

Evaluation of harvest control rules: simple one-parameter versus complex multi-parameter strategies

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ABSTRACT

Harvest control rules (HCR) are sets of well-defined rules that can be used for determining annual fish catch quotas or effort. If a management policy can be expressed as a HCR, then the HCR provides means to determine the total allowable catch unambiguously. In order to improve certain aspects of the performance for these rules (higher yield, lower variability of yield, less risk of decreased population biomass), strategies of increasing complexity have been suggested for fish stocks both in Europe and in North America. But is this complexity necessarily better? Are simple strategies outdated? “Traditional” harvesting strategies (i.e. constant harvest rate, fixed quota and constant escapement strategies) are simple HCRs with only one control parameter (i.e. target harvest rate, catch and escapement, respectively). “Complex” harvest control strategies are here defined as a multi-parameter HCR. In this study, three criteria (average catch and its coefficient of variability and risk of population abundance below a minimum acceptable level) are used to judge the performance of traditional and complex HCRs, utilizing a stochastic age-structured population model that mimics the dynamics of fish populations. Even though the three HCRs performed rather similarly in the different simulations, the simplest HCR achieved the best results overall. The HCRs are further evaluated against each other, paying particular attention to the tradeoffs among the performance criteria and also relating them to bio- and socioeconomic issues.

Keywords: harvest control rules, harvesting strategies, single-parameter rule, multi-parameter rule, stochastic population models, noise, age-structured models

1. INTRODUCTION

Fair and clearly specified management policy is in the interest of all stakeholders of the world's fish resources. Harvest control rules (HCRs) are sets of well-defined sets of laws that can be used for determining annual catch quotas (Cooke 1999, Restrepo and Powers 1999, Johnston et al. 2000) and are an attempt to formulate management strategies that fulfill a clear objective, and can be tailored towards fairness. If a management policy can be expressed as a HCR, then the HCR provides means to determine the total allowable catch unambiguously as a function of stock size.

In order to improve certain aspects of performance of HCRs (i.e., higher yield, lower variability of yield, less risk of severely decreased population biomass), rules of increasing complexity have been suggested for the fish stocks both in Europe (i.e., within the International Council for the Exploration of the Sea (ICES)) and in North America. But is this complexity necessarily better? Are simple strategies outdated?

“Traditional” harvesting strategies, e.g., constant harvest rate, fixed quota and constant escapement strategies (Hilborn & Walters 1992), are simple HCRs with only one control parameter (for the above mentioned strategies, target harvest rate, target catch and target escapement, respectively). Constant harvest rate is a strategy with invariable fishing pressure. A fixed quota strategy entails harvesting a fixed yield. And a constant escapement strategy consists of fishing only after a certain biomass has been surpassed.

An advantage of a simple HCR is that it is easy to describe but it is also inflexible (Thompson 1999). “Complex” harvest control rules are defined here as rules with more than one control parameter. Though these strategies are flexible and can be tailored to optimality, they can also be inaccessible in regards to implementation (Thompson 1999). Although there is no upper limit for the number of control parameters, considering more than three parameters is probably seldom practical. Biological reference points, certain values related to a biological aspect of the fish stock (i.e. spawning stock biomass or number of recruits), are the key component to adding complexity in multi-parameter HCRs.

Today, for example, ICES implements a very simple HCR for North-East Arctic cod which entails adjusting a constant fishing level according to the spawning stock biomass (Skagen et al. 2003). But, fisheries researchers at the Institute of Marine Research in Bergen (Norway) have noted in their recommendations to ICES that setting fishing levels on a year-to-year basis ‘seriously hampers long-time planning within the fishing industry’ (Skagen et al. 2003).

The use of biological reference points (i.e. critical biomass, target biomass or buffer biomass) to help define a precautionary approach is now a common strategy amongst fisheries managers. The precautionary approach is a relatively new tactic adopted by many intergovernmental organizations, including the United Nations Food and Agricultural Organization (FAO), ICES, and the Northwest Atlantic Fisheries Organization (NAFO), as a response to the world's overfishing problem. This approach is a proactive rather than reactive strategy that seeks to ensure the sustainability of fisheries resources through management practices (Mace 2001).

For many fish stocks, the precautionary approach replaces the old-school single-species maximum sustainable yield (MSY) strategy, which proved to be a target that can be routinely exceeded, leading to collapse of the target stock due to overfishing (Mace 2001). Lande et al. (2003) note that a stock harvested with a strategy that deterministically produces the MSY can still collapse due to the fact that stochasticity can interact with the fishing to produce such a collapse or extinction.

In order to develop the precautionary approach into feasible fisheries management, clear harvest regimes needed to be formulated. The birth of the modern harvest control rule came from the scientific working groups of ICES and NAFO, among others. These working groups recommended specific harvest control rules based on the status of the resource and implementing specific reference points based on fishing mortality and biomass (Mace 2001).

Computer models are important and modern tools that can aid in long-term fisheries planning and managing. Skagen et al. (2003) suggest that before an HCR is agreed upon for a fish stock, its performance needs to be evaluated and tested through computer simulations. This is to guarantee, as much as possible, that all management objectives are met (Skagen et al. 2003). Computer models represent the framework for HCR creations and simulations are used as a vital tool for stock management predictions. "Anyone who knows us could not imagine us working without some computer programs. We believe that easy and frequent computation is essential for learning about fisheries stock assessment and management." (Hilborn and Walters 1992, *Preface* p xi)

The merits of using age-structured models include the ease they give to simulate a large variety of management measures (Mesnil 2003). This is especially true when data is stochastically simulated and not based on actual age-length data taken over a long period, which can prove to be unreliable. Stochasticity in age-structured models can cause the extinction of a population that otherwise would indefinitely persist in a deterministic model (Lande et al. 2003).

