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VALUE OF PREDICTING ENVIRONMENTAL VARIATION IN FISHERY MANAGEMENT

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Abstract

Decision-makers are often concerned with forecasts of environmental variables. In accordance with this the quality of forecasts is often discussed. The interest in forecasts also show up in much modeling activity. However, the value of forecasts in terms of improved quality of decisions is not extensively studied. In this article we investigate the value of forecasts by the use of stochastic, dynamic optimization. The case is Northeast Arctic cod (Gadus Morhua) in the Barents Sea. We find that the value of ideal forecasts, when used to their full potential, is around 3 to 5 percent improvement in expected net present value. More realistic forecasts lead to improvements less than one percent. For practical purposes, it is only the forecast for the coming year that matters, long-term forecasts are of no use because the managed fishery is very flexible. These findings suggest that highly simplified forecasts can be used in models. The conclusions are likely to be somewhat sensitive to choice of model, a theme for further research.

1. Introduction

In this article we analyze harvesting policies for a fish species in the case of (partly) predictable environmental variation. The case is Northeast Arctic cod (*Gadus Morhua*) in the Barents Sea. Systematic fluctuations or autocorrelation in environmental variables[1] imply that one can make forecasts of these variables.[2] Many studies show that environmental variation is correlated with the productivity of cod and other species in the Barents Sea[3]. Hence if one can (partly) predict environmental variation, one can also (partly) predict cod growth. Based on this line of reasoning it is often claimed that forecasts of environmental variation is important for fishery management. Here we use a simple surplus growth model for the cod fishery to quantify the value of such forecasts. We investigate the required time-horizon of forecasts and we explore simplified harvesting strategies that still reap most of the benefits of available predictions. The main

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1 See e.g. Hannesson and Steinshamn (1991), Larraneta and Vazquez (1982), Yndestad (1999b), and a large literature on the North Atlantic Oscillation.

2 See e.g. Ottersen et al. (2000), Bretherton and Battisti (2000), and Yndestad (1999b).

3 See e.g. Ottersen and Sundby (1995), Ottersen et al. (1998), Michalsen et al. (1998), Ottersen and Loeng (2000), Sundby (2000), Skjoldal et al. (1992), and Helle and Pennington (1999).

motivation is a need to simplify complicated multispecies models where the optimal use of long-term predictions would contribute to excessive complexity.

Several authors have discussed management strategies in light of environmental variation. For the case with unpredictable stochastic variation Reed (1979) found a constant escapement policy to be optimal in a simple bioeconomic model. Assuming a cyclical environment, Parma (1990) found that spawning stocks should be built up when good environmental conditions are expected. While this policy gives a slight improvement in value over fixed rate policies, it leads to increased interannual catch variability. Walters and Parma (1996) found a modest effect of predictions, and found that a fixed fishing rate (constant fraction of stock caught) performs nearly as well as the optimal policy. In contrast Spencer (1997) found an optimal policy to outperform a fixed fishing rate policy in a model with nonlinear predation, indicating that models (and objectives) matter. Walters (1989) found that the value of forecasts decreases when quotas can be adjusted throughout the year as new stock information becomes available, and he found that the value of predictions degrades very quickly with reduced accuracy of forecasts.

Our findings will be consistent with the earlier findings for simple bioeconomic models. To gain a deeper understanding of the value of predictions, we utilize a result from the field of control theory for the case with a linear model and a quadratic criterion (LQ), e.g. Balchen et al. (1970). This result says that weights on predictions of disturbances in the policy should decline according to the eigenvalues (or inertia) of the optimally regulated system (without predictions). The intuition is that the more flexible the managed system is, the less time is needed to adapt to changing environmental conditions, and the less need there is for long-term predictions. Since our system is nonlinear and the criterion is asymmetric (not LQ), the LQ results cannot be applied directly. Therefore we find corresponding solutions to the non-linear problem. The policy turns out to be quite similar to the policy for the LQ case. Nearly all the weight is put on the forecast for the first year, with minimal weights on longer-term forecasts. While the potential for economic gain is small to begin with, it is quickly reduced when forecasts become less than perfect. These findings indicate that simplified harvesting strategies, which do not rely on all states of the environment, can be found with little loss in economic value. This is also what we find in numerical examples.

Our case is likely to indicate the importance of forecasts of environmental variation for demersal species in other regions of the world as well. In a broader sense, the article indicates how other economic decisions subjected to uncertain forecasts of disturbances could be analyzed. Note however that by using optimization, we assume that the forecasts are being used to their full potential. In real situations managers are not likely to make perfect use of forecasts. Hence our methodology may overestimate the value of forecasts.

Section 2 presents the fishery model and three different models (cases) of environmental variation. Section 3 presents the method used. First we discuss solutions to the linear-quadratic (LQ) case and then we present the optimization method used, stochastic optimization in policy space (SOPS). Section 4 presents the results and section 5 concludes.

