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Models that 'learn' to distinguish among alternative hypotheses

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Abstract

For most fish populations, existing data are insufficient to distinguish among competing hypotheses about the best harvest policy. A common approach is to seek a 'best fit' model, then manage the population as if this model were correct. Apart from the obvious risk of the 'best fit' model being incorrect, this approach fails to consider the value of policy choices that will provide informative variation in abundance and accelerate learning about which hypothesis is correct. Modelling is no substitute for experience, but models do help to determine what type of data to collect and the worth of management options. To cope with uncertainty about population dynamics, we advocate the use of models that explicitly represent alternative hypotheses, the acquisition of data, and managers' response to new information. By including learning in simulation models, we recognize the value of experimental policies that would help distinguish between competing hypotheses. For populations with discrete substocks, replicated experiments can be designed to control for environmental factors. Such management experiments have been implemented or proposed for a number of salmonid and groundfish populations.

Introduction

The primary responsibility of fishery managers is resource conservation. Unfortunately this responsibility often conflicts with learning more about the key production parameters of the population in question. A conservative management policy that keeps the population at some 'optimal' level will give little information about productivity at different stock sizes. In a changing environment, production parameters may actually become more uncertain with time, despite longer time series of data becoming available (Walters, 1987).

The concept of adaptive management is introduced by outlining the steps

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in the typical assessment of an exploited population (Fig. 1). Three levels of analysis are superimposed on this flowchart. The first level, indicated by the block letters and solid arrows, is the status quo or certainty equivalent approach. Historical data on the population in question are compiled and a 'best fit' model is identified that will allow abundance to be predicted as a function of harvest. The optimal harvest rate for the best-fit model is determined and applied to the population. New data are obtained and added to the data base but, as long as the harvest policy remains unchanged, the new data are likely to resemble the old data and the manager may not realize that the best-fit model is incorrect.

The second level of analysis, indicated in the flowchart by adding the italic letters, is the passive adaptive or Bayes equivalent approach. A manager using this approach recognizes that instead of a best-fit model there is a suite of alternative models, each of which may be consistent with historical data. Each alternative model of the population implies a different optimal harvest policy. The best overall policy is taken to be the one that maximizes expected yield when averaged across alternative models, weighted by the relative likelihood of each model being correct. As new observations are added to the data set, the relative likelihoods of each model being correct may change, and the overall best policy may also change accordingly.

The third level of analysis, indicated by adding the open arrows, is the active adaptive or deliberately experimental approach. The manager adhering to this approach recognizes that among various harvest policy choices some are more informative than others about which alternative model (hypothesis) is correct. Application of an active adaptive policy should eventually permit the correct model and corresponding harvest policy to be identified, resulting in an expected long-term increase in yield.

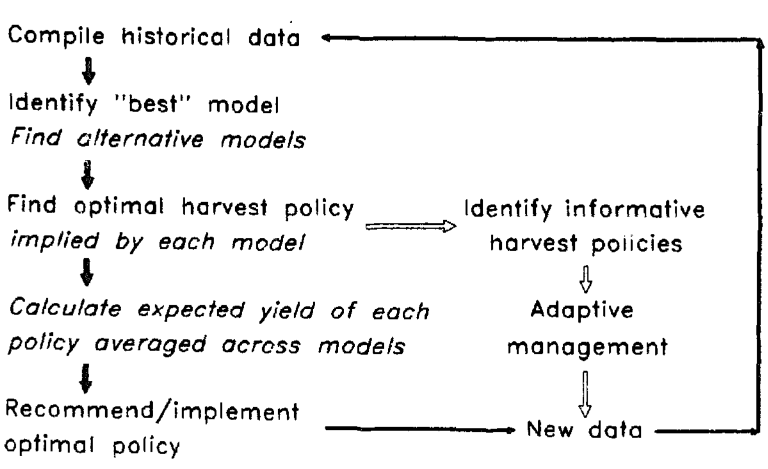

Fig. 1. Steps in the assessment and management of a typical exploited population. The block letters and solid arrows indicate the status quo approach. Italic letters indicate the passive adaptive approach and the open arrows indicate the active adaptive approach.

To reiterate the three approaches, the status quo manager assumes a best-fit model and manages as if that model were correct. The passive adaptive manager recognizes various population models but relies on luck and natural variability to provide information that will allow him to distinguish between them. The active adaptive manager deliberately experiments to identify which model is correct. The decision of whether to experiment or not must be made on a case-by-case basis. Often, moving to the passive adaptive policy results in a large increase in value compared with status quo approaches. If the passive adaptive policy is sufficiently different from the status quo policy, it may be so informative that active experimentation is unwarranted.

