to major change or fine tuning of management policies. Attention will be focused in this paper on the indirect effects of research, although the methods outlined can be applied equally well to evaluating the direct effects.

Section 2 forms the body of the paper and begins with a proposed analytical approach that combines the salient features of bioeconomic op-

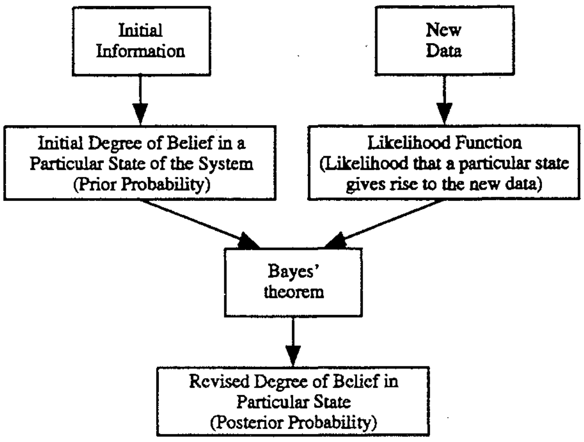

FIGURE 1. Diagrammatic representation of Bayes' theorem.

timization and fisheries management decision making. Using Bayesian methods, Sections 2.3 and 2.4 are devoted to a simple example that is used to illustrate one way of dealing with model uncertainty and the evaluation of expected returns from research. This example is then extended in Section 2.5 to demonstrate ex ante evaluation of expected returns from experimental research for three cases that differ in the manner by which anticipated experimental outcomes are expressed. Section 3 contains some concluding remarks that include a brief discussion of how this paper fits into the existing literature as well as suggestions for extending and clarifying what is presented here.

2. A proposed analytical approach. The most significant impediment to evaluation of returns from research for fishery management is the uncertainty that surrounds almost all aspects of the bioeconomic system being modeled. Uncertainty results from the errors made in model formulation, information processing, measurement and sampling, as well as from natural random variation. The major sources of uncertainty must be accounted for explicitly if the approach developed is to be of practical use in evaluating the costs and benefits of research for fishery management. In order to incorporate uncertainty into our analytical framework, we draw upon statistical decision theory and Bayesian analysis.

2.1. *Fisheries management, learning and decision making.* A central tenet of economics is that researchers and managers, like all rational economic agents, have incentives to acquire information and exploit beneficial opportunities. Decisions made and subsequent behavior are consistent with constrained optimization of an objective function; objectives include maximization of the discounted flow of net returns, maximization of social welfare, maximization of average sustainable yield and minimization of bycatch. Constraints may be institutional (administrative, political, social or physical) or bioeconomic (biological, behavioral or market related).

Decision theory provides researchers and managers with a framework for processing information, emulating learning and accounting explicitly for uncertainty.[4] Central to the approach used in the present paper is Bayes' theorem which concerns revision of degrees of belief about possible propositions, or states of the system being modeled, in the face of uncertainty and the evolution of information.

For present purposes information takes the form of empirical data and degree of belief is expressed as a probability measure or probability distribution. Bayes' theorem yields a rule for modifying the degree of belief in the correctness of a particular proposition after receipt of information. This may be expressed diagrammatically as in Figure 1 (Zellner [1971], p. 10).

The initial information may include, among other things, sample data, results of previous empirical or theoretical studies and casual observations. The initial degree of belief in a particular state of nature[5] is expressed as a conditional prior probability, $P(M_i \mid \Omega_0)$, which is derived from the conditional probability density function (pdf) assigned by the decision maker across all states of the system, M_i, given the initial information set Ω_0. The likelihood function, $L(y \mid M_i)$, is the joint conditional pdf of the new data, y, given (or resulting from) a particular state, M_i. The revised degree of belief, expressed as a conditional posterior probability, $P(M_i \mid y, \Omega_0)$, is the result of combining via Bayes' theorem the prior probability $P(M_i \mid \Omega_0)$ with the likelihood function $L(y \mid M_i)$. Bayes' theorem is an attractively-simple rule that may be stated as follows:

$$P(M_i \mid y, \Omega_0) = \frac{P(M_i \mid \Omega_0) L(y \mid M_i)}{\sum_{j=1}^{n} P(M_j \mid \Omega_0) L(y \mid M_j)}, \tag{1}$$

where n represents the number of possible states of the bioeconomic system. The denominator is a scaling constant that reflects the unconditional probability of obtaining the particular set of new data.

2.2. *Bioeconomic optimization.* Researchers and managers are assumed to maximize one or more objective functions and so act in a manner that is consistent with enhancement of social welfare. Economic surplus is frequently used to measure the net benefits to society that result from economic (including research) activity. In general terms, it is desirable for researchers and managers to allocate resources under their control so as to, ultimately, maximize the present value of the flow of net benefits resulting from their work, subject to applicable constraints. This is most conveniently thought of as a control problem.

The control or dynamic programming approach to resource allocation and management is the basis for the bioeconomic optimization process used in this paper for evaluating returns from research for fishery management. This approach requires specification of the following components: 1) an objective function, 2) feasible control mechanisms and policies, 3) a management decision rule, 4) the system state for alternative feasible models of fishery dynamics[6], 5) observation equations that link the state to measured variables, 6) the modelling of research inputs and impacts, and 7) criteria for evaluating returns from research.

The objective function may be single or multi-attributed and reflects the objective(s) that fishery managers would like to achieve. It is a function of the system state, control and exogenous variables, stochastic elements, fixed or random coefficients and time horizon, and involves the management decision rule of optimizing by choosing the control mechanism and policy that maximizes or minimizes a criterion function.[7] For the single-attribute case this is expressed mathematically as

$$\mathbf{J}(\mathbf{x}, \mathbf{u}, \theta, \mathbf{t}) = \max_{\mathbf{u}} \mathbf{F}(\mathbf{x}, \mathbf{u}, \theta, \mathbf{t}) \tag{2}$$

where $\mathbf{x}$ is the vector of variables (including any variable coefficients) describing and/or included in the fishery system state, $\mathbf{t}$ represents the time period sequence, $\mathbf{u}$ is a vector representing discrete and continuous control options and policies, θ is the vector of stochastic elements in the fishery system and $\mathbf{F}$ is the function to be maximized. Since the value of the objective function is dependent on the state of the fishery system, the evaluation of the state must be specified for all competing feasible models of the fishery dynamics. For each model the state evolution may be characterized in continuous or discrete time. For model i, M_i, a general expression is:

$$\mathbf{x}_t = \mathbf{f}_i(\mathbf{x}_{t-}, \mathbf{u}, \phi, t) \tag{3}$$

where $\mathbf{f}_i$ is an arbitrary function, ϕ is the vector of stochastic elements and random coefficients affecting and/or included in the set of state variables, and $\mathbf{x}_{t-}$ is the vector of state variables in previous time periods or instants. The optimization presented in equation (2) is done subject not only to the constraints implicit in equation (3) but also to the initial conditions of the system.

In order to account for measurement error and the current state, an observation equation must be specified to select state variables that enter the objective function. This permits definition of the likelihood function, which is necessary for both classical statistical inference and Bayesian analysis. For fishery model i, M_i, the observation equation may be expressed as:

$$\mathbf{y}_t = g_i(\mathbf{x}_t, \psi) \tag{4}$$

where g_i is an arbitrary function and ψ is the vector of measurement errors.

Finally, specification of criteria for evaluating returns from research for fishery management can be done after the modelling of research inputs and impacts have been done. The data generated from experimental and analytical research allow updating of the prior information set and, therefore, modification of the optimal control or management strategy. Using Bayesian methods, the value of the research can then be determined ex post by comparing expected posterior returns under the posterior optimal control with those under the prior optimal control. In light of increased pressure on research organizations to predict outcomes and justify planned expenditure, however, ex post evaluations of this type are insufficient for justification of future research. It is important, therefore, that attempts be made at providing ex ante evaluation of returns from research, a topic to be taken up below in Section 2.5.

To clarify the elements of the general bioeconomic optimization problem, consider a simple application. For expository simplicity, we restrict our attention to a set of competing adaptive controls (management policies), a set of competing alternative bioeconomic models and a set of simultaneous institutional constraints. Specification of these controls, models and constraints, as well as an objective function with its associated decision rule, constitutes the setting up of a bioeconomic framework for assessment of the monitoring, learning and adaptive-management processes.

In a simple case optimality conditions from control theory can be used to derive an equation that ensures maximization of the objective function and optimality of the control variable path. When the control variable is continuous, use of control theory in this way can offer considerable advantages for coefficient estimation and inference.[8] When one or more of the control variables take only discrete values, that is, in terms of distinct management policies, optimality conditions are of very limited value. In these cases evaluation of the objective function directly for all competing policies is the most useful strategy for selecting, by grid search, the optimal control. Since research for fishery management is concerned with complex policies rather than a single continuous control variable, grid search in the optimization will often be important in the evaluation of returns from research.

2.3. *An illustrative example: Model uncertainty and ex post enumeration of expected returns.* In the event that management policies are directed at satisfying a single-attribute objective function[9] (for example, maximizing the net present value of the fishery), assessment of the expected returns from the fishery will involve evaluating the expected discounted sum of net returns for each of the competing bioeconomic models.[10] The probability-weighted sum of these expected returns (the weights having been derived via Bayes' theorem) yields the expected returns from the fishery. The policy or control-variable path that maximizes the expected returns will be optimal.

The problem of calculating the expected returns from a fishery for which competing bioeconomic models are feasible typically involves evaluation of the credibility of, or degree of belief in, each alternative model. A recursive procedure suitable for enumerating expected returns from a fishery and determining the optimal management policy can be completed according to the following five steps:

(i) for a particular control policy select one of the competing bioeconomic models and evaluate the likelihood function (defined over the stochastic controls and state variables) and the conditional PV of expected returns to the fishery, given the control policy;

(ii) retaining the control policy, repeat step (i) for all remaining bioeconomic models;

(iii) determine the posterior probability for each bioeconomic model using Bayes' theorem (this is the updated degree of belief in or credibility of the model);

(iv) compute the expected returns from the fishery by summing the posterior probability-weighted returns for each of the competing models; and

(v) repeat steps (i)–(iv) for each of the alternative control policies and select the (optimal) policy which gives rise to the maximum unconditional PV of expected returns to the fishery.

To illustrate this procedure, consider a deliberately simplified example of a hypothetical fishery. Management of the fishery is based on achieving a target escapement or biomass level each year. Any biomass above this level can be harvested as catch. The management objective is to maximize expected sustainable annual catch. Annual "surplus" production, P_t, is given by

$$P_t = (r/m)B_t(1 - (B_t/K)^m) + \eta_t \tag{5}$$

where r is a growth coefficient, B is the biomass in period t, K is the equilibrium biomass in the absence of fishing, m is the catch shape parameter (Pella and Tomlinson [1969]) and η_t is the Gaussian process error with mean zero and variance σ^2.

The dynamics are given in general by equation (3) and, in particular, by

$$B_{t+1} = B_t + P_t - C_t \tag{6}$$

and surplus production is targeted perfectly, so that catch, C_t, is measured without error[11]

$$C_t = P_t \tag{7}$$

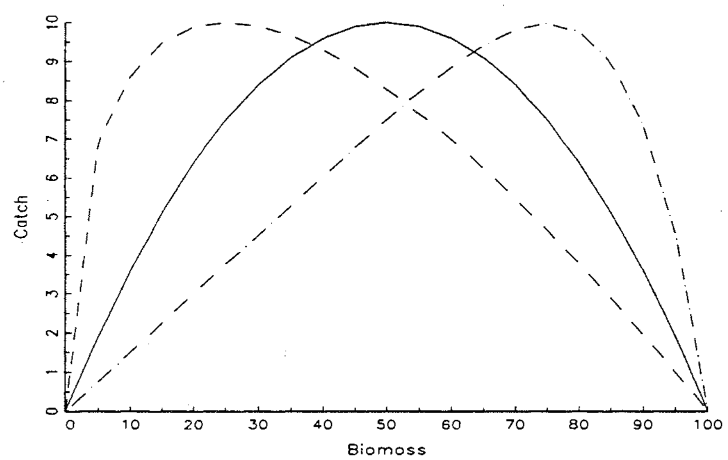

FIGURE 2. Graphical representation of competing models.

This example is unrealistically simple because it implies perfect knowledge of stock size and ability to achieve desired escapements exactly. However, it serves the purpose of exposition related to the issues of evaluating returns from research given model uncertainty.

