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International Institute
for
Applied Systems Analysis

PROCEEDINGS
OF
A WORKSHOP ON SALMON MANAGEMENT

February 24-28, 1975

Schloss Laxenburg
2361 Laxenburg
Austria

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TABLE OF CONTENTS

Hierarchic Decision Problems In The Management of Pacific Salmon

Proceedings of a workshop on salmon management held at the University of British Columbia, Vancouver, Canada

February 24-28, 1975

Introductory Comments

Research on the biological dynamics of salmon populations has progressed far in a number of countries, particularly Canada, Japan, USA, and the USSR. This research has provided the basis for modelling and systems analysis of salmon management in the Northeast Pacific Ocean. IIASA, the University of British Columbia, and Environment Canada have developed a cooperative study to systematically examine a single river basin, as a first step, in hopes of deriving from that case problem a general methodology for studying salmon and other commercial fish populations throughout the world. Until recently, our work had proceeded in isolation from other salmon research, especially the important studies in the Soviet Union. Soviet research has also led to models of the ecological systems of Pacific salmon in the Northwest Pacific Ocean.

It was decided to hold a workshop in Feburary 1975 to review the IIASA salmon studies and to bring in expert advice on future directions for study. The workshop was attended by a most stimulating mix of scientists and managers, representing several disciplines and institutions (see List of Participants).

The workshop was organized as a series of modules, each dealing with one level of the salmon management problem. Initial modules were directed at representation of salmon management as a hierarchic decision problem in relation to many potential uses of water resources. Other modules were concerned with modelling and optimization of biological production and with the organization of the fishing industry (economic production).

Recommendations

Many specific recommendations emerged from the discussions. They were both strategic (e.g., what problems should we study in the future at IIASA) and tactical (e.g., specific questions we should ask within our current framework). The recommendations are summarized below. They are grouped into several headings corresponding to the components of the problem as viewed by the participants. Within each subheading, all recommendations are given, and pertinent extracts of the discussion about that recommendation are included.

1. Trade-offs Between Resources

1.1 Further work at IIASA should stress only the trade-offs between components of the fishery; these are the gill net fishery, troll fishery, seine net fishery, and the recreational fishery.

It was concluded that more general problems of trade-offs between hydrodevelopment, forestry and fisheries were beyond the scope of the current study. Decisions about these trade-offs are rarely made explicitly and it would be difficult to define an actual client.

2. Production Strategies--Fleet Dynamics

2.1 Emphasis should be placed on relating production strategies to fleet dynamics.

There was much discussion of fishermen's preferences regarding distribution of catches. It was agreed that fishermen are a curious crowd and seem to prefer a high variability in catches. Current trends attempt to stabilize catches by increasing the mobility of the fleet.

2.1.1 The effect of fleet mobility on potential distribution in income should be closely examined. Can a highly mobile fleet maintain fairly stable catches? Are the runs up and down the West Coast correlated?

2.1.2 Would increased mobility destabilize individual stocks due to overexploitation in high years and under-exploitation in low years?

2.2 A proposed lottery system for fishing permits on a given river each year should be looked at in the context of the within season control model.

2.3 The within-season control model should be modified to represent daily rather than weekly control patterns.

3. Utilization of Separate Stocks

3.1 The effect of genetic variation between stocks or productivity should be examined.

Strong evidence from the Soviet Union shows great genetic differences between substocks. What implications does this have for potential productivity?

3.2 Some imaginative methods of separate stock utilization would be helpful.

4. Enhancement

4.1 A policy failure analysis for more realistic and complex enhancement programs should be carried out.

It was generally agreed that despite the simple model and objective functions used in the presented work, the technique was very useful and should be carried out for a set of proposed enhancement programs.

4.2 Using a number of different objective functions, a priority list of enhancement facilities should be constructed.

4.3 The irreversibility of decisions in enhancement should be closely examined.

Suggested objective functions are:

i) highest cost/benefit ratio,

ii) minimizing option foreclosure,

iii) maximizing the rate of information gained per each dollar spent on enhancement.

5. International Negotiations

5.1 It was agreed that the problems of international utilization of salmon stocks were currently political and that we could contribute little.

There were two major questions about the relationship between the IIASA work and the international salmon negotiations: 1) could we make any new recommendations? and 2) would the negotiating teams listen to us? We agreed that the consensus was generally no.

Conclusions

Our central overriding conclusion is that there is a strong need for international coordination of fisheries systems analysis work in order to develop a common data base and set of methodologies for rational exploitation of all Pacific salmon populations. Many countries are working on similar biological models and optimization techniques, but there are subjects to which each country can make unique contributions:

witness the Soviet work on population genetics. IIASA can provide an ideal base from which to develop cooperative studies by stimulating contact between key scientists.

The research team presently at IIASA should pursue four major research directions during 1975. First, we should develop more general models for biological production of salmon; these models should be useful for regions within each of the nations with salmon resources, and should be used to indicate the biological production potential of salmon populations. Second, we should examine the biological and economic impacts of salmon enhancement approaches developed in North America as well as transplant efforts with other fish as carried out by Soviet investigators. The general problem of sequential decision making, taking into account the risks due to unknown biological interactions, is an important element of these approaches. Third, we should try to design alternative systems for economic organization of the nonsocialist fishing fleets, so as to make it possible to more closely approach optimum biological management. Finally, we should develop a coherent conceptual framework of indicators for measuring the social, economic, and biological impacts of enhancement and industrial reorganization.

Our cooperating institutions, especially Environment Canada, UBC, and institutes within the Soviet Union, should provide additional data and theoretical anlyses in relation to the four areas outlined above. It would be especially valuable to exchange long run population data (available for systems like the Skeena and Dalnee) with Soviet scientists for comparison of modelling approaches as applied to the same data sets. For the Canadian enhancement and industrial reorganization studies, we will need long run population and catch data for all the major river systems of B.C.; these data should be made available to Soviet modellers.

APPENDIX A

List of Participants

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Institute of Animal Resource Ecology University of British Columbia Vancouver 8, B.C. Canada	- C.S. Holling - Randall M. Peterman - Peter A. Larkin - N.J. Wilimovsky - Nick Sontag - Art Tautz - Pille Bunnell
University of British Columbia (other departments)	- Colin Clark, Mathematics - Martin Puterman, Management Science - Peter Pearce, Economics

APPENDIX B

Papers Presented

The Salmon Case Study: An Overview

Carl J. Walters

This paper is intended as a general perspective on the Salmon Case Study for 1974-75. We review the reasons for choosing the case, indicate how salmon management policy has evolved to the present day, and describe the several research strategies that we are following in attempting to generate alternative policies for the future. We hope that the framework outlined here will prove more generally applicable to problems of renewable resource management.

Rationale

The case study is centered on a single river basin, the Skeena System in central British Columbia. This system is one of about a dozen major salmon producing rivers around the rim of the Pacific Ocean from Japan to California. Salmon are born in the river, then go to sea for one to three years. At sea they may be exploited by an international mix of fishing fleets, but most of the harvest occurs near the river mouth when the adult fish return to spawn and die. Because they have an orderly life cycle, a concentrated period of harvest, and because population size can be easily determined, salmon are considered the most manageable of the large world fisheries. Many fundamental concepts of fishery management (stock-recruitment relationships, economics of exploitation, etc.) have stemmed largely from studies on salmon.

We had five basic reasons for choosing the Skeena River as a case study:

1) Our results should be generalizable to other fisheries around the world, and perhaps to other renewable resources.

2) Our results might have real benefits to people; the Skeena Fishery employs over 1000 men, representing a gross income of several million dollars per year.

3) There is an extraordinary history of data on the ecological dynamics of the system.

4) There is a solid history of data on actual management performance in the absence of systems analysis.

5) Perhaps most important, there is a clearly defined client for our results; we have a good working relationship with Environment Canada, the primary agency responsible for salmon management in British Columbia.

Historical Background

Figure 1 shows historical changes in the two major salmon populations of the Skeena River. Prior to 1950 there was essentially no management, and the system was evolving toward a predator-prey equilibrium between the fishing fleets and the salmon stocks. Fearing that

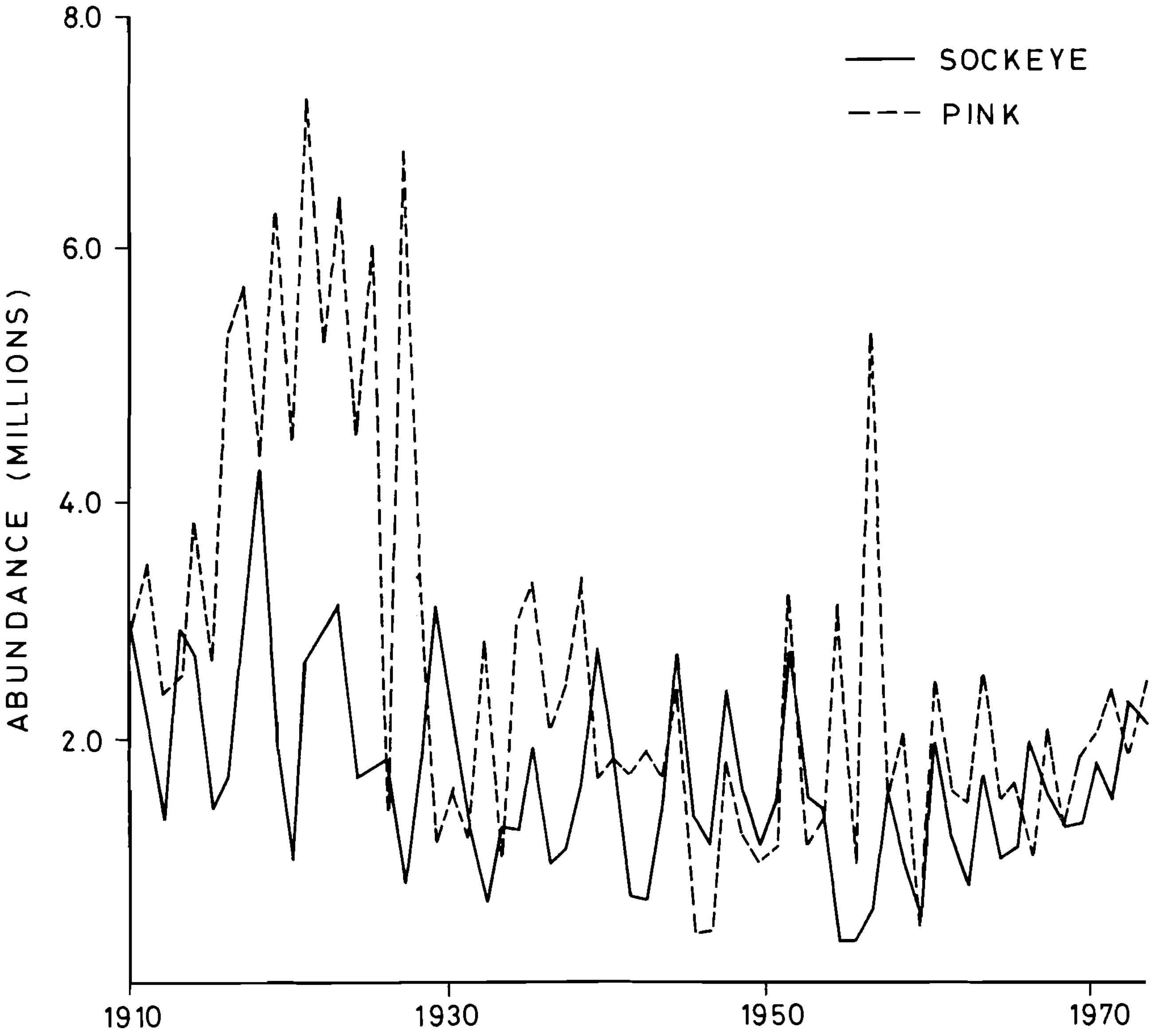

Figure 1. Historical changes in Skeena River salmon populations.

the stocks might be driven to extinction, the Canadian government began instituting catch regulations in the early 1950's. Other nations (particularly Japan) were excluded from the fishery by international agreement (the so-called abstention arrangements) during this period.

Stock sizes began to recover after the mid 1950's, but a disastrous economic situation had arisen by 1970: investment in the fishery was not controlled, so a larger and larger fleet was forced to share the same catch. Beginning in 1970 a program of license limitation was initiated to dramatically reduce the fleet size and presumably make the industry more economically efficient.

Around 1970 it was realized that maximum average catches were likely to result from a "fixed escapement" policy, in which the same number of fish are allowed to spawn each year. This policy was adopted and forms the basis for present management.

British Columbia is in a period of rapid economic growth, so recent years have seen considerable pressure for development of the Skeena Watershed. Several hydroelectric dams have been proposed, and it is likely that there will be urban and industrial development near the river mouth. Thus Environment Canada is having to face a much broader set of issues and institutions (Table 1). So far, the policy has been to completely oppose any watershed development that might influence salmon pop-

Table 1. Institutions and issues in salmon management.

ELEMENTS OF THE SALMON STUDY

CONFLICTING OBJECTIVES

PROBLEM LEVELS

KEY INSTITUTIONS	I SALMON INTRASEASON TACTICS	II SALMON LONG RANGE STRATEGIES	III RIVER BASIN AND REGIONAL MANAGEMENT
INTERNATIONAL: SALMON COMMISSION	Equity in distribution of catches among national fleets	Sustained yields	Maintenance of salmon habitats
FEDERAL: ENVIRONMENT CANADA	Meeting long range targets, equity among users, economic efficiency	Sustained yields, mix of species stocks, enhancement systems	Maintenance of salmon habitats
PROVINCIAL: RESOURCE SECRETARIAT	Opportunities for recreational users	Equity for recreational users	Recreational fisheries and wildlife, forestry
PROVINCIAL: B.C. HYDRO	Short term profits and employment	Stable economic returns and employment	Regional mix of resource industries, induced economic development
INDUSTRY AND ECONOMIC DEVELOPMENT AGENCIES	Short term profits and employment	Stable economic returns and employment	Regional mix of resource industries, induced economic development

ulations; this unyielding attitude will almost certainly have to change in the next few decades, especially in relation to urban and industrial development.

Framework for Analysis

There is no single problem about salmon to which we can direct appropriate systems techniques. Our case study instead deals with a hierarchic set of decision problems, as shown in Figure 2. We assume that broad decisions about regional resource allocation will establish a (time varying) potential for salmon production. Within this potential, there are some basic strategy options for dealing with the enormous stochastic variation in production from year to year (Figure 1). Given a production strategy, there are several options for distribution (utilization) of the catch, ranging from no control (open entry "commons" fishery) to a complete government monopoly where the entire catch is taken by a single large trap. The production and utilization strategies that we may suggest are of no value unless we can show that these strategies can actually be implemented; thus we are examining several possible implementation tactics. Finally, we are concerned with mechanisms to translate the variable catch stream produced by management actions into a more stable and predictable income stream for the fishermen.

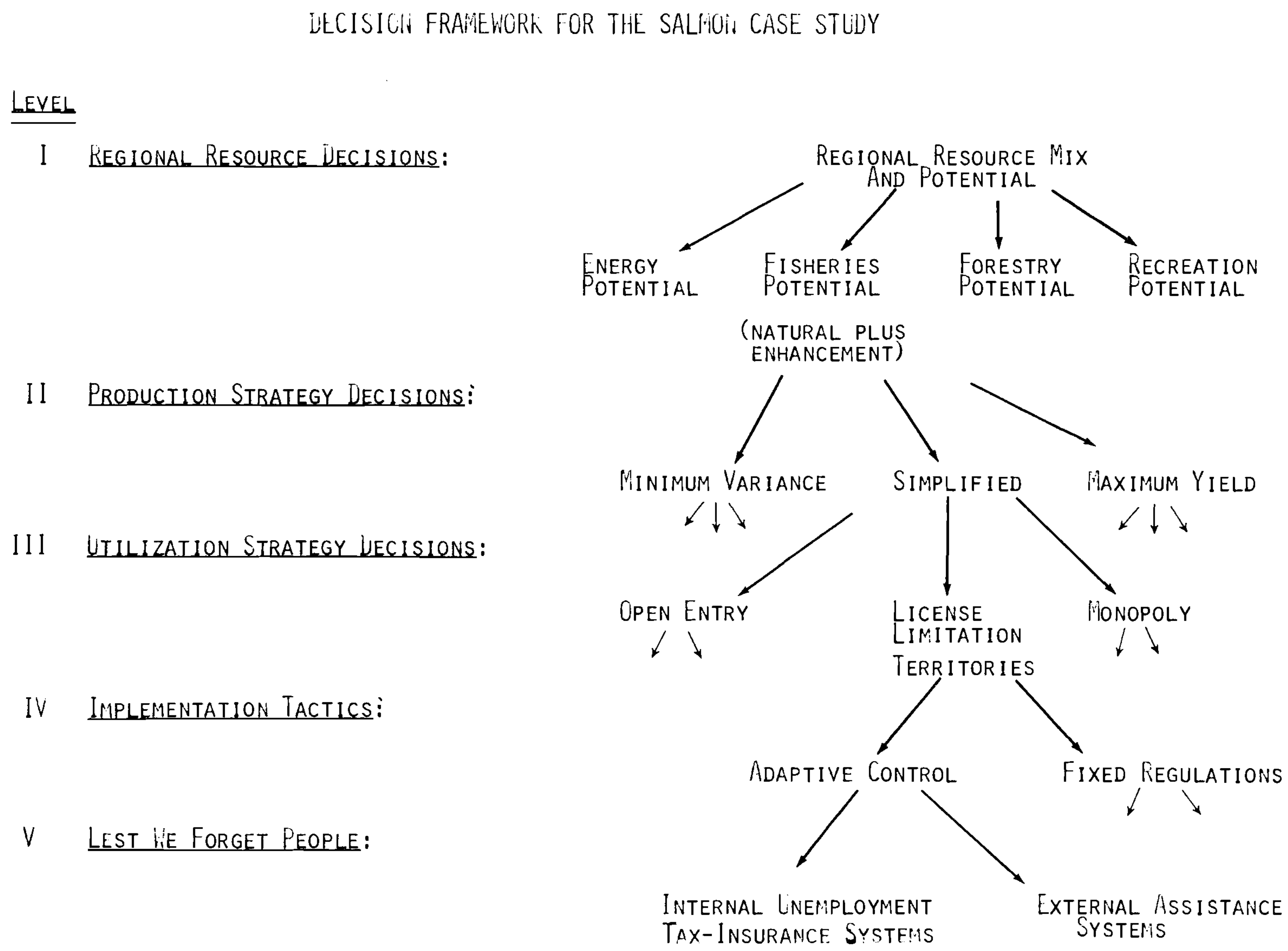

Figure 2. Salmon management seen as hierarchy of decision problems.

We are attempting to analyze the decision system of Figure 2 in two steps. First, we are doing a series of simple optimizations across options at each decision level, assuming an optimal input pattern from the higher levels and perfect control at the lower levels. This first step should allow us to discard some options that are clearly inferior under most objective functions. Second, we are trying to evaluate a sample of the more promising overall options (combinations of options from all five levels) for changes in optima that might result from policy failure, imperfect control at the various levels, or changes in objective functions. This second step is essentially a simulation exercise.

Analytical Procedures

This section gives an overview of the decision options and analytical procedures we are using for each decision level in Figure 2. Each analysis described here is intended to provide a different perspective for decision makers; we feel that a variety of perspectives should be useful even if no single coherent decision framework can be developed.

Level I: Regional Resource Decisions

In cooperation with Environment Canada, the British Columbia Resources Secretariat (forestry, recreational fisheries and wildlife), and B.C. Hydro (energy), we have developed a large scale simulation model for the Skeena System. This model is designed to examine long range (thirty-fifty year) patterns of watershed development, and it consists of five basic components:

1) A synthetic hydrology submodel to generate runoff patterns (monthly) across the watershed.
2) A hydroelectric dam submodel that can accept alternative siting, construction timing, and operating decisions, and can produce regulated storage and water flow patterns for any runoff input sequence.
3) A water quality submodel to simulate transport and degradation of pollutants, particularly silt (associated with hydro dam construction and forestry).
4) A population dynamics submodel for the major salmon and steelhead subpopulations (there are nineteen of these) that use various parts of the watershed; population changes and yields are represented as a function of harvesting policy, water flow, water quality, access to spawning areas (as affected by dams and forestry operations), and enhancement policy (hatcheries, spawning channels, etc.)
5) A recreational fishing submodel to predict recreational demand and catches in relation to

fishing quality and to alternative regional population growth patterns (as might arise from different economic development policies).

This model can accept a bewildering variety of development policies and tactical options (e.g. fishways to allow salmon passage around dams); so far we have used it only in a gaming format with the cooperating agencies to get a broad picture of potential development impacts on salmon. Our results suggest that there are only a few hydroelectric development options which would seriously affect the salmon, and these options have low priority with B.C. Hydro. Clearly we need a more systematic procedure for identifying, testing, and evaluating the various broad options.

Level II: Production Strategy Decisions

The regional resource modelling should provide alternative operating contexts for salmon production, expressed in terms of potential stock productivities and equilibrium stock sizes (carrying capacities) over time. For any context, we can use stochastic dynamic programming to derive optimal control laws for salmon harvesting. These control laws should specify optimal harvest rate (proportion of fish caught each year) as a function of stock size, for a variety of possible objective functions.

We have developed such optimal control solutions under the assumption that watershed conditions will not change, for objective functions emphasizing trade-offs between mean and variability of catches, and for different enhancement options.[1] These solutions take account of the enormous stochastic variation that has been observed in salmon production; they should also be close to optimal for management response to occasional human disturbances (such as dam construction, pulses of toxic mine waste, etc.) which do not have a persistent effect on watershed condition but may cause dramatic stock collapse for a few years.

Level III: Utilization Strategy Decisions

Table 2 shows a spectrum of options for organization of the fishing industry, and a qualitative rating of these options for several benefit indicators. Our plan is to develop this options-indicators table much more fully, substituting a more comprehensive and qualitative set of indicators. Some of these indicators can be readily computed from historical data; others can be developed by making very long stochastic simulations using catch distributions generated in the Level II analysis.

We expect that a small set of dominant options will emerge from the spectrum in Table 2. This smaller set can be examined in relation to a restricted set of indicators, using multi-attribute utility theory. Rather than specify a single best option, we would prefer to

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[1] C.J. Walters, internal paper, 1975. R. Hilborn, internal paper, 1975.

Table 2. Strategic and tactical options for organization of the salmon fishery.

Strategies	Tactical Options	Annual Management Effort	Employment	Profits	Catch	Probability of Policy Failure	Immediate Social Change
OPEN ENTRY	*No catch control	none	high	O-very low	low	highest	+
	*Fixed season catch control	low	high	O-very low	medium	high	+
	*Adaptive catch control	medium-high	high	O-very low	high	low-medium	+
	*tax-insurance control	low	high	O-very low	medium	high	+
RESTRICTED ENTRY	*No catch control	very low	medium-high	high	high	high	+
	*Fixed season catch control	low	medium	high	high	medium	O
	*Adaptive catch control	medium-high	medium	high	very high	low	O
	*Fishing territories	low	medium-low	high	high	low	-
MONOPOLY TRAP SYSTEM	*Fixed season	high	low	very high	very high	low	-
	*Adaptive catch control	very high	low	very high	very high	none	-

identify ranges of indicator weightings for which each option would be optimal (inverse objective function analysis). From preliminary analyses, the most promising options appear to be:

1) Open entry with taxation to limit investment and provide insurance against disasters.
2) Restricted entry with licenses valid only in specified fishing territories.
3) Monopoly trap system, doing away entirely with the fishing fleet.

Present management is close to option 2; evaluation of option 1 will require us to develop a good dynamic model for investment and disinvestment in the fishing fleet ("population dynamics" of the fishermen).

Level IV: Implementation Tactics

The analyses at Levels II and III can provide idealized targets for management, but they will remain academic exercises unless we can demonstrate practical ways to implement them. The biggest practical difficulties occur within each fishing season, when regulations are modified from week to week as catches accumulate and stock size forecasts are revised. At present the key control variable is the number of days open for fishing each week, though there is some regulation of the type of fishing gear (size and type of nets). Though there is license limitation, fishing effort can change dramatically from week to week; fishermen are free to decide when to go out, and whole fleets can move from one river system to another.

A few of the strategies at Level III call for the elimination of within-season regulation of total catch, but in all cases it will be necessary to have mechanisms for distributing the catch across the fishing season; processing (packing and cannery) facilities are limited, and there is risk of genetic damage to the stocks if the fish running at any time receive much heavier exploitation than the fish running at other times.

There are two extreme options:

1) An elaborate adaptive control system involving statistical run and effort forecasts, close monitoring of catches and escapements, and weekly modification of regulations.

2) A simpler and less costly fixed regulation system in which preseason stock forecasts are used to set a schedule of weekly regulations that is not modified during the fishing season.

Figure 3 shows one possible structure for an adaptive control system; we have completed most of the data analysis necessary to fill in the functional components of this system. Using the data and relationships developed for adaptive control, it is a simple matter to design reasonable rules for establishing fixed regulations.

We can test alternative regulatory options by

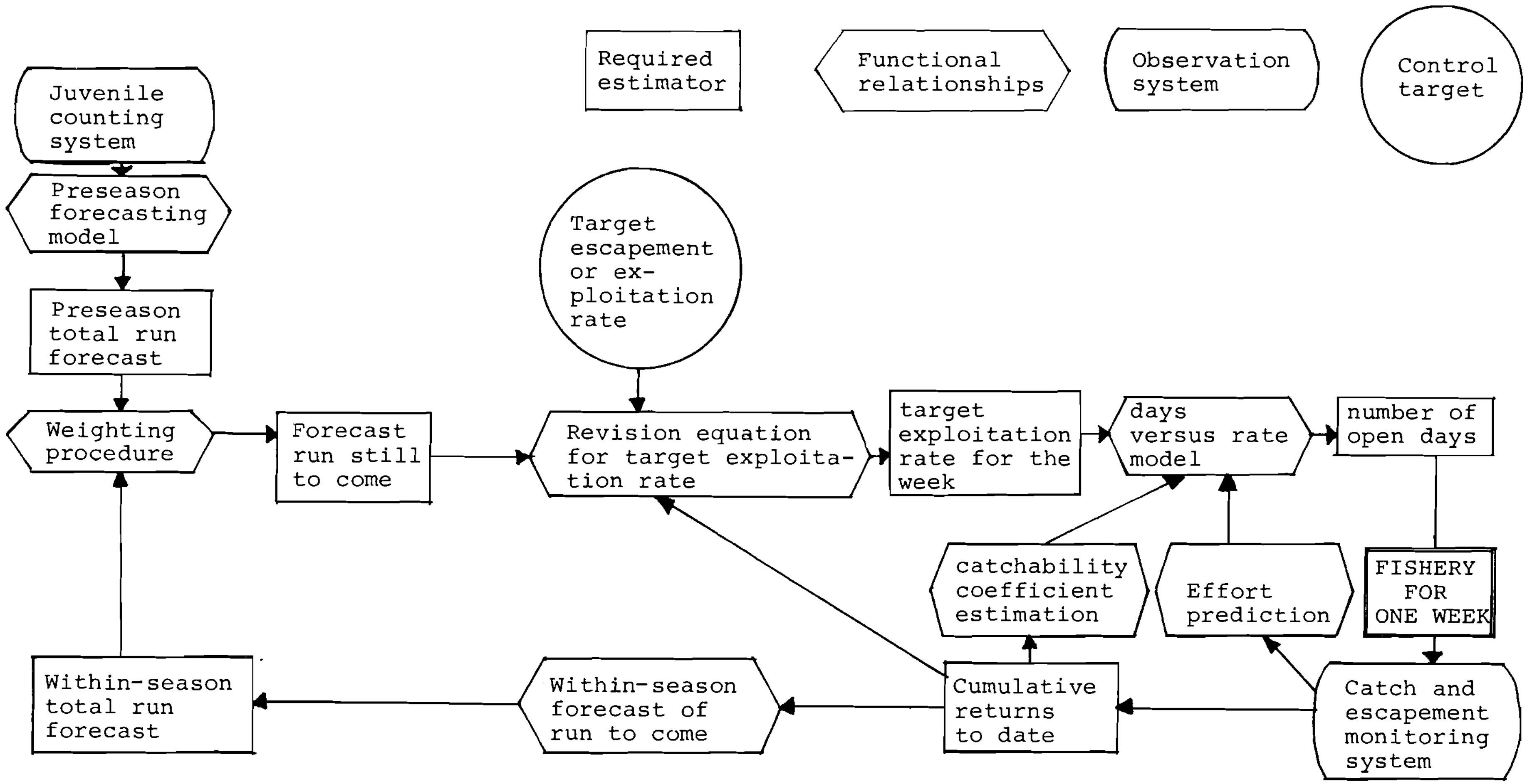
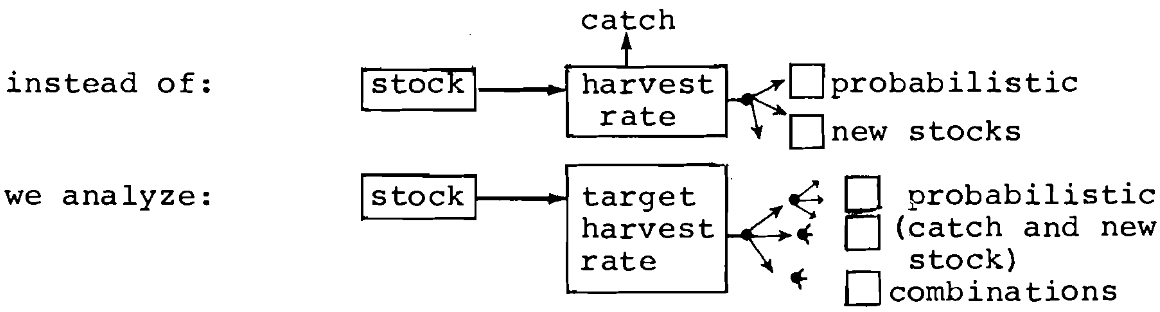


Figure 3. A control system structure for within-season salmon management.

stochastic simulation. Adequate data are available to establish bounds and probabilities for the variety of input situations (forecast errors, changes in timing of fish movements, changes in fishing power per unit of effort) which any control system is likely to face in practice. By computerizing the control system and feeding it a stochastic stream of input situations, we should be able to establish probability distributions for deviations from target catches. These probability distributions can then be used as input for simulation and optimization modelling at decision Levels II and III. For example, we can do the stochastic dynamic programming for optimum harvest rates (Level II) with an extra set of stochastic possibilities:



Level V: Lest We Forget People

Some management choices at decision Levels II, III, and IV might produce good overall biological or economic returns yet be unacceptable or extremely harsh for the individual fisherman. Certainly the maximum yield, fixed escapement production policies are of this type: they result in the highest average catches, but also the greatest year-to-year variation in catches. Under current policy, fishermen will be forced to use existing federal and provincial unemployment insurance programs when no catches are allowed.

An alternative to current policy would be to internalize the unemployment insurance system, by taxing catches in the good years and feeding this money back to the fishermen in the bad years. The simplest system would be to allow each fishing boat to choose a minimum guaranteed income level, then impose a proportional tax on income above this level. Simulation and dynamic programming can be used to estimate the necessary tax rate for any desired minimum income level in conjunction with each possible management strategy from Levels II and III.

An added benefit from some sort of tax-insurance system would be to give Environment Canada more flexibility in choosing basic harvest strategies. Under existing policy, it would probably be politically disastrous to shut down the Skeena fishery for even one year; any proposal of that sort would almost certainly be turned down by the Environment minister.

Coping With The Unexpected: Policy Resilience Analysis

For each of the five decision levels in Figure 2, our analyses are explicitly directed at stochastic variability. However, it would be foolish to assume that we have thought of every possible source of variability and uncertainty, or that there will never be even more extreme conditions than we have detected and represented from historical data. It is easy to list a few of the possibilities:

1) A new source of pollution in the watershed could decimate stocks before it could be detected and controlled.
2) The international treaty system could fail, resulting in overexploitation by high seas fishing.
3) Disease organisms, algae blooms, or some other agent could wipe out enhancement production (at least for a few years).
4) Several drought or flood years could occur in sequence, with especially disastrous effects on pink salmon.
5) An economic depression could drastically lower the value of catches, and stimulate the government to invest in other resource developments (e.g. hydroelectric dams).

The possibilities are almost endless, but the key point is that something bad is bound to happen, and policy combinations with poor performance in the face of the unexpected should be identified and avoided. For example it would be foolish to allow the development of a very large fishing fleet completely dependent on enhancement (hatchery) production; should any production failure occur, this fleet would become a serious economic burden (witness the Peruvian anchovetta fishery).

A new technique developed by Holling and Hilborn may help us to identify such dangerous policies. The technique involves computation of a "resilience number" or indicator for each policy. This number is a measure of the persistence and seriousness of undesirable states that may arise if the policy fails. That is, it is a measure of the resilience of the managed system to bounce back (recover) after a policy failure.

The hope is that we will be able to identify resilient policy combinations that are nearly as productive as the best of the unsafe options. This is not likely; usually the most productive or profitable policies are also the most risky. We are not in a position to judge and weigh the risk aversions of the various interest groups involved in salmon management; these are political problems. Our task then will be to present the production-risk trade-off so that it can be clearly understood by decision makers.

Foreclosure of Options in Sequential Resource Development Decisions

Carl J. Walters

Resource development decisions are often viewed as isolated, incremental problems involving a choice among a series of alternatives at one point in time. Each alternative may be defined by a single investment option, or it may involve closed (feedback) or open loop (fixed) decision rules for future times. But generally the idea is to view the future only in terms of present state and projected (often probabilistic) future events. Recommendations as to best alternatives are usually accompanied by a cautionary comment that future decision analyses (usually by different decision makers) should be made to keep abreast of changing information and goals.

Too often we play down that simple fact that decisions today may foreclose some of our options for tomorrow; large capital investments commit us to policies that try to recover sunk costs, hydroelectric dams permanently destroy landscapes, insecticide spraying leads to explosive preoutbreak conditions, and so forth. We try to represent these problems in the usual decision analysis through introduction of concepts like option value, discounting rate, and "resilience of environmental capital," but these concepts are meaningful only if we can make reasonable probabilistic predictions about the future. Far too often the sad experience has been that our "reasonable predictions" (usually trend projections) are worthless: we almost always omit some key functional relationship, trends have nasty habits of suddenly reversing themselves, and human values can change at an alarming rate (witness the "environmental crisis").

The problem would not be so serious if we could simply ignore or erase each mistake, admit our errors, and start afresh. Nor would it be so serious if each irreversible error were no more damaging than any other (that is, if we really had the economist's unlimited world of possibilities). But the world does not appear to be that way: I hope to demonstrate in this paper that the usual decision making procedures can lead to sequences of situations where each mistake is likely to be more serious than the last.

It is clear that we need a better understanding of the process of option foreclosure (of getting locked in) as it occurs in sequences of decision analyses. We need to find measures of option loss that reflect the possibilities rather than just the identifiable probabilities of policy failure. Hopefully by recognizing and being honest about the foreclosure process as a special kind of decision problem, we can begin to design decision making strategies that move away from the myopia of present planning procedures.

Some Concrete Examples

Before examining some general empirical properties of foreclosing decision sequences, I attempt in this section to clarify the problem with case examples. My intent is to make clear that the problem is not just a matter of nonrenewable resources or irreversible physical changes; that issue has long been of major concern in economics. Nor am I simply concerned about the obvious fact that human values may be impossible to clearly assess and can change unexpectedly, so decisions now may prevent fulfillment of alternative goals later.

The James Bay Development

Canada recently embarked on the largest single resource development project of its history, a hydroelectric power system in the James Bay area of Northern Quebec. The project was largely sold originally on the basis of expected secondary benefits: it was to provide 100,000 jobs for at least two decades. After construction work had begun, some major problems became apparent. First, the employment projection was a bit optimistic; the project will only employ about 12,000 men. Second, there will be rather severe environmental damage. Third, the local Indian culture (1,200 people) will probably be disrupted due to loss of hunting, fishing, and trapping opportunities. The James Bay Corporation and the Quebec government now admit that the project perhaps should never have been started, but they argue that too much money and effort has already been invested for the project to simply be dropped. A serious proposal now is to develop a uranium enrichment industry in the area to make use of the power. The power was to be mostly exported in the first place, but Canada recently has been having second thoughts about exporting electrical energy. Further, Canada's nuclear development is largely based on the Candu heavy water system which does not use enriched fuel (and therefore has much lower energy requirements for fuel processing). The enriched fuel will presumably be exported, resulting in more rapid depletion of future Candu fuel supplies and competition for international sales of Candu systems. The latest proposal by the James Bay Developers is that Canada should switch its own reactors from the Candu system to enriched fuel systems.

The Tallahassee River

Until a few years ago, the US Corps of Engineers had been spending around one million dollars per year on dredging and cleaning operations for the estuary of the Tallahassee River (2000-5000 cfs). Seeing a growing demand for estuarine development (boat basins, domestic and industrial pollution), they decided to divert another river into the system, in order to increase the flow to 40,000 cfs and thereby provide more natural flushing of silt and other pollutants. Unfortunately they neglected to consider a key functional relationship in the hydro-dynamics of the estuary. When the freshwater flow is low (less than about 5000 cfs), the freshwater mixes rapidly with the salt water, and the whole estuary is flushed each day by tidal movement of the mixed input waters. When the flow is increased, the estuary becomes stratified and the freshwater forms a lens over the saltwater. This lens slows the saltwater movement with each tidal cycle; essentially a stagnant pool of saltwater is created over the estuary bottom. This stagnant pool traps silt and other pollutants. The annual dredging cost has now increased to twelve million dollars.

Salmon Enhancement in B.C.

The Canadian government recently decided to increase the productivity of its commercial sockeye salmon populations by investing in artificial spawning areas (a type of "enhancement facility") for some of the adult fish to deposit their eggs. Unfortunately a key functional relationship had not been noticed: the salmon are apparently limited in their total abundance not by spawning areas, but by the productivity of the ocean (where the fish grow up after a short period of freshwater life). The enhancement facilities do increase the number of young produced by each spawning fish, as fewer spawners are needed to reach the abundance limit set by ocean conditions--thus a higher percentage of the adult fish can be taken as catch. However, this creates another difficulty; the fish from enhancement facilities are caught by nets that also take other less productive commercial species and species that are of considerable recreational value. To exploit the enhancement fish at higher rates without overexploiting the other species, it will be necessary to build enhancement facilities for the other species also. In the limit, the less productive natural populations could disapear completely.

The Spruce Budworm

The spruce budworm is a serious forest pest in Eastern Canada. It attacks mature forest trees, and has had periodic outbreaks (every forty to seventy years) at least since the seventeenth century. After World War II, it was decided to use military aircraft to mount an insecticide spraying program over enormous areas of forest land. At first the spraying was directed only at a few areas of mature, valuable forest. However, the land area in mature forest cover has increased steadily, and the spraying program has grown accordingly. The situation is now explosive, with huge areas of mature forest ripe for attack by the insecticide-resistant budworm strain that will inevitably appear.

Chaparral Forests

Many semi-arid areas of western North America and Southern Europe have a vegetation system specially adapted to periodic forest fires. The chaparral vegetation has three layers: grass, deciduous brush and trees, and large coniferous trees (usually pine). The coniferous trees have adaptations to withstand small forest fires: thick bark and seeds which only germinate after exposure to high temperatures. The system has a natural cycle, involving periodic forest fires that clear away most of the brush and small trees without killing the large conifers. Forest management over the past few decades has been explicitly directed at fire prevention; so the brushy fuel has accumulated to dangerous levels in many areas. The costs of fire prevention are becoming progressively higher, and when fires do occur they are hot enough to destroy the coniferous forest. When the large trees are destroyed over large areas, natural rejuvenation is very slow and expensive tree planting becomes necessary. There have also been expensive test programs involving mechanical removal of the brush.

The Whaling Industry

No discussion of resource mismanagement would be complete without at least a passing comment about whales. Though whaling has been a perennial pain for conservationists, the problem has become most transparent since World War II. During the late 1940's and 1950's, several nations developed (or allowed development of) large, mechanized whaling fleets and industrial processing facilities. This development was largely based at first on the Antarctic stocks of blue, fin, and sperm whales. The International Whaling Commission, charged by treaty with recommending effective management policies, became bogged down during the postwar development period over a series of questions involving sustainable biological yields and mechanisms for catch regulation.

Agreement about biological capabilities of the stocks has now been reached (the Antarctic stocks are all depleted and attention has shifted to northern populations), but an even more serious issue has arisen. Japan argues that it should now be allowed to deplete all stocks to the minimum level considered safe to prevent extinction, since it must try to rapidly recover the costs of industrial expansion. In other words Japan claims that it now has too much at stake in the short run; initiation of sound long range policies should be deferred until all of the world's whale stocks have been depleted.

General Properties of Foreclosing Sequences

I could fill many more pages with examples, but the basic issues reappear with monotonous regularity. Nor are they confined to the regional and local scale; witness the current energy crisis and the willingness of American decision makers to consider armed intervention in the Middle East as a possible option for maintaining over-investment in petroleum based industries.

One could argue that the examples simply represent bad decision making and failure to use available methodologies properly. If the decision makers had been more thoughtful in each case and had carefully outlined "decision trees" of future options and uncertainties, they certainly might have done better. But the sad fact is that people are not omniscient, and they quite likely would have done just what they actually did. In each case the problems arose not because of poor probabilistic assessments of recognized uncertainties, but instead because of fundamental relationships that were not recognized at all.

Let us be more precise about the general sequence of events underlying all of the examples (Table 1). In each case there is an initial, apparently intelligent investment decision. This investment has three critical properties:

1) it is based on faith that present trends will continue into the future;
2) it entails an economic and political commitment to try and recover investment costs, even if there is no irreversible loss of nonrenewable resources;

Table 1. Summary of the example problems.

Case	Critical Initial Decision	Factors Overlooked	Endpoint Consequence of the Sequence
James Bay	Hydroelectric development	Power demands, environmental concerns, Indian culture	Rapid depletion of Canadian nuclear fuel reserves, competition for international sales with Candu system.
Tallahassee River	Flow diversion	Estuarine hydrodynamic transition from mixed to stratified	Costly dredging program, loss of environmental quality
Salmon Enhancement	Artificial spawning area	Ocean limitation of population size	Costly enhancement program, loss of natural productivity
Spruce Budworm	Insecticide spraying	Forest growth	Enormous spraying cost, explosive outbreak situation
Chaparral Forests	Fire control	Growth of brushy fire fuel	Intolerable costs for fire control destructive fires
Whaling Industry	Management emphasis on catch control	Dynamics of commercial investment	Choice between large economic loss or extinction of whale stocks

3) its shortcomings (due to failure to recognize some basic relationships) can be alleviated at least temporarily by further investment.

The next step is an additional investment (or use of resources) to try and correct the original mistakes. This second investment is again rational in the same terms as the first; the alternative would be to reverse the original decision and accept the investment loss. (Most decision makers would find that alternative politically and psychologically unacceptable, for obvious reasons.) Thus the sequence is established; some would call this "progress."

If the process of corrective investment could be maintained indefinitely, there would be no problem. But the examples suggest that there are endpoints, with very disturbing properties:

1) Even if it is highly productive, the endpoint system is dangerously simplified, so that <u>qualitatively</u> similar perturbations[1] have much more disasterous relative effects than at the start of the sequence.
2) The endpoint system may be impossibly costly to maintain, yet the largest induced economic infrastructure may depend on its maintenance. The sunk costs (potential loss of capital investment) <u>and</u> the immediate costs of failure are highest.

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[1]These include, for example, bad water flow for one year in the area of a salmon hatchery, a single large input of pollutants, a forest fire.

3) The number of economically acceptable (benefits exceed costs) options for further corrective action approaches zero, even if risk aversion is low.

