WORKING PAPER SERIES

FISHERIES STOCK ASSESSMENT

TITLE XII
Collaborative Research Support Program

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The University of Rhode Island—International Center for Marine Resource Development
The University of Washington—Center for Quantitative Sciences
The University of Costa Rica—Centro de Investigación en Ciencias del Mar y Limnología
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WORKING PAPER SERIES

Working Paper No. 43

An Improved Method for Fitting Gillnet Selectivity Curves to Predetermined Distributions

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ABSTRACT

Monte Carlo optimization with constraints was used to estimate parameters of "skew-normal" selectivity curves for gillnets. Non-linear functions of mesh size were explored in addition to the linear ones described by Wulff (1986). This methodology can be used to estimate the parameters for any distribution used to describe selectivity curves. Better estimates can be obtained than with the search-all method of Wulff which is limited by the amount of computer-running-time required for models with more than four or five parameters. Furthermore, models with parameters defined as polynomial functions of mesh size gave better fits than the simpler linear function models in two of the four cases examined herein.

INTRODUCTION

Gillnets are highly selective, and most of the fish of a given species caught using a specific mesh size are within 20 percent of the optimum size (Hamley 1975). They are widely used in artisanal fisheries of developing countries because they are efficient and relatively inexpensive. For example, in the Philippines gillnets account for about 18 percent of the total demersal catch which exceeds 400,000 metric tons and about 42 percent of municipal pelagic fish landings . Decreasing catches and uncontrolled use of very small mesh sizes are problems typical of many areas of the world including the Philippines. Gillnet selectivity studies are related to the rational use of the resource in a number of ways. These include: (1) choosing a suitable mesh size for management purposes; (2) correction of the size composition of the catch, and (3) correction of the catch per unit effort due to different mesh size efficiencies (Yatsu and Watanabe 1987).

Numerous methods for estimating gillnet selectivities have been developed, and the interested reader is referred to Regier and Robson (1966) and Hamley (1975) for comprehensive reviews of the subject. In summary, methods for estimating selectivities can be classified into five categories (Hamley 1975):

1) Inferences from girth measurements;
2) Use of size distributions of catches. This method gives only crude estimates of selectivity because it does not take into account the abundance of each size class;
3) Direct estimation by comparing catches with known size distributions of the population. This can be done if a known (marked) population is fished or if comparisons can be made with gear of known selectivity. The advantages of direct estimates are that no assumptions are required concerning the form of the selectivity curve, and there is no need to compare catches by different mesh sizes;

4) Estimates of mortality for each size class of fish in a time series of catches can be used as long as constant catchability can be assumed, and

5) Selectivity can be estimated indirectly by comparing size distributions of catches in gillnets of different mesh sizes. This can be done by fitting a predetermined distribution to obtain the Type A curve (selectivity of one mesh size to different sizes of fish) or by using Type B curves (selectivity of different mesh sizes to one size class of fish) as proxies.

Many of the methods for estimation of gillnet selectivity curves are based on one or more of the following assumptions: constant optimum efficiency of capture (height of selectivity curve), constant shape and variance of the selectivity curves, and proportionality of optimum length-at-capture to mesh size (Clarke and King 1986). Data from direct estimates of selectivity may not support these assumptions (Clarke and King 1986).

Wulff (1986) developed a new method which makes no assumptions concerning efficiency [the area under the selectivity curve (Hamley 1975)]. The method depends on the assumption that the selectivity curves for different mesh sizes are similar, and this similarity can be expressed by the relationship between mesh size and certain parameters. Wulff (1986) assumed that optimum selectivity, optimum length at capture and variance of selectivities were all linear functions of mesh size.

The objectives of this study were: (1) to explore other relationships between parameters describing selectivity curves and mesh size; (2) to improve the methodology for estimating the parameters, and (3) to apply the improved method to some published data and assess the results.

METHOD

Following Wulff (1986):

let $N(l)$ = number of fish of size class l in the sampled population

$P(l,m)$ = probability for a fish from $N(l)$ to be caught by mesh size m

$C(l,m)$ = number of fish of size class l caught by mesh size m [$C(l,m)$]

[$C(l,m)$ is a random variable).

Then the probability of catching a single fish is a Bernoulli trial with probability of success $P(l,m)$. In other words, the probability of getting $C(l,m)$ successes in $n(l)$ independent trials can be described by the binomial distribution:

$$f(C(l,m)) = \binom{N(l)}{C(l,m)} P(l,m)^{C(l,m)} (1 - P(l,m))^{N(l)-C(l,m)}$$

If $N(l)$ is large and $P(l,m)$ is small, the binomial is approximated by the Poisson distribution:

$$f(C(l,m)) = \frac{(N(l)P(l,m))^{C(l,m)}}{C(l,m)!} e^{-(N(l)P(l,m))}$$

If the selectivity $S(l,m) = P(l,m)P(\bar{l},\bar{m})^{-1}$ and $\bar{N}(l) = N(l)P(\bar{l},\bar{m})$:

$$f(C(l,m)) = \frac{(\bar{N}(l)S(l,m))^{C(l,m)}}{C(l,m)!} e^{-(\bar{N}(l)S(l,m))}$$

$\bar{N}(l)$ is estimated by $\dfrac{\sum_{i=1}^{m} C(l,m)}{\sum_{i=1}^{m} S(l,m)}$.

Therefore, we can estimate the parameters of the selectivity curves by maximizing:

$$\prod e^{-\frac{\sum_{j=1}^{m} C(l,m)}{\sum_{j=1}^{m} S(l,m)} S(l,m)} \frac{\left(\frac{\sum_{j=1}^{m} C(l,m)}{\sum_{j=1}^{m} S(l,m)} S(l,m)\right)^{C(l,m)}}{C(l,m)!}$$

Maximizing this objective function proved difficult due to large factorials and also because this expression involves the product of large numbers of probabilities. Invariably, a number too small or too large ($C_{ij}!$) for the computer to handle would be reached before the end of calculations. To get around this problem, the function was transformed as follows:

$$\text{maximize:} \quad -\left(\frac{\sum_{j=1}^{m} C(l,m)}{\sum_{j=1}^{m} S(l,m)} S(l,m)\right) + \left(C(l,m) \ln\left(\frac{\sum_{j=1}^{m} C(l,m)}{\sum_{j=1}^{m} S(l,m)} S(l,m)\right)\right) - \ln C(l,m)!$$

The underlying assumption of Wulff's method is that the selectivity curves associated with different mesh sizes are similar (belong to the same family), and this similarity can be expressed by certain parameters which are functions of mesh size. The parameters of any reasonable function describing selectivities can be estimated as long as there is reason to believe that they are functions of mesh size.

Therefore, a choice must be made concerning the form of the selectivity curve. Wulff applied a truncated "skew-normal" distribution to roach (*Rutilus rutilus*) data:

$$S_{ij} = \frac{1}{\sigma(2\pi)^{-.5}} e^{-.5\left(\frac{l_j - l_o}{}\right)^2} \left(1 - .5Q^{1.5}\left(\frac{l_j - l_o}{} - \left(\frac{l_j - l_o}{3\sigma}\right)^3\right)\right)$$

where Q is the coefficient of skewness. If $Q = 0$, this reduces to the normal distribution. Regier and Robson (1966) tested nine methods and concluded that a positive "skew-normal" distribution best described lake whitefish selectivity. The choice of the selectivity function to be fitted using the Wulff method must be made based on the raw data and/or previous studies. In general, skewed distributions seem to adequately describe gillnet selectivities for a variety of species (McCombie and Fry 1960; Regier and Robson 1966; Hamley 1975).

The Wulff method was used to fit skew-normal selectivity curves to four data sets. Selectivity at modal length (l_m), modal length (l_m) and standard deviation (s_m) were assumed to be linearly related to mesh size. For example, for the normal curve:

$$S_{ij} = h_m e^{-.5\left(\frac{l_i - l_m}{s_m}\right)^2}$$

where $h_m = \theta_1 m + \theta_2$

$l_m = \theta_4 m + \theta_5$

$s_m = \theta_6 m + \theta_7$.

In addition, selectivity at modal length was fit as a polynomial and as an exponential function.

Clearly an enormous amount of personal computer time would be required in order to maximize the objective function for a six or higher parameter model, by iterating over a range of values for each parameter. In this study, the amount of time required to maximize the objective function was reduced considerably by using a Monte Carlo optimization method (see Appendix). The multistage Monte Carlo program automatically keeps narrowing the range of feasible solutions until the optimum is reached. In addition, efficiency was improved through careful choice of parameters and by imposing constraints. For example, modal lengths of the catch distributions and the derived selectivity curves are usually very similar. Therefore, a regression of catch distribution modal lengths on mesh size provides a good first approximation of θ_4 and θ_5 for the selectivity curve. For non-normal catch distributions, modal length can be estimated following Sachs (1984) by:

$$l_m = L + b\left(\frac{f_u - f_{u-1}}{2f_u - f_{u-1} - f_{u+1}}\right)$$

where L = lower class limit of the size class with the largest frequency

b = class width

fu = largest frequency in the distribution

$fu\text{-}1$, $fu\text{+}1$ = frequencies in adjacent classes.

Similarly, regressions of catch distribution standard deviations against mesh size can help guide the choice of values for the parameters defining s_m. Preliminary estimates of the parameters defining the relationship between selectivity at modal length (l_m) and mesh size are not as easy to obtain. In order to get the range of possible values for these parameters, preliminary runs were carried out holding the parameters defining l_m and s_m constant for wide ranges of values of the parameters defining l_m.

The efficiency of the computer program was also improved by imposing constraints on the values of l_m and s_m. For example, all values of l_m were forced to lie within the minimum and the maximum lengths of the catch distributions. Furthermore, the values of l_m were found to increase with increasing mesh size. Standard deviations were constrained to be positive and less than some defined upper maximum value. If the constraints are violated, the program jumps to the next set of parameters defining l_m or s_m without going through the calculations of s_{ij} and the objective function, thus reducing computing time substantially.

The computer program for constrained linear or non-linear optimization was written in BASIC and run on an IBM compatible personal computer. It should be noted that a specific program must be written for each situation which defines the objective function and the constraints. An example is provided in Appendix 2 to provide some guidance for the user wishing to apply this method.

DATA

Four data sets were used to test the method. The first data set is that for European roach (*Rutilus rutilus*) used by Wulff to illustrate his method. The catch distributions by mesh size and associated statistics are given in Table 1. The catch distributions are all positively skewed, and the standard deviations remain fairly constant.

The second data set is for Lake Huron whitefish (*Coregonus clupeaformis*) from McCombie and Fry (1960). The distributions and descriptive statistics are presented in Table 2. As with the first data set, the distributions are in general positively skewed, and the standard deviations are essentially constant with increasing mesh size.

The final two data sets concern wedged and tangled walleye (*Stizostedion vitreum*)(Hamley and Regier 1973). The raw data and the calculated statistics are shown in Tables 3 and 4.

The raw data and the associated statistics show that the wedged and the tangled distributions have some different characteristics. The means of the wedged distributions tend to increase with mesh size, whereas the tangled means are essentially the same. Both tangled and wedged distributions have wide ranges, but the standard deviations of the wedged distributions are smaller and seem to decrease with increasing mesh size. If we do not consider mesh size 1.5", the tangled distributions also have decreasing standard deviations with increasing mesh size.

Mesh sizes 2.5, 3 and 3.5" for the wedged data appear to be fairly normal. Distributions for mesh size 3" for the tangled data also seem reasonably normal. Because of the increase in size class at the upper end of the distributions, it was not possible to calculate some of the statistics for all the distributions.

The following mesh size distributions were selected for analysis based on preliminary examination of the data:

wedged = 2.5, 3, 3.5, 4"

tangled = 1.5, 2, 2.5, 3, 3.5".

It should be noted that soft bodied and non-spiny-rayed fishes provide data which are better balanced (unimodal) in contrast to spiny-rayed and harder bodied fish, such as the walleye , which indicates bimodality for a given mesh size. This is related to capture by gilling and by tangling. It is believed that most soft bodied fish are caught by the so-called gilling method where the girth of the fish is clearly related to selection. In the case of the walleye, both methods of capture are considered in the methods described herein.

RESULTS AND DISCUSSION

For the four data sets to which selectivity curves were fitted, objective functions were maximized by using between 6 and 15 sets of 1,000 iterations in each.. The objective functions for the three different models for each data set are given in Table 5, and graphs of the best fitting curves are given in Figures 1 to 4. The selectivity curves are scaled so that optimum selectivity for the smallest mesh size is equal to 1.

For all the models fitted, the best parameter combination provided selectivity curves wherein modal height increased with increasing mesh size (Table 5). This is in agreement with data from direct estimates as noted by Clarke and King (1986). In two out of four cases, optimum selectivity described as a polynomial function of mesh size gave the best fitting model. In the other two cases, a simple linear model gave the best fit. However, the improvements in the objective function were not substantial.

The selectivity curves for the roach were positively skewed, and the standard deviation decreased with mesh size (Figure 1). Modal lengths were similar to those obtained by Wulff. However, in this study, optimal selectivity did not increase with increasing mesh size as rapidly as was found by Wulff. Since the objective function for Wulff's parameters (-247) is less than the ones obtained in this study (-240, -242, -240), this optimization method resulted in more accurate estimation of modal parameters.

