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Do Models Improve Fishery Management?

Empirical Evidence from a Experimental Study

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Keywords: Experiment, theory management

JEL classification: A11, C9,Q22.

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Do models improve fishery management? An experimental study.

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September 3, 1998

Abstract

We have constructed an experiment to test to what extent different types of model improves the management of a two-species fishery. Thus we are not trying to determine what models or tools are the best from a theoretical point of view. Rather we investigate the usefulnes of the models when applied in a practical management task. In particular we compare a simplistic stoachastic optimization model with a more complex one species model of the fishery. We find that both models lead to better management, and when applied together they strengthen each other. That is the models are complementary rather than the competing substitues that theoretical discussions might imply.

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1 Introduction

Models of different forms are the core tool of economic analysis. The advises economists give decision makers may represent general insights derived from stylized models. Alternatively, economists may construct complex large scale models to simulate the consequence of different policy option, often without any definite conclusion as to what option is best. The advice may also be based on some intermediate approach. Decision makers rarely follows these recommendations without alternation. Typically, they will blend the results from numerous analyses, focusing on different facets of the real world. To evaluate the usefulness of model based analyses, we would have to take into account how the information provided by the model is 'filtered through' the decision makers, and ask the question: 'Does the model improve the final decision made by the decision maker.' This is the question we will try to address in this paper.

To answer this question in general is not possible, but to get some insight into the problem, we will in this paper study a particular case. The case in question is the management of fish stocks in the Barents Sea. Even for this narrowly defined case, the usefulness of different models is hard to evaluate. Actual management is a consequence of the choice of many different decision makers, with possibly conflicting objectives. Each individual decision maker has access to several sources of statistics, and different models and model based studies. It is hard to identify the contribution from one particular model. Perhaps one could identify dominating schools of thought in different fishing regions of the world. In this case, however, differences among fishing grounds would complicate comparisons. To overcome these problems, we will in this study use an experimental approach.

We have not encountered similar experimental studies of the practical usefulness of models for social planning. A literature seems to be emerging in the management area. Oz, Fedorowicz and Stapleton (1993) point to the need for experimental studies to assess the benefits of experts systems. Cavaleri and Sterman (1997) and Verstegen et al. (1995) make similar claims for systems modelling and information systems. All three find positive effects of decision support. Webby and Oconnor (1994) find that the usefulness increases with task complexity, they also find no difference between a deterministic and a probabilistic decision tool.

We construct an experiment where students are asked to manage the stocks of cod and capelin in a computer-model of the fish stocks in the Barents Sea. Different students are given different models, or combinations of models. Comparing the results of different groups of students we are able to identify the contribution from each model.

2 The experiment

There is obviously a rich variety of two-species fishery models that could be used for the study, but to succeed in analyzing the results we have to restrict the set of models. We have chosen to focus on two different kinds of model concepts to aid decisions: a simplistic two species stochastic optimization model, and one complex deterministic simulation model consisting of two one-species models. Both models are simplified representations of the cod and capelin stocks in an encompassing and more complex two species model defining our virtual reality. We first describe the virtual reality and the two tool models, and then the experimental design.

2.1 The models

A model of cod and capelin in the Barents sea is taken as the 'virtual' reality. The virtual reality is represented by a two-species, predator-prey model. The model is documented in Moxnes(1992), with minor changes documented in Moxnes and Nyhus (1994). The model has cohorts for both species, both weight and population numbers are represented. Predation is modelled with saturation. Recruitments are random nonlinear functions of mature fish, and recruitment of cod is negatively affected by the amount of juvenile cod. Capelin is assumed to die after spawning. The two species are caught independently, and costs depend on fish density and fleet capacity utilization. The fishing gear for cod is more efficient for higher age classes than for lower age classes. The criterion reflects both infinite horizon present values with constant prices and social costs of unemployment in the two fisheries. The biological part of the model is to a large extent based on Tjelmeland(1990).