General management strategy evaluation along with risk assessment and harvest strategy evaluation is becoming more common among the world's fisheries managers (Hilborn and Walters 1992; Haddon 2001). It is believed that so-called Monte Carlo models (or stochastic dynamic pro-

gramming), such as the one proposed and tested in this thesis, are the future tools for evaluating and implementing successful fisheries management (Hilborn and Walters 1992). I observed the importance of management simulations in fisheries at the latest ICES Annual Science Conference in Tallinn, Estonia. A whole theme session was given to the topic “Evaluation of Fisheries Management Scenarios and the Supporting Data through Simulation” which had 17 paper presentations from several different countries. Indeed today many fisheries managers and scientists around the world use simulation models to help predict stock sizes and model various harvest control rules and recovery plans.

The main objective of this thesis is to evaluate the benefits and disadvantages resulting from three different harvest control rules. The approach is to investigate the performance of harvest control rules using a simple, generic, population model that still captures the essence of fish population dynamics, as opposed to a more narrow focus on a specific case study. I hope that by creating a simple population model and adding new layers of complexity to the classic, well-studied harvest strategies that have only one control parameter (Hilborn and Walters 1992, Restrepo and Powers 1999), this will lead into a better understanding of what can be gained or lost by the implementation of different HCRs.

In this study, three criteria—average yield and its variability, and risk of population abundance below minimum acceptable level—are used to judge the performance of traditional and complex HCRs, utilizing a simple stochastic age-structured population model that mimics dynamics of fish populations. In Section 2, the components of the model and simulation procedures are presented as well as the HCRs tested by the model. These HCRs are then evaluated against each other with the results found in Section 3. Particular attention to the tradeoffs among the performance criteria are paid in Section 4 with a practical discussion including the bioeconomics and practicality of different harvest control rules.

2. MATERIALS & METHODS

2.1 Population & Survival Equations

The population equations describe the model of a theoretical fish stock made up of two age classes:

$$N_0(\text{year}) = f_1 N_1(\text{year}) + f_2 N_{2+}(\text{year}) \quad (1)$$

$$N_1(\text{year} + 1) = s_0 N_0(\text{year}) \quad (2)$$

$$N_{2+}(\text{year} + 1) = s_1 N_1(\text{year}) + s_2 N_{2+}(\text{year}) \quad (3)$$

here, f_i is fecundity at age i and s_i is the probability of survival from age i to age $i+1$. Any fish older than two years continued to belong to the N_{2+} age class throughout its life span.

The Beverton-Holt equation for density dependency (which can not produce chaos) is used for the survival of N_0 (Equation 4). The biological assumption behind the Beverton-Holt stock-recruitment curve is that juvenile competition results in a mortality rate that is linearly dependent upon the number of fish alive in the cohort at any time (Hilborn and Walters 1992). The Beverton-Holt recruitment curve is graphed in Figure 1. Equations 4, 5 and 6 are the survival equations, with stochastic multipliers, used in the population model.

$$s_0 = \frac{\exp(-M_0 \times E_y)}{1 + k \times N_0} \quad (4)$$

$$s_1 = \exp(-(M_1 + F \times V_y)) \quad (5)$$

$$s_2 = \exp(-(M_2 + F \times V_y)) \quad (6)$$

where M_0 , M_1 and M_2 are instantaneous annual natural mortality rates at ages 0, 1 and 2, respectively, and F is instantaneous fishing mortality rate, k is a parameter describing the strength of density dependence and E_y represents environmental variation in the form of a stochastic multiplier.

The density dependent relationship of the spawning stock size [$N_1(t)$ and $N_{2+}(t)$] to the subsequent number of recruits [$N_1(t+1)$] is shown in Figure 1. Here, a classic Beverton-Holt density dependency is assumed in the model's relationship between the spawning stock size ($N_1 + N_{2+}$) and the corresponding new recruits [$N_1(t+1)$], which includes the s_0 equation where Beverton-Holt density

dependency is added (Equation 4). On the subject of stock and recruitment, Hilborn and Walters (1992) state that density independence is a simple and reasonable postulation, but that it has limits. In the natural world, density dependence is clearly observed due to the fact that habitat and food are not found indefinitely.

One can see the changes in recruitment strength resulting from different k parameter values in Figure 1 where higher k values produce a stronger density dependency among the recruits.

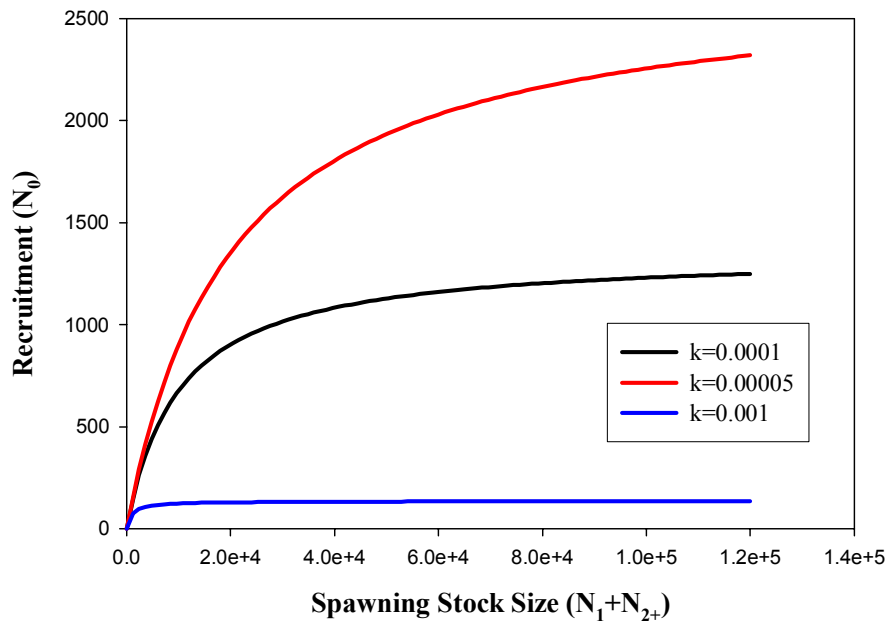


Figure 1 The Beverton-Holt relationship in the deterministic model between the spawning stock size (number of individuals in N_1 and N_{2+}), the resulting recruits with different levels of density dependence strength represented by the k parameter, where $M_0=2.0$. Fecundity parameter values for N_1 and N_{2+} are 10 and 30 respectively.