Note that equations (6) and (7) imply that $B_{t+1} = B_t$, corresponding to the aim of maintaining a constant stock size or annual escapement. The expected production or catch as a function of stock size, B, is shown in Figure 2 for three combinations of m and r. The coefficients for these three models are given in Table 1 and are chosen such that maximum stock size (K) and mean maximum sustainable yield rate $(C^*/K)^{12}$ are identical for each model, the only difference being the stock size, B^*, at which the maximum sustainable catch may be taken.[13]

TABLE 1. Coefficient values for competing models.

Model	r	m	Var $(\eta_t) = \sigma^2$	B^*/K
Model 1	−0.4	−0.5	2	0.25
Model 2	0.4	1.0	2	0.50
Model 3	0.151	7.4	2	0.75

$K = 100$ stock units for each model and the coefficient r is chosen so that $C^* = 10$.

The expected catches for a series of discrete levels of biomass are shown in Table 2 for each of the models. Clearly, if Model 1 is known to be correct, the optimal stock size is 25 units, for Model 2 it is 50 stock units and for Model 3 it is 75. The fourth column in the table shows the expected catch at each stock size given uncertainty about which model is correct. The expected catch under uncertainty is the weighted sum of catches under each model, where the weights are the prior probabilities of each model being correct.[14] In this case it is assumed that each model is equally plausible (a "uniform" prior), so the optimal escapement is at $B = 50$ stock units, and the optimal expected catch is 8.60 stock units. Given this model uncertainty and no further information, and an objective function of the general form of equation (2), the optimal strategy to maximize expected long-term catch is to allow an annual escapement of 50 stock units.[15] This will be referred to below as the prior policy or the optimal strategy under the prior distribution.

Now consider the effect of future observations of catch on model uncertainty. Assuming that the population is in equilibrium and catch is measured without error, as in equation (6), the likelihood of a particular catch level, conditional on B and the model, might be specified, for example, by the function

(8)

$$L(C_t \mid r, m, B) = (2\pi\sigma^2)^{-1/2} \cdot \exp[-(C_t - (r/m)B(1-(B/K)^m))^2/2\sigma^2].$$

Given this likelihood function and the prior probability distribution for the models, it is possible to obtain the posterior distribution for the models as C_t evolves. If, for example, $C_t = 7.3$, given the control $B = 50$, the likelihood of C_t and the prior and posterior distributions for the models are as in Table 3.

Clearly, an observed C_t of 7.3 leads to a firmer belief in Models 3 and 1 and weaker belief in Model 2. This is confirmed by examining Table 2 for $B = 50$, where a catch of 7.3 units is closest to that implied by Model 3 and furthest from that of Model 2. The asymmetry evident in the posterior distribution stems from the asymmetric nature of production across biomass levels for Models 1 and 3; this, in turn, yields different likelihoods for $C_t = 7.3$ and, therefore, different posterior degrees of belief in Models 1 and 3. Under the posterior distribution the maximum expected returns are 8.16 units, as can be observed in Table 4, indicating that B should be controlled at 60 units.[16]

TABLE 2. Returns implied by each model and expected returns under the prior distribution for each biomass.

B	Model 1	Model 2	Model 3	Expected Returns Under Prior Distribution
5	6.94	1.90	0.76	3.20
10	8.65	3.60	1.51	4.59
15	9.49	5.10	2.26	5.62
20	9.89	6.40	3.02	6.44
25	10.0	7.50	3.77	7.09
30	9.90	8.40	4.53	7.61
35	9.66	9.10	5.28	8.01
40	9.30	9.60	6.03	8.31
45	8.83	9.90	6.78	8.50
50	8.28	10.0	7.51	8.60
55	7.66	9.90	8.21	8.59
60	6.98	9.60	8.85	8.48
65	6.25	9.10	9.41	8.25
70	5.47	8.40	9.82	7.90
75	4.64	7.50	10.0	7.37
80	3.78	6.40	9.76	6.65
85	2.88	5.10	8.98	5.65
90	1.95	3.60	7.36	4.30
95	0.99	1.90	4.53	2.47
100	0.00	0.00	0.00	0.00

2.3.1. *Considering different sources of uncertainty.* In addition to the uncertainty already considered, other coefficients, and alternative model structures as well as initial conditions, may be subject to uncertainty. Given that in applied work this is the rule, rather than the exception, an additional level of complexity must be added in the setting of optimal management policy and enumeration of returns from research for fishery management. Indeed, such more complex

TABLE 3. Likelihood and posterior distribution for $C_t = 7.3$ given $B = 50$.

Model	$L(C_t \mid \text{model}, B=50)$	Prior Distribution	Posterior Distribution
Model 1	0.221	1/3	0.405
Model 2	0.046	1/3	0.084
Model 3	0.279	1/3	0.511

TABLE 4. Expected returns under the posterior distribution from Table 3 for each biomass.

B	Expected Returns Under Posterior Distribution
5	3.36
10	4.58
15	5.43
20	6.09
25	6.61
30	7.03
35	7.37
40	7.65
45	7.87
50	8.03
55	8.13
60	8.16
65	8.10
70	7.94
75	7.61
80	7.06
85	6.18
90	4.85
95	2.88
100	0.00

enumeration can be used to value research aimed at dealing with these additional sources of uncertainty.

When uncertainty emanates from more than one source, the recursive procedures used in Section 2.3 must be extended. The prior distribution is then a multivariate one, its dimensions and form reflecting the number of sources of uncertainty and whether each is discrete or continuous. The likelihood is conditioned on values attributed to each uncertain variable. The posterior distribution of the values of all uncertain variables is, therefore, multivariate and enables evaluation of the relative credibility of each possible combination.

2.4. *Assessing the expected returns from research ex post.* Research for fishery management affects both private and public economic returns. Benefits and costs arising from research may be evaluated, in part, by recourse to the functional relationships mentioned in Section 2.2 with respect to direct effects of research on the productive process. This is not a straightforward task, however. If the analysis is performed prior to observed impacts of the research, then one must forecast these impacts, the results of which are open to dispute. Furthermore, even if the analysis is performed after research results are well established and the impacts of the research are incorporated into observed data, accurate determination of net returns to the research is highly problematical because one is not then able to observe the fishery in the absence of the research.

Given the many possible sources of uncertainty impacting upon the analysis, the best that one can do is to evaluate the *expected* returns from research. Research for fishery management involves information collection and processing, which tend to have indirect, rather than direct, effects on the production process, the consequences of which are difficult to predict accurately. Research leading to Bayesian updating of probability distributions when model, initial value and coefficient uncertainties are accounted for, explicitly can be valued by comparing the expected value of perfect information (EVPI) under the prior distribution with that under the posterior distribution. Arguably more useful for applied purposes is to compare the expected value of the fishery objective function under the prior distribution with that under the posterior distribution. This obviously requires that the research be carried out, but its expected value can be determined under appropriate model assumptions prior to its real impact on the fishery.

In the case of the simple example above, the Bayesian-updating research might lead to a change in management policy; that is, a change in the optimal control. Before this research is conducted, the optimal policy for the fishery will be determined under the prior distribution over credible models. After the research is completed, the optimal policy will be determined under the posterior distribution.

Given that the posterior distribution replaces the prior as what is believed by the researchers to be the appropriate distribution, the expected value of information-processing research is given by the difference between the expected values of the fishery objective function resulting from the posterior optimal policy and that resulting from the prior optimal policy, *both under the posterior distribution.* That is,

$$\begin{aligned}\mathcal{E}\ &(\text{value of research})\\ &= \mathcal{E}(PV \mid \text{posterior distribution, posterior policy})\\ &\quad - \mathcal{E}(PV \mid \text{posterior distribution, prior policy})\end{aligned}$$

which will always be positive if the posterior policy differs from the prior policy and will be zero otherwise. The expected value of the research to the fishery, via the objective function, will therefore be positive only if it results in a change in the control. Although one might think of this value as the lower bound on the expected value of the research (because intrinsic, scientific and other values have been omitted from the present objective function), a complete study would involve investigation of multiple objective functions, constraints and other relevant factors so as to capture other aspects of the valuation of returns from research. For example, one objective of this type of research might be to reduce the variance of fishery returns, thus lessening the importance of increased expected (mean) returns.

In the example above, (see Tables 2 and 4) there was a change in the optimal control from $B = 50$ under the prior to $B = 60$ under the posterior distribution. The expected return from processing the information $C_t = 7.3$ is, therefore, $8.16 - 8.03 = 0.13$ units of catch per time period, an improvement of 1.6%.

2.5. *Evaluation of expected returns from experimental research ex ante.* Research for fisheries management encompasses experimental research which provides information that is of use for model discrimination. Biological and ecological research, for example, leads to information on, among other things, growth rates, age structure, productivity, catchability, life-cycle characteristics and spatial distribution of particular fish species.

Ex ante evaluation of expected returns from research begins with examination of the effects of a flexible control policy that might be prompted by possible experimental outcomes or messages. That is, one compares the optimal value of the fishery objective function under the prior information set with the value arising from optimal controls which depend on experimental outcomes that are consistent with the prior. This approach is similar to the one used for assessing the value of a message service (Hirshleifer and Riley [1992]).

2.5.1. *Messages unconditioned.* Reconsider the above example where uncertainty emanates from one source but in the context of proposed research involving a data-collection experiment that yields information about the fishery which can be used to discriminate among possible models or uncertain variables. Assume that three experimental outcomes or messages are possible and the likelihood of their occurrence, given the correctness of a particular model, is as displayed in Table 5. These likelihoods would typically be projected on the basis of past experience in running experiments of the type considered. Such experience might be with alternative stocks of the same species, with similar species or within a theoretical setting. In essence the likelihood function enables answering the question, "Given that a particular model is true, what is the likelihood that the experiment will give rise to messages X, Y and Z, respectively?" The messages might, for example, be alternative catches or indices of abundance that allow discrimination among uncertain aspects of the fishery, including alternative models of population dynamics.

TABLE 5. Likelihood of messages given a model.

Model	Message		
	X	Y	Z
Model 1	0.6	0.3	0.1
Model 2	0.2	0.6	0.2
Model 3	0.1	0.3	0.6

The likelihood given in Table 5 and the prior distribution given in Table 3 yield the joint probability distribution for models and messages displayed in Table 6, the message-conditioned posterior distribution for the models displayed in Table 7 and the expected returns conditioned on control level (B) displayed in Table 8. The joint distribution displayed in Table 6 serves to yield the unconditional message probabilities necessary for invoking Bayes' theorem and enumerating the posterior distribution of Table 7.

TABLE 6. Joint probability distribution for models and messages.

Model	Message			Prior Model
	X	Y	Z	Probability
Model 1	0.200	0.100	0.033	0.333
Model 2	0.067	0.200	0.067	0.334
Model 3	0.033	0.100	0.200	0.333
Unconditional Prior Message Distribution	0.300	0.400	0.300	

TABLE 7. Conditional posterior distribution for models.

Model	Message		
	X	Y	Z
Model 1	0.666	0.250	0.110
Model 2	0.224	0.500	0.224
Model 3	0.110	0.250	0.666

This tabular representation of the use of Bayes' theorem is presented in (Hirshleifer and Riley [1992, pp. 170–178]). Let $J_{i,k}$ denote the probability of a given combination of model and message. Let L_{kli} denote the likelihood of receiving message k, given the model i. Let p_i denote the prior probability of model i. Then Table 6 is constructed by setting $J_{i,k} = L_{kli} \times p_i$ where L_{kli} is obtained from Table 5 and p_i is obtained from the prior distribution of models (Table 3). Let $p*_i$ denote the posterior probability of model i. Then Table 7 is constructed by setting $p*_i = J_{i,k}/q_k$ where q_k is the unconditioned prior probability of message k from Table 6.

Inspection of Table 8 reveals that the optimal control given Message X is $B = 35$ (yielding a return of 9.052 units of catch), the optimal control given Message Y is $B = 50$ (yielding a return of 8.947 units of catch) and the optimal control given Message Z is $B = 70$ (yielding a return of 9.018 units of catch). The expected return across messages is 9.000 units of catch,[17] which compares to an expected return under the prior optimal control (in the absence of consideration of an experiment) of 8.597 units. The expected return from evaluating the likely experimental outcomes is therefore 0.403 units of catch, a gain of 4.7%.

2.5.2. *Messages conditioned on model structure.* The concealment and mobility of fish provide many challenges, particularly for stock assessment researchers. These challenges have been confronted with the aid of modelling assumptions that enable systematic interpretation of relevant experimental and commercial data for estimation and predictive purposes. More generally, experimental research outcomes include model-based analysis of data generated from field experiments. It follows that the messages emanating from experimental research are frequently conditioned on the model used to analyze the data. Such conditional messages will be termed *signals* in what follows. A given experimental outcome can therefore give rise to as many signals as there are competing models.