Two models were used for decision support. The first model was a deterministic version of the virtual reality, except that the linkage between the two stocks were broken, i.e. we used two one-species models. In all equations for capelin where information about the cod stocks was needed, an historical mean of the cod stock was used, rather than the model's own predicted cod stock, and vice versa. Otherwise, the model was identical to the virtual reality, and all parameters were identical to the parameters of the model describing the realty. Each year this deterministic model was used to make 4-year forecast of the two stocks. Two forecasts were presented, for cod corresponding to a yearly catch of either 15 percent or 30 percent of the total stock, while for capelin, the two forecasts were based on 40 percent and 80 percent catch. While the model made no suggestions about optimal policy, these forecasts may have been interpreted as an indication of a reasonable range for yearly catches.

The second model was a two species stochastic optimization model with capelin and cod. In continuous time, the growth equations are of Lotka-Volterra type[1]. The criterium to be maximized is net present value of future catches. The model parameters were estimated from data generated by the virtual reality. The optimization model gives the optimal policy in the form of target escapements, that is the optimal stock after the fishery season is over. (For a further description of this model and the solution algorithm, see Brekke (1996).)

The optimization model disregard much of the detailed information included in the virtual reality. Especially important is the exclusion of information about the year classes. The optimization incorrectly assumes that the two differential equations keeps precise track of the biomass. However, this assumption is false in that capelin that has spawned dies, and that juvenile cod and capelin are not included in the respective biomass mea-

[1]The growth of cod biomass T_t and of capelin biomass L_t is given as

$$\dot{T}_t = a' \left(\frac{\tilde{x}_t L_t^\alpha}{L_t^\alpha + \bar{L}} \right) T_t - \tilde{m}_t T_t - E_{Tt} T_t^{\beta_T}$$

and

$$\dot{L}_t = \tilde{r}_t L_t - m(L_t) L_t - a \left(\frac{\tilde{x}_t L_t^\alpha}{L_t^\alpha + \bar{L}} \right) T_t - E_{Lt} L_t^{\beta_L}$$

Where r is recruitement, m is mortality, and E is catch effort. $\tilde{x}$ is a stochastic variable determining predation. $a, a', \bar{L}$ and β_i, $i = T, L$ are parameters. Stochastic variables are marked with a tilda.

The objective is to maximize net present value of future catches until time τ plus the value of remaining biomass

$$\max \int_0^\tau \left[p_{Tt} E_{Tt} T^{\beta_T} + p_{Lt} E_{Lt} L^{\beta_T} - c_L E_{Lt} - c_T E_{Tt}) \right] e^{-\delta t} dt + S(T_\tau, L_\tau)$$

$S(T_\tau, L_\tau)$ is the value of remaining biomass at the end of the optimization period.

Figure 1: The experiment interface

sures. Hence, when a solution of the optimization is applied to the virtual reality model, oscillations easily occur.

The optimal target escapement for capelin was found to be 7.0 million tonnes, For cod the optimal target escapement depends on the stock of capelin, starting at 0.8 million tonnes at very low capelin stock, increasing linearly in capelin stock until it reaches 1.35 million metric tonnes, when the capelin stock reaches 5.0 million metric tonnes. For higher capelin stock the target escapement is constant at 1.35 million metric tonnes. The students that had access to this model were informed about the optimal target escapements.

2.2 Experiment design

In total 64 students participated in the experiment. Half of the students were from Bergen and the other half from Oslo. A three by three factorial design was used. The two types of decision support represents the first two factors. The third factor was the initial conditions, high or low stocks of both cod and capelin. The realization of the random variable varied among the subjects. However, the same 16 realizations were used for all four combinations of the two types of decision support. The realizations of the random variable will be viewed as a covariate.

The results from the two models were presented to the students in separate areas of the spread-sheet used for the experiment. The screen, as it appeared to students who got both instruments, is shown in Figure 1. The forecasts from the two one-species biological models were presented under the heading 'Help from a biological model', while the target escapements from the optimization model were presented under the heading 'advice from an economist.' In addition students were given information about estimated stock size, which were the true stock size in the virtual reality puss a random error term. They further got information about last years catch, costs, net income, and unemployment. The students had to fill in the fields for quotas, and press the next year button. Then updated information appeared on the screen.

When the students had repeated this for 25 years, the final payoff were given. This payoff reflects the present value of the income during the 25 years, plus the value of the stock at the last year, minus the cost of sector unemployment during the 25 years period.

