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OPTIMAL EXPLOITATION OF MULTIPLE STOCKS BY A COMMON FISHERY: A NEW METHODOLOGY

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Abstract

Optimal harvest rates for mixed stocks of fish are calculated using stochastic dynamic programming. This technique is shown to be superior to the best methods currently described in the literature. The Ricker stock recruitment curve is assumed for two stocks harvested by the same fishery. The optimal harvest rates are calculated as a function of the size of each stock, for a series of possible parameter values. The dynamic programming solution is similar to the fixed escapement policy only when the two stocks have similar Ricker parameters, or when the two stocks are of equal size. Normally, one should harvest harder than calculated from fixed escapement analysis.

Introduction

It is well recognized that many fisheries exploit more than one stock of fish: a stock may consist of separate species at various trophic levels, as in tropical fisheries, or genetically isolated races of the same species, as in Pacific salmon. The problem of optimal harvesting of these mixed fisheries is interesting because the biological understanding of the stock dynamics is frequently quite advanced relative to the methodological tools to determine the optimal harvest. Paulik et al. [7] have presented techniques for calculating the optimal harvest rate for fisheries consisting of up to twenty separate stocks. They use the basic Ricker equation of stock dynamics (Ricker [9] which assumes a deterministic relationship between spawning stock and resultant run. Their solution involves solving a set of equations iteratively by computer to arrive at the optimal exploitation rate.

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There are several weaknesses in their solution, which are due to the analytic intractability of the problem. The authors calculate only the optimal exploitation rate, assuming the population is at equilibrium. There is incredible variation in the actual stock recruitment relationships for salmon populations, and current management practice uses the concept of fixed escapement instead of fixed harvest rate. The fixed escapement policy recognizes that the long term yield is maximized by allowing a fixed number of adult salmon to reach the spawning grounds, irrespective of the number of salmon in the total run. When the stock is at high numbers it can be harvested at a higher rate than when it is at low numbers. Ricker [10] has calculated optimal escapement for several stock recruitment relationships using numerical methods. Paulik et al. calculated the total run and optimal exploitation rate of all stocks at equilibrium. To derive the escapement one multiplies total run times the exploitation rate. It is not clear, however, that a fixed escapement policy is optimal for mixed fisheries. It is shown later in this paper that the optimal escapement is not independent of the relative abundances of the different stocks. Specifically, if the fishery consists of two stocks, determination of the optimal exploitation rate, or escapement, will depend on the sizes of the two stocks. This is not just a theoretical possibility; data collection associated with current management of salmon provides reasonably accurate run estimates of stock sizes so that it is definitely possible to implement these policies.

Methods

Current methods for determination of optimal exploitation rates use simple analytic analysis of very simple stock recruitment models to determine optimal exploitation rates at equilibrium. Much more complicated computer simulation models have been used to study fish stock dynamics, (Larkin and Hourston [5]; Ward and Larkin [15])--but these models have not been used to determine optimal exploitation rates. It is possible to use more complex models to test very simple control laws; for instance, constant harvest or constant escapement. You simply have the same harvest taken every year and then calculate the average catch by simulating a large number of years. This method has been used to look at the role of stochastic variation on simple stock recruitment models (Ricker [10], Larkin and Hourston [5]). It is theoretically possible and computationally practical to do the same sort of analysis on very complex models (Peterman [8]). The main limitation is that the harvest policy must be the same every year. The harvest policy cannot be tied to the size of the various stocks except by fixing a total escapement. If we try to use a simulation approach for every possible combination of harvest rates as a function of stock sizes, the number of computations required rapidly exceeds the ability of modern digital computers. It is easy to understand that we wish to harvest harder when a stock is high than when it is low, as the fixed escapement policy automatically does for a single stock. But for a two-stock example, a fixed escapement policy does not differentiate between a case where two stocks are at moderate densities, and a case where one stock is very low and one is very high. The long term harvest can be increased by determining the harvest rate as a function of the stock sizes of both stocks, when harvesting a mixed stock.

