Policy Consequences of Better Stock Estimates in Pacific Halibut Fisheries

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Working Paper No. 348

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Giannini Foundation of Agricultural Economics
May 1985

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The common property nature of production in ocean fisheries results in the dissipation of economic rents and has led to the development of marine regulatory agencies throughout the world. These agencies face the problem of managing a fishery when the stock of fish is not directly observable. The use of total harvest as an indicator of stock biomass is widespread, although the way in which harvest is used as a statistic of biomass varies from one application to the next. Since the agency's management decisions depend critically upon the estimates of the fish stock, and since these estimates are usually inferred from the actions of economic agents, more efficient methods of making such inference have high potential for improving the management of fish populations.

This paper attempts to circumvent the problem of unobservable stock by testing the applicability of the extended Kalman filter to infer stock size and allow for maximum likelihood estimation of the unknown parameters of a fishery model representing the Pacific Halibut Fishery. The Kalman Filter algorithm provides unbiased, minimum variance estimates of the stock biomass in each time period. The success of this filter in providing estimates of biomass is measured through the prediction error of each equation in each time period. The unknown parameters of the fishery model can then be estimated using the technique of maximum likelihood through the use of prediction error decomposition. This technique has the advantage over other stock production models in that it incorporates the stochastic variability of stock size, catch, effort and all other relationships included in the model. It can also estimate time varying parameters, allow for a variety of functional forms and employ all available information pertinent to the biology and economy of the halibut fishery to explain and predict the level of catch, effort and price. The validity of the model can be tested using the classical statistical techniques.

Theoretical Model

The Kalman filter algorithm is used to provide us with an unbiased estimate of the stock biomass that minimizes the squared difference between the actual and predicted biomass in any time period. This section will explain this algorithm for a general model of a fishery.

The state equation describes the relationship between the unobservable variable and past values of this variable and other observable variables. The measurement equations describe the behavior of the observable variables that are dependent on the stock biomass.

Let the n state variables, X_t and X_{t-1} be vectors of the unobservable variables at time t and t-1, respectively. They represent the stock biomass of the fishery. Let N_{t-1} be a vector of the observable variables that affect the state variables. Examples are water temperature, salinity and strength of currents. This vector also includes catch in time t-1 when escapement, stock minus catch, is appropriate for predicting the population biomass in the next time period. Let θ be a vector of the parameters in the state equation and w_t be a vector of white noise variables.

The state equation is :

$$X_t = f(X_{t-1}, N_{t-1}, \theta) + w_t \qquad w_t \sim N(0,Q) \qquad (1)$$

The r measurement equations describe the relationship between the variables of interest (eg. catch, price, effort, season length) and the factors affecting these variables. Some equations will include stock, others will not. Let Z_t be the rx1 vector of observed variables of interest -- catch, exvessel price and inputs used in production. Let L_t be the vector of observed exogenous and endogenous variables affecting Z_t, -- management restrictions, prices and effort. Let a be the vector of parameters of the measurement equations, and v_t be a vector of white noise variables.

The measurement equations are :

$$Z_t = h(a, X_t, L_t) + v_t \qquad v_t \sim N(0,R) \tag{2}$$

The error terms from the state and measurement equations, w_t and v_t, are assumed uncorrelated.

If these equations are linear, the expectations of the state equations and error covariance equation can be derived regardless of the probability distribution of the state variables. In the case they are nonlinear, the true expectation of the state variable is unknown without some a priori determination of the probability distribution of X_t. In order to obtain practical estimation algorithms for nonlinear systems, the extended Kalman filter requires the expansion of f in a Taylor series about an estimate of X_{t-1} or $X_{t-1|t-1}$. N_{t-1} is an observation of the variables N_{t-1} and Θ is fixed.