For practical purposes we have chosen to use students for the experiment. Students are novices with respect to the actual management problem. Hence they do differ from experienced managers who are familiar with details of the analyses, and who know the positions of relevant interest groups. We can only speculate how students might behave differently from real managers. Novices with little knowledge of the system should benefit more than experts from the tools. Novices with a positive attitude towards analytical tools (as our subjects) should be expected to be less sceptical to the tools than managers. Real decision makers are presented with other goals, constraints, and information than the subjects in the experiment. They might even be presented with other, competing decision tools. Hence real decision makers are likely to put far less weight on the two selected types of decision support than inexperienced students. All these factors could imply that we should expect that the benefits of the tools are overestimated. On the other hand, lacking experience with the tools could also imply that they are not used to their full potential. While there are reasons to expect differences between students and actual decision makers, previous experiment indicate that they could be small and insignificant, at least when participating in the same experiments, see e.g. Moxnes (1998a) and Bakken (1993).

The task is complex in that two species are interconnected and the system is dynamic, non-linear, stochastic, and not fully known (ambiguous). It is know from experimental studies of such systems that misperceptions and mismanagement occur, see e.g. Sterman (1989), Moxnes (1998b) and Brehmer (1992). When complexity increases, decision makers typically rely on simplified, adaptive decision rules leading to degraded performance. Since we are not able to calculate the absolute maximum for each treatment, we do not conclude about any degree of mismanagement in absolute terms.

3 Econometric model

Let Z_i denote the payoff that person i achieved, and let Y_i denote the payoff he would have received had he used the proposal from the optimization model without adjustment. (This payoff can be computed irrespective of whether the person had access to the optimization model or not.) We assume that the payoff depends on wether the student had access to the simulation model, represented by the dummy S_i, the optimization model O_i or whether the initial stocks were high or low H_i. The payoff further depends on two stochastic variables. One representing the stochastic variables in the bioeconomic model, represented by the residual u_i and finally the management skill of individual i, represented by v_i. We thus assume

$$Z_i = \tilde{f}(O_i, S_i, H_i) + (1+e)u_i + v_i. \tag{1}$$

where e is some parameter to be explained below.

A similar model will apply to the payoff that i would have received if he had used the results of the optimization model without any adjustments, but then skill and access to the different models would not matter. Thus we define

$$Y_i = k'' + c'' H_i + eu_i. \tag{2}$$

To allow the bioeconomic uncertainties, represented by u_i, to have different impact on Y_i and Z_i we apply different parameters, $(1+e)$ and e respectively, but for simplicity normalized such that the difference is 1.

Let X_i denote the payoff in excess of what the player would get from following the suggestions from the optimization model without adjustments, i.e. $X_i = Z_i - Y_i$. Then

$$X_i = f(O_i, S_i, H_i) + u_i + v_i. \tag{3}$$

Note that according to this model

$$Z_i = aY_i + f(O_i, S_i, H_i) + u_i + v_i, \tag{4}$$

with $a = 1$. Testing the hypothesis $a = 1$ is thus a test of the model above.

The design of the experiment requires some special considerations on how to handle of the residual u_i. To reduce the noise in the comparison of models, we picked the same realization of the stochastic variable in the virtual reality for all different combinations of models. As 64 students was used in the experiments, and with four different combinations of models, only 64/4=16 different (and independent) realizations of the stochastic variables in the virtual reality was used. Hence there are only 16 different realizations of u_i while there is 64 realizations of v_i. Thus the total residuals $u_i + v_i$ are not independent. Still, estimating $\hat{k}''$ and $\hat{c}''$, we can approximate the residuals as

$$\widehat{eu_i} = Y_i - \hat{k}'' - \hat{c}''H_i \tag{5}$$

We then included this constructed variable as an explanatory variable in a regression version of (4). This turned out to have negligible effects on the results, and we thus only present the results for the simplest equation where $u_i + v_i$ are treated as independent residuals.