Toward A More Precise Definition of the Problem

Let me now state a specific hypothesis: a special kind of pathological decision behavior exists that can arise in perhaps all sequential decision problems. This behavior has its roots in a very human characteristic: we do not like to admit and pay for our past mistakes. The main characteristics of the pathological behavior are increasing investment, increasing costs for system maintenance, foreclosure of decision options, and decreased ability of the managed resource system to absorb qualitatively similar natural perturbations.

One gets the qualitative impression that a single innocuous investment error can lead almost inevitably to destruction of the managed system. Surely such sequences can be avoided in most cases, if we simply recognize their existence and learn to watch out for them at the outset.

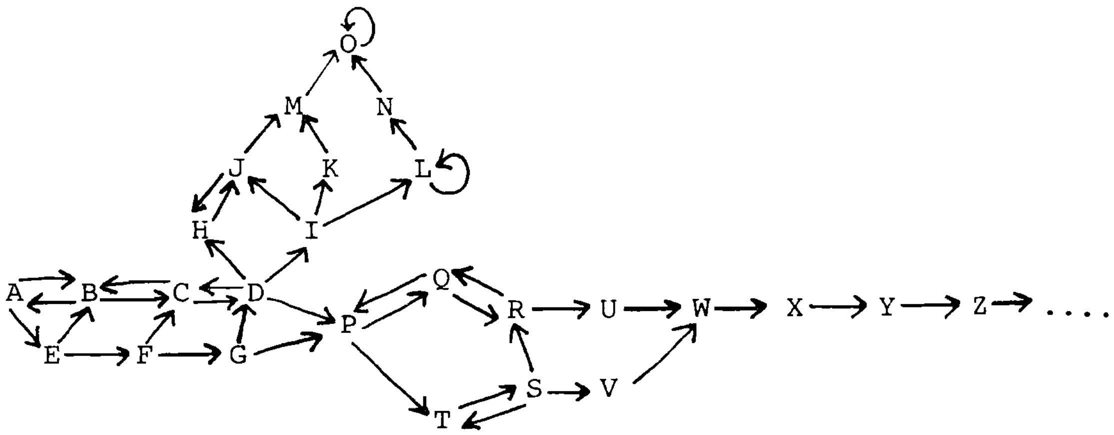
Note that each of the example decision sequences of the previous section begins with a decision that was not actually the first development decision for the resource. In each case I have tried to pick up the decision sequence at the critical point where the foreclosure or locking-in process began in earnest.

My intuitive feeling in that the locking-in process is analogous or equivalent to Holling's "resilience" idea, with some abstract decision space taking the place of his phase space with its stability regions. The idea is that decision combinations that can be applied sequentially for long periods of time without serious consequences should exist. Other decisions (outside of boundaries analogous to stability boundaries) that lead to a positive feedback response (investment making more investment necessary making more...) and a narrowing tunnel of feasible or viable decision combinations also exist.

One way of looking at the analogy is to consider a set of possible investment decisions:

$$\{A,B,C,D,...,n\} \quad .$$

Presumably some of these decisions are sensible only if others have been made. Let us denote by arrows (⟶) those incremental investment decisions that are politically and economically feasible (though not necessarily Pareto admissable) after any initial decision has been made. We can then draw a network of decision transitions:



It appears that networks of this kind can have some very interesting properties:

1) there can be "stable" regions (A B C D E F transitions versus P Q R S T transitions);
2) there can be sequences leading to a positive feedback endpoint (O) as in the budworm and chaparral forest examples;
3) there can be open ended, irreversible sequences (W X Y Z) that depend on the economist's world of unlimited potential substitutes.

Presumably one aim of systems analysis should be to help find sequences that lead out of the traps (witness Holling's budworm work).

Though no one is quite sure, I suspect that the idea of a decision space with its potential traps is partly what Holling meant when he introduced the resilience concept. However, there is no necessary association between state space behavior (stability boundaries, etc.) of the resource system, as opposed to the locking-in process. Holling would call the natural budworm system resilient--it fluctuates enormously but persists over time. There is no reason to believe that the existing, managed budworm system is any less resilient in that sense; it is bound to undergo a very large fluctuation when the insecticides fail, but it will quite probably still exist. In evolving to become a periodic pest, the budworm itself played a game analogous to the locking-in process: it became more and more specialized and efficient at attacking balsam fir trees. Also, it is probably not true that the present managed equilibrium between budworm and trees is less stable in the sense that it has a narrower region of state space stability; it is just that the same qualitative perturbation (insecticide resistence) will cause a much larger state change now.

We can bring the decision space and state space resilience concepts together with a very simple-minded model, based on the whaling example. Let us consider the main decision variable for whaling management to be the level of fleet investment, I (number of operating vessels, say). Suppose that this investment has an annual unit repayment cost or depreciation rate r. The annual fixed costs are then rI. Suppose that the total operating costs for fishing are related to whale population N according to the simple relationship

$$\text{o.c.} = \frac{q}{N} I$$

where q is a constant. Suppose that the boats can take an annual catch equal to cNI (this is reasonable only provided cNI << N), and that each whale can be sold at a price p. Then the boats will not go out unless catch is greater than operating costs, i.e.

$$cNI \geq \frac{q}{N} I$$

that is

$$N \geq \sqrt{\frac{q}{cp}} \quad . \qquad (1)$$

This inequality sets one boundary in the state-decision space. Next, let us pretend that the whale stock can produce an annual <u>sustainable</u> catch (excess of births over natural deaths) $C_s = aN(1 - bN)$ where a and b are positive constants. This equation says that the <u>sustainable</u> catch is small for small population sizes, larger for intermediate populations, and small for large populations. Now let us ask: at what investment levels is it economically <u>feasible</u> (not necessarily profitable) to maintain a given stock size? The answer is given by the simple inequality $pC_s \geq rI + \frac{q}{N} I$

$$\left(\text{provided } N \geq \sqrt{\frac{q}{cp}}\right)$$

which can be rewritten as

$$\frac{aN^2(1 - bN)p}{Nr + q} \geq I \quad . \qquad (2)$$

That is, it is economically feasible to maintain a decision-state combination $\{I,N\}$ only if it satisfies this inequality.

Figure 1 shows how these whale equations look in decision-state space. The space is partioned into regions, based on inequalities (1) and (2) and on the assumption that an extinction threshold for the population exists. Stochastic stock changes or uncontrolled investment would tend to move the system out of the "stable" region where it is economically feasible to maintain the biological system. Likewise, parameter changes could expand or contract the region; examining inequality (2), the suggestion is that price increases should expand the region, while depreciation rate increases (r) should contract it. Within the region, a variety of investment options are available; outside the region to the right, only fixed or increasing investment is feasible. Near the left side of the graph, only fixed investment (followed by collapse) is feasible, and extinction is likely. It is as though there is a narrowing tunnel of feasible next actions as the left-hand boundary of the feasible management region is approached from the right (see Figure 1). The width of the feasible region decreases as investment is increased; thus the system becomes dangerously "unstable" to state and parameter perturbations as investment is pushed to its limit for economically feasible sustained yield management.

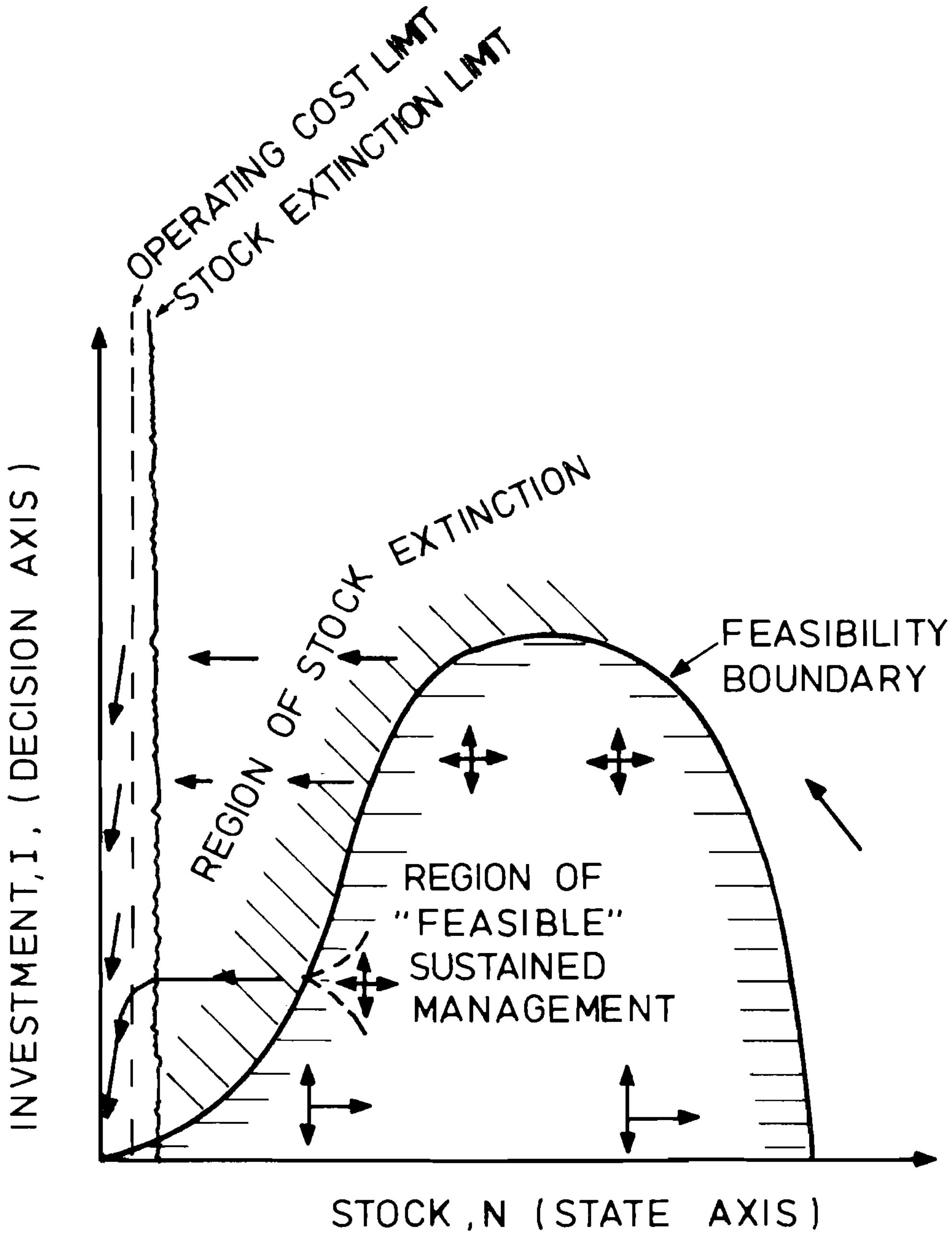
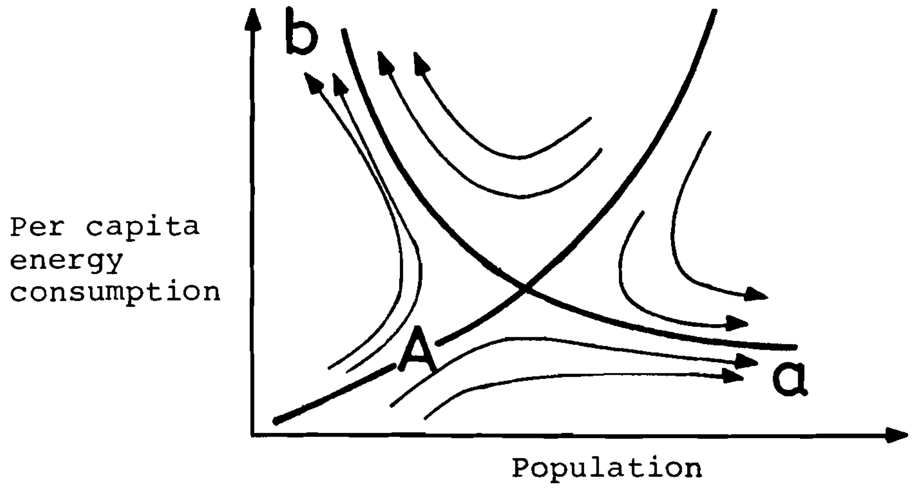


Figure 1. Partitioning of the decision-state space for whale management. Explanation in text. "Feasible" ≡ economic benefits > costs.

Professor Häfele's hypothetical societal equations provide a second kind of example of boundaries in the state-decision space. His equations lead to a phase relationship between energy and population:



He argues that we are now along the separatrix "A" and that we should move away from this separatrix to the right, into the stable growth region "a." I would argue just the opposite: we should make every effort to remain on the separatrix, so as to keep open the option of moving to a low population, high energy system. It is easy to imagine politically feasible investments for moving away from the "b" transient, whereas the "a" transients lock us into a growth situation with few palatable options for retreat.

So What?

The empirical examples above indicate that the process of option loss is triggered by ignorance about the existence of system relationships. If this is so, how can it be possible to avoid the trap, without going to the ridiculous extreme of not investing at all? Strictly speaking, this question has no answer; it is always possible to make mistakes. Let us first ask for simple steps and guidelines that can be followed to at least make the difficult situations less likely.

The first, utterly critical step is to shift our basic way of thinking about systems decision problems. Now we tend to think about single decisions or operating policies, and we work desperately to predict natural system consequences of these. The policy failure analysis of Holling and Hilborn is a good example: we impose a policy on a simulated system, then ask for the system consequences when the policy fails. We should instead be asking about the decision consequences of policy failure--that is, we should ask questions like: "If policy x fails or proves inadequate, what kind of decisions are likely to be taken next?" If we can begin to identify dangerous sequences by asking such questions, it should become much easier to make qualitative choices at each decision point, without resorting to deceptive quantitative indicators like "option value" and "policy resilience."

Some Preliminary House Cleaning

Before identifying some approaches to avoid the locking-in process, let us first identify the culprits that seem to be causing the problem in the first place. This should help narrow the search for better methodologies.

Perhaps the most foolish and short-sighted decision tool now available is deterministic cost-benefit analysis. Supposedly the method takes risks into account through discounting rates and through inclusion of opportunity and option value costs. Cost-benefit analysis is particularly good at leading us into the "economies of scale" trap (witness the James Bay); larger unit investments are one of the surest ways to get boxed into a position from which it is politically infeasible to retreat.

A slightly more attractive set of techniques is available under the general heading "decision making under uncertainty." Decision trees and subjective probability assessments give some hope of helping to better structure our thinking about sequential decision problems. One difficulty is that decision trees become unmanageably large in a hurry, and the "normative form" of analysis may lead us to overlook the dangerous branches. Also decision tree analyses tend to concentrate our attention on future decisions, when we should often be considering retrogressive branches involving the acceptance of investment losses due to past mistakes.

There has been much interest at IIASA in Paretian Analysis and Metagame theory because they help us to think about problems of multiple objectives and conflicting interests. But these methods require a very precise statement of available options and possible outcomes. This requirement may be a great psychological aid (it is nice to feel that a problem is under control, with very explicit boundaries), but the dangers are as great as in cost-benefit analysis.

I have been a strong advocate of large simulation models with lots of control knobs and points for entering decision options. The process of building such models involves a way of thinking that helps to identify the potentially critical functional relationships, but I find a particularly dangerous tendency to be lulled into believing that all of the major factors have been taken into account. We were over a year along into a happy exercise in salmon enhancement modelling before our programmer (Mike Staley) turned up the ocean survival relationship that may trigger a bad sequence of future decisions (see examples section). We should have been concerned with the decision possibilities in the first place, rather than with our detailed modelling of the salmon production system.

Toward Better Methodologies

We must go beyond the trivial awareness that decisions follow one another and can lead into trouble. It seems to me that there are at least three strategic options for further work:

1) We can try to devise better methods for identifying (discovering, anticipating) dangerous relationships and decision sequences. That is, we can try to get rid of the unknowns that cause the trouble in the first place. I see little hope in this direction.
2) We can try to analyze known critical decision points

in hopes that such points have special attributes that make them recognizable even if we cannot see the foreclosing sequence of options that they lead to. There are some obvious possibilities for development of indicators: size of initial capital investment, etc.

3) If we simply admit that it is impossible to avoid foreclosing sequences, we can try to find general strategies for retreating gracefully when mistakes are recognized. Holling's budworm work on spreading of variability in space rather than time is a step in this direction, and so our work on fisheries insurance systems. Another way to discuss this option is in terms of adaptive control: How can we make the process of detecting and correcting errors more effective? I suggest that a useful step in this direction would be to search for "adaptability indicators" analogous to Holling's resilience indicators. These indicators would measure the ease of retreat or cost of going forward from faulty policies.

Hopefully some discussion and argument will help us to identify other options.

Optimal Harvest Strategies for Salmon in Relation to Environmental Variability and Uncertainty about Production Parameters*

Carl J. Walters**

Abstract

A method is developed for incorporating the effects of environmental variability and judgmental uncertainty about future production parameters into the design of optimal harvest strategies, expressed as curves relating stock size and exploitation rate. For the Skeena River sockeye, the method suggests that optimal strategies are insensitive to judgmental uncertainty about the Ricker Stock production parameter, but are very sensitive to management objectives related to the mean and variance of catches. Best possible trade-offs between mean and variance of catches for the Skeena River are developed and a simplified strategy is suggested for improving mean catch while reducing year to year variation.

I. Introduction

Pacific salmon management in recent years has been based on the concept that maximum sustained yield can be obtained by holding escapements at some constant level determined by analysis of the stock-recruitment relationship. Larkin and Ricker (1964), and Tautz, Larkin, and Ricker (1969) showed that such fixed escapement strategies should result in higher mean yields than fixed exploitation rate strategies in the face of high stochastic variation in productivity. However, Allen (1973) has stressed the need to look at other possible management strategies expressed as relationships between harvest and stock size; he shows for the Skeena River that fixed escapement strategies should result in unnecessarily high variance in catches from year to year, and he develops alternative relationships that should cut the variance of catches nearly in half with only about a 15% reduction in mean catch.

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The intent of this paper is to present a set of optimal harvest strategies for salmon, based on trade-offs between the mean and variance of catches. The Skeena River is used as an example, and the optimal strategies are developed by using stochastic dynamic programming. This formidable sounding optimization technique is actually a relatively simple method for testing the multitude of possible future stock changes that harvest and environmental variability may produce, weighting each future change by its probability of occurrence.

Since the technique has seen little application in biology, Section II gives an intuitive introduction to stochastic dynamic programming. Section III presents a variety of harvest strategies for the Skeena River, under different assumptions about environmental variability and using different management objectives, and examines possible management strategies in relation to current management practice on the Skeena River. Section IV analyzes potential trade-offs between mean and variance of catches, and suggests an overall optimal strategy for the Skeena River. It is demonstrated that optimal management policies may bear no clear relationship either to the current (fixed escapement) practice or to the strategy alternatives suggested by Allen (1973).

II. Stochastic Dynamic Programming

The basic concept of dynamic programming was introduced by Richard Bellman in the 1940's (see Bellman, 1961; Bellman and Dreyfus, 1962; Bellman and Kalaba, 1965). It is an optimization technique for systems in which a series of decisions must be made in sequence, where each decision affects the subsequent system state and thus each future decision. Two key ingredients are necessary to apply the method: a dynamic model to predict the next state of the system given any starting state and any decision, and an objective function to specify the value of the return obtained in one time step for any state-decision combination. In stochastic problems, the dynamic model must specify not a single future state but instead must specify probabilities for each new state that might arise after one time step from any starting state-decision combination.

The Dynamic Model

Following most authors on salmon management theory, the simple Ricker model is used in this study as the necessary dynamic model:

$$N_{t+1} = S_t e^{\alpha(1-S_t)} \tag{1}$$

where

N_{t+1} = stock (recruitment) after one generation, in standard stock units (approximately 2,000,000 for Skeena sockeye);

S_t = escapement or spawning population, in stock units;

α = stock production parameter, assumed to be a random variable.

If S_t is held fixed, e^α represents the net stock productivity or recruitment excess (in stock units). This factor arises in nature as a product of several survival factors that vary randomly but may be considered more or less independent of one another. Thus, α, the logarithm of e^α is a sum of random variables and should be normally distributed by the Central Limit Theorem of basic statistics. Allen (1973) provides some empirical justification for this assumption using data from the Skeena River. If S_t is written as

$$S_t = N_t(1 - u_t) \qquad 0 \leq u_t \leq 0\ 1.0 \tag{2}$$

where u_t is the exploitation rate, or <u>decision</u> <u>variable</u>, then we have the first basic ingredient for dynamic programming. The objective is to find an optimal <u>relationship</u> between u_t and N_t, by examining sequences of decisions where the next state arising from any $N_t - u_t$ combination is predicted with the Ricker model using an appropriate probability distribution for α.

As an alternative to the Ricker model, we could simply specify a separate empirical or judgmental probability distribution of recruitment for each conceivable spawning stock (in other words, treat the stock-recruitment relationship as a Markov process). However, even for the Skeena River sockeye there is insufficient data to meaningfully interpolate recruitment probabilities for high and low spawning stocks (Figure 1).

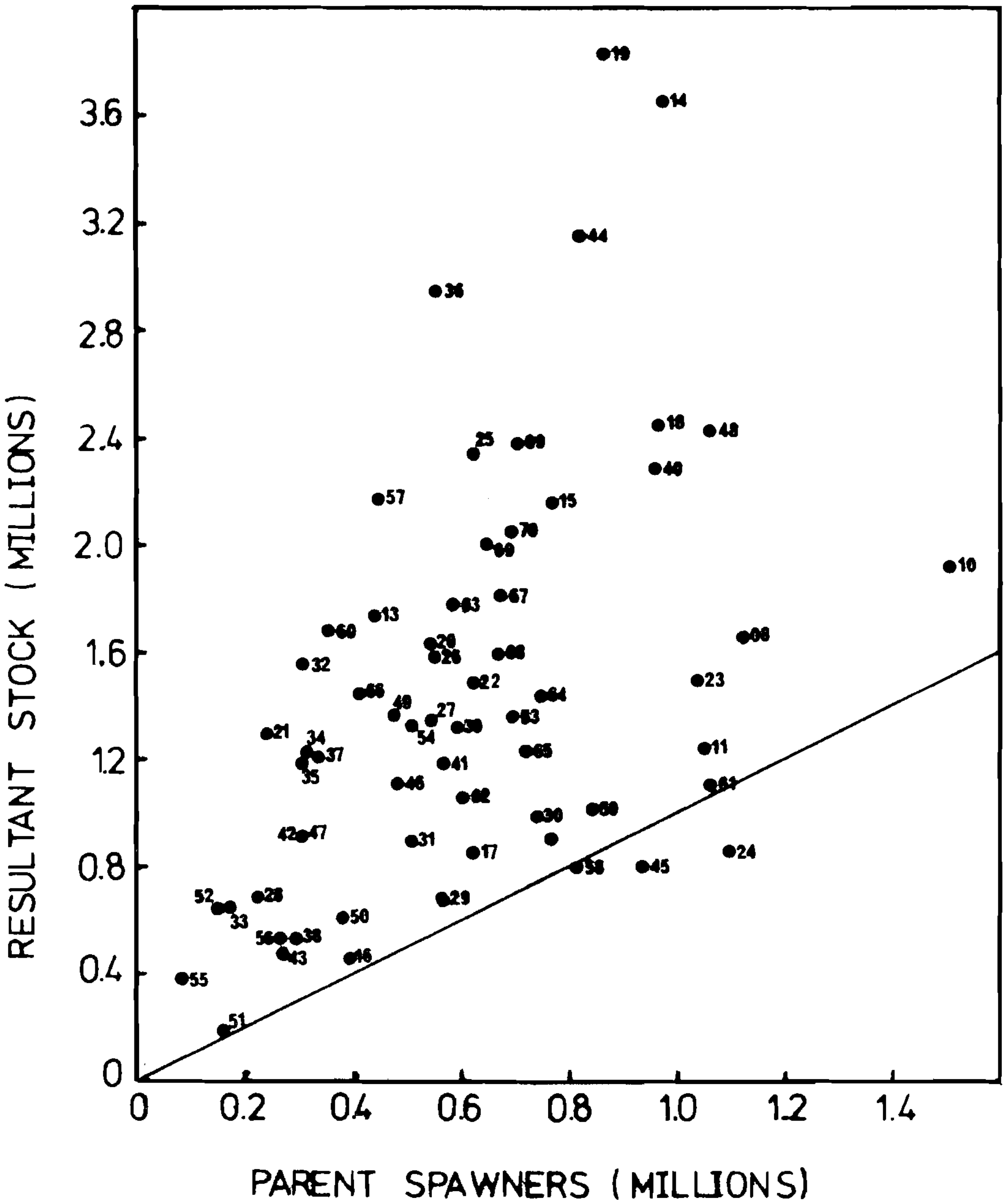

Figure 1. Stock-recruitment relationship for the Skeena sockeye. From Shepard et al. (1964), with recent points from unpublished data provided by F.E.A. Wood, Environment Canada.

The Ricker model appears to be as good a way as any for extrapolation to extreme stock sizes.

The Objective Function

The other basic ingredient, the objective function, may take a variety of forms. For maximizing mean harvest, we can take it to be simply $u_t \cdot N_t$. If variance is important, we can instead try to minimize the variance around some desired catch level; for each time step the relative contribution to variance is then

$$(u_t \cdot N_t - \mu)^2$$

where μ is the desired catch level. Note that if μ is arbitrarily increased to high values that cannot be achieved in nature, the variance contribution at each step becomes essentially linear in $u_t \cdot N_t$. This means mathematically that minimizing the sum over time of squared deviations from high μ values tends toward being equivalent to maximizing $u_t N_t$, as μ is increased. Thus by changing μ we can generate a series of objective functions that range from variance-minimizing to harvest maximizing as μ is increased (this point will be clarified in Section IV).

The Computational Procedure

Given the basic ingredients above, the next step required for dynamic programming is to approximate the continuous variables u_t, N_t and α by a series of discrete, representative levels or states. The concept here is the same as is used in solving differential equations by taking short discrete time steps. By trial and error, it was found necessary for this study to use thirty discrete population levels, each representing an increment of .05 stock units (N_t = 0.0, 0.05, 0.1,...,1.45), thirty discrete exploitation rates at intervals of 0.03 (U_t = 0.0, 0.03, 0.06,...,0.82), and ten discrete α values (α discretization will be presented in Section III).

The reader is referred to Figure 2 for the following explanation. Suppose we look at any discrete stock size at some time step, and think about applying many possible harvest rates to it (left hand "decision branches" in Figure 2). For each harvest rate a return (harvest or contribution to variance) can be computed, but the recruitment subsequently resulting from this escapement will be uncertain (right hand "probability branches" in Figure 2). Suppose that we specify probabilities for each possible new stock size that might be produced, <u>and suppose that we already know (somehow) what future returns can be expected for each of these new stock sizes</u>. Then for each harvest rate, we can find an <u>expected</u> overall value: it is simply the return this year, plus the sum of products of probabilities of getting new stock sizes times the expected future returns for these new sizes. In other words, we take each possible future and weight it by its probability of occurrence to give an expected value for future returns; this expected future value is added to this year's return to give

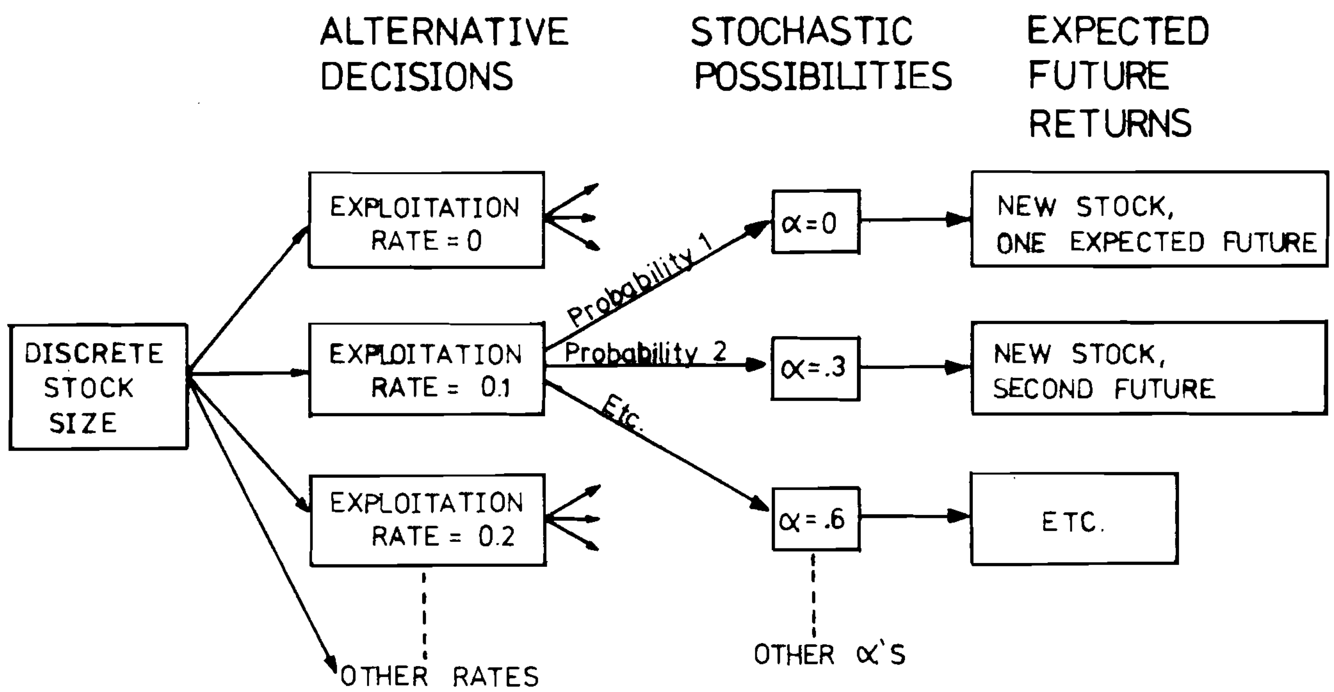

Figure 2. Decision branches and probabilistic outcomes for any starting stock size (explanation in text).

the overall value for the harvest rate-present stock combination for the particular time step under consideration. The process can be repeated for each possible harvest rate, and afterward it is a simple matter to choose which rate gives the best overall return.

We can next choose another stock size, and try many possible harvest rates on it. Again providing that we already know what future returns can be expected for each new stock size that might result and that we can associate a probability with each possibility, it is a simple matter to choose the best harvest rate for this second stock size.

The whole process is repeated for a third stock size, a fourth, and so on until the optimal harvest rate for every reasonable stock size has been computed. The result is a set of stock-harvest combinations that can be plotted against one another as a smooth curve; this curve is called the <u>optimal control law</u> for the time step under consideration.

The real trick in dynamic programming is to get the expected future returns for each new stock size that can result for each starting $u_t - N_t$ combination. This trick, the key discovery of Richard Bellman, is remarkably simple: we work <u>backward</u> in time from an arbitrary end point ($t = K$). Values are assigned to different stock sizes at this endpoint, and these values are used to look ahead at the endpoint from one time step backward ($t = K - 1$). After getting overall values for each stock size one step back from the endpoint, we can then move back another step (t = K - 2), and look ahead to the values just computed for t = K - 1. This backward recursion process is repeated over and over (t = k - 3, K - 4, etc.)

After several backward recursion steps, a phenomenon emerges that forms the central basis for this paper: the endpoint values cease to have any effect, and the optimal exploitation rate for each stock size becomes independent of the time step. The optimal control law or harvest strategy curve is then said to have stabilized; this usually occurs within ten to twenty steps for the Ricker model. Certain computational tricks are necessary to insure that the stable control law is valid, since the new stocks produced at each forward look may not correspond exactly to any that have already been examined for the next time step forward. This interpolation problem is solved by being careful to examine enough discretized stock sizes and exploitation rates.

The key feature of stochastic dynamic programming is that it explicitly takes account of all the possible futures that are considered likely enough to be assigned probabilities of occurrence. Furthermore, it makes no difference whether these probabilities are chosen to represent judgmental uncertainty (Raiffa, 1968) about deterministic parameters, or true stochastic variation in parameter values, or some combination of these sources of uncertainty.

III. Optimal Strategy Examples

This section develops a set of judgmental probability distributions for the α parameter of equation (1), using the Skeena River sockeye as an example. These probability distributions are then used to demonstrate the form of optimal harvest curves obtained by the procedures outlined above, for different objective functions. Simulation results are presented to show the likely consequences of applying the harvest curves, in terms of probability distributions of catches and stock sizes. Finally, alternative harvest curves are compared to actual management practice on the Skeena River.

α Distributions for the Skeena River

Using the data in Figure 1, a set of empirical α values can be computed as

$$\alpha_i = \ln\left(R_i / S_i\right) / \left(1 - S_i / S_e\right)$$

where

i is the data point;

R_i, S_i are the recruitment and spawner values;

S_e is the replacement number of spawners in the absence of harvest.

S_e was taken to be 2,000,000 spawners, and the results for α are presented in Figure 3, top panel. As Ricker (1973) points out, there has been a decrease in the mean value of α in recent years. With some imagination, one might conclude that the frequencies had been drawn from a normal distribution; luckily, no such assumption is necessary in order to apply stochastic dynamic programming.

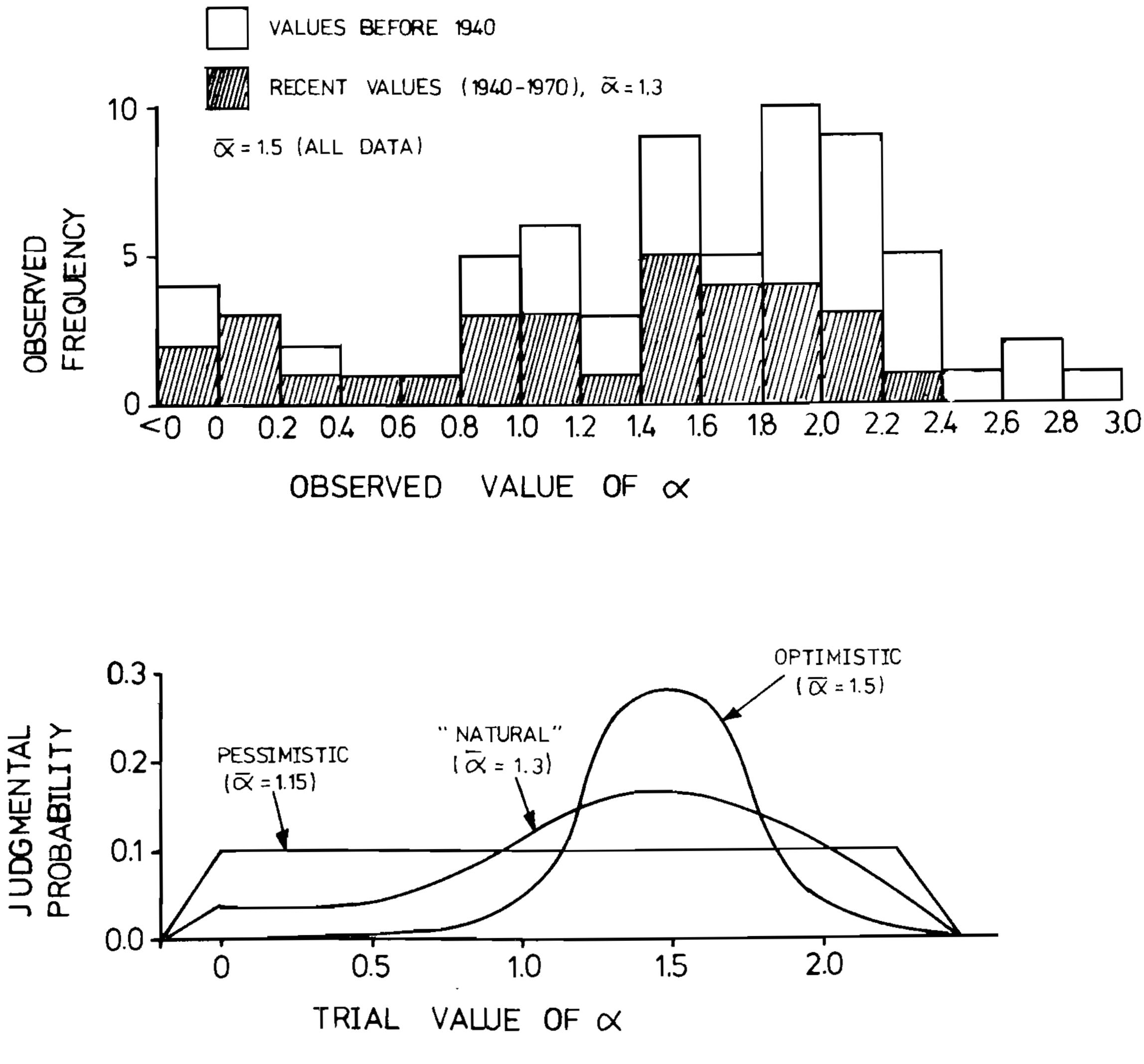

Figure 3. Observed distribution of the Ricker production parameter α (equation 1) for Skeena River sockeye, and three judgmental probability distributions for possible future values.

The bottom panel of Figure 3 shows three judgmental probability distributions that a decision maker might draw after examining the top panel. These test distributions are all truncated at zero and 2.3, for computational convenience (test runs showed that extreme values have little effect for the present problem). The distribution marked "pessimistic" (for obvious reasons) assumes an even distribution of α values in the future. The distribution marked "natural" is the author's rendition of the data, weighting recent years more heavily. The "optimistic" distribution might be drawn by a decision maker who believes that the good production rates of recent years (Figure 1) will continue in the future due to better management practices of some sort. An important concept behind these distributions is that the stochastic dynamic programming solution can be made to take a variety of intuitive judgments into account beyond the hard facts of past observations.

Form of the Optimal Solution

The judgmental probability distributions in Figure 3, combined with equations (1) and (2) and with several objective functions, were used to obtain a variety of optimal solutions. For the computer freaks, I used a PDP 11/45; each solution required about 100 sec of computer time (30 N_t levels $\times$ 30 u_t levels $\times$ 10 probability levels $\times$ 20 time steps). The discrete N_t - u_t optimal solutions were connected as smooth curves for presentation here.

Let us first examine the dome shaped band of optimal harvest curves indicated by horizontal shading in Figure 4. All three curves were generated by trying to minimize the objective function $(H - .6)^2$, that is by trying to minimize the variance of catches around a mean value of 0.6 million fish. The top curve represents the strategy that should be followed if the optimistic probability curve for α (Figure 3) is considered best; the lower two curves represent optimal strategies for the natural and pessimistic α probabilities of Figure 3, respectively. The most important conclusion to be drawn from these curves is that the optimal strategy (for minimizing $(H - .6)^2$) is quite insensitive to the judgmental probability distribution for α, except when stock size is between 0.4 and 1.0 million fish. In hindsight, it is easy to give intuitive reasons for the shapes of the curves: very low stocks should not be fished since recovery will be slowed, and high stocks should be fished lightly so as to avoid high, variance-generating catches. An assumption of the Ricker curve becomes important for high stock sizes, namely that large numbers of spawners will not result in very low recruitment in later years.

Similar results are obtained for the objective of trying to minimize the variance of catches around a mean value of 1.0 million fish (vertical shaded curves in Figure 4). Again the prediction is that low stocks should not be fished at all, while high stocks should receive moderate exploitation.

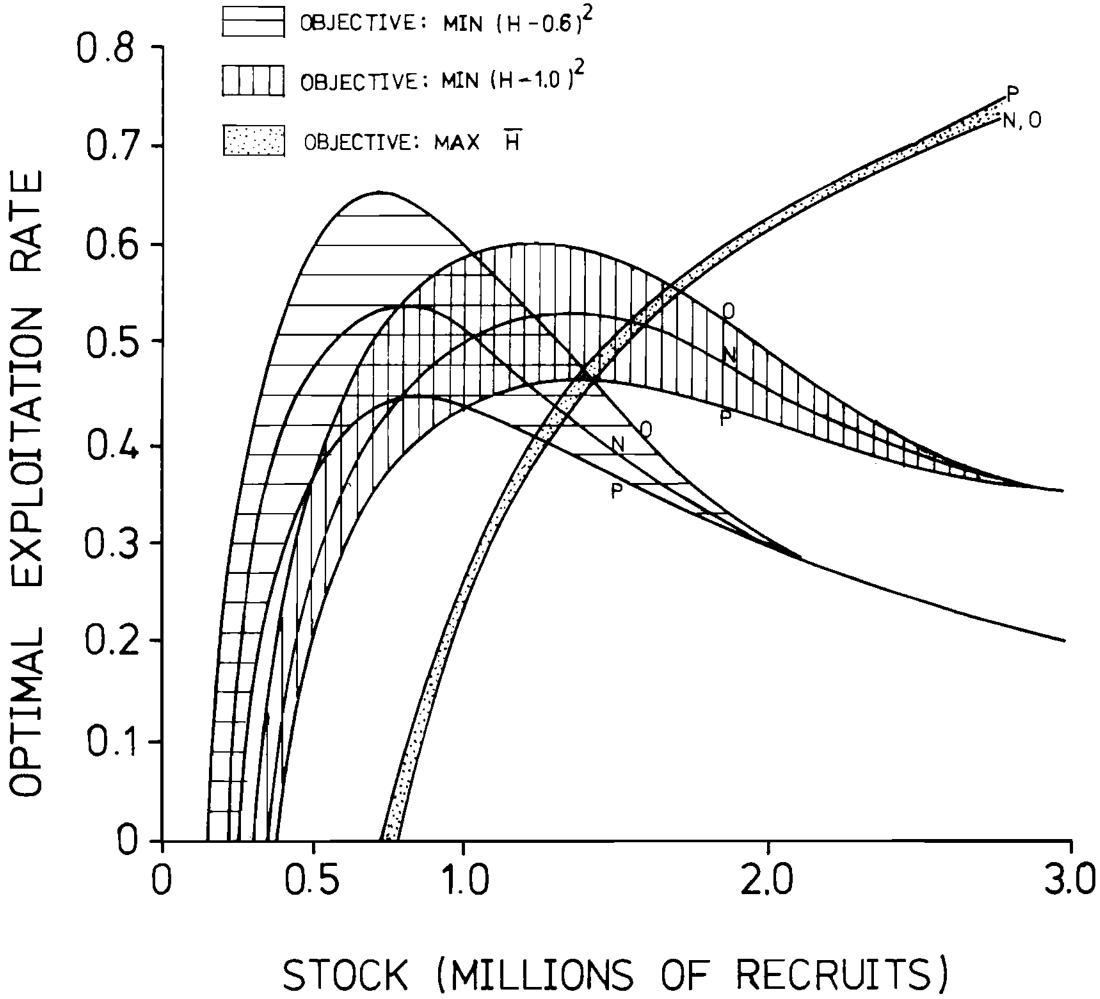

Figure 4. Optimal harvest strategies for three different objective functions, using the optimistic (O), "natural" (N), and pessimistic (p) probability distributions of Figure 3.

The most interesting curves in Figure 4 are for the maximum harvest objective function. These curves essentially call for a constant escapement of around 0.8-1.0 million spawners, as suggested by earlier authors. Also, the optimal strategy is almost independent of the judgmental probability distribution for α. In other words, current management polices on the Skeena River should result, if they can be followed, in maximum average catches even if the future distribution of α values is quite different from what it has been.

Predicted Catch and Stock Size Distribution

Since the stochastic optimal solutions are based on the assumption that there is no certain future population trend, the anticipated returns by applying them are best presented as probability distributions. The simplest way to approximate these distributions is by making very long simulation runs, using equations (1) and (2), with an appropriate random number generation procedure for α values.