$$X_t = f(X_{t-1|t-1}, N_{t-1}, \Theta) + F_x(X_{t-1|t-1}, Nt1, \Theta)(X_{t-1} - X_{t-1|t-1}) + w_t + R_1 \tag{3}$$

where F_x contains elements in row i column j equal to $\partial f_i / \partial X_j \,|_{X_{t|t-1}}$ where R1 represents the remaining terms of this expansion. Dropping all but the first order approximation, the expectation of the state vector is

$$E(X_t) = X_{t|t-1} = f(X_{t-1|t-1}, N_{t-1}, \Theta) \tag{4}$$

where

$$E(X_{t-1} - X_{t-1|t-1}) = 0 \tag{5}$$

with variance

$$P_{t|t-1} = F_x(X_{t-1|t-1},N_{t-1})P_{t-1}F_x(X_{t-1|t-1},N_{t-1})^T + Q \quad (6)$$

where

$$P_{t-1} = E(X_{t-1|t-1} - X_{t-1})(X_{t-1|t-1} - X_{t-1})^T$$

Equations (4) and (6) provide estimates of the state vector and error covariance matrix given all past observations. Given a prior estimate of the state, $X_{t|t-1}$, we seek an updated estimate, denoted $X_{t|t}$ given the actual observation of Z_t. $X_{t|t}$ contains all information up to and including time t. Motivated by the linear relationship of the ordinary and generalized recursivve least squares estimator, we seek a filter in the linear recursive form:

$$X_{t|t} = a_t + K_t Z_t \quad (7)$$

where a_t and K_t, the gain matrix, is to be derived given the conditions of unbiasedness and minimim variance. a_t is chosen from the conditon that the estimate X_t be unbiased (i.e., $E(X_{t|t} - X_t) = 0$). This implies that $a_t = X_{t|t-1} - K_t\hat{h}(a,X_t,L_t)$ or

$$X_{t|t} = X_{t|t-1} + K_t[Z_t - \hat{h}(a,X_t,L_t)] \quad (8)$$

where $\hat{h}$ denotes the expected value of h.

The optimal gain matrix, K_t, is chosen to minimize an appropriate function of the error covariance matrix, P_t.

$$P_t = E([X_{t|t} - X_t][X_{t|t} - X_t]^T) \quad (9)$$

Substituting equation (8) for X_t and equation (2) for Z_t into equation (9) and using the relationship $P_{t|t-1} = E((X_{t|t-1} - X_t)(X_{t|t-1} - X_t))$, $R_t = E(v_t v_t^T)$, v_t is uncorelated with $X_{t|t-1}$ and X_t, and P_t is independent of Z_t we obtain

$$P_t = P_{t|t-1} + K_t\, E([h(X_t,L_t,a) - \hat{h}(a,X_t,L_t)][h(a,X_t,L_t) - \hat{h}(a,X_t,L_t)]^T)K_t + E([X_{t|t-1} - X_t]*[h(^\circ) - \hat{h}(^\circ)]^T)K_t + K_t E([h(^\circ) - \hat{h}(^\circ)][X_{t|t-1} - X_t]^T) + K_t R K_t^T \quad (10)$$

We want an estimate of the (approximate) conditional mean of X_t that is minimum variance estimate; that is, it minimizes the class of functions:

$$J_t = E[(X_{t|t} - X_t)^T S(X_{t|t} - X_t)]$$

for any positive semidefinite matrix S. We can choose S = I and choose K_t to minimize

$$J_t = E([X_{t|t} - X_t]^T[X_{t|t} - X_t]) = \mathrm{trace}[P_t] \quad (11)$$

Taking the trace of both sides of equation (10), substituting the result into equation (11) and solving the equation $\partial J/\partial K = 0$ for K_t gives us the desired optimal gain matrix:

$$K_t = -E([X_{t|t-1} - X_t][h(a,L_t,X_t) - \hat{h}(a,L_t,X_t)]^T)* [E([h(^\circ) - \hat{h}(^\circ)][h(^\circ) - \hat{h}(^\circ)]^T) + R]^{-1} \quad (12)$$

From the substitution of equation (12) into equation (10) and some manipulation the result is,

$$P_t = P_{t|t-1} + K_t E([h(^\circ) - \hat{h}(^\circ)][X_{t|t-1} - X_t]^T) \quad (13)$$