When experimental outcomes depend on model choice, it is necessary to modify the process by which one assesses expected returns from the research. Essentially this amounts to setting aside the notion that a particular experiment will lead to unique messages that are uninfluenced by the choice of analytical model.

Experimental outcomes predicted as pre-posterior distributions. In order to demonstrate a case of this type, reconsider the simple example of Section 2.3. The uncertainty across models prior to experimental research is given, as before, by the prior (in this case, equal probabilities for each model). The research is designed to reduce this uncertainty. A manifestation of this reduction in uncertainty would be for the posterior

TABLE 8. Expected returns conditioned on message and unconditional returns weighted over prior message distribution.

Control (B)	Expected Returns			
	Message X	Message Y	Message Z	Prior
5	5.136	2.875	1.697	3.200
10	6.734	4.340	2.768	4.586
15	7.713	5.489	3.700	5.619
20	8.350	6.42	4.534	6.436
25	8.753	7.194	5.294	7.096
30	8.976	7.810	5.987	7.613
35	9.052	8.287	6.618	8.016
40	9.002	8.633	7.189	8.310
45	8.841	8.852	7.699	8.503
50	8.579	8.947	8.146	8.597
55	8.222	8.918	8.522	8.590
60	7.773	8.759	8.812	8.479
65	7.234	8.465	8.990	8.253
70	6.602	8.020	9.018	7.894
75	5.869	7.405	8.834	7.373
80	5.025	6.585	8.351	6.647
85	4.050	5.514	7.439	5.653
90	2.916	4.126	5.922	4.302
95	1.584	2.329	3.552	2.473
100	0.000	0.000	0.000	0.000

distribution across models, after the research is conducted, to indicate a higher weight or probability for one of the models (hopefully, the "true" model). Such posterior distributions could be specified prior to the research being conducted if there is some information on how likely it is that the research will specify the true model, given the choice of a discrete set of possible true models. These "pre-posterior" distributions could be based on previous experience with experimental research of the type to be undertaken.

The simplest example of this approach is to consider the case of perfect information (Hilborn and Walters [1992]). Given a perfect experiment, the posterior distribution will have a probability of one for the true model and zero for all other models. This is illustrated in Table 9 where the pre-posterior distributions across models are represented by the rows in the table, each conditioned on which model is the true one. Note that the "unconditioned posterior" (calculated across the three possible pre-posteriors, each weighted by the prior on the appropriate true model) must be the same as the prior distribution. There is no new information being added just by considering possible outcomes of the research.

TABLE 9. Pre-posterior distributions across models, conditioned on each model being true. The case of perfect information from the experiment.

	Pre-posterior Across Models			
	Model 1	Model 2	Model 3	Prior on True Model
Model 1 true	1	0	0	1/3
Model 2 true	0	1	0	1/3
Model 3 true	0	0	1	1/3

Unconditioned posterior	1/3	1/3	1/3

Given the possible results shown in Table 9, the expected value of research which could generate such results is measured easily. Clearly, if the correct model is always identified, the correct optimal control (B^*) for that model can always be applied after the research is completed. In the present example, this will result in an expected catch of 10 units no matter which model is correct. The expected return across all possible models is, therefore, 10 units of catch. This can be compared with the expected value of 8.597 units under the prior. Consequently, the expected value of the perfect experiment is 1.403 units of catch per time period, an improvement of 16.3%.

A similar analysis can be used to derive the value of research which produces less than perfect information. This outcome is illustrated in Table 10. In this case there is a 0.8 probability that the research will correctly identify the true model, and a 0.1 chance that it will identify each of the other models. Given that there will still be some uncertainty as to the true model after such an experiment, it is necessary to evaluate the optimal control given each of the possible pre-posterior distributions. The expected returns for each possible control (B) given each pre-posterior distribution are shown in Table 11. The optimal control for each is shown at the bottom of the table, together with the expected returns for that optimal control given the true model on which the pre-posterior is conditioned. The expected returns are derived from Table 2. Note that the apparent B^* given the pre-posterior from Model 1 (PP1) is at $B = 30$, rather than the true optimal $B = 25$ for Model 1. This generates a less than optimal expected return, which may be attributed to the less than perfect information derived from the experiment. There is a similar reduction in performance if Model 3 is correct. Taking the expectation across the prior on models (and hence pre-posteriors), the expected return following this experiment is 9.915 units of catch per time period, an improvement of 15.3%.

TABLE 10. Pre-posterior distributions across models, conditioned on each model being true. An example of less than perfect information from the experiment.

	Pre-posterior Across Models			
	Model 1	Model 2	Model 3	Prior on True Model
Model 1 true	0.8	0.1	0.1	1/3
Model 2 true	0.1	0.8	0.1	1/3
Model 3 true	0.1	0.1	0.8	1/3
Unconditioned posterior	1/3	1/3	1/3	

Extending the analogy, we might hypothesize a number of possible outcomes (sets of pre-posteriors) from a proposed experiment, varying according to the quality of the information generated; the quality being judged according to its ability to identify the true model. A set of possible cases is illustrated in Table 12, with the cases varying from perfect information through to disinformation where there is a high probability of identifying the wrong model. The expected returns for each case are shown in Table 13, where the expected returns are obtained (as already outlined above) for each case by:

1. choosing for each pre-posterior the optimal control corresponding to the maximum expected return over the distribution of models,

2. finding the return associated with this control assuming the model which generated the pre-posterior is correct, and

3. obtaining the expectation of these returns over all three models, i.e., the average across models, weighted by the prior probabilities).

Also shown in the second column of Table 13 is a "prior" across possible cases; that is, a prior effectively across "success" of the research. When these are used to weight the expected returns for each case, the overall expected return to the experiment can be calculated. In this case it is 9.255 units of catch. Given that the unconditioned prior distribution yielded 8.602 units, the expected return from considering the experiment is 0.653 units per time period, an increase of 7.6%.

Stimulating experimental outcomes. In the previous section, the outcomes of an experiment are predicted as pre-posterior distributions. This approach requires a good deal of subjective judgment in specifying the pre-posteriors. However, in some situations a more direct approach to specifying the expected outcomes of an experiment can be possible. In these cases the outcomes of the experiment, that is, the actual data which might result from the experiment, are simulated directly, and these data are then used to update the prior distribution to a posterior using Bayes' rule.

Returning to the same example, consider the case in which it is proposed to make a single observation of next year's catch. Section 2.4 considered an example where such an observation was used post hoc to evaluate the returns from such an "experiment." To consider the same

TABLE 11. Expected returns conditioned on pre-posteriors from Table 10. Also shown is the optimal control B^*, for each pre-posterior, and the expected return for that B^* conditioned on the true model, $V(B^*/M_i)$. PP_i refers to the pre-posterior expected returns conditioned on Model i.

Control B	Expected returns		
	PP_1	PP_2	PP_3
5	5.821	2.290	1.490
10	7.431	3.896	2.436
15	8.331	5.256	3.275
20	8.854	6.412	4.050
25	9.128	7.378	4.777
30	9.221	8.165	5.463
35	9.171	8.776	6.112
40	9.003	9.214	6.727
45	8.735	9.482	7.307
50	8.380	9.581	7.846
55	7.944	9.509	8.336
60	7.434	9.266	8.757
65	6.852	8.848	9.080
70	6.197	8.250	9.256
75	5.463	7.464	9.214
80	4.640	6.476	8.846
85	3.712	5.268	7.997
90	2.655	3.812	6.454
95	1.434	2.073	3.921
100	0.000	0.000	0.000

B^*	30	50	70
$V(B^*/M_i)$	9.909	10.000	9.837

TABLE 12. Pre-posterior distributions across models, conditioned on each model being true. Sets of pre-posteriors for a variety of cases are shown, with cases varying according to the "success" (or information content) of the experiment.

Case and True Model	Pre-posterior Across Models		
	Model 1	Model 2	Model 3
Case 1: Perfect Information			
Model 1	1	0	0
Model 2	0	1	0
Model 3	0	0	1
Case 2: Good Information			
Model 1	0.8	0.1	0.1
Model 2	0.1	0.8	0.1
Model 3	0.1	0.1	0.8
Case 3: Moderate Information			
Model 1	0.6	0.3	0.1
Model 2	0.3	0.4	0.3
Model 3	0.1	0.3	0.6
Case 4: Poor Information			
Model 1	0.45	0.30	0.25
Model 2	0.30	0.45	0.30
Model 3	0.25	0.30	0.45
Case 5: No Information			
Model 1	1/3	1/3	1/3
Model 2	1/3	1/3	1/3
Model 3	1/3	1/3	1/3
Case 6: Disinformation			
Model 1	0.2	0.4	0.4
Model 2	0.4	0.2	0.4
Model 3	0.4	0.4	0.2

TABLE 13. Expected returns for each case, and probabilities of case.

	Expected return	Probability of case	Return
Case 1: Perfect Information	10.000	0.1	1.000
Case 2: Good Information	9.915	0.2	1.983
Case 3: Moderate Information	9.576	0.2	1.915
Case 4: Poor Information	9.235	0.2	1.847
Case 5: No Information	8.602*	0.2	1.720
Case 6: Disinformation	7.892	0.1	0.789
Expected return across cases			9.255

experiment ex ante, the outcome can be simulated using equations (5) to (7), and the resulting observation of catch used (via equation (8)) to arrive at a posterior across models. The "control" in the year of the experiment is $B = 50$, the optimal control under the prior. The results are simulated a large number of times (10,000) for each model being true. In each such simulation, the resulting posterior is used to determine an optimal control given that posterior, and the value of that control is assessed using its expected value given the model which generated the observation. This value is compared with the value of the control given the prior (and given the same "true" model), giving an overall return for that particular simulation. Note that this return can be negative.

The sequence is, therefore,

(i) select the control for the year of the experiment,

(ii) select from the prior distribution one of the models to be true,

(iii) generate an observed catch C_t given the control and model,

(iv) calculate the posterior across models given the observation C_t,

(v) calculate the future expected return given the posterior,

(vi) calculate the future expected return R_{prior} given B_{prior} and the true model,

(vii) obtain the return to the experiment as $R_{\text{post}} - R_{\text{prior}}$,

(viii) repeat steps 3 to 8 a large number of times to get an expected value given the model,

(ix) repeat steps 2 to 9 for each model and weight the returns by the prior across models to get an overall expected return from the experiment.

Given that the control for the year of the experiment is $B = 50$ (the optimal control under the prior), the results of the evaluation, presented in Table 14, are at first glance somewhat surprising. The overall expected return is 0.124, which is small compared to the expected value of perfect information of 1.398 catch units per time period. The expected returns conditioned on each model being true suggest why the return is so low. In simulations where Model 1 is true, the expected return is -0.525 units, for Model 2 the expected return is -0.059, while for Model 3 true the expected return is 0.956.

Inspection of Figure 2 and Table 2 suggests why this is so. The expected value of the catch at $B = 50$ does not discriminate well between Models 1 and 3. Thus, an observation generated by Model 1 is nearly as likely to give a higher posterior weighting to Model 3 as to Model 1, although it will likely give a lower weighting to Model 2. Given a higher weighting on Model 3, the optimal control under the posterior is likely to be greater than $B = 50$, resulting in a negative expected return for that observation. For example, if the posterior is such that $B = 55$ is optimal, the expected return given Model 1 is 7.665 units which, compared to the prior optimal control of $B = 50$ (8.284 units), is a net loss of -0.619 units. If the observation given Model 1 does result in higher weighting to Model 1, the posterior weight on Model 3 is still likely to be relatively high, and the control under the posterior may be $B = 45$. This results in a net positive return of 0.548 units, but note that this is less than the loss that occurs under $B = 55$, which is almost equally likely. There is a slight asymmetry in the production functions which induces this result.

Given Model 2 is true, all expected returns to the experiment will be either zero or negative since the prior control ($B = 50$) is already at the optimal point for this model. It is only for Model 3 that the results yield a positive return to the experiment. Another point to note is that the mean posterior across all simulations is equal to the prior. There is no information being added by this process of simulation.

The results of this simulation exercise indicate strongly that the "experiment" is not a very informative one. This leads to the suggestion that a more informative experiment may be to alter the control in the year of the experiment. Inspection of Figure 2 suggests that either $B = 25$ or $B = 75$ is much more likely to discriminate among alternative models than $B = 50$ and, in particular, should discriminate better between Models 1 and 3. The results of repeating the evaluation using $B = 25$ and 75 are also shown in Table 14.

TABLE 14. Expected returns given Controls B and models.