Figure 5 presents catch distributions from 5000 year simulation trials, for the optimal harvest curves from Figure 4 that should be used if the "natural" α distribution is considered most credible. Results are also presented for a harvest curve shown in Figure 7, that was obtained by trying to minimize the variance of catches around a mean value (not achievable) of 2.0 million fish. The results in the top panel of Figure 5 were generated by actually using the "natural" distribution to choose different α values for each

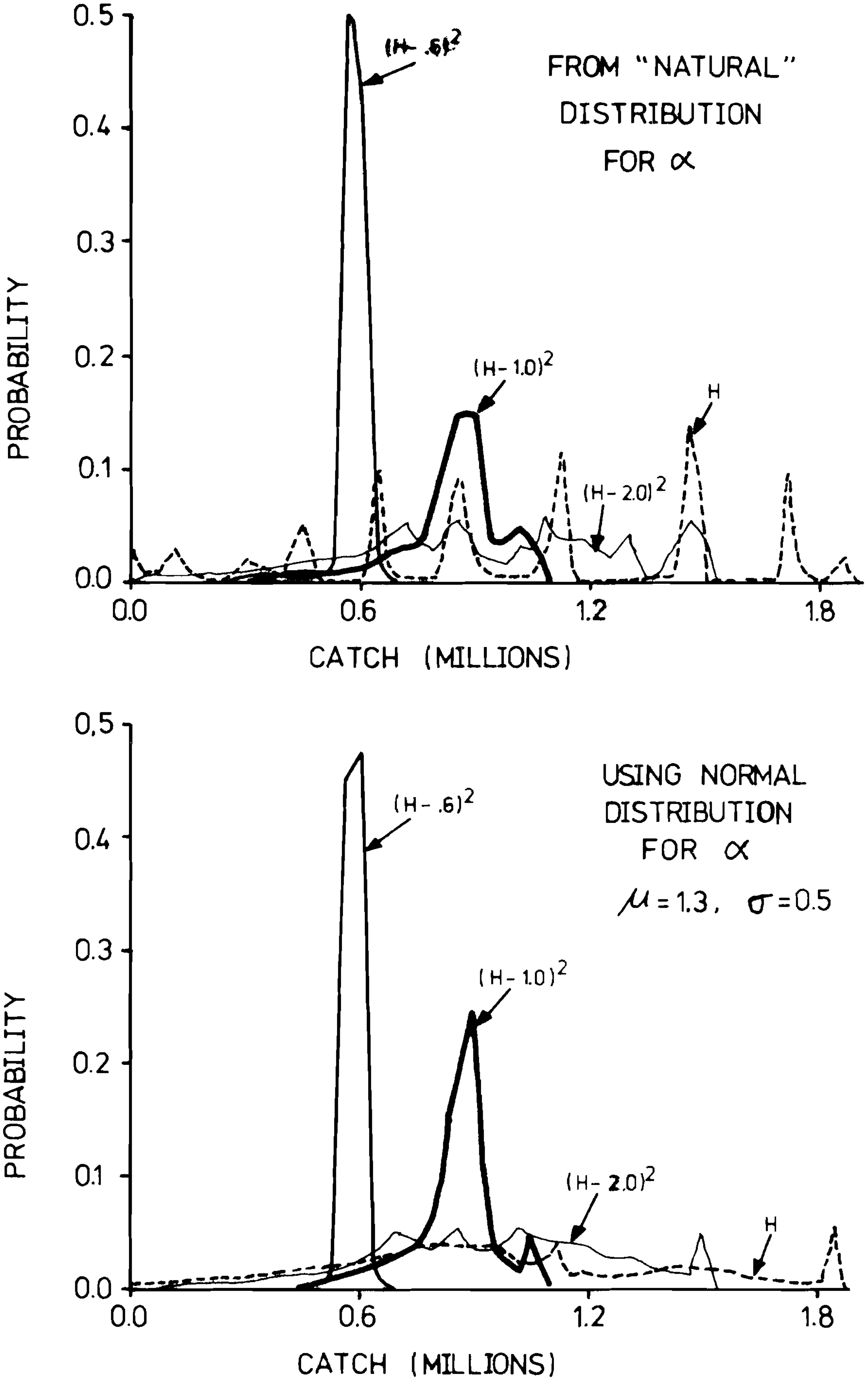

Figure 5. Predicted probability distributions of catches using the "natural" optimal strategies of Figure 4.

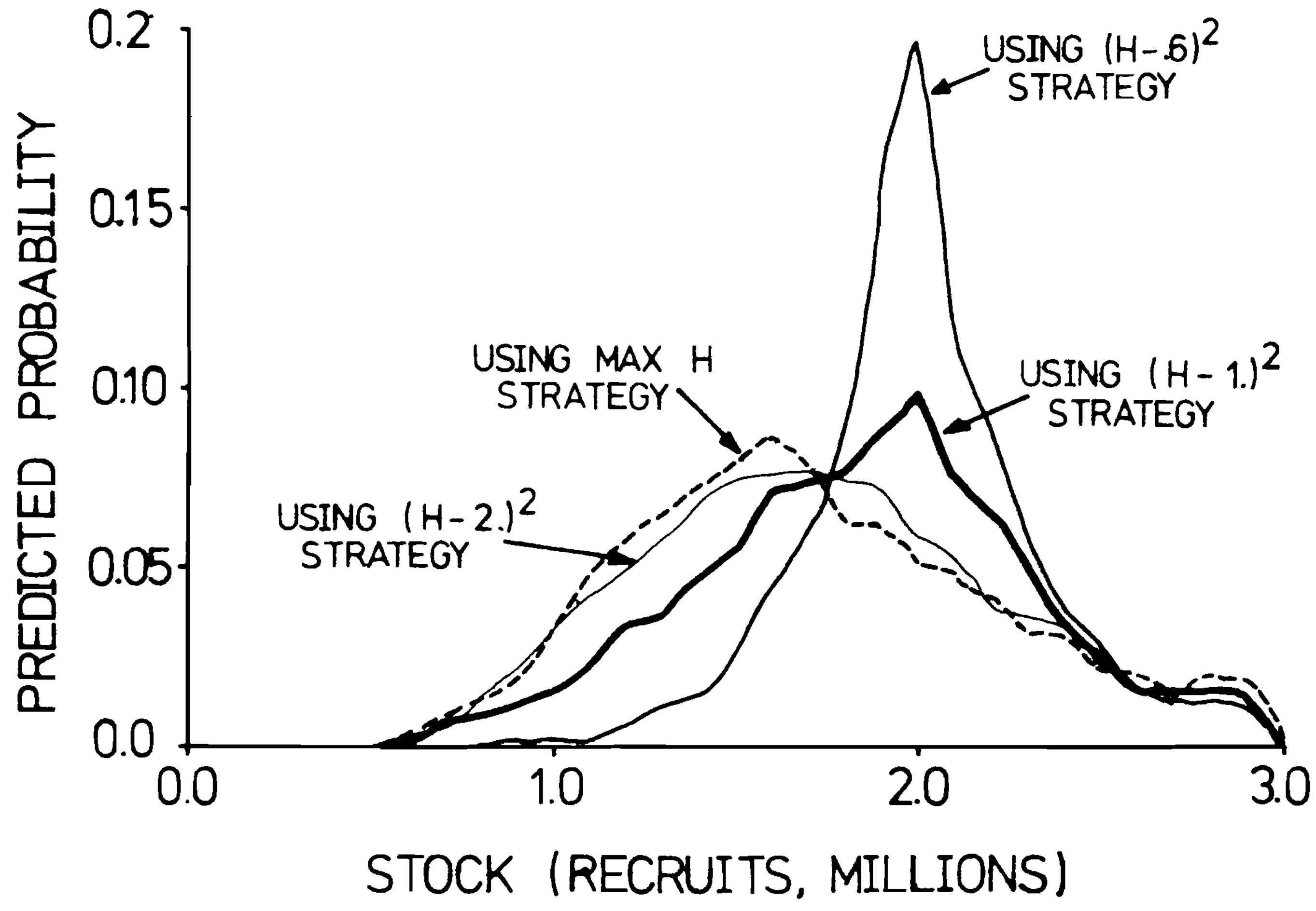

Figure 6. Predicted probability distribution of stock sizes associated with the catches of Figure 5.

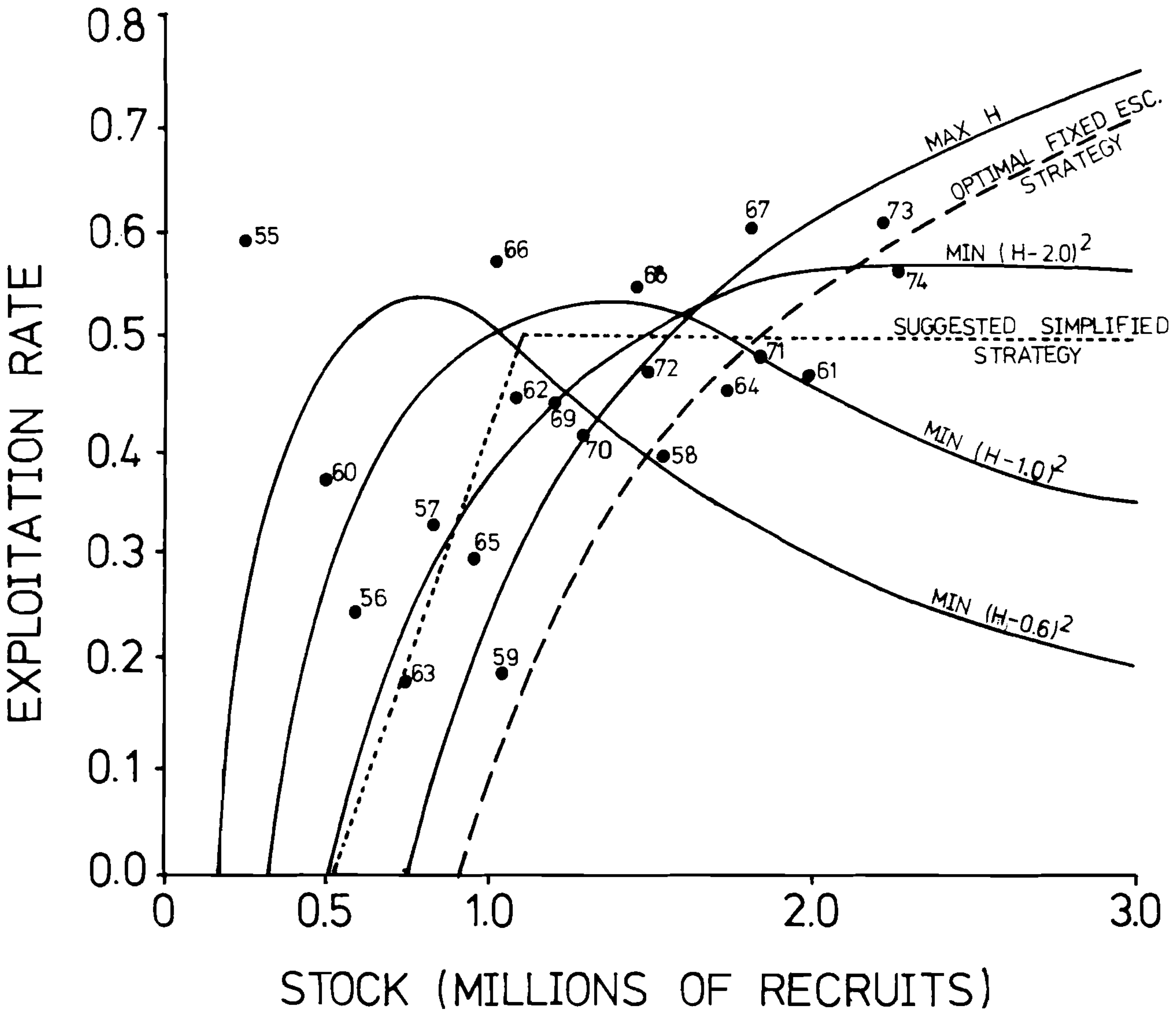

Figure 7. Optimal strategies for different objectives compared to actual management practice on the Skeena River, to the optimal fixed escapement policy, and to a simplified alternative.

simulated year; the results in the bottom panel were generated by choosing α values from a normal distribution with mean 1.3 and standard deviation 0.5 (after Allen, 1973). The results are quite similar, again suggesting that the optimal strategies should be insensitive to the realized future distribution of α values. The roughness of the curves for the "natural" α distribution is due to the numerical approximation procedure used in the simulation program.

There should be an additional benefit from the variance-minimizing strategies, as shown in Figure 6. The variance of recruitment stock sizes increases progressively, and the mean stock size decreases for strategies that place more emphasis on maximizing mean catch. This is a surprising result, since the catch maximizing strategies tend to produce stabilized escapements.

Comparison to Actual Management Practice

Catch and escapment statistics kindly provided by F.E.A. Wood, Environment Canada, were used to compute actual harvest rates for the Skeena River sockeye (Figure 7). It is apparent that management practice in recent years has been able to follow the best fixed escapement policy quite closely. The optimal harvest curves in Figure 7 (all for "natural" α assumption) represent a spectrum of possible objectives based on trying to minimize the variance of catches around a series of increasing values.

For the fifteen year period before 1970, Figure 7 suggests that management practice more closely followed a strategy of trying to minimize the variance of catches. The correlation could be purely spurious, but it is tempting to speculate. Management decisions are open to pressure from the industry to allow higher catches in low stock years, and the industry may be unwilling to accept excessively high catches in the good years. If fishing decisions have been affected in these ways in recent years, one wonders about the wisdom of pursuing fixed escapement policies. This question is the central topic of the following section.

IV. Trade-offs between Mean and Variance of Catches

The results in Allen (1973) and Figures 5 and 6 clearly suggest that management strategies can be devised to significantly reduce the variance of catches without intolerable losses in average yield. The aim of this section is to quantify the best possible trade-off relationship between mean and variance of catches, so that the question of what is "intolerable" can be subjected to open negotiation. This analysis leads to a simplified optimal harvest law that can be practically implemented as an alternative to fixed escapement policies.

Definition: The Pareto Frontier

It is necessary to introduce a concept at this point that may be unfamiliar. Suppose one picks a value for the variance of catches, and then asks for the maximum mean catch that can be obtained at this level of variance. Presumably there is some answer to this question, and some optimal harvest strategy that will do the job. One can then pick another variance value and ask the same question about mean catch. If one demands 0.0 variance in catches from the Skeena River, then the maximum mean catch is not likely to exceed about 0.4 million. On the other hand, if one says that any variance is tolerable, then he can be presented with the maximum harvest strategy from Figure 7 with its associated mean value. The set of variance-mean combinations that can be generated in this way is known as a Pareto Frontier. In any decision problem where there are trade-offs between different kinds of benefits, the highest achievable combinations are said to define the Pareto Frontier. Presumably the only management strategies worth considering are those which generate points along the frontier.

The variance minimizing objective functions used to obtain the harvest curves of Figure 4 and 7 are asking essentially the same questions, but in reverse; for any desired mean value, they ask for a minimum variance harvest curve. Unfortunately, stochastic dynamic programming does not permit us to ask the questions the other way around without doing excessive additional computation. As we ask for higher and higher mean values with the variance-minimizing objective functions, the optimal solutions place more and more weight on getting higher catches, and correspondingly less on reducing variation (which is always large if the desired mean value is impossibly high).

Application to the Skeena River Sockeye

Thus the harvest strategies in Figure 7 should generate (approximately) values along the mean-variance Pareto Frontier. Figure 8 presents this frontier for two possible α distributions. Points along the upper frontier were obtained by 5000 year simulations with "natural" α probabilities and associated optimal harvest curves, while points along the lower frontier were obtained by simulating with the pessimistic α probabilities and their associated harvest curves. Observed catch-variance combinations for the past two decades have been well below the potential suggested by the "natural" α distribution. Since the catch-variance combination since 1960 has been well above the pessimistic frontier, and stocks have increased steadily over this period, the pessimistic frontier is clearly too conservative. The main suggestion of Figure 8 is that the average catch of the past decade could be either:

1) maintained with an extreme reduction in variance (using an $(H - .8)^2$ strategy curve);
2) increased by 25% (0.2 million fish) while maintaining the same variance (using an $(H - 2)^2$ strategy curve);
3) or increased by (perhaps) 39% (0.3 million fish) while increasing the variance by about 50%.

The average catch over the 1970-1974 period has actually been around 0.9 million fish, as it should be according to Figure 8, but a variance estimate for this short period would hardly be meaningful.

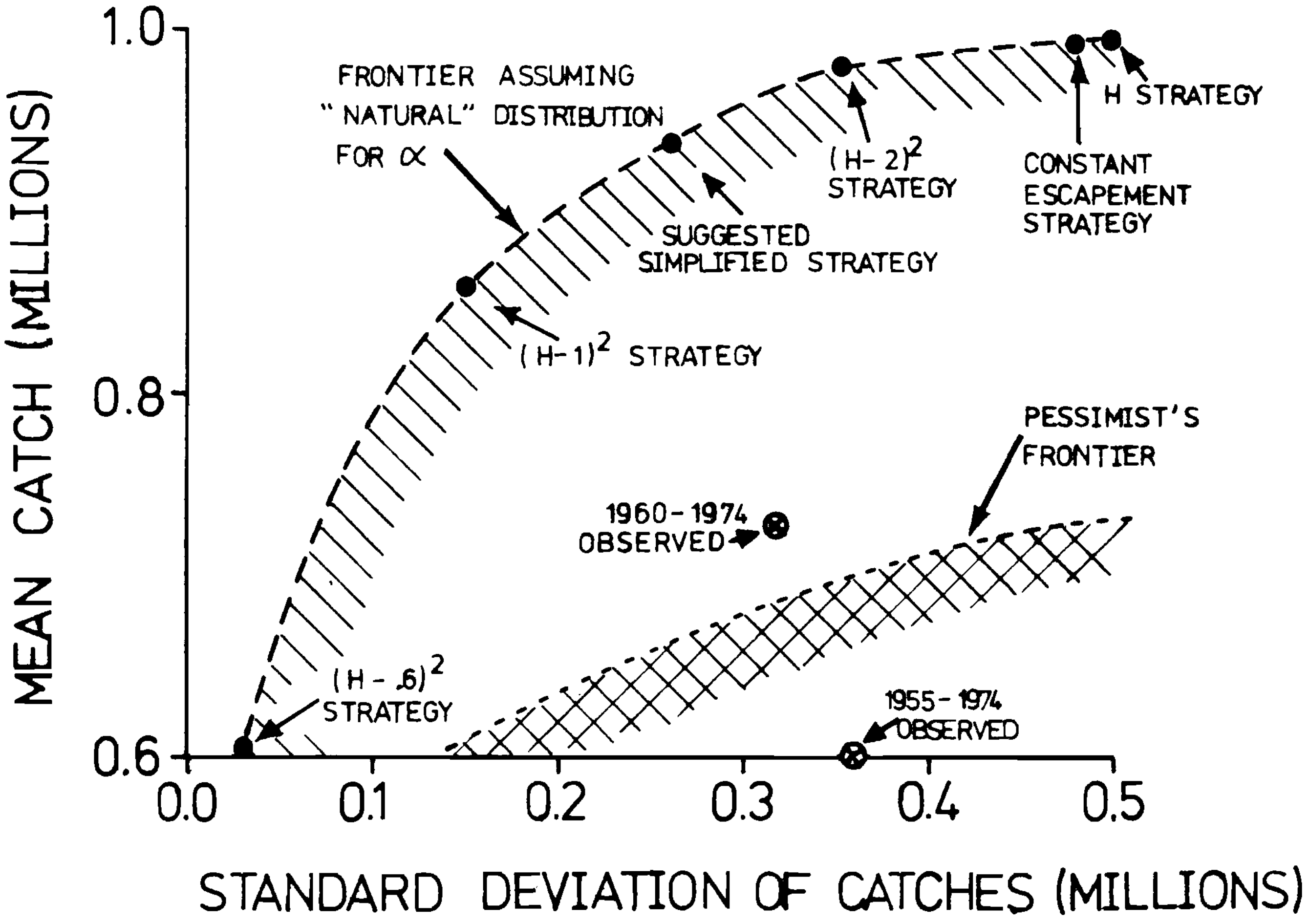

Figure 8. Pareto Frontier for best possible combinations of mean and variance of catches, for the Skeena River (explanation in text).

A Simplified Strategy for Practical Implementation

The optimal strategy curves based on variance minimization would be difficult to implement in practice, since they call for very good control of annual exploitation rates. Figure 7 suggests that such control is not yet available, even if it were possible to negotiate a best point along the Pareto Frontier of Figure 8. Thus a simplified strategy is suggested in Figure 7. This strategy recommends to:

1) take no harvest from stocks less than 0.5 million fish;
2) use exploitation rates between 0 and 50% for stocks between 0.5 and 1.0 million fish;
3) use a 50% exploitation rate for all stock size above 1.0 million.

This strategy should result in a mean-variance combination (Figures 8 and 9) nearly on the frontier of best possible combinations, with a mean catch (0.94 million fish) near the 1970-74 observed average and a 20% reduction in variance from the 1955-1974 average. By calling for a fixed exploitation rate (and thus fixed effective fishing effort) most of the time, the simplified strategy should be less costly to implement since it should not require close monitoring of escapements during each fishing season.

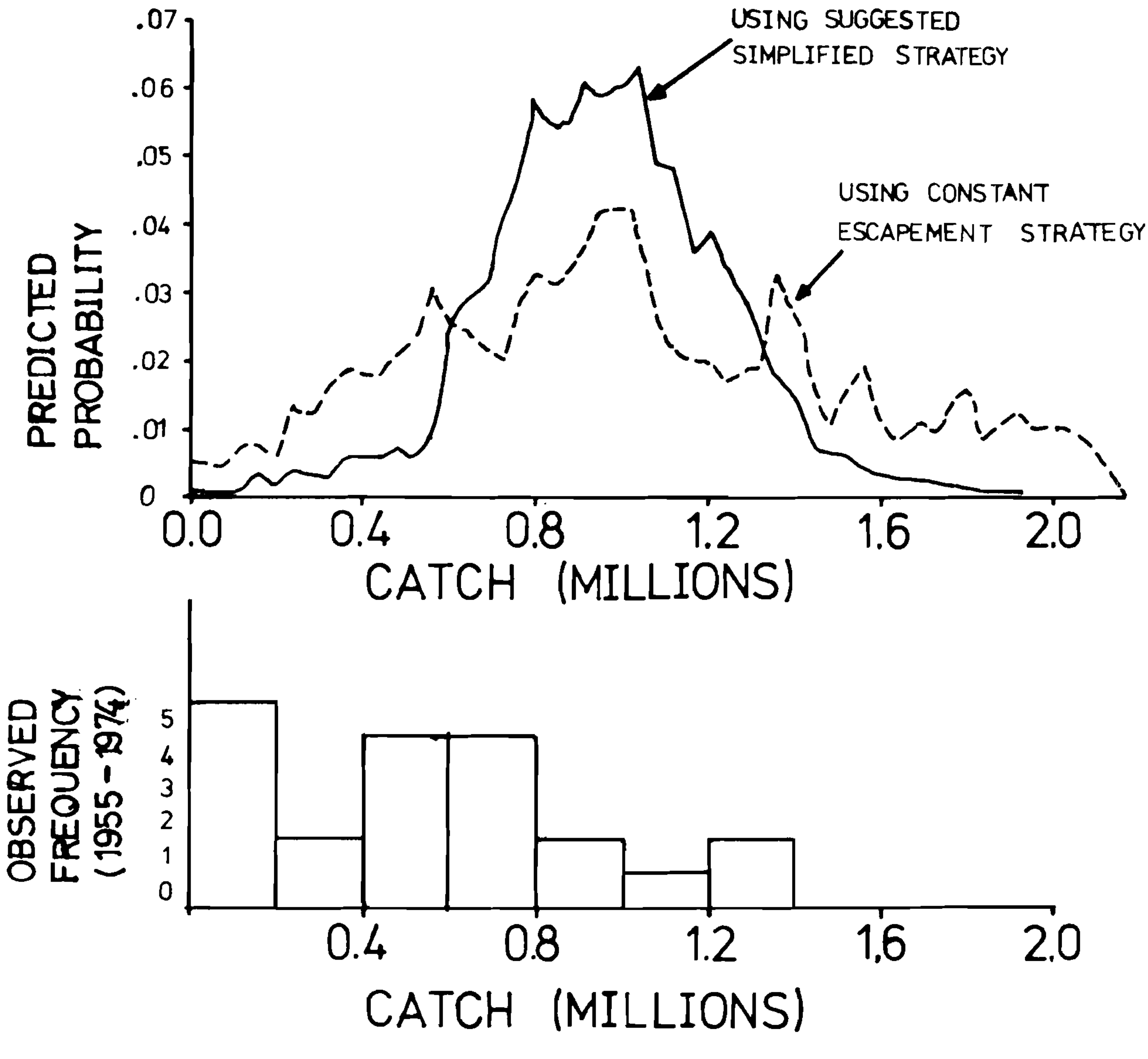

Figure 9. Predicted probability distributions of catches using the simplified strategy curve in Figure 7 as opposed to the best fixed escapement strategy. Recent actual catches are shown for comparison.

V. Conclusions

While I have concentrated on the Skeena River as an example, the methods outlined in this paper should be applicable in many fisheries situations. The stochastic programming solutions can be performed with any stock model that has relatively few state variables (≤ 7 for modern computers), and it is certainly possible to design more complex objective functions to take a variety of cost and benefit factors into account.

To summarize the previous sections:

1) Stochastic dynamic programming provides a mechanism for incorporating judgmental uncertainty about production parameters into the design of optimal managemental strategies.
2) Optimal strategy curves (exploitation rate versus stock size) are relatively insensitive to the judgmental probability distribution for the Ricker stock production parameter.
3) Optimal strategy curves are very sensitive to changing management objectives related to mean and variance of catches.
4) Strategies for reducing the variance of harvests should also lead to higher and more predictable stock sizes.
5) Potential trade-offs between mean and variance of catches can be quantified along a Pareto Frontier for decision negotiations.

6) Simplified strategy curves can be developed that give nearly optimal results.

Acknowledgments

The ideas in this paper are the result of discussions with scientists at the International Institute for Applied Systems Analysis, Vienna, especially Jim Bigelow, John Casti, and Sandra Buckingham. Special thanks to Peter Larkin and F.E.A. Wood for suggesting the direction to look.

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Optimal Harvest Strategies For Pink Salmon In The Skeena River: A Compressed Analysis

Carl J. Walters

In an earlier report,[1] I described a methodology for determining optimal harvest strategies in relation to uncertainty about stock production parameters. This note demonstrates the application of that procedure to pink salmon (odd year cycle) of the Skeena River. The procedure involves four basic steps:

1) a simple dynamic model is chosen to give a reasonable empirical representation of population changes in relation to harvest rate (e.g. Ricker Curve);

2) stock recruitment data are used to derive an empirical probability distribution for the key production parameter of the dynamic model, and this empirical distribution is used to derive judgmental probability distributions for future production rates;

3) stochastic dynamic programming is used to solve optimal relationships between exploitation rate and stock size (recruitment), for a series of objective functions which reflect increasing interest in mean catch as opposed to stability of catches over time;

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[1]C.J. Walters, "Optimal Harvest Strategies for Salmon in Relation to Environmental Variability and Uncertainty about Production Parameters," January 1975.

4) by examining the optimal strategy curves for different objectives, a simplified strategy curve is derived and compared to best possible results from the exact strategies.

Figures 1-7 show the results of the analysis using pink salmon data kindly provided by F.E.A. Wood, Environment Canada. Assumptions of the analysis are indicated in the figure captions.

The key recommendations from the analysis are that

1) Stocks less than 1.0 million should not be exploited.

2) Stocks above 1.5 million should recieve a fixed exploitation rate of around 0.4.

This strategy should result in a mean catch of close to 0.9 million (only 3% less than can be obtained by the current fixed escapement policy), with only about one-half of the variability that is likely to result from the fixed escapement policy. The frequency of zero catch years using the simplified strategy should be around 4%, while the fixed escapement policy is likely to result in zero catches more than 10% of the time.

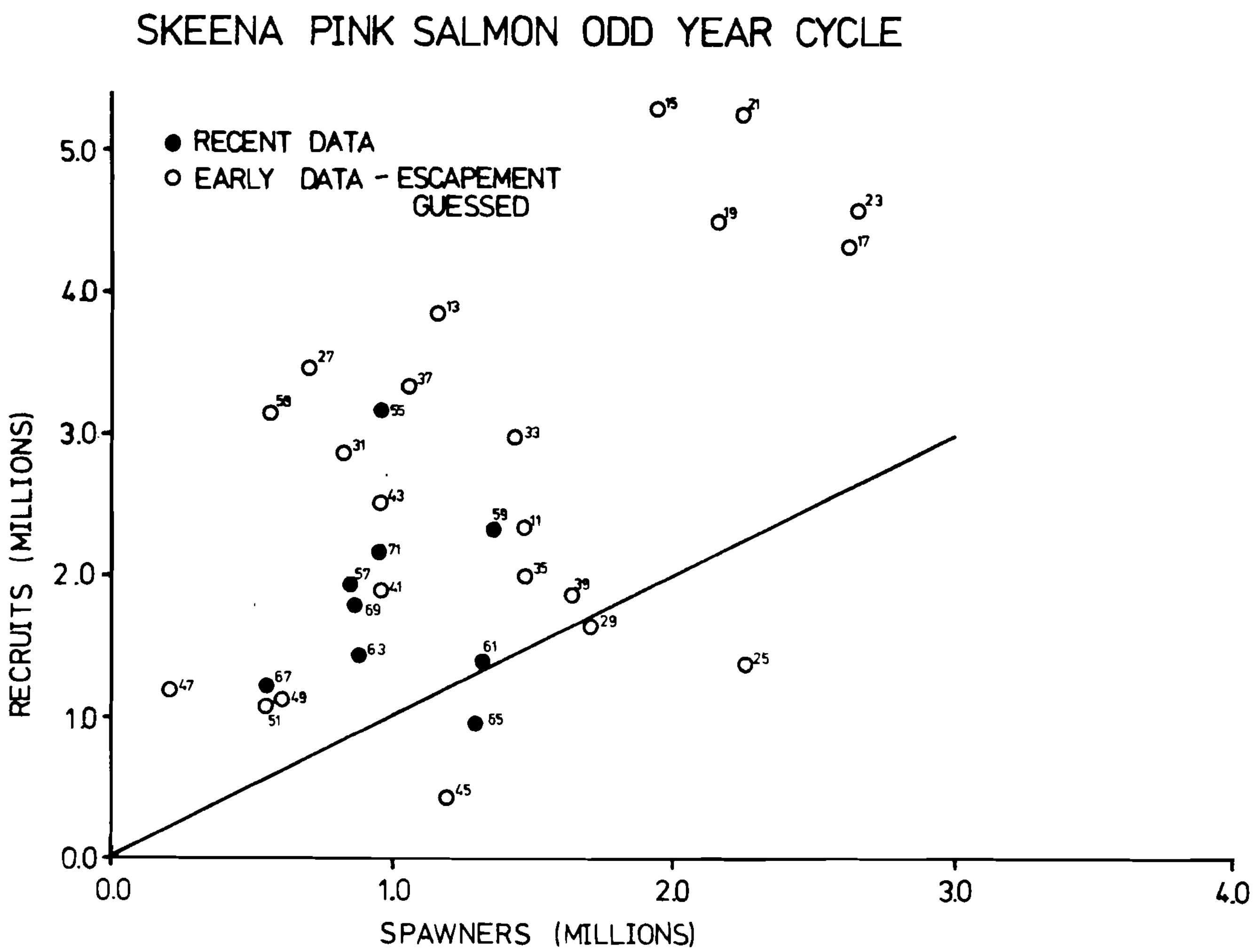

Figure 1. Stock-recruitment relationship for Skeena River pink salmon, odd year cycle. Dates next to points indicate spawning years. Spawners for years before 1955 guessed at one half of total stock. This is probably too low for the early years; the equilibrium (unfished) stock was assumed for the analysis to be about 3.0 million fish.

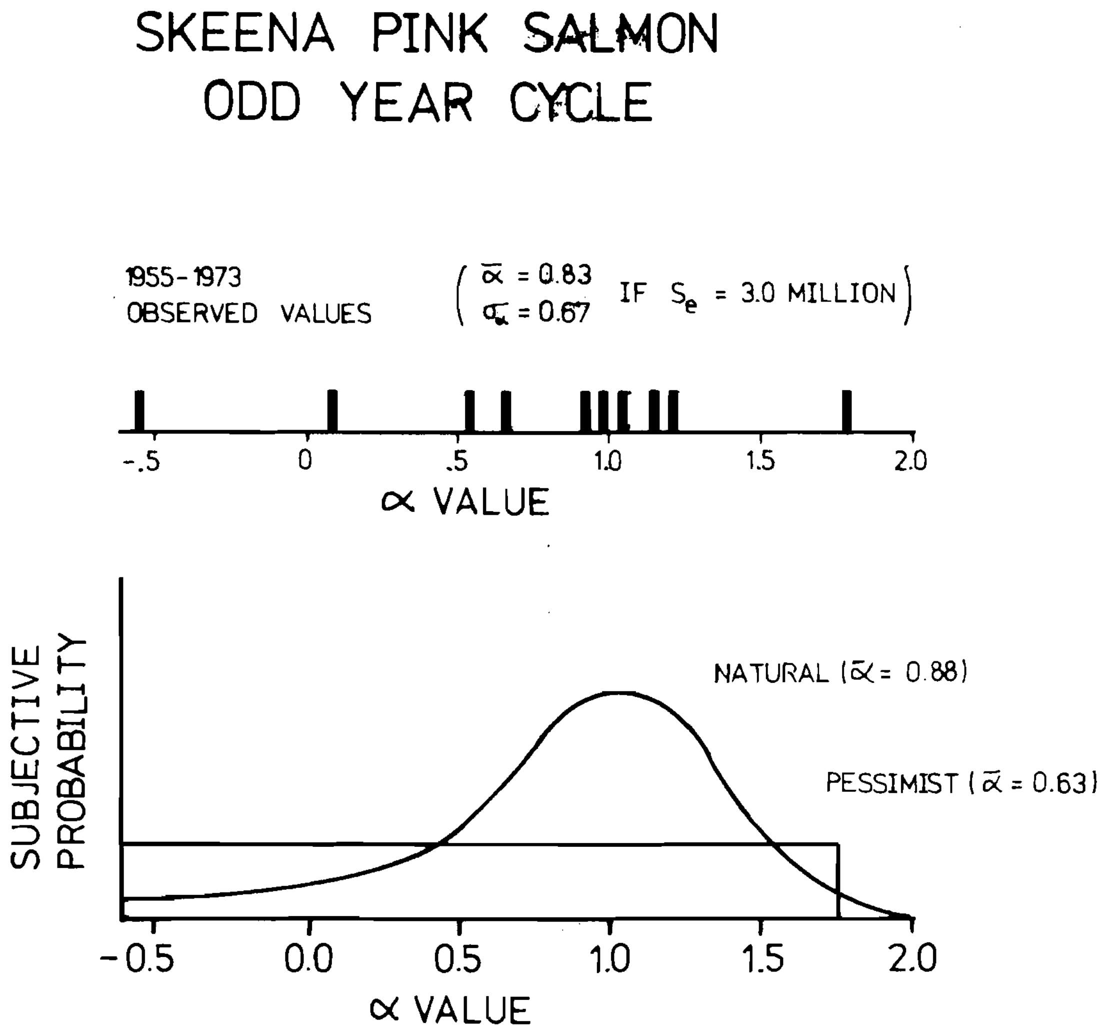

Figure 2. Empirical and judgmental probability distributions for the Ricker Production Parameter α, using data from Figure 1 and assuming an unfished equilibrium stock of 3.0 million.

The model $N_{t+1} = S_t e^{\alpha(1-S_t)}$ defines α where

N_{t+1} = recruits/3 million, S_t = spawners/

3 million, t = 2 year generations. Note the observed and assumed (judgmental) high probability of very poor production values. The "natural" probability distribution assumes less than replacement production ($\alpha < 0$) in about one out of every twenty years.

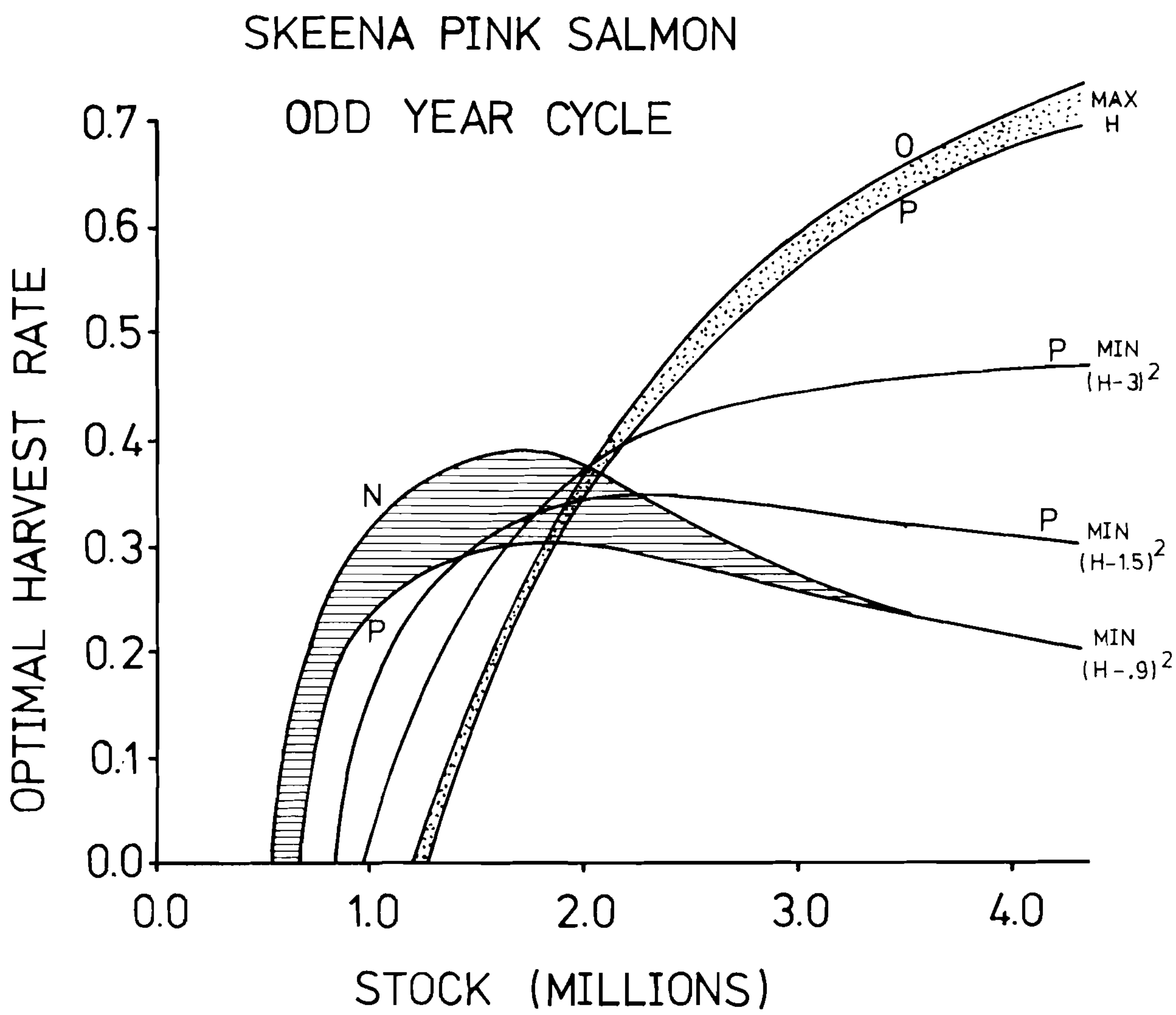

Figure 3. Optimal strategy curves derived by stochastic dynamic programming for different objective functions and judgmental probability distributions for α. N = natural α distributions of Figure 2, P = pessimistic α distributions of Figure 2. Objective functions are as indicated; $(H - \mu)^2$ curves are optimal for minimizing variance around mean catch of μ.

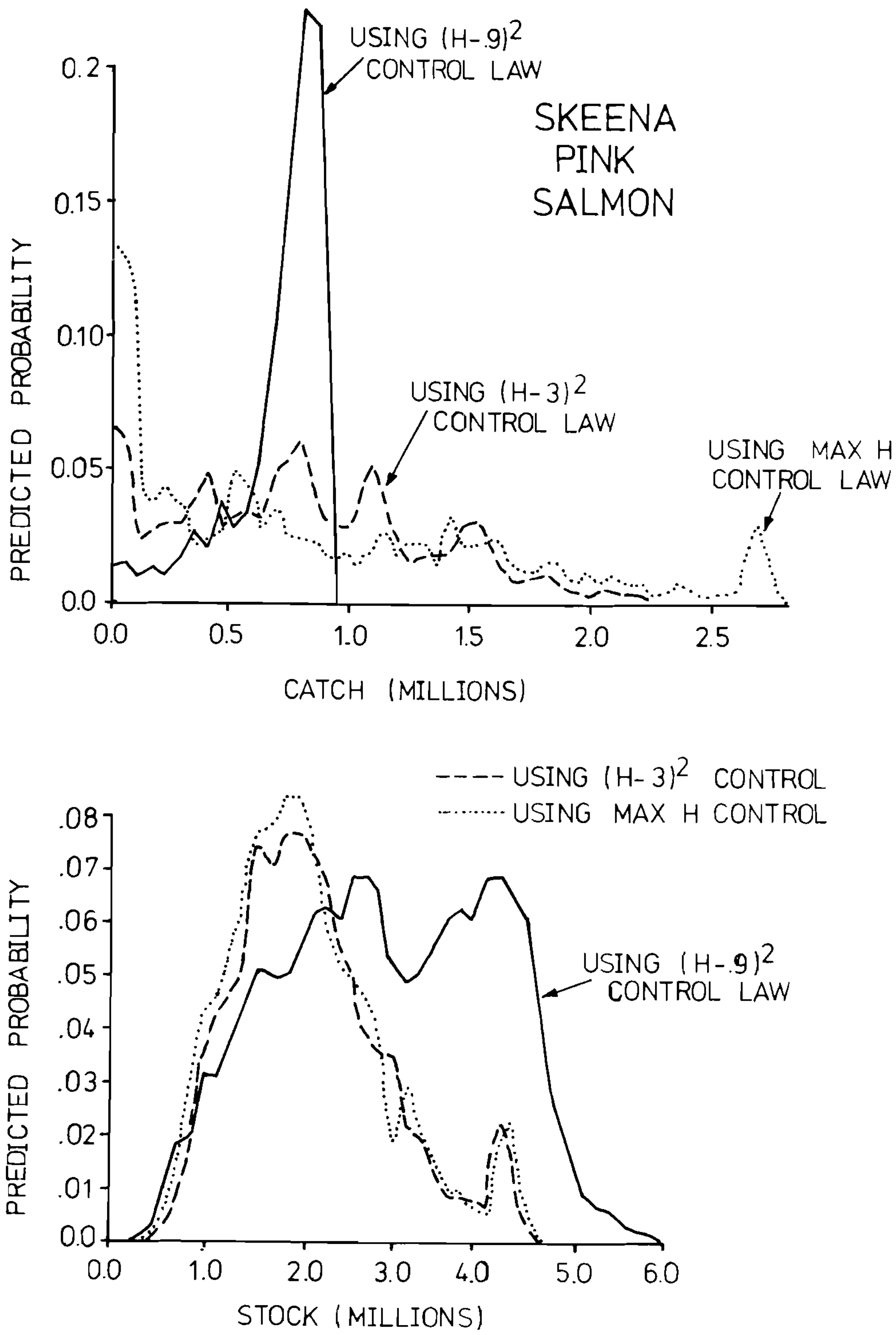

Figure 4. Probability distributions of catches and stocks likely to result from application of the optimal strategies in Figure 3. Based on 5,000-year simulations using α normally distributed with mean 0.8 and standard deviation 0.67 (see Figure 2).

Note that the $(H - .9)^2$ variance minimizing strategy results in a bimodal distribution of stock sizes, indicating the existence of two near-equilibrium levels; historical data shows a similar pattern, with high stocks mostly prior to 1930. The simulation would not have resulted in this prediction if the exact optimal harvest curve for α normally distributed ($\mu = 0.8$, $\sigma = 0.67$) had been computed and used.