A new methodology has recently been introduced to fisheries management (Walters [14] which eliminates the computational constraints and greatly widens the scope of optimization in fisheries. Walters used the technique of stochastic dynamic programming first developed by Bellman. (See Bellman [1]; Bellman and Dreyfus [2]; Bellman and Kalaba [3]. For other applications of dynamic programming to ecological problems, see Shoemaker [13], and Sancho [11].) For a good description of stochastic dynamic programming, see Walters [14]. Briefly, stochastic dynamic programming allows one to calculate optimal control policies by a procedure that involves the number of computations increasing linearly, instead of geometrically, with the number of time steps. It requires approximation due to discretization of the state variables (stock size) and the control policies (harvest rates). Walters used an example of a single salmon stock, discretized into thirty population levels, with thirty discretized exploitation rates and ten discrete stochastic possibilities. This requires running a simulation of the stock dynamics 9000 times per year. Using the simulation approach of following all possible paths into the future, say twenty years, this would have required 9000^{20} simulations, clearly beyond the scope of current computers. However, using stochastic dynamic programming, only 9000 x 20 simulations were required. This requires only a few seconds on a modern digital computer.

Stochastic dynamic programming has five main advantages over previous analytic techniques. They are:

1) The stock recruitment model can be as complex as desired; the number of parameters in the model does not affect the computation time required or the reliability of the results.

2) Parameters may be stochastic. However, as the number of stochastic possibilities considered for the parameter values increase, so does computation time.

3) There may be judgmental uncertainty about parametric values. This is analogous to the stochastic variability of parameters, but conceptually distinct.

4) The objective function (what is maximized) can be as complex as desired. It does not need to be

"long term catch"; it can be "dollar value of catch," "total employment generated from the fishery," or any combination of factors.

5) Discounting rates can be introduced into the model with no problem. The total objective does not need to be summed over time $[\Sigma(0_i)]$, but may be multiplicative $[\Pi(1 + 0_i)]$.

Although the number of computations goes up linearly with the number of time intervals, it goes up geometrically with the number of state variables and stochastic parameters. Thus we are practically restrained to optimizing models with on the order of five state variables.

I have chosen to use the standard Ricker stock recruitment model of salmon dynamics (Ricker [9]). Most will remember:

$$R = S \exp (\alpha(1 - \frac{S}{B})) \quad , \qquad (1)$$

where

R = the total number of offspring that will return as adults,

S = the number of spawners,

α = a parameter of productivity,

B = the number of spawners at which the average number of returning fish per spawner is one.

I have chosen this model because it has been used by almost all recent work on salmon stock dynamics, and particularly by Paulik et al. [7], and Walters [14]. This facilitates comparison of results. I used twenty discrete levels for each stock of eighteen discrete harvest rates, and ten stochastic outcomes. Although a Ricker model was used for the stock recruitment relationship, other commonly used models of fish stock recruitment such as the Beverton-Holt (Beverton and Holt [4]) or the Schaefer model (Schaefer [12]) could be substituted.

The state of a single stock at a time interval is described by a single number, the stock size. We can in theory deal with up to about five separate stocks without running into computational problems. However, it is difficult to present and understand the results of optimization with five state variables, so I have chosen to use just two stocks for demonstration purposes. If this technique were used in actual management; it could easily be used on mixed stocks of five separate stocks.

Results

Since the calculation of optimal control policies requires computations on a computer, no general solution can be presented. What I will do is present optimal control solutions for a series of possible parameter values for two stocks, and generalize from these results. From equation (1) we can see that the dynamics of each stock are governed by two parameters, α and B. For any two stocks, there are five unique relationships between parameters. They are:

1) α values are the same and B values are the same;

2) one stock has a higher α value, and B values are the same;

3) stock 1 has a lower α value, and stock 2 has a lower B value;

4) stock 1 has a lower α value and a lower B value;

5) the α values are the same, but one has a lower B value.

Stochastic dynamic programming calculates a control law (harvest rate) as a function of the state variables (the two run sizes). To present the control laws generated by the optimization procedure, I drew harvest rate isoclines on a grid with the run size of stock 1 on the X-axis and the run size of stock 2 on the Y-axis. Figure 1 presents the control laws for a case where stock 1 has an α value of 1.0 and a B value of 1.0. Stock 2 has an α value of 2.2 and a B value of 0.4. These parameters correspond to case 3 above.