Equations (8), (12), and (13) provide updating algorithms when a measurement, Z_t, is taken. The expectations inside these algorithms depend on the probability density function of X_t to calculate $\hat{h}(a,X_t,L_t)$. For the same reason used in finding the expectation of the state variables, expand $h(a,X_t,L_t)$ in a Taylor series about $X_{t|t-1}$:

$$h(a,L_t,X_t) = h(X_{t|t-1},L_t,a) + H_x(X_{t|t-1},L_t,a)[X_t - X_{t|t-1}] + R2$$

where $H_x(\bullet)$ is the r x n matrix whose ijth element is equal to $\partial h_i/\partial X_j|X=X_{t|t-1}$. Truncating the remainder, R2, substituting this approximation for $h(a,X_t,L_t)$ into equations (8), (12), and (13) and carrying out the expectations produces the extended Kalman filter measurement update equations. In summary we have:

$$X_t = f(X_{t-1},N1,\Theta) + w_t \qquad w_t \sim N(0,Q) \tag{A}$$

$$Z_t = h(a,L_t,X_t) + v_t \qquad v_t \sim N(0,R) \tag{B}$$

$$X_{t|t-1} = f(X_{t-1|t-1},N_{t-1},\Theta) \tag{a}$$

$$P_{t|t-1} = F_x(X_{t-1|t-1},N_{t-1},\Theta)P_{t-1}F_x(X_{t-1|t-1},Nt11,\Theta) + Q \tag{b}$$

$$K_t = P_{t|t-1}H_x^T(X_{t|t-1},L_t,a)*(H_x(\bullet)P_{t|t-1}H_x(\bullet)^T + R)^{-1} \tag{c}$$

$$X_t = X_{t|t-1} + K_t[Z_t - h(a,X_{t|t-1},L_t)] \tag{d}$$

$$P_t = [I - K_tH_x(X_{t|t-1},L_t,a)]P_{t|t-1} \tag{e}$$

This system of equations will provide us with an estimate, $X_{t|t}$, that is a minimum mean squared unbiased estimator forthe state vector X_t. Given $X_{t|t}$, N_t, and L_{t+1}, we can predict $X_{t+1|t}$ by X_{t+1} and Z_{t+1} by $Z_{t+1|t}$.

This algorithm is called the extended Kalman filter. The gain matrix in equation (c) contains random variables that depend on the estimate $X_{t|t-1}$ through the matrices $F_x(X_{t|t-1},N_{t-1},\Theta)$ and $H_x(X_{t|t-1},L_t,a)$. This is because we have chosen to linearize f(.) and h(.) about the current estimate of X_t. Also, the (approximate) estimateion error covariance matrices, P_t, are also random, depending on the time-history of X_t--i.e., the actual estimation accuracy is trajectory dependent. Therefore, the sequence K_t and P_t must be computed in real time inserting the values for $X_{t|t-1}$ and $X_{t|t}$ at each iteration.

Since the matrix P_t in equation (e) is an approximation to the true covariance matrix due to the linearization of f(.) and h(.), actual filter performance should be verified by Monte Carlo simulation. Estimation accuracy is increased by using higher orders in the Taylor series expansion of f(.) and h(.). According to Gelb, the extended Kalman filter has been found to yield accurate estimtes in a number of important applications.

The use of this algorithm requires initial estimates of X_1 and P_1. They can be obtained through some knowledge of the stock size or estimated using maximum likelihood estimation to be discussed next.

Maximum Likelihood Estimation of the Unknown Parameters

Now that we have chosen a technique for estimating the stock biomass in each time period, we want to estimate the unknown parameters in the state and measurement equations. If w and v are normal and X_o has a normal distribution with mean, x and variance P_o, then the joint density of Z is

$$\mathrm{LogL}(Z) = -(TN/2)\log 2\pi - (T/2)\log|R| - (T/2)(Z-E(Z))^T R^{-1}(Z-E(Z))$$

This likelihood function can be rewritten using the definition of conditional probability.