	$B = 25$	$B = 50$	$B = 75$
Model 1 true	1.387	−0.525	1.408
Model 2 true	−0.437	−0.059	−0.566
Model 3 true	2.270	0.956	2.043
Mean over models	1.073	0.124	0.962

The results indicate that both $B = 25$ and $B = 75$ are much more informative experiments, achieving a substantial proportion of the expected value given perfect information. These two controls may be regarded as "adaptive" management experiments (Walters [1986]). Note that, as explained above, the expected returns given Model 2 true are always negative.

A final point to note is that these simulations have not taken proper account of two complications. One is that there is a transient return associated with changing the control in the year of the experiment (positive in the case $B = 25$, negative for $B = 75$) relative to the prior optimal control. The second is that a full simulation of outcomes for future returns would have to take account of the possibility that B may be less than B_{opt} due to high negative values of η_t in certain years.

3. Concluding remarks. A framework for analyzing returns from research for fishery management has been presented to augment methods used to date. A very simple example has been used to illustrate the linkages among the value of information, scientific experimentation, optimal control and decision making.

Three approaches to ex ante evaluation of returns to research have been described, and each may be used appropriately in different circumstances. The approach conditioned on messages may be appropriate where the experimental outcome is likely to be one of a small set of possible outcomes, the likelihood of which can be related to each model in the prior. Moving away from the example used in this paper, this approach might be used to evaluate genetic research on stock structure, where the underlying models are mixed versus separate stocks, and the outcomes are the identification of separate stocks. Prior experience with such research suggests that there is a significant chance that it will fail to detect differences that really exist, and this can be taken into account in assigning likelihoods of experimental outcomes. The two approaches which are conditioned on models vary according to whether it is feasible to simulate experimental outcomes directly. Simulation is preferable, but now always possible for many types of research.

The simulation approach described in this paper fits into a broader framework which has seen widespread use in evaluating, for example, fishery management strategies, e.g., Hilborn and Walters [1992], IWC [1989]. The main difference in these cases is that the aim is to evaluate alternative harvest strategies using Monte Carlo simulation, rather than just the outcomes of research. The reason that the former represents a broader framework is that such evaluations often include simulating on-going monitoring of the fishery and the use of such data in stock assessments for management. They thus include an important component of "research," although only a limited sub-set, e.g., monitoring of relative abundance and age structure. Examples of this approach which have explicitly included a wider interpretation of research include Powers and Restrepo [1993], Sainsbury [1988, 1991].

It is important to keep in mind, when using the approach described in this paper, that the underlying rationale is to improve attainment of fishery management objectives, not just reduced uncertainty as a result of research. As indicated above, the most informative experiment is not always the optimal experiment, particularly where the experiment itself involves deliberate perturbations to stock abundance (experimental management). This trade-off between management performance and reduction in uncertainty is dealt with extensively in the adaptive control literature, e.g., Walters [1986].

The underlying approach described herein requires the development and use of priors to describe model or coefficient uncertainty. There is an extensive literature on use of priors (see Walters [1986] for their use in adaptive management of renewable resources) which in many cases may be based on expert judgment and prior experience. Similarly, the development of pre-posteriors is also likely to require expert opinion and judgment, particularly in relation to the probability of success of a proposed experiment. The subsequent decisions on choice of experiment will certainly be influenced by both the priors and pre-posteriors. What the method provides is a rational basis for evaluation of costs and benefits. Although the priors may introduce a subjective element into the analysis, the other methods for evaluating research, described in the introduction, also rely on subjective judgments.

Clearly, there is a need to expand almost all elements of what has been presented here. First, a great deal more attention must be paid to valuing returns and including costs and, therefore, incorporating important aspects of the methods mentioned in the introduction. Using annual catch and ignoring both research and production costs are simplifications that need to be revised for applied work. Second, consideration needs to be given to the use of multiple objective functions by fishers and fishery managers. It is obvious that maximization of catch is not the sole (or perhaps even a credible) objective function. Third, the effects of risk and uncertainty on decision making need to be incorporated so as to assess better both the decision-making process and the returns from research for fishery management. Detailed case studies demonstrating these extensions are likely to be the most effective means of illustrating the practical use of the framework presented.

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ENDNOTES

1. See, for example, Cranston [1974], Moore and Baker [1969a], Pesseinier and Baker [1971] and Shumway [1977].

2. General treatments of CBA include Irvin [1978], Layard [1972], Mishan [1977] and Pearce [1983].

3. Among many useful references are Bravo-Ureta and Rieger [1990], Bredahl and Peterson [1976], Chavas and Cox [1992], Davis [1981], Evenson [1967], Griliches [1957], Pandey, Lindner and Meed [1993] and Scobie, Mullen and Alston [1991].

4. This and subsequent sections draw on Hilborn and Walters [1992], Hirshleifer and Riley [1992], Sainsbury [1988, 1991], Thompson [1992], Zellner [1971], Raiffa and Schlaifer [191].

5. The state of nature refers to the condition or state of the bioeconomic system of which the fishery forms part and is represented in mathematical form. This mathematical representation or model may be limited to conditional probability functions for individual parameters or may involve quite complicated dynamic equations.

6. Various hypotheses about the evolution of the fishery give rise to different bioeconomic models of fishery dynamics. These models determine the form of the fishery system state.

7. Note that the term "coefficient," rather than "parameter," is used throughout this paper when referring to model components. The term "parameter" is reserved for moments of probability distributions of random variables and coefficients.

8. See McDonald [1991], McDonald and Hanf [1992], Horwood, Jacobs and Ballance [1990] and Thompson [1992].

9. The objective, described generally by equation (2), is interpreted broadly as that of maximizing expected returns from the fishery, including amenities and externalities not necessarily reflected in market data.

10. Expectations are taken with respect to the stochastic processes specified in the bioeconomic state equations.

11. This measurement equation corresponds to equation (4) with the error vector ψ omitted.

12. C^* is the maximum possible sustainable catch.

13. A more general discussion of model uncertainty might include examination of distinctly different model structures.

14. See Table 3.

15. This is obtained by a) evaluating the catch for each model and each possible value of B, b) finding the expected catch over the prior distribution for models for each value of B (that is, the prior probability-weighted average catch across models reported in Table 2), and c) choosing the optimal control (value of B) that coincides with the highest expected catch. Note that, in this simplified example, no account is taken of any adjustment to catch in the first year resulting from selection of a particular escapement (level of B).

16. The gain from obtaining the posterior, i.e., observing the catch and updating the prior, is given by comparing 8.16 with the expected value under the prior optimal control of $B = 50$, which is 8.03. Hence, the gain from updating the prior is expected to be $8.16 - 8.03 = 0.13$ units of catch (a 1.6% expected improvement per annum). This calculation is revisited below in Section 2.4.

17. This is the weighted average return across messages where the weights are given by the message probabilities.

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APPENDIX B

McDonald, A.D., Smith, A.D.M., Punt, A.E., Tuck, G.N. and Davidson, A.J. (1997). Empirical Evaluation of Expected Returns from Research on Stock Structure for Determination of Total Allowable Catch, Natural Resource Modeling, 10(1), 3-29.

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EMPIRICAL EVALUATION OF EXPECTED RETURNS FROM RESEARCH ON STOCK STRUCTURE FOR DETERMINATION OF TOTAL ALLOWABLE CATCH

A. DAVID MCDONALD
ANTHONY D.M. SMITH
ANDRE E. PUNT
GEOFFREY N. TUCK
ADAM J. DAVIDSON
CSIRO Marine Laboratories
GPO Box 1538
Hobart, Tasmania 7001
Australia

ABSTRACT. An approach to incorporating new information using Bayes' theorem is applied to obtain estimates of expected returns from research on stock structure for determination of total allowable catch (TAC). Expected returns are measured relative to quantitative performance criteria that are inferred from fishery management objectives. Principles of the approach are outlined and a detailed case study of Tasmanian orange roughy is reported.

1. Introduction. Growing pressure on research scientists to justify their funding has recently prompted fisheries researchers to pay more formal attention to evaluating expected gains from research (see for example, Walters [1986], Hilborn and Walters [1987], Sainsbury [1991] and Powers and Restrepo [1993]). The present paper details the application of Bayes' theorem to enumerating expected returns from stock-structure research for determination of total allowable catch (TAC) in the Tasmanian orange roughy fishery.

2. Background. Orange roughy (*Hoplostethus altanticus*) is a deep-sea species found at depths of 750-1400 meters. Orange roughy aggregations are distributed widely in the temperate latitudes of both northern and southern hemispheres. It is a very slow growing species, maturing at 20 to 40 years of age, at lengths of between 30 and 36 centimeters, and is thought to have a lifespan in excess of 100 years. Recruitment to fisheries is coincident with first spawning, although little is known about pre-recruitment behavior or recruitment processes (Staples et al. [1994]).

Commercial fishing for orange roughy began off western Tasmania in 1986. The fishery expanded to eastern and southern waters with the discovery of a large spawning aggregation in 1989. There are currently about 20 fishing vessels operating in the fishery, having declined from 50 vessels in the early 1990's. The fishery is now based primarily in the eastern and southern management zones which are treated as separate fisheries with independent stocks. At present the annual TAC is 2000 tonnes(t) for the southern zone and 3000t for the eastern zone. It is thought that current stocks are at about 30% of virgin biomass. There is considerable doubt, however, about whether the two zones have separate stocks.

The management strategy adopted in the fishery depends on stock structure. Management based on the assumption of a single stock might, for example, lead to total allowable catch being allocated with no restriction on spatial concentration of effort. If, in fact, two stocks exist then fishing pressure on each of the two stocks could be suboptimal. Likewise, if management is based on a false assumption of separate stocks then fishing costs are likely to be higher than they would be otherwise.

Management objectives for the Tasmanian orange roughy fishery are set by the Australian Fisheries Management Authority (AFMA) and are detailed by Chesson [1996]. The primary objective is to ensure that the orange roughy resource is exploited in an ecologically-sustainable manner. This has been interpreted as attempting to maintain the spawning biomass of each stock above 30% of the equilibrium spawning biomass prior to the onset of significant commercial fishing in 1989 (that is, 30% of B_*, where the pre-1989 biomass is denoted by B_*). In the event that the stock is below 30% of B_* with a probability of at least 0.5, the management strategy is aimed at restoring the stock to 30% of B_* over a 5–10 year period.

The second management objective stated is to maximize the economic efficiency of the fishery. It is assumed that what is meant by this statement is that managers, having satisfied the first objective, will attempt to allow fishers to catch their allocation in an economically-efficient manner. In the process of achieving the first objective, therefore, the second objective ensures that managers attempt to use policies that are consistent with maximization of the present value of the flow of harvests. The third objective stated, which will not impact directly on what is discussed in the present paper, is to provide efficient management services to, and on behalf of, the Australian government.

Achievement of the two main management objectives is heavily dependent on the nature of the stock structure in the fishery. Management strategies may differ markedly for the single stock and dual stock cases and so research directed at resolving which is most likely will potentially have a significant impact on the fishery. In addition, even under the assumption of separate stocks, the considerable uncertainty about the appropriateness of assuming such a stock structure might impact the final strategy adopted by managers. Clearly a reduction in uncertainty about stock structure that results from research will have an effect on management policies and strategies, and so affect fisher activity and the dynamics of the resource.

3. The analytical approach. The analytical approach used herein to evaluate expected returns from stock-structure research follows that summarized by McDonald and Smith [1995]. It is a Bayesian approach in the sense that it involves modelling management decision making in the face of many sources of uncertainty, including that surrounding research outcomes. The approach therefore requires specification of a model that links the manager's decision-making process to fishery research and the dynamics of the fishery.

As noted above, the management objectives for the Tasmanian orange roughy fishery are to maintain a spawning biomass of at least 30% of B_* and to do so in an economically-efficient manner. Given the model assumptions set out below, this is equivalent to choosing the time series of total allowable catches (TAC's) that maximize the expected net present value (NPV) of the fishery subject to maintenance of the spawning biomass at no less than $0.3B_*$ with a probability of at least 0.5. That is, the management objective function is,

$$J = \max_{\text{TAC}} \varepsilon\text{NPV} \tag{1}$$

subject to the sustainability constraint and a population dynamics model, including appropriate initial conditions.[1]

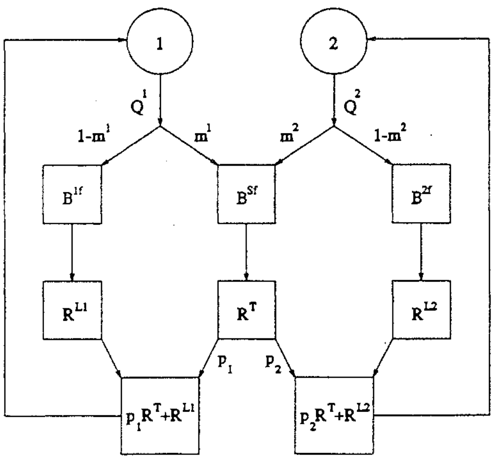

FIGURE 1. A graphical representation of the two-stock model with local and aggregated spawning. The proportion of mature fish from stock i that spawn is given by Q^i, and m^i is the proportion of the spawning fish from stock i that reproduce in a common spawning aggregation. The Bs represent spawning female biomasses, and the Rs are the subsequent number of offspring produced. The proportion of the offspring from the spawning aggregation that move back into stock i is given by p_i.