The modelling challenge is to estimate the value to the fishery of making informative policy decisions. The estimation involves simulating not only population dynamics but also the feedback of information into the management process. Simulation modelling is an essential precursor to any management experiment because the actual experiment is likely to involve substantial short-term costs and impacts on many users of the resource.

In this paper we first outline our general approach to modelling learning and the value of information. We then give examples of applications to Fraser River sockeye salmon, Pacific ocean perch, and yellowtail flounder. Finally we recommend, in general, when to experiment and how much additional yield to expect. Our objective in this paper is to show readers how their particular management problems fit into the adaptive management framework.

Modelling learning and the value of information

The formal evaluation of policy options involves the following five steps (Walters, 1986).

1. Identify a strategic range of hypotheses consistent with historical data

These hypotheses should make unique predictions about the population response to harvesting. From a management perspective, it is not necessary to distinguish among hypotheses for which the optimal harvesting policy would be the same, even though their mechanisms may be very different. The alternative hypotheses can be different model forms or different parameterizations of the same functional form. The models may be discrete alternatives or a continuous range of parameter values. The model set is often identified by consensus in workshops. It is desirable to include in the model set one or two extreme alternatives that have a low probabilities of being correct, but if correct would imply radically different harvest policies.

2. Develop a stochastic model of future learning

Develop a stochastic model of future learning, incorporating the population dynamics of the species in question, collection of new information and the change of fishing regulations in response to new information. The latter two components are a challenge to modellers, since they involve simulating variability in both data gathering and the procedures used to analyze the data, to arrive at recommendations for policy change. In essence, this step involves simulating the whole process of fisheries stock assessment.

3. Identify harvest policy options

Identify harvest policy options, including the status quo policy as a baseline, the optimal policy for each of the alternative hypotheses, and deliberately experimental policies. The policy options are also often reached by workshop consensus. Active adaptive policies will include an experimental period, t_{exp}, plus a period $T-t_{exp}$ during which the results of the experiment are applied to manage the population (Fig. 2). With an open-loop policy, the manager assumes that whichever hypotheses is most likely at the end of t_{exp} is correct. The length of the experimental period depends on the response time of the population. If the duration of the experiment is too short, there is a risk of choosing the wrong model as correct. If t_{exp} is too long, the harvest may be forgone by not switching to the optimal policy soon enough. If the learning response time is unknown or may be variable depending on natural accidents,

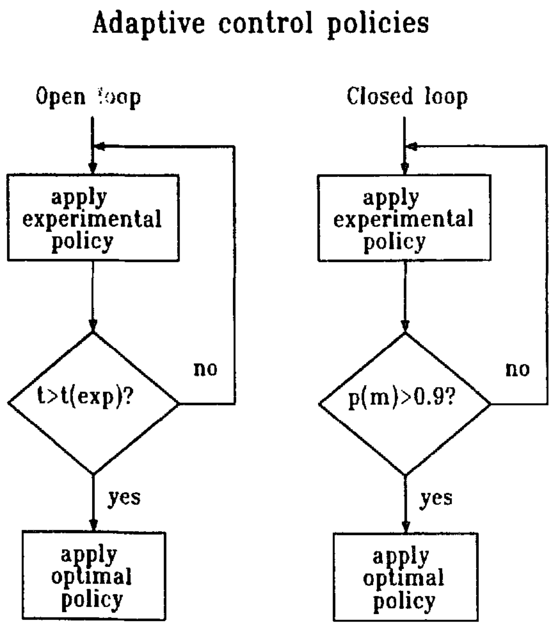

Fig. 2. Adaptive feedback control policies. t_{exp}, fixed experimental duration; p(m), relative likelihood of a model being the correct model.

a closed-loop policy can be used. In this case the experiment is continued until the relative likelihood of one of the hypotheses exceeds a critical level such as 0.9. The relative likelihood assigned to each model (L_j) is the likelihood of observing the data (l_j) given the parameters of model j, standardized by the likelihoods of all k alternative models:

$$L_j = l_j / \sum_k l_k$$

4. *Define performance measures for ranking hypothesis/option outcomes*

The simplest performance measure is the cumulative catch over the planning horizon T, or the average catch per year. The present value of a resource is the discounted sum of catches over a long (or infinite) time horizon. Discounting recognizes the fact that a unit of catch today generally has a higher utility than the same unit of catch harvested in the future. The use of net value as a performance measure accounts for variable prices and the cost of harvesting the resource. Risk-averse utility functions may be used for situations in which there is a large penalty associated with a decline in yield. Risk-averse utility functions can be obtained by taking the logarithm of yield or some other power transformation. The optimal risk-averse harvest strategy gives up some of the average yield to reduce the variance in yield. Alternatively, the variance of yield can be used explicitly as a penalty term in a multi-attribute function (Quinn et al. 1990).

