DEALING WITH UNCERTAINTY IN MANAGEMENT OF FISHERIES: CONTRADICTORY ADVICE AND A NEW APPROACH

Daniel S. Holland, Gulf of Maine Research Institute, dholland@gmri.org
Guillermo E. Herrera, Bowdoin College, gherrera@bowdoin.edu

ABSTRACT

Fisheries management is complicated in nearly all fisheries by various types of uncertainty. Numerous economics and fisheries science publications prescribe adjustments to harvest strategies in the face of uncertainty. The conclusions and recommendations from this body of work are conflicting in many cases, are often dependent on critical but unrealistic assumptions, and are often impractical. In this paper, we review and compare the conclusions of economists and fisheries scientists on managing fisheries under uncertainty. We identify the common findings and discuss the divergent ones. We also attempt to explain why the theoretical conclusions of this literature have rarely been heeded by fisheries managers. Finally, we discuss a simulation based approach known as management strategy evaluation (MSE) that is designed to identify harvest strategies that are both robust to various types of uncertainty and capable of balancing multiple economic, social and biological objectives.

Keywords: Fisheries, Harvest Strategies, Uncertainty, Management Strategy Evaluation

INTRODUCTION

The depletion and collapse of fisheries is widespread. The economic mismanagement of fisheries is still more commonplace as the examples include but are not limited to most cases of depletion and collapse. Fisheries management is rendered less effective in many cases by uncertainty in the size, composition and spatial distribution of stocks; uncertainty in stock dynamics; stochastic variation in growth of the fish stock that can not be predicted accurately; error in implementation of management prescriptions; and unpredictable variation in various economic parameters, such as costs and prices.

The economics, ecology and fisheries science literature is replete with studies addressing different aspects of uncertainty and how to adjust harvest strategies and research efforts in the face of uncertainty. However the conclusions and recommendations from this body of work are conflicting in many cases, are often dependent on critical but unrealistic assumptions, and are often impractical because they conflict with legal requirements or they fail to take into account the need to balance conflicting objectives of stakeholders (e.g. social concerns, economic efficiency and biological risk).

In this paper we compare conclusions and advice on managing fisheries under uncertainty from economists and fisheries scientists. We identify the consistent and conflicting findings and discuss the reasons for conflicting advice. We also discuss reasons why fisheries managers have generally not utilized these findings to attempt to optimize harvest strategies for specific fisheries. Finally we discuss a simulation based approach to addressing uncertainty known as management strategy evaluation (MSE) that is designed to identify harvest strategies that balance potentially conflicting economic, social and biological objectives and are robust to uncertainty.

OPTIMAL HARVEST STRATEGIES UNDER UNCERTAINTY

Early work on optimal harvest strategies under uncertainty (e.g. Reed 1978, 1979) focused solely on uncertainty in growth of the fish stock and utilized highly stylized models with many simplifying assumptions to make the models tractable. As researchers built on this early work they began to relax some of these simplifying assumptions and consider other sources of uncertainty and the possibility of partial predictability of growth. A review of this research suggests limited generalizability of Reed's initial work; a variety of biological, economic and informational factors can alter the implications of uncertainty for optimal harvest strategy substantially.

Uncertain growth

Much of the economic and fishery science literatures on optimal harvest strategies under uncertainty build on the seminal work of Reed (1978, 1979). Reed introduces stochastic growth to a simple discrete-time model of the fishery where stock states follow a Markovian process. He assumes that the fish stock in the next period is a function of an "expected or average recruitment function" multiplied by an independently and identically distributed random variable, Z, with unit mean. The average stock-recruitment function is assumed to be concave exhibiting "normal compensation". Growth takes place after harvest, so future stock is a function of the escapement level. The per unit harvest cost is assumed to depend only upon the size of the prior stock level, not the quantity of harvest or effort. Output price is fixed, so the profit function is linear for a given stock level. Reed assumes that the stock at the beginning of the period is known with certainty, but because of a random growth shock, the future stock is uncertain. He concludes that the optimal policy is to allow a constant escapement every period, regardless of stock at the beginning of the period (provided the initial stock is larger than the desired escapement). Furthermore, where catchability is assumed to be either constant or decreasing in stock size, the optimal escapement level with stochastic growth is higher, and average harvest is lower, than the deterministic case with the difference increasing with the variance of Z.