The whitefish selectivity curves are only slightly skewed, relatively narrow, and the standard deviation increases only slightly with increasing mesh size (Figure 2). A narrow selection range for this species might be expected and suggests that most of the fish are caught n the same manner (gilled). This is in keeping with a soft bodied, non-spiny rayed fish.

The wedged walleye selectivity curves are not as narrow, and the standard deviation of optimal length decreases with increasing mesh size (Figure 3). In contrast, the curves for tangled walleye are more positively skewed, and the standard deviations are much larger (Figure 4). While the raw catch data for the tangled walleye is not of high quality, the results are not surprising since one would expect tangling to be less selective than gilling or wedging.

In this study, optimum length and its standard deviation were modeled as linear functions of mesh size only. Clearly, other relationships could have been explored as well. Finding the best model requires testing all possible combinations for modal selectivity, modal length, and the standard deviation of modal length.

This method of estimating the parameters of selectivity curves is a big improvement over the "search-all" method of Wulff. Whereas the Wulff method cannot realistically handle more than five or six parameters, the Monte Carlo optimization method maximizes the objective function of eight parameter selectivity curves (the polynomial optimal selectivity case) within a reasonable amount of computer time. Ideally, several runs should be carried out for each model to ensure that there is convergence to the same combination of parameters.

It is concluded that the Monte Carlo method of constrained optimization is a flexible and useful technique for the critical estimation of parameters of mesh selection curves. It can handle complex data, such as the walleye data illustrated—as well as the more conventional data provided by the other examples.

REFERENCES

Clarke, D.R., and P.E. King. 1986. The estimation of gillnet selection curves for Atlantic herring (*Clupea harengus* L.) using length/girth relations. J. Cons. int. Explor. Mer, 43:77-82.

Conley, W. 1981. Optimization: A simple approach. Petrocelli Books, Inc. 148 p.

Hamley, J.M 1975. Review of gillnet selectivity. J. Fish. Res. Board Can. 32:1943-1969.

Hamley, J.M., and H.A. Regier. 1973. Direct estimates of gillnet selectivity to walleye (*Stizostedion vitreum vitreum*). J. Fish. Res. Board Can. 30:817-830.

McCombie, A.M., and F.E.J. Fry. 1960. Selectivity of gillnets for whitefish, *Coregonus clupeaformis*. Trans. Am. Fish. Soc. 89:817-830.

Regier, H.A., and D.S. Robson. 1966. Selectivity of gillnets, especially to lake whitefish. J. Fish. Res. Board Can. 23:423-454.

Sachs L. 1984. Applied statistics: A handbook of techniques. Springer-Verlag. 707 p.

Wulff, A. 1986. Mathematical model for selectivity of gillnets. Arch. Fish Wiss. 37:101-106.

Yatsu, A., and Y. Watanabe. 1987. Mesh selectivity of gillnets for slender tuna *Allothunnus fallai* Serventy (Scombridae). Nippon Suisan Gakkaishi 53: 947-952.

Table 1. Frequency distributions of roach and descriptive statistics by mesh size. Raw data from Table 1 in Wulff (1986).

	Mesh Size (mm)					
Length (cm)	30	32	34	36	38	40
20-20.9	4	1	0	0	0	0
21.21.9	21	4	1	0	0	0
22-22.9	24	28	3	0	0	0
23.23.9	27	30	15	4	0	0
24-24.9	36	41	33	18	1	0
25-25.9	36	46	35	42	12	3
26-26.9	17	51	38	55	43	7
27-27.9	10	26	30	57	33	18
28-28.9	8	20	21	34	26	23
29-29.9	1	5	13	17	33	28
30-30.9	1	7	11	18	19	30
31-31.9	3	8	2	7	21	28
32-32.9	3	3	1	8	13	21
33-33.9	0	4	2	6	5	14
34-34.9	2	1	1	11	10	8
35-35.9	3	1	0	6	8	14
36-36.9	0	0	0	2	7	8
37-37.9	0	0	0	0	0	5
38-38.9	0	0	0	0	0	1
Total	196	276	206	285	231	208
Mean	24.9	26.0	26.7	28.1	29.5	31.1
Std. Dev.	2.9	2.6	2.2	2.8	2.9	2.9
Skewness	1.4	0.9	0.6	1.1	0.7	0.4
Kurtosis	5.8	3.9	3.5	3.6	2.7	2.5
P(χ^2 test for normality)	<.005	<.005	<.01	<.005	<.005	<.95

Table 2. Frequency distributions of whitefish and descriptive statistics by mesh size. Raw data from Table 2 in McCombie and Fry (1960).

	Mesh Size (inches)								
Fork Length (inches)	1.75	2	2.25	2.5	2.75	3	3.5	4	4.5
7.5-8.0	16	0	0	0	0	0	0	0	0
8.0-8.5	38	22	0	0	0	0	0	0	0
8.5-9.0	20	35	1	0	0	0	0	0	0
9.0-9.5	5	13	7	0	1	0	0	0	0
9.5-10.0	3	30	7	5	1	0	0	0	0
10.0-10.5	2	23	42	35	4	0	0	0	0
10.5-11.0	3	29	72	104	25	4	0	0	0
11.0-11.5	0	28	116	169	105	16	1	1	0
11.5-12.0	2	0	26	98	78	28	0	0	0
12.0-12.5	1	2	12	42	62	59	1	0	0
12.5-13.0	0	1	11	56	105	86	14	0	0
13.0-13.5	0	0	10	35	84	111	40	1	0
13.5-14.0	0	0	2	13	31	70	35	1	0
14.0-14.5	0	0	2	5	15	36	48	6	0
14.5-15.0	0	0	0	0	5	15	28	13	0
15.0-15.5	0	0	0	0	3	12	25	13	4
15.5-16.0	0	1	1	0	2	2	19	17	6
16.0-16.5	0	0	0	0	0	0	11	23	14
16.5-17.0	0	0	0	0	0	5	20	31	28
17.0-17.5	0	0	0	0	0	5	8	42	51
17.5-18.0	0	0	0	0	0	1	3	30	32
18.0-18.5	0	1	0	0	0	0	3	28	45
18.5-19.0	0	0	0	1	0	0	1	12	26
19.0-19.5	0	0	0	0	0	0	0	4	13
19.5-20.0	0	0	0	0	0	0	0	2	7
20.0-20.5	0	0	0	0	0	0	0	1	3
20.5-21.0	0	0	0	0	0	0	0	0	0
21.0-21.5	0	0	0	0	0	0	0	0	1
Total	90	185	309	563	521	450	257	225	230
Mean	8.6	9.9	11.2	11.6	12.3	13.2	14.7	16.9	17.7
Std. Dev.	0.9	1.3	0.9	1.0	1.0	1.1	1.4	1.3	1.0
Skewness	2.0	1.9	1.1	1.3	0.3	1.0	0.6	-0.6	0.2
Kurtosis	7.4	12.3	6.3	8.0	2.9	5.5	2.8	3.8	3.2
P(χ^2 test for normality)	<.005	<.005	<.005	<.005	<.005	<.005	<.005	<.05	<.95

Table 3. Frequency distributions of wedged walleye and descriptive statistics by mesh size (1968-1970 data combined). Raw data from Table 2 in Hamley and Regier (1973).

	Mesh Size (inches)				
Total Length (cm)	2.5	3	3.5	4	4.5
27-29	2	0	0	0	0
29-31	1	0	0	0	0
31-33	11	1	0	0	0
33-35	10	9	0	0	0
35-37	5	3	5	0	0
37-39	4	7	23	0	0
39-41	1	4	37	2	0
41-43	0	3	61	3	0
43-45	1	1	33	6	0
45-47	1	0	12	7	0
47-49	0	0	9	5	0
49-53	0	0	0	0	2
53-57	0	0	0	0	1
57-61	0	0	0	0	1
Total	36	28	180	23	4
Mean	34.4	37.2	41.8	44.9	51.5
Std. Dev.	3.7	3.2	2.7	2.5	1.9
Skewness	1.06	0.31	0.20	-0.41	0.32
Kurtosis	4.56	1.95	2.83	2.12	0.97
P(χ^2 test for normality)	0.0047	0.17	0.08	0.56	0.51

Table 4. Frequency distributions of tangled walleye and descriptive statistics by mesh size (1968-1970 data combined). Raw data from Table 2 in Hamley and Regier (1973).

	Mesh Size (inches)						
Total Length (cm)	1.5	2	2.5	3	3.5	4	4.5
27-29	0	1	0	0	0	0	0
29-31	0	1	2	0	0	0	0
31-33	0	2	3	0	0	0	0
33-35	1	1	10	1	0	0	0
35-37	1	1	8	4	4	0	0
37-39	2	3	20	3	2	0	0
39-41	1	3	8	10	7	0	0
41-43	2	3	15	3	7	0	0
43-45	2	2	9	2	8	2	0
45-47	1	2	13	1	6	2	1
47-49	1	3	3	1	3	0	0
49-53	0	0	0	0	5	0	1
53-57	0	0	2	0	2	0	0
57-61	0	0	0	0	2	0	1
61-65	(1)	0	0	0	4	1	1
65-69	0	0	0	0	1	0	2
Total	11	22	93	25	51		
Mean	41.1	39.8	40.2	40.0	46.4		
Std. Dev.	4.3	6.0	4.97	3.3	7.94		
Skewness	-.06	-.33	(-.10)	0.44	*		
Kurtosis	1.66	1.99	2.11	2.93	*		
P(χ^2 test for normality)	0.95	0.69	*	0.11	*		

*values not calculated because of increase in size class width

Table 5. Objective functions for the different models.

Optimum selectivity model (h_m)	Data Set			
			Walleye	
	Roach	Whitefish	Wedged	Tangled
linear $\theta_1 m + \theta_3$	-240.0	-448.1	-107.0	-135.6
polynomial $\theta_1 m + \theta_2 m^2 + \theta_3$	-242.4	-437.4	-106.0	-132.5
exponential $\theta_1 \exp(m\theta_3)$	-240.2	-444.0	-107.7	-133.5

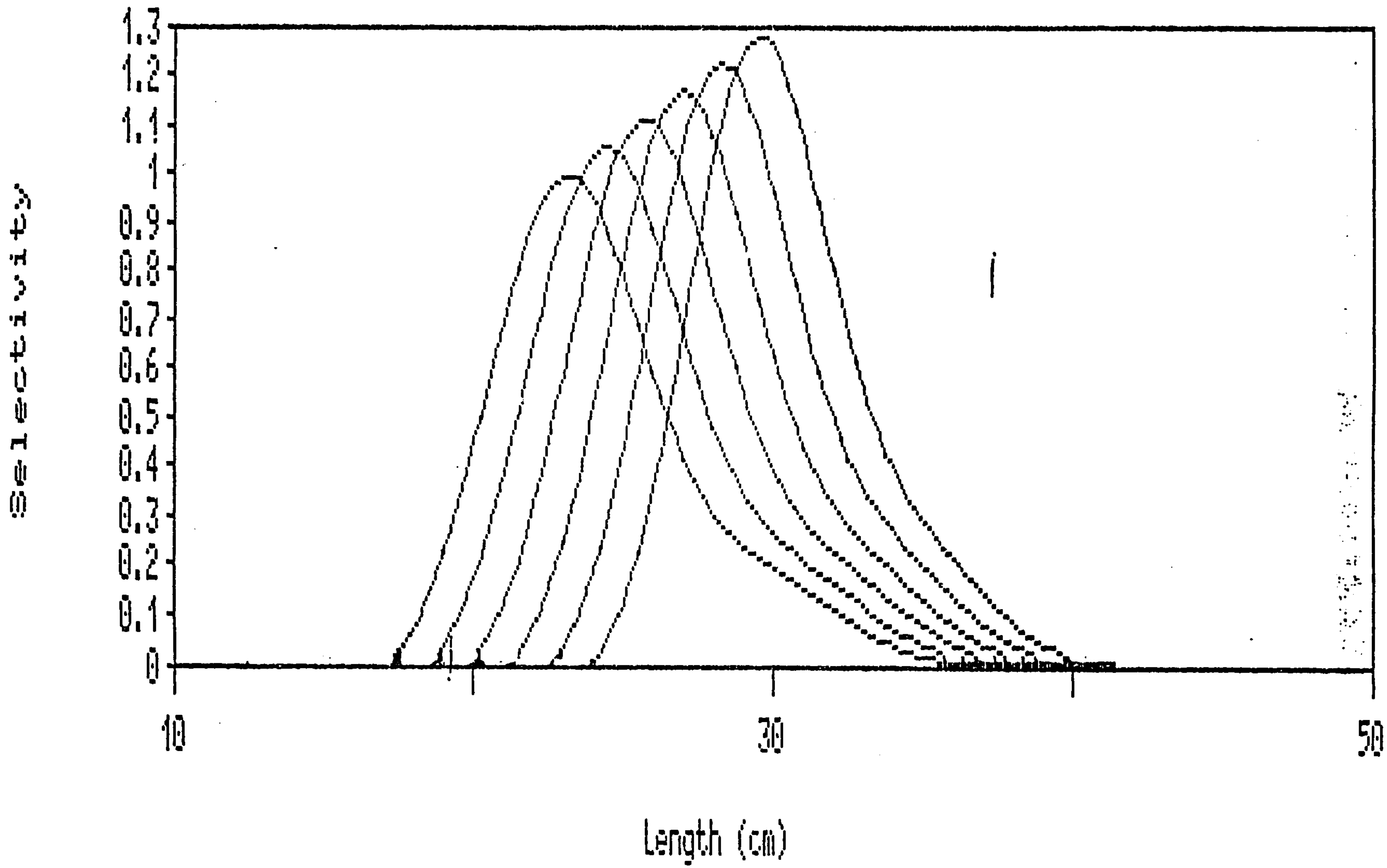

Figure 1. Selectivity curves for roach (mesh sizes 30, 32, 34, 36, 38, and 40 mm). The model parameters are: h_o = 5.79m + 7.36, l_o = 0.61m + 6.1, s_o = -0.04m + 4.4, and Q = 0.19. The curves are scaled so that optimum selectivity for mesh 30mm is equal to one.