$$\log L(Z) = \sum_{t=1}^{T} \log l(Z_t|Z_{t-1},\ldots,Z_1) + \log l(Z_1)$$

The first term on the right hand side of this equation is the distribution of each Z_t conditioned on past values of this variable. The second term is the unconditional distribution of Z_1. This expression allows us to write the likelihood function in terms of the errors associated with the prediction of Z_t given $Z_{t-1},\ldots, Z_1$. We denote this prediction as $Z_{t|t-1}$. These errors are

$$e_t = Z_t - E(Z_t/Z_{t-1},\ldots,Z_1)$$

$$e_t = Z_t - Z_{t|t-1}$$

$$e_t = Z_t - h(a,X_{t|t-1},L_t)$$

$Z_{t|t-1}$ is the optimal predictor of Z_t given $X_{t|t-1}$. The variance of e_t is

$$F_t = E[e_t e_t^T] = E[(Z_t - Z_{t|t-1})(Z_t - Z_{t|t-1})]$$

$$F_t = E[(h(a,X_t,L_t) - h(a,X_{t|t-1},L_t))*h(a,X_t,L_t) - h(a,X_{t|t-1},L_t))] + R$$

Since the expection in the above equation is nonlinear in the stock biomass, we need to use the probability distribution of X_t in order to evaluate this expectation. We avoid this, however, by expanding h in a Taylor series about $X_{t|t-1}$. We substitute the first order of this expansion for $h(a,X_t,L_t)$ in the previous equation and take the expectation. The result is

$$F_t = H_x * P_{t|t-1} * H_x^T + R ,$$

where H_x and $P_{t|t-1}$ is as described above and H_x is evaluated at $X_{t|t-1}$

Given the normality assumptions above, the likelihood function is

$$\log L(Z_1,\ldots,Z_T) = -(TN/2)\log 2\pi - 1/2 \sum_{t=1}^{T} \log|F_t| - 1/2 \sum_{t=1}^{T} e_t^T F_t^{-1} e_t$$

Given initial estimates of the parameters, Θ and a, we choose the values of these parameters to maximize this likelihood function. Under regularity conditions it can be shown that the parameters are asymptotically normal with mean Θ_o and A_o and variance equal to the inverse of the information matrix. It is assumed that the random variables are asymptotically independent. If the initial parameter estimates are consistent, then the maximum likelihood estimates will be asymptotically unbiased and asymptotically efficient.

Application to the Pacific Halibut Fishery

The International Pacific Halibut Commission (IPHC) was established in 1923 by a treaty between Canada and the United States. IPHC's purpose is to rehabilitate and maintain Pacific Halibut stocks at or near maximum sustainable yield. Since they cannot directly observe the stock of halibut, they rely on changes in catch per unit effort and age composition studies to manage the resource. The Halibut fishery is divided into three management areas in the North Pacific Ocean as shown in figure 1. The management tools used by IPHC are gear restrictions, size limits, the regulation of incidental catch and an annual quota on total catch. The quota is enforced by closing the halibut fishing season when the quota is met.

Although halibut are exploited by a variety of vessel types that are shared with other fisheries, only one type of gear, longline skate, has been in use since the early days of the fishery. Halibut are processed as fresh or frozen and are marketed through channels that have changed slowly over time. Management of the fishery began in 1924.

The biology of the fishery is such that fishermen exploit a large number of year classes simultaneously. For this reason, Crutchfield states that the Halibut fishery is "ideally characterized by the traditional biomass-fishery model." Halibut are demersal and are found on the continental shelf of the North American coast from Santa Barbara, California to Nome, Alaska.

Although the stock of halibut in any one time period is not directly observable, it plays a role in the determination of catch, effort and season length. By developing a systematic filter that uses this information to infer the biomass in each time period, we can estimate a simultaneous equations model of the Pacific Halibut fishery. The model includes a state equation describing the behavior of the stock biomass over time. The measurement equations include a price demand equation, a harvest equation, an effort equation and a season length equation.

The price demand equation describes how exvessel price is determined given harvest, income, and cold storage holdings. The catch equation describes the effect of effort and stock biomass on total catch in area 2. Effort is measured using the number of skate soaks employed in harvesting the fish. The effort equation describes the effect of halibut price, stock biomass, and the quota on the amount of applied effort. The season length equation relates season length in days to the quota, stock biomass and effort.