Pindyck (1984) obtains quite different results from a continuous time model. He assumes that current resource stock is known with certainty, but that instantaneous change in the stock is (in part) random. Because stock growth function is concave, stochastic fluctuations in the stock reduce the expected rate of growth (an implication of Jensen's inequality). Because the cost function is convex in stock size, stochastic fluctuations in stock size increase expected extraction costs over time. Pindyck shows three impacts of growth uncertainty: (i) fluctuations reduce the value of the stock, and because variance increases with stock size, there is an incentive to reduce the stock size by harvesting faster; (ii) fluctuations increase expected harvest costs, also motivating faster extraction; and (iii) for a given extraction rate, fluctuations reduce the expected growth rate and hence the optimal extraction rate. The overall net effect of these three factors is indeterminate. Thus the optimal policy may be either more or less conservative than the deterministic case, depending on the strength of the opposing effects. However, when the growth function is skewed to the left (e.g. with a Gompertz growth function in place of the logistic) and price is elastic, an increase in variance is more likely to increase the optimal extraction rate. Pindyck attaches some important caveats to his conclusions: "If we do not observe current stock size with certainty at all times and observation is with error and lags, if changes in demand extraction lag and respond only slowly to price changes, the "second best" extraction policy may be more conservationist... particularly if a small amount of overharvesting when stock is low could result in a catastrophic collapse."

Partially Predictable future growth

Several studies consider cases where variation in future growth is at least partially predictable, due to serial correlation in productivity, e.g. in the case of cyclic patterns tied to climate cycles. Parma (1990) uses delay-difference model with stochastic Ricker recruitment function. She assumes multiplicative i.i.d. noise, but with a parameter defining the cyclically varying average recruitment rate. She further assumes fixed output price and zero harvest cost. While constant escapement is an optimal policy with stationary stochastic recruitment, Parma shows optimal escapement to vary in the presence of cyclic average recruitment. Optimal escapement is lower (i.e. optimal harvest rate higher) when recruitment conditions are poor, and higher when recruitment conditions are good. This tends to reinforce the cyclic variation in the stock and harvests, creating boom-bust cycles. Parma finds that the ability to forecast longer-term environmental trends has little value unless slow growth makes it infeasible to maintain optimal escapement levels.

Costello et al. (2001) extend Reed's (1979) analysis using a nearly identical model but assuming the manager has partial, but imperfect, information about future growth. Their findings closely parallel those of Parma (1990). Costello et al. allow price to vary stochastically, but assume it is not a function of quantity; costs are linear in harvest and vary only with stock size. Like Reed (1979), they therefore assume profit function is linear in harvest for a given stock size. Under these assumptions, Costello et al. conclude constant escapement is no longer optimal. Rather, harvest should be reduced (escapement increased) when expected growth in the future is higher than average, and increased when future expected growth is lower than average. Under their assumptions about cost and prices, it is only valuable to have information one year in advance.

Costello et al. (1998) develop a bioeconomic model of the Coho salmon fishery and derive the value of information from improved El Nino forecasting. They use a three cohort model with stochastic density-dependent survival and a Ricker recruitment function whose slope is a random variable determined by the El Nino phase. They assume exogenous price and constant marginal costs, but include fixed costs and non-malleable capital. Recreational consumer surplus is calculated based on benefit transfer and existence value, and hatchery costs are included. They find that a perfect El Nino forecast results in an annual welfare gain of approximately $1 million, while imperfect forecasts lead to smaller gains. Results also suggest that optimal management in the face of uncertainty involves a 'conservative' management strategy, with lower harvest, higher wild fish escapement, and lower hatchery releases than in the absence of such uncertainty. When expected future growth is lower because El Nino predicted, it is optimal to harvest more now (reduce escapement) and when future growth is higher, it is optimal to reduce harvest. The value of forecasts beyond one year is low so research money is better spent on increasing the accuracy of the one-year forecast.

Singh et al. (2006) develop a dynamic model which simultaneously incorporates random stock growth and costly capital adjustment. They calibrate the model to the Alaskan pacific halibut fishery. Their key assumptions include: logistic growth with random growth shocks following a Markov process (serially correlated shocks are also considered); downward sloping demand; a quadratic cost function; dynamic fleet size; and partially malleable capital investments. They show that increasing marginal costs and downward sloping demand cause smoothing relative to the optimal escapement policy with constant price and marginal cost. Under these assumptions they show it is optimal to build up the fleet when growth is good (with positive serial correlation), in anticipation of higher future catch levels, and decrease the fleet when growth is poor. The variability of the control and state variables is reduced under i.i.d. shocks relative to serially correlated shocks. For low and high stock sizes, the optimal harvest rate is lower than the best constant harvest rate – it is only slightly higher at intermediate stock levels.