The E_y value is graphed in Figure 2 and found from a determined probability, p , a symmetric probability for a transition from a “good year” to a “bad year” or vice versa. A “good year” signifies the environmental multiplier (E_y) to equal 0.5 and a “bad year” equals 1.5. No fishing mortality occurs before the age of 1 year. In order to mimic imperfect control of fishing mortality, stochasticity was also added to F values in some simulations. In these cases, noise was added multiplicatively with a parameter, V_y , defined as $\text{LogNorm}(1, \sigma_F^2)$ which is a log-normal distributed non-negative random deviate with a mean of one and variance σ_F^2 .

Figure 3 assembles Equations 1-6 as well as the stochastic multipliers (E_y and V_y) in a graph. The parameters used for the model are shown in Table 1.

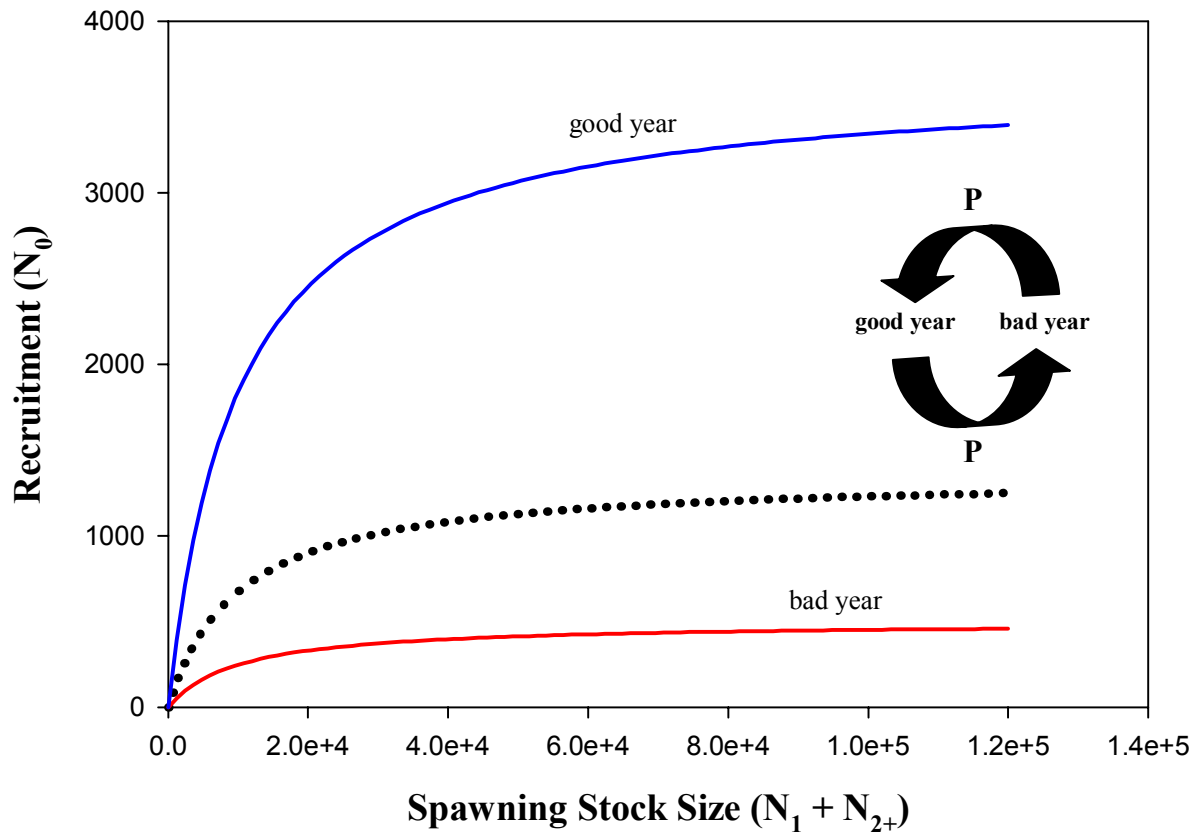


Figure 2 Equation 4 in graph form showing the environmental multiplier (E_y) stochasticity and its effects on the recruitment in the model. The “good year” represents a 0.5 multiplier to the M_0 in Equation 4 and a 1.5 multiplier for a “bad year”. The dotted line is the recruitment curve without the environmental multiplier. The schematic drawing (inset) of the environmental stochasticity illustrates the probability of going from a “good year” to a “bad year” and vice versa.