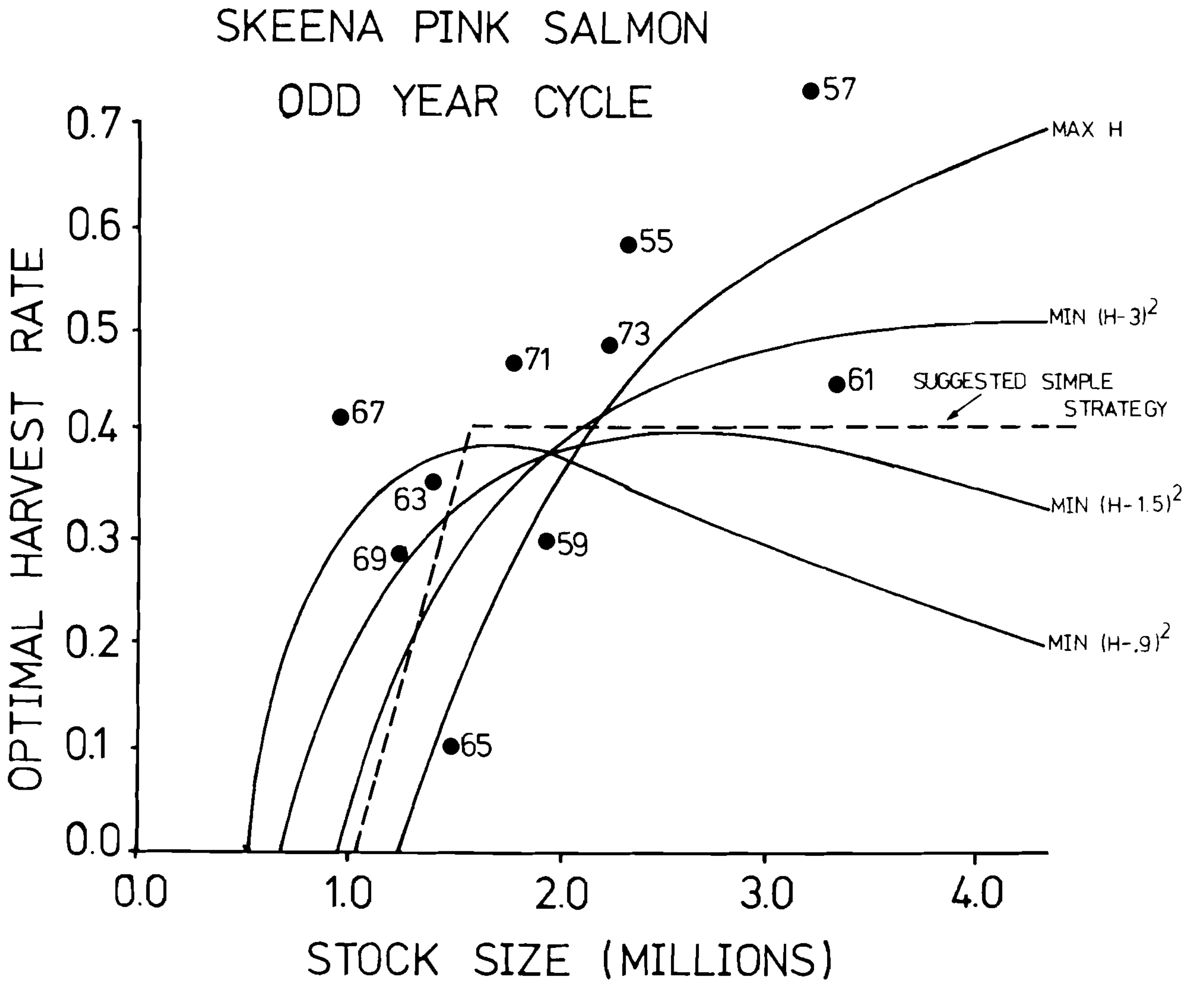

Figure 5. Optimal harvest curves compared to actual management practice, and a suggested simple strategy. Optimal curves derived by assuming the "natural" α distribution of Figure 2. It is not clear what the actual strategy has been, but management actions have been complicated by the joint exploitation of sockeye salmon.

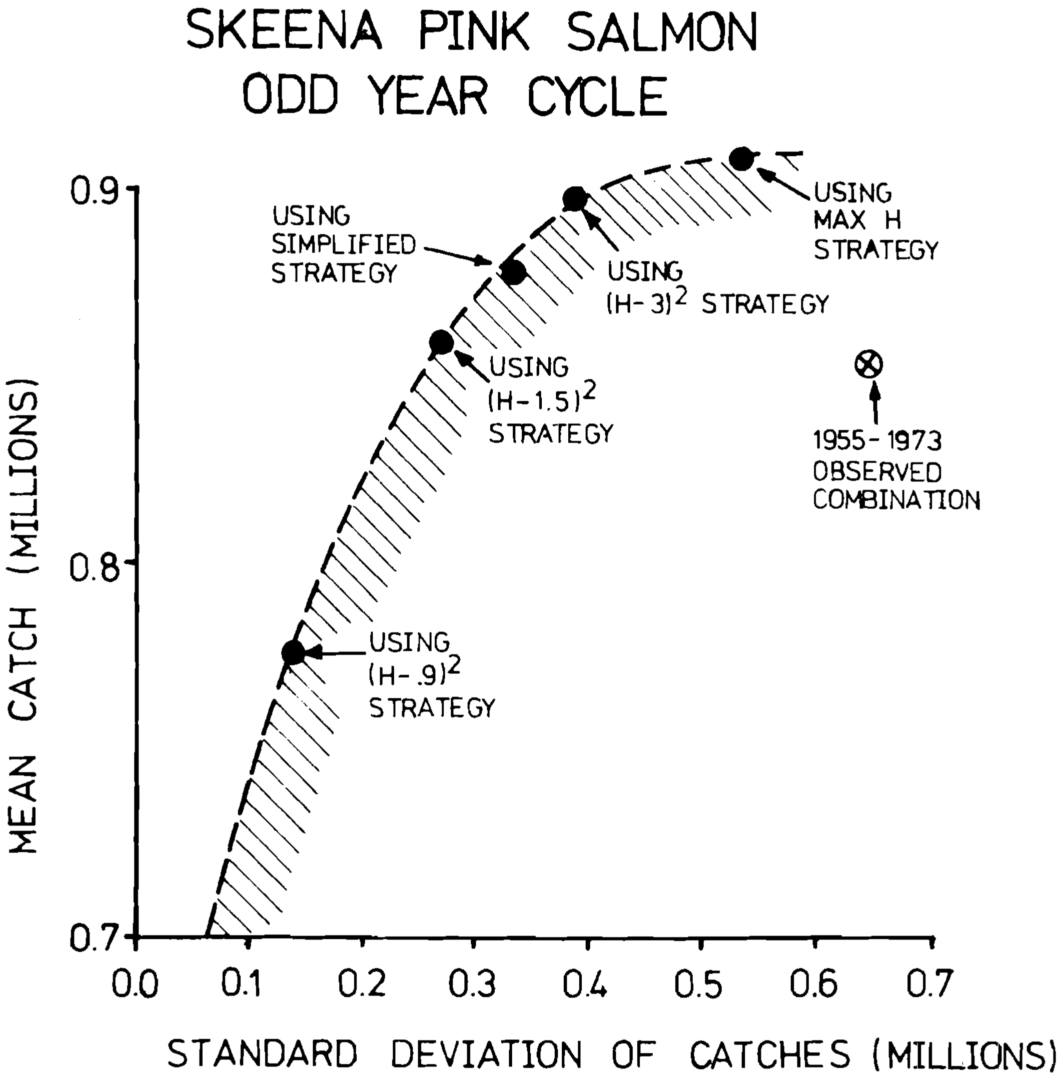

Figure 6. Pareto frontier of best strategies for trading off between mean and variability of catches. It is almost impossible to find a strategy which completely eliminates variability since very poor production years are common (see Figure 2).

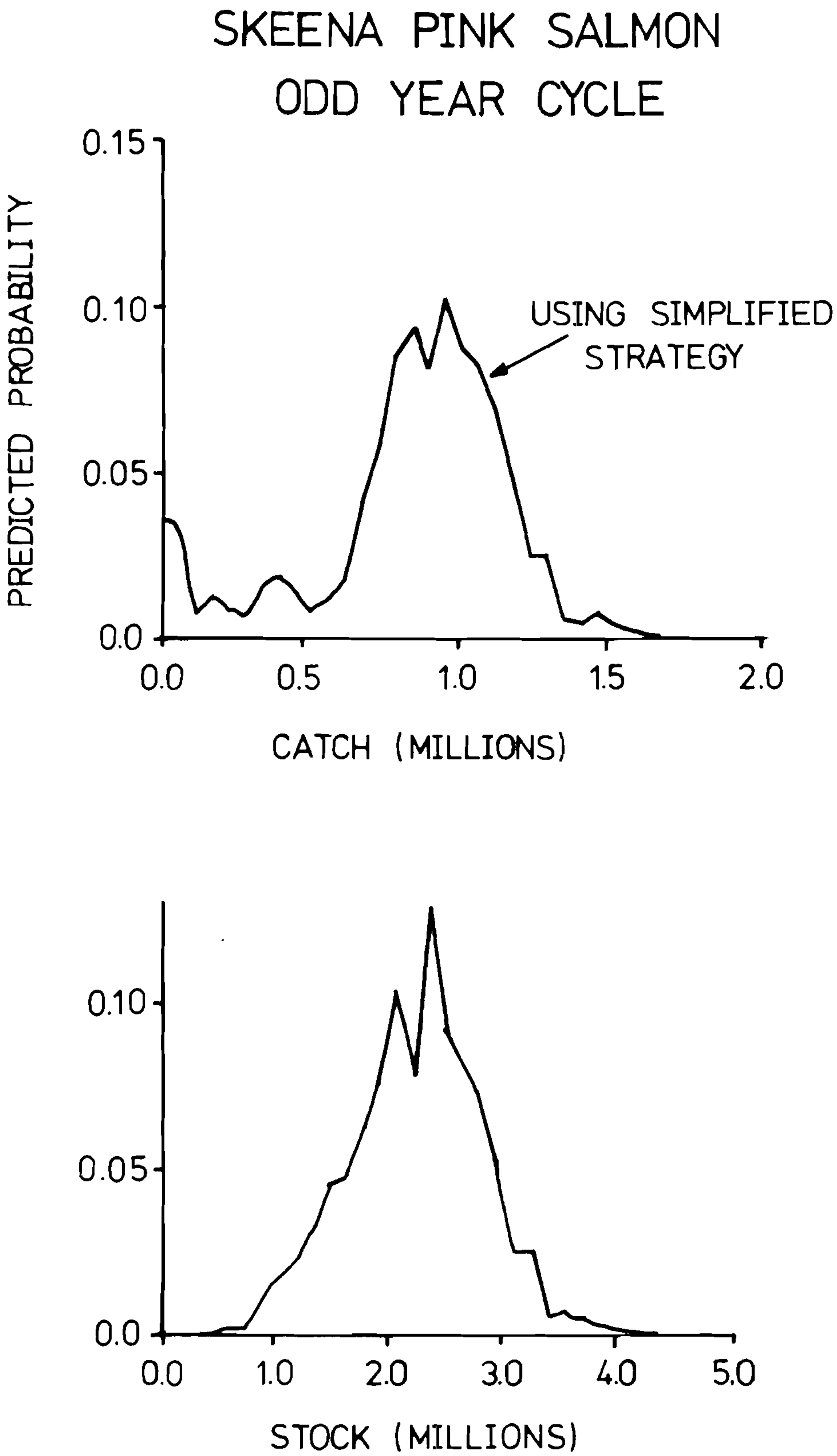

Figure 7. Predicted distributions of catch and stock size using the simplified strategy shown in Figure 5.

A Policy Failure Analysis of Salmon Enhancement Programs

Ray Hilborn

Introduction

The Canadian government has established a policy of enhancing natural salmon runs on the west coast. The basic concept of enhancement for commercial species is to provide additional artifical spawning grounds. In effect this creates new salmon stocks. The Fulton River spawning channels are the best example currently in operation; more such developments are being considered.

There are several potential problems with such stock enhancement facilities. In this paper I wish to consider long range problems associated with achieving an optimal exploitation of both enhanced and natural stocks. I have discussed this problem earlier (Hilborn, 1974) and used a deterministic model to find what would happen to a natural salmon stock being harvested simultaneously with an enhanced stock with a higher productivity. Briefly, the problem is that in order to optimally harvest the combined stocks, the natural stock (with a lower productivity) would be kept at lower stock levels, thus subjecting it to a higher probability of random extinction. This concept is summarized in Figure 1 which shows the equilibrium stock level of the natural stock when a combination of natural and enhanced stocks are harvested at maximum sustained yield. The larger and more productive the enhanced stock is made, the lower is the equilibrium size of the natural stock.

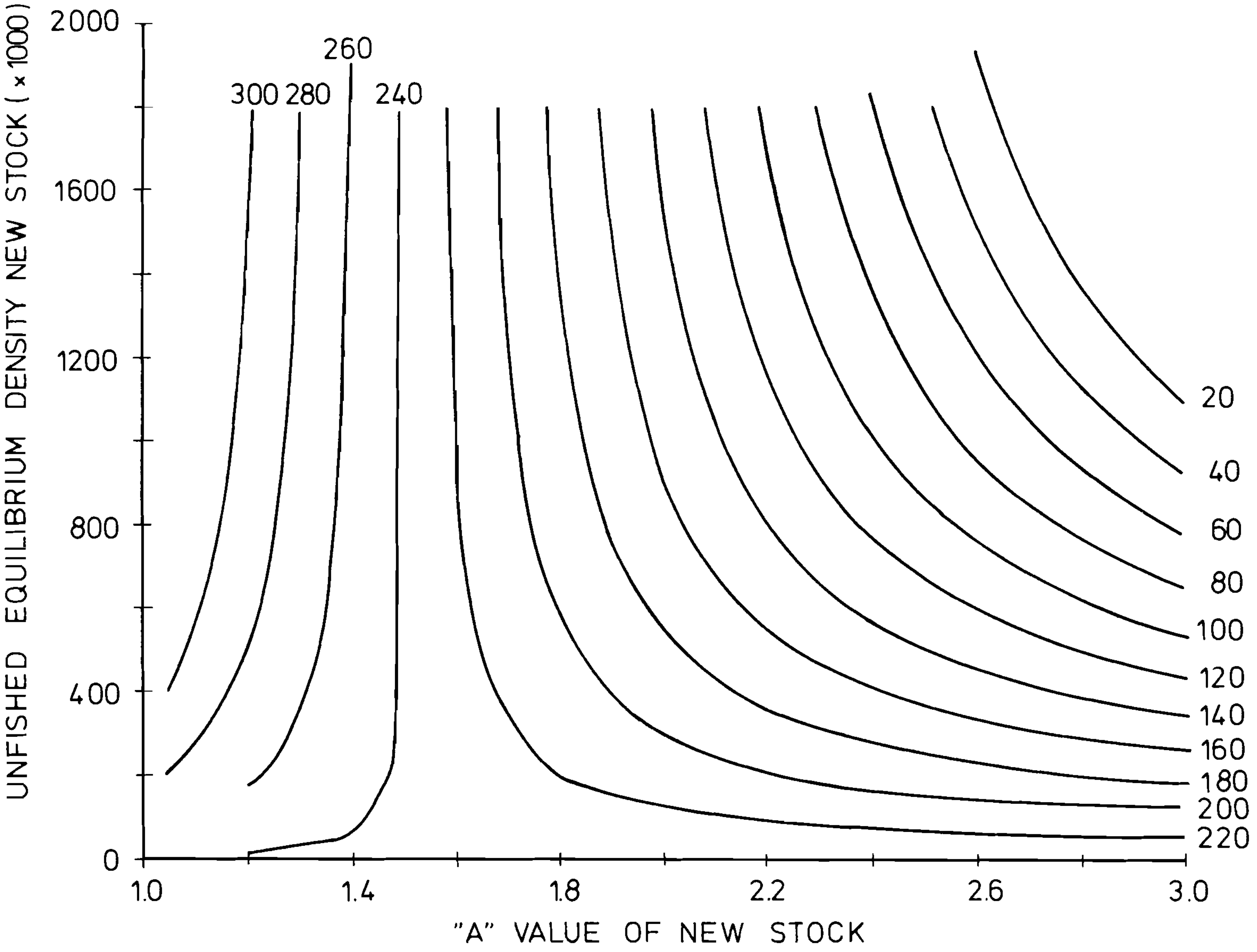

Figure 1. Equilibrium density of old stock (x 1000)
SI = 600 000 AI = 1.5.

This model was deterministic; in nature there is a very high variance in productivities. Walters (1975) has looked at optimal exploitation rates for stochastic models of a single stock and derived several alternative policies for maximization of yield or minimization of variance of yield. My approach was to use the same stochastic dynamic programming optimization technique, but I applied it to a combination of natural and enhanced stocks. The optimal policies thus derived were analyzed by a new technique for policy failure analysis. The technique described in detail later consists of taking a single management policy and asking what happens in the event of a disaster. The two types of disaster I consider in this paper are 1) complete failure of the enhanced stock, and 2) two consecutive generations with very poor productivity.

<u>Policies Analyzed</u>

I have considered five possible management strategies. In all cases I assume a single natural stock with a Ricker equilibrium density of two million and a productivity of 1.3, and an enhanced stock with a Ricker equilibrium density of two million and a productivity of 1.8. The five management policies considered were:

1) long term maximized yield using dynamic programming optimization;

2) maximization of the following objective function:

   objective = the harvest + 2 * the natural stock size. (This objective function should prevent the natural stock from ever reaching very low levels);

3) a harvest curve (derived by dynamic programming) designed to minimize the variance of the harvest around 1.9 million fish per year;

4) a constant harvest rate of .594, which is the optimum long term harvest rate for a deterministic population. See Hilborn (1974) for equations;

5) a maximum yield policy (from dynamic programming) for the natural stock, with no enhancement at all.

For all of the policies except 4), stochastic dynamic programming was used to determine the actual harvest policies. This is the best method currently available for complex non-linear dynamic models. All programs and conceptual development were done independently from those of Walters (1975), and our results were identical for the single stock case under policies 1), 2), and 5). This gives us greater confidence than usual with our own programming.

The next section presents the technique of policy failure analysis used and then applies it to a very simple case, our five salmon policies. This is primarily an exercise in methodology. Now that we are satisfied that it works, we will later apply the methodology to a more realistic salmon model which keeps track of the age classes, has adults returning at four and five years, etc.

Policy Failure Analysis

Policy failure consists of an unexpected occurrence in the managed system which disrupts maximization of the objective function. Such failure may be due to natural events such as poor weather, disasters, etc., or man-made changes or restrictions outside our control as system managers. For instance, the decision to build a hydro development on an important salmon stream made by another agency would be a policy failure to a salmon manager. Some kinds of policy failure are explicitly taken into account in stochastic dynamic programming situations. For instance, several years of poor productivity are a possible stochastic outcome recognized in the optimization. In general, the kinds of policy failure we wish to consider will be external to the model and we will have to artifically cause the failure to happen in the model. We then see how the system, as represented by the model, would respond to this form of failure.

In this salmon analysis, the two years of bad productivity, or weather, are implicitly optimized using stochastic dynamic programming. We consider this a policy failure only to explicitly look at the time stream of payoffs if we do get these two bad years. The total enhancement failure is completely external to the model and is more typical of the types of policy failure usually considered with this type of analysis.

There are three steps in the analysis of policy failure. First, we must decide which types of policy failure we wish to consider; second, we must assess the subjective probability of each of these failures occurring; and third, we must find a set of techniques for assessing the consequences of the failure. The end product of policy failure analysis should be a table listing for every policy, the possible forms of policy failure, the probability of failure, and the cost of failure (Table 1).

Defining the objective functions and the types of policy failure is a task best suited for system managers in concert with systems analysts. There are no formal rules for this step in the analysis and I will not consider it further. Calculating the probabilities of the failures occurring is also a difficult task. If the policy failure is a natural event, some form of historical time series analysis may prove the best technique. If the failure is a man-made one, deciding the probability of failure is a subjective judgment and is probably best left up to the management agency.

Having ignored the first two steps in policy failure analysis, we believe we can offer some good techniques for assessing the cost of policy failure. To measure this cost, we must first define what the payoffs are so that we know what we lose by a policy failure. This again touches on the

Table 1.

IDEAL POLICY FAILURE ANALYSIS TABLE

		POLICY 1	POLICY 2	POLICY 3
POLICY FAILURE 1	PROBABILITY			
	COST			
POLICY FAILURE 2	PROBABILITY			
	COST			
POLICY FAILURE 3	PROBABILITY			
	COST			

question of objective functions, and for salmon we used the total annual catch as the measure of payoffs. We have a much more sophisticated method of measuring payoffs for complex systems such as the budworm, and this method is described elsewhere. Given our payoffs (total catch), we ask what happens when a policy failure occurs.

We now must introduce the concept of manager's time scale (MTS). MTS is a measure of over what period the manager responsible is interested in what happens to the system. If the system itself is rapidly changing and policy failures will happen over a short period, for instance a strike in a municipal sewage treatment plant, then the MTS is very short. If the system is a much slower one and problems arise slowly and have long effects, then the MTS will be much longer. An example of this might be an erosion prevention program, or forest management, both of which have long time periods associated with management. The MTS is also a function of the institutional framework of the management agency. If the persons responsible for responding to policy failure change rapidly, then the MTS will tend to be much less than if the same person tends to be in charge for long periods of time. Given these considerations, the persons performing the policy failure analysis must select what they believe the appropriate MTS, but the policy failure analysis can be done for several possible MTS's and the results compared. For the salmon analysis we have chosen five generations (twenty-twenty-five years) as the appropriate time scale.

The purpose of choosing a MTS is that when we ask: "What happens to our payoffs if this type of policy failure occurs?" we must have a time scale in which to assess the consequences of the failure. Our technique is to run the model for the MTS under each type of policy failure and measure the payoffs under that failure. This is a bit more complicated than meets the eye. The cost of policy failure greatly depends on the state of the system when policy failure occurs, and the state of the system at the time of policy failure. This in turn depends on the management tactics being used. Our technique involves running the model for many intervals (5000 years) under each management option to assess the long term payoffs over the MTS. This must be repeated many times so that the state of the system at the point of policy failure will assume a frequency distribution similar to the long term frequency distribution. For complex cases like the budworm, discrete states are defined and the long term probability of being in that state is multiplied times the cost of failure if the system was in that state (this whole procedure for the budworm is described elsewhere).

We can now construct the first table of cost of policy failure (Table 2). For a simple objective function such as annual catch it is fairly easy to see what happens under

Table 2.

BENEFITS
(AVERAGE ANNUAL CATCH IN MILLIONS)

MANAGEMENT POLICY

	A MAXIMIZE YIELD	B MAINTAIN OLD STOCK	C MINIMIZE VARIANCE	D FIXED HARVEST RATE	E NO ENHANCEMENT ONLY OLD STOCK
LONG RUN AVERAGE	2.50	2.15	1.82	2.36	1.01
5 YEARS FOLLOWING ENHANCEMENT FAILURE	1.03	.87	.99	.92	1.03
5 YEARS FOLLOWING 2 VERY BAD WEATHER YEARS	1.77	1.56	1.56	1.62	.71

policy failure from this table. However, there is a further step in the analysis: We shall attempt to directly measure the "resilience" of various management tactics. Without going into an in-depth review of resilience, let me define a resilient strategy as one whose payoffs are not reduced by a policy failure. Let us scale everything from zero to one so that a strategy that loses no payoff by policy failure has a "resilience" of one and a policy that loses the maximum amount of payoff has a resilience of zero. Thus resilience is defined as

1.0 - (payoffs before policy failure--payoffs after policy failure).

The payoffs must also have been scaled between zero and one. What I have used as the maximum was the highest payoff found under any management strategy, which for this study is the long term payoffs under the maximum yield strategy (A). Thus we can present a new payoff table (Table 3) with all payoffs scaled between zero and one, and from this table calculate a resilience table (Table 4). A slight problem with this analysis is that any strategy which does not have a long term payoff of 1.0 cannot have a resilience of zero even if the stocks are completely wiped out. We might alternatively define the resilience as the proportion of payoffs lost under policy failure. The basic question is whether we are interested in the absolute magnitude of payoff loss, or the relative one.

Table 3.

BENEFITS SCALED TO A MAXIMUM OF 1.0

A	B	C	D	E
1.0	.86	.73	.94	.40
.41	.35	.40	.37	.41
.71	.62	.62	.65	.28

Table 4.

RESILIENCE INDICATORS

	A	B	C	D	E
Resilience Of Long Term Benefits	1.0	.86	.73	.94	.40
Resilience To Enhancement Failure	.41	.49	.67	.43	1.0
Resilience To Bad Weather	.71	.76	.89	.71	.88

In more complex ecological systems it is possible to produce irreversible effects due to some management practices and policy failures. The only irreversible effect possible for this salmon model is the total elimination of a stock, which does not happen under any of our proposed management tactics. For systems where irreversible changes do occur, we want to assess the long term cost of the policy failure as well as the cost during the MTS. To do this we must run the model for a very long period after policy failure, again repeating it many times to approximate the natural distribution of states at the point of policy failure. This would produce an additional column at the bottom of each table, listing long term benefits after a policy failure.

Discussion

Despite the simplifying assumptions used in this model, we can draw some useful conclusions from the results in Tables 2, 3, and 4. It is clear that policy 1), the long term yield optimization, produces the highest yield under all policy failure. This is not surprising, considering the technique of dynamic programming used: the rules for optimal yield have been worked out for situations when the enhanced stock is at low levels, or when there are two consecutive generations of poor productivity. The second policy, maintenance of old stocks, does not look particularly good. The size and productivity of the natural and enhanced stock used here never brought the natural stock near extinction, so the yield after policy failure was not better for this policy than the maximum yield. The minimized variance policy looks very good. Although the long term yield is considerably lower than the maximum yield, there are many benefits to maintaining a somewhat constant harvest. The fleet may not have the capacity to harvest at the highest possible rates and the canneries may not be able to process the really big runs. Both the fishermen and the canners may well be willing to sacrifice a little in long term yield for a much more reliable income. Walters (1975) has discussed this also. Under the two types of policy failure considered here, the minimized variance policy is particularly good. It is very resilient to both these failures (see Table 4), and the actual harvests are not substantially lower than the maximized yield policy. The fifth management policy was included mostly for comparison.

The fixed harvest rate policy is clearly inferior to the dynamic programming optimization of policy 1). This is natural and really not worth any more discussion. Since there was no enhanced stock to fail, it has a resilience of 1.0 to enhancement failure. The resilience to bad weather was high because the changes were small relative to the value used as the maximum. If the ratio method of calculating resilience (mentioned earlier) had been used, then the resilience of the no-enhancement policy would have been comparable to that of the maximum yield policy for two stocks.

It is clear that the best policy is either the maximum yield or minimized variance. The choice is up to the decision makers. This analysis makes it clear what is sacrificed in total yield for a more steady income. A distribution of incomes similar to that presented by Walters (1975) might prove a useful addition when presenting these options to a policy maker. We are now examining the possibilities of an automatic insurance system which would allow the fishermen to be paid back in bad years for money accumulated in good years. However, this does not resolve the problem of cannery capacity. We shall test these conclusions against the more complex model, but from our current understanding of the system it is difficult to see how our conclusions will differ.

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A Control System for Intraseason Salmon Management

Carl J. Walters and Sandra Buckingham

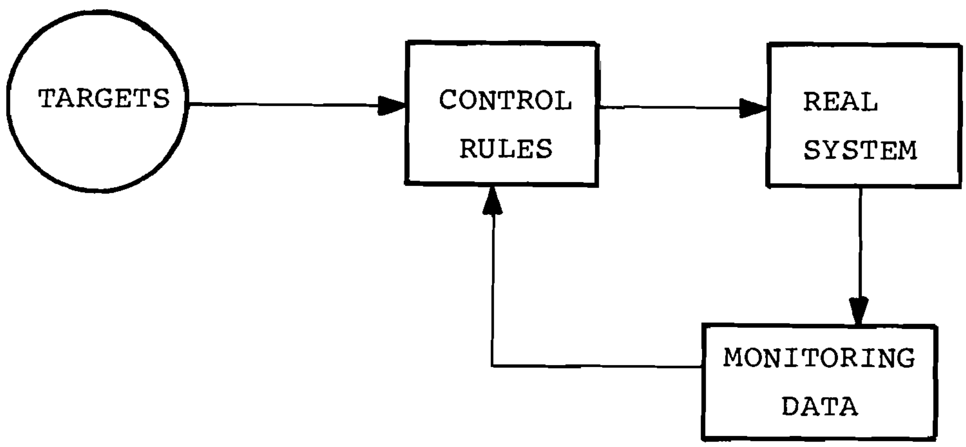
Management of Salmon populations in large rivers like the Skeena (B.C.) is usually done in two stages. First long range goals and data are used to set annual target exploitation rates for each stock or population that spawns in the river [2]. Second, actions are taken within each fishing season to regulate catches so as to produce the target exploitation. The most difficult monitoring and decision problems are associated with intraseason management; the purpose of this paper is to outline a control system for dealing with these problems.

At the beginning of each fishing season, the salmon manager has only crude estimates of the expected runs (A "run" of any species is the number of fish attempting to enter the river; catch is removed from the run, leaving escapement = run - catch.) He also has estimates of the proportion of the run that will enter the river during each week of the season. As the season progresses he must monitor catches and escapements so as to improve his estimates of the total runs, and set harvest regulations accordingly. Current management practice involves week by week regulation of exploitation rates (proportion of run actually caught) by changing the number of days open. At the end of each week, the number of open days for the next week is announced. Historical data is used to estimate the relationship between exploitation rate and days fished, but this relationship is by no means perfect since the number of fishing boats is poorly controlled.

The fishermen, unfortunately, have only limited ability to discriminate among the various species that may be entering the river during any week. Each stock has a different optimum exploitation rate, and may suffer genetic damage in the long run if some segments of it (e.g. early running fish receive different exploitation rates from others. Essentially the weekly exploitation rate is a blanket measure that must be applied across all stocks which are present at that time.

The General Control Framework

The basic idea of a control system is very simple:



Given a real system that cannot be fully observed (the fishery), monitoring data is used, along with targets (goals), to decide on controls (regulations). The aim of control system design is to produce a good set of "control rules" for translating accumulated data into management actions or controls.

Figure 1 diagrams the functional elements for an intra-season salmon control system. The basic control variable is the number of "open days" for fishing each week; the elements of the diagram show the various calculations (functional relationships) and intermediate estimators which should be used in arriving at a control value for each week.

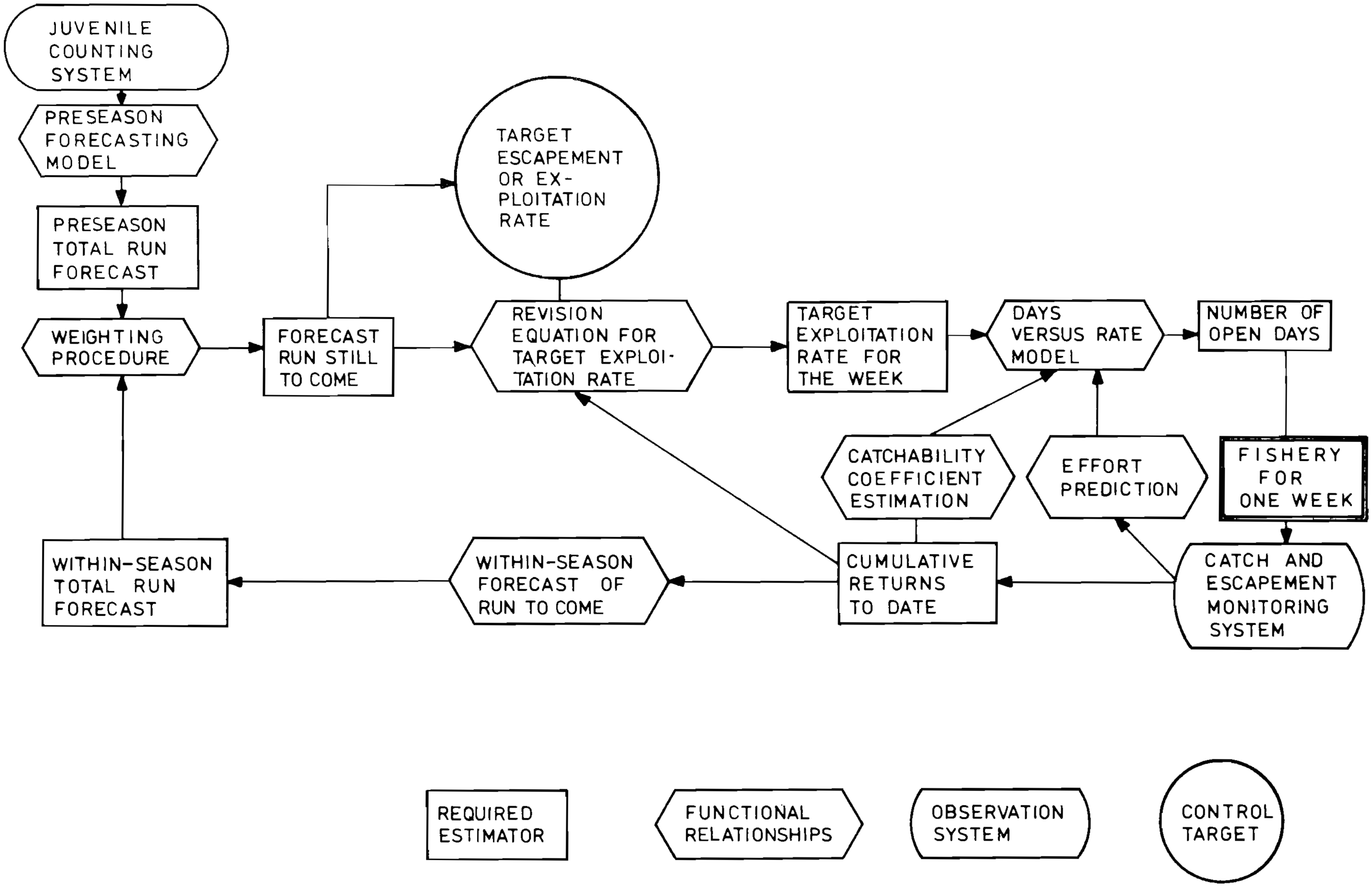


Figure 1. Elements of a control system for within-season salmon management. Components explained in text.

The flow of information is as follows:

1) a preseason forecasting model is used to generate initial estimates of the runs to come;

2) before the beginning of each week, cumulative catch and escapement data are used to generate: a) a prediction of fishing effort (boat-days) for the week, and b) a new estimate of the total run size;

3) the new estimate of total run size is combined with the preseason forecast to give a revised overall forecast of the total run;

4) the revised overall forecast and cumulative catch to date are compared to the overall target rate in order to decide a target rate for the week;

5) the number of open days to allow is calculated as a function of the target rate for the week, the predicted effort, and the expected catchability coefficient (proportion of stock taken by one unit of effort).

Steps 2)-5) are repeated each week; thus the control system proposed in Figure 1 results in changing regulations as new information is obtained.

Elements of the Control System

This section develops the conceptual components of Figure 1 in more detail and provides an empirical basis for implementing the system in practice. Extensive use is made of unpublished data kindly provided by F.E.A. Wood and Ed Zyblut of Environment Canada.

Control Component 1: Preseason Run Forecasts

Many kinds of data and models could be used for run forecasting, and the various alternatives should be carefully compared in terms of costs relative to statistical accuracy. Figure 2 shows one possibility for the Skeena sockeye, based on river flow data and downstream smolt counts. This forecasting model and several alternatives are described more fully elsewhere [1]; essentially they are non-linear regression formulae based on the Ricker stock-recruitment model. All methods take the age distribution of returning adults into account, and both could be made at least two years before they are actually needed for management. The various methods give similar expected forecasting errors:

Method	Variance of Forecasts
escapement-flow (no smolt counts)	3.02×10^{11}
smolt counts-flow	2.24×10^{11}

(A variance of 2.24 X 10" means a standard deviation of 469,000; about 67% of the forecasts should be within 469,000 of the actual runs.)

Staley [1] has developed similar forecasting models for pink salmon (Figure 3). The best of these models has a variance of 0.46×10^{12}, using escapements and river flows as regression inputs.

Whatever the preseason forecasting system that is considered best, its key characteristic for this analysis is its forecasting variance. The variance is used to weight

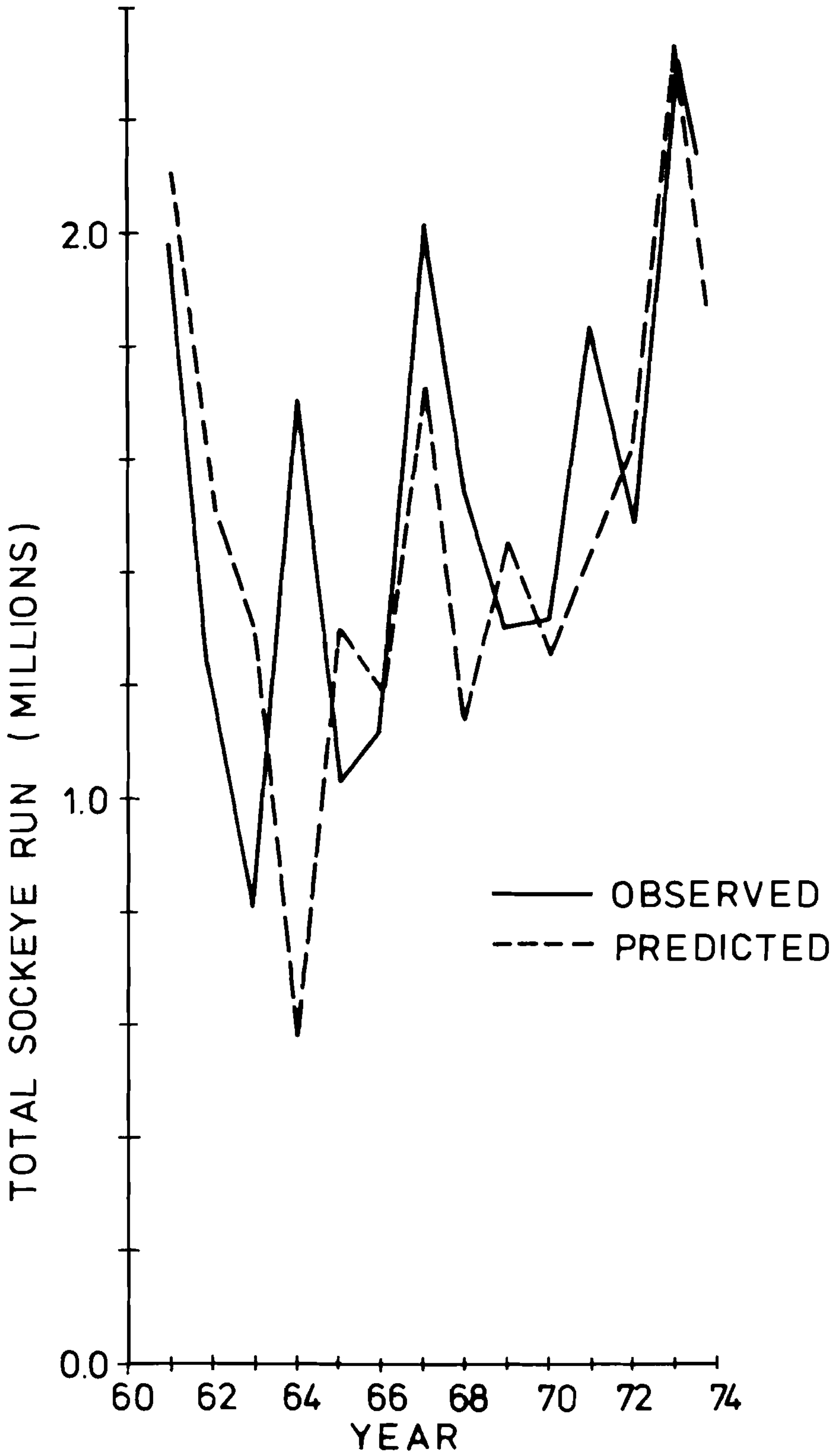


Figure 2. Preseason sockeye forecasts using smolt counts and stream flow. From M.J. Staley (in preparation).

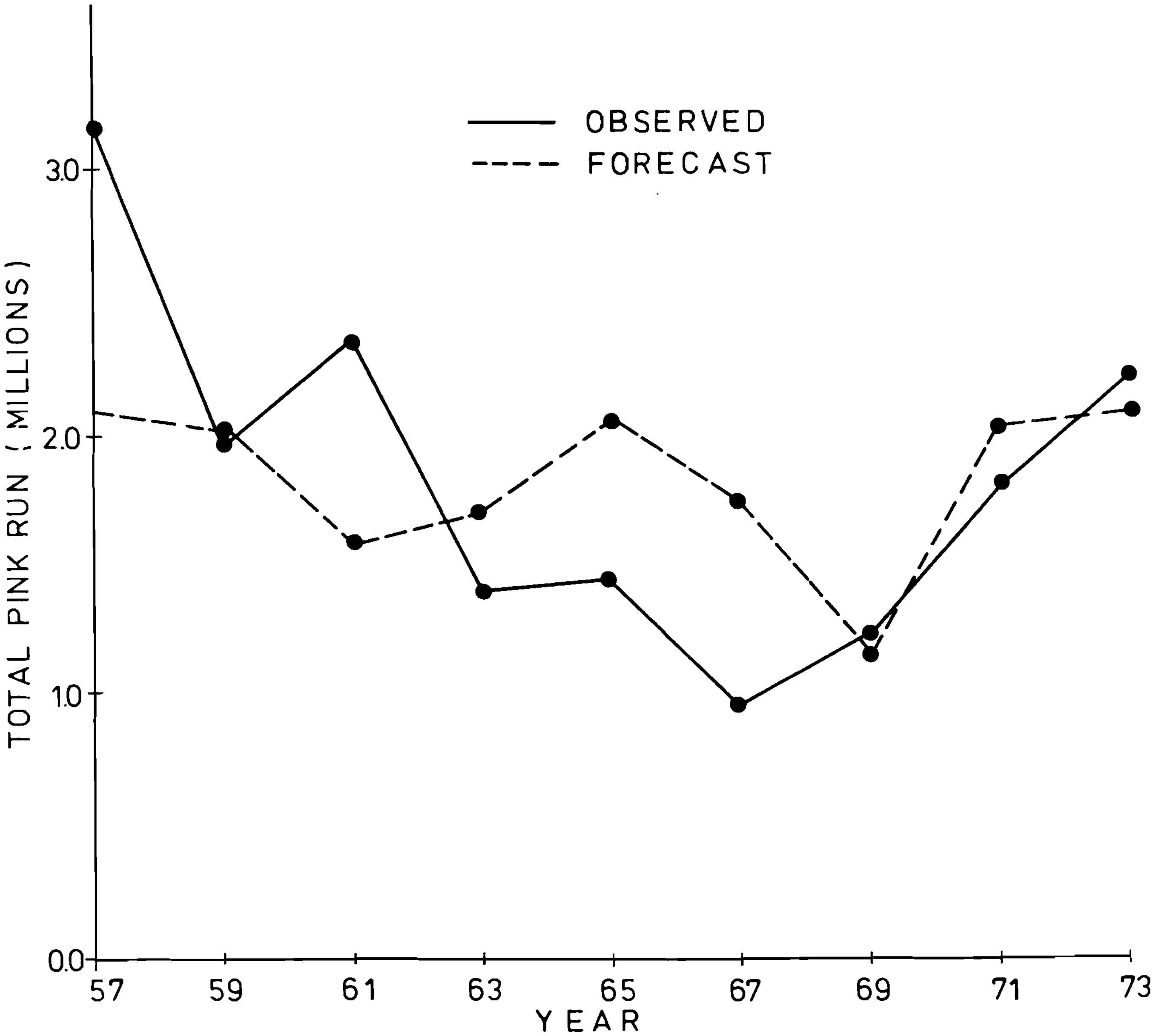


Figure 3. Preseason forecasts for odd year pink salmon, using a Ricker model and stream flow data from M.J. Staley (in preparation).

preseason versus within-season run estimates to arrive at a (changing) best overall prediction for the run.