In general, the total value (V_i) of policy option i is a sum of catch during the experimental period, t_{exp}, plus the catch after the optimal policy u^* is applied.

$$V_i = \sum_{t=1}^{t_{\mathrm{exp}}} (C_t | u_i) + \sum_{t=t_{\mathrm{exp}}+1}^{T} (C_t | u^*)$$

Thus the total period T is split into an experimental stage followed by a stage during which the results of the experiment are applied. If the population in question is currently overexploited, the experiment will likely involve forgoing current catch to rebuild the stock to a level at which a higher yield could be sustained. If planning horizons are short or if the future is heavily discounted, the improvement in expected catches for $t = t_{\mathrm{exp}} + 1$ to T will be seen as small compared with the losses during the experimental period. If the population is currently underexploited the experiment may produce short-term gain with a risk of long-term losses. In either case, T must be long enough to account for the long-term value of the resource, especially for long-lived species.

5. Compute expected performance for each option across all hypotheses

The prior probabilities can be calculated with a statistical procedure, or they may be based on simple intuition. Each hypothesis, or state of nature, has a different optimal harvest policy, as indicated by the bold type in Table 1. The overall value of policy choice i is the mean of its values for the hypotheses, with each value weighted by the prior probability. The best policy choice is then the one with the maximum expected benefit. The ranking of policy options is generally insensitive to the prior probability assigned to each model unless the prior probabilities are extremely high or low.

Adaptive management of replicated populations

If only one population is used for adaptive management, the experiment is not well designed because there is no control and no replication. Effects of policy changes over time cannot be distinguished with confidence from potential effects of environmental change. For populations that exist as discrete substocks, it is possible to design replicated experiments and to trade-off catches among stocks to minimize forgone catch. The value of a replicated management experiment depends on the extent to which substocks share information about production parameters and respond similarly to environmental perturbations. If the substocks are identical, the correct model should apply to all of them. At the other extreme, if there is no shared information among substocks, it is necessary to experiment on each one individually. The most likely situation is that substocks share some but not all demographic parameters, and respond similarly to some environmental effects. The amount of shared information can be determined by fitting population models to historical data and testing whether parameters are significantly different among stocks. If there is some shared demographic information it is possible to learn

Table 1
Expected value (V) of policy options

		State of nature				Weighted mean
		H_1	H_2	H_3	H_4	
Prior probability		p_1	p_2	p_3	p_4	
Policy choice	u_1	V_{11}	V_{12}	$\mathbf{V_{13}}$[a]	V_{14}	$V(u_1)$
	u_2	$\mathbf{V_{21}}$	V_{22}	V_{23}	V_{24}	$V(u_2)$
	u_3	V_{31}	$\mathbf{V_{32}}$	V_{33}	V_{34}	$V(u_3)$
	u_4	V_{41}	V_{42}	V_{43}	$\mathbf{V_{44}}$	$V(u_4)$
	$\vdots$					

[a]Bold type indicates the optimal policy.
H, hypotheses or states of nature; p, probability.

more quickly which hypothesis is correct than would be the case with a single stock.

Applications of the adaptive learning approach

Fraser River sockeye salmon

A striking feature of many sockeye salmon (*Oncorhynchus nerka*) stocks is the tendency for cyclic patterns in abundance (e.g. Eggers and Rogers, 1987). Most Fraser River sockeye return to spawn at age 4, a necessary but insufficient condition for the existence of 4-year cycles. Despite the efforts of renowned fishery scientists, such as Thompson, Ricker and Larkin, the cause of this phenomenon (cyclic dominance) remains equivocal. The two most likely explanations are brood–year interactions during the lacustrine stage of the life cycle and depensatory fishing (Collie and Walters, 1987). Whether or not there is a biological explanation, the status quo policy of cyclic escapement targets has served to maintain the cycles, which makes it impossible to refute the depensatory fishing hypotheses.

The stock-recruitment data (Fig. 3) are consistent with a range of models. Most of the data are from the low end of the spawning abundance scale. The initial slope of the spawner–recruit curve is well determined, but recruitment