The unobservable stock biomass in area 2 is represented as an equation relating biomass in the current year to past escapement (biomass minus direct and indirect catch in area 2. Using this state equation and the measurement equations discussed above, a Kalman filter for nonlinear equations has been developed that provides an unbiased, minimum variance estimate of the stock biomass in each time period. This filter provides prediction errors for each time period. A prediction error is the difference between the actual value of catch, effort, price and season length and the predicted value obtained through the use of the expected value of stock biomass conditioned on all past observations of the observable variables and the hypothesized stock biomass equation. The parameters of this model can be estimated and confidence intervals formed using maximum likelihood estimation.

PACIFIC HALIBUT FISHERY MODEL

STOCK

$$stock_t = s(1) * (stock_{t-1} - catch_{t-1})^{s(2)} + \epsilon_{st}$$

CATCH

$$catch_t = c(1) * stock_t^{c(2)} * effort_t^{c(3)} + \epsilon_{ct}$$

EFFORT

$$effort_t = e(1) * stock_t^{e(2)} * halprice_t^{e(3)} * quota_t^{e(4)} + \epsilon_{e_t}$$

SEASON LENGTH

$$season_t = sl(1) + sl(2) * stock_t + sl(3) * effort_t + sl(4) * quota_t + \epsilon_{slt}$$

HALIBUT PRICE

$$halprice_t = h(1) + h(2) * (catch_t + catch3_t + catch4_t) + h(3) * pincome_t + h(4) * holdings_t + \epsilon_{ht}$$

The initial parameters are nonlinear two stage least squares estimates using IPHC estimates of stock biomass in area 2 obtained from migratory cohort analysis. After each iteration, the parameters are used to obtain e_t and F_t from the Kalman filter algorithm.

Results

The conditional and updated estimates of biomass in the area 2 Pacific Halibut Fishery are presented in Tables 1 and 2. The parameter estimates obtained from the numerical optimization are presented in Table 3.

TABLE 1: CONDITIONAL ESTIMATES OF PACIFIC HALIBUT BIOMASS 1936-1982
With Standard Deviations (in round weight/metric tons)

YEAR	STOCK(t/t-1)	STD DEV
1936	56324.1	3605.6
1937	45858.9	4597.9
1938	40922.6	4807.6
1939	42675.4	4838.2
1940	40855.0	4819.4
1941	40952.0	4808.2
1942	43309.5	4807.1
1943	45813.9	4803.6
1944	46749.1	4805.9
1945	49733.7	4808.5
1946	53446.2	4784.9
1947	51493.7	4774.5
1948	53059.2	4775.4
1949	55157.2	4765.9
1950	56419.6	4760.6
1951	56709.4	4757.3
1952	54002.9	4754.9
1953	53749.0	4763.0
1954	55117.0	4796.2
1955	54937.5	4796.8
1956	59190.5	4786.8
1957	55185.1	4795.9
1958	54749.0	4779.2
1959	53528.8	4787.2
1960	52247.2	4791.5
1961	50147.0	4807.9
1962	50369.9	4808.7
1963	48083.3	4802.3
1964	43520.2	4847.9
1965	47330.4	4857.2
1966	42835.1	4889.5
1967	43394.9	4880.4
1968	42643.9	4912.2
1969	44200.1	4931.3
1970	38944.0	4940.7
1971	37102.0	4964.0
1972	36227.7	5005.2
1973	34716.7	5024.3
1974	34407.1	5050.0
1975	32850.2	5085.7
1976	28601.9	5116.6
1977	26363.6	5112.6
1978	32090.6	5101.3
1979	33329.5	5102.0
1980	34294.0	5086.0
1981	35430.6	5092.8
1982	35320.6	5096.5

TABLE 2: UPDATED ESTIMATES OF PACIFIC HALIBUT BIOMASS 1936-1982
With Standard Deviations (in round weight/metric tons)