Control Component 2: Within-Season Run Estimates

Cumulative run timing curves for the Skeena are presented in Figure 4. It is apparent that there is considerable variation from year to year in the proportion of fish that have entered the fishery by any date; we can find no simple way to predict whether a given year will be "early," average, or "late." Figure 4 also presents variance estimates for the cumulative proportion of fish returned, by date (these variance estimates were calculated directly for each date by taking sums of squares deviations of the observed proportions for the date from the mean observed proportion); these variance estimates are essential in developing a method for weighting within-season versus preseason run estimates.

Given the cumulative catch plus escapement up to any date, and the mean cumulative proportion expected to have returned by that date (Figure 4), the within-season total run estimate is simply

$$\text{total run estimate} = \frac{(\text{Catch + Escapement to date})}{(\text{Cumulative Proportion to date})} \; . \quad (1)$$

Dr. J. Bigelow of IIASA has kindly developed an approximate (second order) variance estimator for this run estimate; it is

$$\sigma^2_{W_t} = \frac{R_t^2 \sigma^2_{P_t}}{P_t^4} \left[1 + 2 \frac{\sigma^2_{P_t}}{P_t^2} \right] \quad (2)$$

where

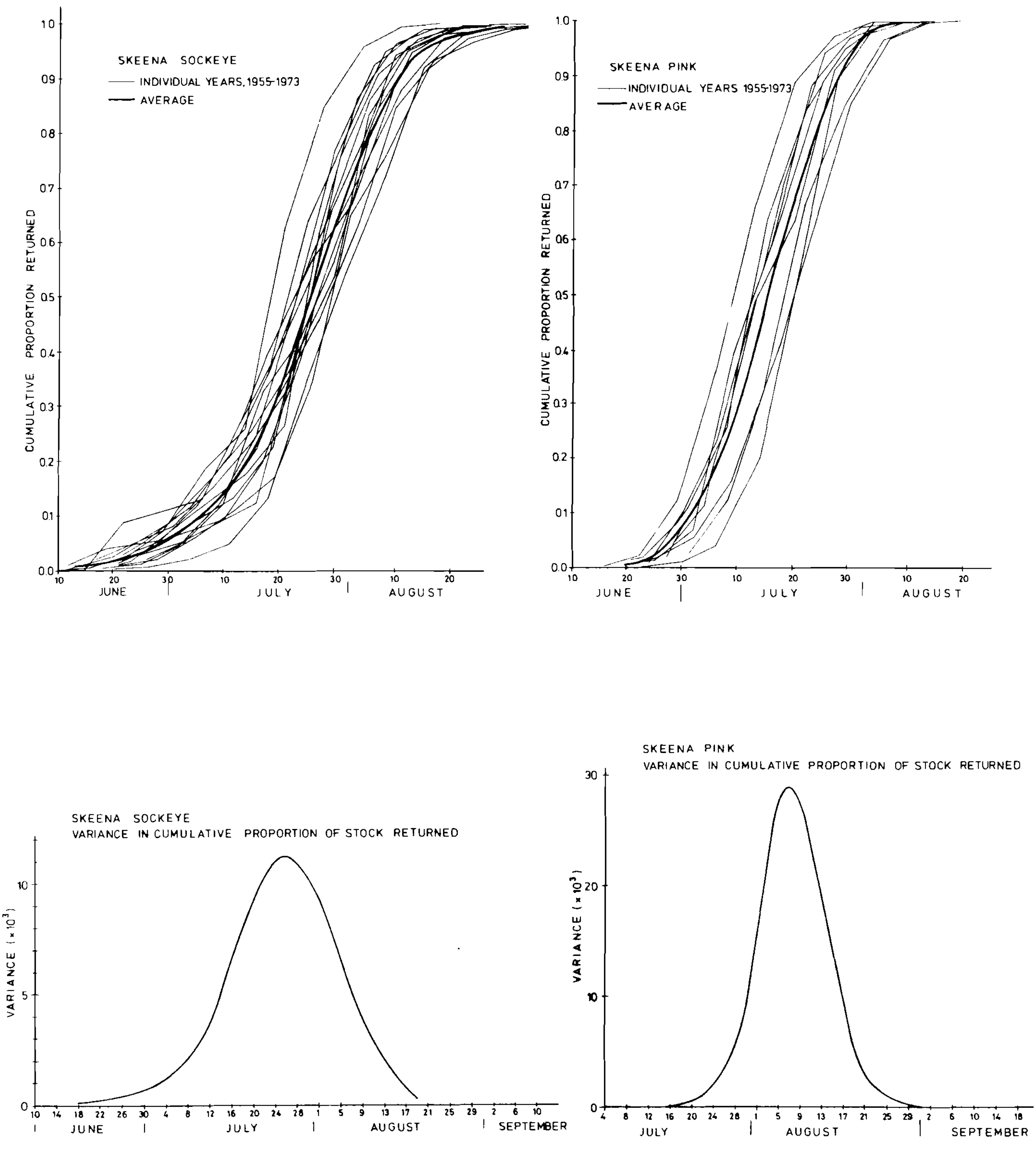


Figure 4. Cumulative return curves for Skeena River sockeye and pink salmon, and estimates of year to year variance in the cumulative proportion.

$\sigma^2_{w_t}$ = variance of the total run estimate for time t in the season;

$\sigma^2_{P_t}$ = variance of the cumulative proportion returned (Figure 4);

P_t = mean cumulative proportion returned at time t (Figure 4);

R_t = cumulative catch plus escapement up to time t.

Note that the variance estimate $\sigma^2_{w_t}$ consists of a "weighting factor" which can be computed from data in Figure 4, multiplied by the square of cumulative catch plus escapement. Weighting factor curves for the Skeena are presented in Figure 5; the variance estimate for the within-season run estimate at any date is simply the Figure 5 weighting factor times (catch + escapement to date)^2. It is apparent from Figure 5 that the within-season total run estimates are quite unreliable until over half of the run is past.

There is, of course, a fly in the ointment: cumulative catch plus escapement is never known exactly as of any date; cumulative escapement is measured at the spawning grounds, with a time delay of at least one week. An escapement estimate for each week is available from test fishing, and the variance of this estimate should be incorporated into equation (2) for future analyses.

Control Component 3: Weighted Overall Run Estimates

The next step is to find a way of weighting the preseason and within-season run estimates (previous two subsections) to give the best overall run estimate for each date. Suppose we consider writing this overall estimate as a weighted average of

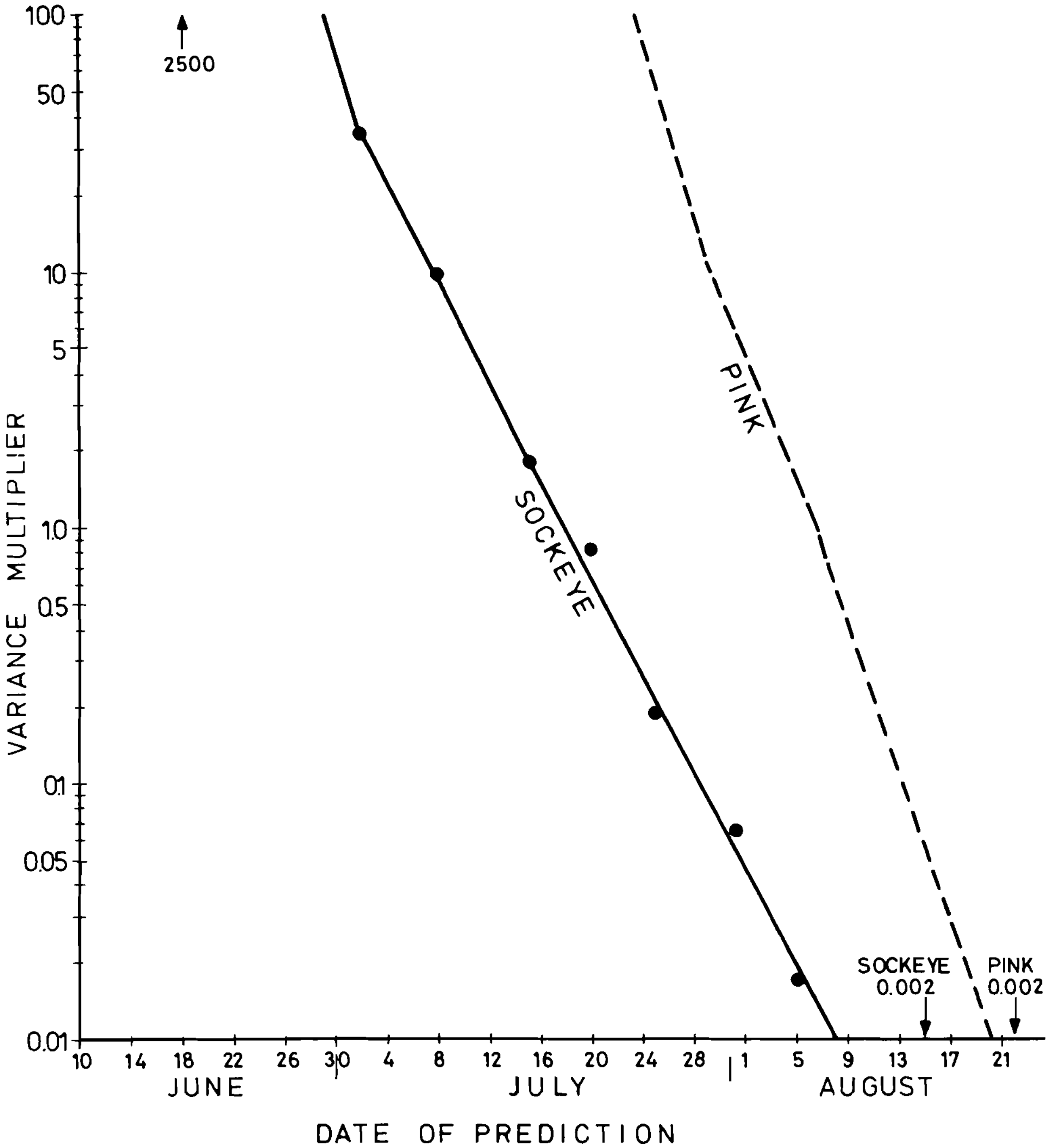


Figure 5. Weighting factors for computing variances of within-season total run estimates. Explanation in text.

the two estimators:

$$\hat{\hat{R}} \equiv \begin{pmatrix} \text{overall run} \\ \text{estimate based} \\ \text{on data to time} \\ t \end{pmatrix} = W_t \begin{pmatrix} \text{Preseason} \\ \text{estimate} \end{pmatrix} + (1-W_t) \begin{pmatrix} \text{within} \\ \text{season} \\ \text{estimate} \end{pmatrix} \quad (3)$$

where W_t is the weighting factor ($0 \leq W_t \leq 1$). The variance of the overall run estimate is then

$$\sigma^2_{\hat{\hat{R}}_t} = W_t^2 \, \sigma_f^2 + (1-W_t)^2 \sigma^2_{w_t} \quad (4)$$

where

σ_f^2 = variance of preseason forecast (see component 1, subsection above);

$\sigma^2_{w_t}$ = variance of within-season forecast (see component 2, subsection above).

This formula suggests a way of choosing the W_t so as to minimize $\sigma^2_{\hat{\hat{R}}_t}$. If we differentiate equation (4) with respect to w_t and solve for the minimum, we get

$$W_t = \frac{\sigma^2_{w_t}}{\sigma_f^2 + \sigma^2_{w_t}} \quad . \quad (5)$$

This equation implies that W_t should be near 1.0 early in the season (when $\sigma^2_{w_t}$ is very large), and decrease progressively as $\sigma^2_{w_t}$ decreases.

Sample weighting curves using equation (5) and variance estimates from the previous subsections are presented in Figure 6. Since $\sigma^2_{w_t}$ depends on catch plus escapement, no single weighting curve can be drawn and used under all conditions. The sample curves were developed using average catches plus escapements, and they should be adequate for most practical situations. To illustrate the use of Figure 6 in conjunction with equation (3), let us suppose that it is July 5, that we

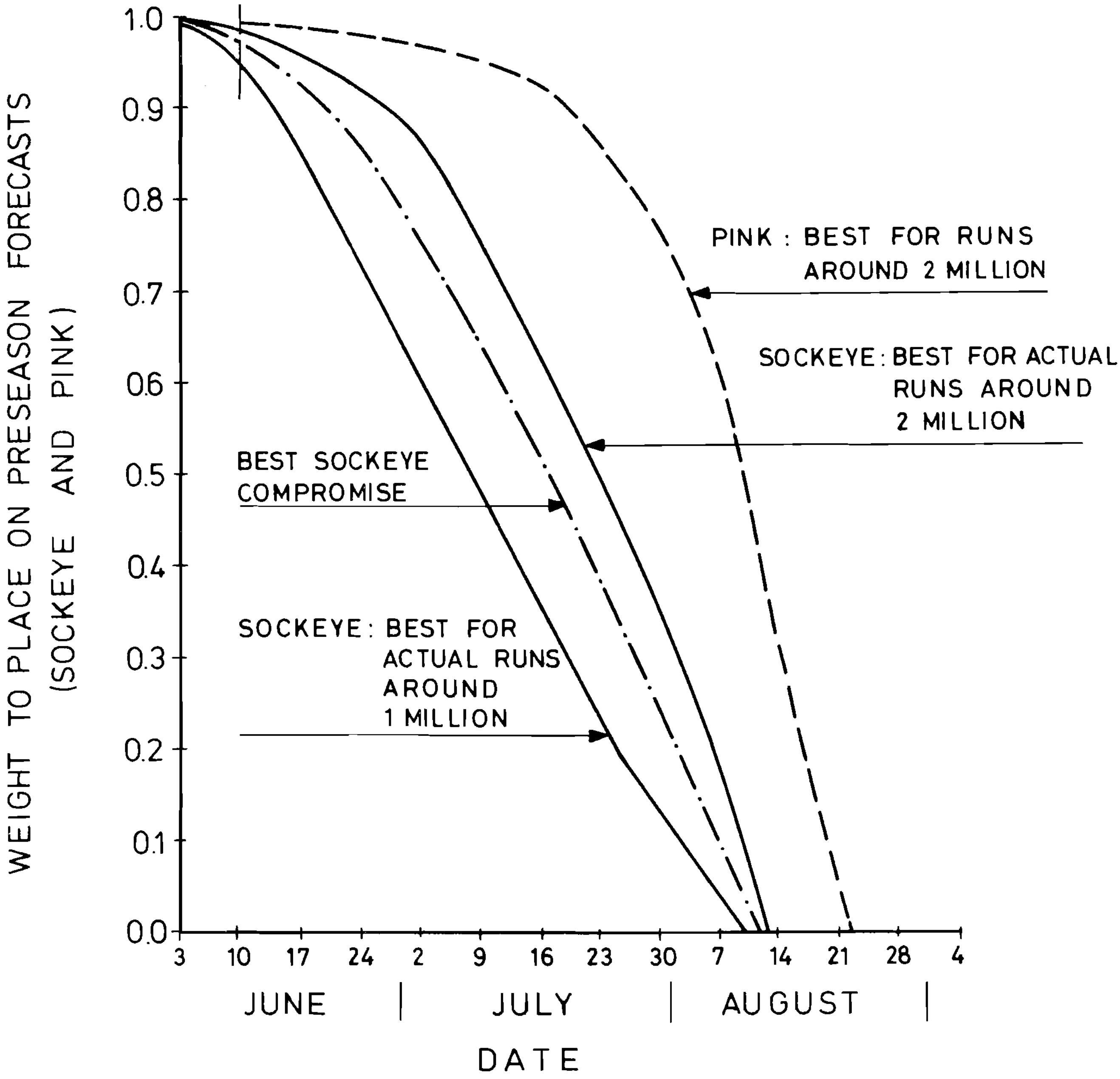


Figure 6. Weighting factors for preseason versus within-season total run estimates. Explanation in text.

have a preseason sockeye forecast of 1.8 million, and that the catch plus escapement to date has been 0.15 million. From Figure 6 the approximate weighting factor for July 5 is 0.7. Using Figure 4, we estimate that 10% of the fish have already passed, so the within-season run estimate is 0.15 million/0.1 = 1.5 million. The best overall run estimate as of July 5 is then

$$R_{\text{July 5}} = (0.7)(1.8 \text{ million}) + (0.3)(1.5 \text{ million})$$
$$= 1.71 \text{ million sockeye.}$$

Control Component 4: Weekly Target Exploitation Rate

It would be easy to establish a target exploitation rate for each week if there were only one stock; we would simply take

$$\text{target rate} = \frac{(\text{total desired catch}) - (\text{catch to date})}{(\text{total remaining run})} .$$

Using this target calculation would result in the same rate every week if a) run timing were exactly average, b) the run forecast were perfect, and c) effort were perfectly controllable. Otherwise, the calculation is simply saying that the rate should be kept as steady as possible relative to the best estimate of the remaining run to come.

The analysis becomes much more difficult for overlapping sockeye and pink runs. The overall (total season) target rates for the two species will almost always be different. There are three management possibilities:

1) try to design special gear regulations to allow more selective exploitation;
2) try to design a complex target curve for weekly exploitation rates, considering relative run sizes

at different times [3];

3) simply switch from managing one species to managing the other at some fixed time (for example when the pink catch becomes the largest).

An example of a complex target curve is shown in Figure 7; for known run size and perfect effort control, curves of this type would minimize the week-to-week variation in exploitation rate seen by each stock, subject to the constraints that the overall target rate for both species be met [3]. However, it is difficult to apply such curves consistently in the adaptive control context; to do so would require the manager to redo a fairly large dynamic programming optimization every week through the season, which is hardly practical.

We favor the switching option, because it can be practically implemented and efficiently programmed for simulation tests. Let us assume that management will be switched from sockeye to pinks at time "T" within the season (most likely around July 30), and that the overall target exploitation rates are

E_s (Sockeye, e.g. 0.5)

and E_p (pink, e.g. 0.4).

These may be revised each week as the overall run estimates are revised. Let the cumulative proportions of fish that are expected to have arrived before any time "t" be

${}_sP_t$ (sockeye)

and ${}_pP_t$ (pink).

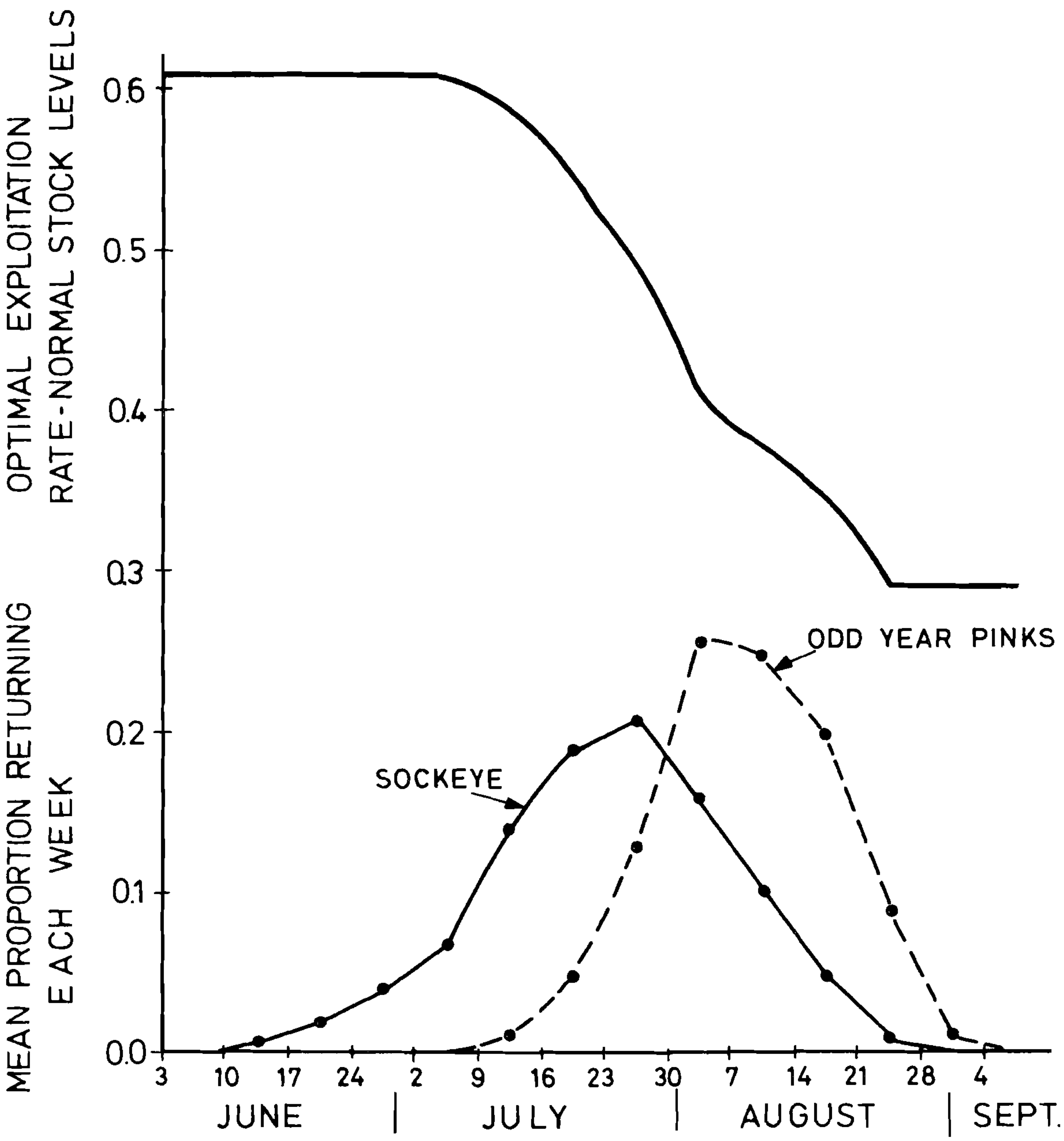


Figure 7. A complex target curve for weekly exploitation rates; this curve could be reasonably followed only if effort were completely controllable and total runs were known exactly. Practical application not recommended.

(These expected proportions are given in Figure 4.) Thus ${}_sP_T$ is the proportion of sockeye that should have arrived by the switch time (${}_sP_T$ = 0.68 for July 30 switch). Let the <u>cumulative catches</u> up to time t be

$${}_sC_t \qquad \text{(sockeye)}$$

and

$${}_pC_t \qquad \text{(pink)}.$$

Let the <u>best total run estimates</u> as of time t be (component 3) above)

$${}_s\hat{\hat{R}}_t \qquad \text{(sockeye)}$$

and

$${}_p\hat{\hat{R}}_t \qquad \text{(pink)}.$$

(Note that these run estimates are based partly on preseason forecasts and partly on catch plus escapement up to time t.)

By analogy with the single stock case, we argue that the exploitation rate for weeks prior to T (the "sockeye weeks") should be set as

$$\begin{array}{l}\text{target rate} \\ \text{(weeks } t < T)\end{array} = \frac{E_s\,{}_s\hat{\hat{R}}_t - {}_sC_t - (1-{}_sP_T)E_p\hat{\hat{R}}_s}{({}_sP_T - {}_sP_t)\hat{\hat{R}}_s} .$$

This equation is actually simple: the numerator is (total desired sockeye catch) less (sockeye catch to date) less (sockeye catch expected during the "pink weeks" after time T); the denominator is the expected total run over the remainder of the sockeye weeks. The equation can give negative rates if sC_T is already too large; in this case the exploitation rate should be zero.

For weeks T and after (the "pink weeks"), the analogous equation is

$$\begin{array}{l}\text{target rate} \\ (\text{weeks } t \geq T)\end{array} = \frac{E_p \; {}_p\hat{R}_t - {}_pC_t}{(1 - {}_pP_t)\; \hat{R}_p} \;.$$

This equation is simply the additional desired pink catch divided by the additional expected pink run. It may give negative rates, especially if the pink catch during the sockeye weeks has been high; in such cases the optimal rate is obviously zero.

The switching policy outlined above should lead to difficulties only in the extreme years when no catch of one or the other species is desired. Our long range production analyses indicate that such situations should occur less than once per decade, especially if variance minimizing harvest strategies are used. We will examine the consequences of these infrequent policy failures in a later section.

Control Component 5: Within-Season Effort Forecasting

Figure 8 shows that weekly effort levels can be predicted from catch per effort the previous week. Apparently the fishermen base their decisions at least in part on how well the fishing has been. However, catches in previous years seem to also play some role; the run in 1972 was late, but fishing effort started to increase as usual (high points for 1972 in Figure 8). The simplest assumption is that the fishermen use a weighted prediction of catch per effort:

$$\begin{matrix}\text{expected}\\\text{catch/effort}\end{matrix} = D_t \begin{pmatrix}\text{catch/effort}\\\text{last year for}\\\text{week } t\end{pmatrix} + (1-D_t)\begin{pmatrix}\text{catch/effort}\\\text{week } t\text{-1 this}\\\text{year}\end{pmatrix}$$

where D_t is a weighting factor $(0 \leq D_t \leq 1)$ that appears to change as shown in Figure 9. This expected catch per effort can be used as the point along the X axis of Figure 8, and effort predicted from the trend curve.

There has been significant license reduction since 1971, and this is reflected as decreasing asymptotes of the curves in Figure 8. It appears that we can nicely simulate alternative licensing policies simply by changing the asymptote, though higher asymptotes appear to be associated with increased willingness to fish when the expected catch rate is low (apparently a natural human reaction to competition). Open entry investment and disinvestment processes could also be simulated by changing the asymptote according to simple dynamic rules (e.g. increase the asymptote when last year's

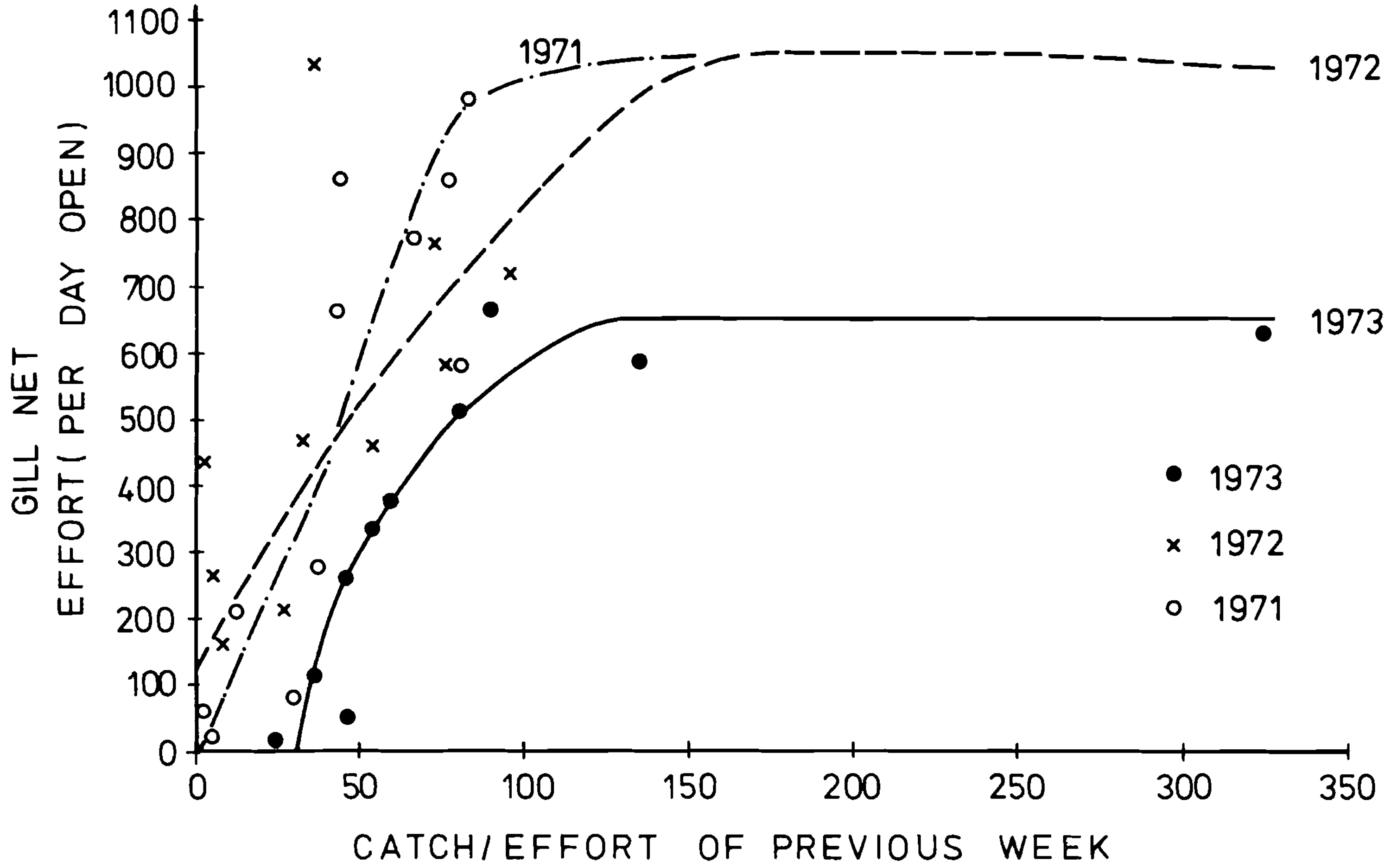


Figure 8. Prediction curves for weekly fishing effort as a function of last week's catch per effort. Note that asymptote depends on licensing policy.

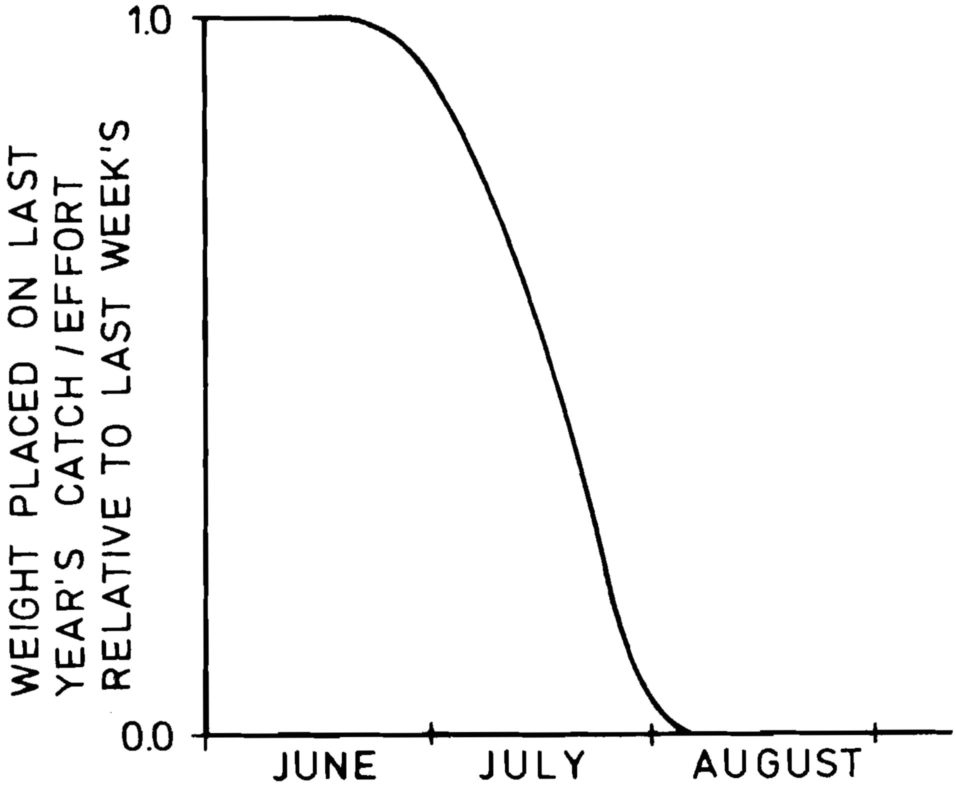


Figure 9. Weighting curve that fishermen appear to use in deciding whether to fish each week. Explanation in text.

returns were good, and decrease it after several years of poor returns).

The effort functional response (Figure 8) places severe constraints on management attempts to even out the exploitation rates across each fishing season. It appears that it will usually be necessary to over-exploit the later segments of each run, since the fishermen are likely to miss the early segments. If the government encourages the fishermen to go out earlier, then the prediction curve will of course have to be modified.

Control Component 6: The Open Days Calculation

The components outlined above result in a target exploitation rate and a predicted effort level for each week. The final control step is to calculate the number of open days that should be allowed. Figure 10 shows the observed relationship for 1971-1973 between exploitation rate and total gill net effort (fishing days per open day times number of open days). This relationship is not good; apparently the same effort levels result in higher exploitation rates when stock sizes are low (early and late in the season). The average relationship can be described by a "catch curve."

$$U = (1 - e^{-c(Ed)}) \qquad (6)$$

where

U = realized exploitation rate,
c = catchability coefficient,
E = effort per day open,
d = days open.

From Figure 10, $c \approx 0.0008$, but this coefficient is likely to change in response to technological innovation (e.g. better gill nets and more purse seine conversion).

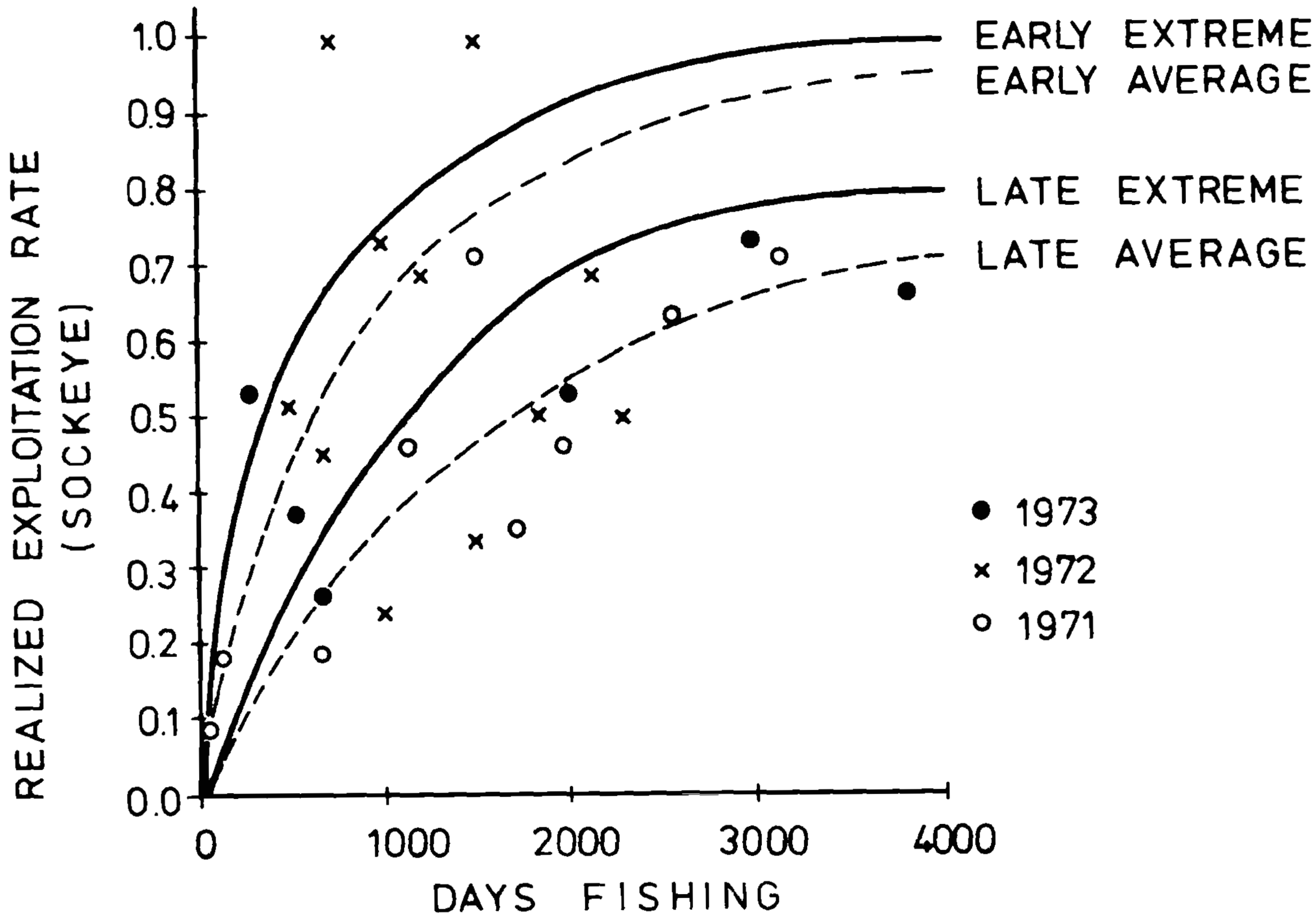


Figure 10. Observed relationship (1971-1973) between gill net effort and weekly exploitation rate.

For a crude estimate of open days to allow, we can substitute the target exploitation rate for U and the prediction effort (component 6)) for E in equation (6), and solve for d. This gives:

$$\text{days open} = \frac{\left(\ln(1 - \begin{matrix}\text{desired expl.}\\ \text{rate}\end{matrix}\right)}{- c \left(\begin{matrix}\text{predicted effort}\\ \text{per day open}\end{matrix}\right)} \quad . \qquad (7)$$

This equation can of course predict that the number of open days should be very large, especially if the predicted effort is low; in that case it seems best to allow six open days. Also there should be no serious harm in rounding to the nearest half day.

Equation (7) might be improved considerably by making c variable over time in relation to expected stock size and rates of fish movement through the fishing area. Though we have considered only the gill net fishery, the procedure could be applied separately for the purse seine fishery. Also, it is obvious that estimates of c should be modified from year to year (and perhaps also within each season) using information on changing fishing power.

Performance Tests for the Proposed System

Clearly the control system proposed above should not be implemented unless it can be convincingly demonstrated to perform better than the existing, more intuitive system. The essential questions are: can the system meet overall target exploitation rates for most input situations, and does it result in a smooth sequence of exploitation rates across each season? By "input situation" we mean a combination of run forecasting errors, run timing patterns, and patterns of stochastic variation around the predicted effort and exploitation rate relationships (Figures 8 and 10).

Simulation Testing Procedure

Obviously there are an infinite number of possible input situations, but by simulation we can face the control system with long sequences of randomized inputs representing a reasonable sampling of the possibilities. If the random inputs are chosen with probability distributions estimated from actual historical variability, we should be able to generate reasonable probability distributions for control errors.

The simulation test procedure is very simple. For any simulated year, we provide the control system (equations of the previous section) with the following inputs:

1) total sockeye and pink stock sizes, generated from escapements in previous simulation years using an appropriate stochastic model for the stock-recruitment relationship (e.g. Walters [2]);

2) preseason forecasts equal to the total stock sizes from (1) plus a random error term chosen from a distribution with variance appropriate to the forecasting system (e.g. normal with mean 0.0 and variance 2.24×10^{11} for sockeye);

3) a run timing pattern for the year, chosen at random from a representative set of possible patterns (Figure 4);

4) a series of random multipliers (with mean 1.0) to generate variability in effort levels and catchability coefficients from week to week, around their expected values as given in Figures 8 and 10;

5) a control strategy curve giving desired overall exploitation rate as a function of total stock size, for each species (e.g. as in Walters [2]).

We then go through these steps for a long series of years (e.g. 500); any serious control failures that are likely to happen in practice (due to some peculiar combination of inputs) should appear somewhere in the sequence. By including escapement ⟶ recruitment dynamics in the simulation, we should also be able to detect any serious long term trends that control errors may introduce.

Boundary conditions (fixed parameters) for any simulation sequence include the maximum effort per day open, the mean catchability coefficients, and the control strategy curve. By doing many simulation sequences with different boundary conditions, we should be able to measure how basic policy changes (e.g. gear changes, number of licenses) are likely to affect the "controllability" of the seasonal fishing system.

Results of Performance Tests

Figure 11 shows the results of three 500-year test simulations, using different maximum effort levels (licenses available) per day open. In each case the control system was trying to follow a simple strategy curve (solid lines in Figure 11) suggested by Walters [2]. Each graph point represents the overall exploitation rate achieved for one simulation year.

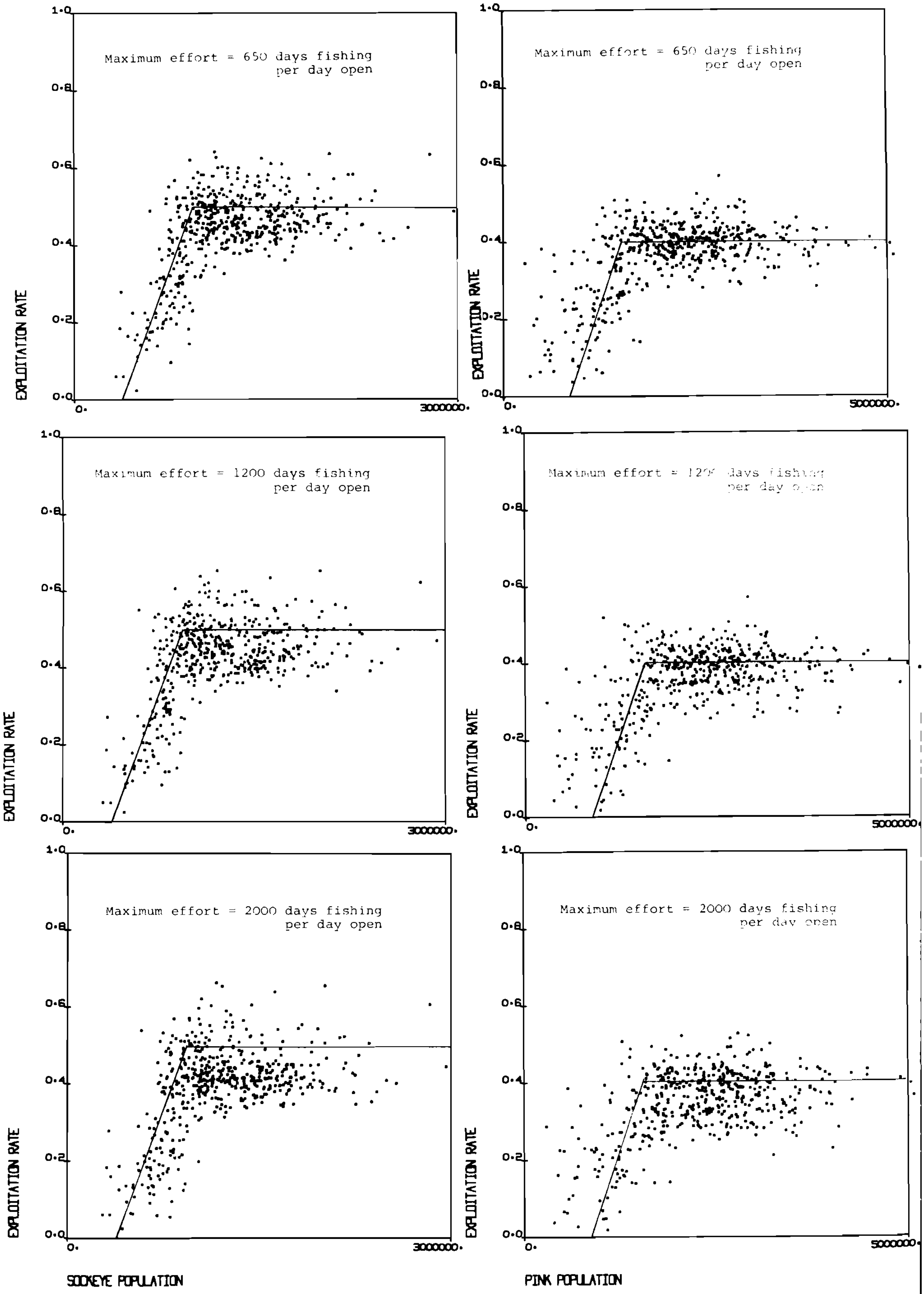


Figure 11. Simulation performance tests for the control system (explanation in text). Solid lines are target curves Panel A-600 licenses available; Panel B-1200 licenses available; Panel C-2000 licenses available (see footnote one on next page).