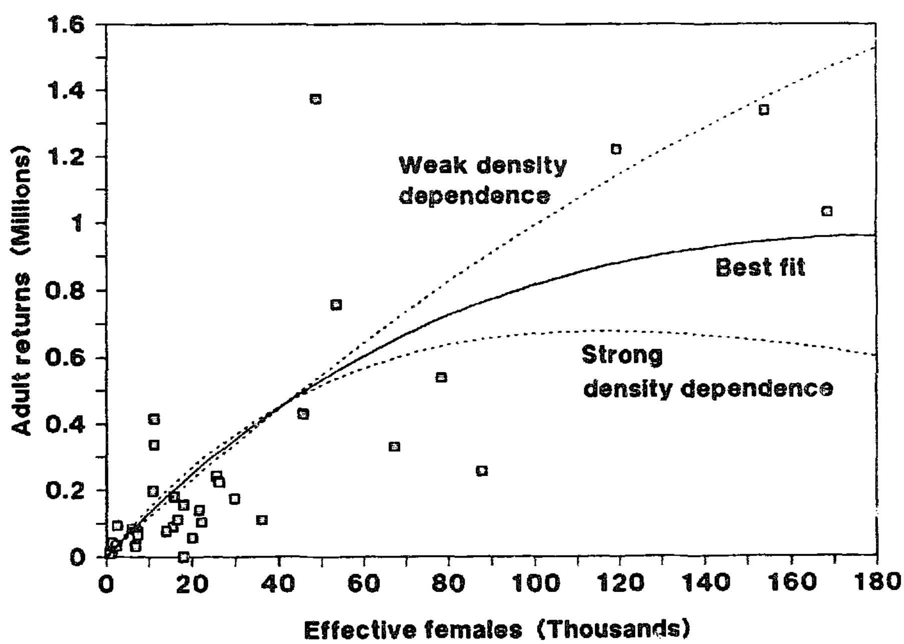

Fig. 3. Early Stuart sockeye salmon (*Oncorhynchus nerka*) stock–recruitment data. Effective females is the number of female spawners, corrected for the generally small percent of retained eggs. The three curves represent different hypotheses about recruitment at high stock sizes. The strong density dependence curve represents expected recruitment with brood–year interactions; the best fit line assumes no brood–year interactions.

at high stock sizes is very uncertain. The obvious experiment would be to increase stock size and see what happens, but how big an increase should be sought? The initial slope of the spawner–recruit curve determines the optimal exploitation rate. If the stock is harvested at this rate, it should eventually increase up to a level corresponding to whichever model is correct. A deliberately experimental approach would seek a more rapid increase to the hypothesized optimal stock size.

The preceding paragraph only considered one of the Fraser River stocks, the Early Stuart. A full analysis of Fraser River sockeye salmon includes the ten major substocks (Collie et al., 1990). Fitting the stock–recruitment data for ten stocks with a pooled regression model allowed the initial slope to be estimated with more precision than would be possible with only one stock.

A stochastic simulation model was constructed incorporating the estimated stock–recruitment relationships, the age structure of the stocks and the correlation structure of unexplained residuals. Harvest policies that have been considered for Fraser River sockeye are: (1) status quo harvest rates of around 80%; (2) lower harvest rates of around 70%; and (3) experimentally rebuilding some low runs with 50% harvest rates for four generations. The optimal harvest rate, based on present stock–recruitment data, is about 70%; thus option (2) is the passive-adaptive optimum policy. Option (3) is an active adaptive policy because it involves experimenting to see if small runs will increase when fishing pressure is reduced.

Cumulative 40-year total catches of Fraser River sockeye were calculated with 100 Monte Carlo simulations of each policy/hypothesis combination (Table 2). Irrespective of which hypothesis is correct, there is a 50% expected increase in yield as a result of switching from the status quo to the passive adaptive policy. At current prices this increase would be worth on the order of $1 billion. An additional 5% increase is expected from the experimental rebuilding policy. This example is somewhat unusual in that the ranking of

Table 2
Expected 40-year catches of Fraser River sockeye salmon[a]

Harvest policy	Depensatory mechanism		Increase over status quo (%)
	Fishing	Brood–year interactions	
Status quo (high harvest rates)	266	158	
Passive adaptive (lower harvest rates)	394	238	+50
Experimental rebuilding of small runs	412	246	+55

[a]Catches in millions of fish.

the policies is the same for both alternative models. Therefore, the prior probability assigned to each model affects only the expectation of total yield and not the choice of optimal policy.