2. Models of bioeconomics and environment

We want to maximize the infinite horizon expected net present value

$$J_\infty = E\left[\sum_{t=0}^{\infty} r^t p_t\right] \tag{1}$$

for the fishery by seeking a feedback policy for harvest or total quota. Here r is the discount factor. Yearly profits are given by

$$p_t = ph_t - \int_{s_t}^{x_t} \frac{c}{x^b} dx = ph_t - \frac{c}{(1-b)}\left(x_t^{(1-b)} - s_t^{(1-b)}\right) \tag{2}$$

Revenues are given by a fixed price p times harvest h_t. The cost per unit effort is given by c and the catch per unit effort is given by x^b, where x denotes the instantaneous size of the fish stock. Total costs are found by integrating over the interval from the escapement level $s_t = x_t - h_t$ to the pre catch stock level x_t (Clark (1985). Since most of the cod is exported at a fixed price, we maximize national income and not the domestic consumer surplus. This choice also makes it easier to compare our findings to earlier results by Reed (1979).

The stock dynamics evolve according to the following time-discrete stochastic surplus growth model, Schaefer (1957):

$$x_{t+1} = ((r+1)s_t + as_t^2)(1+w_t) \geq x_m \tag{3}$$

with parameters r and a. The influence from the environment is represented by w_t. This variable represents variations in recruitment, weight growth, and natural mortality including predation. The parameter x_m denotes a lower limit for the stock to avoid extinction or negative stock values in case of extreme negative outcomes for w_t. Parameter values are based on estimates for Northeast Arctic cod, see Table I.

We make three different assumptions about the environment in order to examine the importance of forecasts.

Case 1. First we make the standard assumption that w_t is identically and independently distributed (i.i.d.), as in e.g. Reed (1979).

$$w_t \sim N(0, s_w) \tag{4}$$

The standard error of w_t is found when estimating Equation 3, s_w=0.15. Case 1 disregards observed tendencies towards autocorrelation.

Case 2. We describe the environment by an autonomous model that produces a pure sine-wave, a model which disregards observed irregularities.

$$w_t = b_1 w_{t-1} + b_2 z_{t-1} \quad (5)$$

$$z_t = w_{t-1} \quad (6)$$

The choice of parameters $b_1$and b_2 and initial values w_0 and z_0 is such that the model produces a sine-wave with constant amplitude (there is no disturbance term). Two states are needed to produce a cycle with an optional period. Thus the basic model with its state x_t is augmented with the two states w_t and z_t (or w_{t-1}). When we find the optimal harvesting strategy as a function of all three states, we will assume that w_t and z_t are measured perfectly.

Consistent with observed recruitment cycles of Northeast Arctic cod, Hannesson and Steinshamn (1991), we choose a period length of 8.4 years. The amplitude is set such that the standard deviation of the environmental disturbance w_t becomes 0.15, i.e. equal to the value of s_w assumed above. Parameter values and initial conditions (w_0 and z_0) are shown in Table I. The phase shift parameter n is drawn from a uniform distribution such that the sine-wave will start anywhere in the range 0 to $2p$. Using Monte Carlo simulations, the variable phase shift makes the sine-wave case more similar to the case with pure random noise, which is random also in the initial year.

In this second case, we interpret w_t to represent temperature in the Barents Sea, an environmental variable which is measured with good accuracy. Temperature variations in the Barents Sea seem to fluctuate systematically with earth nutation and are correlated with the North Atlantic Oscillation, Yndestad (1999b). The pattern however is not perfectly described by a simple sine-wave.

That temperature (and correlated inflows of water into the Barents Sea) is important for cod is indicated by several studies. Fluctuations with similar frequencies to the ones for temperature are found in the dynamics of Northeast Arctic cod, Yndestad (1999a), and in the recruitment data, Hannesson and Steinshamn (1991). Temperature is found to be important for recruitment of cod (Ottersen and Sundby (1995)), weight growth of cod (Michalsen et al. (1998)), spatial distribution of cod (Helle and Pennington (1999) and Ottersen et al. (1998)), and growth of prey species (Ottersen and Loeng (2000), Skjoldal et al. (1992), and Sundby (2000)).

Case 3. We use a model estimated on actual data. Using temperature data for September[4] we get the following result (p-values in parentheses)

$$\underset{}{T_t =} \underset{(0.006)}{0.34T_{t-1}} - \underset{(0.28)}{0.13T_{t-2}} + \underset{(0.000)}{3.89} \quad (7)$$

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[4] September temperatures (Kola meridian) are likely to be the most representative monthly temperatures for cod growth. The September temperature is highly correlated with temperatures in the months June, July, and October (on average r=0.92), months of great importance for prey growth (plankton, capelin etc.). The September temperature is also highly correlated with the spring temperatures in the spawning grounds in northern Norway (water flows from the spawning grounds towards the Kola meridian).