The control system obviously does not perform perfectly, especially for lower population sizes; low pink populations are almost always exploited at higher rates than desired. Better control is achieved at high population sizes: the simulated fishing effort in good seasons is more evenly distributed across weeks (the fishermen are willing to go out earlier), so there are more weekly opportunities to correct control errors. At low population sizes, the fishermen do not bother to go out except during the few peak weeks (mid-July to mid-August), so there are fewer opportunities to correct control errors. Figure 11 indicates that this problem would not be alleviated by increasing the number of licenses[1] available; the control system performs about as well when there are 2000 licenses (above 1970 level) as when there are 600 licenses (near the present level).

Figure 12 shows test simulations with strategy curves that should result in maximum average catch in the long run (essentially fixed escapement strategies, as currently used in practice). As measured by scatter around the target curves, control failure appears to be much more likely for these strategies than for the simplified strategy suggested by Walters (compare Figure 11). The maximum-yield strategies tend to produce lower average population sizes, which (as mentioned above) result in lower early-season effort and thus in fewer weekly opportunities to correct control errors.

As a final example, let us suppose that someone has devised a perfect method for preseason run forecasting. As shown in Figure 13, use of this method should result in surprisingly little improvement in control system performance. The other sources of uncertainty (run timing, realized effort,

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[1]By "license" in this context we mean a potential day fishing per day of open season. The actual number of licenses would be fewer.

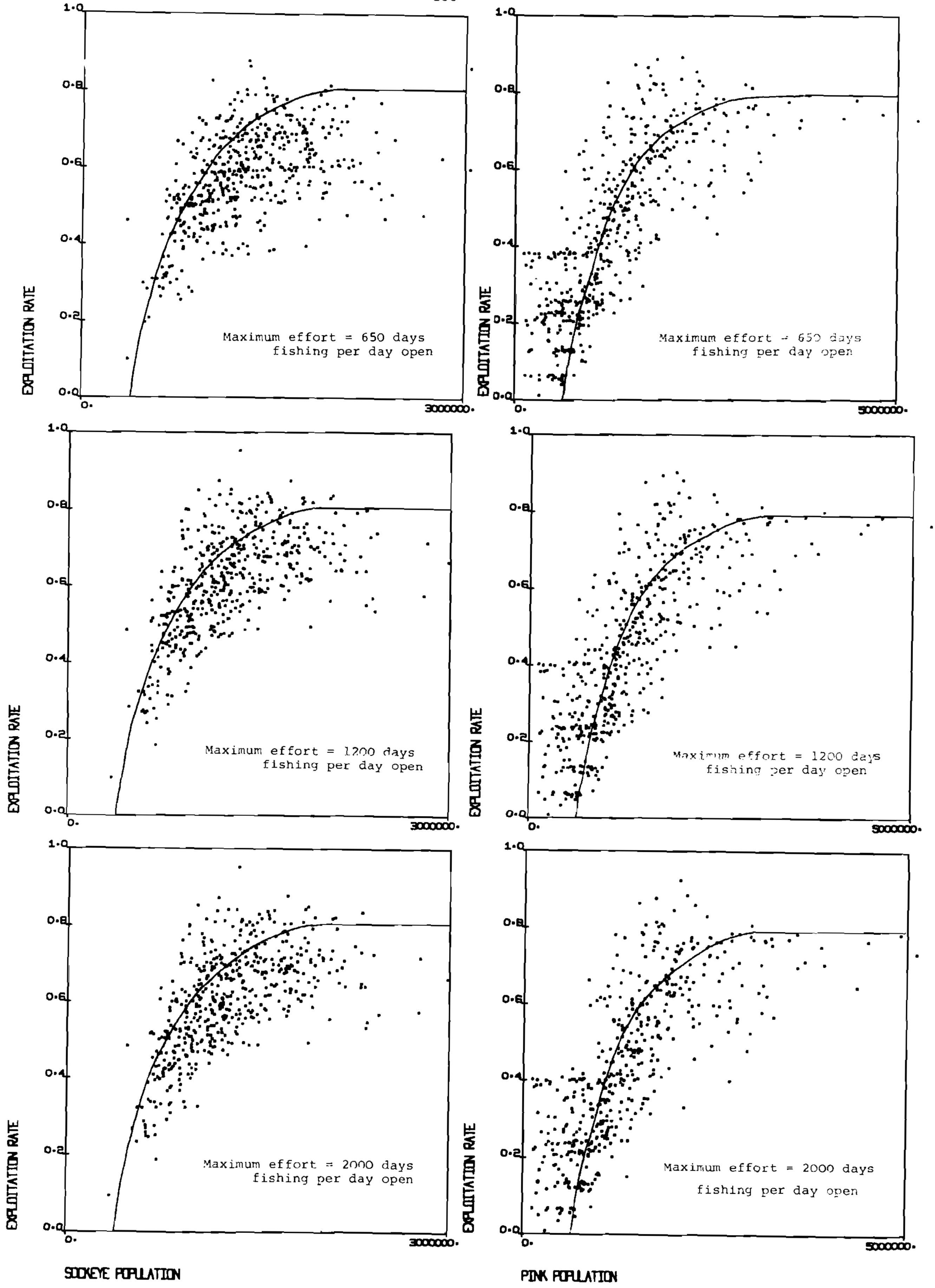

Figure 12. Simulation performance tests where the target curves are chosen to give long term maximum sustained yield. Panel A-600 licenses available; Panel B-1200 licenses available; Panel C-2000 licenses available (see footnote one).

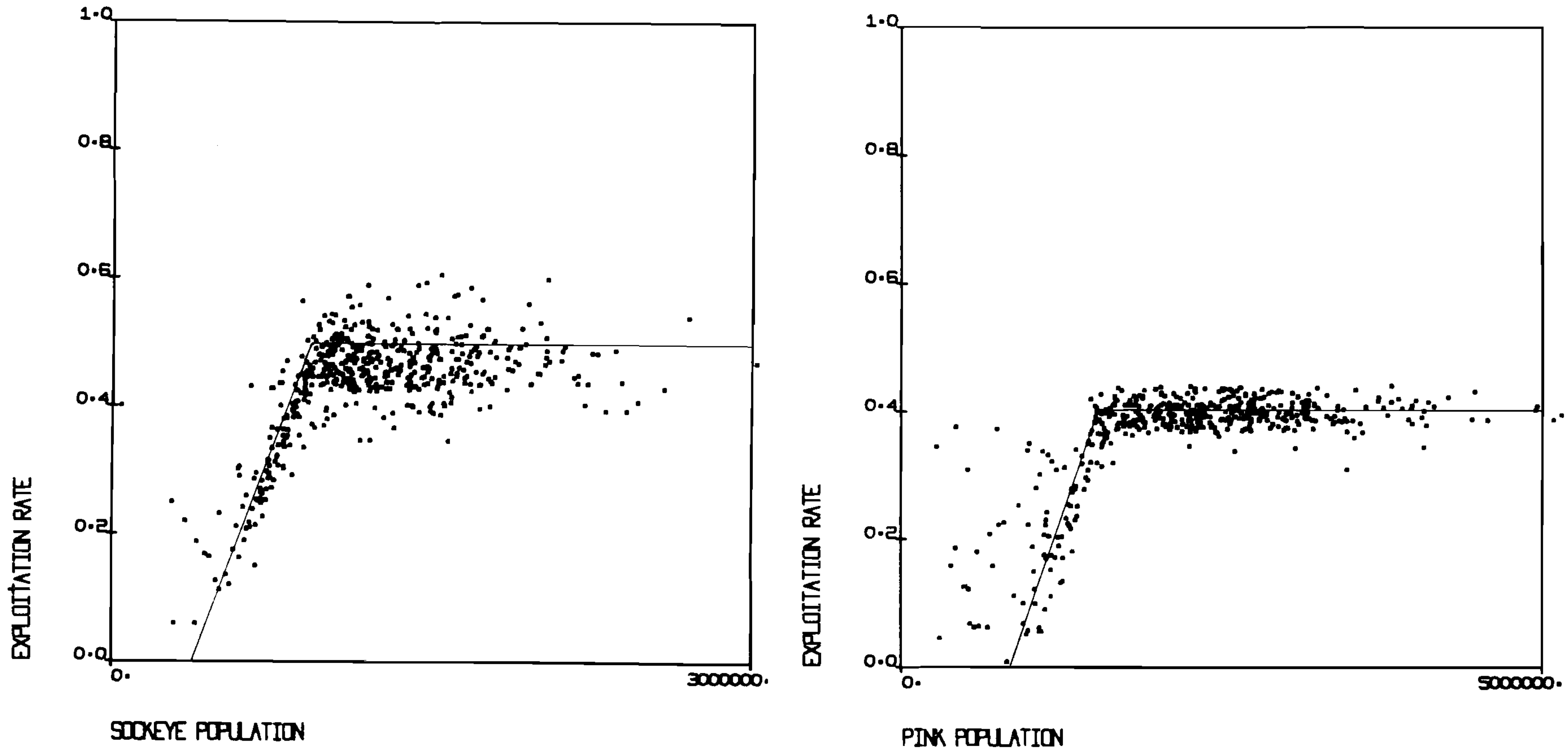

Figure 13. Control system performance assuming perfect pre-season stock forecasts. Compare Figure 11.

catchability coefficient) appear to be much more important than the preseason forecast. The implication of this observation for future research work is obvious: more emphasis should be placed on prediction of effort and catchability. In simple terms, it does little good to have better preseason run forecasts if most of the control problems are concentrated later in the season when run estimates are already fairly good due to within-season data.

It is difficult to compare the control error patterns in Figures 11-12 to actual management practice, since management control targets have apparently changed several times in recent years. Walters [2] presents management performance data(observed exploitation rates versus population size) for 1955-1974 on the Skeena River; this data shows about as much variability as Figures 11-12.

In terms of within-season stability of exploitation rates, the proposed control system does appear to be better than the intuitive system now used (Figure 14). Current control policy results in erratic fluctuation of exploitation rates through each season; the control system should help to eliminate this fluctuation.

In summary, the major difficulties in within-season management appear to revolve around the unwillingness of fishermen to go out when catches are expected to be low. Opportunities for management control are largely limited to a few weeks during the middle of each season. More management attention should be directed to methods for spreading fishing effort evenly across each season.

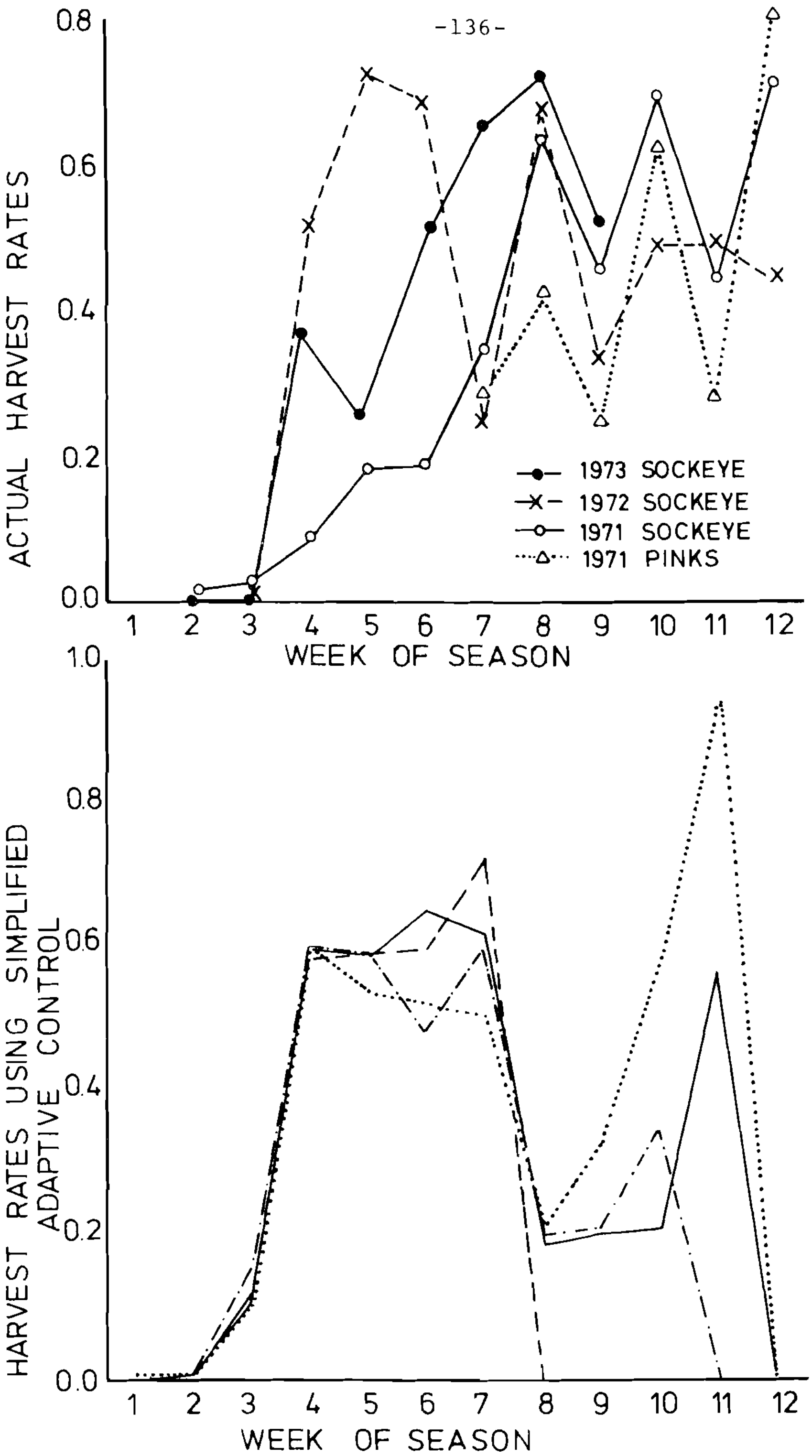

Figure 14. Observed seasonal variability in exploitation rates compared to expected variation using the preposed control system. Simulation results were chosen at random from a 500-year simulation run; more extreme simulated patterns are obtained only when the desired pink and sockeye rates differ very markedly.

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[3] Walters, Carl J. "Regulation of Escapement for Overlapping Runs of Sockeye and Pink Salmon." Internal paper, 1974.

A Predator-Prey Model for Discrete-Time Commercial Fisheries[1]

M. Gatto,[2] S. Rinaldi,[2] and C. Walters[3]

Abstract

A very simple discrete-time predator (boats) - prey (fish) model for the description of the dynamic behavior of a fishery is presented. The stability properties of the system are analyzed in some detail and the sensitivity of the equilibrium with respect to the catchability coefficient, the length of the fishing season and the investment coefficient of the fleet is analyzed. Finally, a simple procedure is presented and used for estimating the characteristic parameters of the fleet of a few fisheries. The agreement between the data and the predicted results is quite satisfactory when considering the crudeness of the model.

1. Introduction

In the literature on commercial fisheries, the dynamics of fish populations is often described by means of a set of differential (difference) equations in which variables such as effort and dimensions of the fleet enter as constant parameters or as driving variables. However, in the real world, economic variables are not fully controllable and are strongly influenced by the dynamics of the fish population itself. A fleet is normally sensitive (at least over long periods of time) to catches in recent years, or in other words, to investment (Smith [11]; Fullenbaum, Carlson,

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Bell, and Smith [5]; Wang [12]). Thus it should be, in general, more appropriate to consider the dimension of the fleet (e.g. number of boats) as a state variable rather than as a parameter or as a control variable. Modern modelling techniques and system theory make it possible to add such dimensions without losing the analytical tractability that is considered a virture of classical fishery dynamics models.

The structure of a general model which is consistent with this suggestion is shown in Fig. 1. The driving forces acting on each subsystem are constant in time only if the fishery is not controlled by a supervisory agency and if the surrounding environment of the fishery does not vary in time (no trends in the economy, no improvements in fishing technology, no deterioration of the habitat,...). This limit case of behavior of the system will be called "natural evolution" of the fishery in order to distinguish it from cases of "controlled evolution" obtained when decision makers fix over time the values of some of the driving forces (e.g. number of spawners to be released from hatcheries, length of fishing season, taxes, number of licenses, subsidies,...). A controlled evolution is usually obtained through a feedback as shown in Fig. 2, where the controller receives information about the state of the system and consequently makes a decision. To analyze and compare the controlled evolution of a fishery corresponding to different feedback policies, it is first necessary to have a model for the description of the natural evolution of the fishery and to know how basic properties of that model (e.g. equilibrium and its stability) are influenced by parameter values.

The aim of this paper is to present a very simple discrete-time model of the kind described in Fig. 1 (see Sect.2), and then prove the existence of an asymptotically stable equilibrium for its natural evolution (see Sect. 3) and discuss the sensitivity of this equilibrium with respect to those parameters which are potential driving variables of a controlled evolution (see Sect. 4). Finally, a very simple scheme for the estimation of the parameters of the model is given in Sect. 5.

The model presented in this paper is very crude because both the fish population dynamics and the evolution of the fleet are described by means of a first order difference equation. Thus, the fishery turns out to be considered as a classical predator (boats) - prey (fish) system. It must be noted that this paper does not represent the first attempt to describe a fishery as a predator-prey system. Commercial fisheries have already been described as continuous-time predator-prey systems (e.g. Smith [11], Fullenbaum, Carlson, Bell, and Smith [5], Wang [12]). The continuous time description is, in general, more elegant but can give rise to serious disadvantages when the model is used for designing the best control policy: continuous-time models require that the decision maker is operating continuously in time, while in almost all commercial fisheries decision makers are operating in discrete time (e.g. once per year). Moreover, in some special fisheries (e.g. Pacific salmon) the discrete-time description is definitely necessary because of the short, pulsed character of fishery effort. Finally, the particular type of data available for commercial fisheries makes it possible to estimate the parameters of discrete models only.

2. The Model

Let B_t, N_t and C_t be, respectively, the number of boats, the number of fish and the total catch in year t. Then, the model is specified by two difference equations for the dynamic behavior of boats and fish and by an equation giving the catch C_t as a function of B_t and N_t. The particular equations used in the remainder of this paper are as follows:

$$B_{t+1} = sB_t + i \frac{C_t}{B_t} \quad , \tag{1a}$$

$$N_{t+1} = (N_t - C_t) \exp \left[a \left(1 - \frac{N_t - C_t}{N_E} \right) \right] \quad , \tag{1b}$$

$$C_t = N_t \left[1 - \exp (-cB_tT) \right] \quad . \tag{1c}$$

In the first equation (fleet dynamics) s and i are "survival" and "investment" coefficients of the fleet; therefore $0 < s < 1$ and $i > 0$.

The second equation is the well-known Ricker model where $(N_t - C_t)$ is the number of spawners in year t, N_E is the natural equilibrium of the fishery and e^a is the growth factor $(0 \leq a \leq 2)$.

The last equation is the commonly used "catch equation" and simply states that the catch C_t is proportional to the recruitment N_t and is an increasing and bounded function of the fishing rate cB_tT (c is the usual catchability coefficient and B_tT is the effort = number of boats x length of the fishing season). The three pairs of parameters $(s,i),(a,N_E),(c,T)$ appearing in Eq. (1) are assumed for the foregoing discussion to be constant in time.

By substituting the catch expression into the first two equations one obtains the description of the dynamics of the fishery in the form

$$B_{t+1} = f_B(B_t,N_t) \quad , \tag{2a}$$

$$N_{t+1} = f_N(B_t,N_t) \quad , \tag{2b}$$

where the functions f_B and f_N are given by

$$f_B(B_t,N_t) = sB_t + i\,\frac{N_t}{B_t}\left[1 - \exp\,(-cB_tT)\right] \quad , \tag{3a}$$

$$f_N(B_t,N_t) = N_t\,\exp\left[a - cB_tT - a\,\frac{N_t}{N_E}\cdot\exp\,(-cB_tT)\right] \quad , \tag{3b}$$

so that the natural evolution of the fishery is nothing but a trajectory in the state space of the system described by Eqs. (2-3).

Some comments on the assumptions underlying Eq. (1) are now needed in order to bound the validity of the model.

The weakest point of the model is certainly the description of the dynamics of the fleet. There are in fact different reasons why Eq. (1a) might not be considered satisfactory. First, there may be a considerable time lag between investment decisions and actual appearance of boats in the fleet. Second, Eq. (1a) does not take into account the age structure of the fleet which could be of some importance, especially in the case of a sudden change in fishing technology (note that, by definition, this cannot occur during the natural evolution of the system). Third, the investment $I_t = iC_t/B_t$ is assumed to be linearly related to the catch per boat while a more realistic assumption should be that the investment is an increasing and strictly convex function of the catch per boat; however, this assumption would seriously increase the difficulty of the discussion below. Fourth, and probably most important, is that in real fisheries the investment I_t does not depend only upon the catch per boat of the previous year, but also upon all the prior history of the fishery. This could be taken into account by assuming that I_t is a weighted sum of the catches per boat in the past, i.e.

$$I_t = \sum_{k=o}^{t} i^{t-k+1} \frac{C_k}{B_k} \quad , \tag{4}$$

so that

$$I_{t+1} = iI_t + i \frac{C_{t+1}}{B_{t+1}} \quad .$$

Thus, under this assumption the fishery would be described by a third order model of the kind

$$B_{t+1} = f_B(B_t, I_t) \quad ,$$

$$I_{t+1} = f_I(B_t, N_t, I_t) \quad ,$$

$$N_{t+1} = f_N(B_t, N_t) \quad ,$$

and the dynamic behavior of such a model would certainly be smoother than the one predicted by Eq. (2), because of the "filtering" effect introduced by Eq. (4). Finally, in many fisheries the number of boats present every year is subject to apparently random fluctuations due to the mobility of the boats and the competition among fisheries. Thus, the dynamics of the fishery can be described only very roughly by Eq. (1a). As an alternative, one could use a stochastic description of the kind

$$B_{t+1} = sB_t + i \frac{C_t}{B_t} + \Delta_t \tag{5}$$

with a fairly high variance of the noise Δ_t (in Sect. 5, the stochastic process Δ_t will be assumed to be normally distributed).

For the dynamics of the fish population, the situation is not as fuzzy because the limits of validity of the Ricker model (1b) have been well studied (e.g. Cushing and Harris [2]). The most important phenomena that are missing in this model are the effects of the age structure of the population, a time delay in the stock-recruitment relation and the stochasticity induced by random fluctuations of the quality of the habitat. The first two criticisms could in principle be overcome by using a higher order model, while the third requires a detailed description of the influence that some suitable environmental indicators have on the life cycle of the fish, a very difficult problem indeed. A synthetic way of solving this problem consists of multiplying the stock-recruitment function by a random factor α_t, i.e.

$$N_{t+1} = \alpha_t (N_t - C_t) \exp \left[a \left(1 - \frac{N_t - C_t}{N_E} \right) \right] , \qquad (6)$$

where α_t can be interpreted as a measure of the probability of survival in year t. Since the number of causes of death in the life cycle of a fish is very high and since these causes can be considered essentially as independent of each other, it follows that the stochastic process α_t can be reasonably assumed to be lognormal.

Finally, the catch equation is open to considerable criticism (Paloheimo and Dickie [10]), since it does not take schooling and nonrandom boat searching into account. To add some realism, a stochastic term can be included to give

$$C_t = N_t \left[1 - \exp \left(-\beta_t c B_t T \right) \right] , \qquad (7)$$

where β_t is again a lognormal stochastic process because it arises as a product of several essentially independent efficiency factors such as weather.

In the next two sections the deterministic behavior ($\Delta_t = 0$, $\alpha_t = 1$, $\beta_t = 1$) of the fishery is analyzed. In Sect. 5, Eqs. (5-7) and the assumptions of the stochastic processes Δ_t, α_t and β_t are used to devise a satisfactory scheme for the estimation of the parameters.

3. Stability Properties

The purpose of this section is to find the equilibrium states of the model, discuss their stability and, in general, study the properties of the natural evolution of the fishery.

By definition, the equilibrium states are the solutions of Eq. (2) with $B_t = B_{t+1} = \bar{B}$ and $N_t = N_{t+1} = \bar{N}$, i.e.

$$\bar{B} = s\bar{B} + i\,\frac{\bar{N}}{\bar{B}}\,[1 - \exp(-c\bar{B}T)] \quad , \tag{8a}$$

$$\bar{N} = \bar{N}\exp\left[a - c\bar{B}T - a\,\frac{N}{N_E}\exp(-c\bar{B}T)\right] \quad . \tag{8b}$$

A trivial solution of this system of equations is given by the origin of the state space, $(\bar{B},\bar{N}) = (0,0)$. Since $\bar{B} = 0$ if and only if $\bar{N} = 0$, it is possible to assume $\bar{B} \neq 0$ and $\bar{N} \neq 0$ in Eqs. (8) and solve them with respect to $\bar{N}$:

$$\bar{N} = \frac{1 - s}{i}\,B^2 \Big/ [1 - \exp(-c\bar{B}T)] = v(\bar{B}) \quad , \tag{9a}$$

$$\bar{N} = N_E\left(1 - \frac{c\bar{B}T}{a}\right)\exp c\bar{B}T = h(\bar{B}) \quad . \tag{9b}$$

The shapes of the two isoclines $v(\bar{B})$ and $h(\bar{B})$ given by Eqs. (9) appear in Fig. 3; these isoclines demonstrate that there always exists one and only one equilibrium state $(\bar{B},\bar{N})$ with $\bar{B} \neq 0$ and $\bar{N} \neq 0$, which is called the productive equilibrium state from now on.

Let us now linearize the system around its two equilibrium states in order to study their stability properties. The linearized system is

$$\begin{bmatrix} \Delta B_{t+1} \\ \\ \Delta N_{t+1} \end{bmatrix} = \begin{bmatrix} \frac{df_B}{dB} & \frac{df_B}{dN} \\ \\ \frac{df_N}{dB} & \frac{df_N}{dN} \end{bmatrix} , \begin{bmatrix} \Delta B_t \\ \\ \Delta N_t \end{bmatrix} = F \begin{bmatrix} \Delta B_t \\ \\ \Delta N_t \end{bmatrix} \qquad (10)$$

where ΔB_t and ΔN_t are the variations with respect to a steady state and the matrix F is evaluated at the equilibrium.

In the case of the origin the matrix F turns out to be given by

$$F = \begin{bmatrix} s & icT \\ 0 & \exp(a) \end{bmatrix} ,$$

so that the eigenvalues are s and exp (a). The former is smaller than one, while the latter is greater than one, and this implies the origin in an unstable equilibrium state. More precisely, the origin is a saddle point, the eigenvectors being the B axis and the vector

$$\begin{bmatrix} & 1 \\ icT & \exp(a) - s \end{bmatrix} ,$$

and the trajectories in the neighborhood of the origin are shown in Fig. 4 where successive states are joined by a straight line.

Working out the derivatives indicated in Eq. (10) and using Eq. (9) it is possible to prove that the matrix F evaluated at the productive equilibrium $(\bar{B},\bar{N})$ is given by

$$F = \begin{bmatrix} icT\,\dfrac{\bar{N}}{\bar{B}} - c\bar{B}T + sc\bar{B}T + 2s - 1 & (1 - s)\,\dfrac{\bar{B}}{\bar{N}} \\ -c\bar{N}T(1 - a + c\bar{B}T) & 1 - a + c\bar{B}T \end{bmatrix} .$$

Since $(\bar{B},\bar{N})$ is not available in closed form, explicit computation of the eigenvalues is impossible. Nevertheless, the discussion of the stability of the equilibrium can be performed in an indirect way recalling that the eigenvalues of a 2 x 2 matrix lie within the unit circle when the following two inequalities are satisfied

$$|\Pi| < 1 \quad , \qquad (11a)$$

$$|\Sigma| < 1 + \Pi \quad , \qquad (11b)$$

where Π and Σ are, respectively, the product and the sum of the eigenvalues. Since Π and Σ are the determinant and the trace of the matrix F, it is possible to show that under the assumption

$$c\bar{B}T < 1 \quad ,$$

which is satisfied in most commercial fisheries, conditions (11a) and (11b) are verified, i.e. the productive equilibrium is always asymptotically stable. A proof of this statement can be found in Appendix 1.

Though the analysis so far performed is a stability analysis in the small, there is no evidence for the productive equilibrium state not being stable in the large. This assertion is essentially validated by the existence of a region of attraction R containing $(\bar{B},\bar{N})$, i.e. a region satisfying the following two properties:

a) any trajectory starting from a point in R is contained in R (R is an invariant set),

b) any trajectory starting from a point outside of R reaches R in a finite number of transitions.

A proof of the existence of such a region can be found in Appendix 2.

Finally, simulation of the model shows that, depending upon the values of the parameters, monotonic or oscillatory transients can be obtained. In Fig. 5 an example corresponding to the exploitation of a virgin fishery $(B_O = O, N_O = N_E)$ is shown. Two transients are plotted for two different values of parameter cT: trajectory A is obtained in the case of poor technology and/or short length of fishing season $(cT = 1.5 \times 10^{-3})$, while trajectory B is obtained in the opposite case $(c = 3.5 \times 10^{-3})$. It is worthwhile noticing that in case A there is no oscillatory behavior, while in case B there are periods of temporary overinvestment followed by periods of overexploitation of the fish population, a fact which has been observed in commercial fisheries.

4. Sensitivity of the Productive Equilibrium

As pointed out in the previous section, the productive equilibrium $(\bar{B},\bar{N})$ cannot be given a closed form expression. Nevertheless, the sensitivity of this steady state with respect to some parameters can be determined in a qualitative way.

With this aim, it is convenient to study first how the isoclines v(B) and h(B) are influenced by the parameters. It is interesting to notice (see Fig. 6) that curve v(B) does not depend separately on s and i, but on $\frac{1-s}{i}$, i.e. on the ratio between mortality and investment, and that it approaches, for large values of B^2, a limit parabola independent of c and T. On the other hand, curve h(B) does not depend (see Fig. 7) upon s and i, but only upon cT, a, and N_E. By intersecting h(B) with v(B), it is easy to understand how the equilibrium point varies with $\frac{1-s}{i}$ and cT: these variations are shown in Fig. 8.

The following general conclusions can be drawn:

a) If $a < 1$, the population $\bar{N}$ is decreasing with cT and increasing with $\frac{1-s}{i}$. If $a > 1$, then the statement above is still valid for large values of cT and low values of $\frac{1-s}{i}$. In simple terms, if the fishery is characterized by a low reproduction rate then the size of the stock at the equilibrium is decreasing with the catchability coefficient, with the length of the fishing season, and with the survival and investment coefficient of the fleet. If, on the contrary, the fishery is characterized by a high reproduction rate, then the stock size is a dome-shaped function of the same parameters.

b) The number of boats $\bar{B}$ is decreasing with $\frac{1-s}{i}$ while it is first increasing and then decreasing with cT. In other words, greater values of the survival and investment coefficients imply larger sizes of the fleet, while too large values of the catchability coefficient and of the length of the fishing season give rise to a small equilibrium fleet size.

As for the equilibrium catch $\bar{C}$, observe that Eq. (1a) yields

$$\bar{C} = \frac{1 - s}{i} \bar{B}^2 \quad , \tag{12}$$

which is the limit parabola shown in Fig. 6. With this in mind, it is easy to realize that the catch $\bar{C}$ is a dome-shaped function of $\frac{1 - s}{i}$ and cT. An important index for the fishery is the equilibrium catch per boat $\bar{J}$ which (see Eq. (12)) turns out to be given by

$$\bar{J} = \frac{1 - s}{i} \bar{B} \quad . \tag{13}$$

The following two simple but important properties of this index can be proved to be valid:

c) The catch per boat is increasing with the ratio $\frac{1 - s}{i}$.

d) The catch per boat is first increasing and then decreasing with cT.

To study how $\bar{J}$ varies with $\frac{1 - s}{i}$, it is sufficient to plot the curves of constant catch per boat given by

$$\frac{N}{B} \left[1 - \exp\,(-BcT) \right] = \text{const.}$$

and intersect them with the curve of Fig. 8b, which is the locus of the equilibrium states obtained for different values of $\frac{1 - s}{i}$ (see Fig. 9). It is easy to verify that, since $a < 2$, the curves of constant catch per boat intersect the equilibria locus only once; therefore $\bar{J}$ is an increasing function of $\frac{1 - s}{i}$.

To prove property d) it is sufficient to remark that in view of Eq. (13), $\bar{J}$ has the same dependence upon cT as the number of boats, i.e. it is first increasing and then decreasing with cT (see Fig. 10). Therefore, there exists a length of the fishing season which maximizes the catch per boat.

Property d) is of particular interest because it points out the possibility for a fishery to be in the equilibrium state B of Fig. 10. A suitable change of the length of the fishing season will then generate a transient from state A to state B, the latter being characterized by the same number of boats and the same catch per boat but by a greater number of fish and by a shorter length of the fishing season, a definite advantage in the management of the fishery. The transient from state A to state B is characterized by a remarkable initial disinvestment which, nevertheless, could be compensated for by temporarily providing subsidies to the fishery.

5. Parameter Estimation

A procedure for the estimation of the parameters of the model is outlined below. The method consists in working out separately the least squares estimation of the parameters of the three components of the fishery.

Suppose that the variables B_t, C_t, N_t and T_t (note that the length of the fishing season is now allowed to be varying in time) have been measured for a certain number of years ($t = 1,2,\ldots,n$) during which there has been no evidence of relatively important changes in the economy (s and i are constant), in technology (c is constant) and in the quality of the environment (a and N_E are constant). Then, consider first the catch function in the form given by Eq. (7); from this expression one obtains

$$\log c = \frac{1}{n} \sum_{t=1}^{n} \log \left(\frac{1}{B_t T_t} \log \frac{N_t}{N_t - C_t} \right) - \frac{1}{n} \sum_{t=1}^{n} \log \beta_t \quad , \tag{14}$$

in which the term $\frac{1}{n} \sum_{t=1}^{n} \log \beta_t$ goes to zero as n approaches infinity because it is an estimate of the mean value of a normally distributed random variable which is known to have zero mean value (recall the assumptions on β_t). Thus

$$\log \hat{c} = \log \sqrt[n]{\prod_{t=1}^{n} \frac{1}{B_t T_t} \log \frac{N_t}{N_t - C_t}} \tag{15}$$

is an unbiased estimate of log c and the variance of this estimate is proportional to the variance of the noise and decreases with n as $\frac{1}{n}$. Moreover, this estimate is the one which minimizes the expected value of the square of the difference between log c given by Eq. (14) and all its possible estimates.

As far as the estimation of the parameters s and i is concerned, it is very simple to prove (e.g. Lee [7]) that if the noise Δ_t in Eq. (5) is a normally distributed independent noise with zero mean value, then the least squares estimate is unbiased, consistent, and given by

$$\begin{bmatrix} \hat{s} \\ \hat{i} \end{bmatrix} = (P'P)^{-1} \, P'p \quad , \tag{16}$$

where the matrix P and the vector p are given by

$$P = \begin{bmatrix} B_1 & C_1/B_1 \\ B_2 & C_2/B_2 \\ \vdots & \vdots \\ B_{n-1} & C_{n-1}/B_{n-1} \end{bmatrix} , \quad p = \begin{bmatrix} B_2 \\ B_3 \\ \vdots \\ B_n \end{bmatrix} , \tag{17}$$

and P' denotes the transpose of P.

Finally, the estimation of parameters a and N_E can also be carried out by means of a linear expression of the kind (16) as pointed out in the literature (Dahlberg [3]). In fact, from Eq. (6) one obtains

$$a + (C_t - N_t) \frac{a}{N_E} = \log \frac{N_{t+1}}{N_t - C_t} - \log \alpha_t \quad ,$$

and $\log \alpha_t$ has the same properties as Δ_t in Eq. (5). Thus, in this case

$$\begin{bmatrix} \hat{a} \\ \dfrac{\hat{a}}{\hat{N}_E} \end{bmatrix} = (Q'Q)^{-1} Q'q \quad , \tag{18}$$

where

$$Q = \begin{bmatrix} 1 & C_1 - N_1 \\ 1 & C_2 - N_2 \\ \vdots & \vdots \\ 1 & C_{n-1} - N_{n-1} \end{bmatrix} , \qquad q = \begin{bmatrix} \log N_2/N_1 - C_1 \\ \log N_3/N_2 - C_2 \\ \vdots \\ \log N_n/N_{n-1} - C_{n-1} \end{bmatrix} . \tag{19}$$

In conclusion, the estimation of the parameters of the fishery can be carried out separately for the three subsystems shown in Fig. 1 by means of Eqs. (15-19). Thus, through this procedure one can separately evaluate the validity of Eqs. (1a), (1b) and (1c) and therefore deduce which parts of the model are satisfactory and, eventually, which are not. Moreover, this scheme requires only simple subproblems to be solved, a definite advantage from a computational point of view (for example, in this case two 2 x 2 matrices must be inverted instead of a 4 x 4 matrix). In this respect, it is important to note that if the number of fish N_t is unknown (which is usually the case) the scheme outlined above cannot be used. However, the estimation of the parameters can still be carried out by introducing Eq. (1c) into Eq. (1b) in such a way that N_t and N_{t+1} are eliminated. Thus, a new difference equation is obtained that can be used to estimate the three parameters a, N_E and c. The disadvantages introduced by the lack of information on N_t are that the estimation procedure is no longer linear and that a problem of dimension three must be solved instead of two subproblems of dimension two and one.

Since there is already a large body of literature on estimation of catchability coefficients and parameters of the Ricker model, further examples are unnecessary. Fig. 12 demonstrates the effort model fit for five fisheries; two kinds of predictions are shown:

1) one year forecasts (predicted values based on observed values from previous year),

2) simulation forecasts (predicted values based on simulated values from previous year).

The one year forecasts are reasonably good in most cases: at least the qualitative direction of change is usually predicted correctly. On the other hand, the simulation forecasts usually lead to large cumulative errors after a few years. These errors suggest some major weaknesses of the simple effort model:

1) investment time lags may delay effort growth (example: fin whales, 1950-1960),

2) effort changes may reflect mobility to other fishing areas (example: halibut and cod),

3) sudden large effort pulses may occur without apparent simple explanation (examples: Peru anchovy, California sardine).

Thus it appears inadvisable to use the simple effort model except for qualitative, short run forecasts.

6. Conclusion

The model outlined in this paper is obviously too crude for practical, quantitative application. Our intent has been to suggest an approach to development of wider perspectives on problems of fishery dynamics, in hope of identifying new management strategies which take the dynamics of fishing, as well as fish, into account. The qualitative conclusions in Sect. 4 may be reasonable guidelines for the design of such strategies. Probably the greatest weakness of our simple analysis is failure to take alternative fishing locations and species into account; with modern, flexible fishing gear it may be economical to deplete some stocks (zero productive equilibrium) while subsisting on or profiting from others.

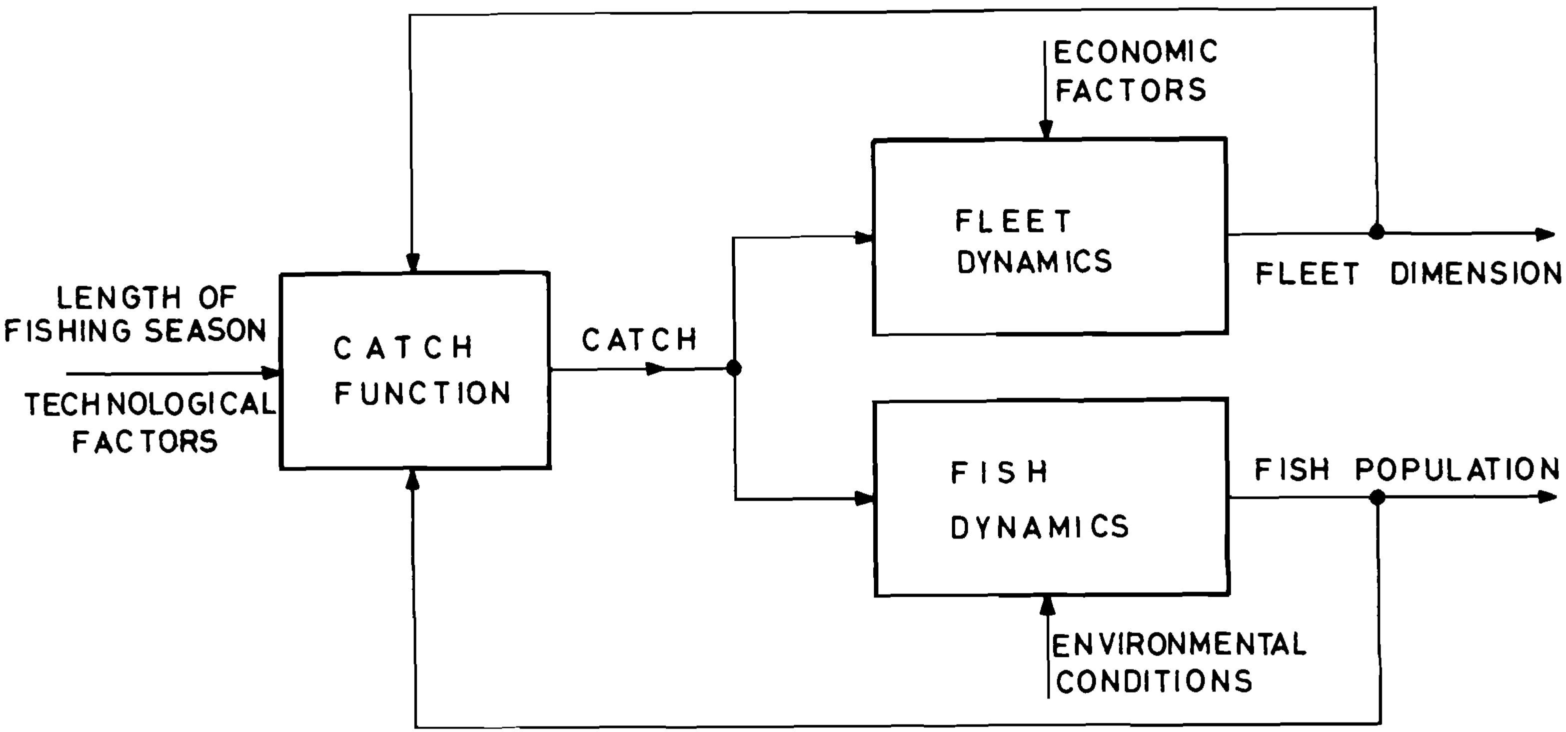


FIGURE 1. GENERAL STRUCTURE OF A FISHERY MODEL.