The isoclines for harvest rates of 0, 0.3, 0.5, and 0.7 are drawn. Since stock 2, on the Y-axis, is more productive, there is a higher harvest rate for low values of stock 2 than there is for low values of stock 1. In order to compare these results with a constant escapement policy, we must utilize some simple relationships. We know that:

$$\text{Escapement} = (\text{Run of stock 1} + \text{Run of stock 2}) * (\text{Harvest rate}) \quad . \qquad (2)$$

From this we can calculate that

$$\text{Run of stock 2} = \frac{\text{Escapement}}{\text{Harvest Rate}} - \text{Run of stock 1} \; . \qquad (3)$$

This equation enables us to plot the harvest rate isoclines on the stock 1, stock 2 surface. It is also evident that all

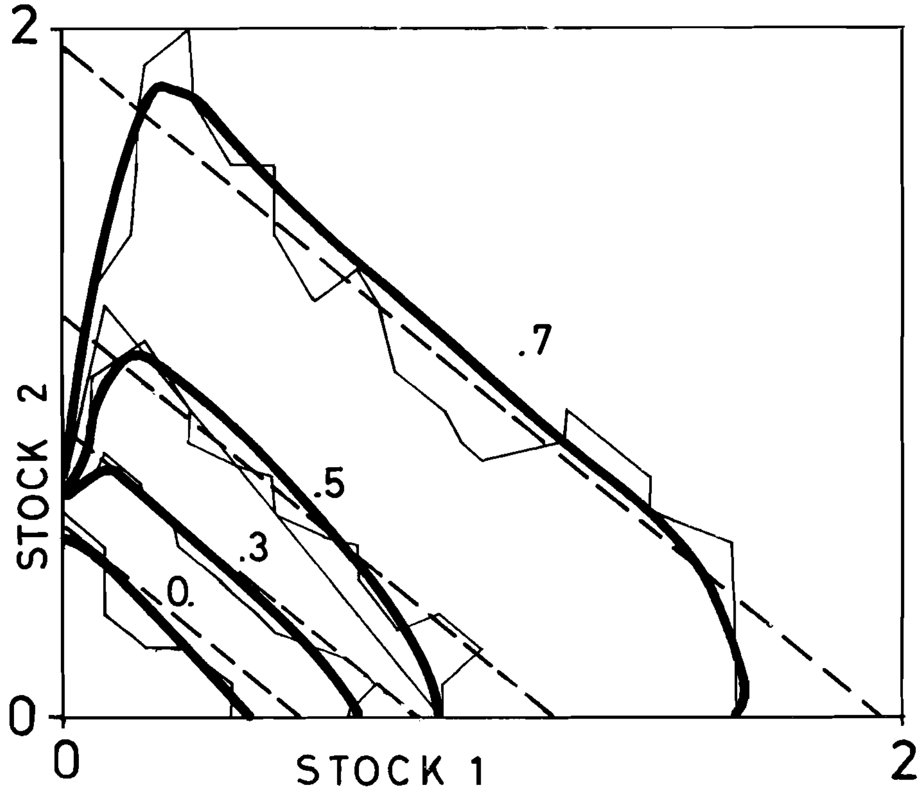

Figure 1. Harvest rate isoclines derived from dynamic programming (thick solid line) and fixed escapement (dashed line). α and B values are 1.0 and 1.0 for stock 1, and 2.2 and 1.0 for stock 2.

isoclines will have a slope of -1. This means that using a constant escapement policy, the optimal harvest rate lines will always be the same shape, independent of the parameters α and B. The harvest rate isoclines under a fixed escapement policy have been drawn as dashed lines in Fig. 1. It is obvious that the optimal solution from the dynamic programming algorithm is quite different from the fixed escapement law derived from Paulik et al. [7]. Figures 2 and 5 present similar plots for cases 1, 2, 4 and 5.