4 Empirical results

We first estimate equation (4) to test the hypothesis that $a = 1$. We find that $\hat{a} = 0.98$, and that $R^2 = 0.93$. The hypothesis is clearly not rejected. The other estimates were very equal to the ones given below. Thus the data are fairly consistent with the model above. We next estimated (5), to compute an estimate of eu_i as above. Including the estimated eu_i as a explanatory variable in (3) we found that $e \approx 10$. Hence more than 90% of the variation induced by the stochastic terms of the virtual reality model is included in Y_i. For the error term in the X_i-equation, we find that the variance of v_i is almost 20 times that of u_i, and this explains why the correlation in error term does not influence the estimate. This finding also implies that the variation in X_i, is mainly due to skill, and not luck, whereas the variation in total score Z_i is more due to luck than to skill, since $(1 + e)u_i$ has more than five times the variance of v_i.

Table 1: ANOVA results

	Estimate	t-ratio
Intercept	1972.6*	4.87
Optim.	1013.6*	2.51
Simul	1053.0*	2.61
High stock	-1170.7*	-2.90
Opt.*Sim	-221.7	-0.55
Opt.*High	850.2*	2.11
Sim.*High	-342.3	-0.85
All	-256.3	-0.64

To estimate the different effects we conducted an ANOVA analysis. This corresponds to a regression of X_i with dummies S_i, O_i, H_i, S_iO_i, S_iH_i, H_iO_i and finally $S_iH_iO_i$. The results are reported differently from the regression case, as deviation from the appropriate sample mean. Below, we will reinterpret them in terms of coefficients in a regression equation. Due to the experimental design, deleting any of the dummies will not affect any of the ANOVA estimates. There is thus no need to estimate different versions of the model.

All *-marked estimates are significant at a 5% level. There is a significant effect of access to either one of the two models. Moreover, compared to the advise from the optimization model, the students do worse when initial stocks are high. Finally, the benefit of the optimization model is higher when the initial stock is high. All the other estimates are clearly insignificant.

The ANOVA analysis is a special case of linear regression. The linear regression estimates may thus be derived from the ANOVA estimates. Including only significant parameters, we find the following linear regression result.

$$X_i = 1927 + 327 \cdot O_i + 2106 \cdot S_i - 4042 \cdot H_i + 3401 \cdot H_iO_i + u_i + v_i.$$

All these coefficients can be derived from the ANOVA results[2]. The effect of the simu-

[2]To se how there results can be derived from the ANOVA results, note that the estimates in the ANOVA analysis is the difference in average values between different subsets of the sample. Thus the average value of X_i for those with access to the simulation model is thus 1053 billion NOK higher than

lation model is significant, but there is no significant effect of interaction on the variable representing acess to the simulation model. Note that the intercept is not the sample mean, but the mean in the subsample with low initial stock and no tool. In the regression analysis the coefficient for O_i would not be significant. It is the combined effect of access to the optimization model and a low initial stock. Each of the two coefficients are significant, but we cannot conclude on the significance of the difference. All the other parameters from the regression are significant at a 5% level.

4.1 Discussion

To get an idea of the size of these coefficients, we compare with the average score when using the optimization model without adjustments, i.e. the average Y_i which is about 17.2 billion NOK. Most significant coefficients are thus in the range 10-20 % of the average score. Measured by the effect on X_i, the value of each tool is about 2 billion NOK. The development of the simulation tool is based on previous work and the cost hard to identify, but the optimization model was developed exclusively for this experiment, and the development cost was less than 0.2 million NOK. With this benefit measure the benefit to cost ratio thus exceed 10 000. Note that the payoff Z_i is calibrated to real life data, thus if the effect on X_i should resemble some of the real life benefits of such a tool, but we expect real life benefits to be far less, as in real life conflicts of interest, lobbying, and competition with already existing decision support tool would limit the benefits. Moreover, our perfect knowledge of the virtual reality simplified the task of constructing the tools, and hence their quality is too high to be realistic. Still we think that the experiment indicates that it is likely that the development of such tools will

the average for the whole sample. As half the sample has access to this model, this implies that the average for those who do not have the model is 1053 billion NOK below the total average, while 1053 above for those with access to the model. The total effect of access to the model is thus 2106 billion NOK. For the optimization model the connection to the ANOVA analysis is a bit more complex. When $O_i = 1$, and $H_iO_i = 0$, we have to add the effect of having the optimization tool (2×1013.6 billion NOK) and the effect of not starting at a high initial stock (2×-850.2 billion NOK). In total the effect of the optimization model with low initial stocks is 327. Similarly, the coefficient for high initial stock is combined, i.e.e twice the effect of high stock less the combination of high stock and optimization model: $-4042=2\times(-1170.7-850.2)$. The HO coefficient counts a combined effect, and the double effect of high and optimization should be counted twice ($3401=4\times850.2$).

defend it's cost.