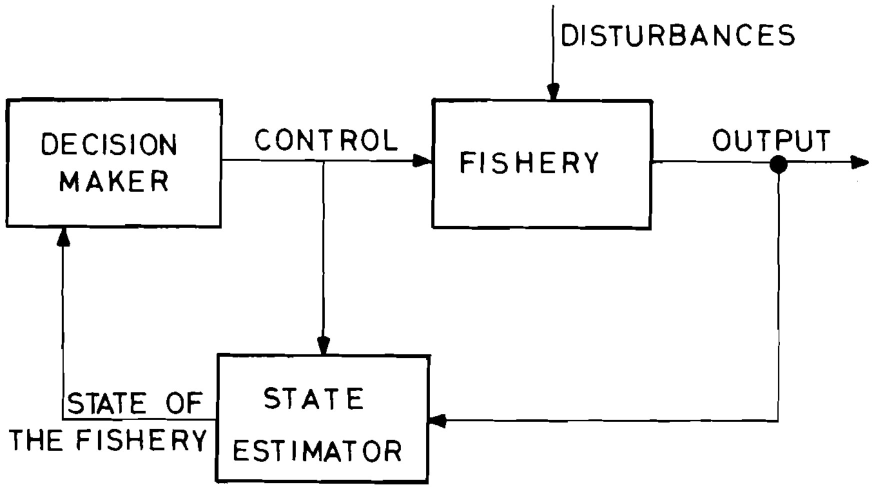


FIGURE 2. CONTROLLED EVOLUTION OF A FISHERY
(CONTROL = LENGTH OF FISHING SEASON, TAXES, SUBSIDIES, ...;
OUTPUT = SAMPLES OF CATCH, NUMBER OF BOATS,
SAMPLES OF RECRUITMENT, ...;
DISTURBANCES = TRENDS IN THE ECONOMY, DETERIORATION OF
THE HABITAT, CHANGE IN TECHNOLOGY, ...).

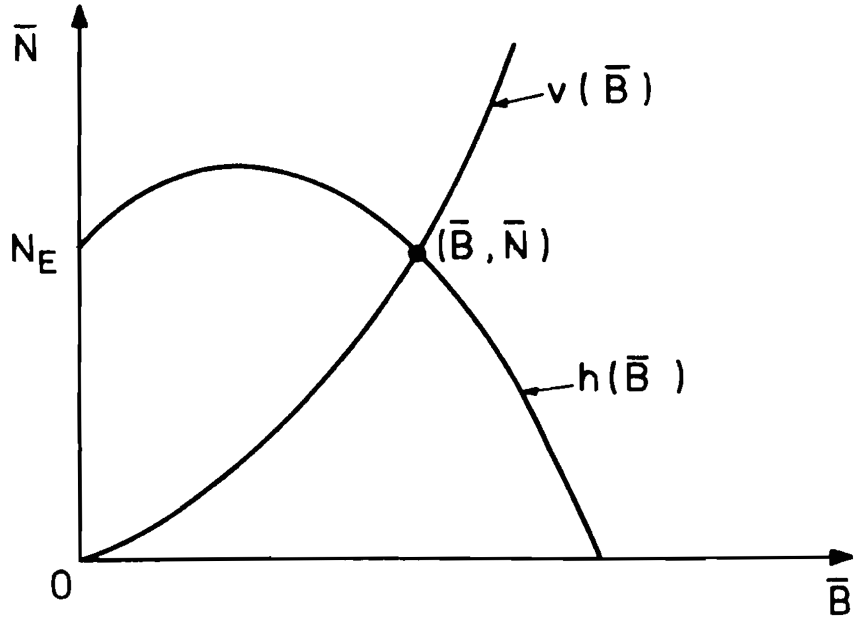


FIGURE 3. THE ISOCLINES $v(\bar{B})$ AND $h(\bar{B})$.

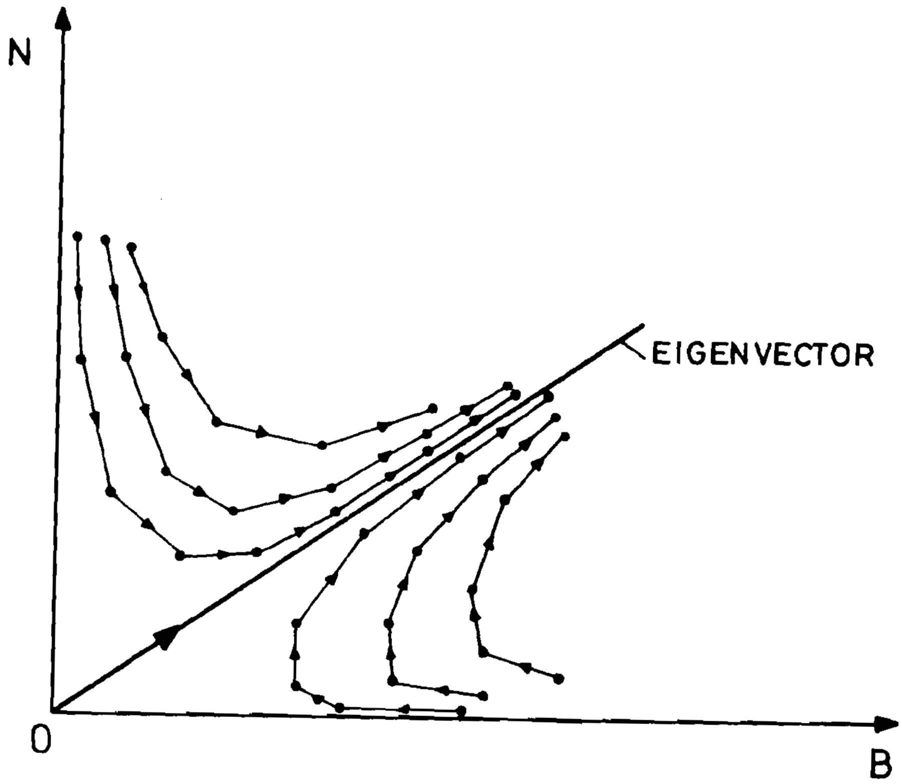


FIGURE 4. THE ORIGIN IS A SADDLE POINT.

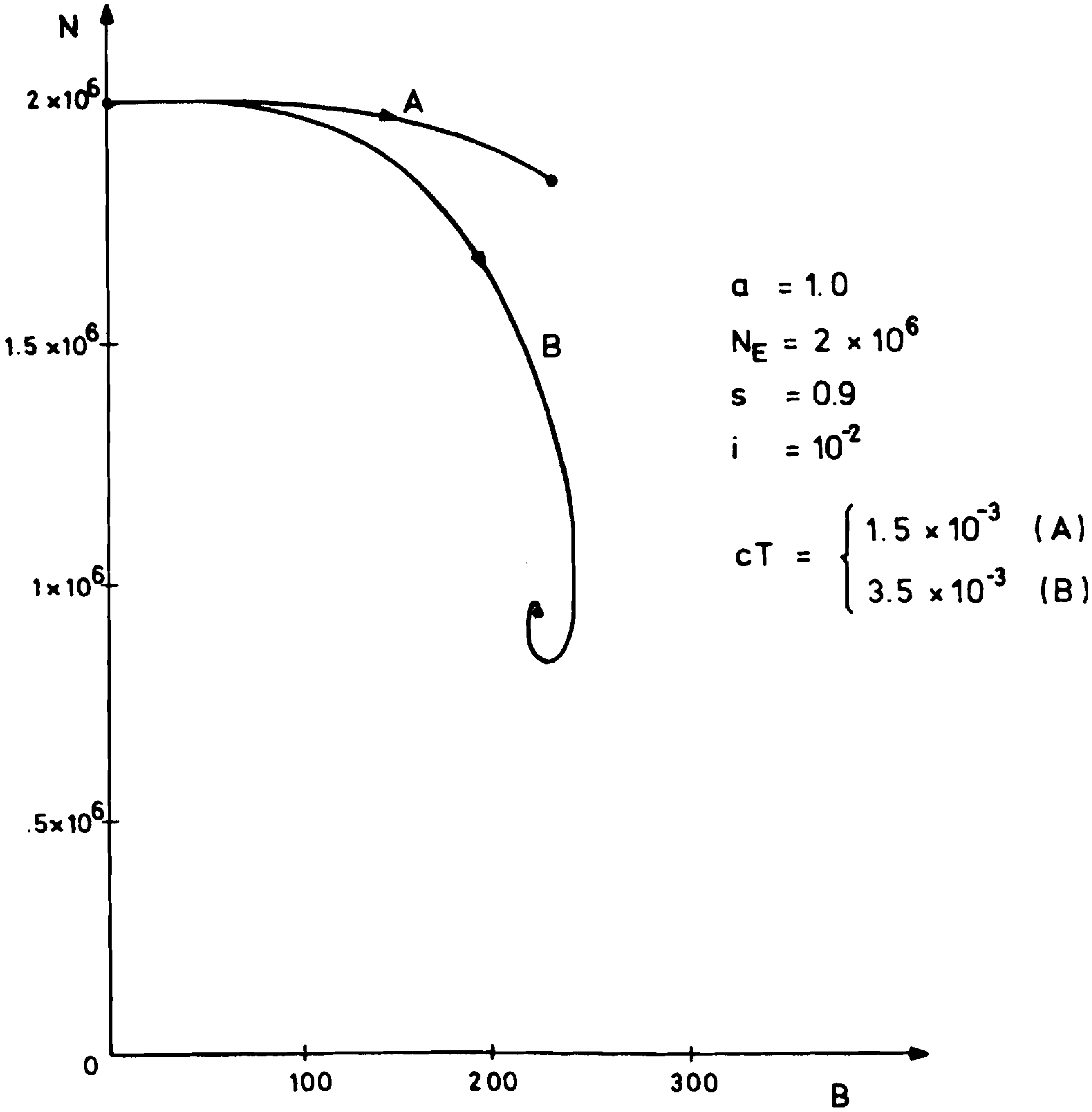


FIGURE 5. NATURAL EVOLUTIONS OF A VIRGIN FISHERY.

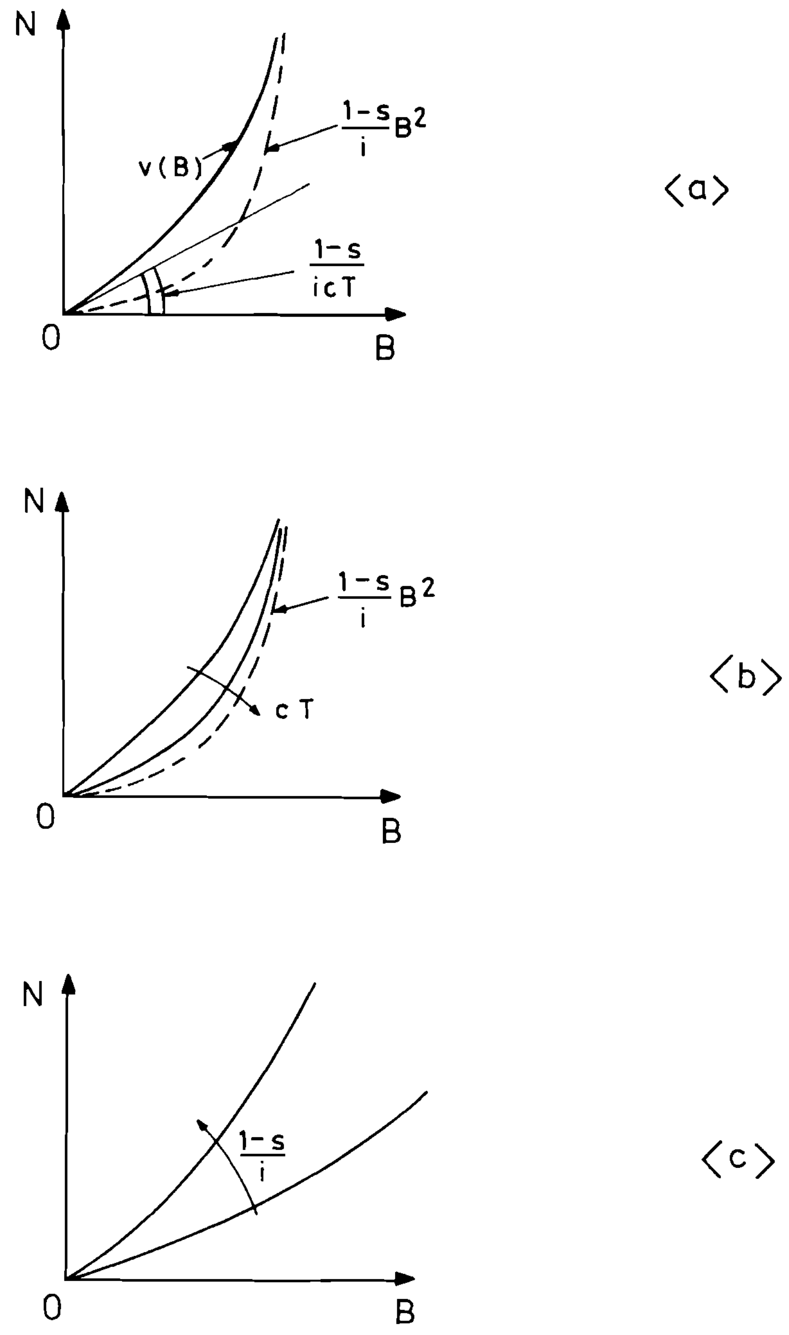


FIGURE 6. THE INFLUENCE OF THE PARAMETERS ON THE ISOCLINE v(B) ⟨a⟩ THE CURVE v(B), ⟨b⟩ THE INFLUENCE OF cT, ⟨c⟩ THE INFLUENCE $\frac{1-s}{i}$.

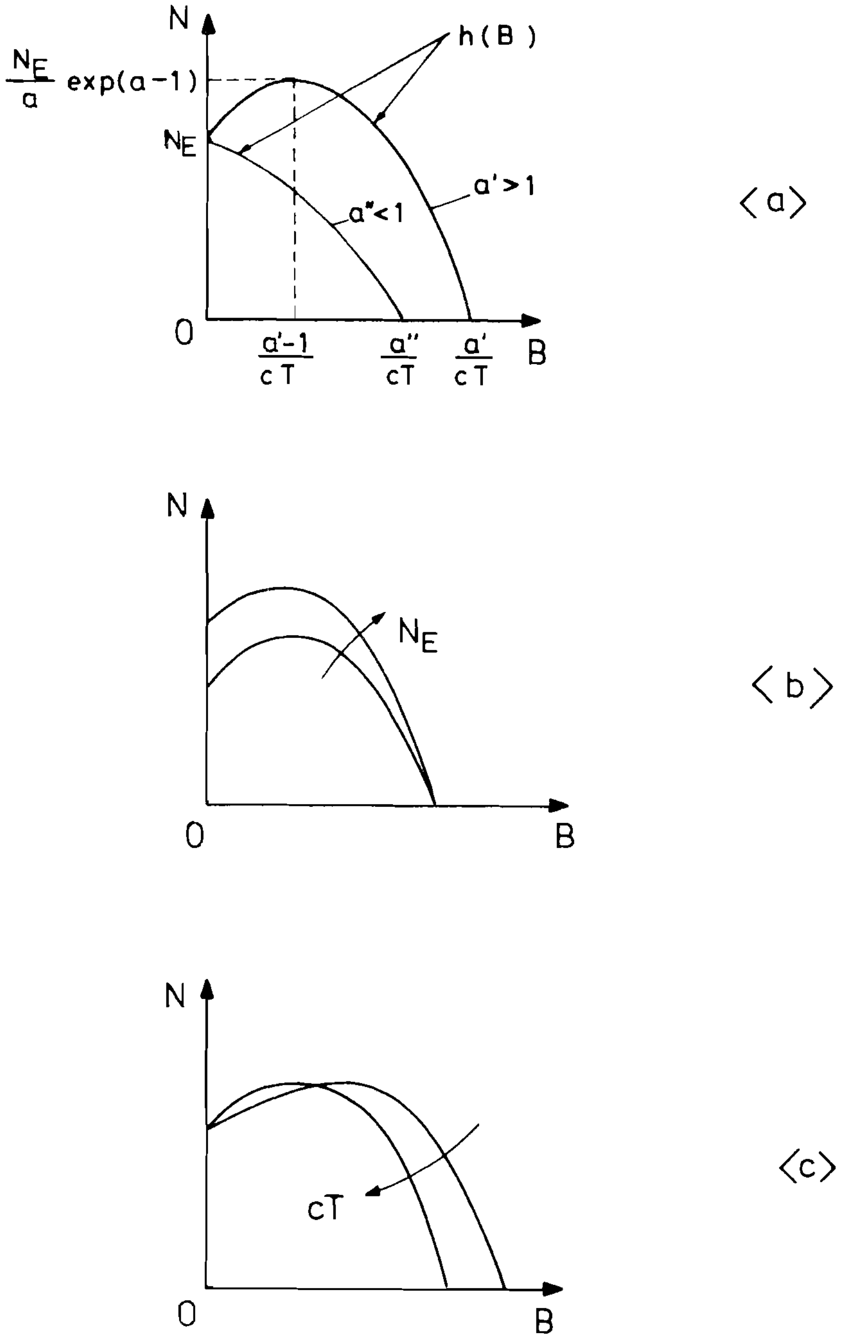


FIGURE 7. THE INFLUENCE OF THE PARAMETERS ON THE ISOCLINE h(B)
⟨a⟩ THE CURVE h(B), ⟨b⟩ THE INFLUENCE OF N_E,
⟨c⟩ THE INFLUENCE OF cT.

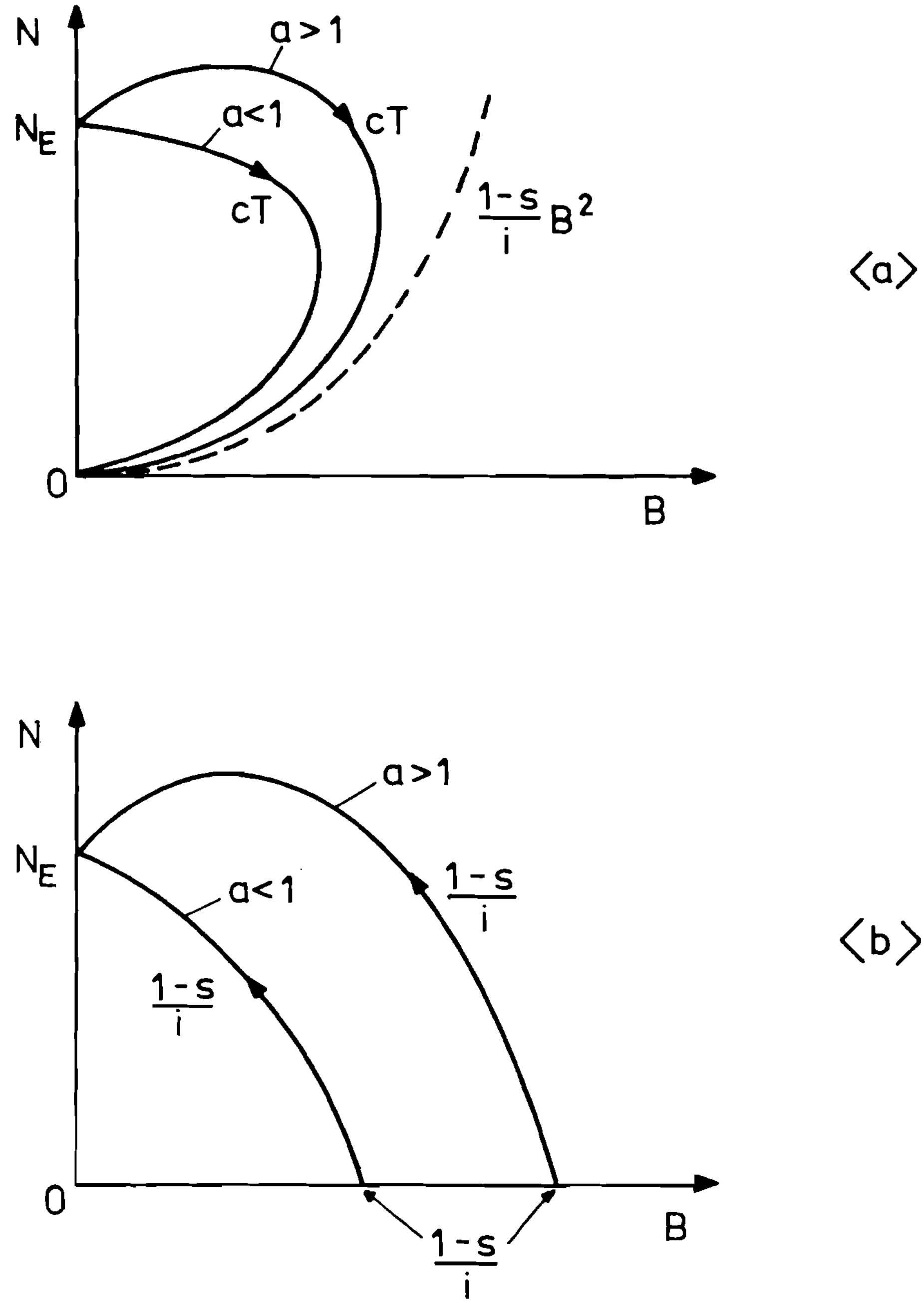


FIGURE 8. VARIATIONS OF THE PRODUCTIVE EQUILIBRIUM
⟨a⟩ WITH RESPECT TO cT
⟨b⟩ WITH RESPECT TO $\frac{1-s}{i}$.

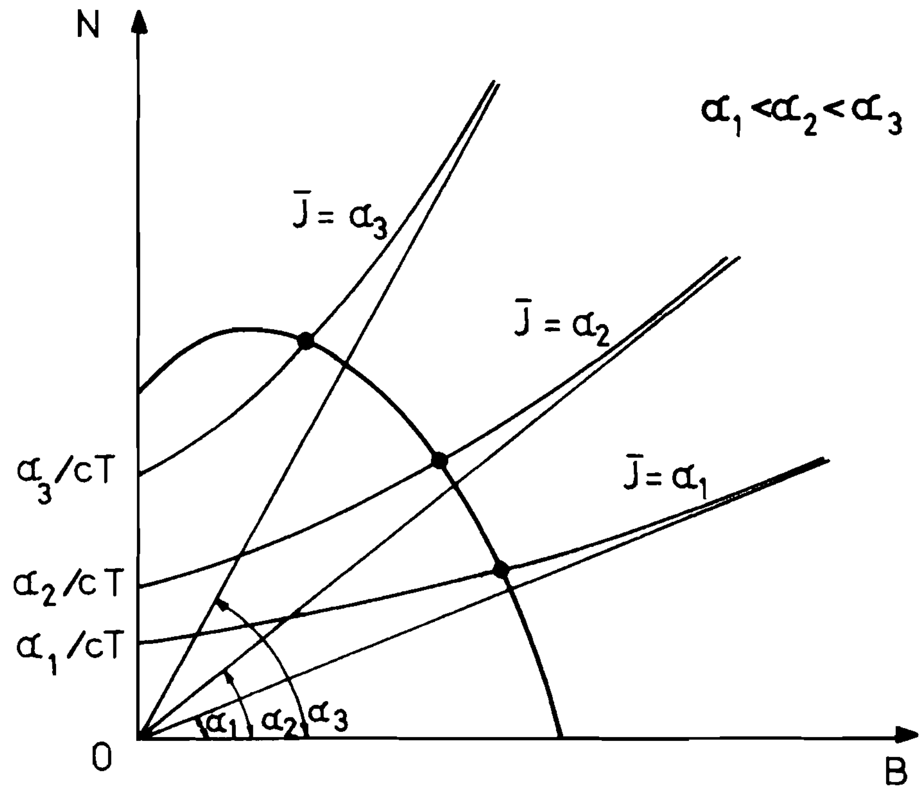


FIGURE 9. THE CATCH PER BOAT AS A FUNCTION OF $\frac{1-s}{i}$.

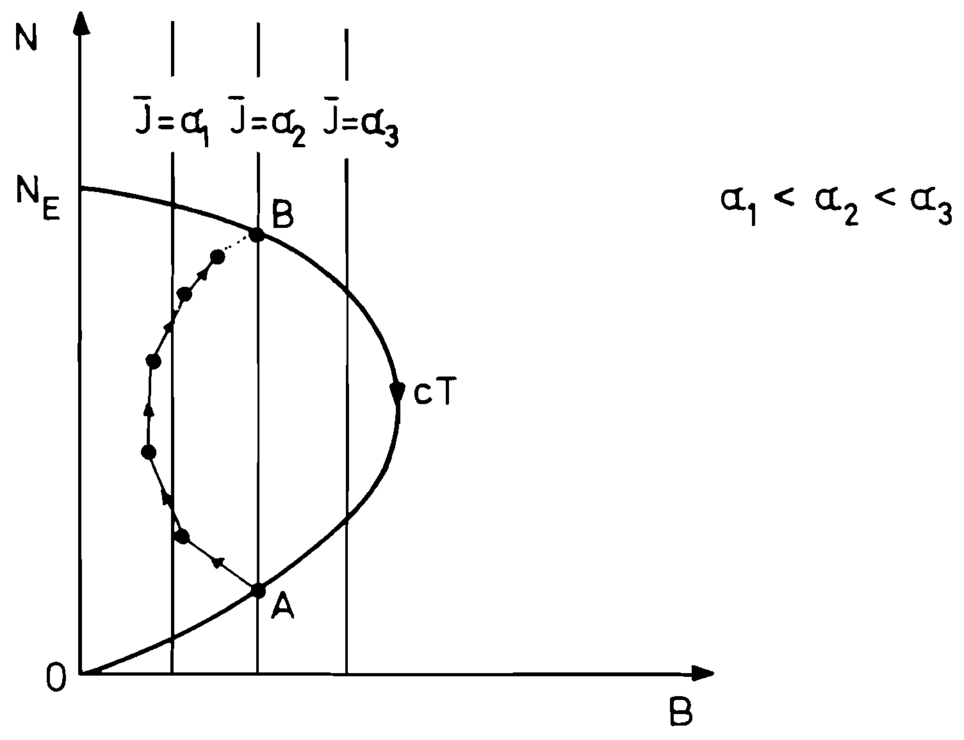


FIGURE 10. EVOLUTION OF THE FISHERY FROM PRODUCTIVE EQUILIBRIUM A TO PRODUCTIVE EQUILIBRIUM B.

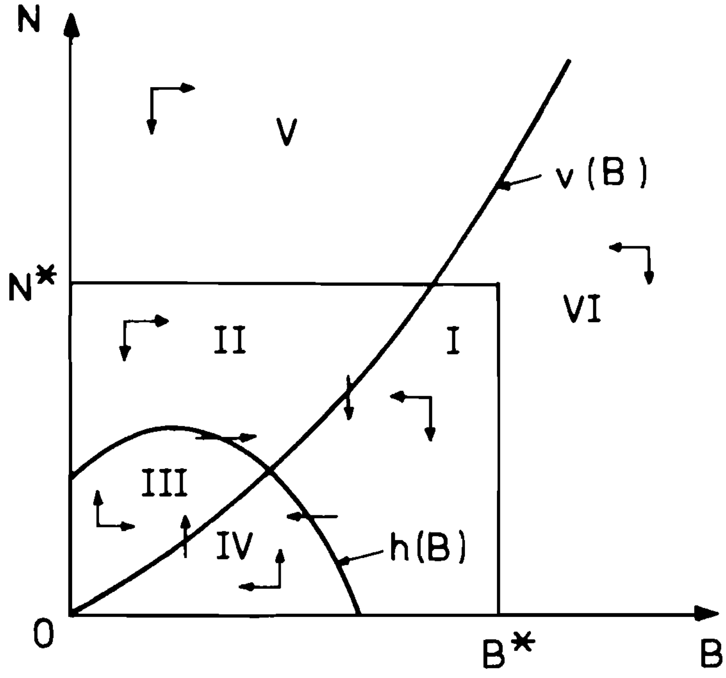
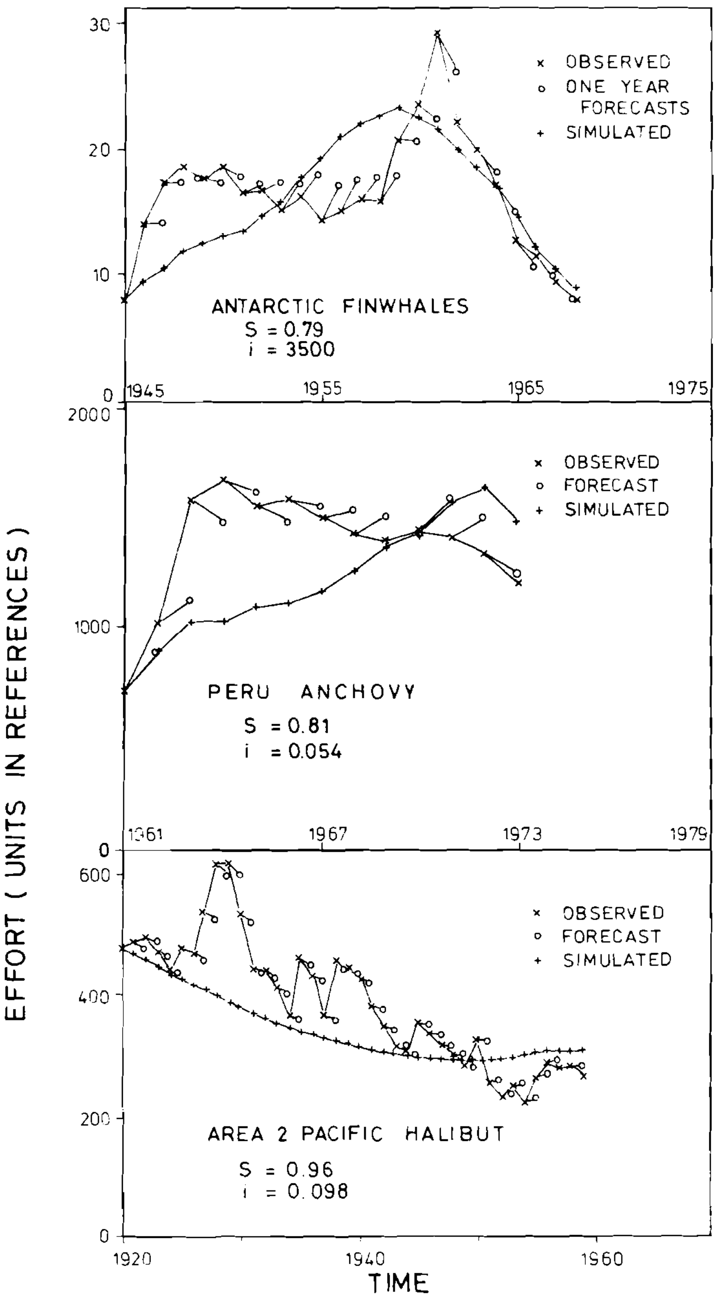


FIGURE 11. THE REGION OF ATTRACTION.



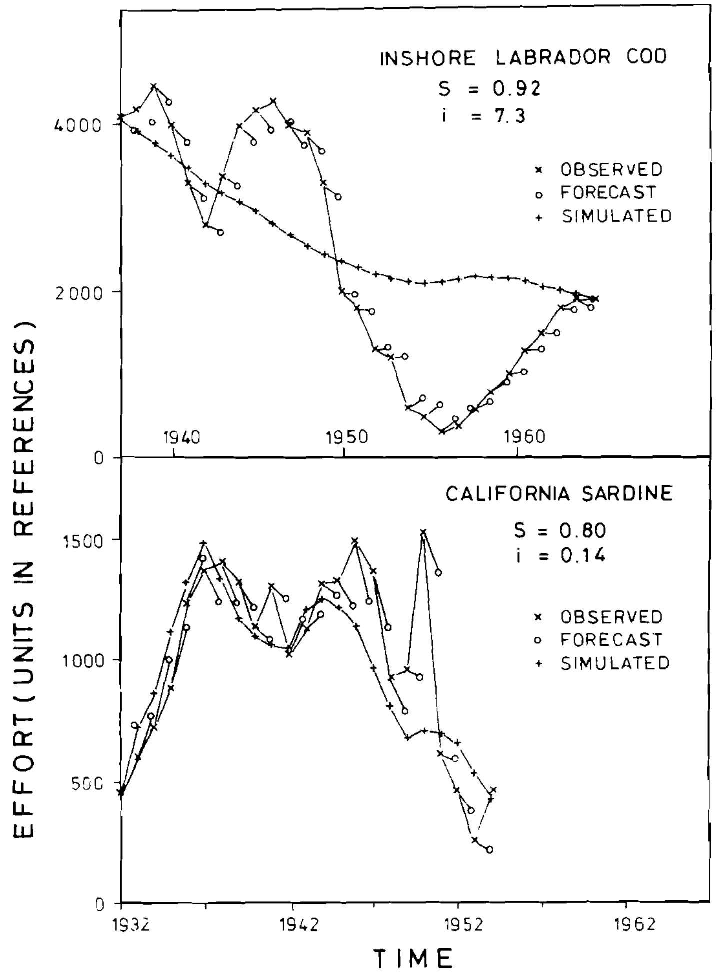


FIGURE 12. EXAMPLE OF PARAMETER IDENTIFICATION FOR THE FLEET DYNAMICS EQUATION. "FORECAST" VALUES ARE PREDICTED FROM PREVIOUS OBSERVED VALUES; "SIMULATED" VALUES ARE PREDICTED FROM PREVIOUS PREDICTED VALUES. DATA SOURCES WERE: WHALES-INTL.WHALING COMMISSION [6]; ANCHOVY-ANCHOVETA EXPERT PANEL [4]; HALIBUT-CHAPMAN ET AL [1]; COD-MAY [8]; SARDINE-MURPHY [9].

APPENDIX 1

Let λ_1, λ_2 be the eigenvalues of the system obtained by linearization around the productive equilibrium $(\bar{B}, \bar{N})$. Moreover, let

$$\Sigma = \lambda_1 + \lambda_2 \quad , \qquad \Pi = \lambda_1 \lambda_2 \quad ,$$

and suppose

$$0 < a < 2 \quad , \qquad 0 < s < 1 \quad , \qquad \bar{B}cT \leq 1 \quad .$$

The aim of this appendix is to prove that

a) $|\Pi| < 1$,

b) $|\Sigma| < 1 + \Pi$.

<u>Proof of a)</u>

First of all recall that Π is the determinant of the matrix F, i.e.

$$\Pi = (1 - a + \bar{B}cT)(icT \frac{\bar{N}}{\bar{B}} + 2s - 1) \quad ;$$

since $\bar{B}cT < a$ (easy to check),

$$-1 < 1 - a < 1 - a + \bar{B}cT < 1 \quad .$$

Therefore, it is sufficient to prove that

$$-1 < icT \frac{\bar{N}}{\bar{B}} + 2s - 1 < 1 \quad ,$$

or, replacing $\bar{N}$ with $v(\bar{B})$ given by Eq. (9a),

$$-1 < (1 - s)\frac{\bar{B}cT}{1 - \exp(-\bar{B}cT)} + 2s - 1 < 1 \quad . \qquad \text{(A1)}$$

Notice that $\frac{\bar{B}cT}{1 - \exp(-\bar{B}cT)}$ is an increasing function of $\bar{B}cT$; hence, since $0 \leq \bar{B}cT \leq 1$, its minimum value is 1 (for $\bar{B}cT = 0$) and its maximum value is $\frac{1}{1 - \exp(-1)}$ (for $\bar{B}cT = 1$). Thus, the first inequality in (A1) is proved. As for the second one, note that

$$(1 - s)\frac{\bar{B}cT}{1 - \exp(-\bar{B}cT)} + 2s - 1 < \frac{1 - s}{1 - \exp(-1)}$$

$$+ 2s - s = \frac{(1 - 2\exp(-1))s + \exp(-1)}{1 - \exp(-1)}$$

But since $0 < s < 1$, it follows that

$$(1 - 2\exp(-1))s + \exp(-1) < 1 - \exp(-1) \quad ,$$

which implies the second inequality in (A1).

Proof of b)

Remember that $\sum$ is the trace of F, i.e.

$$\sum = 2s - a + \bar{B}cT\left(s + i\frac{\bar{N}}{\bar{B}^2}\right) \quad .$$

Let us first prove that

$$-1 - \Pi < \sum \quad .$$

In fact

$$-1 - \Pi - \sum = -1 - icT\frac{\bar{N}}{\bar{B}} - 2s + 1 + aicT\frac{\bar{N}}{\bar{B}}$$

$$+ 2sa - a - ic^2T^2\bar{N} - 2s\bar{B}cT$$

$$+ \bar{B}cT - 2s + a - s\bar{B}cT - icT\frac{\bar{N}}{\bar{B}} \quad ,$$

or substituting $\bar{N}$ with $v(\bar{B})$,

$$1 + \Pi + \sum = 2s(2 - a) - \bar{B}cT(1 - 3s)$$

$$+ (2 - a)(1 - s) \cdot \frac{\bar{B}cT}{1 - \exp(\bar{B}cT)}$$

$$+ \frac{(1 - s)(\bar{B}cT)^2}{1 - \exp(-\bar{B}cT)} \quad .$$

If $3s - 1 > 0$, of course $1 + \Pi + \sum > 0$; otherwise, notice that

$$\frac{(1 - s)(\bar{B}cT)^2}{1 - \exp(-\bar{B}cT)} > (1 - 3s)\bar{B}cT \quad ,$$

so that $1 + \Pi + \sum > 0$.

Now, it must be proved that $\sum < 1 + \Pi$. After some cumbersome computations, one obtains

$$\sum - 1 - \Pi = (1 - s)\left(\bar{B}cT\left[\frac{a - \bar{B}cT}{1 - \exp(-\bar{B}cT)} + 1\right] - 2a\right) \quad , \tag{A2}$$

and, since $s < 1$, the second term of the right-hand side of Eq. (A2) must be proved to be negative. Now, since

$$\frac{a - \bar{B}cT}{1 - \exp(-\bar{B}cT)} < \frac{a - \bar{B}cT}{\bar{B}cT - \frac{(\bar{B}cT)^2}{2}} \quad ,$$

it turns out that

$$\bar{B}cT\left[\frac{a - \bar{B}cT}{1 - \exp(-\bar{B}ct)} + 1\right] - 2a < \frac{2a - (\bar{B}cT)^2}{2 - \bar{B}cT} - 2a$$

$$= \frac{-2a(1 - \bar{B}cT) - (\bar{B}cT)^2}{2 - \bar{B}cT} \quad ,$$

and the last expression, in view of the assumption $\bar{B}cT < 1$, is negative.

APPENDIX 2

In this appendix the region R given by

$$0 \leq N \leq \frac{N_E}{a} \exp\,(2a - 1) = N^*$$

$$0 \leq B \leq s\sqrt{\frac{i\ N_E \exp\,(2a - 1)}{a(1 - s)}} + icT\,\frac{N_E}{a} \exp\,(2a - 1) = B^*$$

is proved to be a region of attraction.

To achieve this purpose it is necessary to prove that

a) any trajectory starting from a point in R is contained in R,

b) any trajectory starting from the outside of R reaches R in a finite number of transitions.

Proof of a)

First of all, notice that if $N_t \geq 0$, $B_t \geq 0$, then $N_{t+1} \geq 0$, $B_{t+1} \geq 0$ (this follows trivially from Eqs. (2)-(3)). Therefore, a) is proved once it is proved that $N_t \leq N^*$ and $B_t \leq B^*$ imply $N_{t+1} \leq N^*$ and $B_{t+1} \leq B^*$. An inspection of Fig. 11 (where the arrows show the direction of the transitions) suggests that the last statement is proved if

i) (N_t, B_t) belonging to regions II or III implies $B_{t+1} \leq B^*$, and

ii) (N_t, B_t) belonging to regions III or IV implies $N_{t+1} \leq N^*$.

In order to prove i) notice that (N_t, B_t) belonging to region II or III is equivalent to

$$\frac{1 - s}{i}\ \frac{B_t^2}{1 - \exp\,(-cB_tT)} < N_t \leq N^* \quad , \quad B_t > 0 \quad .$$

From equation

$$B_{t+1} = sB_t + iN_t \left(\frac{1 - \exp(-cB_tT)}{B_t} \right)$$

it follows that

$$B_{t+1} \leq sB_t + icTN_t \quad .$$

But

$$B_t^2 < \frac{i}{1-s} (1 - \exp(-cB_tT))N_t \leq \frac{i}{1-s} N_t \quad ,$$

i.e.

$$B_t < \sqrt{\frac{i}{1-s} N_t} \quad .$$

Then

$$B_{t+1} < s \sqrt{\frac{i}{1-s} N_t} + icTN_t$$

and, since $N_t \leq N^*$, it follows that $B_{t+1} < B^*$. To prove ii), recall that

$$N_{t+1} = N_t \exp \left[a - cB_tT - a \frac{N_t}{N_E} \exp(-cB_tT) \right] \quad .$$

Since $N_t \geq 0$ and $B_t \geq 0$ it turns out that

$$N_{t+1} \leq \exp(a) N_t \quad .$$

On the other hand, if (N_t, B_t) belongs to regions III or IV, then $N_t \leq \frac{N_E}{a} \exp(a - 1)$ (see Fig. 11). Therefore, it follows that $N_{t+1} \leq N^*$.

<u>Proof of b)</u>

Consider Fig. 11 and notice that in regions V and VI there is no equilibrium state and no cycle, since every transition starting from there is characterized by a decrease of N. Therefore, a trajectory starting from outside of R will reach, after a finite number of transitions, a point (B_t, N_t) such that $N_t < N^*$. If (B_t, N_t) belongs to R, property (b) is proved; otherwise it must belong to region VI, and therefore, after a suitable number of transitions, will be: $B_t < B^*$, i.e. $(B_t, N_t) \varepsilon R$.

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New Techniques for Policy Evaluation in Complex Systems: A Case Study of Pacific Salmon Fisheries

I. Methodology

Randall M. Peterman*

Abstract

The complexity of exploited ecological systems creates difficulties for the manager who must decide among alternative policy options. Some methods for overcoming these difficulties are presented in this paper, using examples from the salmon fishery of the Skeena River system in British Columbia. The described methods produce a "desk-top optimizer," a tool which permits decision makers to perform fairly sophisticated "optimization" operations at their desks instead of having to rely on decision theorists or operations researchers. Also discussed are various system indices which should become part of the information used by managers. These indices include measures of resilience (ability to absorb the effects of unexpected events), costs of failures in management policies, and costs of uncertainty of various types.

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Introduction

Ecological systems are by definition complex; the number of important relationships between system components is usually enormous. When a decision maker is faced with determining the relative merits of various management policy options, this characteristic of high dimensionality becomes a serious problem. He must try to trace through all of the relevant interactions to decide the potential impacts on various parts of the system. With complex systems, it becomes difficult, if not impossible, to deal with all of the information which is necessary to make responsible decisions; some information is bound to be overlooked and not taken into account. MacKenzie (1974) and Rothschild (1973) have forcefully argued that there is indeed much room for improvement, not only in the way we use our present data and knowledge in managing systems, but also in the way we decide which information is relevant for decisions at various levels. This paper attempts to provide 1) a brief discussion of some existing formal methods of analyzing complex systems, and 2) a description of some new techniques which may help decision makers evaluate the relative merits of different policy options.

Relatively recently, there have emerged a number of techniques which have partly overcome some of the problems of analyzing complex systems. The first of these methods, linear programming, can handle large numbers of interactions but is constrained by the assumption that all relationships are linear or can be approximated as such (Dantzig, 1963). This assumption is, of course, not valid for ecological systems, which are characterized by numerous nonlinearities. The second technique, dynamic programming, is able to cope with nonlinearities, but it can only handle unrealistically small numbers of state variables (4-8) (Clark et al, MS). Simulation modeling, on the other hand, is able to handle several hundred state variables and nonlinear functional relations. The only limitation on its usefulness in the present context appears to be the presentation of all the information produced by numerous simulations in a form that is comprehensive yet easily understood and used by the manager. Gross et al (1973) discuss some new techniques which overcome these problems of simulation and which were applied to a big-game management situation. Gross' group made use of a graphical technique (nomogram) which summarizes, in a small space, a great deal of information from a number of simulations.

I have applied this nomogram technique to a salmon management problem and have extended the method in a variety of ways. In particular, relatively sophisticated decision analysis and optimization operations can now be performed by decision makers in a straightforward way which they can easily understand. This new methodology circumvents one of the present obstacles to application of operations research techniques to environmental management problems --the credibility gap between managers and their resident "optimization" experts. This paper will describe the new methods, and the second paper in this series will enumerate the results of its use.