A large proportion of the temperature variation is not systematic and must be considered random noise (standard error of 0.46 ^{o}C as compared to an average temperature of 4.92 ^{o}C). Thus the purpose of the case 2 sine-wave model is primarily to indicate an upper limit for the usefulness of perfect forecasts. The model in Equation 7 on the other hand may not be the best one we could produce, the R^2 is only 0.11. Allowing for earlier lags we find that the R^2 does not increase above 0.11 if $T_{t\text{-}3}$ is included, it increases to 0.18 if $T_{t\text{-}4}$ is included, and it hardly increases above that level when four more lags ($T_{t\text{-}5}$ to $T_{t\text{-}8}$) are included (R^2=0.19). Thus, when we rely on the model in Equation 7 we are likely to undervalue the usefulness of forecasts, i.e. we establish a lower limit for the usefulness in our bioeconomic model.

In order to get the same standard deviation of the environmental disturbance w_t as in the previous cases, we use the following description in the model

$$w_t = 0.34 w_{t-1} - 0.13 w_{t-2} + e_t \qquad (8)$$

where

$$e_t \sim N(1, s_e) \qquad (9)$$

The standard deviation (s_e=0.143) for e_t is set such that the standard deviation for w_t becomes equal to what was assumed in the previous cases, s_w=0.15. In this connection remember that disturbances in the net growth of cod are not only caused by measurable temperatures, other factors also contribute to variations. Initial states x_0 are given by a uniform distribution and initial values of the disturbance states, w_0 and z_0, are given by normal distributions.

Table I: Model parameter values and initial values from (Moxnes (forthcoming)).

Name	Value	Name	Value
c	3.0	r	0.95
p	6.0	s_w	0.15
r	0.75	s_e	0.143
a	-0.18	b_1	1.466
b	0.6	b_2	-1.000
x_m	0.05		
x_0	U(0.5,4.0)	n	U(0,1)
Case 2, w_0	$\sqrt{2}s_w \sin(2pn)$	Case 3, w_0	N(s_w,1)
Case 2, z_0	$\sqrt{2}s_w \sin(2p(n-1/T)$	Case 3, w_{-1}	N(s_w,1)
T	8.4		

3. Method

First we describe shortly the solution to the optimization problem for the LQ case. Next we show how stochastic optimization in policy space (SOPS) can be used to solve the nonlinear and asymmetric case (not LQ) for the three different assumptions about the description of environmental disturbances.

We simply refer the basic results for the LQ case as they are presented in Balchen et al. (1970). To find the optimal solution, they explicitly model the process that produces the disturbances (e.g. Equations 5 and 6 or Equation 8). The original model and the disturbance model forms an augmented model. Since in their case the problem is still LQ, it follows immediately that the optimal control is a linear function of all current states.

$$u = G_1 x_1 + G_2 x_2 \qquad (10)$$

where x_1 denotes the states of the original system and x_2 denotes the states of the disturbance process. Balchen et al. show that the feedback from the original states is the same as in the case with no disturbance (the matrix G_1 is not changed by the augmentation of the model). (This solution requires that both the original states and the states of the disturbance process are measured perfectly.)

Balchen et al. also show an alternative solution where the optimal policy is found as an explicit function of predictions of the disturbance *w*. The solution can be written

$$u = G_1 x_1 + G_{21} \int_t^{\infty} e^{\Lambda_U (t-t)} G_{22} w(t) dt \qquad (11)$$

where G_1 is the same matrix as in Equation 10, and G_{21} and G_{22} are constant matrices. L_U is a diagonal matrix with the eigenvalues for the optimally controlled system without disturbances. That is, $u=G_1x_1$ is included in the system description such that the equation for this system reads

$$dx/dt=Ax_1+BG_1x_1=Ux_1 \qquad (12)$$

where *A* and *B* are the system matrices. With negative eigenvalues, the formula in Equation 11 puts declining weights on future values of the disturbance *w*. The weights decline rapidly for a system with little inertia (implying large values of L_U) and vice versa. While it is usually unrealistic to assume perfectly known disturbances for ever, Equation 11 gives deep insight into the importance of making perfect long-term predictions. Clearly, systems with little inertia when policies are in place, are not in need of long-term forecasts.

To get a first indication of the importance of long-term forecasts for our fishery problem we start by writing down the optimal policy for the case without forecasts. This is a (non-linear) constant target escapement policy, Reed (1979):

$$h= g(x-x^*) \geq 0 \qquad (13)$$

where *g* is a constant equal to 1.0 and x^* is the escapement level. We only consider the linear portion of the policy when $x>x^*$. (The case with $x<x^*$ is not very interesting because for low values of *x*, the harvest will equal zero no matter what the forecasts look like.) Next we reformulate the stochastic difference equation model (Equation 3)

into a deterministic differential equation, using a simple first order approximation ($dx/dt=(x_{t+1}-x_t)/1$).

$$dx/dt=(r+1)(x-h)+a(x-h)^2-x \qquad (14)$$

Then we insert for h from Equation 13 and differentiate to find the system matrix

$$U=l_U=r-rg+2a(x-g(x-x^*))(1-g)-g, \qquad x>x^* \qquad (15)$$

Since our system is one-dimensional, U is a scalar and thus equal to the eigenvalue l_U. With an optimal policy of g=1.0 in place, the equation collapses to l_U=-1.0. Thus the forecast of the environmental disturbance one year ahead in time is weighted by 0.37 relative to the current disturbance, the forecast two years ahead is weighted by 0.14 etc. The following method will be used to find out if these findings hold up when we depart from this linearized case.