Discussion

From the results in Figures 1 - 5, it is clear that fixed escapement is the optimal policy only when the two stocks have the same α and B values (case 1). Thus, a fixed escapement policy for managing mixed stocks of salmon is optimal only under very restrictive circumstances. The results obtained above suggest that in general one should harvest a mixed stock harder when the ratio of the two stocks strays away from 1:1.

This suggests that as one stock becomes much more significant than the other, the management should proceed as if it were the only stock. It appears that the expected benefits from reducing the harvest rates when one stock becomes low are outweighed by the loss of catch from the reduced harvest. It must be stressed however, that these conclusions apply only for the objective function maximized: expected annual average yield. If other factors such as stock diversity were to be included in the objective function, the optimal control laws would undoubtedly change.

Stochastic dynamic programming appears to be the best current method for producing control laws for mixed stocks of fishes. The fact that the above examples were worked for Pacific salmon should not cause one to forget that the techniques used are completely generalizable to a very large class of fisheries and other ecological problems. The primary limitation is in the number of state variables, but for any renewable resource where some analog of a stock recruitment curve can be constructed, then a single variable, the stock, is sufficient to describe the population, and stochastic dynamic programming can be used. The main limitations occur when age/class phenomena become important, so that several numbers are required to describe a population. However, for almost all fisheries problems, a stock-recruitment relationship is the basis of present management, so using dynamic programming as an optimization technique would seem to be most appropriate. (See Parrish [6].)

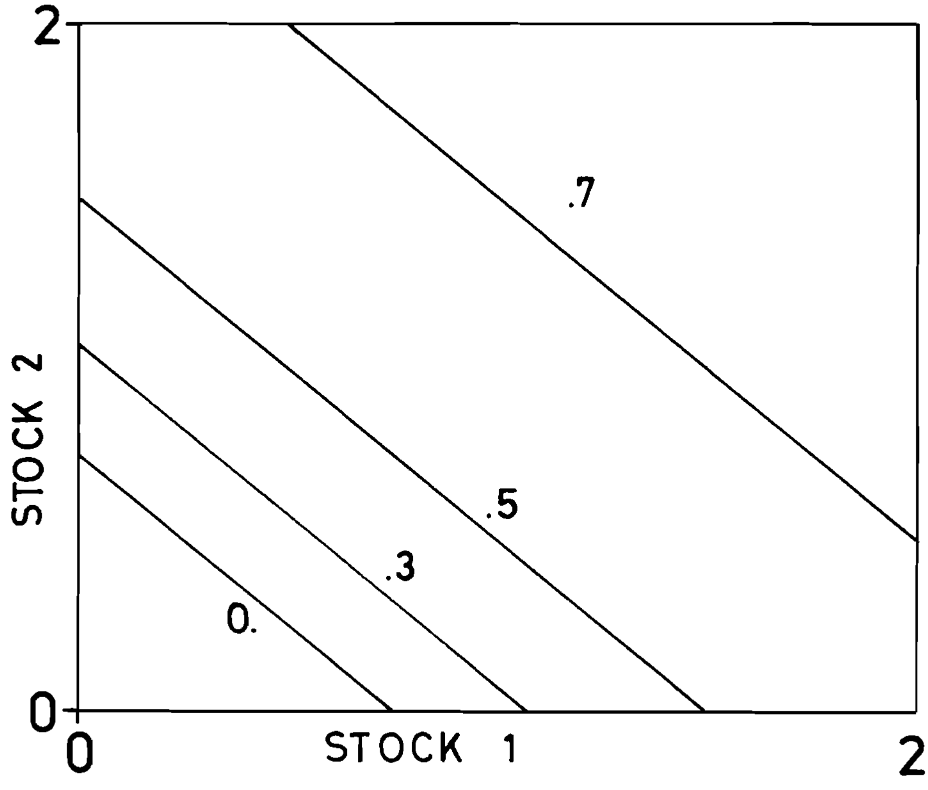

Figure 2. Harvest rate isoclines for case 1 in text. Solution from dynamic programming and fixed escapement are identical. α and B values for both stocks are 1.8 and 1.0.