Slope rockfish off the British Columbia coast

The formative work on adaptive management (Walters and Hilborn, 1976) focused on Pacific salmon; more recently the adaptive approach has been extended to groundfish (e.g. Sainsbury, 1988, 1991). Our second example is an experimental management plan for slope rockfish off the British Columbia coast. The assemblage of slope rockfishes is dominated by one species, Pacific ocean perch (*Sebastes alutus*) which has historically been the most abundant and provided most of the commercial catch. Catches of Pacific ocean perch peaked in the 1960s and subsequently declined, presumably from overfishing (Fig. 4). Pacific ocean perch is known to be a long-lived, ovoviviparous, slow-growing fish. The main uncertainty is total stock size, because of difficulties surveying rockfish abundance. The managers' response to uncertainty has been

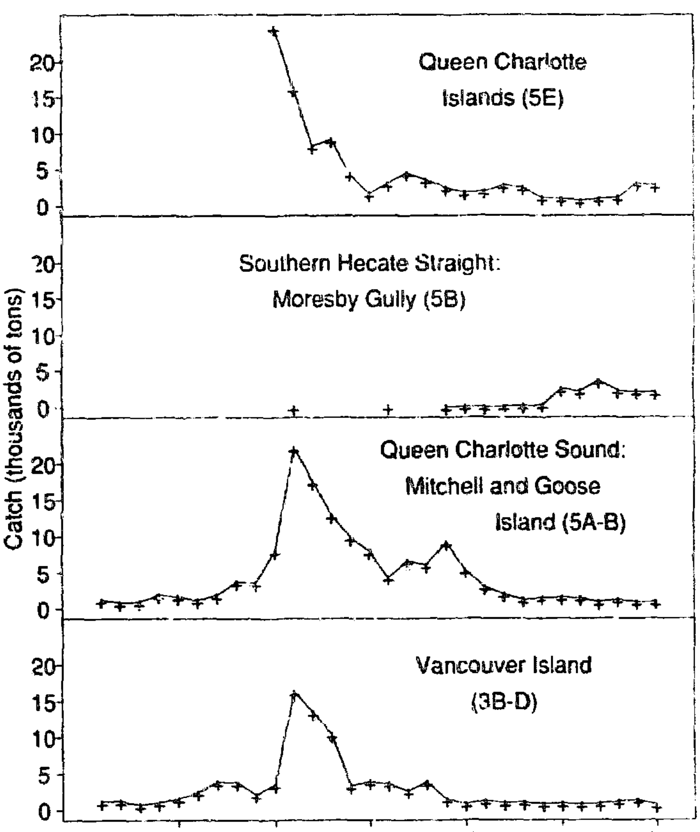

Fig. 4. Catches of Pacific ocean perch (*Sebastes alutus*) in four areas off the British Columbia coast.

to set very conservative quotas; fishermen feel that recent high catch rates justify more liberal quotas.

An experimental management plan was formulated jointly by fishermen, managers and members of the academic community (Walters and Collie, 1989). The first component of the plan was to divide the British Columbia coast into seven experimental units corresponding to current management areas. Three areas would be opened to free fishing for slope rockfish, three areas would have continued quota management and one would be closed as a refuge. The second component of the plan was a standardized relative abundance survey to be conducted by the trawlers. The final component was a set of contingency plans on how to change the fishing regulations in case of stock collapse in the open areas.

The alternative hypotheses for this fishery are generated from estimates of current stock size. For example, in Goose Island Gully, the range is from 10 000 to 60 000 tonnes. For each estimate of current stock size, we generated a production hypothesis by backcalculating how large the stock must have been and how high its recruitment rates must have been originally to reach the hypothesized current level, given measured catches. This backcalculation (or 'stock-reduction analysis', Kimura et al., 1984) provides a production–stock size relationship when accompanied by some assumptions about the stock–recruitment relationship; we assumed recruitment proportional to stock for stock less than one half the unfished level.

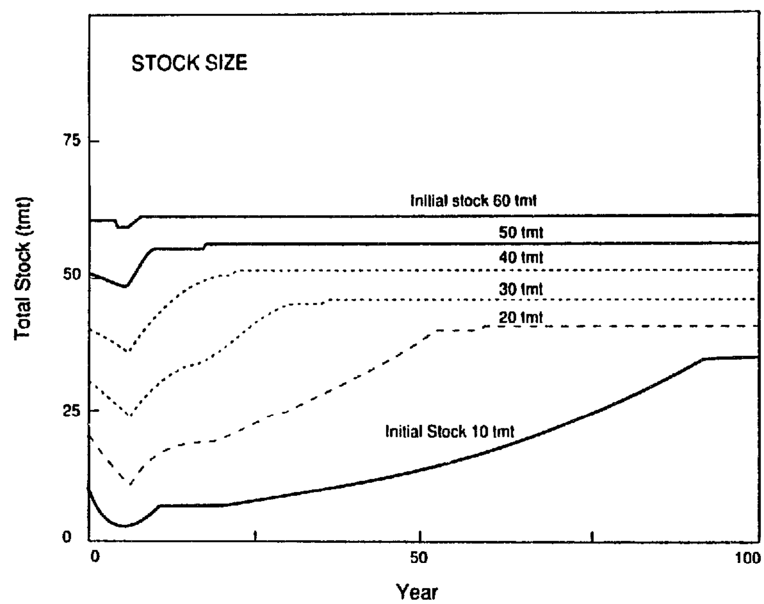

Fig. 5. Expected abundance of Pacific ocean perch in Goose Island Gully subject to 5 years of free fishing followed by quota management corresponding to whichever stock-size hypothesis appears correct. The various lines indicate the different initial stock-size hypotheses. (Reproduced from Walters and Collie, 1989.)