Other sources of uncertainty

Clark and Kirkwood (1986) consider a similar model to Reed (1979), but assume the manager knows the escapement in the previous period but is uncertain about stock in the current period. Like Reed (1979), they assume stock in the subsequent period is a function of a concave average recruitment function that is multiplied by an i.i.d. random variable. Escapement is known with certainty at the end of each period (after the harvest decision), so stock in the next period is a random variable with known distribution and expected value. Clark and Kirkwood simplify the analysis by focusing solely on maximizing the discounted value of harvests over time, ignoring harvest costs and assuming a constant output price. By assuming that stock size is uncertain at the time of the harvest decision, Clark and Kirkwood obtain results that contradict Reed (1979); the constant escapement policy is shown to no longer be optimal. Furthermore, while optimal expected escapement is generally higher than under Reed's assumptions, for some moderately low expected recruitment levels optimal expected escapement is less conservative. The same is true for high expected recruitment levels when variance is also high. Clark and Kirkwood go on to show that the value (as a percentage of total value) of decreasing uncertainty about stock size at the time of the harvest decision can be high for cases with high variance in recruitment (e.g. providing as much as an 80% gain in value when variance is one).

Sethi et al. (2005) extend the work by Reed (1979) and Clark and Kirkwood (1986) by considering multiple forms of uncertainty, including random variability in growth or recruitment, inaccurate stock size estimates, and inaccurate implementation of harvest quotas. They develop a bioeconomic model with these three sources of uncertainty, and solve for optimal escapement based on measurements of stock abundance in a discrete-time model. In the absence of uncertainty, they find the optimal policy is a constant escapement bang-bang policy. The optimal policy does not differ greatly from constant escapement when uncertainty is small, or even for higher levels of uncertainty in growth and quota implementation. Inaccurate stock estimation affects policy in a fundamentally different way than other sources of uncertainty: While higher measurement error unambiguously lowers the level at which the fishery is shut down, optimal escapement changes ambiguously as a function of measured stock. Notably, Sethi et al. find that high uncertainty in stock size leads to a lower expected escapement level for intermediate to high measured stock levels, relative to the deterministic case or the case with only the other two forms of uncertainty. They also find that, with high uncertainty regarding stock size, the optimal policy reduces the probability of extinction relative to an optimal constant escapement policy. They find that the optimal policy can lead to significantly higher rents and lower extinction risk than the optimal constant escapement policy when there is uncertainty about stock size, but with uncertainty only in growth and in implementation, the gains from moving away from constant escapement are small.

Unstable equilibria, biomass shifts, and depensation

The analysis discussed above do not consider fisheries that are vulnerable to collapse at low population levels or dramatic shifts in productivity due to environmental change or predator-prey relationships. Spencer (1997) uses a surplus production model incorporating a varying nonlinear rate of predation. It yields multiple stable equilibria and, when forced with autocorrelated variability, can result in rapid flips in stock abundances between low and high equilibria. He finds the optimal policy requires conservative exploitation rates during poor environmental (low growth) conditions and heavier exploitation during good conditions. This is in direct contrast to the results of Costello et al. (2001) and Parma (1990). The result is driven by the possibility of the stock “flipping” to the lower equilibria; the optimal policy reduces the probability of that occurrence. The optimal policy provides more than twice the mean annual benefits of a constant harvest rate policy.

Johnston and Sutinen (2001) explore optimal management with an uncertain biomass shift that results in collapse of the target species and replacement by another species (either valuable or not). When the probability of the shift is unrelated to stock size, the optimal policy involves a higher exploitation rate. If the probability of the shift is affected by stock size, more conservative management is called for, but the existence of a valuable replacement species increases optimal exploitation.

Conclusions from review of optimal harvest strategy literature

The discussion above illustrates that general prescriptions for managing fisheries under uncertainty are limited. The optimal harvest strategy will depend on the specific types and relative magnitude of different types of uncertainty in combination with the biological and economic characteristics of a particular fishery. Simplifying assumptions about the biology or the economics structure of the fishery may substantially alter the optimal policy, and great care must be taken in prescribing policy based on these simplified models. Economic factors such as increasing marginal costs, inelastic demand and nonmalleable capital (which were assumed away in early analysis) tend to move the optimal policy away from fixed escapement toward harvest rate policies that smooth harvest over time. Predation and other factors that cause depensation may justify a risk averse approach to management.