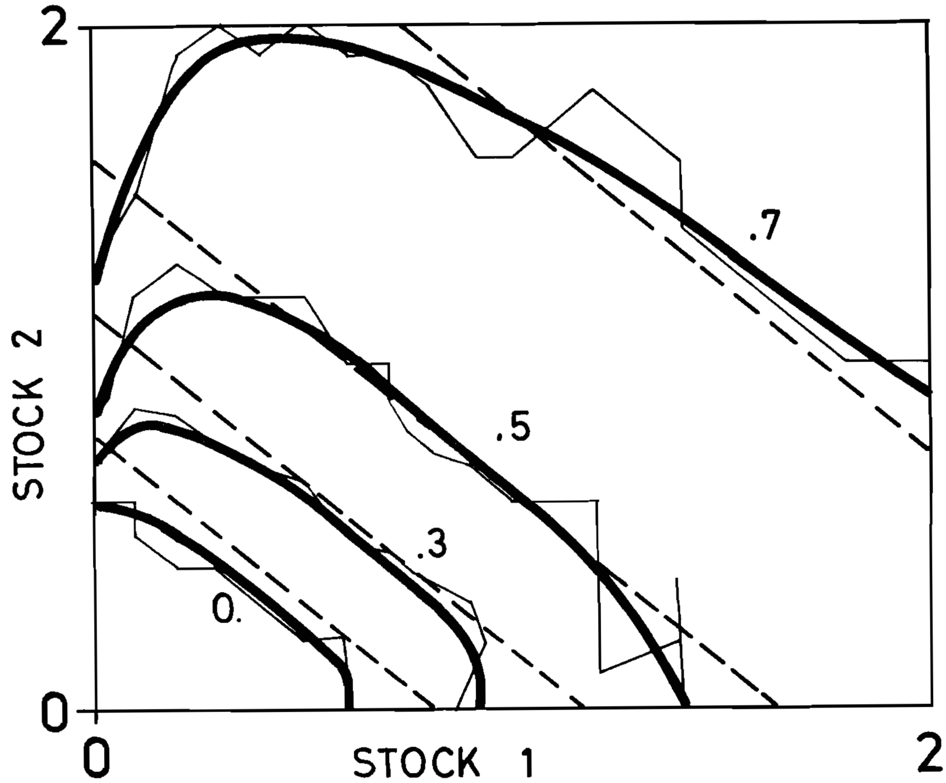

Figure 3. Harvest rate isoclines derived from dynamic programming (thick solid lines) and fixed escapement (dashed lines). α and B values are 1.0 and 1.0 for stock 1, and 2.2 and 1.0 for stock 2.