The fishery model augmented by the disturbance process represents a third order non-linear system with an asymmetric objective function, i.e. not LQ. For this type of problem, dynamic programming is the standard method to find optimal policies. Before we go on we note a couple of peculiarities regarding our problem. First, when the disturbance is a pure sine-wave, only an ellipse of the state space for w_t and z_t is visited, see illustration in Figure 1. Second, in addition to finding a feedback policy which depends on all current states, we also want to find an approximate policy which depends on future predictions rather than the current states of the disturbance model. For these reasons we see standard dynamic programming as less practical than an alternative method which we have readily available.

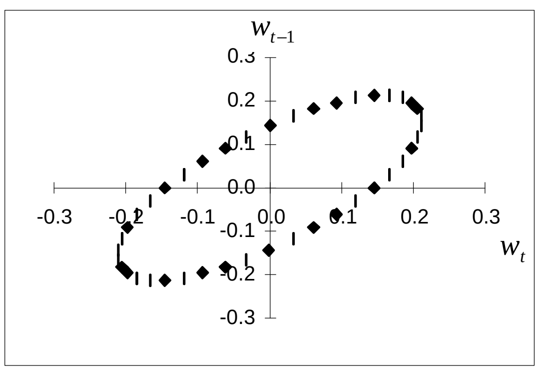

Figure 1: Phase plot for w_t and w_{t-1} when disturbance model produces a pure sine-wave.

The method is stochastic optimization in policy space (SOPS). The practical implementation of the method used here is described in detail in Moxnes (forthcoming), otherwise see e.g. Walters (1986), Polyak (1987), Ermoliev and Wets (1988), Gaivoronski (1988), and Bertsekas and Tsitsiklis (1996). Broadly, the method transforms the problem of stochastic dynamic programming into a problem of deterministic nonlinear optimization. I.e. maximize

$$J(q) = \frac{1}{M}\sum_{m=1}^{M}\left[\sum_{t=0}^{T} r^t p_t\left(x_t, h_t\right)\right] \tag{16}$$

where $J(q)$ is a Monte Carlo estimate of the infinite horizon expected net present value J_∞ with M Monte Carlo runs over T years, and where q is a vector of policy parameters in the harvesting or quota strategy

$$h_t = h\left(x_t, q\right) \geq 0 \tag{17}$$

For logical reasons, the harvest is restricted to positive values. The system model used in the Monte Carlo simulation is as described in section 2. Just note that the random variables w_t in Equation 4 or e_t in Equation 8 are changed to respectively w_{tm} and e_{tm}. Thus besides varying with time t, the random variables also vary over Monte Carlo runs m. The same sequence of random variables (same seed) is used for each evaluation of $J(q)$. This assumption makes the search problem deterministic. M=500 and T=50. By restricting ourselves to infinite horizon problems (sufficiently well approximated by T=50), time is left out of the policy function.

The optimal solution is a nonlinear function of the current values of all the state variables. Apriori we do not know what function characterizes this solution. Therefore we rely on a flexible policy function, which does not restrict the solution very much. The flexible policy is based on interpolation between grid points. Even though we are mostly interested in a three-dimensional harvesting policy, we start by explaining the procedure in one dimension. The policy h_t is given by

$$h_t = q_i(i - (x_t - j)/d) + q_{i+1}((x_t - j)/d - (i-1)) \geq 0 \tag{18}$$

where j is the location of the first grid point, d is the distance between grid points, and the policy parameter q_i denotes harvest at grid point i, where i is determined by

$$1 \leq i = \text{int}((x_t - j)/d) + 1 \leq 4 \tag{19}$$

Compared to the discrete representation in dynamic programming, we note that the state variable x_t and the policy h_t are continuous variables. The grid points denote the kinks in the piecewise linearized policy. Five grid points are used, and we note that the formulas extrapolate beyond the end grid points. In the two dimensional case, when the states are denoted $x_{1,t}$ and $x_{2,t}$, the policy h_t is given by

$$\begin{aligned} h_t = {} & (q_{i,j}\{i - (x_{1,t} - j_1)/d_1\} + q_{i+1,j}\{(x_{1,t} - j_1)/d_1 - (i-1)\})(j - (x_{2,t} - j_2)/d_2) + \\ & (q_{i,j+1}\{i - (x_{1,t} - j_1)/d_1\} + q_{i+1,j+1}\{(x_{1,t} - j_1)/d_1 - (i-1)\})((x_{2,t} - j_2)/d_2 - (j-1)) \geq 0 \end{aligned} \tag{20}$$