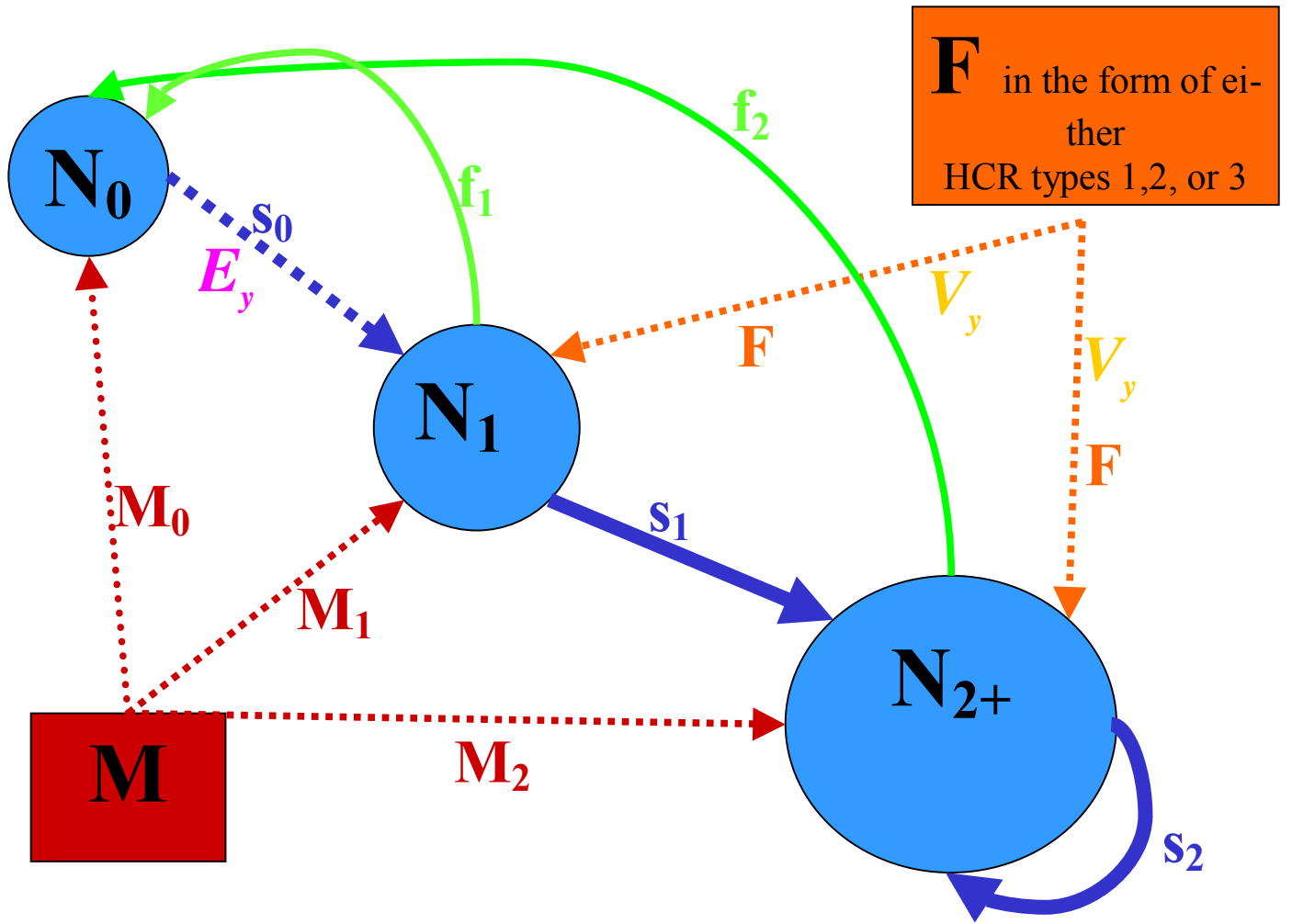


Figure 3 Schematic drawing of the population model used in this study. N_0 , N_1 and N_{2+} are the three age classes and s_0 , s_1 and s_2 the corresponding survival probabilities. The parameter f is fecundity, M_0 , M_1 and M_2 are instantaneous natural mortality rates at ages 0, 1 and 2, respectively, and F is instantaneous fishing mortality rate applied according to the harvest control rule chosen. E_y represents environmental variation in the form of a stochastic multiplier and fishing noise was added multiplicatively with a parameter, V_y .

TABLE 1 The population model's parameters and their values.

Symbol	Description	Value	Unit
w_1	weight of age 1 fish	1	w
w_2	weight of age 2 fish	3	w
M_0	natural mortality for N_0	2	t^{-1}
M_1	natural mortality for N_1	0.4	t^{-1}
M_2	natural mortality for N_{2+}	0.2	t^{-1}
f_1	fecundity at time 1 proportional to the weight of N_1	10	ind.
f_2	fecundity at time 2 proportional to the weight of N_{2+}	30	ind.
k	k used in Beverton-Holt s_0	0.0001	ind^{-1}
N_0	N_0 at year 0	0	ind.
N_1	N_1 at year 0	1	ind.
N_{2+}	N_{2+} at year 0	1	ind.
E_y	Environmental stochastic multiplier		
p	Environmental variability probability	0.1-1.0	
σ_F^2	Fishing variance	0.00-0.1	ind.
R_0	net reproductive rate	3.96	ind

R_0 is known as the expected lifetime production of offspring (Stearns 1992). An R_0 value was found to measure the maximum potential expected reproductive success of the modeled fish population used in this study. Equation 7 shows the R_0 for the model in the absence of fishing and environmental stochasticity:

$$R_0 = \frac{\exp(-M_0) \times (f_1 + \exp(-M_1) \times f_2)}{(1 - \exp(-M_2))} \quad (7)$$

Where s_0 , s_1 and s_2 are survival probabilities for N_0 , N_1 and N_2 and f_1 and f_2 are fecundity values for N_1 and N_2 . Generally, an R_0 value of >1 describes a population which is growing and an R_0 value of <1 describes a population which declining and not viable. If each individual in the population produces one offspring, then the population is in a steady state and the $R_0=1$ (Mylius and Diekmann 1995). The R_0 value of the model used for the HCR simulations was 3.96, using the parameter values given in Table 1.

2.2 Harvest Control Rules (HCRs)

Three different types of harvest control rules were used in the model (Figure 4). Type 1 was a one-parameter and therefore the simplest HCR in which the fishing mortality (F_{const}) is constant and thus represents a “traditional” harvest strategy. Type 2, had two control parameters: the threshold biomass parameter (B^*) and the corresponding fishing parameter (F_{max}). Type 2 represents the most “complex” of the evaluated HCRs due to the proportional fishing occurring before the threshold biomass (B^*). An escapement strategy is modeled by Type 3 which has also two control parameters: F_{max} and B^* .

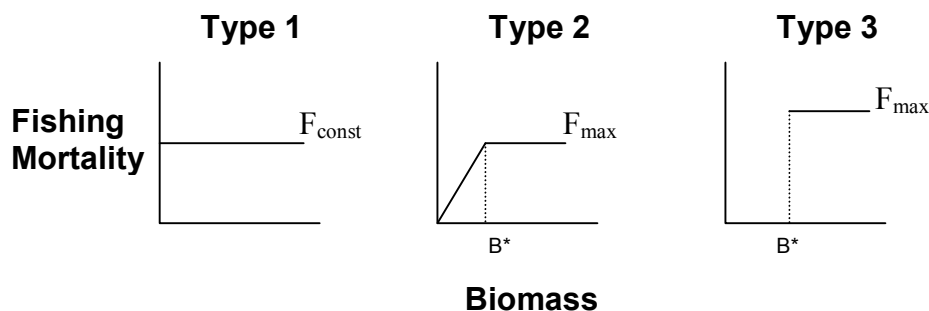


Figure 4 The three harvest control rule types used in the simulations.