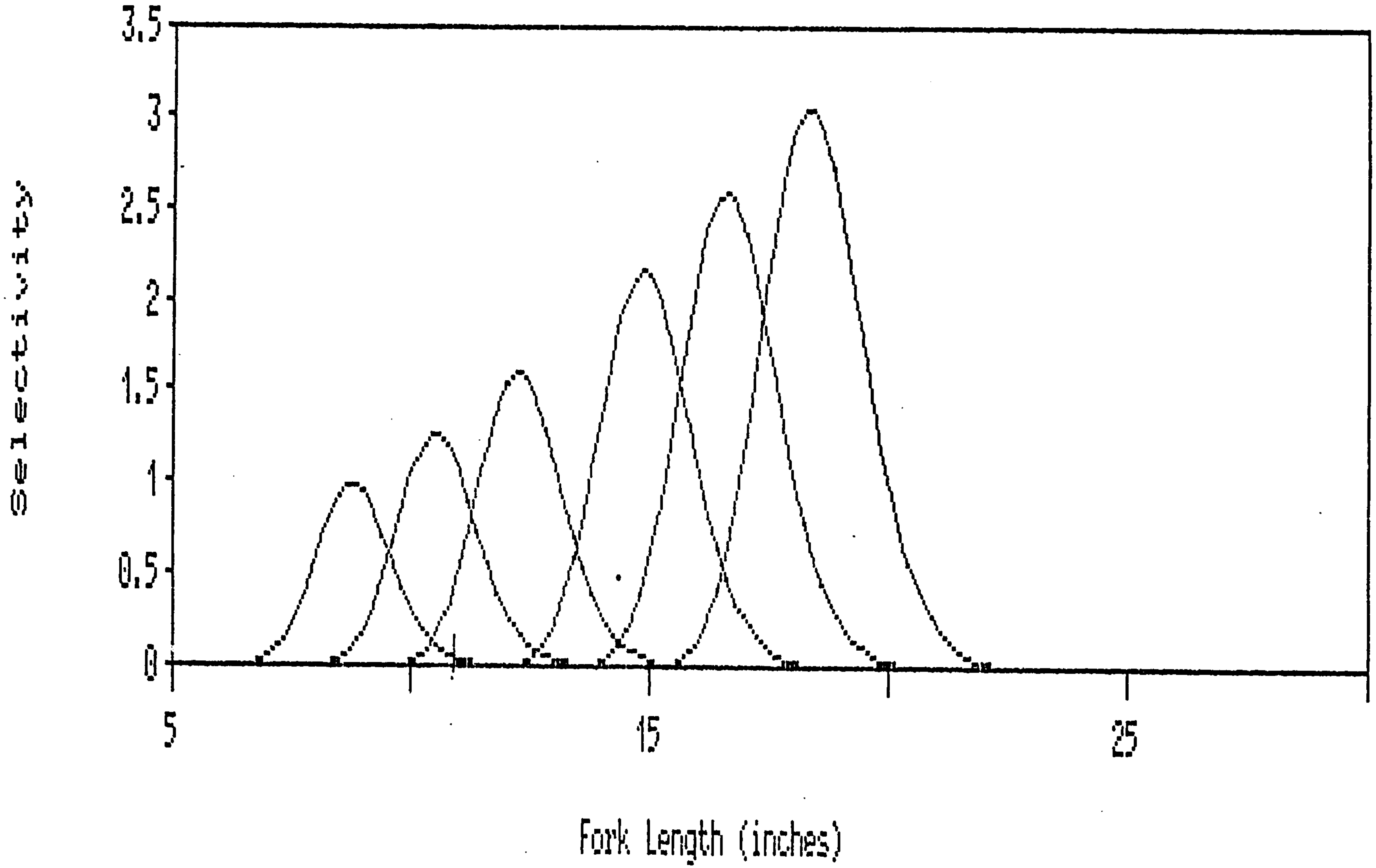

Figure 2. Selectivity curves for whitefish (mesh sizes 1.75, 2.25, 2.75, 3.5, 4.0, and 4.5 inches). The model parameters are: $h_o = 10.4m + 3.8m^2 + 15.9$, $l_o = 3.5m + 2.6$, $s_o = 0.1m + 0.6$; and $Q = 0.27$. The curves are scaled so that optimum selectivity for mesh 1.75 inches equal to 1.

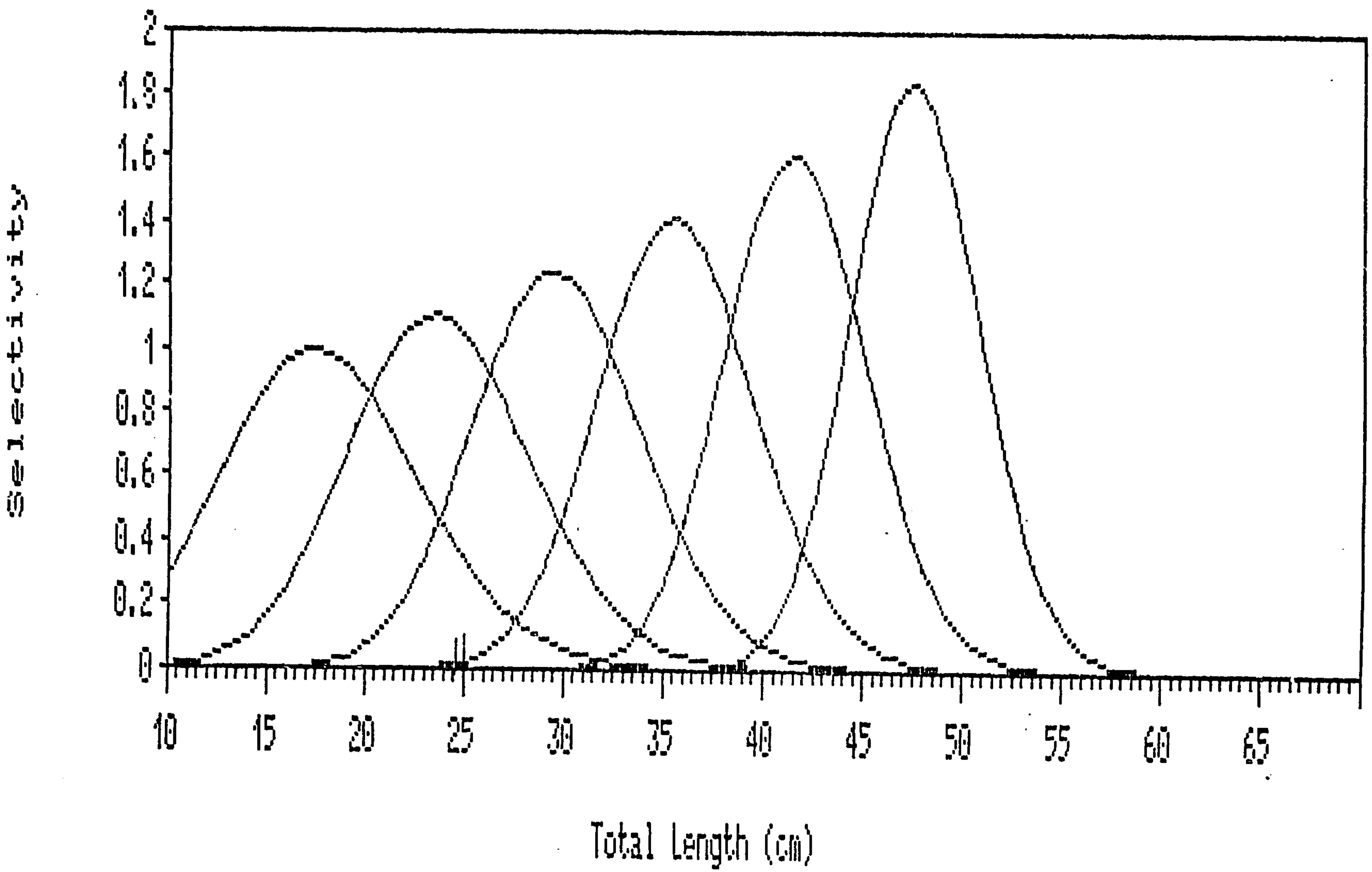

Figure 3. Selectivity curves for wedged walleye (mesh sizes 1.5, 2, 2.5, 3, 3.5, and 4 inches). The model parameters are: $h_o = 0.23m^2 + 3.2$, $l_o = 11.9m$, $s_o = -0.7m + 6.0$, and $Q = 0.02$. The curves are scaled so that optimum selectivity for mesh 1.5 inches is equal to 1.

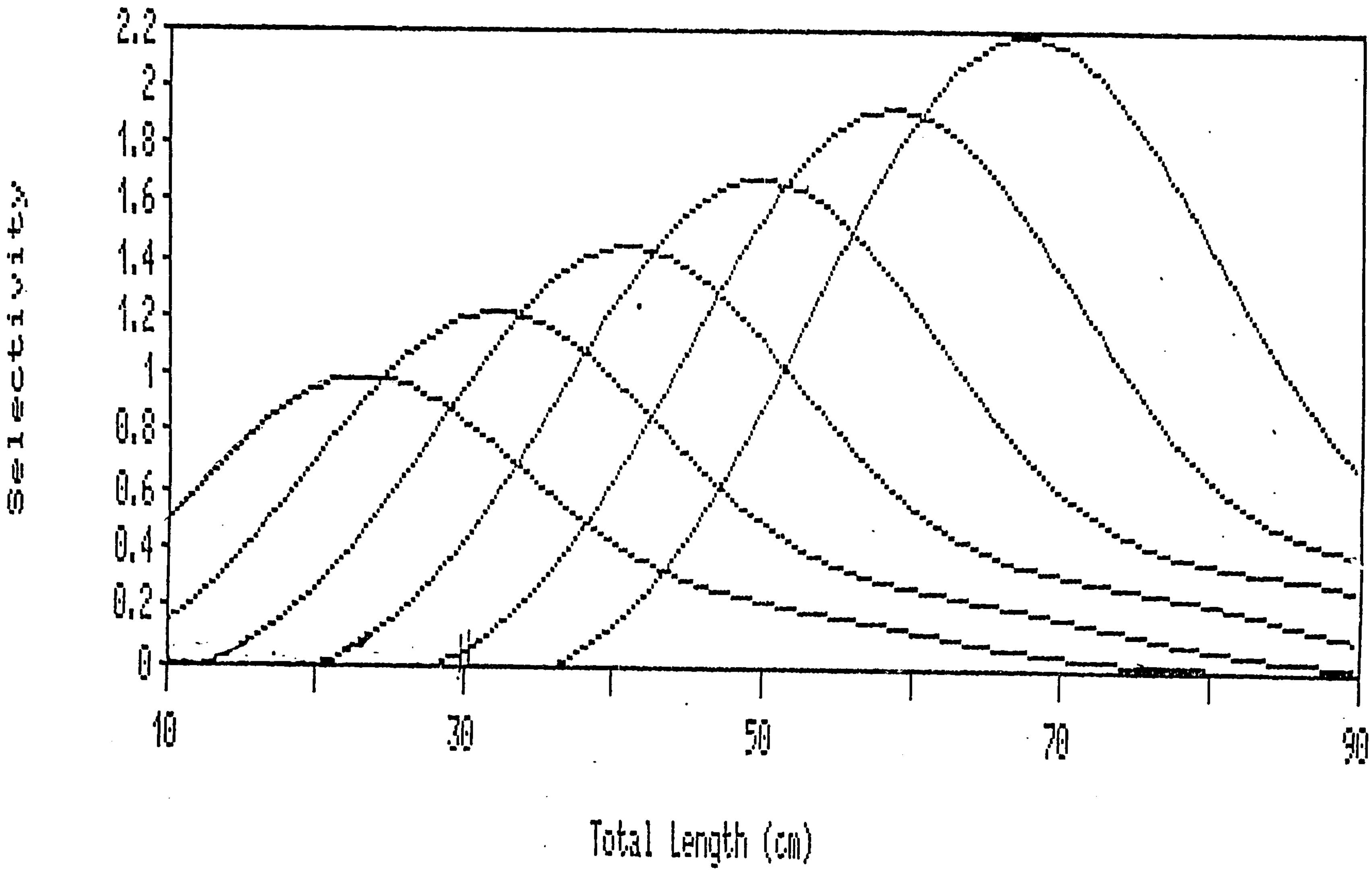

Figure 4. Selectivity curves for tangled walleye (mesh sizes 1.5, 2, 2.5, 3, 3.5, and 4 inches). The model parameters are: h_o = 7.5m + 7.1, l_o = 18.9m, s_o = 1.6m + 11.7, and Q = 0.02. The curves are scaled so that optimum selectivity for mesh 1.5 inches is equal to 1.