Legal requirements in many countries (e.g. maximum exploitation rates, biomass limits and rebuilding requirements) may inhibit the ability of managers to follow economically optimal harvest policies. These constraints must be considered when determining the optimal policy. For example, the optimal escapement level for a constant escapement policy will be altered if there is a constraint on the exploitation rate when the population is observed to be at a high biomass. It may also be important to consider objectives in addition to profit maximization such as reducing biological risk or maintaining stable harvest levels. Industry tends to prefer more stable harvest over time: to maintain markets and avoid market gluts, plan investments in nonmalleable capital, because of risk aversion, etc. Perhaps for these reasons most fisheries are managed with constant harvest rate policies with decisions generally made on the basis of median model predictions. If harvest strategies are explicitly altered to account for uncertainty, it is typically an ad hoc approach of reducing the TAC from whatever would have been indicated by the target mortality rate if the assessment was certain.

A tailored modeling approach that accounts for specific biological and economic characteristics of the fishery, different sets of objectives and constraints (i.e. other than expected discounted or average rents over time), and various types and levels of uncertainty is likely to be more useful to fishery managers and stakeholders than results from more generic analysis. An approach known as Management strategy evaluation (MSE) which is described in the next section is explicitly designed to develop management strategies that are robust to uncertainty, though if is generally not oriented toward finding economically optimal strategies.

MANAGEMENT STRATEGY EVALUATION

MSE is a general methodology aimed at designing and testing decision rules that dictate how TACs or other management controls are set and adjusted. MSE is explicitly aimed at finding decision rules (heuristics for adjusting TACs or effort levels) that are robust to natural variation in the system as well as uncertainty and error in stock assessments. The goal is to assess the performance of different rules in balancing competing objectives, e.g.: low risk of overfishing; stability in TACs over time; and maximum catches or profits. Decision rules are contingent upon the values of a set of indicators from the fishery. Such indicators may be output from a formal stock assessment, or something simpler such as commercial CPUE. The decision rule may use a combination of indicators and could use results from a formal assessment only in some years (e.g. every second or third year). Managers and stakeholders agree a priori about the indicator data, the decision rules, and the period over which the rule will be used. This approach has several potential advantages over the traditional pattern of regular or periodic stock assessments, each followed by a decision process to determine the TAC. Harvest decision rules that are robust to uncertainty are identified; MSE uses a Monte Carlo approach, typically assuming the different sources of uncertainty and variation are uncorrelated; in this case 1000 realizations of each scenario are evaluated. The process leads to explicit definition of management objectives. All participants in the fishery can be involved in the choice of rule and a long-term view is fostered. Less frequent stock assessments may be needed; and the process appears more transparent and fair to fishers than the traditional approach.

The main advantage of MSE is its flexibility. The methodology allows for evaluation of complex biological systems, complicated management strategies and constraints, and multiple sources of uncertainty. For example, Holland et al. (2005) use an MSE framework to evaluate alternative management strategies for the Otago and Southland rock lobster fisheries in New Zealand. Their analysis combines a spatial, sex and length-structured simulation model of the fishery with an economic module that converts catches and effort into revenues and costs. Alternative decision rules for adjusting TACs are evaluated, as well as alternative spatial management strategies: separate quota management areas with either separate or jointly adjusted TACs, and amalgamation of the two areas into a single quota management area. The decisions rules tested all use standardized commercial CPUE as the primary indicator but adjust the TAC differently contingent upon the level and time trend of CPUE. In deference to stakeholders' preference for stable TACs, the rules do not allow TACs to be changed in sequential years. The framework employed by Holland et al. accommodates testing of complex decision rules for determining TACs in tandem with other important aspects of regulations (e.g. size limits, spatial management policies, and eliminating the requirement to release egg-bearing females). A variety of sources of uncertainty and natural variation are considered: error in the CPUE index as a measure of true abundance; variation in the frequency of molting; alternative assumptions about migration patterns and rates; alternative assumptions about the larval distribution process (e.g. sink-source dynamics); variation in larval survival and settlement; implementation or enforcement error (i.e., differences between the catch and TAC); and variation in prices by size, grade, and season.