2.3 Simulation Procedures

FORTRAN was the computer language chosen for implementing the model. The analytical solution for the population dynamical equilibrium was calculated using the computer program *Mathematica* and the deterministic model's parameters were tested. Sensitivity analyses were run in the deterministic model for each of the parameters. These results were graphed and analyzed to test the model's sensitivity to the given constant parameters.

To evaluate the HCRs, two sets of simulations were run. For the first simulation, the model was run for a time cycle of 5,000 years. The first hundred years were used to allow the fish population to reach a stochastic steady state. Years 100-5,000 were then used to analyze the long-term performance of the three different harvest control rules implemented. Different combinations of environmental and fishing stochasticity were used to further assess each HCR.

The second simulation used fixed environmental and fishing stochasticity parameters and then evaluated each HCR for this specific condition. The values of the predetermined environmental and fishing stochasticity parameters were 0.25 and 0.025, respectively. The time cycle for this simulation was 50,000 years for the purpose of smoothing out the data and dampening the stochasticity.

The three criteria used to rate each harvest control rules' performance were: average yield, coefficient of variation (CV) in yield (defined as the standard deviation/average yield * 100), and "risk". Risk was defined as the probability of population biomass being below a minimum acceptable level, here set to 10% of "virgin" biomass, i.e., average biomass in absence of fishing. Risk described in this study can be related to the "precautionary approach" aspect of some international harvest control rules today.

Using loops in the main code, a large combination of different fishing mortality (F) and threshold biomass levels (B^*) was calculated by the *FORTRAN* program created. The average annual yield, CV and risk for each of these combinations were then evaluated to come up with an "optimal solution" for each HCR. The optimal solution is one where annual average yield is maximized and CV and risk minimized.

Adjusting the p parameter levels, which controlled the good year/bad year probability of environmental variation, controlled the environmental stochasticity in the model. Changing the variance level, σ_p^2 , controlled the stochasticity applied to the fishing mortality levels.

3. RESULTS

3.1 Examining the Model

The model was first checked to correctly represent an age-structured, deterministic fish population. In Figure 5, the dotted line shows the dynamics of the theoretical fish population in the absence of fishing and survival and fishing stochastic variance.

The addition of the stochastic noise to the survival of the N_0 age group is also illustrated in Figure 4. The spawning stock size ($N_1 + N_{2+}$) fluctuates most with lower p values and is consequently most stable when $p=0.9$.

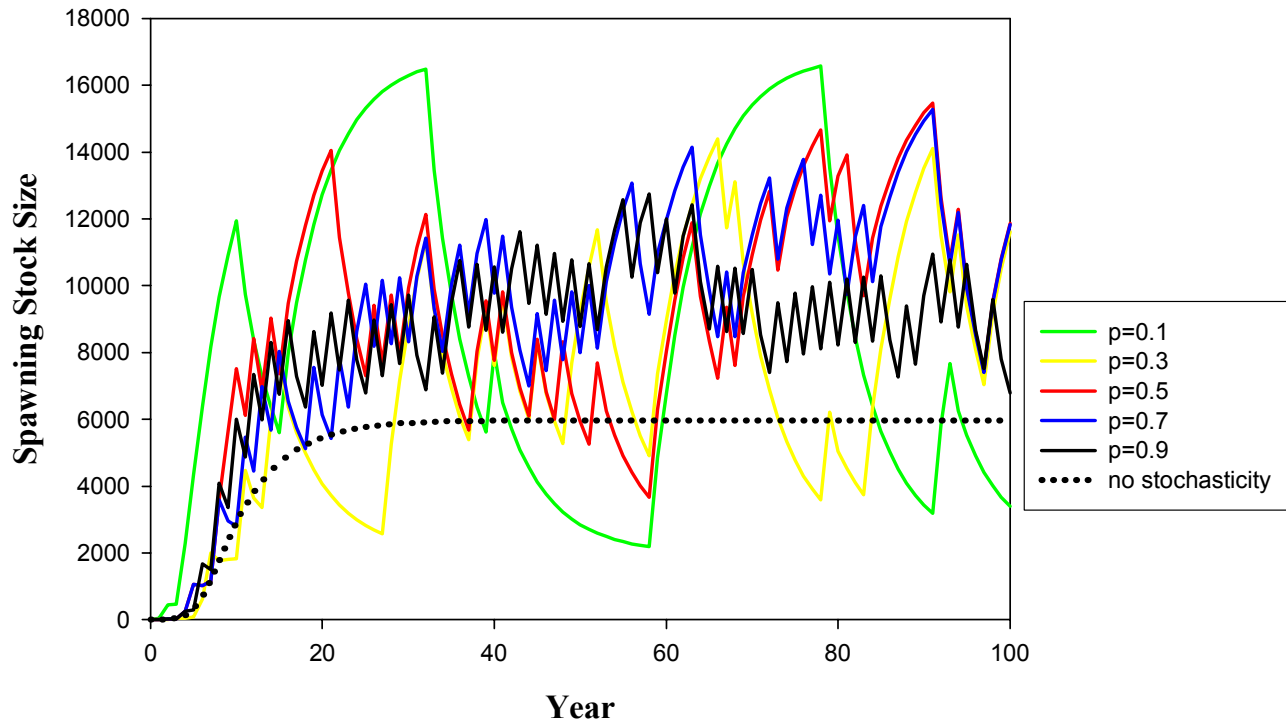


Figure 5 Different probability, p , values and their effect on the model's spawning stock size. The p represents the probability of the environmental variable to go from a "good year" to a "bad year".