APPENDIX

The program SELECT.OAS must be modified for different distributions. In the following example, a skew normal selectivity distribution is used, and it is defined by T1, ... T9, Q, D1, B1, B2, B3, B4, and S(I,J). A normal distribution can be fit by setting Q = 0. The catch distribution data must be typed in at the end of the program. Once this has been done, the program can be saved and run. The user will be asked to define a number of variables:

N1 - the number of parameters to estimate

N2 - the number of size classes in the catch distributions

N3 - the number of mesh sizes

N4 - the mid-point of the smaller size class

N5 - the size class interval size

N6 - the number of outer loops (at least 6 for a 5 parameter model, increases with more parameters)

N7 - the number of inner loops (at least 500)

N8 - the lower bound for modal length (usually the smallest size in the catch distributions)

N9 - the upper bound for modal length (usually the largest size in the catch distribution)

N10 - the lower bound for the standard deviation of modal length

N11 - the upper bound for the standard deviation of modal length.

The user will also be asked to input initial estimates and lower and upper bounds for the parameters T1, ... T0, and Q. The optimization will not work if the range of possible values for a parameter goes from negative to positive (for example, -2 to 2). To get around this problem, two runs should be made with the parameter defined from -2 to 0 and 0 to 2. For example, in the following case, the model describes decreasing standard deviation of modal length with increasing mesh size so the parameter T7 is given a range of -4 to 0 by inputting lower and upper bounds of 0 and 4 and defining T7 = X(5) * -1.

```
1000 CLS : PRINT : PRINT : PRINT
1010 PRINT "                          program  SELECT.BAS
1020 PRINT "
1030 PRINT "       Karim Erzini, GSO, Narragansett, RI  02882
1040 PRINT "
1050 PRINT " This is a multistage Monte Carlo optimization program for fitting
1060 PRINT " gillnet selectivity curves to predetermined distributions. The
1070 PRINT " user must type in the catch distributions for each mesh size at
1080 PRINT " the end of the program before running it.
1090 PRINT "
1100 REM ---------------- Definition of variables -----------------------------
1110 PRINT "                       Definition of variables:
1120 PRINT
1130 INPUT " N1, the number of parameters to estimate       ";N1
1140 INPUT " N2, the number of size classes                 ";N2
1150 INPUT " N3, the number of meshes                       ";N3
1160 INPUT " N4, the midpoint of the smallest size class    ";N4
1170 INPUT " N5, the size class interval size               ";N5
1180 INPUT " N6, the number of outer loops (at least 6)     ";N6
1190 INPUT " N7, the number of inner loops (at least 500)   ";N7
1200 INPUT " N8, lower bound of modal length                ";N8
1210 INPUT " N9, upper bound of modal length                ";N9
1220 INPUT " N10, lower bound for standard deviation        ";N10
1230 INPUT " N11, upper bound for standard deviation        ";N11
1240 PRINT
1250 INPUT " Do you want to make corrections (Y/N) ";D1$
1260 IF D1$="Y" OR D1$="y" THEN 1110
1270 DEFSNG A-Z
1280 DIM LL(N2),M(N3),C(N2,N3),S(N2,N3),Q(N2),R(N2,N3),Z(N2),LO(N3),UP(N3)
1290 DIM CC(N2),F(N2,N3),SS(N2),A(N1),B(N1),L(N1),N(N1),U(N1),X(N1),P(N1)
1300 PRINT : RANDOMIZE : PRINT : X = 1 : F=2 : M=-99999!
1310 REM ------ Input initial estimates, and bounds of parameters ---------
1320 PRINT "     Input initial estimates, and bounds of parameters:"
1330 PRINT "           - last one is Q                              ": PRINT
1340 FOR I=1 TO N1
1350  PRINT "parameter ";:PRINT I
1360  INPUT "initial estimate   ";A(I)
1370  INPUT "lower bound        ";B(I)
1380  INPUT "upper bound        ";N(I)
1390  PRINT : PRINT
1400 NEXT I
1410 PRINT : PRINT
1420 PRINT " index        estimate     lower bound     upper bound
1430 PRINT
1440 FOR I=1 TO N1
1450  PRINT I, A(I), B(I), N(I)
1460 NEXT I
1470 PRINT : INPUT "Do you want to make changes (Y/N) ";D2$
1480 IF D2$="N" OR D2$="n" THEN 1540
1490 INPUT "index of row to change "; I1
1500 INPUT " initial estimate      "; A(I1)
1510 INPUT " lower bound           "; B(I1)
1520 INPUT " upper bound           "; N(I1)
1530 GOTO 1410
```

```
1540 REM --------------- Definition of midpoints of size classes -----------
1550 LL(1) = N4
1560 FOR I = 2 TO N2
1570     LL(I) = LL(I-1) + N5
1580 NEXT I
1590 REM --------------- Inputting of mesh sizes ---------------------------
1600 PRINT " Inputting of mesh sizes:" : PRINT
1610 FOR I = 1 TO N3
1620   PRINT "mesh";:PRINT I;: INPUT " ";M(I)
1630 NEXT I
1640 PRINT : PRINT " Mesh sizes are : "
1650 FOR I=1 TO N3
1660  PRINT I, M(I)
1670 NEXT I
1680 PRINT
1690 INPUT " Do you want to make changes ";D3$
1700 IF D3$="N" OR D3$="n" THEN 1740
1710 PRINT : INPUT " index of mesh to change "; I2
1720 PRINT I2;: INPUT " mesh "; M(I2)
1730 GOTO 1640
1740 REM --------------- Sum of catches by size classes ---------------------
1750 FOR I = 1 TO N2
1760     Z(I) = 0
1770     FOR J = 1 TO N3
1780         READ C(I, J)
1790         Z(I) = Z(I) + C(I, J)
1800     NEXT J
1810 NEXT I
1820 REM --------------- Calculate log of catch factorial -------------------
1830 FOR I=1 TO N2
1840  CC(I) = 0
1850  FOR J=1 TO N3
1860   IF C(I,J)=0 THEN 1870 ELSE 1890
1870   F(I,J)=0
1880   GOTO 1930
1890   IF C(I,J)=1 THEN 1870 ELSE 1900
1900   FOR K=1 TO C(I,J)
1910    F(I,J)=F(I,J) + LOG(K)
1920   NEXT K
1930   CC(I) = CC(I) + F(I,J)
1940   NEXT J
1950 NEXT I
1960 REM  ------------------MONTE CARLO OPTIMIZATION------------------------
1970 REM
1980 FOR JJ=1 TO N6
1990 ZZZ=0
2000  FOR II=1 TO 9999999!
2010 PRINT JJ,II,ZZZ,S9,M
2020   FOR KK=1 TO N1
2030    IF A(KK)-N(KK)/F^JJ < B(KK) THEN 2050
2040    GOTO 2070
2050    L(KK) = B(KK)
2060    GOTO 2080
2070    L(KK) = A(KK) - N(KK) / F^JJ
2080    IF A(KK) + N(KK) / F^JJ > N(KK) THEN 2100
```

```
2090     GOTO 2120
2100     U(KK) = N(KK) - L(KK)
2110     GOTO 2130
2120     U(KK) = A(KK) + N(KK) / F^JJ - L(KK)
2130     X(KK) = L(KK) + RND(X) * U(KK)
2140  NEXT KK
2150 REM ------------ Parameters defining optimal selectivity ----------------
2160 REM ---------------- opt. sel. = t1*m + t2*m^2 + t3 -------------------
2170   T1=X(1)
2180   T2=X(2)
2190   T3=X(3)
2200 REM ------------ Parameters defining modal length -----------------------
2210 REM -------------------- modal length = t4*m + t6 -----------------------
2220   T4=X(4)
2230   T6=X(5)
2240      FOR III=1 TO N3                ' constraints on modal length
2250       LO(III)=(M(III)*T4) + T6
2260       IF LO(III)<N8 THEN 2720
2270       IF LO(III)>N9 THEN 2720
2280     NEXT III
2290 REM ---------- Parameters defining standard deviation ------------------
2300 REM ----------------- std. dev. = t7*m + t9 ----------------------------
2310     T7=X(6)*-1
2320     T9=X(7)
2330        FOR KKK=1 TO N3              ' constraints on std. devs.
2340          TS=(T7*M(KKK)) + T9
2350          IF TS<=N10 THEN 2720
2360          IF TS>N11 THEN 2720
2370        NEXT KKK
2380      Q=X(8)                         ' coeff. of skewness
2390 ZZZ=ZZZ+1
2400 IF ZZZ<N7 THEN 2430
2410 GOTO 2730
2420     REM -------- Calculation of selectivities and objective functions ---
2430      FOR I = 1 TO N2
2440        SS(I) = 0
2450       FOR J = 1 TO N3
2460         M1=M(J)
2470         D1  = (T1*M1)+(T2*M1)+T3           ' optimal selectivity
2480         B1  = LL(I) - (T4 * M1)  - T6      ' optimal length
2490         B2  = (T7*M1) + T9                 ' std. dev. of opt. length
2500         B3  = (31 / B2) ^ 2
2510         B4  = EXP(-.5 * B3)
2520         REM ---------- Selectivities ------------------------------------
2530         S(I,J) = ABS((D1*B4 * (1 - ((.5*Q*(B2^1.5))) * ((B1/B2) -((B1^3)/((
(B2^3))))))) : IF S(I,J)<1E-35 THEN S(I,J)=0
2540         SS(I) = SS(I) + S(I,J)
2550        NEXT J
2560      NEXT I
2570      S9 = 0
2580      FOR I = 1 TO N2
2590       IF SS(I)=0 THEN 2670
2600       FOR J = 1 TO N3
2610        A1=Z(I)/SS(I) : A2=A1*S(I,J)
2620        IF A2=0 THEN 2660
```

```
2630        A3=LOG(A2)
2640        A4=C(I,J)*A3
2650        S9 = S9 + (A4 - A2 - F(I,J))      ' objective function
2660       NEXT J
2670      NEXT I
2680      IF S9=0 THEN 2720
2690      IF S9>=M THEN 2710   ' testing for improvement in obj. func.'
2700      GOTO 2720
2710      M = S9: FOR I=1 TO N1: A(I) = X(I) : NEXT I
2720  NEXT II
2730 LPRINT "loop ";:LPRINT JJ : PRINT "loop ";:PRINT JJ
2740 LPRINT " parameter    estimate ": PRINT " parameter   estimate "
2750 FOR I=1 TO N1
2760  PRINT I, A(I) : LPRINT I, A(I)
2770 NEXT I
2780 PRINT
2790 PRINT "Objective function = ";: PRINT M
2800 LPRINT "Objective function = ";: LPRINT M
2810 LPRINT : LPRINT : PRINT : PRINT
2820 NEXT JJ
2830 PRINT "OPTIMAL COMBINATION:" : PRINT
2840 LPRINT "OPTIMAL COMBINATION:" : LPRINT
2850 LPRINT " parameter    estimate ": PRINT " parameter   estimate "
2860 FOR I=1 TO N1
2870  PRINT I, A(I) : LPRINT I, A(I)
2880 NEXT I
2890 PRINT
2900 PRINT "Objective function = ";: PRINT M
2910 LPRINT "Objective function = ";: LPRINT M
2920 LPRINT : LPRINT : PRINT : PRINT
2930 PRINT "-----------------------------------------------------------------"
2940 REM ------------ Catch distributions by mesh size ----------------------
2950 DATA 2,0,0,0
2960 DATA 1,0,0,0
2970 DATA 11,1,0,0
2980 DATA 10,9,0,0
2990 DATA 5,3,5,0
3000 DATA 4,7,23,0
3010 DATA 1,4,37,2
3020 DATA 0,3,61,3
3030 DATA 1,1,33,6
3040 DATA 1,0,12,7
3050 DATA 0,0,9,5
```

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Bioeconomic Models

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INTRODUCTION

When asked to write a paper on the topic of bioeconomic models for fisheries, I was pleased by the honor but chagrined by the difficulty of finding something new to say. No claim of novelty is made for the paper which follows; it is a literary discussion of bioeconomic models. For a more technical discussion, see Meuriot (1987) or Clark (1976, 1985).

The Random House dictionary lists some twenty definitions of "model". For our purposes, a model may be considered as "a system of postulates, data and inferences presented as a mathematical description of an entity or state of affairs". Bioeconomic models are ones for which most of the postulates and data are biological or economic in nature. Models are typically a technique or method used to derive a conclusion or "truth" whose validity is perceived as more or less independent of the truth of the finer details used in their derivation. We shall return to this point in discussing the meanings of model validation. In common usage, models are usually stated in the language of mathematics. The text accompanying a model will typically contain verbal or graphic relationships based on some underlying scientific theories, and the model will incorporate such relationships via algebraic statements. Except for trivially simple models, the implications of these relationships are not intuitively obvious and the model is a device for exercising and/or integrating selected theories or relationships.