YEAR	STOCK(t/t)	STD DEV
1936	45213.6	2301.4
1937	41893.4	2510.3
1938	43303.9	2567.4
1939	42842.0	2524.2
1940	43340.6	2511.9
1941	44062.1	2537.0
1942	45582.4	2559.7
1943	47680.9	2572.3
1944	50700.3	2605.5
1945	52197.6	2611.2
1946	54049.5	2580.0
1947	53979.6	2595.7
1948	56067.2	2602.5
1949	56284.6	2606.8
1950	56559.7	2605.1
1951	56758.2	2578.3
1952	56472.2	2586.3
1953	58855.7	2640.7
1954	61250.8	2639.8
1955	59853.8	2664.2
1956	60884.5	2640.9
1957	57768.5	2615.8
1958	56557.2	2615.0
1959	55689.4	2608.4
1960	54700.1	2615.3
1961	53134.0	2612.0
1962	51763.9	2518.5
1963	46417.3	2588.5
1964	45522.1	2640.8
1965	45105.0	2630.0
1966	45125.3	2625.7
1967	42490.8	2654.5
1968	42081.2	2694.9
1969	41811.4	2642.4
1970	38212.0	2644.8
1971	35966.8	2679.0
1972	34520.4	2678.7
1973	31992.5	2702.4
1974	29487.7	2717.5
1975	28510.5	2680.0
1976	26683.6	2635.2
1977	28078.5	2722.3
1978	28693.4	2742.4
1979	30425.1	2739.9
1980	30271.0	2764.0
1981	30480.4	2766.5
1982	30743.6	2773.2

TABLE 3

PARAMETER ESTIMATES OF THE PACIFIC HALIBUT FISHERY MODEL

STOCK

s(1) = 7.551
s(2) = 0.842

CATCH

c(1) = .0120
c(2) = 0.810
c(3) = 0.663

EFFORT

e(1) = 0.017
e(2) = 0.111
e(3) = 0.378
e(4) = 0.879

SEASON LENGTH

sl(1) = 209.3
sl(2) =-0.010
sl(3) =-0.0222
sl(4) = 0.0308

HALIBUT PRICE

h(1) = 415.92
h(2) =-0.0101
h(3) = 0.3897
h(4) =-0.1555

Optimal Halibut Quota

We used dynamic stochastic policy to compute the optimal feedback rule for the management of the area 2 Pacific Halibut Fishery. Revenue was taken as the objective of the management agency. This is imperfect for several reasons, the most obvious of which is the neglect of costs. More fundamentally, the Commission is able to determine the degree of inefficiency in the fishery by setting the quota. Quota determines season length which in turn determines the proportion of the year that the fisherman engage in some other pursuit and the capital stock is under utilized. The Commission may also wish to weight the number of fisherman employed or the consumer surplus generated by the fishery as well as the revenue to the fisherman. Nevertheless, this study concerns itself only with the revenues to the fisherman.

In this policy simulation only quotas are examined. As explained earlier, gear restrictions and size limits are also important regulatory tools. Both of these other tools seem to be better examined in a model where the age structures are described.

Given the small number of state and control variables, there are many choices for the method of constructing an optimal control. Direct use of dynamic programming with the error terms simulated would preserve the structure of the model and provide the best answer. Since the model is somewhat preliminary and that method is cumbersome, expanding the model in Taylor series to produce a linear quadratic Gaussian control problem was the method chosen. The model was expanded about its values in the last year for which there is data, 1982. (Another possible method would be to compute the deterministic optimal control and minimize variations about it as Athans, among others suggests).

With these caveats, the control model is,

$$\max_{u} \sum_{k=1}^{T} r^{-k+1}(gx_k + hu_k - x_kGx_k - u_kHu_k) + r^{-k}(gx_T + x_TGx_T)$$

subject to

$$x_k = Ax_{k-1} + Bu_{k-1}$$

The values of the parameters were found by the linearization described above and they are:

Values for Optimization

name	value
A	1.3
B	-1.13
g	51.12
h	197.23
G	.000576
H	.0173
r	1.07

The solution method was to use the recursion equations given in Athans(1972). When the problem was specified as having 15 periods, we found that the first 5 periods had essentially the same control rule, indicating that this was also the rule for a very long horizon problem. This optimal control was:

$$u = -6279 + .467x$$

where u is the optimal quota and x is the stock expressed as deviations from their values in 1982. The form of the control reflects the linearization, variables were measured from their 1982 values. Thus, the quota is its 1982 value, 5430, less a large constant, plus .467 times the difference between the current stock and the 1981 stock. Given this feedback rule, the optimal policy is to have a negative quota, which is impossible. Instead, the quota should be kept zero until stock size rises high enough. One can calculate that point by solving:

$$x = Ax + B\ (.467x - 6279)$$

for x which gives 31,000. This implies that the optimal policy is to let the stock grow until it is approximately double the estimated stock in 1981. Without any fishing whatsoever, this will take about 3 years in this model. So the policy conclusion is to undergo a moratorium for several years. Of course the linearization of the model and the lack of consideration of steady employment as an objective vitiate this conclusion as a serious policy prescription. The direction -- less fishing -- to get a higher present value of catch is however likely correct.

Value of Better Information

The value of a dynamic stochastic program is well known to depend upon the variance of the estimates of the state variable, even though, in the linear quadratic case the optimal policy is independent of these variances. Estimates of stock that have lower variance can then be transformed directly into estimates of increased value of an optimal program. For our model the formula is

$$dV/d(var) = .129$$

where V is the value of an optimal program. Thus, for the 1973 value of stock, the present value of the loss to having less than perfect information was 3.25 million dollars. For comparison, the value of the fishery for one year is about 12.0 million dollars, or its present value is about 171 million dollars. So the value of information is about 2 % of the value of the fishery.

Of course, not all of the value of information can ever be captured because perfect information on a fishery is unobtainable. To get some idea of how much the value could be increased through better stock estimates we compared an estimate of stock based on the IPHC estimate with xcond. The IPHC made stock estimates until 1973 and we regressed the last ten years of these estimates on xcond. The regression had a coefficient of 1.38 and a standard error of 4296. Thus the variance of the stock estimate (1.38 times IPHC estimate) is 2.61 times the variance of xcond. To put this another way, using the affine transform of the IPHC estimate that comes closest to the filter estimates would, just through the variance effect, cost an additional 5.3 million dollars in lost expected present value revenues. This shows that the value of the information from filtering is potentially quite large.

The value of better stock estimates is direct as well as comming through better information. The feedback rule developed shows that half of all mistakes in the stock estimates are immediately translated into mistakes in the quota set. Thus, in the optimal feedback rule, policy is very important to the correct stocks.

In conclusion, better estimates of stocks would change policy in the two obvious ways shown by dynamic stochastic programming: There is a direct value to information with less noise and there is value to choosing the right control rather than the wrong control. The stock estimates presented here use a radically different methodology from those made by the IPHC. Basicly they sacrifice considerable biological detail while gaining statistical method. They formalize the notion that catch per unit effort measures stock, but give up the age classification of the population. Under these circumstances it is impossible to announce which stock estimates are right. Their differences, as the above numbers make clear are more than worthwhile running down, which is, of course, the topic of our further research.

Since this analysis takes into account the dynamics of the halibut fishery, the optimal quota is established using optimal control methods. Because the Kalman filter provides an estimate of the variance of stock biomass (predicted vs. actual), we can determine the degree to which additional controlled sampling of the population (as well as other factors that may provide information of stock biomass) will reduce the variance of stock estimates. Then we can estimate the value of reducing this variance in terms of the difference it makes in the fishery management plan.

A Kalman filter approach to unobservable variable problems has been used in navigation and engineering. This project is an extension of state space models and Kalman filter theory to economic problems where there exist unobservable variables and time varying parameters. The results of this project can be used by IPHC to predict the pattern of harvest,effort and prices given various management strategies. Using optimal control theory, IPHC can determine the value of new information as well as optimal quotas, opening date, size limits and other management tools that will extend the fishing season and allow for more efficient use of the halibut resource. The methodology used in this project can be applied to other fisheries since the Kalman filter can be adapted to conform to the information and knowledge relevant to the biology, economy and management of each individual fishery.

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