3.1. *Population dynamics.* An age-structured population dynamics model is used to trace the population dynamics of Tasmanian orange roughy. It allows a full exploration of the effects of past and future harvests on the population, given a range of hypotheses about the population's stock structure. By adjusting the parameters of the model, a fully mixed population, or a population with independent spawning can be investigated, as well as combinations of these extremes (see Figure 1).

For management purposes the fishery is divided into two main zones, namely, the southern and eastern zones (see Figure 2). The eastern zone fishery concentrates on a single winter spawning aggregation at St. Helens Hill. The southern zone fishery harvests several non-spawning aggregations found on deep-sea pinnacles. Current stock assessments are based on population models that assume that the stock is either a single, well-mixed population, or that the southern zone (zone 1) and eastern zone (zone 2) populations are reproductively isolated. It is also possible that a proportion of the zone 1 population moves to zone 2's spawning aggregation at St. Helens Hill to reproduce, and fish that

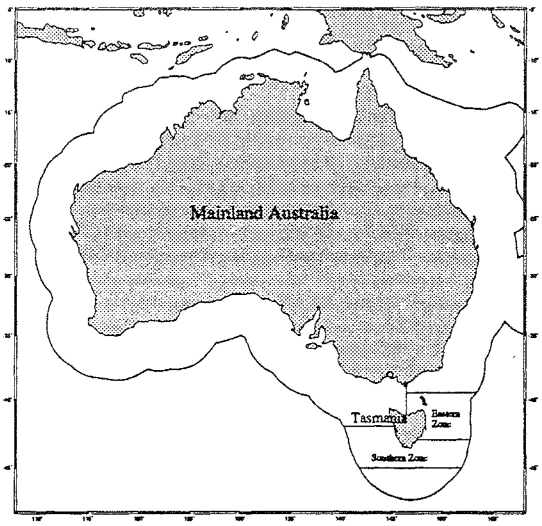

FIGURE 2. A map of Australia showing the main orange roughy management zones surrounding Tasmania.

remain in zone 1 breed locally. The St. Helens Hill aggregation may therefore include fish from both zones, or only zone 2 fish, depending on the level of mixing.[2]

The three major components of the model, described in the Appendix, are the population updating equation, the stock-recruitment relationship and the initial conditions. These components are combined to make use of available data via a likelihood function.

3.2. *The likelihood function.* For each local stock, relative or absolute indices of biomass may be available. From these indices and the population model, the likelihood of a particular population trajectory (i.e., a set of parameters for the dynamic model) can be determined. If there is more than one biomass index then, assuming independence, the overall likelihood is the product of the individual index likelihoods, regardless of whether they are absolute or relative indices.

3.2.1. *Absolute indices.* For a particular series of absolute indices, e.g., an egg or larvae survey, for local stock i, assume that the observed biomass indices, O_j^i, are independent and normally distributed with means E_j^i (the expected biomass from the population model) and coefficients of variation c_j^i (assumed known). The subscript $j = 1, \dots, n^i$ indexes an observation for a particular absolute index for local stock i. Thus $O_j^i \sim N(E_j^i, (c_j^i E_j^i)^2)$ for $i = 1, 2$ and $j = 1, \dots, n^i$.

The likelihood of the biomass indices, O_j^i, is then

$$L_a^i = \prod_{j=1}^{n^i} \frac{1}{c_j^i E_j^i \sqrt{2\pi}} \exp\left(\frac{-(O_j^i - E_j^i)^2}{2(c_j^i E_j^i)^2} \right). \tag{2}$$

3.2.2. *Relative indices.* As well as a measure of the absolute biomass, a relative index may also be used, e.g., an acoustic survey or catch per unit effort. Such an index reflects fluctuations in biomass and, while not being an exact measure of the biomass, is assumed to be proportional to it. As before, assume that the observed biomass indices, O_j^i, are independent and normally distributed with means $q^i E_j^i$, where q^i is a constant of proportionality known as the catchability coefficient[3], and (assumed known) coefficients of variation c_j^i. Thus $O_j^i \sim N(q^i E_j^i, (c_j^i q^i E_j^i)^2)$ for $i = 1, 2$ and $j = 1, \dots, n^i$.

The likelihood of the observations, O_j^i, is then,

$$L_r^i = \prod_{j=1}^{n^i} \frac{1}{c_j^i q^i E_j^i \sqrt{2\pi}} \exp\left(\frac{-(O_j^i - q^i E_j^i)^2}{2(c_j^i q^i E_j^i)^2} \right). \tag{3}$$

4. The estimation algorithm. The objectives determine how one values the fishery and, therefore, the value of research that impacts on the fishery. This follows because the success of management is gauged by how well objectives are met. In the Tasmanian orange roughy fishery the objectives are focused narrowly and so provide a convenient numeraire. We now make use of the objective function in valuing stock-structure research.

Evaluating expected returns from research on stock structure involves calculating the expected returns from the fishery with and without the research. This can be done prior or posterior to conduct of the research and entails evaluation of the credibility of, or degree of belief in, each alternative stock structure. As is made clear above, the degree of separation of the eastern and southern zone stocks is captured by the mixing parameter m^1, so stock-structure research in the Tasmanian orange roughy fishery is focused on this mixing parameter and the virgin biomass in each zone. The mixing parameter is included to reflect patterns of migration of zone 1 fish to the St. Helens Hill spawning aggregation in zone 2.[4]

Returns from stock-structure research emanate from two sources: returns from making use of information as it becomes available and anticipated returns that accrue from proposed experiments. The uncertainty that characterizes major features of the Tasmanian orange roughy fishery restricts our attention to the assessment of expected returns, where the expectation is taken with respect to the distribution of specified random variables. The major sources of uncertainty that we consider are the pre-1989 biomass in zone 1, B_*^1, and zone 2, B_*^2, and the mixing parameter, m^1. This uncertainty is expressed as a joint uniform prior distribution with $B_*^i \sim U[10\,000, 200\,000]$, $i = 1, 2$ and $m^1 \sim U[0, 1]$.

Given the prior distribution, the population model, historical catch data and the parameter restrictions given in the Appendix, and subject to relevant constraints, one can evaluate the objective function and so find the annual series of TAC's that maximizes the expected NPV of the fishery; that is, determine $\mathrm{TAC}^{\alpha}_{prior}$. The expected NPV of the fishery is obtained for a given catch strategy by calculating the NPV for each sample point of the joint distribution for B_*^1, B_*^2 and m^1 and then taking the expectation with respect to this distribution. The NPV for each sample point is calculated in the present research as follows:

$$\begin{aligned}\mathrm{NPV} &= \sum_{i=1}^{2}\sum_{y=1}^{100} e^{-(y-1)\rho} C_y^i \\ &\quad - \sum_{i=1}^{2} (0.3B_*^i - B_{100}^i)^{(1.3 - B_{100}^i/B_*^i)} I(B_{100}^i < 0.3B_*^i).\end{aligned} \tag{4}$$

The first term on the righthand side of equation (4) represents the NPV of the stream of catches, under some simplifying assumptions, where y indexes the year in the planning horizon, ρ is the discount rate and C_y^i is catch from zone i in year y. The simplifying assumptions implied are (i) the real per unit value of the biomass that is allocated to, and the catches taken by, fishers remain constant throughout a planning horizon of 100 years[5], implying a unit price of one roughy dollar (R$), (ii) real marginal costs are constant throughout the planning horizon and so can be ignored.[6]

The second term on the righthand side of equation (4) is a penalty function that reflects the cost of violating the fishery's ecological sustainability, where B_y^i is zone i biomass in year y and $I(B_{100}^i < 0.3B_*^i)$ is an indicator function taking the value one when the expression in parentheses is true and taking the value zero otherwise. This penalty function is applied in order to take account of both the frequency and severity of violation of the constraint that the biomass in the terminal year should not fall below $0.3B_*^i$ and that, if the probability of violating this constraint exceeds 0.5, then the associated catch strategy is deemed infeasible.[7]

The rationale for the penalty, the form of which is somewhat arbitrary, is that the ecological sustainability constraint implies a desire for conservation of the fishery for use by future generations and, therefore, an infinite planning horizon. Such a desire is consistent with the view that the critical biomass $0.3B_*^i$ increases in real value over time at a rate that exceeds the real discount rate. Indeed, it also implies that the further the biomass is depleted below $0.3B_*^i$, the greater is the rate of increase in value of the remaining stock. The stated form of such a penalty is included, therefore, so that, even for catch strategies that satisfy the constraint at the end of the planning horizon with a probability of at least 50%, there are mild penalties for moderate violations and relatively severe penalties for gross violations of the constraint.

Experimental data can be used to update the prior distribution; that is, to obtain a posterior distribution for B_*^i, $i = 1, 2$ and m^1 using Bayes' theorem. The historical experimental data available for the Tasmanian orange roughy fishery include both relative and absolute indices of abundance. The annual series of TAC's that maximizes the expected NPV of the fishery under the posterior distribution can then be determined. This yields $\mathrm{TAC}_{\mathrm{post}}^{\delta}$ and $\varepsilon\,\mathrm{NPV}_{\mathrm{post}}^{\delta}$. The expected return from making use of current experimental data can then be enumerated as

$$\varepsilon R = \varepsilon\,\mathrm{NPV}^{\delta}_{\mathrm{post}} - \varepsilon\,\mathrm{NPV}^{\alpha}_{post} \tag{5}$$

where $\varepsilon\,\mathrm{NPV}^{\alpha}_{\mathrm{post}}$ is the expected NPV of the fishery using $\mathrm{TAC}^{\alpha}_{\mathrm{prior}}$ but evaluated under the posterior distribution.

In addition to the experimental data already available, we also consider the consequence of a scientific experiment in 2005 that yields a fishery-independent absolute index of abundance for Tasmanian orange roughy. The expected return from conducting this experiment can be estimated *ex ante* by evaluating $\varepsilon\,\mathrm{NPV}^{\eta}_{\mathrm{pse}}$ under pseudo-posterior distributions that are updated versions of the posterior distribution (which incorporates historical data). These pseudo-posterior distributions result from simulating the future experimental outcome, as detailed in Section 4.1.

4.1. *Simulation procedure.* The simulation procedure used to evaluate the expected returns from stock-structure research for the Tasmanian orange roughy fishery is most conveniently expressed in steps as follows.

1. Specify the joint prior distribution for B^1_*, B^2_* and m^1, denoted $p^{\alpha}(B^1_*, B^2_*, m^1)$, and identify feasible catch strategies. The feasible catch strategies for the present case are annual TAC's that are to be put in place over an infinite planning horizon. There are 441 catch strategies considered: these range from zero to 8000 tonnes per annum for each zone, in 400 tonne increments. As mentioned above, the infinite planning horizon is approximated by imposing annual TAC's for 100 years.

2. Select a catch strategy (that is, one of the possible pairs of strategies for the two zones), and a sample point from $p^{\alpha}(B^1_*, B^2_*, m^1)$, and calculate the projected NPV of the fishery over a 100 year planning horizon with 1995 as year 1. Note, however, that the TAC is set equal to the biomass in years when the biomass is smaller than the chosen catch-strategy TAC.

3. Repeat step 2 (but retaining the same selected catch strategy) for many sample points ($N = 1000$ in the present case) from $p^{\alpha}(B^1_*, B^2_*, m^1)$.

4. Repeat steps 2 and 3 for all possible catch strategies and select as optimal the catch strategy $\mathrm{TAC}^{\alpha}_{\mathrm{prior}}$ that maximizes $\varepsilon\,\mathrm{NPV}_{\mathrm{prior}}$ from

only those strategies for which $P(B^i_{100} \geq 0.30 B^i_*) \geq 0.5$, $i = 1, 2$. That is, from the strategies that ensure a terminal spawning biomass at no less than 30% of virgin biomass with a probability of at least 1/2, select the one that maximizes the expected NPV of the fishery. Label this catch strategy $\mathrm{TAC}^{\alpha}_{\mathrm{prior}}$.