where the policy parameter $q_{i,j}$ denotes the value of h_t at grid point ij, where i and j are determined by

$$1 \le i = \text{int}((x_{1,t} - j_1)/d_1 + 1 \le 4 \quad (21)$$

$$1 \le j = \text{int}((x_{2,t} - j_2)/d_2 + 1 \le 4 \quad (22)$$

The policy surface over one cell of the two dimensional grid is illustrated in Figure 2. Harvesting in each of the corners is set independently by the values of $q_{i,j}$. If the observations $x_{1,t}$ and $x_{2,t}$ fall within the shown grid cell, the policy value for this combination of inputs is found as illustrated by the dashed lines. Two interpolations are performed in the x_1 direction (for x_2 equal to 0 and 1). The results are used to establish the dashed line lying in the policy surface. A last interpolation along this line in the x_2 direction produces the sought after policy value. With several grid cells, policies for adjacent cells will intercept along a common surface border line, e.g. the line given by q_{12} and q_{22}. Hence the entire policy surface will be continuous but not differentiable. Beyond the outer cells of the grid, the formula extrapolates. Note that the individual cell surfaces are not restricted to planes.

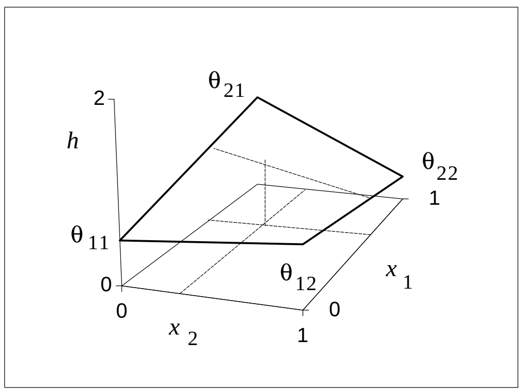

Figure 2: Illustration of the policy surface over one grid cell.

Policies for the three dimensional case can be found by the same logic. The above procedure for the two dimensional case is performed for two values in the x_3 direction, e.g. for x_3 equal to 0 and 1. Then one interpolates between the two policy values found in the x_3 dimension. Higher order policies are found similarly by doubling the previous effort and interpolating in the last dimension. Thus the number of policy parameters in each cell grows exponentially with the dimension.

A standard nonlinear search technique (Fletcher-Powell variable metric) is used to find the policy parameters q. The search routine provides accurate parameter values judged by variations between repeated searches with different starting points for the parameter set q_0. Naturally, accurate parameters are only found in subsets of the state space that are visited (e.g. the ellipse in the w_t and z_t space) and where the policy is of importance for the criterion. By varying starting points q_0 we increase the probability that a global optimum is identified.

4. Results

First we find the optimal policy $h(x_t)$ for the standard case with random, unpredicted disturbances (Equation 4). Table II (and Figure 3) shows that by using SOPS we replicate and quantify the constant target escapement policy found by Reed (1979). The slope deviates slightly from 1.0 within each grid cell (q_i-q_{i-1}). This reflects that the policy adapts to the particular outcomes of the random variable over the M=500 Monte Carlo simulations. As a further test of the importance of the particular outcomes of the random variables, we find the solution for a policy which depends on the entire augmented state vector, $h(x_t,w_t,z_t)$. Since the random variable in this case is independent from time to time, the only reason why the policy should give a better result is the increased ability to adapt to the particulars of the outcomes. We find J equal to 55.87, i.e. only marginally higher (0.03 percent) than what was found for $h(x_t)$. As expected the policy comes out as independent of w_t and z_t.

Table II: Policy parameters q_i at grid point x_i and criterion values J. (Policy parameters for x_i=5 are not shown since they unreliable due to few observations in this range).

Case and policy		q_i [million tons]			J
x_i:	1	2	3	4	Billion NOK
Case 1: Random disturbances 1-dimensional policy	-1.3	-0.16	0.86	1.87	55.86
Case 1: Random disturbances 3-dimensional policy					55.87
Case 2: Sine-wave model 1-dimensional policy for Case 1	-1.3	-0.16	0.86	1.87	56.05
Case 2: Sine-wave model 3-dimensional policy					58.84
Case 2: Sine-wave model 1-dimensional policy, with forecast	-1.30	-0.12	1.00	1.84	58.79
Case 2: Sine-wave model 1-dimensional policy, no forecast	-1.31	0.14	0.82	1.58	56.78
Case 1: Random disturbances 1-dimensional policy, with forecast	-1.30	-0.15	0.85	1.85	57.56
Case 3: Estimated disturbance model 1-dimensional policy from Case 1	-1.3	-0.16	0.86	1.87	55.88
Case 3: Estimated disturbance model 3-dimensional policy					56.14

Next we consider case 2 where the disturbance model produces a perfect sine-wave with period of 8.4 years. The amplitude is such that the standard deviation of the sine-wave equals the standard deviation for the random disturbance in case 1. In both cases the expected value equals zero. First we simply apply the optimal policy for the case with random, unpredictable disturbances. The value of J becomes slightly higher than in the random case, 56.05 versus 55.86 (0.34 percent). Even though standard deviations are equal, a slight difference should be expected due to the remaining differences between the distributions. We use the J value of 56.05 as our reference when we next find the optimal three-dimensional policy for the augmented system, $h(x_t,w_t,z_t)$.