To understand why the tools are useful, note first the positive intercept. Remember that X_i is the score exceeding what the suggestions from the optimization would have given. Thus the intercept measures how much better than the optimization model a student does without any model to help his decisions. Thus we find that the students, with no help from any model, get an average payoff of 1.9 billions NOK more than we would get from using the suggestion from optimization model. This is a bit striking. With no experience and no tools, and a low initial stock, the students outbeat the optimization model! Is then the model useless?

The ANOVA estimate of the importance of the optimization model suggests otherwise, but consider first the effect of the high initial stock. This coefficient is negative and significant, adding the intercept and the effect of high initial stock, we find that the expected score with a high initial stock is -2.1 billion NOK. Thus if the initial stock is high, the optimization model outbeat the average student with no tools.

To understand this finding, we need to understand the suggestion from the optimization model. The advice from the optimization model reflects that only for large capelin stocks is the capelin more valuable in the market than as food for the cod. Thus the optimal policy is to keep the capelin stock at or below 7.0 million tonnes. Another point is that for large stocks of cod, the stock will grow at a rate lower than the interest rate, and fishing will be optimal until the stock is at a level where the growth rate is equal to the interest rate. This is very roughly stated, obviously, costs have to be taken into account.

Suppose that the initial stocks are close to the optimal target escapement, and that the students follow a rule of thumb strategy to keep the stocks constant. (The discussion below indicate that this was the case to some extent.) This rule of thumb would then closely track the advise from the optimization model. If the students in addition were able to take the other objectives into account, we might have an explanation of why they outbeat the optimization model. On the other hand, if the initial stock is high, the rule of thumb is far from the optimal policy, and the optimization model outbeat the students. This is one possible explanation for this finding.

Next, how can we explain the ANOVA estimate that the optimization model is useful, while the regression result is that the coefficient for O is insignificant? A possible interpretation may be found along the same lines. Since there is a dummy OH for the combination of high initial stock and access to the optimization model, the coefficient for O measures the effect of the optimization model when the stock is low. Then, the rule of thumb is essentially equal to the advise from the optimization model. With a high initial stock, the true value of the optimization model is revealed. And we note that this coefficient is significant.

Is there any evidence that the students actually used such a rule of thumb. To test this we analysed whether the average stocks after 10-15 years, or alternatively 20-25 years, were influenced by the initial stock. Following an optimal strategy, initial transients should not be observed after 10 years time. In accordance with this, we find that there is no effect of initial stocks on later stocks of capelin. However for cod, the students who got high initial stocks kept a significantly higher cod stock both at 10-15 years and at 20-25 years of management. This supports the hypothesis that they included initial stocks as an element in their rules of thumb. Relying on historical stocks indicates that the subjects saw little scope for learning. We also found that those with access to the optimization model kept a significantly lower stock after both 10-15 year and 20-25 year. This supports the claim that the advice from the optimization model had an impact. Access to the simulation model had no significant impact on the stock.

Also the simulation model gives a significant contribution to the total performance. Why is the simulation model beneficial? The above results indicate that the simulation tool does not help to find a proper target for the cod stock. Nor do we find that the simulation tool helps stabilize harvests and keep unemployment low. (While the optimization tool contributes to a small and significant increase in unemployment, the simulation tool produces an even smaller and insignificant reduction in unemployment).

Based on our knowledge about the models, we suspect that the inclusion of cohorts in the simulation tool is what makes it most valuable, see Spulber (1985) and Mendelsohn (1978). The aggregation over cohorts in the optimization model implies that the following two situations are treated equally: First a situation with a given biomass and mostly old fish. Second a situation with the same biomass level but with mostly young fish. The simulation tool would indicate that future biomass levels are the most sensitive to harvesting in the second case. Hence it suggests a lower quota in the second than in the first case. (Note that the resulting strategy is not necessarily a stabilizing one in terms of quotas and employment).