5. Incorporate experimental data (available up to and including 1995) with the use of Bayes' rule to obtain the joint posterior distribution for B^1_*, B^2_* and m^1, denoting this distribution $p^{\delta}(B^1_*, B^2_*, m^1)$.

6. Repeat steps 1–4 replacing $p^{\alpha}(B^1_*, B^2_*, m^1)$ with $p^{\delta}(B^1_*, B^2_*, m^1)$ and obtaining $\mathrm{TAC}^{\delta}_{\mathrm{post}}$, the optimal catch strategy under the posterior that gives rise to $\varepsilon\,\mathrm{NPV}^{\delta}_{\mathrm{post}}$.

7. Determine the expected return from incorporating the experimental data *ex post* from

$$\varepsilon R^{\delta} = \varepsilon\,\mathrm{NPV}^{\delta}_{\mathrm{post}} - \varepsilon\,\mathrm{NPV}^{\alpha}_{\mathrm{post}} \tag{6}$$

where $\varepsilon\,\mathrm{NPV}^{\alpha}_{\mathrm{post}}$ is the expected NPV obtained from using $\mathrm{TAC}^{\alpha}_{\mathrm{prior}}$ but evaluated under the posterior distribution $p^{\delta}(B^1_*, B^2_*, m^1)$.

8. Evaluate expected returns from possible future experiments by updating $p^{\delta}(B^1_*, B^2_*, m^1)$ to a number of simulated pseudo-posterior distributions, $p^{\eta}(B^1_*, B^2_*, m^1)$, using anticipated experimental outcomes *ex ante*. This involves instigation of a learning or review period, as well as simulation of future observations and generation of model predictions. One must first select a trial catch strategy which, in the present case, lasts for 10 years and is one of the 441 catch strategies given above. At the end of this trial period a scientific experiment is supposed: operating a research vessel to perform an egg or larvae survey, for example, and so obtain an absolute index of biomass. In light of the experimental evidence, the catch strategy will be reviewed for the remaining 90 years of the planning horizon.

In order to simulate the experimental outcome in a manageable way a sample of size $S = 100$ is taken from $p^{\delta}(B^1_*, B^2_*, m^1)$, generated in Step 5. These sample points will be referred to as seeds (for simulating future experimental observations). For a given trial catch strategy and a particular experimental outcome, this sample generates 100 realizations of the future based on $p^{\delta}(B^1_*, B^2_*, m^1)$, which incorporates the information from past catches and research-vessel experiments. Each of these realizations includes B^1_{10} and B^2_{10}, the biomass predictions from the model for each zone in 2005, the supposed future biomass survey year. The simulated experimental outcomes can then be obtained. In the present case the resulting observations are assumed to be distributed as lognormal with mean B_{10}^{i} and coefficient of variation (cv) of 0.5. That is,

$$O_{10}^{i} \sim \ln N(B_{10}^{i}, cv = 0.5). \tag{7}$$

Ten experimental outcomes are drawn from this distribution for each of the 100 seeds (and for each of the 441 trial catch strategies). Each trial catch strategy, therefore, generates 1000 simulated experimental outcomes, each of which produces a pseudo-posterior distribution, $p^{\eta}(B_*^1, B_*^2, m^1)$, a Bayesian update of $p^{\delta}(B_*^1, B_*^2, m^1)$.

For each seed/trial-catch-strategy combination there are 10 experimental outcomes simulated and, therefore, there are 10 pseudo-posterior distributions for which one can re-evaluate all post-2005 catch strategies. Given the objectives for the fishery, naturally one chooses the optimal post-2005 catch strategy for each of the experimental outcomes and so one can calculate the expected NPV (over these outcomes) of the post-2005 strategy for each seed, for a given trial strategy. Repeating this for and taking the expectation over all seeds, and adding the expected NPV of the trial-period catches, yields the expected NPV of the trial catch strategy (in combination with the optimal post-2005 strategy). Repeating this for the remaining trial strategies enables choice of the expected NPV-maximizing trial strategy, giving rise to $\varepsilon\,\mathrm{N\bar{P}V}_{\mathrm{pse}}^{\eta}$.

The expected return from the future research is then given by

$$R^{\eta} = \varepsilon\,\mathrm{N\bar{P}V}_{\mathrm{pse}}^{\eta} - \varepsilon\,\mathrm{NPV}_{\mathrm{post}}^{\delta *}, \tag{8}$$

where $\varepsilon\,\mathrm{NPV}_{\mathrm{post}}^{\delta *}$ is the expected NPV from applying $\mathrm{TAC}_{\mathrm{post}}^{\delta}$ but evaluated only over the 100 seeds selected above.

5. Results. The simulation procedure detailed in Section 4.1 was used first to locate a set of feasible catch strategies from a course grid.[8] This set of strategies then provided the basis for evaluating expected returns from stock-structure research for the Tasmanian orange roughy fishery. The chosen sample size of $N = 1000$ was the largest that available time permitted.[9] The basic empirical results are reported in Tables 1–3 below, corresponding to real discount rates of 0, 0.03 and 0.06.

For a zero discount rate, under the prior distribution the maximum NPV of R$252 591 is obtained with catch strategy 11 (TAC's of zero in zone 1 and 4000t in zone 2). Under the posterior distribution this strategy yields an NPV of R$363 178, which compares to R$421 749 from strategy 112 (TAC's of 2000t in zone 1 and 2400t in zone 2), which is optimal under the posterior distribution. These results imply an expected return from past experimental research of R$58 571.

Expected returns attributable to a 10-year trial strategy, followed by experimental research in 2005 and an optimal catch strategy thereafter, are given in Table 3. In the no discounting case, the maximum expected NPV of R$566 373 results from strategy 251 (TAC's of 4400t in zone 1 and 7600t in zone 2 for 1995–2005). To compare with this, the appropriate expected return from the optimal strategy under the posterior (that is, from strategy 112) is R$480 931. This implies an expected return from the planned research of R$85 442. These and the results obtained using discount rates of 3% and 6% are summarized in Table 6.

Based on historical data, the chosen model and particular parameter restrictions given in the Appendix, it is clear that for all chosen discount rates expected returns from completed stock-structure research for the Tasmanian orange roughy fishery are positive. That is, we have found that the expected return from previous research is approximately R$58 571, R$49 177 and R$31 852 at discount rates of 0.00, 0.03 and 0.06. For the proposed research the expected returns are R$85 442, R$74 648 and R$69 619.[10]

In order to quantify the expected value of stock-structure research in the Tasmanian orange roughy fishery, it is worth noting that, on the basis of present market prices, one roughy dollar is equivalent to around 2000 Australian dollars (A$). This implies that the expected returns from past stock-structure research given in Table 6 have a range of A$63 million to $117 million, depending on the discount rate chosen. Likewise possible future stock-structure research has an expected return of between A$140 million and A$171 million.

TABLE 1. Simulation results under prior distribution.

Catch Strategy	Zone 1 TAC	Zone 2 TAC	εNPV(R$) for Discount Rates 0.00	0.03	0.06
1	0	0	0	0	0
2	0	400	40400	13040	7047
3	0	800	80497	25805	13823
4	0	1200	119006	37116	19168
5	0	1600	154863	46296	22466
6	**0**	**2000**	186810	52189	**22593**
7	**0**	**2400**	212820	**52917**	17694
8	0	2800	231635	47638	6977
9	0	3200	244013	37243	-8618
10	0	3600	251021	22961	-27828
11	**0**	**4000**	**252591**	4578	-50893
12	0	4400	248086	-18734	-78649
13	0	4800	234697	-49566	-113693
14	0	5200	207863	-92152	-160219
15	0	5600	174553	-139160	-210844
16	0	6000	131237	-194248	-269212
17	0	6400	82994	-252215	-330115
18	0	6800	34728	-308051	-388514
19	0	7200	-18426	-367043	-449729
20	0	7600	-63930	-416608	-501178
21	0	8000	-103197	-458438	-544573
22	400	0	39106	11887	5917
23	400	400	79374	24816	12857
24	400	800	118300	36541	18614
25	400	1200	154044	45478	21644
26	400	1600	185900	51274	21660
27	400	2000	211632	51680	16426
28	400	2400	230522	46465	5763
29	400	2800	241170	34235	-11690
30	400	3200	247057	18777	-32102
31	400	3600	249412	1190	-54384
32	400	4000	245552	-21535	-81570
33	400	4400	229220	-55506	-119781
34	400	4800	201215	-99382	-167630
35	400	5200	166540	-147839	-219736
36	400	5600	120628	-205599	-280807
37	400	6000	67978	-268011	-346171
38	400	6400	15861	-327744	-408495
39	400	6800	-40734	-390155	-473147
40	400	7200	-90100	-443532	-528418
41	400	7600	-132137	-488081	-574542
42	400	8000	-177347	-534781	-622539
43	800	0	69500	16813	5217
44	800	400	108941	28958	11378
45	800	800	145955	39092	15589

TABLE 2. Simulation results under posterior distribution.

Catch Strategy	Zone 1 TAC	Zone 2 TAC	εNPV(R$) for Discount Rates 0.00	0.03	0.06
6	**0**	**2000**	202000	65198	**35235**
7	**0**	**2400**	241998	**77836**	41881
11	**0**	**4000**	**363178**	90103	30246
81	1200	6800	-384190	-764297	-860326
82	1200	7200	-418252	-794090	-890454
83	1200	7600	-445185	-816789	-913232
84	1200	8000	-463903	-831522	-927874
85	1600	0	161600	52158	28188
86	1600	400	202000	65198	35235
87	1600	800	242400	78237	42282
88	1600	1200	282800	91277	49329
89	1600	1600	323200	104316	56376
90	1600	2000	363541	117297	63364
91	**1600**	**2400**	400617	**127013**	**67087**
92	1600	2800	419364	118507	52597
93	1600	3200	393509	66245	-5571
94	1600	3600	312978	-37996	-115454
95	1600	4000	177109	-192687	-275240
96	1600	4400	29782	-352554	-439408
97	1600	4800	-125353	-514623	-604916
98	1600	5200	-254319	-645392	-738243
99	1600	5600	-352220	-741454	-836072
100	1600	6000	-416337	-801513	-897241
101	1600	6400	-460257	-840987	-937380
102	1600	6800	-497488	-873479	-970149
103	1600	7200	-526313	-898669	-995565
104	1600	7600	-548511	-916016	-1012693
105	1600	8000	-562749	-926428	-1022887
106	2000	0	201116	64315	34352
107	2000	400	241440	77278	41322
108	2000	800	281737	90214	48266
109	2000	1200	321974	103091	55150
110	2000	1600	361777	115533	61600
111	2000	2000	399363	125759	65833
112	**2000**	**2400**	**421749**	120795	54878
113	2000	2800	395428	67864	-3988
114	2000	3200	296251	-55545	-133099
115	2000	3600	147301	-223464	-306172
116	2000	4000	-12729	-396057	-483114
117	2000	4400	-181253	-571437	-661969
118	2000	4800	-322370	-714719	-807903
119	2000	5200	-427811	-818203	-913205
120	2000	5600	-497144	-882896	-978947
121	2000	6000	-546506	-927385	-1024086
122	2000	6400	-586832	-962841	-1059850

TABLE 3. Simulation results under pseudo-posterior distributions.

Catch Strategy	Zone 1 TAC	Zone 2 TAC	εNPV(R$) for Discount Rates 0.00	0.03	0.06
91	1600	2400	475313	142998	74205
112	2000	2400	480931	146786	77495
240	4400	3200	513349	174772	102259
241	4400	3600	523346	179619	105822
242	4400	4000	527825	183250	108990
243	4400	4400	528916	186135	111789
244	4400	4800	536704	190446	115262
245	4400	5200	542905	194613	118540
246	4400	5600	545888	197499	121453
247	4400	6000	546515	199547	123828
248	4400	6400	542725	200667	125595
249	4400	6800	554144	205426	128983
250	4400	7200	544756	203731	129036
251	4400	7600	566373	212012	134212
252	4400	8000	560425	211998	135395
253	4800	0	481664	147910	79294
254	4800	400	486549	151690	82522
255	4800	800	491245	155460	85747
256	4800	1200	496059	159195	88960
257	4800	1600	501759	163251	92238
258	4800	2000	505953	166839	95403
259	4800	2400	506750	169628	98206
260	4800	2800	516116	174560	101899
261	4800	3200	520103	178181	105024
421	8000	0	486015	159470	91758
422	8000	400	488464	162505	94588
423	8000	800	496098	167008	98206
424	8000	1200	500853	170667	101329
425	8000	1600	505007	174201	104433
426	8000	2000	510229	178022	107636
427	8000	2400	514301	181539	110716
428	8000	2800	520526	185620	114028
429	8000	3200	525157	189287	117138
430	8000	3600	530939	193235	120409
431	8000	4000	535784	197015	123568
432	8000	4400	539866	200388	126581
433	8000	4800	544014	203702	129451
434	8000	5200	536105	203311	130567
435	8000	5600	548150	208875	134456
436	8000	6000	549187	210870	136511
437	8000	6400	548692	212313	138167
438	8000	6800	550308	214361	140024
439	8000	7200	550951	215731	141441
440	8000	7600	551005	216874	142730
441	8000	8000	550180	217646	143824

The reader will notice that, for the positive discount rates, the optimal trial strategy prior to the supposed research involves the extremes of the TAC's considered. Time constraints prevented examination of a more extensive set of management strategies in the present paper. It is worth noting, however, that this result is not surprising for Tasmanian orange roughy when the discount rate is positive, given the nature of recruitment to the fishery.[11] Clearly there is an incentive to run the stock down in the initial 10-year trial and allow it to recover later so that the penalty for violating the terminal constraint is reduced. There is an obvious need for further investigation of catch strategies in the trial period, and this forms part of ongoing research.