3.2 Sensitivity Analyses

A series of sensitivity analyses were conducted in a time cycle of 1,000 years to test the model's responses to different numerical values of the parameters used and to gain confidence in the model itself. Neither fishing mortality nor stochasticity is included in the sensitivity analyses.

A range of values of M_0 plotted in Figure 6 show the resulting equilibrium N_1 and N_{2+} values. There is a negative relationship between the population abundance and increasing M_0 .

Figure 6 illustrates a negative relationship to an asymptotic line between the number of individuals in the N_{2+} population and M_I . The numbers approach zero when M_I is 6. The same relationship is seen in Figure 6 when the sensitivity of M_2 is tested.

The k parameter value, expressed in the survival equation for N_0 , defines the strength of density dependence within the resulting N_I cohort. The model shows a rapid decrease of the number of individuals in N_I when the k parameter value is increased (Figure 6).

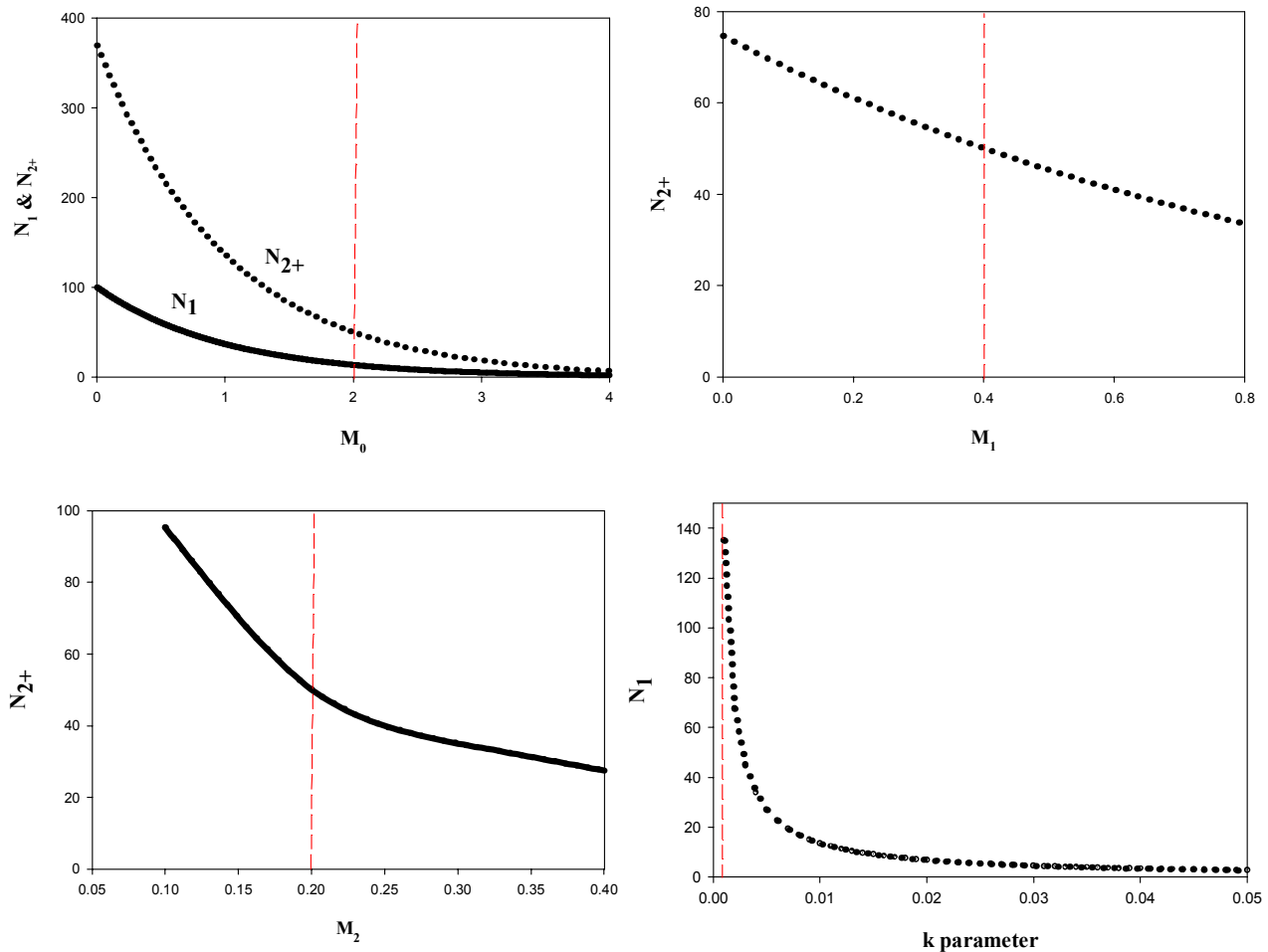


Figure 6 Different values of M are plotted against the resulting N_I and N_{2+} to test the sensitivity of the M parameters. Accompanied is also an analysis of the sensitivity of the survival equation for N_0 (expressed as number of individuals in N_I) to increasing k parameter values. The red dotted line represents the parameter values used in the model (Table 1). The N_I cohort reaches extinction (<1 individual) when the k parameter is at 0.136. A time cycle of 1,000 years was used for each of the graphs.

Next, the average yield was found using the deterministic model for HCR Type 1 and a series of k parameter values. A clear peak shows the maximum average yield of 13060 units found at a fishing mortality of 0.5 with a corresponding k parameter value of 0.0001. Increases in the k parameter value lead to a substantial decrease in average yield in HCR Type 1 (Figure 7) due to elevated

density dependency pressures among the recruits in the fish stock. A k parameter value of 0.0001 was then used for further simulations (see Table 1).