Table III shows the exact result in terms of the policy parameters q_{ijk}, (i represents the fish stock x_t, j represents w_t and k represents z_t). The solution is stable and not sensitive to starting values q_0 with the exception of all parameters that are not in the neighborhood of the ellipse in the w_t and z_t plane. From Table II we see that the three-dimensional policy for the augmented model yields an expected net present value 5.0 percent above the value produced by the constant target escapement policy. Since this policy builds on perfect knowledge and measurements of disturbances, it represents an upper limit for improvement in this case.

Table III: q_{ijk} at grid points x_t, w_t, and z_t. 3-dimensional policy, case 2 sine-wave model.

		x_i				
w_t	z_t	1	2	3	4	5
-0.2	-0.2	-0.85	0.14	1.12	2.12	3.28
-0.1	-0.2	-1.23	-0.26	0.67	1.71	3.15
0.0	-0.2	-1.25	-0.76	0.56	1.38	3.06
0.1	-0.2	-0.99	0.16	0.80	2.08	3.28
0.2	-0.2	-1.12	-0.04	1.24	2.09	3.24
-0.2	-0.1	-0.51	0.48	1.45	2.48	2.88
-0.1	-0.1	-0.55	0.23	0.71	1.98	2.94
0.0	-0.1	-0.83	-0.43	0.45	1.57	2.76
0.1	-0.1	-0.93	-0.62	0.38	1.24	3.00
0.2	-0.1	-0.84	-0.26	0.60	1.46	3.17
-0.2	0.0	-0.30	0.72	1.85	2.43	3.14
-0.1	0.0	-0.51	0.55	1.59	2.70	3.30
0.0	0.0	-0.95	-0.12	1.15	1.89	2.97
0.1	0.0	-1.25	-0.57	0.38	1.50	2.72
0.2	0.0	-1.00	-0.61	0.17	1.23	2.76
-0.2	0.1	-1.23	0.65	1.01	1.84	2.80
-0.1	0.1	-0.52	0.65	1.56	2.58	3.07
0.0	0.1	-0.85	0.38	1.38	2.23	2.85
0.1	0.1	-0.82	-0.02	0.99	1.65	2.88
0.2	0.1	-1.14	-0.60	0.40	1.39	2.55
-0.2	0.2	-1.22	-0.21	0.75	2.27	3.02
-0.1	0.2	-1.27	0.09	1.34	2.01	2.98
0.0	0.2	-1.28	0.33	1.32	2.55	2.77
0.1	0.2	-0.93	0.00	1.04	2.00	3.12
0.2	0.2	-1.28	-0.38	0.60	1.62	2.61

Table III has all the details, however it is tiresome to interpret. Therefore the policy is illustrated in two dimensions in Figure 3 together with the constant target escapement policy for the case with random disturbances. The arrows indicate the direction of the movement. When the stock is low, harvest equals zero because a period with rapid growth is expected. As the stock starts to decline, the harvest is kept high because a period with low growth is expected.

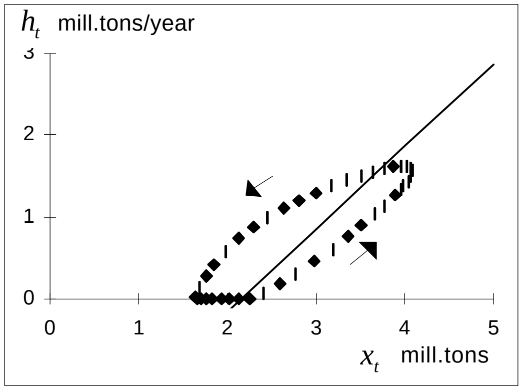

Figure 3: Constant target escapement policy (solid line) and trajectory of optimal policy (squares).

Figure 4 shows the same pattern along the time axis (thick lines): the harvest is low before the period with rapid growth in the stock etc. This figure also show the development for the constant target escapement policy (thin lines). In both cases the sine-wave disturbances are the same and they are in phase with each other. Clearly, the optimal policy leads to a more volatile fishery. Measured by the standard deviation of the harvest, the optimal policy leads to an increase in the variability of 38 percent (from 0.45 to 0.63 million tons per year). If the model had included costs of variability, marginal unit costs increasing with effort, or prices which decrease with increasing supply, the variability would not have increased as much, and the benefits of forecasts would probably be smaller.