Since the benefit of the simulation model is not significantly different from the benefit of the optimization model, we cannot say that one of the tools is better than the other. The following observations are of some importance for a closer comparison of the tools. While the optimization model is fit to the virtual reality as best as we could, the simulation model is an exact replicate of the biological part of the virtual reality, with the exception of the predation terms. Both models are applied to uncertain estimates of the stocks in the virtual reality. To simplify the programming, however, the simulation model was initialized each year with the exact same age distribution as the virtual reality. While the relative strength of age classes above the recruitment level are typically known more precisely than total stock levels, exact knowledge is an exaggeration. Hence, in terms of model accuracy, the study is biased in favour of the simulation tool. Whether this bias matters, depends on the sensitivity to model errors for the two tools. Finally we note that the simulation tool suffers from a lack of economic variables. With predictions of economic consequences of quota policies, it might have become easier for the subjects to search for profit maximizing strategies.

We could have achieved different results by using different tools and assumptions. The design is likely to have influenced the comparison between optimization and simulation, and between economics and biology. The choices made reflect rough approximations to two existing tools. Both tools prove to have positive effects in the experiment, and it seems possible to explain why this is so.

The two models compete for attention. In a setting like this experiment, the students only get a few minutes to assimilate the results from the models, while more profound insights may take months to comprehend. We would thus expect an effect of the competition for attention. If students can only assimilate the information from one of the models, adding a second model would not give extra benefit, as found in Moxnes (1998b). The estimation results indicate that the effect is indeed negative, but small and insignificant.

We are able to make simple tests of behaviour based on available time-series data for each subject. As reported above we found evidence of a permanent effect on stocks from the initial stocks. We further tested a simple model for each of the resources explaining quotas as a function of last years quota, own and other stock level, and unemployment in own fishery. We find no effect of either the stock level of the other resource or of unemployment, absolute t-ratios are all below 0.35. The stock level of own resource is highly significant for both resources, with an average t-ratio for all subjects of 7.9 for capelin and 5.4 for cod. Last years quota has average t-ratios of 2.2 and 3.0 respectively. Hence we find some evidence of a certain smoothing of the quotas. Average coefficients which are highly significant give the following equations for the two species: For capelin

$$K_{t+1} = 0.23K_t + (1 - 0.23)(0.32R_t + \text{const.}) \tag{6}$$

where K_t is quota in year t, and R_t is the resource stock estimate in year t. Similarly for cod

$$K_{t+1} = 0.30K_t + (1 - 0.30)(0.34R_t + \text{const.}) \tag{7}$$

The right-hand parenthesis has the interpretation of indicated quota, the rest of the equation describes how this indicated quota is delayed. Note that both quotas follow a rule which has a much lower slope (0.32 and 0.34) than the slope of 1.0 implied by the target escapement rule predicted by the optimization model for stock sizes above target escapement[3]. Interestingly, the observed behaviour deviates from the target escapement rule in the same direction as predicted by more elaborate optimization models valuing stability, increasing marginal costs, and measurement errors, Moxnes (1996) and Moxnes (1997).

The coefficients in (6) and (7) are estimated for all individual students. The ones reported above, are the averages. We have also studied how these coefficient varied between students, depending on treatment. We find two significant effects of the optimization model on the capelin management strategy. First, with high initial stocks, access to the optimization models increases the weight on current stock. Second, access to both the simulation model and the optimization model gives a higher weight on lagged quota. For

[3]If the subjects had followed a strict target escapement rule while the stocks fluctuated around the target, low slopes should be expected because we estimate a linear rather than a nonlinear model. (zero to the target and then increasing at slope one.) However, inspection of the individual data reveal that virtually no subject sets quotas equal to zero when the stocks are below the targets. The predominant pattern is a straight line.

cod management strategy, we find that access to the optimization results in management strategies with less weight on previous quota, and more weight on current stock. The negative effect on the weight of previous quota is reinforce with a high initial stock. All these results are in line with the results above.

The simulation model have no effect on the cod management strategy, but have an effect on the capelin management strategy, reducing the weight on last year quota, and reducing the weight on current stocks. A possible explanation is that the simulation model often predicted fluctuation in future stocks of capelin, and that this attracts special attention to the capelin management. As the simulation model presents forecasts, we may expect that it induces more forward looking behaviour, and thus reduces the focus on past quotas or current stock.