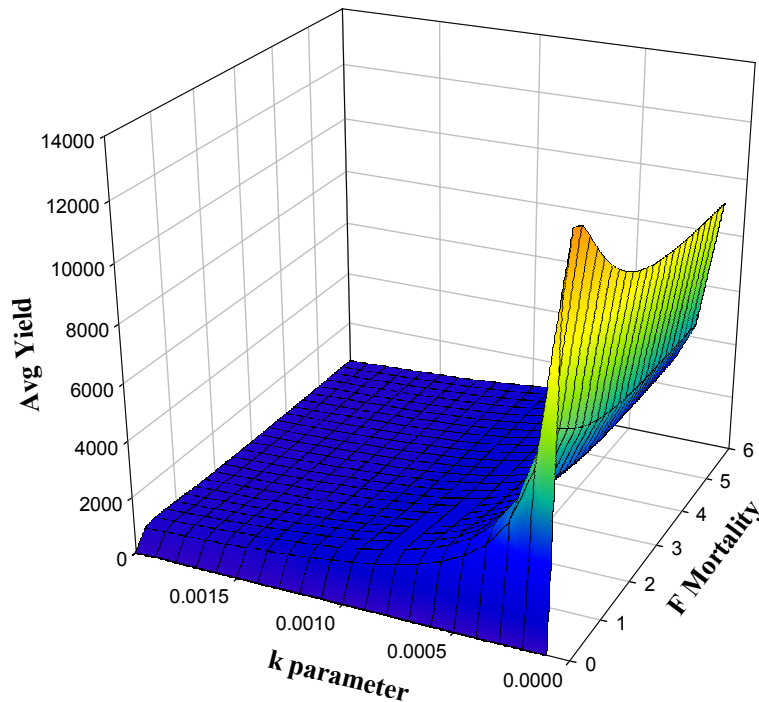


Figure 7 HCR Type 1 and the resulting average annual yield for a time cycle of 1,000 years. HCR Type 1 was simulated with the deterministic population model with different levels of the k parameter and fishing mortality.

3.3 Simulations of Harvest Control Rules

Two sets of simulations were conducted to determine maximum average yield and the resulting CV and risk for each of the three HCR types. The first simulation had different combinations of environmental variability and fishing variances. The second simulation was situation specific, meaning two set values of environmental variability and fishing variances were selected and the resulting performances of each HCR type were studied. In order to determine the “optimal solution” for each HCR, the highest average annual yield was first found with the corresponding CV and risk levels noted. Tradeoffs between high yield and corresponding CV and risk are probable and discussed.

3.3.1 General Simulation

In general, the three HCR types performed similarly in maximum yield (of the time cycle of 5,000 years), and the resulting CV and risk, especially at high p values (0.4 and 0.5). Figure 8 dem-

onstrates a clear tradeoff between CV/risk and high average yield. However, the results from the first simulation in Figure 8 suggest that Type 1, the traditional constant catch harvest rule, out-performed the more complex control rules in all three criteria for this simulation (see Table 2) giving the highest yield and lowest corresponding CV and risk.

For the risk criterion, HCR Type 2 performed generally best, out-performing Type 1 and 3 at low levels of p and fishing variance. However, there is a noticeable spike at the highest fishing variance level (0.1) and a p value of 0.2. It is not known if this spike represents a robust feature of HCR Type 2, but is most likely an anomaly. Each HCR performed very similarly in regards to CV values at all levels of stochasticity in Figure 8, which were in fact quite high levels with no situation lower than 50% variation in yield. Type 3 shows two peaks with the highest CV values (at 81 and 82.9).