Table 3
Expected 100-year yields of Pacific ocean perch

Harvest policy	Hypothesized 1987 stock size[a]					
	10	20	30	40	50	60
Status quo total allowable Catch	35	80	80	80	80	80
5-year experiment with 3 tt annual catch	**51**	**102**	**131**	163	187	205
10-year experiment with 3 tt annual catch	34	88	125	**169**	**201**	**218**
Perfect information (massive survey)	82	169	178	229	255	292

[a]Yields and stock sizes in thousands of tonnes (tt).

The proposed experiment was an open-loop policy involving either 5 or 10 years of liberalized fishing in the open areas, followed by a quota corresponding to the model that appeared most likely at the end of the experimental period. The differential response to a 5-year experiment (Fig. 5), depending on initial stock size, should allow the different hypotheses to be distinguished. Particularly if the low stock size hypotheses is correct, the long response time of Pacific ocean perch could require many years of forgone catch. Cumulative 100-year yields, calculated as means of 50 Monte Carlo simulations, are listed for one experimental area, Goose Island Gully (Table 3). Expected yields from the experimental policies are much higher than for the baseline quota management. Much of this increase results from improved survey monitoring. However, even with the expanded survey, expected yields under the experimental plans are considerably less than if current stock size were known exactly. Overall, the 5-year experiment has a marginally higher expected yield than the 10-year experiment.

Yellowtail flounder in the northwest Atlantic

The yellowtail flounder (*Pleuronectes ferrugineus*) is a commercially important flatfish on the east coast of North America. There are six main substocks recognized for management purposes, of which the Grand Banks, Georges Bank and Southern New England stocks are the largest. The problem has been declining abundances for most of the stocks, declines which have been particularly acute in New England.

Our modelling approach was to fit a delay–difference model (Deriso, 1980; Schnute, 1985) to catch and relative abundance data. We used the delay–difference model because it can be fitted to stocks for which there are no catch-at-age data and because it provides a computationally efficient way to predict future abundance of age-structured populations. There were basically three parameters to estimate: q, a and b. The catchability coefficient, q, scales relative abundance to absolute abundance. The other two parameters define the Ricker stock-recruitment relationship: a is maximum productivity at low stock size and b is the coefficient of the density-dependent term.

An example fit of the delay-difference model is shown for Georges Bank yellowtail flounder (Fig. 6). The model was fitted to catch and relative abundance data from 1960 to 1985, with commercial catch per unit effort (CPUE) as the primary relative abundance index and the trawl-survey index as auxiliary data. We considered CPUE to be proportional to the square root of biomass ($\text{CPUE}=q\sqrt{B}$), an assumption which improves the agreement between the CPUE and trawl-survey indices. Relative abundance was then simulated from 1986 to 1990 with the delay-difference model and the observed catches. The delay-difference predictions have an acceptable prediction error, except that they do not account for recruitment variability, such as the appearance of the relatively strong 1987 year-class in 1989. According to the delay-difference model fit, the observed catches for the recent 5-year period resulted

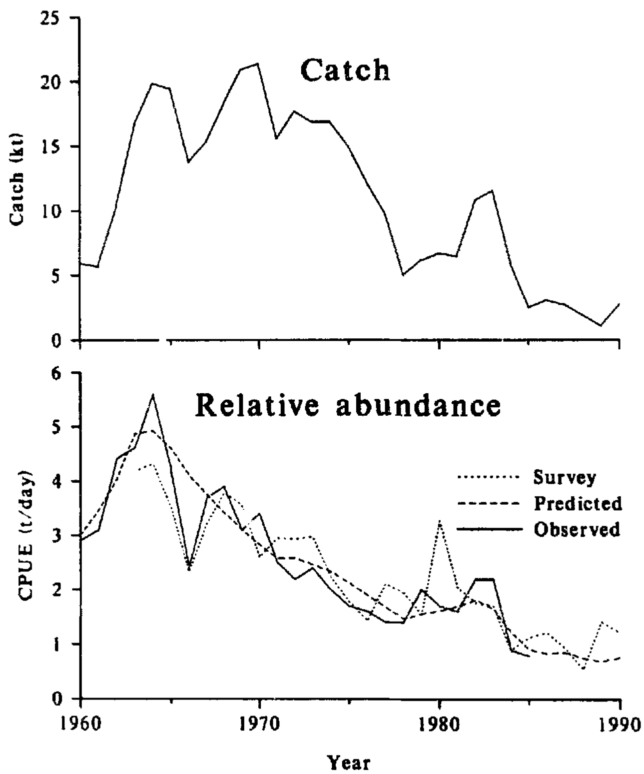

Fig. 6. Fit of the delay-difference model to catch and relative abundance data for Georges Bank yellowtail flounder (*Pleuronectes ferrugineus*). The model was fit to the data up to 1985 and simulated from 1986 to 1990 with the fitted parameters and observed catch. The trawl-survey data were square-root transformed and scaled to be in the same units as catch per unit effort (CPUE).