The use of models has proliferated in the last three decades. The proliferation has encompassed virtually all disciplines, including fisheries sciences. While such models have clearly advanced in power and specificity, the pioneering works were Warming (1911), Baranov (1918), Pearl (1925), Gordon (1954), Schaefer (1954) and Beverton and Holt (1957). However, it is humbling to reflect on the disparity between progress in modeling ability and public policy progress in implementing the knowledge gained from such models.

The discussion will proceed as follows. The chosen point of departure is a brief, simplistic statement of the "fisheries economics problem". This statement is presented for readers who may be unfamiliar with economic analysis of resource conservation issues. For the sake of brevity, the reader is asked to accept a great deal on faith in this statement. The references at the end of this paper include several more detailed statements. This statement of the fisheries economics problem will be followed by a nomenclature of the commonly used models and by a discussion of certain attributes which a given model may possess. Specifically discussed are the degree of generality or partiality of models, dynamics versus statics, deterministic versus stochastic, and optimization versus simulation. The topic of model validation, which is always one of controversy, is discussed briefly in a final section.

Bioeconomic models have been developed in order to understand how public policies will affect fishermen and consumers of fish products. The variables of interest include the availability of fish for harvest, costs, prices and indices of economic welfare. Before proceeding to a classification of models, it may be of interest to sketch briefly, the kind of story which such models tell. To do this concisely, one must abstract from a great many complicating details, some of which will be discussed later. As indicated in their definition, models are typically a technique or method used to derive a conclusion or "truth" whose validity is more or less independent of the finer details used in their derivation. This use of models is similar to the story tellers use of parable and allegory.

The "fisheries economics problem" stems from the finite regenerative capacity of fish stocks and from the fugitive nature of the resource. A fugitive resource is one which belongs to none until it is reduced to possession; i.e. captured. With "normal" goods and services, a market system evolves an elaborate system of property rights, contracts etc. Such rights encourage an efficient use of resources which includes conservation. In particular, a farmer reserves enough seed stock to plant next year's stock. A farmer can do this rationally only because property rights (usually) protect the reserve stocks from consumption by neighbors or theft. In an open access fishery, each fisherman could deliberately choose to catch less than he is capable of catching in order to increase next years' harvest. He could, but he would be quite mad to do so unless there is a collective agreement that all will abstain in like manner. In a sense then, the economics of fisheries management is concerned with the gains which are possible if a collective agreement can be reached and enforced at reasonably low cost. What a bioeconomic model does is describe and perhaps quantify, the collective loss which ensues if agreement cannot be reached; i.e. if open access continues.

For economy of expression, it is common to measure this loss by the "economic rent" which is dissipated. One reason for choosing this measure is that it is of direct economic significance to fishermen. It is the misfortune of economics that such words as "profit" and "rent" sound the same as words which we all understand from everyday conversation. As used in economics these terms mean something quite different from the lay usage. This difference in the meaning of words can lead to misunderstandings. A better term for economic rent would probably be producers' surplus and there is less likelihood of its being confused with a non technical term. Producers' surplus measures the earnings of crews, captains and owners in excess of what could be earned elsewhere (opportunity cost). This measure is quite different from pecuniary earnings of crews, captains and owners. For example, consider an hypothetical crew member who earns "X" Francs per year as a crewman. Suppose the prevailing non-fishing wage incomes in his or her home port are 0.75X Francs per year. Then the crewman's producer surplus is the difference or 0.25X Francs per year. Under the lay systems commonly used in fisheries, there is a possibility for analogous surpluses accruing to capital (returns to the investor(s) in excess of normal rates of return and to management (captains shares and bonuses in excess of what the captain could earn elsewhere). Under open access, the tendency will be for more fishermen to enter the fishery which diminishes the catch per unit effort (CPUE), causes average cost per kilo of fish to rise and causes producers' surplus to decline toward zero. Thus, under open access, the earnings of our hypothetical crewman, will tend toward 0.75X instead of X Francs per year.

Note that this description of events has no normative content. It does not say that fishermen ought to avoid zero producers' surplus. That is for fishermen to decide. There is another side to the coin, however. The dissipation of producers' surpluses is achieved by fishermen bidding scarce resources away from other sectors of the economy. This process deprives consumers of benefits. From the point of view of a central government, the dissipation of producers' surpluses in fisheries is unfortunate because it indirectly costs consumers. For every crewman like our hypothetical one, consumers are indirectly losing 0.25X in extra goods and services which would have been produced if fishery access had been restricted. From this perspective, the dissipation of producers' surpluses does have normative implications. One would like to encourage public policies which do not deprive consumers directly or indirectly. However, if one justifies intervention in terms of economic benefits, it also follows that the benefits saved should exceed the costs of management and enforcement required for their generation.

A common objection to the economic approach to fisheries is that economic models seem to say that substantial numbers of people "should" be forced to leave their way of life. This interpretation of what economic models say is too literal. In practice one should focus not on the current status of a fishery but on its probable status in two or three decades if the status quo is not stabilized. This changes the terms of discussion from policies which may be socially disruptive to policies which reduce future disruption. In particular, if it is difficult for people to leave a low income region and an industry, one must be careful about the rate at which adjustments are made. If our hypothetical crewman were forced to leave the fishery and cannot find employment elsewhere, this would be an implicit admission that his opportunity cost was really zero. This possibility can be over emphasized; it is not plausible that everyone always has zero opportunity cost. Moreover, if one looks toward the future rather than the present, is it wise to encourage expansion based on an overexploited resource? Would it be better to stabilize at the current fleet size and facilitate emigration by those best able to emigrate to other regions? Would it be better to stimulate other sectors in the region? These are difficult questions and it is unreasonable to expect fisheries managers to address them in a policy vacuum. However, it is reasonable to suggest that fishery managers should raise such issues at appropriate levels.

For established families in areas remote from commercial centers, the potential earnings of fishermen outside fishing may be very low. Low incomes in a region does not necessarily indicate dissipation of producers' surplus. The dissipation process tends to occur in both high income and low income regions and is conceptually different from the problem of low incomes. The existence of low incomes in a region implies lower cost fishing. If crewmen in high and low income regions were to receive the same payments from fisheries, the producers' surplus of a crewman in the low income region would exceed that of a crewman in the high income region by the interregional wage differential. This distinction between incomes and producers' surpluses is perhaps not fully explained in some economic discussions.

Another objection sometimes raised to the economic approach to fisheries management is the use of discounting procedures. A reviewer of a draft of this paper suggested that this may be an issue for readers. It is possible to build a mathematical model and parameterize it in such a way that "optimal" economic use leads to extinction. For those who distrust an economic approach, the mere existence of models which advocate extinction is "proof" that discounting is ethically indefensible. Note however, that mathematics is the language of all possible worlds and to say that one has imagined a world in which a problem can arise does not mean the problem is a real one. It may be that an alternative to rejecting discounting is to recognize other social values such as existence value. For example, if discounting were to suggest that extinction of whales is economically optimal, I would be very suspicious of the model assumptions and range of validity. In particular, people place a value on the continued existence of whales and this value can be measured. It is a value which whale harvesters cannot readily capture and which it is therefore rational for them to ignore. The economists resolution of this problem is not to discard discounting per se, but to introduce the existence value of stocks explicitly. Ultimately, of course, if the high cost of steel or capital or labor makes conservation "economically" inefficient, society can overrule economic efficiency and opt for a higher savings (conservation) rate. It does not need to reject the general usefulness of any particular input price such as that of capital. The discount rate is the price we must pay to induce current consumers to defer current consumption in order to enjoy greater consumption in the future. If the level of conservation seems inadequate for some reason, one could "blame" depletion on too high prices for steel or labor; there is no obvious reason why the discount rate should bear the brunt of such attacks. In many cases, a high discount rate is the conservationist's best friend. For example, the destructive ecological consequences of large scale water development projects were made to seem justifiable by using artificially low discount rates. Proper use of discounting is likely to ensure that real wealth will be increased in the future; not decreased.

If the reader has found the preceding paragraphs rather terse, he has cause since considerable economic theory is compressed into them. Anyone familiar with economists will not be surprised to learn that we sometimes argue about such matters. It is regrettable that economics is not a simpler subject and I a more lucid expositor.

We can be quite rigorous in developing the theory. On occasion, empirical measurement can be similarly rigorous. More often however, resources for economic research are very limited and one must settle for various indices which are related to the fisheries economics problem and for which data are more readily available. These include declining CPUE, increasing fleet size and/or vessel sizes with stable catches, trends in accounting profits, loan default rates, etc. None of these indices is conclusive but they can serve as useful flags that problems may be developing. In this common situation of imperfect information, the more rigorous concepts, although not always used, remind us of the imperfections of the indices we are forced to use.

The bioeconomic models which have been used in fisheries can be categorized in various ways. Fisheries biologists and applied mathematicians who pioneered in this area, commonly distinguish between age-class structured (or dynamic pool) models of the resource and stock production (or lumped parameter) models of the resource. Each has certain characteristics which may be good or bad depending on the questions for which one seeks answers. Within these two categories, one may find numerous sub-categories, but these two are adequate for our purposes.

Perhaps the most widely known of the dynamic pool models are those associated with the work of Beverton and Holt (1957). The age class structured representations involve separate, explicit specification of recruitment processes and tracking through time of each age-class of fish. This approach blends well with the way in which biologists tend to think of fishery resources.

The stock production models (Schaeffer, 1957; Pella and Tomlinson, 1969) typically abstract from the age-class structure of the fish population. An advantage of this abstraction is a great gain in simplicity. The stock production representation regards age class as negligibly important and also subsumes recruitment relationships in the single stock production relationship. By so doing considerable economy of symbols and ease of mathematical manipulation is achieved. Conversely, this representation ignores most of the species data and information collected by fisheries biologists. Such data as growth rate, fecundity, age at maturity are irrelevant in this approach. In practice, such information is not ignored, but it is introduced in an ex post manner rather than being an integral part of the model.

In a stock production model, a given biomass will be projected to follow the same trajectory over time whether it consists of new recruits or the remains of a ten year old age cohort. The growth and decay of a stock , as projected by such a model, depends only on its magnitude, the intensity of fishing pressure and random events. This disadvantage is unimportant for many fisheries where management is sought. It is unimportant because, in such fisheries, fishing mortality decimates entering year classes so quickly. For example, in the lobster fisheries of New England, U.S.A, approximately 90 percent of lobsters are caught within six months of attaining legal size. Under such intense predation, there can be no significant variation in age class structure. However, if fishing mortality were altered dramatically, one may find higher variance in the estimated parameters of stock production models and perhaps unreliable dynamic forecasts.

It is common, using the richer framework of dynamic pool models, to distinguish between "recruitment" and "growth" overfishing. If recruitment is dependent on stock size and if fishing mortality is too high, the numbers of fish of reproductive age may become too small to sustain recruitment and the entire population may collapse. This would be recruitment overfishing. Growth overfishing is conceptually quite different and related more to yield per recruit. Consider a typical fish from an entering age cohort. It is small and if unharvested, would grow to become a big fish. As fishing mortality increases, the probability of its surviving to become a big fish decreases. Stated another way, as fishing mortality increases, the age class structure is compressed toward the minimum legal or marketable size. If too high, this age class compression can reduce physical yield and/or average price. Such reductions are the basis of yield overfishing. Recruitment overfishing carries with it the potential for stock collapse. Such collapses are of biological as well as economic concern. Growth overfishing, on the other hand, is fundamentally an economic issue to which we will return later. At this point we should note that in stock production models, it is not possible to tell whether variations in catch per unit effort (CPUE) are reflections of recruitment overfishing or growth overfishing.

From an economic perspective, these characterizations of the resource are important also. The most commonly presented economic models of the fishery are built around simple stock production models (Clark, 1985). The choice of foundation may involve either (1) simplicity and a desire to obtain analytical solutions rather than numerical simulations, or (2) the availability of parameter estimates required by dynamic pool models.

The stock production and dynamic pool representations contain some similarities and differences in their economic implications. The similarities concern the consequences of restrictions on fleet size. For a given (i.e., a fixed) fleet size, it is possible to project future catch, costs and revenues for a "planning horizon" extending T years into the future. Practically speaking, a planning horizon of 20 to 30 years will prove adequate for most purposes. The net cash flow of each year must be discounted to the present and summed. The resultant sum is termed the "present value" of the projected stream of future receipts. The preceding statement abstracts from the complication of initial conditions. To be rigorous about such matters, one would have different results depending on the fleet and stock sizes from which one begins. In practice this is not much of a problem because one always begins from the status quo.

If we lived in a deterministic world, our calculations would be mostly done at this point. However, as discussed later, we live in a world of random events. This randomness can be reflected by making the model stochastic. To make the model stochastic requires that the calculations described above be repeated a "large" number of times. Usually, 30 repetitions will be adequate. On each repetition, each source of randomness (e.g. recruitment, prices, etc.) is assigned an appropriate (random) value. The resultant present values of net cash flows (wealth) must be averaged to obtain the expected or average wealth for that fleet size. The reader is cautioned that there are some subtleties of national income accounting buried in the above terms of net cash flows and wealth. In particular, the costs used should reflect opportunity costs of inputs. Actual cash payments to captain and crew may exceed opportunity cost and will therefore include a portion of the producers' surplus or economic rent which we wish to measure as a residual. In the case of a proposed change which would reduce fleet size, the relevant opportunity cost of labor may be quite low since it depends on their employment prospects outside fisheries. These distinctions were discussed very briefly in the introduction to this paper.