Tables 4 and 5 are included to provide an indication of how close the fishery comes to the sustainability constraint at the end of the planning horizon. The optimal strategies with no discounting (strategy 11 under the prior and strategy 112 under the posterior) lead to a steady stream of catches throughout with stock recovery sufficient to satisfy the terminal constraint and avoid excessive influence of the penalty function on the NPV. In the positive discount-rate cases the population dynamics lead to somewhat unusual results: the optimal catches are lower (strategies 6 and 7 under the prior and strategy 91 under the posterior) and the final state is further from violating the sustainability constraint than in the zero discount-rate case. This can be explained as follows. In the zero-discount case catches in all years contribute equally to the NVP. High catches early in the planning horizon followed by biomass-constrained catches (as a result of stock depletion) and then a return to high catches (after stock recovery) could, in the absence of the penalty function, yield the same NPV as consistent low-medium catches through the planning horizon. The choice of the optimal catch strategy given no discounting, therefore, will depend crucially on both the penalty function and the terminal sustainability constraint. In the case of positive discount rates, however, catches further into the future contribute less and less to the NPV; there is, therefore, a tendency for the optimal strategy to concentrate positive catches away from the end-of-planning horizon years. Addition of the penalty function reinforces this tendency and results, for slow-growing orange roughy, in low (but positive) catches for a high proportion of the early to middle years of the planning horizon, followed by biomass-constrained catches as the stock recovers in later years. This also results in a lower probability

TABLE 4. Probability that the final stock exceeds 30% of the initial stock under the prior.

Catch Strategy	Zone 1 TAC	Zone 2 TAC	$P(B^1_{100} > 0.3B^1_*)$	$P(B^2_{100} > 0.3B^2_*)$	$P(B^1_{100} + B^2_{100}) > 0.3(B^1_* + B^2_*)$
1	0	0	1.000	1.000	1.000
2	0	400	1.000	0.999	1.000
3	0	800	0.998	0.987	0.996
4	0	1200	0.985	0.957	0.985
5	0	1600	0.964	0.921	0.961
6	**0**	**2000**	**0.945**	**0.863**	**0.926**
7	**0**	**2400**	**0.903**	**0.796**	**0.886**
8	0	2800	0.863	0.736	0.832
9	0	3200	0.811	0.668	0.775
10	0	3600	0.772	0.591	0.725
11	**0**	**4000**	**0.721**	**0.519**	**0.663**
12	0	4400	0.661	0.431	0.588
13	0	4800	0.602	0.354	0.514
14	0	5200	0.530	0.273	0.432
15	0	5600	0.460	0.208	0.349
16	0	6000	0.392	0.157	0.275
17	0	6400	0.329	0.116	0.219
18	0	6800	0.281	0.078	0.176
19	0	7200	0.228	0.041	0.130
20	0	7600	0.182	0.032	0.093
21	0	8000	0.147	0.015	0.067
22	400	0	0.959	1.000	1.000
23	400	400	0.958	0.997	0.996
24	400	800	0.937	0.979	0.984
25	400	1200	0.910	0.945	0.960
26	400	1600	0.888	0.894	0.927
27	400	2000	0.847	0.826	0.887
28	400	2400	0.801	0.767	0.830
29	400	2800	0.754	0.696	0.775
30	400	3200	0.714	0.635	0.720
31	400	3600	0.668	0.549	0.661
32	400	4000	0.610	0.468	0.584
33	400	4400	0.547	0.387	0.508
34	400	4800	0.480	0.311	0.426
35	400	5200	0.419	0.226	0.342
36	400	5600	0.351	0.175	0.269
37	400	6000	0.293	0.125	0.210
38	400	6400	0.247	0.094	0.166
39	400	6800	0.191	0.053	0.120
40	400	7200	0.148	0.033	0.082
41	400	7600	0.116	0.020	0.058
42	400	8000	0.091	0.011	0.042
43	800	0	0.863	1.000	1.000
44	800	400	0.853	0.994	0.984
45	800	800	0.832	0.969	0.962

TABLE 5. Probability that the final stock exceeds 30% of the initial stock under the posterior.

Catch Strategy	Zone 1 TAC	Zone 2 TAC	$P(B^1_{100} > 0.3B^1_*)$	$P(B^2_{100} > 0.3B^2_*)$	$P(B^1_{100} + B^2_{100}) > 0.3(B^1_* + B * 0^2)$
6	**0**	**2000**	**1.000**	**1.000**	**1.000**
7	**0**	**2400**	**1.000**	**0.976**	**1.000**
11	**0**	**4000**	**0.964**	**0.589**	**0.897**
81	1200	6800	0.023	0.003	0.006
82	1200	7200	0.020	0.001	0.004
83	1200	7600	0.019	0.000	0.003
84	1200	8000	0.018	0.000	0.003
85	1600	0	1.000	1.000	1.000
86	1600	400	1.000	1.000	1.000
87	1600	800	1.000	1.000	1.000
88	1600	1200	1.000	1.000	1.000
89	1600	1600	1.000	1.000	1.000
90	1600	2000	0.993	0.986	0.995
91	**1600**	**2400**	**0.895**	**0.893**	**0.932**
92	1600	2800	0.723	0.717	0.743
93	1600	3200	0.487	0.531	0.549
94	1600	3600	0.335	0.321	0.359
95	1600	4000	0.202	0.190	0.195
96	1600	4400	0.128	0.094	0.101
97	1600	4800	0.074	0.057	0.063
98	1600	5200	0.046	0.035	0.034
99	1600	5600	0.028	0.018	0.018
100	1600	6000	0.016	0.007	0.010
101	1600	6400	0.014	0.003	0.006
102	1600	6800	0.012	0.001	0.004
103	1600	7200	0.011	0.000	0.003
104	1600	7600	0.011	0.000	0.003
105	1600	8000	0.010	0.000	0.003
106	2000	0	0.961	1.000	1.000
107	2000	400	0.960	1.000	1.000
108	2000	800	0.959	1.000	1.000
109	2000	1200	0.947	1.000	1.000
110	2000	1600	0.873	1.000	0.991
111	2000	2000	0.713	0.963	0.923
112	**2000**	**2400**	**0.535**	**0.827**	**0.743**
113	2000	2800	0.369	0.624	0.540
114	2000	3200	0.254	0.399	0.351
115	2000	3600	0.145	0.238	0.189
116	2000	4000	0.093	0.122	0.097
117	2000	4400	0.050	0.075	0.064
118	2000	4800	0.029	0.044	0.034
119	2000	5200	0.016	0.025	0.018
120	2000	5600	0.009	0.010	0.009
121	2000	6000	0.007	0.004	0.005
122	2000	6400	0.005	0.001	0.004

of violating the terminal constraint than is the case for no discounting, because lower rates of stock depletion occur with low catches.

In addition to the above measures of expected returns it is worth displaying graphically what has been learned about stock structure in the Tasmanian orange roughy fishery. The posterior distribution (which incorporates all historical research data) for the mixing parameter m^1, is displayed in Figure 3. This indicates little departure from the uniform prior distribution and so available historical data appear to be uninformative with respect to the mixing parameter. It is, therefore, still unclear what proportion of zone 1 fish migrate to St. Helens Hill in zone 2 for spawning. The patterns evident in the tables, however, lead to a more interesting conclusion. Under both the prior and posterior distributions the optimal TAC for zone 1 is consistently lower than that for zone 2, a pattern that is compatible with zone 1 being a source of recruitment to the zone 2 fishery via spawning migration.

Consistent with this evidence Figures 4 and 5 display the posterior distributions for pre-1989 biomass in zones 1 and 2. These distributions indicate that B_*^1 is most likely to be within the range 75,000–160,000 tonnes and that B_*^2 is most likely to be between 30,000 tonnes and 135,000 tonnes.

The upshot of this graphical evidence is that the assumption, for management purposes, of completely separate stocks in zones 1 and 2 is not supported by the evidence, given the chosen model and the restrictions applied to it. The catch strategy changes that flow from making use of this information result in changes to the expected NPV of the fishery and, therefore, positive expected returns from stock-structure research for Tasmanian orange roughy. These expected returns must obviously be compared to expected costs before a decision is made on whether to proceed with the proposed research.[12]

TABLE 6. Optimal catch strategies and expected returns from research.

Discount Rate	Optimal Strategy			Expected Return (R $)	
	Prior	Posterior	Pseudo-Posteriors	Past Research	Future Research
0.00	11	112	251	58571	85442
0.03	7	91	441	49177	74648
0.06	6	91	441	31852	69619

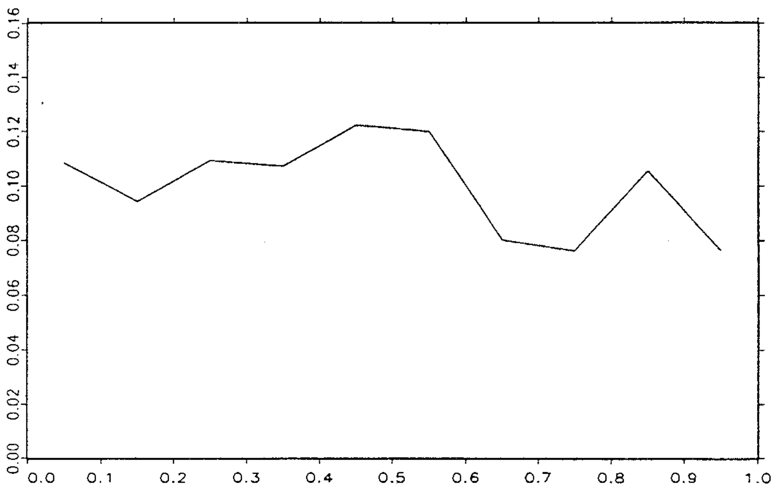

FIGURE 3. Posterior distribution for mixing parameter m^1.

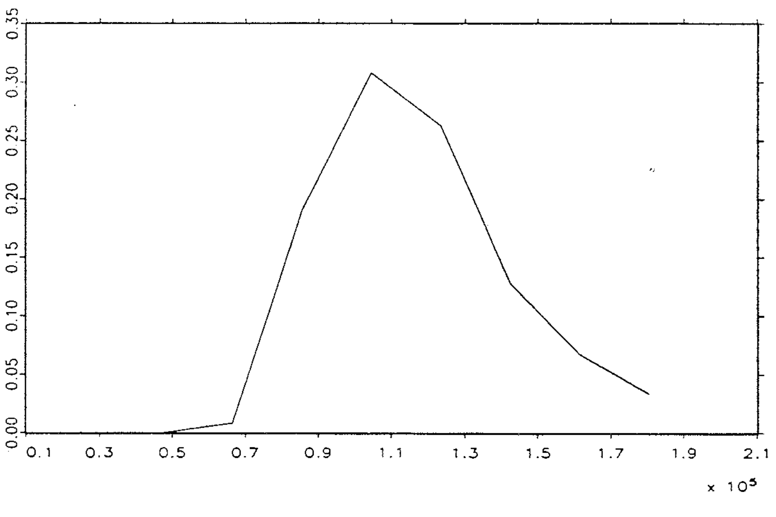

FIGURE 4. Posterior distribution for zone 1 pre-1989 biomass (B_*^1).