4.2 The questionnaire

A questionnaire before the experiment starts shows that nearly all the subjects have a sufficient understanding of what the criterion is. Two subjects writes that they are supposed to maximize quotas. Most subjects are also able to point out major differences between the virtual reality and the tools. However, a few subjects seem to bring in their own general ideas about differences between tools and realities.

The subjects were asked about their belief in models for the purpose of public management. On a scale from one to five the average rating was 3.5 (63 percent). In a post questionnaire, the students were asked about their willingness to pay (WTP) for having the tools available in case they were to repeat the experiment for another fishing area. On average the WTP for the optimization tool was NOK 53 and NOK 58 for the simulation tool. The difference is not significant. The WTP measures for the two tools were positively correlated. On average, all those who had one or two tools available in the experiment, had a total WTP for the two tools of 202 percent of the actual value of the two tools as measured by the experiment (significantly higher than 100 percent). Similarly, those who had no tool available had a relative WTP of 312 percent. If one can trust the WTP measures, there is a tendency to overestimate the value of both tools.

The subjects were also asked how useful the experiment would be as a supplement to ordinary education. The average rating was 4.0 (75 percent). When commenting, the subjects pointed out the value of getting practical experience with the tools, of experiencing uncertainty, complexity, and dynamics which are often assumed away in education, and the value of experiencing the need for strategy and familiarity.

When asked to what extent they tried to smooth fisheries from year to year, the average rating was 3.2 (57 percent), with no significant difference between the tools. When asked to what extent they tried to stabilize the resources at the level in the initial year, the average rating was 2.5 (38 percent). With the optimization tool available, the average was 2.4 compared to 2.7 when it was not. The difference is not significant.

5 Conclusion

We have performed a laboratory experiment to investigate the practical usefulness of two decision tools to aid quota setting for cod and capelin. An optimization tool was chosen to reflect economic literature on two-species management under uncertainty, while a simulation tool was used to represent biological single species models. In total 64 students were asked to manage a virtual fishery with or without access to the tools.

The tools turned out to have approximately the same positive effect on management, but the models were useful for different reasons. The optimization tool helped the subjects to identify appropriate target stocks. When the optimization tool was lacking, subjects tended to equate the target with historical stocks. The simulation tool had a slight stabilizing effect. However, we speculate that its major beneficial effect resulted from its cohort structure. On average, access to one or two tools helped increase the score by 18 percent.

For the particular laboratory setting we conclude that the two tools are not substitutes as a narrow methodological focus might imply. Rather the tools appear to be complements. Moreover, the tools have moderate rather than crucial impacts. This might come as a surprise, at least for the students who overestimated strongly the value of the tools.

Can we generalize from the laboratory results?

- First, as found in previous studies, the benefits of tools are likely to depend on the complexity of tasks and the quality of tools. Hence the experiment is of little value with respect to predicting the value of other tools. Nor can the experiment be used to make general conclusions about simulation versus optimization and economics versus biology.

- Second, it might even be problematic to generalize from the experiment to the actual management of cod and capelin in the Barents Sea. If real managers have a better intuitive grasp of the management problem than students, the potential for the tools is reduced. If real managers are pushed by interest groups, while being uncertain about their own intuitive strategies, the tools could have a greater potential in reality than in the laboratory.

- Third, it seems likely that tools tend to be complements rather than substitutes, if the tools attack different subproblems. Complementarity could also follow from differences among decision makers, for whom it might matter how a story is told. For instance among decision makers with different educational background.

- Fourth, decision makers are not likely to follow advises closely. For instance, most of those who received the optimization tool only, were far from using an exact target escapement policy. In the experiment, adjustments tended to improve the results. This might not always be the case. Hence one should be careful in infer practical usefulness of a model from its theoretical properties.

A possible question for future research is wether similar conclusions on the usefulness of different types of models hold in a more general context and with other management problems. This one experiment is not sufficient to draw general conclusion as to the usefulness of optimization models versus simulation models. The usefulness of a model obviously depends on its quality, e.g. the accuracy with which it describes the phenomenon it is actually meant to describe. Since such aspects of quality is hard to compare, comparisons of the models relative usefulness is hardly informative. On the other hand, we would think that this problem is less for studies of the kind of problems where the two model appears relatively most useful.

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