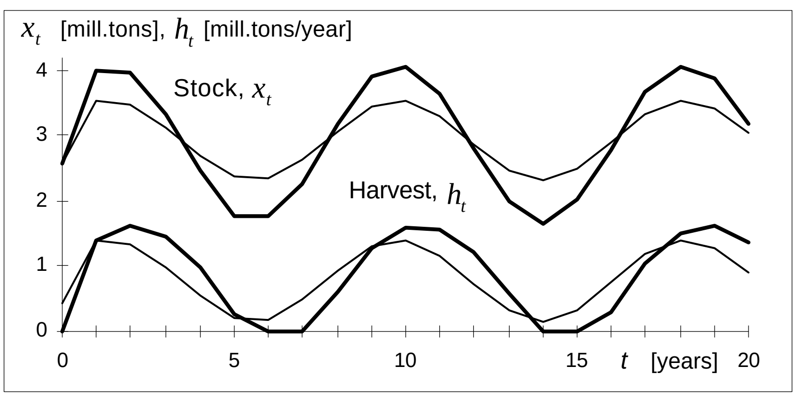

Figure 4: Stock size (upper two curves) and harvests (lower two curves). Optimal policy (thick lines) and constant escapement policy (thin lines).

Next we test a simplified harvesting policy inspired by Equation 11 for the LQ problem, i.e. instead of using a three-dimensional policy we use a policy with weights on (perfect) forecasts of future disturbances. One reason for doing this is that this formulation drastically reduces the number of policy parameters to be searched for. We measure the loss in terms of the reduction in the expected net present value J. A second reason is that we want to get an impression of how far into the future it is important to make forecasts. We use the following adaptation of Equation 11:

$$h_t = h(x_t + \sum_{k=1}^{H} q_{w,k} w_{t+k}) \tag{23}$$

Within the parenthesis we maintain a linear relationship, where the policy parameters $q_{w,k}$ put weights on future disturbances w_{t+k}. The time horizon is denoted by H. To take account of the fact that the problem is not LQ, we search for a nonlinear function h using interpolations as in Equations 18 and 19. By this choice we allow for a variable target escapement type of harvesting policy. Since our choice of policy function puts some restrictions on the policy, we do not expect it to produce a fully optimal solution.

We start by searching for parameters using case 2, the sine-wave model. Since the sine-wave is perfectly autocorrelated, we do not get improvements in the criterion when forecasts beyond w_t is used. Thus this case is not suited to estimate weights on forecasts of future disturbances. However, this case is interesting because we are able to compare the result to the truly optimal results produced above. Table II shows the resulting policies and criterion values. The weight on the one-year forecast of the disturbance is $q_{w,1}$=-2.90 (not shown in the table). Interestingly, the criterion is only reduced by 0.08 percent by using the simplified forecasting model, J equals NOK 58.79 billion as compared NOK 58.84 billion for the three dimensional policy. This is promising with regard to simplification.

Note that it is not only the inclusion of the forecast that leads to the good results when using the policy in Equation 23. Also the adaptation of the policy, which is now nonlinear, contributes to the criterion. Table II shows that compared to the constant target escapement policy for Case 1, harvest is higher at low stock levels and lower at high stock levels. This is consistent with the tendency seen in Figure 3 (the squares).

To get a better indication of the pure effect of using a forecast in case 2, we repeat the last search without the forecasts ($q_{w,k}$=0 for all k). Table II shows that the resulting value of J is still 1.3 percent above the value obtained with the constant escapement policy, NOK 56.78 billion versus NOK 56.05. Hence the nonlinearity makes a difference. The table shows that in the case with no forecast, the policy deviates even more from the constant target escapement policy.

Now we turn back to the case with random disturbances, case 1, and allow for forecasts in the policy (Equation 23). For illustrative purposes we make the highly unrealistic assumption that random events can be forecasted perfectly. From the preceding tests we expect a criterion value close to the truly optimal one, and we expect an improvement above the no forecast case of around 3.5 percent (Case 2 with one-dimensional policy, forecast versus no forecast). These numbers serve to indicate the validity of the ensuing results since we do not know the truly optimal policy for case 1.

Table II shows that in the case with random disturbances the forecasts lead to an improvement in the criterion of 3.0 percent (from NOK 55.86 to 57.56 billion). This is quite close to what was obtained in case 2 (3.5 percent) and we see little reason to suspect that the obtained result is very far from the truly optimal solution. Table II shows that the policy is still a constant target escapement policy. This must reflect the lack of autocorrelation in w_t as compared to the sine-wave case.