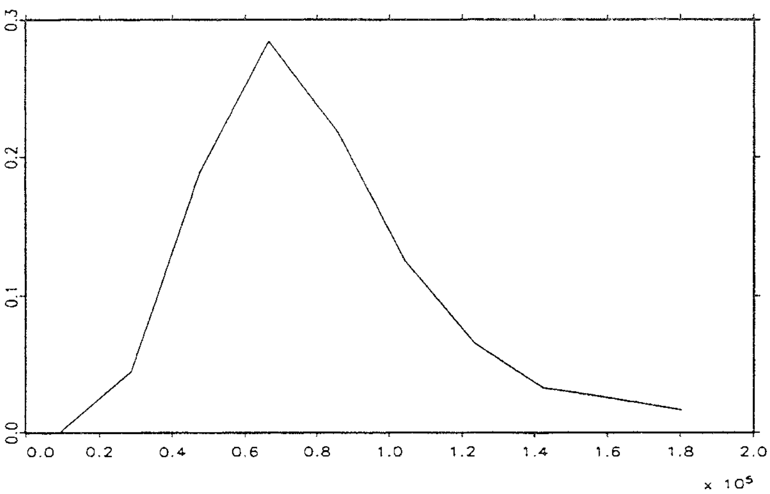

FIGURE 5. Posterior distribution for zone 2 pre-1989 biomass (B_*^2).

6. Conclusion. Expected returns from research into the stock structure of the Tasmanian orange roughy fishery have been evaluated. The approach used draws on Bayes' theorem and a model that links management decision making to fishery research and the dynamics of the fishery. The empirical results indicate that past research has been informative, although considerable uncertainty remains. Given the underlying assumptions, the expected value of this research appears to be substantial. Furthermore, consideration of future stock-structure research gives rise to non-zero expected returns.

APPENDIX

A.1. *Resource dynamics.* The population model is a discrete-time, sex- and age-structured model with three season classes; namely beginning, middle and end-of-season.[13] Numbers-at-age are recorded at the beginning of the season and biomasses at mid-season. Thus, fish of age a in local stock i have dynamics given by,

(9)
$$N^i_{y+1,a} = e^{-M}\Big(N^i_{y,a-1}e^{-F^i_{y,b}}\big(Q^i m^i e^{-F_{y,S}}+1-Q^i m^i\big)+U^i_{y,a-1}\tau_a\Big),$$
$$2 \le a < x$$

(10)
$$U^i_{y+1,a} = e^{-M} U^i_{y,a-1}(1-\tau_a), \quad 2 \le a < x$$

(11)
$$N^i_{y+1,a} = e^{-M-F^i_{y,b}}\left(Q^i m^i e^{-F_{y,S}} + 1 - Q^i m^i\right)\left(N^i_{y,x} + N^i_{y,x-1}\right), \quad a = x$$

where $N^i_{y,a}$ and $U^i_{y,a}$ are the number of recruited and unrecruited fish respectively of local stock i that are of age a at the beginning of year y. Stock i refers to the stock in the southern zone ($i = 1$) or the stock in the eastern zone ($i = 2$). The maximum age-class, which is taken to be a plus-group, is given by x.

The instantaneous rate of natural mortality is given by $M = 0.046$. The instantaneous fishing mortality rate for the period between the beginning of the season and mid-season is $F^i_{y,b}$, where $F^2_{y,b} = 0$ assuming there is no eastern zone harvest during this period. For the period between mid-season and the end of the season, the fishing mortality rate is $F_{y,S}$.

The parameter Q^i is the proportion of the mature biomass of stock i that spawns, in either the local site or the aggregation, and is set to 0.7 for female fish. The proportion of the total spawning biomass of stock i that reproduces in the spawning aggregation (zone 2) is given by m^i.

The proportion of unrecruited animals of age $a - 1$ which recruit at age a, τ_a, is defined by,

(12)
$$\tau_a = (\phi_a - \phi_{a-1})/(1 - \phi_{a-1}),$$

where ϕ_a is the fraction of animals of age a which would be recruited if the population were at its deterministic equilibrium level, and is defined by

(13)
$$\phi_a = \begin{cases} 0 & a < a_r - s_r \\ (1 + e^{-\ln(19)(a-a_r)/s_r})^{-1} & a_r - s_r \le a \le a_r + s_r \\ 1 & a > a_r + s_r. \end{cases}$$

The parameters $a_r = 31$ and $s_r = 9$ are the age-at-50%-recruitment and the parameter that describes the extent of gradual recruitment. The ln(19) term is required so that $\phi_a = 0.05$ at $a = a_r - s_r$, and

$\phi_a = 0.95$ at $a = a_r + s_r$. Thus ϕ_a's less than 0.05 and greater than 0.95 are set to 0 and 1 respectively.

A.2. *The stock-recruitment relationship.* Mature individuals aggregate and produce offspring which, at age one, number

$$N^i_{y,1} = 0 \tag{14}$$

$$U^i_{y,1} = \frac{p_i(1/2)B^S_{y-1}}{\alpha + \beta(1/2)B^S_{y-1}} + \frac{(1/2)B^i_{y-1}}{\alpha_i + \beta_i(1/2)B^i_{y-1}} \tag{15}$$

$$= p_i R^T_{y-1} + R^{L,i}_{y-1}, \tag{16}$$

where the αs and βs are stock-recruitment relationship parameters (defined in Section A.3). The proportion of the eastern zone spawning aggregation's offspring that migrate to the southern zone is given by p_1. Similarly, $p_2 = 1 - p_1$ is the proportion that remains in the eastern zone. The number of one year olds of both sexes that are produced in the spawning aggregation in year y is given by R^T_y, and the number of one year olds produced at the local spawning site of local population i is $R^{L,i}_y$. The mid-season mature female biomass for the spawning aggregation in year y is one half the total mid-season mature biomass, B^S_y, where

$$B^S_y = \sum_{i=1}^{2}\sum_{a=1}^{x} e^{-M/2-F^i_{y,b}} N^i_{y,a} w_a Q^i m^i, \tag{17}$$

and the mid-season mature female biomass for the local spawning site in local population i is one half the total local mid-season mature biomass, B^i_y, where

$$B^i_y = \sum_{a=1}^{x} e^{-M/2-F^i_{y,b}} N^i_{y,a} w_a Q^i (1 - m^i). \tag{18}$$

The mass (in tonnes) of a fish of age a is given by w_a:

$$w_a = a(L_a)^b \tag{19}$$

$$L_a = L_\infty(1 - e^{-\kappa(a-t_0)}), \tag{20}$$

where $L_\infty = 39.06$, $\kappa = 0.06$, $t_0 = -3.18$ are parameters of the Von Bertalanffy growth equation, and $a = 0.00004$ and $b = 2.9$ are input parameters relating length (cm) to weight (tonnes).

A.3. *Initial conditions.* If the population were not exploited, the initial numbers-at-age in year y_1 would be given by

$$N^i_{y_1,a} = R^i_1 \phi_a e^{-M(a-1)}, \quad 1 \le a \le x-1 \tag{21}$$

$$N^i_{y_1,a} = R^i_1 \frac{e^{-M(x-1)}}{1-e^{-M}}, \quad a = x \tag{22}$$

$$U^i_{y_1,a} = R^i_1 (1-\phi_a) e^{-M(a-1)}, \quad 1 \le a \le x-1, \tag{23}$$

where $R^i_1 = (p_i R^T_0 + R^{L,i}_0)/2$ is the number of one year olds that are initially in stock i if the population were at its deterministic equilibrium in the absence of harvesting. The R^i_1 terms are determined from the relationship,

$$B^i_* = R^i_1 \left(\sum_{a=a_r-s_r}^{x} \phi_a w_a e^{-M(a-0.5)} + w_m \frac{e^{-M(x-0.5)}}{1-e^{-M}} \right) \tag{24}$$

$$= R^i_1 X, \tag{25}$$

which states that the virgin recruited mid-season biomass is equal to the sum over recruited fish of the numbers-at-age multiplied by the weight-at-age (giving a biomass). Recalling that numbers-at-age are taken from the beginning of the season, the biomass is then discounted by a natural mortality factor to give the mid-season biomass. Thus from equation (25),

$$R^i_1 = \frac{B^i_*}{X} \tag{26}$$

$$= p_i R^T_0 + R^{L,i}_0. \tag{27}$$

The migration parameter, p_i, which defines the proportion of the aggregation's offspring that move into or stay in stock i, is found by rearranging equations (26) and (27). Noting that $p_2 = 1 - p_1$ by definition and,

$$B^1_* + B^2_* = (R^T_0 + R^{L,1}_0 + R^{L,2}_0)X, \tag{28}$$

the migration parameter is

$$p_1 = \frac{B_*^1(R_0^T + R_0^{L,2}) - B_*^2 R_0^{L,1}}{(B_*^1 + B_*^2)R_0^T}. \tag{29}$$

The parameters of the three stock-recruitment relationships, α and β for the aggregation and α^i and β^i for $i = 1, 2$ for the local spawning, are defined by the following equations

$$\alpha = \frac{B_*^{S,f}(1-h)}{4hR_0^T} \tag{30}$$

$$\beta = \frac{5h-1}{4hR_0^T}, \tag{31}$$

and

$$\alpha^i = \frac{B_*^{i,f}(1-h^i)}{4h^i R_0^{L,i}} \tag{32}$$

$$\beta^i = \frac{5h^i-1}{4h^i R_0^{L,i}}, \tag{33}$$

where the steepness parameters, h and h^i, both set equal to 0.75, are the fraction of the total number of 1-year olds in the virgin population (R_0^T or $R_0^{L,i}$) expected if the total mature biomass is at 20% of its equilibrium level. The virgin mid-season mature female biomass for the eastern zone spawning aggregation and the local spawning grounds are $B_*^{S,f}$ (see equation (17)) and $B_*^{i,f}$ (see equation (18)) respectively.

A.4. *Fishing mortality.* Due to the temporal aspect of the fishery, there are two instantaneous fishing mortality rates to be determined, namely $F_{y,b}^i$ and $F_{y,S}$. Consider first the period from the beginning of the season until just prior to mid-season. There is no eastern zone harvest during this period and so,

$$F_{y,b}^2 = 0. \tag{34}$$

Southern zone fish are harvested and the catch, $C_{y,b}^1$, is then equated to the loss in biomass attributed to harvesting during this period to determine the fishing mortality rate, $F_{y,b}^1$. The catch equation is,

$$C_{y,b}^1 = \frac{F_{y,b}^1}{F_{y,b}^1 + M/2}(1 - e^{-F_{y,b}^1 - M/2})B_{y,b}^1, \tag{35}$$

where $B^1_{y,b}$ is the biomass of recruited fish in stock 1 (the southern zone) at the beginning of year y,

$$B^1_{y,b} = \sum_{a=a_r-s_r} N^1_{y,a} w_a. \tag{36}$$

At mid-season, mature individuals migrate to the eastern zone spawning aggregation where they are harvested. The total catch from the eastern zone spawning aggregation is $C_{y,S}$. To determine the instantaneous fishing mortality rate, $F_{y,S}$, the catch is equated to the biomass lost due to harvesting during the final period,

$$C_{y,S} = \frac{F_{y,S}}{F_{y,S} + M/2}(1 - e^{-F_{y,S}-M/2})(B^1_{y,S} + B^2_{y,S}), \tag{37}$$

where $B^1_{y,S} + B^2_{y,S}$ is the total mature biomass from both stocks in the spawning aggregation, and

$$B^i_{y,S} = \sum_{a=a_r-s_r} N^i_{y,a} e^{-F^i_{y,b}-M/2} w_a \chi_a Q^i. \tag{38}$$

ENDNOTES

1. $\mathcal{E}$ is the expectation operator.
2. It should be noted that zone 2 fishing is concentrated on St. Helens Hill and therefore the zone 2 TAC will include migratory fish from zone 1.
3. The prior assumed for $\ln(q^i)$ is Uniform on $(-\infty, \infty)$ (see McAllister et al. [1994]).
4. The mixing parameter m^2 is set to unity for the Tasmanian orange roughy population because there has been no evidence of spawning in zone 2 other than at St. Helens Hill.
5. Given the sustainability objective and therefore potential for an infinite social planning horizon, and the longevity of orange roughy, a 100-year planning horizon is considered to be reasonable.
6. These assumptions are being revised for the Tasmanian orange roughy fishery in ongoing work.
7. Note that this terminal condition is less restrictive than is applying the constraint in all periods of the planning horizon.
8. Programming was done in Fortran 90 and the simulations were run on a desktop computer.

9. A limited sensitivity analysis indicated that the ranking of catch strategies is not sensitive to sample size although the magnitudes of expected returns are affected in a minor way.

10. See immediately below equation (8).

11. Due to the late age of recruitment to the fishery, the effects of large harvests on the stock are not felt dramatically in the short term.

12. The present cost of an egg survey is about A$300,000.

13. To simplify the exposition, reference to sex differences in the following model description have been omitted.

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