The fleet size can then be set at a different (hypothetical) level and the preceding calculations repeated. These calculations are too tedious to do by hand but with computers the computational task is feasible. Alternatively, if the underlying mathematics can be simplified enough, it may be possible to derive analytic expressions for expected wealth which can be evaluated rather easily. In general, this degree of simplification is not possible on an a priori basis, although experience may show that similar results emerge from a simplified model.

The results of the calculations just described will be a set of values for expected or average wealth at each fleet size of interest. Under most plausible situations, intermediate values can be estimated via interpolation. If the results are plotted in a graph, they will appear similar to the curve shown in Figure 1. In Figure 1, the vertical axis measures expected wealth and the horizontal axis measures fleet size. The units of measurement are arbitrary and will depend on the country and fishery.

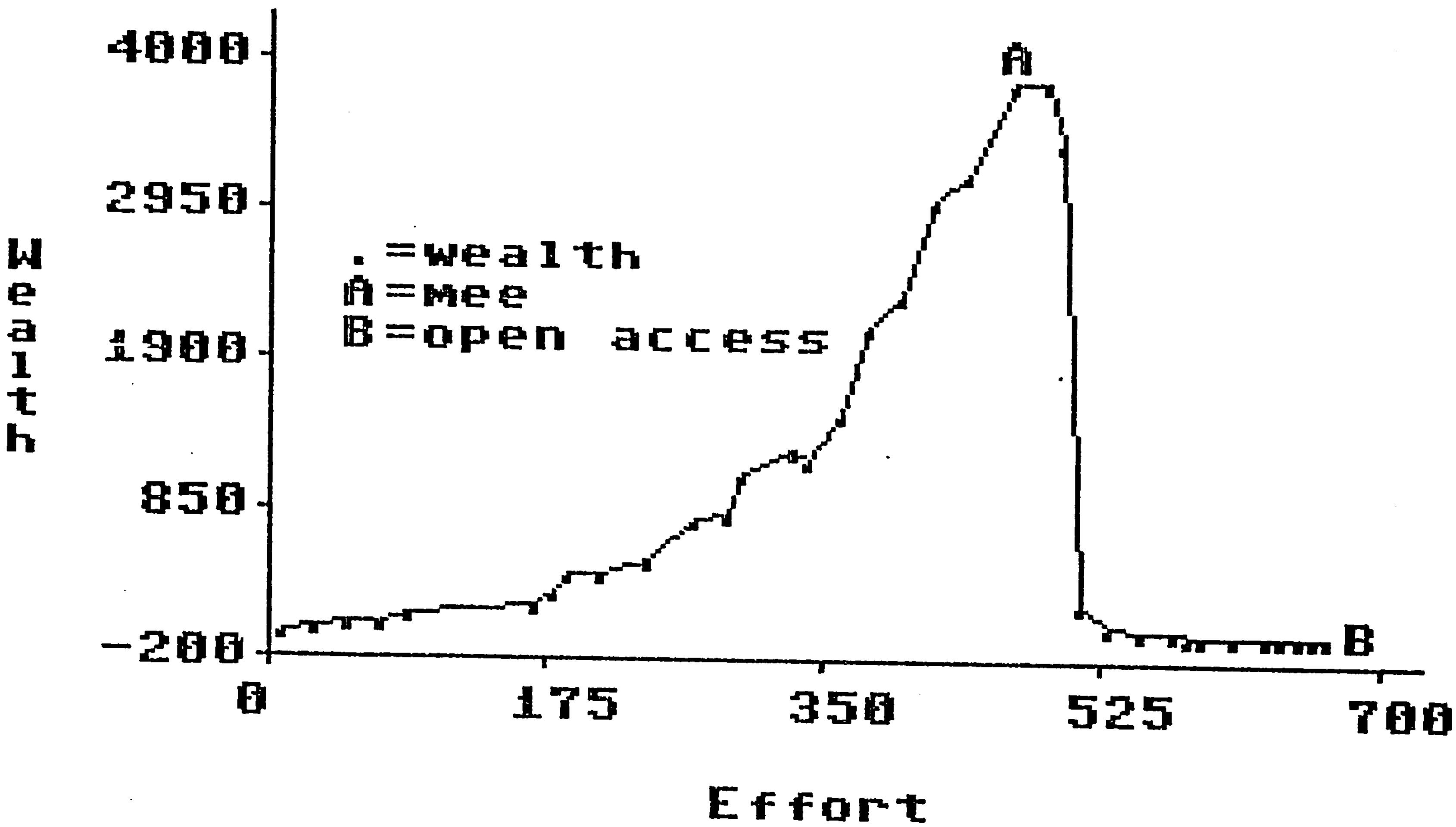
What can we infer from a curve such as that in Figure 1? In a very general way what Figure 1 shows is that, as fleet size is increased (starting from no fleet), expected wealth increases rapidly, then reaches a maximum at point A. Point A is often referred to as the point of "Maximum Economic Efficiency" or MEE. The associated fleet size, E, is the economically optimum fleet size and the associated wealth is W. If fleet size is increased beyond E, then expected wealth will decline and eventually reach zero at a point denoted by B in Figure 1. Point B represents the open access or free entry equilibrium. The differences in wealth between Point B and any other point of interest on the curve in this Figure measure the potential gains from a collective agreement which avoids the open access equilibrium or "tragedy of the commons", to use Hardin's eloquent phrase.

Lurking behind the curve in Figure 1 is an associated relationship between fleet size and expected annual catch. If we were to rescale the vertical axis (expected catch) so that it can be superimposed on Figure 1, we would find another curve much like that already shown in Figure 1. The new curve of expected sustainable yield would increase, reach a maximum, termed "Maximum Sustainable (Expected) Yield" (MSY) and then decline with further increases in fleet size. However, two differences would be observed between the two curves. First, the MEE fleet size would be considerably less than the MSY fleet size. Secondly, the expected yield curve would usually, but not always, be highly asymmetric about MSY. Frequently, the right tail will be very elongated, indicating that excessive fleet sizes cause only modest reductions in expected catch. Figure 1 actually has some peculiar features which will receive discussion later since some concepts and terminology must first be established.

Up to this point, both stock production and dynamic pool models would tell the same general story. Naturally, they would differ on detail and one or the other may be more reliable for a given fishery. It is at this point that a divergence occurs. Because stock production models are statistical in nature, they make no essential use of detailed scientific information and have little more to say. The dynamic pool models are able to analyze other aspects of regulation which are associated with the age at first exploitation. Within limits, increases in the age at first exploitation can have three interesting effects.

The first of these effects may be an increase in recruitment potential or a decrease in anxiety over potential recruitment collapse. The second effect

Fig. 1:Wealth vs Effort



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is a shift upwards and to the right in the relationship between expected physical yield and fleet size. This effect increases potential net economic productivity via a physical yield effect. The third effect is exerted through the size/age class structure of prices. Typically, larger fish are worth more per unit weight than are small fish of the same species. This price differential may reflect consumer preferences or higher product recovery percentages or both (Gates, 1975; Meuriot and Gilly, 1986). In some cases, a size-price discount may exist. This is the case with some clams in New England. To avoid tedium, let us assume the "usual" case of a price premium for larger fish. The combined effects of expected yield and price enhancements shift the curve shown in Figure 1 upward and to the right. The implications of this shift are:

1. For any given fleet size, profits can be increased by judicious choice of age at first exploitation.
2. Achievement of maximum wealth from a fishery requires joint selection of both optimum fleet size and age at first exploitation.
3. Failure to limit fleet size will result in a zero wealth equilibrium, such as point A, whether or not age at first exploitation is optimized.
4. The product enhancement effect of age at first exploitation can confer a significant economic benefit on consumers. For an illustration of this point, see Richardson and Gates, (1985).

Limited empirical analyses of growth overfishing suggest that of the total economic benefits to fishermen realizable from effort and age at first exploitation regulations, approximately 90-95 percent are realizable by regulating fleet size alone and little or none are realizable unless fleet size is regulated. Thus limited entry is almost an economic sine qua non of fisheries management. Two exceptions to this must be noted. The first is where recruitment collapse can be shown to be induced by overfishing. This is a plausible danger for cetaceans but the only scientific demonstrations for this danger in marine fishes (that I am aware of) are for anadromous species. The second is the product enhancement effect mentioned above. The future benefits of age at exploitation regulations will be accompanied by short run losses to fishermen. Depending on the interest rate, they may never recover these short run losses. However, if consumers benefit by more than the loss suffered by fishermen, there is still a net economic gain to society.

Economic relationships which may be included or abstracted from in bioeconomic models include:

- The effect of variations in landings on prices.
- The effect of fish size distribution on prices.
- The dynamics of investments in vessels and human capital.
- Heterogeneity of fleets and distributional effects of management.
- The effects of macroeconomic policies on natural source industries.

While it would be interesting to discuss each of these economic topics, to do so would move us more into economics per se than I take to be the limits of my assignment; just as analogous forays could be made into the realm of fisheries biology. However, there are other ways of examining models which cut across disciplinary lines, viz.:

- Partial vs. General Equilibrium
- Dynamics vs. Statics
- Stochastic vs. Deterministic
- Stable, Multiple and Chaotic Equilibria
- Single vs. Multilevel decision making
- Optimization versus simulation

The following section will contain a short discussion of each of these topics and their implications for bioeconomic models.

Models differ greatly in how they are assembled, what they show and how they show it. To evaluate some of these differences it is helpful to understand certain characteristics or attributes of models. For discussion purposes each is presented as a series of polar alternatives. This should not be taken literally, since a model may fall anywhere along a spectrum of possibilities.

<u>Partial versus General Equilibria</u>.

Scientists often analyze alternative "equilibrium" situations. The term equilibrium is used to describe a point or region, toward which a system tends to gravitate. A marble in a tea saucer is attracted toward the base of the saucer so the base is termed the equilibrium point or "attractor" for the marble. In these analyses, equilibria may be partial or general. In practice the partial versus general distinction is not a dichotomy but a spectrum of possibilities. The possibilities in economics range from the effect of an input price change on a firm's demand for that input to the simultaneous equilibrium of all economic agents in an economy. More specifically, the "partiality" question can be illustrated by imagining an hypothetical biologist who analyzes the effect of gear regulation, assuming effort is constant and his counterpart economist who analyzes the implications of new product development, assuming new supplies are forthcoming at constant price. Both are being excessively "partial" in their respective analyses and their results will be quantitatively, if not qualitatively incorrect.

The mesh regulation, if successful, will alter catch per unit effort (CPUE) which will probably induce a change in fishing effort. The higher demand which results from new product development will increase fishing pressure and probably lead to a reduction in stocks and a rise in average cost of harvest. Thus, neither will give a correct description of the consequences of the change being analyzed. The choice of position on the partial-general equilibrium scale is ultimately judgemental and dependent on what decisions are involved. Because all models are partial, it is useful in modeling to explicitly state those variables which are accounted for in the model and those which are not. The former are termed "endogenous" variables while the latter are termed "exogenous" or "predetermined". Thus, in the above example, the hypothetical biologist treated fishing effort as exogenous and the hypothetical economist treated fish stocks as exogenous. In both cases the variables are really endogenous. In this example, integration of the two parts is not difficult and is typical of the integrative role of bioeconomic models. Another example of partial versus general equilibrium analyses would be single versus multiple species equilibria. One of the multiple species models in biology is similar, in a mathematical sense, to the input-output models of Leontief which have been useful in economics as well.

Dynamics versus Statics.

This discussion of bioeconomic models began with a distinction based on how population dynamics are represented. It would seem then that all bioeconomic models must be dynamic. Not so. One of the first exercises in treatises on population dynamics is one of eliminating dynamics. This is achieved by replacing differential or difference equations of motion with a "steady state" or "static" solution. The infamous "maximum sustainable yield" or MSY is a particular point on such a steady state curve or envelope. In economics such solutions are widely used also. When used appropriately, such models are quite adequate and simpler than dynamic ones. Perhaps some simple examples will serve to illustrate the difference between statics and dynamics.

A simple physical system is our first example and one to which we will return repeatedly. Imagine a tea saucer with a marble placed anywhere on its interior surface. Intuitively, we "know" that the marble will come to rest on the flat zone of the saucer's interior. At this zone, which may be a singular point, the marble is said to be in "equilibrium" because there are no unbalanced forces sufficient to offset friction and gravity. Now suppose we place in the bottom of the saucer a hard disc of the same diameter as the bottom of the saucer. The new equilibrium zone or point of the marble will be the same as before except for a vertical displacement by the thickness of the disk. This comparison of two or more equilibrium points before and after insertion is the essence of statics or "comparative statics" as it is frequently termed in economics. To contrast the ex ante and ex post equilibrium points, we did not find it necessary or even interesting to discuss the motion of the marble following insertion of the disk and during the period of re-equilibration.