The Skeena Salmon

The system which was chosen for development of these techniques was the Skeena River salmon fishery. Sockeye, pink, and chinook salmon are the main species of importance in this northern British Columbia river. There are four reasons for choosing this system for study: 1) a fairly complex set of biological and physical interactions has been studied; 2) information bases are relatively good for Skeena salmon, both when compared with other salmon systems and when compared to other complex ecological systems; 3) broader social and economic questions are relevant; and 4) a multi-million dollar program is being started on enhancement of Pacific salmon and a means is needed for assessing the potential impacts of various management policy decisions. The basic components of the Skeena salmon system can be reviewed by briefly describing the simulation model of this system which was put together in the spring of 1974 by experts from the Canada Department of the Environment and modelers from the University of British Columbia. This model uses the most recent data available, and its structure reflects the present understanding of the relationships among the components of the natural ecological system.

There are four major subsections of the model: water flow, stock-recruitment and enhancement facility development, management, and harvest. The water flow submodel calculates relevant seasonal water flows in each of eleven geographical regions in the Skeena watershed, using historical hydrological data and random number inputs. The stock submodel represents thirteen different stocks covering three species and each stock is represented by as many as six age classes. The age-at-return to spawning grounds is fixed at two years for pinks but is a probability distribution for sockeye and chinooks, with most fish returning at four or five years of age. In addition, each stock has its own within-season distribution of run timings. A Ricker stock-recruit curve is used to calculate the number of eggs produced by each stock each year. The fry and smolt survivals of each stock are affected, respectively, by winter and spring water flows in the appropriate geographical locations.

Ocean survival of fish is assumed either to be constant or to fluctuate randomly about that level. Three kinds of enhancement facilities are handled: hatcheries, incubation boxes, and spawning channels. These facilities can be established at any time on any river system, and fish to initially stock these units come from natural populations.

The management submodel attempts to simulate the week-to-week regulation of commercial fishing which is allowed during a ten-week period when stocks return to enter spawning grounds. With a particular set of desired escapement levels, the management of fishing days allowed per week is performed through a complex set of calculations which adjusts the expected run timing distribution curve by estimates of previous egg production, smolt survival and early-season catch statistics. Actual harvesting of the fish is done by recreational fishermen, Indians, and three types of commercial boats. Each of these groups has its own fixed catchability coefficient and the number of fish caught is determined by the catch equation.

The Case Study

A manager of an ecological system would like to know the effects of a wide range of possible management policies on all parts of his system. Each manager has some specific facts and ideas in mind when he attempts to describe how the system which he is trying to manage works. These facts and ideas constitute his mental or conceptual "model" of the system. If he can believe that the simulation model is at least an approximate encapsulation of his conceptual model, he has a useful tool at his disposal. However, as anyone who has built a complex model knows, there is such a large number of management manipulations which can be made, and so many relevant state variables that should be monitored, that it is very difficult to get an intuitive feeling for the behaviour of this complex system. In more specific terms, it is difficult to picture the shape of the n-dimensional state-space.

One partial solution to this dimensionality problem was presented by Gross et al (1973). Their "nomograms" are useful because they show the contoured surfaces of a number of state variables as a function of two management policies. Some nomograms from the Skeena model are shown in Figure 1. Note that the axes of all the graphs are identical; they are two management policies which can be implemented at different levels. Each graph shows the isopleths or contours for a different output variable such as average pink catch or minimum yield for Indians during the simulated time period. The contour maps are created from interpolation between thirty-six points on the grid. Each point in this grid is the result of a twenty-five year simulation where the two management policies, desired pink escapement and number of sockeye spawning channels (each with a capacity of 1600 spawners) are set at the levels which correspond to each particular X-Y coordinate.

There is nothing basically new in the way these nomograms are generated; the principles behind them are commonly used in fisheries management. For instance, yield isopleth diagrams (Beverton and Holt, 1957) illustrate the catch from a fishery with various levels of two management options: in most cases, amount of fishing mortality and minimum age harvested. The nomograms in Figure 1 show the mean catches resulting from two other management options, desired pink escapement and amount of sockeye enhancement. But it is recog-

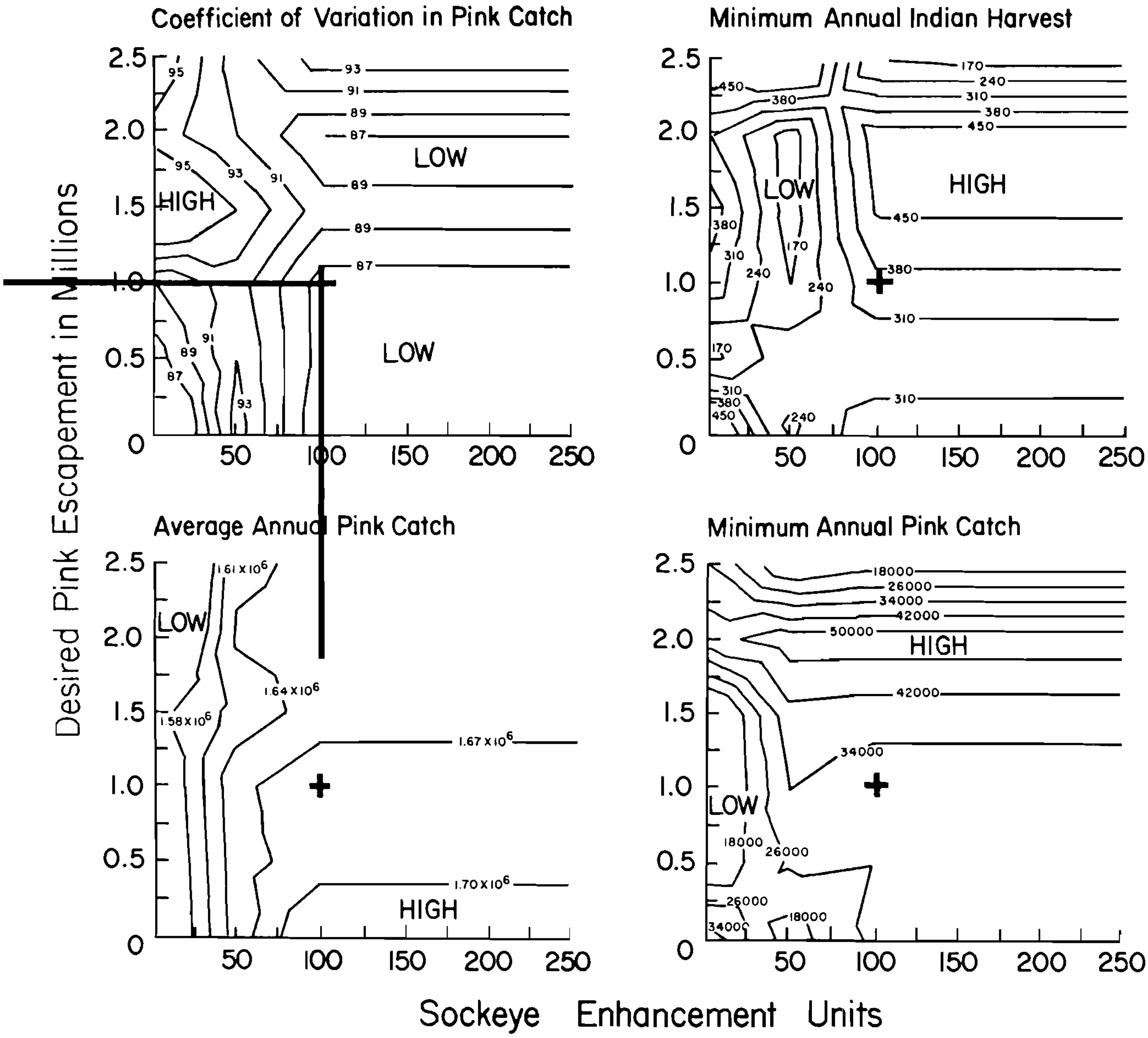

Figure 1. Some nomograms from the Skeena salmon model. All X and Y axes are the same: two policies can be implemented at different levels. "Sockeye enhancement units" is the number of spawning channels (at 1600 spawners per channel) and the other axis is self-explanatory. These policy axes create a "policy space" which is discussed in the text. Pink catch refers only to the commercial fishery catch, whereas Indian harvest refers to the noncommercial catch. "Minimum annual..." is the lowest number for that indicator during the simulated time period.

nized that there are many indices of the effects of two management options which a manager may use in deciding upon appropriate combinations of these options. Therefore, the nomograms in Figure 1 show isopleths not only of mean catch, but also other statistical measures, such as minimum catch, variability of catches over time and catch distribution between commercial and Indian harvesters.

The reason one management option shown relates to pink salmon while the other relates to sockeye is the overlap in run timings of these species in the Skeena River. This overlap causes management decisions aimed at any one species to affect the other. Any other pair of management options could have been chosen; the present ones serve merely to illustrate the technique.

Taking a sheet of paper bearing all of the relevant nomograms (only four representatives of which are shown here), one can overlay a clear plastic sheet with pointers which show identical coordinate locations on all graphs. These locations correspond to a particular set of management policies (see Figure 1).

The variables whose surfaces are shown in the nomograms are referred to interchangeably as impact indicators (Holling et al , 1974), performance measures (Gross, 1972), or goal indicators (MacKenzie, 1974), because they are indices which the manager uses in evaluating the effects of his policy decisions. Later, I will discuss the criteria which one uses in choosing which impact indicators to calculate.

Gross et al (1973) pointed out four functions of the policy nomograms:

1) they provide an instant review of the information which is relevant for making a policy decision, i.e. they are a graphical information retrieval system;

2) they demonstrate certain limits to the system (e.g. whether it is possible to achieve a catch greater than some amount);

3) the user can experiment with alternative management plans merely by moving around the plastic overlay with its pointers. For instance, Figure 2 shows the difference between the effects of Policy 1)(desired pink escapement equal to one million, and 100 sockeye spawning channel units established) and those of Policy 2)(pink escapement equals 1.5 million, and fifty sockeye spawning channel units);

4) constraints on management may be imposed by certain desired maximum or minimum limits. For example, a manager, for political reasons, may not want the minimum annual Indian harvest to go below 200 fish, so he darkens the region below this contour on the "minimum Indian harvest" surface. After shading out different constraint regions on several graphs, he is left with a region within which he must work --a "planning window."

Five other functions of the nomograms have emerged from the present study:

5) trade-offs between the different components of a decision-maker's objectives or goals become readily apparent. The pointers on all surfaces show for each policy which impact indicators are being maximized at the expense of which others. This is particularly useful in a complex management situation where the manager finds it difficult to intuitively keep track of the trade-offs in his ob-

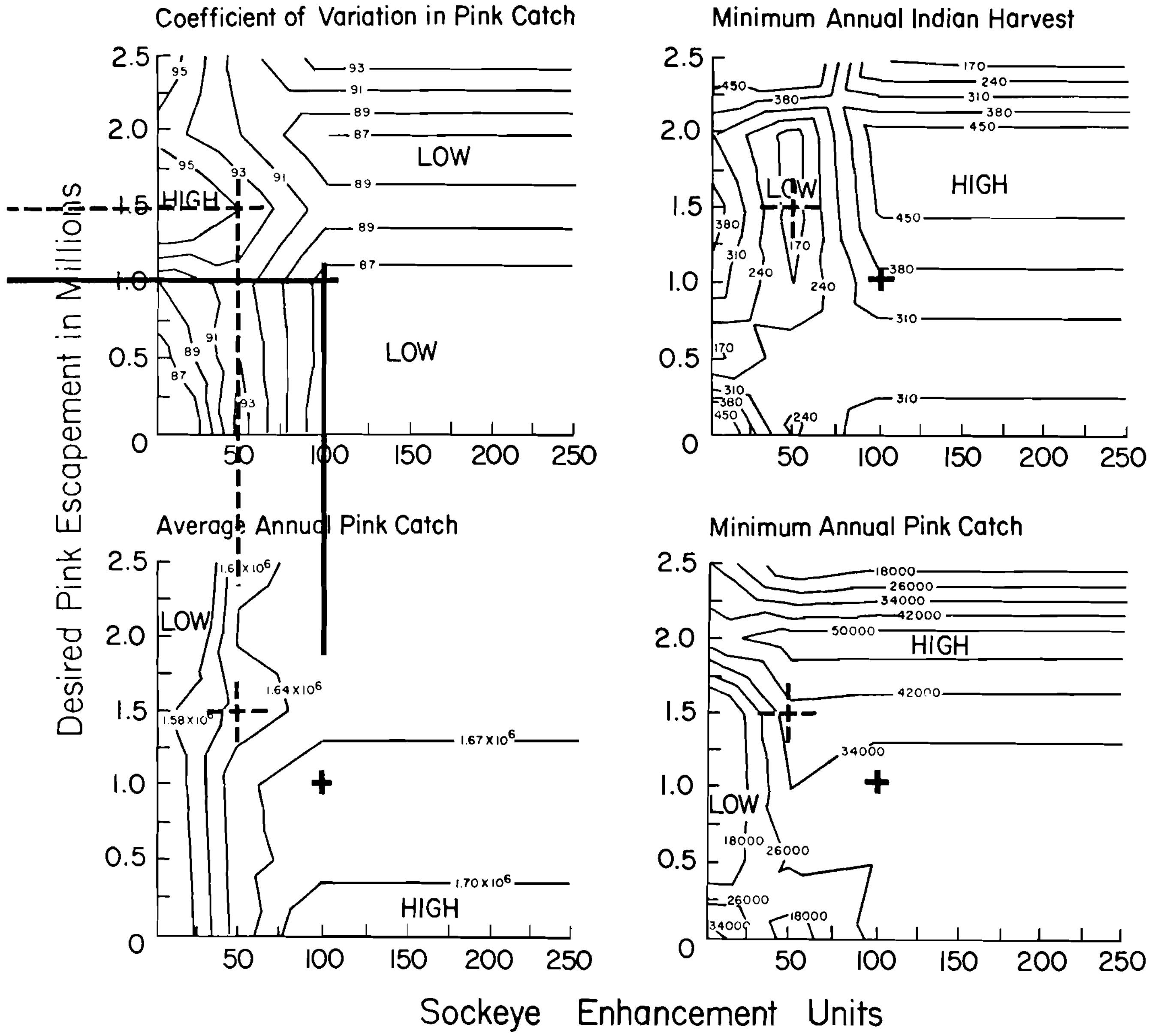

Figure 2. Policies 1) and 2) have different effects in terms of the impact indicators shown. Solid line crosses are for Policy 1) and dotted line crosses are for Policy 2).

jectives for different parts of the system;

6) the steepnesses of the slopes on the surfaces indicate how far off the maximum one may be if the desired levels of management policy are not exactly achieved. Desired escapement levels and spawning channel output can never be precisely attained, so there is going to be a probability distribution around the desired point which will describe where the actual management policy levels end up. One can then look at the changes in surface heights at various points along this distribution in order to calculate the "costs" of uncertainty (in terms of lower levels of various impact indicators actually achieved);

7) each manager can use his own value judgments and biases in deciding which impact indicators are relevant to his particular level of decision making and what their relative importances will be. This issue of different importance weightings will be pursued shortly;

8) measures of the state of the system, other than those normally used by managers, can also be presented in the nomograms. For instance, one can include measures of system resilience (Holling, 1973), or ability to cope with unexpected changes in factors such as water flow or ocean survival. Such resilience measures might be stock (genetic) diversity or minimum size of unutilized fish stocks;

9) the surfaces on different nomograms can be combined into one conglomerate surface either by mathematical weighting and summing or by using plastic overlays as described in a later section. The user can then explore the changes in optimum policies caused by (a) using different impact indicators with different weightings, and (b) assuming different states of external conditions (e.g.

economics). The validity of this method depends on the assumption, to be discussed later, that the weightings assigned to different impact indicators are independent and additive.

Choice of Impact Indicators

In order to maximize their usefulness, the set of procedures described in this section attempts to follow as closely as possible the steps which decision makers intuitively follow when determining which set of policy decisions is best for a given problem.

The first step is to define the list of relevant impact indicators. This is a critical stage, and this list is determined by a number of considerations. First, one must define the scale of the system which will be managed. What are the spatial boundaries of the system, and over what time span is one interested in maximizing his goals and looking at interactions between system components? Also, what are the disciplinary boundaries of the managed system? Do they encompass economic and sociological factors, or should these be left out of the simulation model and handled only in the manager's mental or conceptual models?

Second, what precisely are the management goals, in terms of both the above criteria and the parts of the system which the manager wishes to recognize as important? For example, does he want to maximize the catch over the next five years, or does he want to minimize the risk of stock extinction during the next ten years?

Third, the impact indicators chosen for consideration must be able to characterize the variety of system states which may result from an extremely wide range of possible management policies. Additionally, the list of indicators should only be as long as necessary; any superfluous information which is not useful to or discernible in the real world by the manager is irrelevant.

Fourth, the design of impact indicators (and the simulation model) should take into account the conceptual model of the manager. Figure 3 shows a hypothetical mental model of one type. The point here is that in addition to the above criteria for choosing impact indicators, the relevant indicators should also be determined by the inputs needed by the manager's other mental submodels that are not explicitly represented in the computer simulation model. For example, dollar landed value of the catch may be an important input to the decision-maker's economic mental model, and minimum Indian harvest may be a significant political consideration. Therefore, the biological simulation model should calculate these indices. If one recalls that the simulation model is an aid to, rather than a replacement for, the manager's conceptual models, it is easier to remember that the simulation model still needs to interact with other submodels of the system, be they mental or mathematical.

The fifth and last determinant of choice of impact indicators is encompassed under the heading of resilience indicators (already discussed) and costs of failure (Clark et al, MS). This last concept relates to the idea that rare random events still have a finite probability (of 1.0) of occurring, given enough time. That "one-year-in-a-hundred landslide" may occur next year, or that improbable spawning channel failure may occur two years hence,

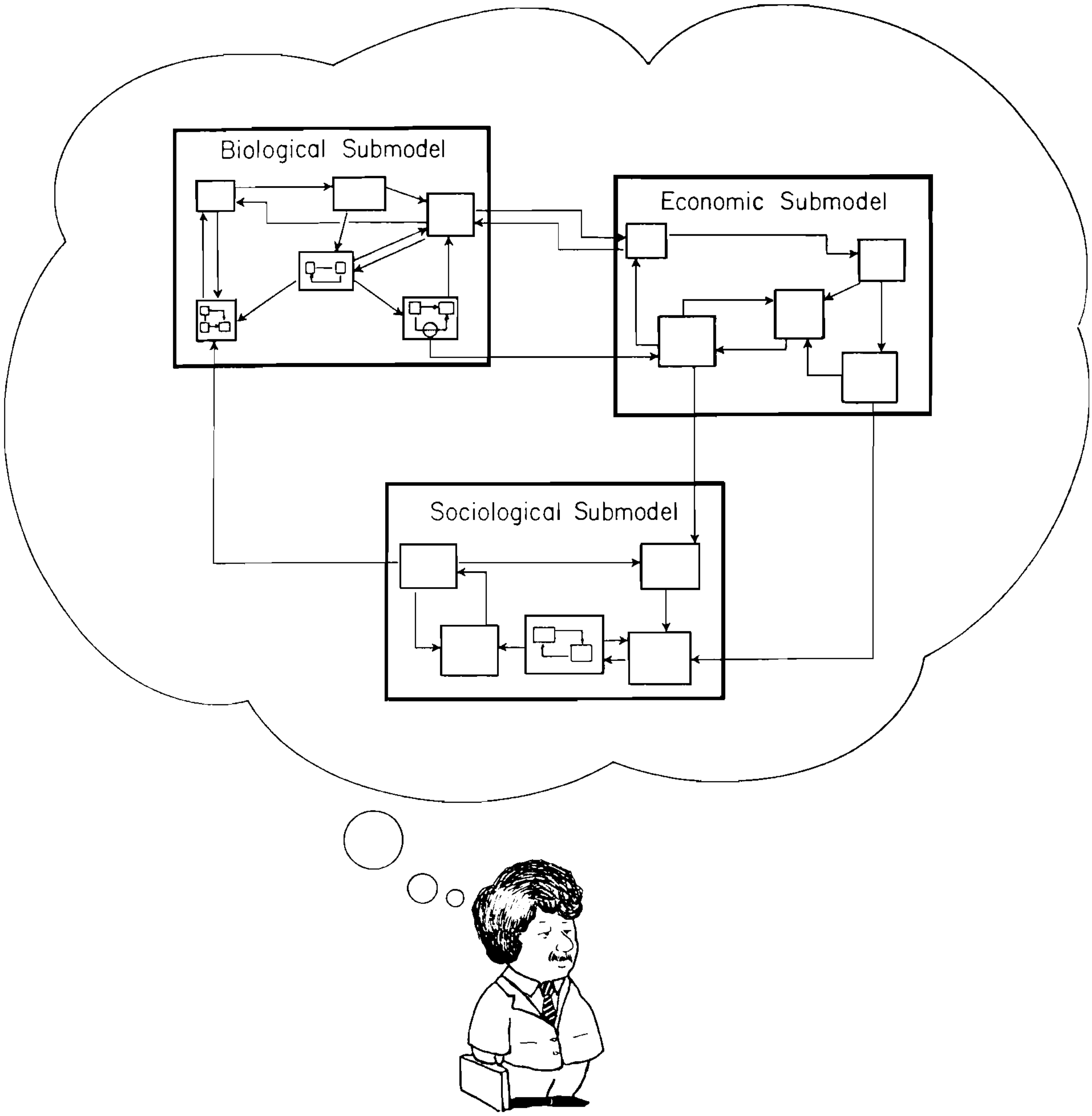

Figure 3. An example of a mental model used by a manager when considering the effects of various policy decisions. Note that there are connections between the biological, economic and sociological "submodels."

and one should either design the management system to be able to cope with such rare events or at least have calculated ahead of time the potential costs of such "failures" in the system. These costs need not be in terms of dollars; they may be described by decreased Indian harvest, or lower stock diversity. Such "failure" costs will differ under different management policy regimes and, therefore, impact indicators which calculate the costs of these failures can and should become an important component of the manager's decision-making apparatus.

These five criteria for defining impact indicators will help produce a complete list of factors which must be output from the simulation model, which is presumed to already exist before this set of techniques is applied. Numerous simulations are performed using different levels of policies in the manner already described and impact indicators are presented in a series of nomograms.

Using the Nomograms for Determining Optimum Policies

The nomograms illustrate the contoured surfaces of the impact indicators in relation to particular policy options. Ideally, what the manager wants to do is choose those impact indicators which are relevant to his policy decision, combine their surfaces, and come up with a picture of which policies get the system to the optimal points on that combined surface. A number of steps must be followed during this process.

First, the manager must decide which of the relevant impact indicators he wishes to maximize (e.g. cumulative sockeye catch) and which he wishes to minimize (e.g. the number of stocks close to depensatory mortality levels). Second, each of the contour graphs of these indicators must be scaled to the same values, say, 0 to 1, based on how close each point is to the maximum (or minimum) on its particular graph. Third, the manager must clarify his own value judgments and put relative weightings on each of these indicators. For instance, he might decide that maximizing commercial sockeye catch is twice as important to him, in terms of his overall objectives, as maximizing Indian harvest. Therefore, the former factor would get twice the weighting as the latter. The only constraint on the combination of relative weightings is that they should all add to some constant value, say 1.0. The fourth step is to combine the surfaces of the relevant impact indicators, taking into account their relative importance weightings. This can easily be done mathematically by performing weighted summations of points across the policy grid. However, one of the goals of the exercise described in this paper is to create a technique which enables a manager to make judicious use of available understanding and data in determining optimal policies at his desk, without interacting with a computer. In effect, we want to create a "desk-top optimizer."

The way that this is done is by performing the weighted summations of surfaces visually, not mathematically. Each contour graph in the set of nomograms has its heights represented by shades of gray, the highest area being darkest and the lower areas grading into lighter shades, similar to McHarg's (1969) method of analyzing land use conflicts. Each graph also has replicates, with each replicate being given any one of the possible importance weightings (e.g. 0.2 to 0.8) which may be assigned to that indicator by a manager. Those replicates with higher assigned weightings have a darker range of shades of gray present on the contours than will the lower weighted graphs (Figure 4). In fact, the darkest area on each replicate graph is directly proportional to the weighting.

Each graph is then reproduced on a clear sheet of plastic, one graph per sheet. The user then combines the surfaces of all relevant impact indicators merely by choosing the sheets with the appropriate weightings and overlaying them. Against a light background, the areas which encompass the highest parts of the composite graphs and which overlap will produce the darkest resultant regions (Figure 5). The darkest area will correspond to the "optimum" policy set, here defined by two management variables, pink escapement and sockeye enhancement. The resulting regions of different shades of gray can then be traced out, and the implications of the user's value judgments become clear for various management policies.

A qualifier is needed at this point. The term "optimum" policy as used in this paper refers to the best policy which can be achieved, <u>but only</u> with respect to those attributes of the system which are explicitly taken into consideration. There is no assumption made that such policies are still "best" if additional criteria of policy impacts (e.g. sociological ones) are considered.

After determining the optimum policies, the user can go back to the original set of unshaded nomograms, set his pointers on the optimum points on the X-Y axes, and then clearly see which indicators are being compromised. This graphical means of determining optimum policies and visualizing tradeoffs between components of the manager's total objectives cannot help but be

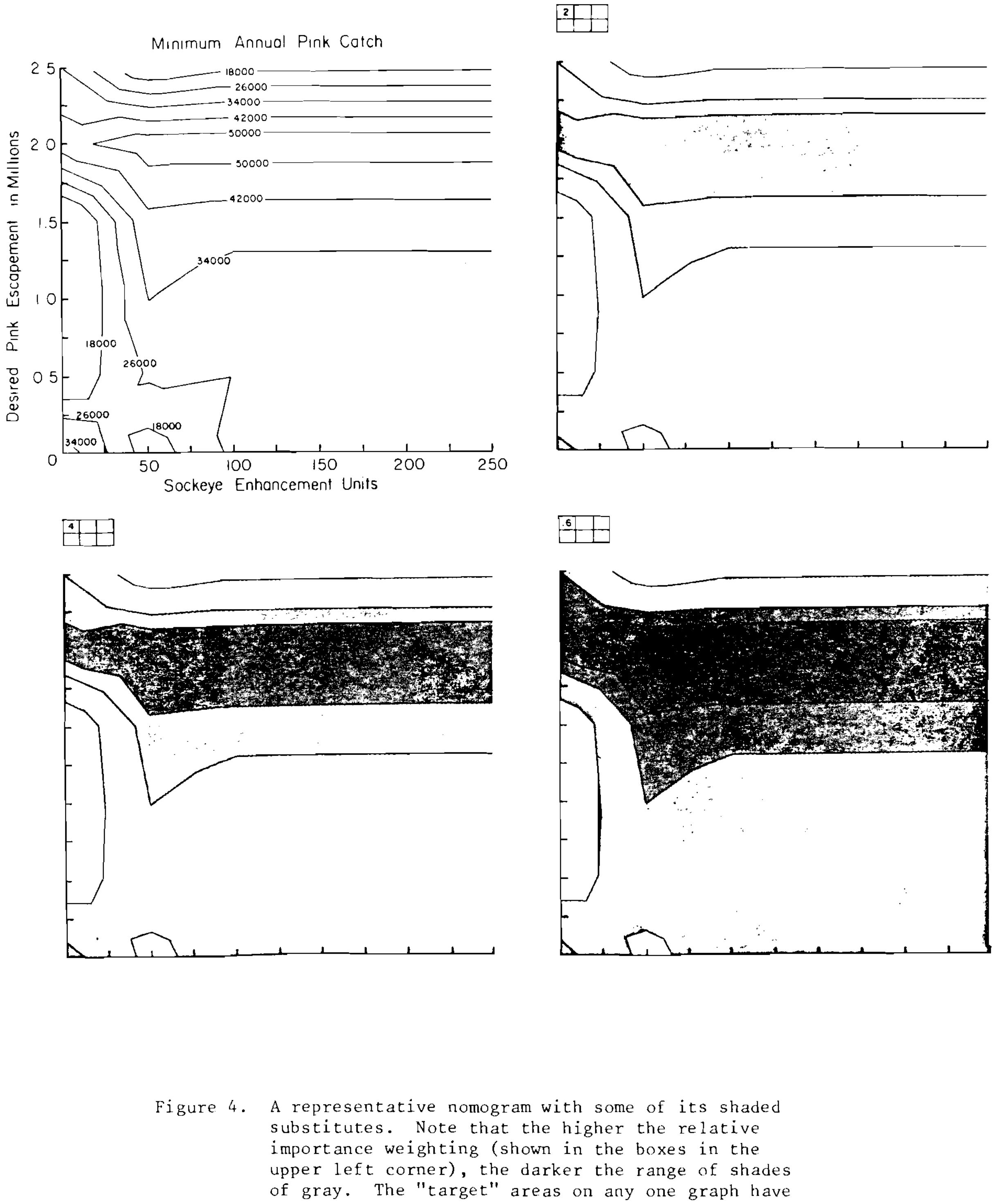

Figure 4. A representative nomogram with some of its shaded substitutes. Note that the higher the relative importance weighting (shown in the boxes in the upper left corner), the darker the range of shades of gray. The "target" areas on any one graph have the darker grays.

.6	.4	

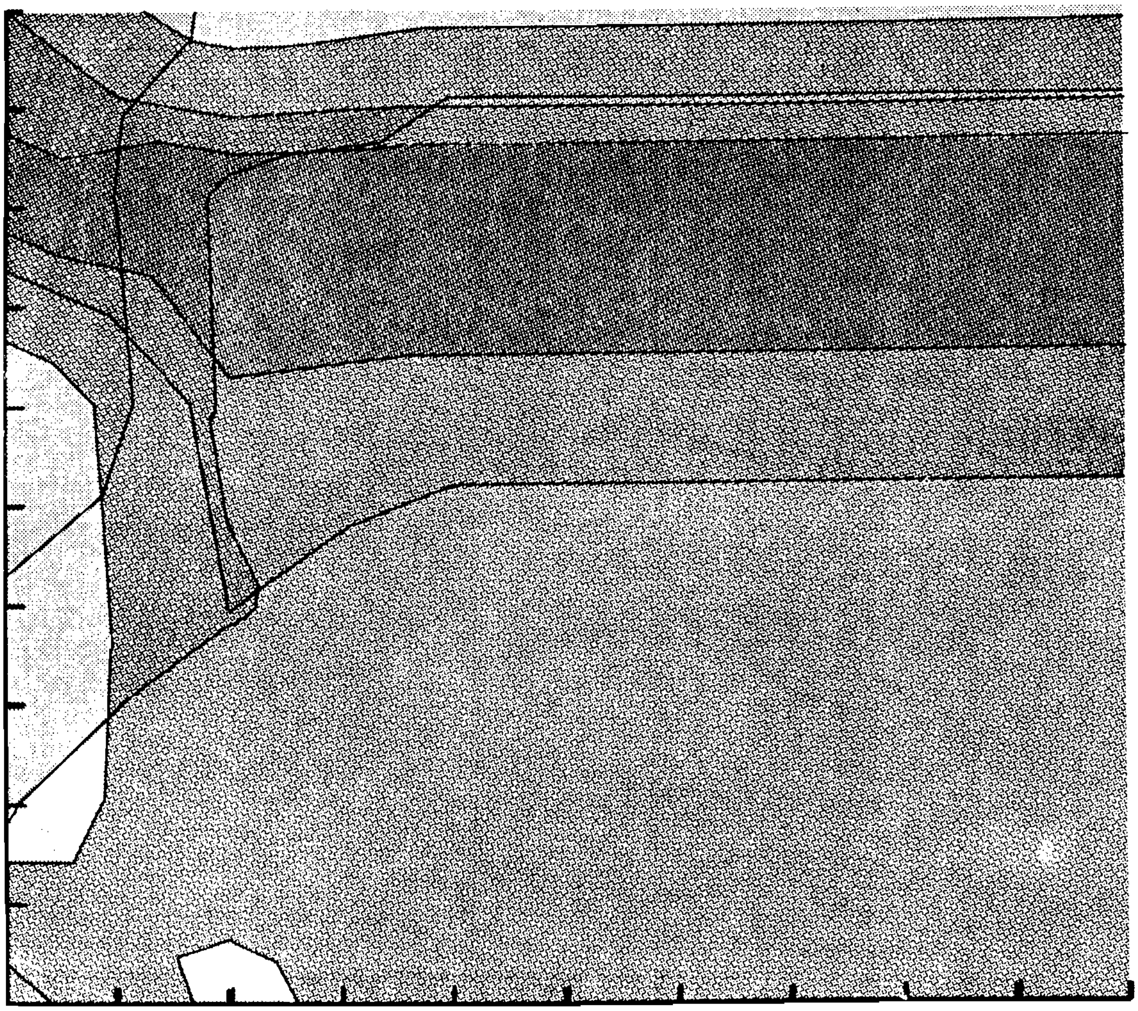

Figure 5. A simple example of how one determines the "optimum" policy by overlaying appropriate impact indicator nomograms. This composite graph is the result of overlaying the "Minimum annual pink catch" nomogram with a weighting of 0.6 on an "Average annual Indian harvest" nomogram with a weighting of 0.4. The darkest regions indicate where the "optimum" policies are, as described by the corresponding values on the X and Y axes, but "optimum" only with respect to these two indicators. Up to five or six indicator graphs can be overlaid with this technique.

clearer than present means, which are more intuitive, less quantitative, and in most cases less comprehensive (MacKenzie, 1974; Braybrooke and Lindblom, 1970).

The set of techniques described should be used iteratively in determining short-range policy optimums, not long-range ones. There are two reasons for this. First, new data which result in changes in nomogram surfaces may become available, perhaps causing large changes in our estimation of the best policies. Second, changing social values may cause changes in the relative importance ratings given to various impact indicators, again possibly changing "optimum" policies.

Extension of the Techniques

There are a number of other applications of these shaded nomogram techniques. First, one can determine how different the optimal policies would be if extreme conditions in driving variables (e.g. water flow) were encountered or if there were simulated "failures" in the management system (e.g. enhancement facilities). When the costs of such failures are taken into account, it could be that the optimum policies would be different from those determined from the runs where no "failures" were assumed to occur.

Other costs can be injected into this decision-making scheme which are associated with uncertainties of two kinds. First, there is the uncertainty of final location in policy space (as opposed to desired location). The relevant question for the manager is, "What are the costs (in terms of deviation from optimums) resulting from this uncertainty of final location in policy space?" Or in other terms, "How steep are the slopes of the surface around the optimum?" In a case where there are two equally high peaks on the final overlaid surface, this kind of uncertainty would force the manager to choose management options which would result in getting on that peak with the gentlest surrounding slopes. This way, there will be a smaller drop in height if there is any deviation from expected location in policy space.

The second type of uncertainty cost is related to the first but is associated with how much the isopleths shift when different assumptions are made about how critical functional relations in the model are shaped. One wishes to know how wrong the optimum policies might be if we were uncertain about the structure of the model (and our understanding) which formed the basis of the policy decisions. This uncertainty cost can also be crudely approximated by the slopes of the impact indicator surfaces at points surrounding the desired location in policy space. In other words, a contour map of uncertainty costs can be generated for each nomogram, and these cost nomograms can be taken into account as part of the decision-making process, if desired. Alternatively, one could handle the uncertainty concerned with model structure by running the simulation using various assumptions about critical functional relations and then plotting only the contour lines from the least optimistic set of results.

Because of the uncertainties mentioned above, the exact "optimum" area delineated in the composite overlays by the contour lines should not be taken too seriously. In fact, we should probably only be concluding that "We should be up in this corner as opposed to down in this corner." One way of ensuring that this is the only possible conclusion is to eliminate the contour lines, grading the shades of gray gradually into one another so that there are no sharp boundaries.

Advantages of the "Desk-Top Optimizer"

The described techniques constitute a "desk-top optimizer" which does not have any of the drawbacks of dynamic or linear programming. The full-scale simulation model can be used to generate the graphs; no model simplification is required. Also, the manager does not need to interact with a computer or computer expert, and he can try out most of his management scenarios at his desk.

Note also that this technique is extremely flexible in that different users (or the same user at a later time) can choose different impact indicators and/or different relative importance ratings for those indicators. The technique merely provides a way of quantitatively assessing the implications of each set of value judgments. The implications of these judgments (importance weightings) can easily be ascertained by seeing how different the "optimum" policies are which result from each set of weightings. This will give the decision maker a measure of the "robustness" of the optimal policies to changes in the structure of his objective. Costs of failures and uncertainties of various types can also be given different importance values in the overall decision-making process, depending on the attitude of the manager toward taking "risks."

This flexibility that enables each manager to design his own complex "objective function" (weighted set of goals) is a major improvement over dynamic programming methodology. All one needs to create a "desk-top optimizer" is a model which represents the behaviour of the real-world system to the level of resolution required, and which runs relatively quickly on the computer. The Skeena salmon model from which these examples are taken has nineteen pages of coding and costs $0.50 per twenty-five-year simulation. Therefore, a large number of scenarios can be run at relatively little cost when compared with dynamic programming models.

Probably the most significant advantage of the "desk-top optimizer" is that a manager has at his immediate disposal all of the relevant biological information which he needs to make a responsible decision, and the information is easily understood because it is in graphical form. So not only does the manager have all of the information before him that was previously supplied by the "experts," he also has some simple (previously esoteric) techniques for making good use of that complex information. This elimination of the credibility gap between the decision maker and his decision theorist or operations research consultant is not complete (as will be discussed in a moment), but it is at least greatly reduced, as are the concomitant errors in data interpretation and data needs that always arise when a decision maker interacts with a consultant.

The "desk-top optimizer" also permits the creative design of management policies with specific goals in mind (Clark et al, MS). In other words, the manager can easily determine what his best policies are for given goals or objectives rather than merely describing all of the different impacts of a certain management policy imposed from above.

Related to this topic is the possibility for the manager to evaluate a wide range of alternative policies. All one has to do is ensure that simulations are done over a wide range of policy options and that there are sufficient impact indicators produced to reflect unexpected changes in all parts of the system.

Disadvantages of the Technique

There are a few problems which make the "desk-top optimizer" less than the perfect solution to the manager's problems. First, there is still a credibility gap between the manager and the quantitative specialists, but it is now in a different place; now it centers on the simulation model. Before any part of the nomogram technique is useable, a credible simulation model must be available. There are three possible ways to increase the manager's level of confidence in the simulation model:

a) the manager can actually participate, along with the field biologists, in putting together the model. A credible model can be assembled in a relatively short time in an intense "workshop," using the methods described by Walters (1974) and Walters and Peterman (1974). If nothing else, this preliminary model can serve as the basis for future, more comprehensive models;

b) the results produced by the simulation model can be presented at several levels of detail, any of which a manager can consult (Gross et al, 1973). This could range from a very detailed set of step-by-step results to coarser level summaries of calculations. The manager can choose that level which most fits his degree of understanding of the structure of the model. Part of this multilevel data system could even be a graphical representation of all the input data and functional relations in the model so that the manager could trace through a series of steps in exactly the same manner as the computer model;

c) results which are opposite of those expected by the manager can, if adequately supported by tracing through why they occurred, inspire confidence in the model. This may result from some complex interactions which a manager finds difficult to follow through intuitively but which may be handled unambiguously by the model.

The second problem with the "desk-top optimizer" is that the system of weighted visual summing of shaded surfaces assumes a linearity and independence among terms of the user's objective function. This function describes the user's overall objective as the sum of the impact indicator values, each weighted by its relative importance rating. The linearity part of this assumption does not appear to be critical; Slovic and Lichtenstein (1971) have evidence that linear objective functions are as appropriate as nonlinear ones. However, impact indicators should be lumped or disaggregated so that the weightings put on each indicator are independent of the levels of other indicators.

The third problem is getting managers to quantify their weightings schemes for impact indicators. However, there are some techniques available in decision theory for coping with this problem (Slovic and Lichtenstein, 1971).

Fourth, the manager must define the levels of resolution which are applicable to each contour surface. That is, one must take into account that small differences in heights may not be detectable in the real world due to sampling error or that such differences may not matter in terms of distinct policy acts.

Fifth, nomograms are, at present, limited to inclusion of only two or three policy axes. Ideally, one would like to search through an n-dimensional set of indicator surfaces with n-policy options. This can easily be done on a computer version of the "desk-top optimizer," but the aim of the present work is to produce noncomputer tools which a decision maker can use at his desk. Ways of solving this problem are presently being explored.

Finally, we are forced by the old nemesis of dimensionality into compressing time series data into indices which can be shown on a few nomograms (e.g. averages over species, variances over time, minimums, etc.). If a manager needs to see changes in system variables over time, such information can be made available as part of the "multilevel" data system in which those coarse-level indices which are shown on the nomograms can be broken down into their more detailed components. For example, a manager may want to see how the total pink catch is broken down by stock, or how such catches changed over time for a particular set of management policies. The data bank from which the compressed indices were calculated can be accessed and time series data can be plotted.

Preliminary Results

There are some preliminary results of using the described techniques which are worth mentioning. First, by merely inspecting the shapes of the contours on any one graph, interesting relations between the two illustrated management options appear. For example, the nomogram of average annual commercial pink catch shows that for low levels of sockeye enhancement (0-40 units), changing the desired pink escapement hardly affects the actual pink catch. However, at higher sockeye enhancement levels, there is the expected effect of changing pink escapement on pink catch. This result illustrates the sometimes subtle interactions between management options. The second result of interest is shown on the minimum annual pink catch graph. The steepness of the slope of this surface increases as desired pink escapement increases. This is important from the standpoint of the manager who knows that the actual escapement will end up somewhere near the desired level, but never right on it. A given deviation from desired escapement will result in different changes in the indicator, depending on the desired escapement. Such effects of uncertainty should therefore be an important consideration for a decision maker. The final result deals with the trade-offs between impact indicators when certain combinations of the two management options are chosen. For example, setting the desired pink escapement at two million and sockeye enhancement anywhere above 100 spawning channel units, both minimum annual pink and Indian catches are at their highest possible values. However, these high values cannot be maintained if management policies are changed to obtain the highest possible annual pink catch. Such unavoidable trade-offs between the different components of a manager's objectives are useful to realize. These preliminary results will be expanded upon and others will be discussed in the second paper in this series.

Conclusion

Despite the drawbacks listed previously, the "desk-top optimizer" appears to have great potential for use in managing complex ecological systems. This is because the value of the technique must be measured on a relative scale, not an absolute one. In the words of Walters and Bunnell (1971), "We need to ask whether it (simulation in general) can complement, or do better than, the usual intuitive approach to management." I think that by permitting the manager to see immediately in graphical form the varied effects of different policy decisions, we cannot help but improve the state of ecological systems management. This is true even though we may, at this point, only be able to quantify and use the described methodology for one section (the biological) of the whole system which is being managed. The techniques described in this paper are one possible answer to MacKenzie's (1974) plea for development of "efficient techniques for optimal choice among alternative policy goals or objectives, and among strategies for the attainment of those goals...."

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APPENDIX

Further Lines of Research

Several lines of work emerge as important topics to pursue:

1) A completely computer-based optimization routine could be developed in parallel with the desk-top version, using exactly the same procedures except that relative importance weightings would be represented numerically rather than with shades of gray. The advantages of this computer routine would be that nonlinear objective functions and any number of impact indicators could be used.

2) The multilevel information presentation system is an important key to understanding the intricacies of the working model and closing the credibility gap between the manager and the modeler. This line of work should be pursued vigorously, ensuring that several imaginative ways of presenting the relevant data are created.

3) A way of expanding above two the policy dimensions displayed on the nomograms is needed for both the desk-top optimizer and the computer-based one.

4) We need faster and cheaper methods for producing the shaded contour graphs than with "Letratone." Computer graphics plotters and machines which transmit pictures over phone lines are two obvious possibilities.

5) For particular management situations, we need to find the most useful and informative indices into which time series data can be compressed (e.g. means, coefficients of variation, mean rate of change, etc.).

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