Although the MSE in Holland et al. (2005) produces information about profits, variability of profits and expected quota value, these are not the only (or even primary) metrics of interest to stakeholders. In fact, stakeholders in this fishery agreed upon six primary management objectives (Bentley et al. 2003b): maximize catch; maintain high abundance (which reduces harvest costs); minimize frequency of catch adjustments; minimize risk of low biomass levels; maximize the rate of rebuilding; and maintain a wide range of lobster sizes (because market size preferences and the resulting pricing structure has been changeable in the past). The MSE evaluation produced information on the full distribution of potential outcomes (from the 1000 trials of each scenario) for a variety of metrics including the average and variability of TACs stock sizes, probability of stocks falling below critical thresholds, rebuilding time frames, etc. The distributional impacts of the alternative spatial management policies, particularly how quota values would be affected by amalgamating the two quota areas, proved to be of great interest to stakeholders when results were presented. The Monte Carlo framework produces a rich set of information on the full distribution of outcomes, but communicating the results can be difficult, particularly to stakeholders without scientific training. The tendency is to focus on mean or median behaviors of the system, but it is important to communicate the variation in outcomes and to identify decision rules with performance that is robust to that uncertainty.

For MSE, an operating model is used to generate ‘true’ ecosystem dynamics including the natural variation in the system (Figure 1). Data are sampled from the operating model to mimic fisheries and research surveys (and the noise associated with them), and then these data are passed to the assessment model. The assessment model estimates parameters such as indicators of current abundance. The assessment model may be a formal assessment model or a simple indicator such as a calculation of standardized CPUE – whatever will actually be used to feed into the decision rule. Based on this assessment and the decision rule, a management decision is made (e.g., annual or multi-year TACs). Fleet effort and catch are then modeled and fed into the operating model. By repeating this cycle we can simulate the full management cycle. We can test the effect of modifying any part of this cycle, including management decisions about TACs and possibly other measures, such as spatial closures. Alternative decision rules are tested and compared by running thousands of stochastic simulations each of several years to identify the performance of the rule based on multiple metrics under the range of conditions (both natural variation and noise in assessments) that is likely to occur. We then look for a decision rule that performs “well” under the range of conditions based on the pre-determined objectives and constraints. For example, we might be looking for a rule that leads to stock collapse less than X% of the simulation runs, has a low average variance in TACs over time, and a relatively high average catch and stock size. Choice of decision rule will generally involve a compromise between the various objectives.

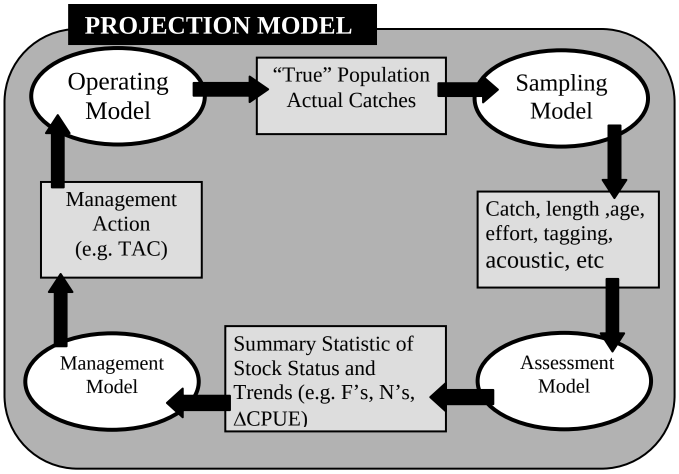

Figure 1: Typical Structure of an MSE Simulation Model

Typically a timeline is agreed upon for re-evaluation of the management procedure. For example it might be agreed to follow it for four years and then re-evaluate, unless it became clear it was not working correctly prior to that (e.g., anecdotal evidence from the fishery such as major decline in catch rates suggests something outside the range of expected events is occurring). The management procedure may also have a set of meta-rules that pre-specify actions in response to unexpected circumstances such as recruitment “failure” below levels predicted by the operating model, CPUE changes outside bounds of the operating model, substantial changes in biological parameters, outside impacts not accounted for in the model, etc.

There very few examples of MSE incorporating economics. A rare exception is Holland (2005) where mean and variance of profitability were included in the evaluation. However, there are many ways that economists can contribute to MSE: Modeling of implementation error should account for behavior of fishermen using economic models; MSE should include variation and uncertainty in economic variables and consider economic risk (e.g. loss of markets if fishery is closed); and MSE should build in profit or other welfare measures as a component of decision rule assessment.