In freshman economic principles, students are taught that reductions in the supply of wheat will lead to a rise in the price of wheat, ceteris paribus, and to a rise in the price of commodities such as bread which are produced from wheat. Nothing is said about the time lag between supply reductions and increases in wheat and bread prices or their time paths of adjustment. This deliberate abstraction from time is characteristic of static methods. A similar static (i.e. "timeless") statement could be made about the effects of ocean upwelling on fish biomass. Changes in ocean upwelling patterns can trigger a complex chain of ecological responses with dramatic effects on fish biomass. In both cases the statements are not wrong, but depending on the application of such statements, one may feel that something is missing. What is missing, by design, is an explicit statement of time paths or "trajectories" of price and biomass. The existence of predictable trajectories is usually presumed by model builders but developments in the theory of chaotic systems suggest that the existence of predictable trajectories can be an illusion we inherit from classical science.

In fisheries management, "yield per recruit" models are a widely used family of static models. Yield per recruit models are very useful for characterizing the long term effects of variations in fishing mortality and age at first exploitation. Their usefulness lies in their simplicity. For example, they have been incorporated in a static bioeconomic model (Gates and Norton, 1974). There are, however, disadvantages to using such static approaches in bioeconomic models. In economics and business one is never indifferent to the timing of events. Suppose a management measure will initially reduce catches but lead to an eventual increase in biomass and catches. During the interim, loan payments must be deferred and perhaps additional funds must be borrowed to survive for a better tomorrow. It matters a great deal whether the interest rate on loans is high or low and whether "tomorrow" is next year or ten years hence.

The time lag depends, inter alia, on the fishable life of the species while the discount rate fluctuates with the national economy and perhaps with fisheries policies. Such temporal and financial aspects are included in a bioeconomic model by the standard financial technique of discounting the net revenues over time. In order to do this, one must have explicit trajectories for economic variables. To be rigorous, one would need interest rate forecasts. In practice, it has been customary to treat the interest rate as if it were constant as well as exogenously determined. Explicit trajectories may be derived via original equations of motion or via a Bayesian approach.

If, as appears to be the case with many fisheries, there is no demonstrable effect of stock size on recruitment over the relevant range, then the time period for biological adjustment is determined by a biological parameter; the fishable life of the species. If, as is commonly assumed in bioeconomic models, the adjustment rate of fishing effort is rapid relative to biological stock adjustment rates, then the fishable life of the species is a reasonable estimate of the time duration for system adjustment. The initial and terminal equilibrium points are known from a static yield per recruit model, as is the time interval of adjustment. Intermediate points of the adjustment trajectory can be approximated by linear or quadratic interpolation and discounting procedures applied to the estimated trajectory. While imprecise, such methods are not necessarily less so than trajectories generated via arbitrary equations of motion estimated from noisy data on CPUE. Alternatively, one can work with difference equation, age class structured models and generate explicit "correct" trajectories. The cost of this alternative is a considerable increase in complexity and computational time. On the economic side, the dynamics of fleet investment decisions is little studied and poorly understood.

<u>Stochastic versus Deterministic</u>.

A stochastic model is one in which there are sources of randomness. A deterministic model abstracts from randomness; usually by replacing random variables by a measure of central tendency (mean, median or mode). The tea saucer system used earlier to illustrate comparative statics can be pressed into service to illustrate stochastic events. Suppose the table on which the saucer rests is shaking in an earthquake. Intuitively, we would expect the marble to be in random motion around the bottom of the saucer but tending to move toward the same equilibrium zone. Deferring, for the moment, questions of stability, the introduction of randomness in this simple system poses no great problems for our intuition; we simply generalize the earlier notion or equilibrium from a literal one of zero motion to one of random motion in the neighborhood of the equilibrium zone. Unfortunately, not all systems are as undemanding of our intuition as this one.

The most obvious example of randomness in a bioeconomic model is recruitment. Much biological research is being done on the determinants of recruitment, such as ocean upwelling. To the extent that such determinants are themselves random, the research changes the level at which randomness enters a model. Such a change can be useful, if it provides advance information to public and private decision makers. Note the interaction of dynamics and stochastics here; knowledge of lagged or delayed stochastic events can be exploited in making decisions.

There are many other sources of random events besides recruitment. Unfortunately, if random variables are used ad lib, it becomes increasingly difficult to separate noise from signal. Thus, the hard choices involve judgements about what random events are more important than others. Concerning such choices it is sometimes useful to do simple sensitivity analyses using a deterministic model. Sensitivity analyses can suggest which sources of variation are likely to dominate system behavior. The complexities introduced by dynamics and by stochastics tend to increase exponentially when both are introduced. A simple deterministic simulator may have to run for (the equivalent of) 50 years. Introduction of a random variable requires that the 50 year run be replicated enough times (let us say, 30) to characterize system behavior. With falling real costs of computer hardware and software, computational burdens are becoming less important although they are still significant costs. By simplifying models and using mathematics instead of computers it is sometimes possible to obtain analytic solutions with little or no computer time. It is increasingly the case that the choice between numerical simulation versus analytic methods revolves around requirements for the investigator's scarce time; rather than computer time per se. For plausibly complex systems, the choice between a priori oversimplification and tedious computation is not always easy.

Stability, Multiple and Chaotic Equilibria.

The notion of stability arises inevitably in dynamic models. Our tea saucer example can be exploited again to contrast "equilibrium" and "stability". The marble is "in equilibrium" on the bottom interior of the saucer because its potential energy is at a local minimum. Now, suppose the marble is given a small push to initiate motion. Our intuition tells us that friction and gravity will cause the marble to return eventually to its equilibrium zone at the bottom of the saucer. The trajectory followed by the marble requires some terminology to describe several possible behaviors. The system as described is stable in that it will converge on the equilibrium zone. The convergence may be monotonic which is to say, it does not "overshoot" and rise part way up on the other side of the saucer. Conversely, convergence may be oscillatory but dampened so that the oscillations gradually die out. We would expect our saucer and marble system to exhibit either monotonic or oscillatory convergence, depending on such factors as the steepness of its sides, how wide and smooth the bottom is, etc.

Alternatively, a dynamic system may not converge on the equilibrium if displaced; i.e. the equilibrium may be unstable. This is unlikely with our saucer because , as described, it is a conservative system; friction and gravity attract the marble toward the point(s) of minimum elevation. A current term for such equilibrium points or zones is an "attractor". By supposing the saucer is placed on an oscillating base, we can easily imagine an unstable attractor. The marble then oscillates around the equilibrium zone indefinitely. Such unstable systems may oscillate in a bounded pattern or a limit cycle. If the oscillations of the table are too violent or are in phase with the oscillations of the marble so as to cause continued acceleration of the marble, then the marble will eventually achieve an escape velocity and transgress the cusp of the saucer. Such behavior would be explosive or unbounded instability. One tends to dismiss the relevance of such explosive systems on the grounds that their explosive nature makes them of only transient relevance. A more appropriate attitude would be that preservation of such systems requires intervention to alter their dynamics. An example of such deliberate intervention would be the use of governors on steam and internal combustion engines, or automobile shock absorbers to dampen the oscillations induced by rough roads before the oscillations cause breakage. One might interpret Keynesian macroeconomic stabilization policies as an economic analogue of a governor mechanism.

Stability and convergence have another possible attribute; local versus global stability. Our saucer cum marble system has a stable attractor but only in a local sense. If the marble is given too hard an initial impulse, the marble achieves escape velocity and escapes to a new equilibrium outside the saucer. It is lost, presumably forever, unless retrieved by some external person or event. Similarly, an equilibrium may be locally stable but if displaced too far, may become unstable. For example, a controlled fission process becomes uncontrolled or explosive beyond a certain critical mass.

A fishing fleet has some similarities with the saucer analogy. A perturbation in profits initiates a process of investment or disinvestment which continues until a (near) zero wealth condition is restored. The introduction of limited entry measures destroys the equilibrium property of zero wealth in a way analogous to the way that inserting a disk in the saucer caused a vertical displacement of the marble's equilibrium zone. One normally supposes the global instability of the saucer system does not apply to the fishing fleet example. That is, extremely poor profitability may cause a fleet to decline in size through attrition or transfer. However, we would normally suppose this process to be reversible; a return of profitability would induce fleet expansion to original levels. On the resource side, however, irreversibility may apply. Perhaps a more appropriate analogy would be an escargot dish or a muffin tin where the multiple cavities correspond to multiple species equilibria. Under small perturbations, the system returns eventually to the status quo equilibrium. With a sufficiently large perturbation, such a system becomes locally unstable and undergoes a transition to a different equilibrium state.

In recent years, the possibility of multiple equilibria has had to share the stage with the even less comforting concept of "fractal" systems (Mandelbrot, 1982; Crutchfield, et al., 1986) which can exhibit chaotic behavior. It is possible to have surprisingly simple non-linear dynamic systems which are deterministic and yet which are quasi-random (chaotic) in their oscillations. Two curious and significant aspects of chaotic systems are (1) they do not require an external perturbation , such as a random shock or pulse, to enter a chaotic phase and (2) they seem to arise naturally in non linear discrete time systems (Hofstadter, 1981). The mathematics of such systems are not well understood from an analytical perspective but there is interest in chaotic systems by physicists, engineers, biologists and economists. In the past, our penchant for simplicity favored the formulation of models so simple that such behavior could not occur. That penchant may prove to have been excessive. The dynamic approach has, for two centuries, assumed the existence of an adjustment path or trajectory which is predictable except for some background noise associated with measurement error. With chaotic systems, a predictable trajectory may not exist; even for a model which appears to be totally deterministic. In Part II, Figure 1 was used to illustrate the effects of alternative fleet sizes on the wealth generated by an hypothetical fishery. In fact the equations used to generate Figure 1 included a stock production model which is strongly chaotic for fleet sizes less than that associated with point A in the Figure. The discounting procedure, like averaging, masks the annual fluctuations. With a planning horizon of 30 years, the underlying chaos is revealed only by the "bumpiness" of the wealth curve. The region to the right of point A is chaotic also, but at the resolution scale of Figure 1, the chaos is not evident.

Multiple versus Single Level Decisions and Strategic Behavior.

Economics has emulated the physical sciences in adopting mathematical approaches. It is fair to say that until von Neumann and Morgenstern (1947) the mathematics used was entirely borrowed. von Neumann and Morgenstern showed a potentially grievous error in blind application of methods so successful in natural science. In order to apply the techniques of optimization to social systems it was convenient to postulate an hypothetical entity termed a "central decisionmaker". This entity was omnipotent and, for good measure, omniscient (OOCD). For such an entity it merely a technical problem to grind out a utopian scenario for any problem. The problem is that, as a senior fisheries biologist once remarked to me, "We can't get there from here". What is overlooked by the central decisionmaker formulation is that there are typically multiple decisionmakers, each of whom has control over some but not all the levers of power. If decisionmakers at one level dislike those at another, they may react strategically. This may seem more an overdue rediscovery of politics rather than a profound distinction. In any case, multiple decision levels severely limit the possibilities for collective rationality. Society may have to settle for second, third or even "n^{th}" best choices. The limitations implied by multiple decision levels are operative whether one wishes to pursue an economic management criterion or a "conservation" objective. At a minimum, the existence of multiple decision levels forces one to examine such topics as enforcement, incentives and compensation possibilities. The expression "strategic behavior" will be used repeatedly in the following sections. It is a rather sweeping term for reactive behavior by individuals in a multiple decision level context.

A fundamental difficulty with multiple decision levels is the potential for coalitions and strategic behavior. As an hypothetical example, consider the problem of high seas enforcement with limited enforcement capacity. An OOCD approach would simply examine the expected penalty/payoff ratio for a "representative" violator. By raising the penalty, the OOCD would keep violation rates acceptably low. Now suppose the fleet members (N) form a coalition. Suppose the coalition designates n of the N vessels to engage in activities which violate regulations. These "sacrificial lambs" effectively absorb instantaneous enforcement capacity. The remaining N-n vessels of the coalition can violate with near impunity. To be effective, the penalty level must then be relative not to the catches of the n sacrificial lambs but to the catch of the entire coalition of N vessels. The necessary level would presumably balance expected penalties against expected economic gain from violations. Whether such coalitions are relevant in the real world is an empirical question, but the possibility is at least useful to illustrate coalitions and how they complicate analysis. It is difficult to imagine, a priori, all plausible coalitions much less to predict whether, in a given instance they will be implemented.

An even simpler example of the complications implied by strategic behavior involves the spatial distribution of enforcement. Even in the absence of strategic behavior (collusion), it is a non-trivial problem to discover the least cost travel circuit for surface enforcement vessels subject to a minimum acceptable expected detection rate. This problem has been studied by Lepiz and Sutinen (1985) using mixed integer linear programming and a generalization of the "travelling salesman" problem. The possibility of strategic behavior complicates this problem still further. One of the attributes of such a least cost circuit is predictability via analysis or observation. If a predictable circuit is followed, detection can be foiled easily by violators. The most obvious, and ad hoc, way to cope with such strategies might be to identify the N lowest cost circuits. From these select "several" circuits which differ significantly in the paths followed. On each trip, use a randomization procedure to determine which route will be followed. Note that, in contrast to a private property rights approach, detection is relying on a centralized approach. With private property rights, detection and enforcement relies for the most part on decentralized self interest. The police power of the state is necessary only in exceptional instances to enforce procedural requirements of civil law.