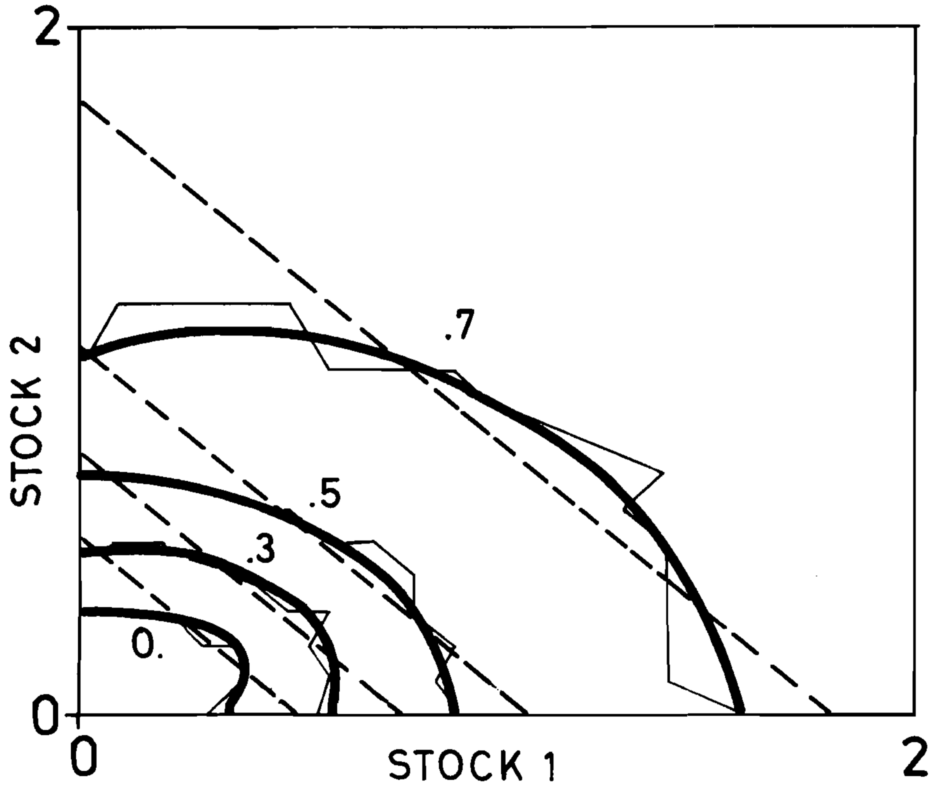

Figure 4. Harvest rate isoclines derived from dynamic programming (thick solid lines) and fixed escapement (dashed lines). α and B values are 1.0 and .4 for stock 1, and 2.2 and 1.0 for stock 2.

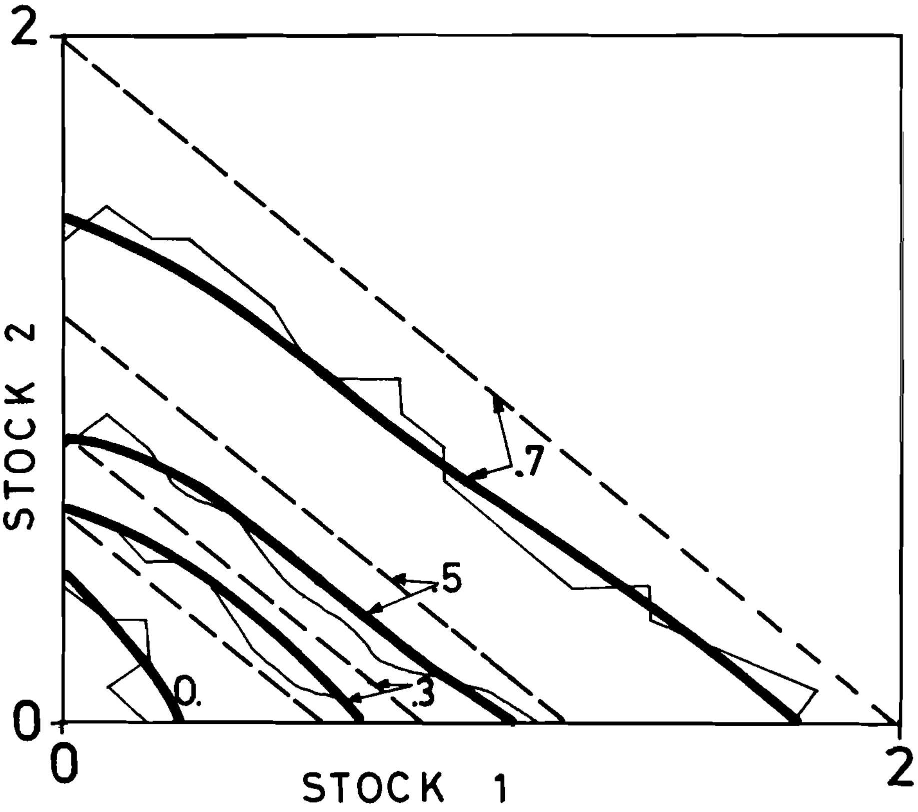

Figure 5. Harvest rate isoclines derived from dynamic programming (thick solid lines) and fixed escapement (dashed lines). α and B values are 1.8 and .4 for stock 1, and 1.8 and 1.0 for stock 2.

Table 1. α and B values used in optimizations.

Case No.	Stock 1		Stock 2	
	α	B	α	B
1	1.8	1.0	1.8	1.0
2	1.0	1.0	2.2	1.0
3	1.0	1.0	2.2	0.4
4	1.0	0.4	2.2	1.0
5	1.8	0.4	1.8	1.0

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