CONCLUSIONS

Economically optimal harvest strategies can be affected by multiple types of uncertainty, information assumptions, and their interaction with environmental, biological, and economic characteristics of the fishery. The results of prior theoretical and empirical studies of optimal harvest under uncertainty are in part contradictory. Stakeholders may have multiple and conflicting objectives, and it may not be feasible or reasonable to combine them into a single objective function. Furthermore, legal mandates place limits on feasible policies. Approaches to dealing with uncertainty by fishery manages have generally been confined to putting confidence intervals around assessment predictions and choosing strategies that have some probability of meeting mortality or biomass objectives (usually 50%).

MSE is a flexible approach that allows for a balance between multiple objectives identifies harvest strategies robust to various types of uncertainty. Simulation can accommodate more realistic modeling of the fishery than dynamic optimization. The inclusion of economic models and metrics could substantially improve the MSE methodology. In particular, economists can contribute to MSE by modeling profits (net benefits) rather than just gross harvest levels and stock abundance; improve implementation by more realistically modeling the behavioral response of harvesters to regulations and incentives; and develop decision rules that create incentives for fisheries to provide information which will improve subsequent decisions.

REFERENCES

Bentley, N., Breen, P.A., Starr, P.J., and Sykes, D.R. 2003b. Development and evaluation of decision rules for management of New Zealand rock lobster fisheries. *New Zealand Fisheries Assessment Report* 2003/29.

Butterworth, D.S. and Punt, A.E. 1999. Experiences in the evaluation and implementation of management procedures. *ICES Journal of Marine Science* 56:985-988.

Clark C.W and G.P. Kirkwood 1986. On uncertain renewable resource stocks: optimal harvest policies and the value of stock surveys. *Journal of Environmental Economics and Management* 13:235–244.

Costello, C., R. Adams, and S. Polasky. 1998. The value of El Nino forecasts in the management of salmon: a stochastic dynamic assessment. *American Journal of Agricultural Economics* 80: 765-777.

Costello, C., S. Polasky, and A. Solow. 2001. Renewable resource management with environmental predictions. *Canadian Journal of Economics* 34(1): 196-211.

Holland, D.S., N. Bentley and P. Lallemand 2005. A Bioeconomic Analysis of Management Strategies for Rebuilding and Maintenance of the NSS Rock Lobster Stock in Southern New Zealand. *Canadian Journal of Fisheries and Aquatic Sciences* 62(7);1553-1569.

Johnston, R and J. Sutinen 1996. Uncertain biomass shift and collapse: Implications for harvest policy in the fishery. *Land Economics* 72(4):500-518.

Kirkwood, G.P. 1997. The revised management procedure of the international whaling commission. In *Global trends: fishery management.* Edited by E.K. Pikitch, D.D. Huppert, and M.P. Sissenwine. American Fisheries Society Symposium 20, Bethesda, Maryland: 91-99.

Parma, A. 1990. Optimal harvesting of fish populations with non-stationary stock-recruitment relationships. *Natural Resource Modeling* 4(1):39-76.

Punt, A.E. 2000. Extinction of marine renewable resources: a demographic analysis. *Pop. Ecol.* 42:19-28.

Reed, W.J. 1978. The steady state of a stochastic harvesting model. *Mathematical Bioscience* 41:273–307.

Reed, W.J. 1979. Optimal escapement levels in stochastic and deterministic harvesting models, *Journal of Environmental Economics and Management* 6:350–363.

Sethi, G., C. Costello, A. Fisher, M. Hanemann, and L. Karp. 2005. Fishery management under multiple uncertainty. *Journal of Environmental Economics and Management* 50(2):300-318.

Singh, R., Q. Weninger and M. Doyle 2006. Fisheries management with stock growth uncertainty and costly capital adjustment. *Journal of Environmental Economics and Management* 52(2):582-599

Smith, A.D.M., Sainsbury, K.J. and Stevens, R.A. 1999. Implementing effective fisheries management systems - management strategy evaluation and the Australian partnership approach. *ICES Journal of Marine Science* 56: 967-979

Spencer, P.D. 1997. Optimal harvesting of fish populations with nonlinear rates of predation and autocorrelated environmental variability. *Canadian Journal of Fisheries and Aquatic* 54: 59-74.