In an illustration of the multiple level decision problem, Meuriot (1983) compared the producers' surplus extractable in a multiple level context with the rent extractable in an OOCD context. His results indicated a one-third reduction in the maximum rent realizable from fees because domestic vessels are exempt from fees and, when fees are high, it is more profitable for foreign processor vessels to buy from domestic vessels and thereby avoid the fees. Since his study, fees have declined from 45 million dollars per year, to miniscule levels. This represents a wealth transfer caused by a statutory requirement of cost allocation/recovery via discriminating fees levied only on foreign harvesters. In addition, the open access nature of the fishery probably means that the wealth redistribution has been accompanied by a reduction in real national wealth; i.e. a reduction in economic efficiency.

This result could be used as a rationale for changing the law which currently forbids nondiscriminating fees. However, the point of this example is not the wisdom of the wealth redistribution, per se. The point is rather, the 50 percent overestimation of revenues realizable from fees.

Optimization and Simulation.

Optimization techniques are firmly entrenched in many disciplines, including economics and biology. By optimization we mean a formal (mathematical) technique for finding the "best" solution. The interpretation of "best" depends on the problem, but may be illustrated by a few examples:

. minimum cost diets for fish
. maximum profits for a fishing fleet
. maximum economic benefits from a fishery
. minimize risk subject to achieving an acceptable one constraint
. maximize biomass
. maximize sustained yield of a biomass
. minimum cost detection/enforcement circuits

By simulation we mean a technique for systematically examining alternative strategies or policies to determine which are "better" or "worse". One could say that, if carried to its logical limit, simulation can be a technique for optimization and, conversely, optimization techniques may be used as part of a simulation process. This trivializes the difference between optimization and simulation. Typically problems for which simulation is used are too complex to warrant realization of a formal "optimum". The complexities typically involve some of the attributes discussed earlier; partiality, dynamics, stochastics, etc.

Dynamic optimization is newer than static optimization methods. Lucid expositions of dynamic optimization in fisheries may be found in Clark (1976,1985) and Meuriot (1987). Early theoretical work was done by Hotelling fifty years ago using the calculus of variations and by Burt using dynamic programming twenty-five years ago. Dynamic optimization also means finding the "best" solution. However, unlike static optimization which yields a single optimum value for each decision variable, dynamic optimization yields a time path or trajectory for each decision variable. If, for example, we wished to send a rocket to the moon, we would need to know and control its position at each instant en route. This example is not entirely accidental; the development and popularization of control theory are, to a considerable degree, outgrowths of the space program. The spread of control theory into economics has been associated with an explosion of applications using control theory and the maximum principle. Most earlier works (most notably in benefit-cost analyses of public water resource investments) were content to calculate the present value of a few alternative scenarios with or without stochastic events and select from the "better" candidates.

It is clearly the case that optimization methods are essential for learning concepts and principles of fisheries economics/ management. A course in fisheries economics can now be intellectually more stimulating than it could have been two decades ago. Indeed, there are now textbooks on fisheries economics which would be very different in content had they been written two decades ago. A large part of the differences would be related directly or indirectly to dynamic optimization. As a means of clarifying theory, optimization methods have been essential.

At an applications level, one finds a mixture- some analysts reveal a preference for optimization; others for simulation of discrete policy alternatives. The choice in such matters involves objective differences such as inherent complexity of the problem. It seems likely that the choice also involves differences in training and personal taste. About the only safe comment about such matters is that both are here to stay.

Does the choice between optimization and simulation matter at a policy level? In an empirical sense, this is difficult to judge since so little has been implemented in fisheries. In particular, the central issue in fisheries policy is still whether or not to have limited entry. The central issue is not the optimum dynamic adjustments of effort and catch. The latter is a "lower" level technical question. The adjective "lower" is not used pejoratively. This issue has not changed much since the analyses of Warming (1911), Gordon (1954), Scott (1955), Christy (1964) and Crutchfield and Pontecorvo (1969). Indeed, as Meuriot (1985) makes clear in his treatise, a post-World War II European conference in London indicated a keen awareness by participants of the nature of the open access problem in fisheries. Then, as now, there was a failure of political consensus. As a result of this inability to form a coalition of nations, the fishing nations of Europe embarked on a negative sum game of using their national treasuries to preserve (via fleet subsidies) their respective national shares in international fishery resources. Unfortunately, such behavior, while individually rational in the short run, is even worse (from economic efficiency and conservation criteria) than an international policy of laissez-faire, open access. It is a tautology that failure to optimize can result in significant suboptimization. However, in my judgement, it is unlikely that we will ever manage natural resources in a dynamically optimum way. This does not mean that optimization methods are useless. They are essential for a clear understanding of what we wish to accomplish but should perhaps not be taken too literally in empirical applications.

IV. Model Validation

Models may be calibrated and estimated statistically in one step, that is to say, the entire model is estimated directly from a data set of observed values of system variables. The bulk of econometric models are of this type. At the other extreme are what might be termed "synthetic" models in which components are assembled or synthesized into a model of how the system is thought to operate based on knowledge of components. An example of statistical estimation/calibration would be estimation of demand functions for fish products (Meuriot, 1987). The synthetic approach is exemplified by the "budgeting" or "economic engineering" approach which lends itself well to modern spreadsheet software packages. Another, more sophisticated example would be the system dynamic models which received much publicity from the Club of Rome/ Limits to Growth study. In general, the dynamic pool models must use the synthetic approach to synthesize a model from disparate bits of data and information. The stock production models are less dependent on synthesis and can rely primarily on statistical estimation from CPUE data. Even here, linkage with economic data is necessary.

Although space does not permit much explanation, I should mention the "identification problem" inherent in this approach. Time series data on CPUE and effort are regarded by biologists as grist for a downward sloping relationship between CPUE and effort. The same data, to an economist is grist for an upward sloping relationship between effort and CPUE. The biologist's relationship is a theoretical relationship fundamental to stock production models. The economist's relationship is also theoretically fundamental; it is (except for a transformation involving the ratio of fish prices to the cost of effort) the supply curve for effort. What reason do we have to expect that an ordinary least squares regression estimate will be the biological one sought versus the economic one? The answer, barring further information, is none. In general, the estimate will be an unidentifiable mixture of the two relationships. Each is fundamental to the respective disciplines; the empirical estimate may be of value to neither. Such relationships are suspect because of the identification problem. My own experience is that it is easier to get a positively sloped relationship between effort and CPUE, indicating a dominant "signal" from the effort-supply relationship. There are possibilities for "unscrambling" the mixture. They require specification of both relationships and the existence of observations on relevant exogenous variables which affect one relationship but not the other. Candidates for such exogenous variables might be environmental variables such as temperature, wind, upwelling, etc. on the biological side, and interest rates and vessel costs on the economic side. The important point here is that neither relationship can be estimated correctly in isolation from the other.

Validation of models raises other questions. One of these is the importance of "realistic" assumptions. The two extremes are (1) the realism of assumptions is largely irrelevant; only the accuracy of results for variables of interest matters and (2) The adequacy of a model should be judged, in part, by the realism of its assumptions. One can certainly agree that, ceteris paribus, realistic assumptions are more satisfying than unrealistic ones. But if realistic assumptions make the model many times more complex and still yield the same answers for variables of interest then which is the preferred model? An important component of position (1) is sufficiency versus necessity. A necessary condition or assumption is one which, if invalid, causes the complete invalidation of the theory or model. A sufficient condition or assumption is one which is adequate to sustain a theory or model but which is not necessary to the model. The adherents of position (1) argue that sufficiency of assumptions facilitate simplicity and derivation of testable implications which are then either consistent or inconsistent with observable results. If observable implications are consistent with observation, this carries no implications for the validity of the assumptions made (Boland, 1979; Simon, 1968, 1979). If observable implications are inconsistent with observation, then the theory, as developed is untenable. Provided unrealistic assumptions can be shown to be unnecessary but useful simplifications, no harm is done. Critics of this "instrumentalist" approach are not convinced; perhaps because it is easy to slide unwittingly over the necessity chasm.

Another topic in validation is various technical methods for checking the "validity" of models against data. There is an extensive literature of this type and the interested reader may wish to read the review by Naylor and Finger (1971). Since their review there has been an explosion of work in statistics, engineering (systems theory) and economics. This literature is highly technical but a reasonably current review is provided by Moore (1985). This review provides a good insight into why it is so difficult to forecast economic events. Unfortunately, we have a long way to go in theory and data collection before our ability and aspirations correspond. Much the same can surely be said of fisheries research.

Validation can mean different things to different people. First of all, there is the ubiquitous fact of strategic behavior. If an interest group dislikes the implications of results and policy implications, it will be considered fair game to sabotage credibility via various stratagems. One of these is to point to "unrealistic" assumptions and imply, either directly or obliquely that the model results are "obviously" invalid. A possible test for such strategic behavior may be to postulate an even less realistic set of assumptions which yields conclusions favored by the group.

A more fundamental problem is that in many models, it is simply too time consuming and expensive to test all assumptions for necessity/sufficiency (Naylor and Finger, 1971). To the extent that particular assumptions are objectionable and can be shown to be sufficient rather than necessary, the objections should be anticipated and preparations made by testing the robustness of results to the assumptions. For example, regardless of its factual validity, the assumption of atomistic competition in fisheries is probably innocuous for allocation decisions. However, if factually incorrect, the assumption of perfect competition would be misleading for distributional issues (Rothschild, et al., 1977; Clark and Munro, 1980).

Among the pitfalls in working with fisheries data, there is the little acknowledged fact that aggregate catch and effort statistics may be based not on complete enumeration but on samples. Provided the sampling procedures are reasonably stable over time, this is not a problem for the biological side of bioeconomic models. However, when linkage is made with vessel cost data, it may be found that revenues are only a fraction (perhaps 50 percent) of breakeven. Based on my own limited experience, this represents not fraud but holes in data collection procedures. The data for reported trips are good but many trips are not reported. This kind of practical problem can be finessed in statistical models by using data in ways that exploit relative values; i.e. ratio variables. They do require some explanation when presenting to fishermen for whom gross revenues and costs determine business survival.

V. SOME CONCLUDING SPECULATIONS

A difficulty in presenting bioeconomic models is the appropriate mode of presentation for different audiences. In a presentation among professional biologists, concern is likely to be raised over what many nonbiologists might find obscure. The same can be said of a presentation to professional economists. Among fishermen the questions posed are more likely to be distinctly business oriented. This is one reason why models were characterized as having an educational/socialization role; of assembling individuals of differing experience and training to work on a common problem and to produce results that are plausible to many. When viewed in this way, another test of "validity" is its acceptance. Although fidelity to real world data is important, there may be other criteria such as plausibility to users which is as much psychological as objective validity. The storyteller has long exploited the persuasiveness of allegory and parable over dry logic. Perhaps a similar felicity of expression would help in presenting models.

Macroeconomic forecasting has received much criticism lately. Much of this criticism has been ill deserved in the sense that professional forecasts have averaged one percent mean square error. This performance is better than that of informal critics. However, the confidence intervals of forecasts degrade rapidly as one projects further into the future. This is inevitable with stochastic dynamic systems. The possibility of chaotic systems raises serious problems for forecasting and control of dynamic systems. Near the beginning of this century, the mathematician Poincare made the prescient remark that small errors in non-linear systems may be magnified rather than vanishing with the passage of time. It is possible to obtain good fits (hindcasting) to historical data with many alternative models. However, the possibility of chaotic systems, makes the plight of economists and biologists less isolated. It now appears that in even simple physical/ engineering systems with chaotic regimes, the ability to forecast is inherently limited (Crutchfield, et al., 1987). In such systems, future states may be bounded only by gross inequalities reflecting physical laws. If economic and biological systems are chaotic, perhaps attempts to forecast are ill placed. Perhaps more emphasis should be placed on statistical and "long run" performance indices and less on dynamic fine-tuning policies. For example, in Figure 1, point A which maximizes wealth is the focus of most economic discussions. Virtually all fisheries economics models used to date are non-chaotic, or at least presumed to be so. A fishery such as that depicted in Figure 1 admits another interpretation. Note the precipitous decline of wealth to the right of point A. One suspects that given such a world, coupled with various uncertainties of measurement, enforcement and stochastic events, most people would advocate a point to the left of the precipice, even at some loss in expected wealth. On other hand, if people strongly dislike annual variability, the region to the right of point A might be preferred, despite low expected wealth, because it has low variance.

Much has been made in recent years of the importance of dynamic rather than static analyses. The validity of this position would seem to depend on the precision of projected trajectories. My own experience with univariate and multivariate time series methods is that our forecasts beyond a year are not very precise. If such is the case, one must question the merits of dynamic elegance versus long term stable attributes. For example, in many fisheries, CPUE declines very slowly at high rates of exploitation. This probably invalidates the adjustment paths forecast by the Schaeffer model on which many dynamic analyses are premised because the Schaeffer model predicts a linear decline in CPUE. The alternatives of Pella-Tomlinson or a dynamic pool model are more cumbersome but perhaps more appropriate for applied research. The ordinal conclusions of simpler models seem, for the most part valid, but the cardinal predictions they yield may be quite misleading. An analysis which exploits steady state attributes and interpolates intermediate points may yield better estimates of present value changes than the simplistic Schaeffer model.

The conjectures expressed in these paragraphs may be reinforced by the existence of strategic behavior. Each time change is proposed, the passions of conflicting interest groups tend to be aroused. It may be better to accept suboptimal stable measures than to continuously risk all on a throw of the political dice.