in exploitation rates greater than 50%, keeping the stock at a low abundance level. Interestingly, the model also predicts that if exploitation rates were decreased the stock would rebuild quite rapidly.

Since 1964, the Georges Bank yellowtail flounder stock has exhibited a classic 'one-way' trip or decline in abundance. Although the delay–difference model fit is good (Fig. 6) the parameters are very uncertain because of the lack of a recovery in abundance. We used the joint confidence regions of parameters a, b and q to identify alternative models or hypotheses consistent with the data. The confidence regions are long and thin, meaning that most of the parameter uncertainty is in one dimension. We identified five alternative models based on a range of Ricker a values; once a is fixed, b and q are constrained within narrower intervals along the long confidence region.

The alternative models were incorporated into a computer program that simulates the populations according to the delay–difference equation and uses filtered biomass estimates to determine which model is correct (Collie and Walters, 1991). The computer simulation can be considered a management game. The program simultaneously simulates a number of alternative models, one of which is correct. It is the simulated manager's job, by setting harvest rates and gathering data, to identify the correct model (Fig. 7). In this ex-

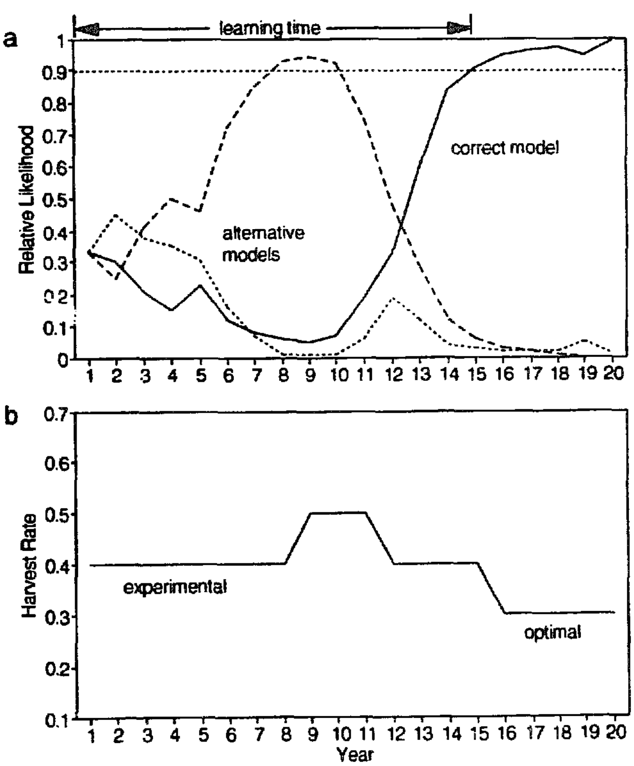

Fig. 7. Hypothetical simulation of adaptive learning. (a) Relative likelihood assigned to each of three alternative models. (b) Harvest rate applied to the population in the corresponding years. Learning time is defined as the number of years to identify the correct model.

ample, a closed-loop decision rule is used: once the relative likelihood assigned to a model is 0.9 or greater, the 'manager' switches to the optimal policy for that model the following year.

In the hypothetical example (Fig. 7), there are just three alternative models for a single population. The three models were initially assigned equal likelihoods and an initial harvest rate of 0.4 applied. In Year 8, it appeared that the dashed model was correct and in Year 9, the harvest rate was raised to the optimal level for that model, 0.5. Three years of the high harvest rate revealed that the dashed model was incorrect and the manager reverted to the initial harvest rate until identifying the correct model in Year 15. This simulation therefore accounts for the possibility of assuming that the wrong model is correct.

In the actual simulations of yellowtail flounder there were six substocks and five alternative models. We assumed that the stocks share a common a value, but that the b and q parameters are stock-specific. The a parameter is related to the intrinsic rate of increase at very low stock sizes, and is thus most likely to be shared. Whichever model (a value) is assumed correct for one stock is assumed correct for all stocks. This assumption of a shared parameter shortens the learning time to identify the correct model to an average of about 15 years (Collie and Walters, 1991).