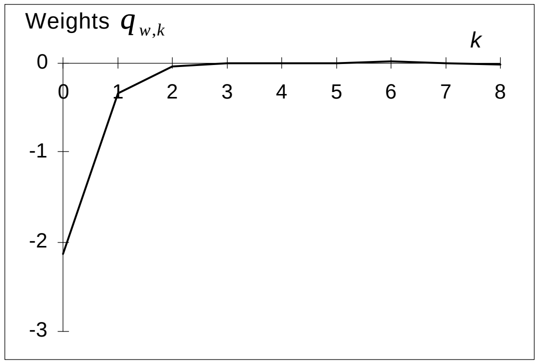

Figure 5: Weights $q_{w,k}$ on forecasts of disturbances w_t.

Figure 5 shows how the weights on forecasts decline with the time horizon.[5] In this case the estimates are very stable over repeated searches as one should expect in a case without autocorrelation. Relative to the weight on the one year forecast, the weight on the two year forecast (k=2) is 16 percent and the weight on the three year forecast is 2 percent.

The weights are similar to what was indicated by the analysis in Section 3, i.e. an eigenvalue around -1.0. Clearly, there is little use for forecasts with a time horizon beyond 1 or 2 years. If we repeat the preceding search with a time horizon of H=1, the criterion value drops by only 0.07 percent compared to the case with H=9 years. Again this indicates that simplification is warranted.

Finally we turn to case 3, where we use a model of the disturbance (temperature) that is based on time series estimates, Equation 8. When we use the constant target escapement policy from case 1 and no forecast, this model yields an expected net present value of NOK 55.88 billion (approximately the same as for case 1 with pure noise). Augmenting the fishery model with the estimated disturbance model and using a three dimensional policy, we find that the criterion value increases by 0.46 percent to NOK 56.14 billion. That is a small improvement. Even if the model had been twice as good at predicting disturbances, the potential for improvement should be considered small. Most certainly it is not worthwhile to use a three-dimensional policy. The policy in Equation 23 with a one year forecast will capture most of the rather small potential for improvement.

5. Conclusion

In this article we have tried to understand and quantify the value of forecasts of disturbances in a fishery model. The received literature already provides solutions for cases with linear models and quadratic criteria (LQ). Here we have used optimization in policy space (SOPS) to find solutions for a nonlinear fishery model with an asymmetric criterion (not LQ). To find optimal harvesting policies we augmented the original fishery model with a model of the disturbance process.

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5 Minor deviations from zero at high values of k are due to the particulars of the random sequences.

For a model of Northeast Arctic cod we find that there is a certain potential for value improvement in case disturbances can be forecasted perfectly, a between 3 and 5 percent increase in expected net present value. Most of this potential (99.9 percent) can be captured by a simplified harvesting policy, where only a forecast for the coming year is used. Using a less than perfect, however estimated forecasting model for temperature, assuming temperature is the only disturbance, reduces the potential improvement to less than one percent. Again most of the potential could be captured by a simplified policy. Furthermore, our use of optimization may lead to overoptimistic expectations regarding the direct value of forecasts used in real decision making. Practical decision making is not likely to reap the full potential of forecasts. Also note that effort spent on forecasting takes resources away from strategy formation, and one may wonder whether the whole process of forecasting may distract the process of policy design. In this regard, keep in mind how difficult it is to come up with near-to-optimal strategies for stochastic, dynamic, nonlinear problems. Thus one may wonder if resources diverted to forecasting gives as high a return as other activities pertaining to policy making.

The identified effect of forecasts on harvesting is intuitively appealing. If fish growth is expected to be high in the next year, harvesting is reduced for the moment. The fish left in the sea experiences a higher than normal growth and more can be harvested later. Expected growth below normal implies increased harvest for the moment. Forecasts beyond one year are of little or no value as long as it takes little time to adjust the fish stock through harvest, i.e. when the managed system is flexible.

Several aspects of the problem at hand are topics for further research. Including capacity restrictions and investment delays in the model makes the system less flexible and could imply that longer term forecasts become more valuable. Our results may also be sensitive to the choice of bioeconomic model and the inclusion of measurement error. Regarding predation, the method used here could be used to find harvesting policies for cod in light of forecasts of prey species like capelin. However, since there is feedback from cod to the prey species, while there is no such effect of cod on climatic variations, this problem is better dealt with within a multispecies framework. Furthermore, the method can be used to investigate the economics of stabilization. The policies found here typically increase the variability of harvests and efforts. By putting weight on effort variation in the criterion, and by including increasing marginal unit costs and prices that depend on harvest rates in the model, the costs of acting according to forecasts would increase. Probably the value of forecasts would decrease.

The results obtained for our case imply that there is little value in long-term forecasts of climatic variation for management purposes. This is true even if near-to-perfect forecasts could be produced from stable oscillators like the earth’s nutation. This does not mean that information about systematic variations in environmental variables is of no value. Time-series data of climatic variation can help reduce uncertainty in model parameter estimates. If only recent fishery data are available, model parameters could be biased since the environmental conditions are not representative for longer time periods and for the near-term future for which the model will be applied. Understanding cyclical tendencies is of course also valuable in itself and can contribute to better structure of fishery models in the future.

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