Initial harvest policies considered were the optimal harvest rates for each model (Table 4). The optimal harvest rate is a function of only the Ricker a value; the higher the value, the higher the initial harvest rate. One hundred Monte Carlo trials were simulated for each initial harvest rate/model pair. Yields reported in Table 4 are summed over six substocks, cumulated over 50 simulated years (discounted 3% per annum) and averaged over 100 random trials. Yield is obviously higher for more productive models, and the difference in yields is greater for the highest initial harvest rate. Yellowtail flounder stocks are currently at low levels of abundance. If a high initial harvest rate is applied and the low productivity model is in fact correct, abundance stays

Table 4
Cumulative combined 50-year yields (million tonnes) of all six yellowtail flounder stocks[a]

		Ricker a value					Average across models
		0.0	0.3	0.6	0.9	1.2	
Prior probability		0.2	0.2	0.2	0.2	0.2	
Initial harvest rate (%)	30	**1.67**	1.71	1.63	2.13	2.33	1.89
	35	1.62	**1.73**	1.66	2.17	2.41	**1.92**
	42	1.45	1.66	**1.67**	2.23	2.50	1.90
	48	1.11	1.46	1.63	**2.24**	2.55	1.80
	56	0.65	0.96	1.48	2.18	**2.56**	1.57

[a]Each value is the mean of 100 Monte Carlo trials, with catch discounted 3% per annum.

low and it is impossible to distinguish the correct model. It is impossible to locate where on Table 4 the actual stocks lie, because of parameter uncertainty. The best guess is that $a = 0.3$–0.6, the harvest rate for maximum yield, u_{max}, is about 0.4 and current harvest rates are above u_{max} (Anonymous, 1991). The actual situation therefore appears to correspond to the lower left-hand corner of Table 4, in which there is almost no learning about which model is correct.

Averaged across models, and without adaptive learning, the 42% initial harvest rate gave the highest long-term yield; with learning, the 35% harvest rate was optimal. The lower harvest rate was beneficial, not only because it allowed the stocks to recover from low abundance, but also because it speeded learning about which hypothesis was correct. There appeared to be no additional benefit from introducing deliberate contrasts in stock size by applying different initial harvest rates to different stocks; the most informative and productive policy was to apply low initial harvests rates to all stocks (Collie and Walters, 1991). This is another example for which a large increase in yield is expected from moving to the passive adaptive optimum policy. Much of the expected increase results from pooling the information from a number of substocks, so as to provide joint estimation of environmental effects and one production parameter.

Discussion

As illustrated by the three examples, the optimal experimental policy must be chosen on a case-by-case basis. In the rockfish example the hypothesis of high current stock sizes is tested by liberalizing fishing in the open areas. In contrast, the yellowtail flounder and some runs of sockeye salmon are currently at low levels of abundance, and the experimental policy is to reduce harvest rates. With replicated populations, the optimal experimental policy often must be sought by ad hoc methods, because there are so many experimental design possibilities that it is impractical to simulate the value of each one. The ad hoc approach encourages creative brainstorming to identify policy options, but there remains a risk of overlooking an even better experimental design.

In general, switching from the status quo to the passive adaptive optimal policy may be quite valuable, if the optimal policy is sufficiently different from the status quo. Walters (1986) cautioned that real people manage more conservatively than our numerical control systems so that, in practice, the benefits of passive adaptive management may not be realized. The increase in value from moving to an adaptive policy is often partly due to improved monitoring or a different way of analyzing the data. The expected increase thus reflects the value of information processing as well as the value of changing management policies. Population monitoring is an essential ingredient of adaptive management plans, particularly if deliberate experimentation is contemplated.

In spatially replicated populations there are opportunities to trade-off catches among replicates, which spreads the risk and lessens the short-term cost of experimentation. If there is information shared among replicates, a pooled method of analysis should decrease the uncertainty about shared demographic parameters and environmental effects. Salmon populations are good candidates for adaptive management because they exist in discrete spawning stocks. However, many salmon stocks are exploited in mixed-stock fisheries, which dramatically reduces the opportunity to apply different harvest treatments to different stocks. Many groundfish populations exist as semi-discrete subpopulations that are managed and fished as separate stocks. However, it is unclear how much mixing there is among stocks, and any significant amount of mixing could compromise experimental harvest policies.

The purpose of the simulation models we use is not to predict future abundance of harvested resources. On the contrary, it is because future abundance is so uncertain that adaptive management is necessary. The main reason for simulating adaptive learning is to calculate the value of information in the same units as the value of harvesting the resources. With the use of common units, it is possible to weigh the benefits of experimentation against the costs.

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