HCR TYPE 1

HCR TYPE 2

HCR TYPE 3

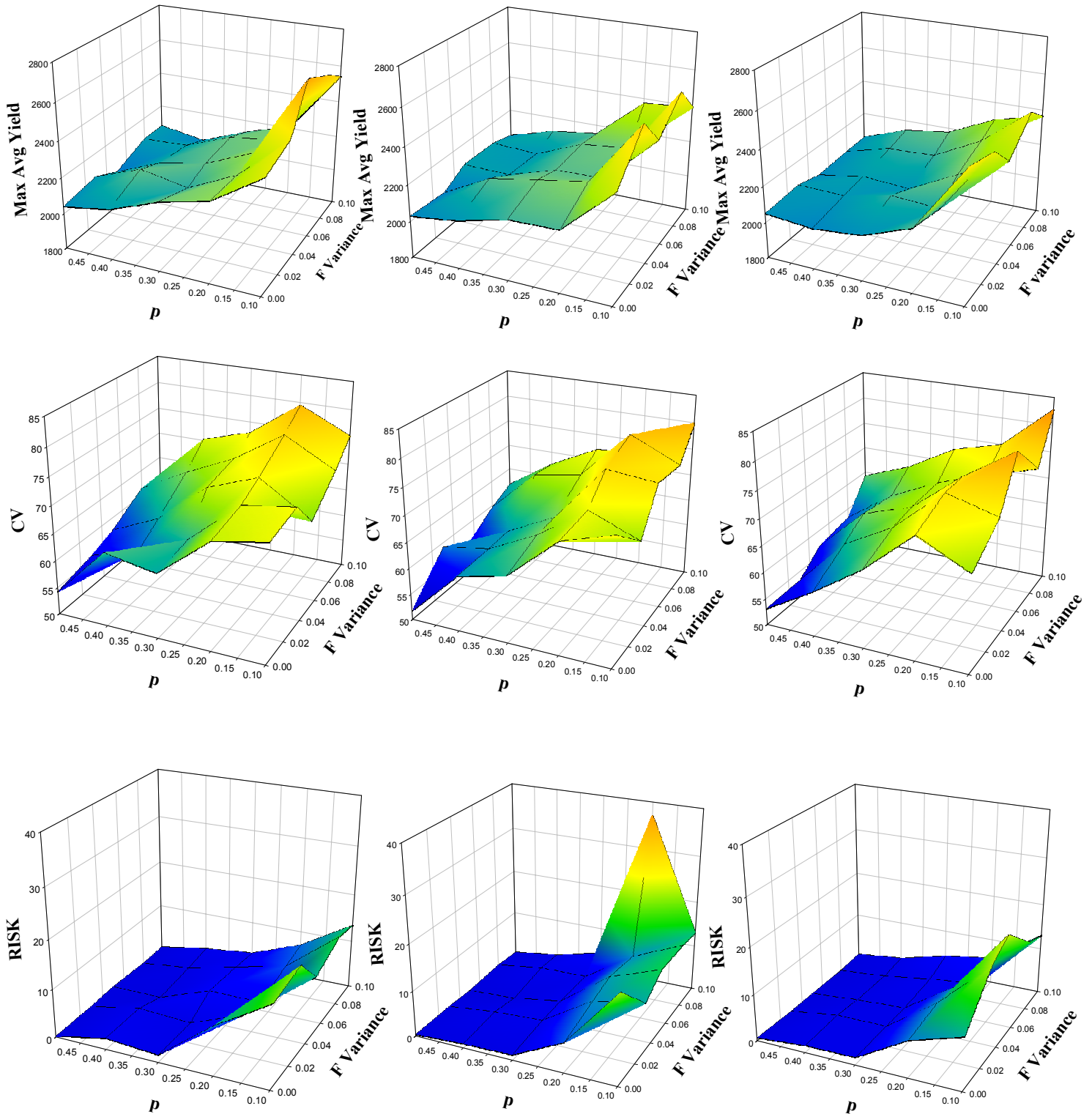


Figure 8 Results (maximum average annual yield, CV and risk) from the computer model simulation of three different harvest control rules. The simulation was run for 5,000 years and the results were optimized to include the maximum average yield for the time cycle for different levels of p and fishing variance (σ_F^2).

Table 2 A summary of the maximum values (average annual yield, CV and risk) from the computer model simulation presented in Figure 8 of three different harvest control types with corresponding p and fishing variance (σ_p^2) levels in parentheses.

	Avg Yield	CV	RISK
TYPE 1	2705 (0.1, 0.05)	79.5 (0.2, 0.1)	14 (0.1, 0.008)
TYPE 2	2584 (0.1, 0.03)	80 (0.1, 0.1)	37.5 (0.2, 0.1)
TYPE 3	2517 (0.1, 0.0)	82.9 (0.1, 0.1)	22 (0.1, 0.05)

3.3.2 Specific Situation Simulation

For the second simulation, each of the HCR types were simulated in a time cycle of 50,000 years, in order to smooth out the stochastic data effects, using fixed p and fishing variance parameters of 0.25 and 0.025, respectively. The results for all three of the HCRs show similar maximum average yield at the same fishing mortality level of 0.4. Figure 9 and Figure 10 each clearly show increasing CV and risk with increasing fishing mortality. A clear spike of the average yield in Figure 9 shows the maximum average yield for HCR Type 1. Arrows point to the maximum average yield for HCR Types 2 and 3 in Figure 10.

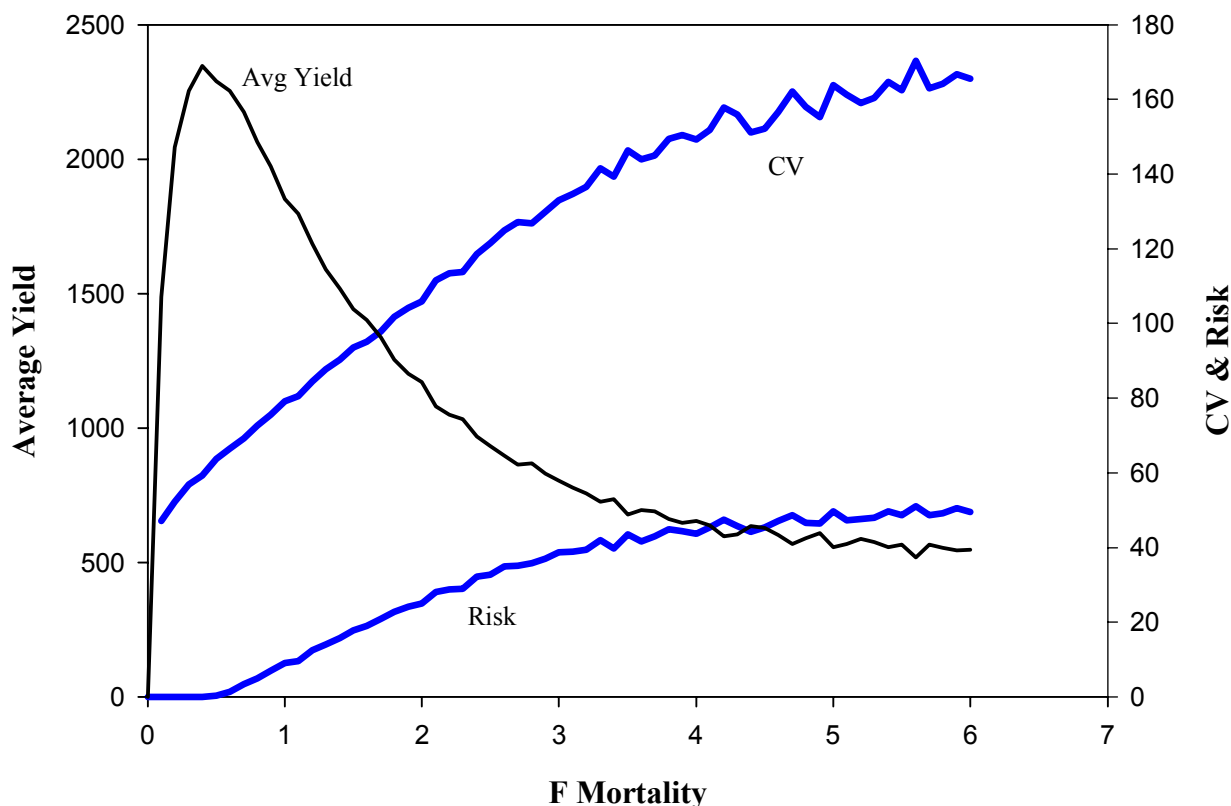


Figure 9 A summary of results (fishing mortality, and the resulting average annual yield, CV and risk) from the situation specific computer model simulation of HCR Type 1. The simulation was run for a time cycle of 50,000 years with set p (environmental variation) and fishing variance (σ_p^2) values of 0.25 and 0.025, respectively.

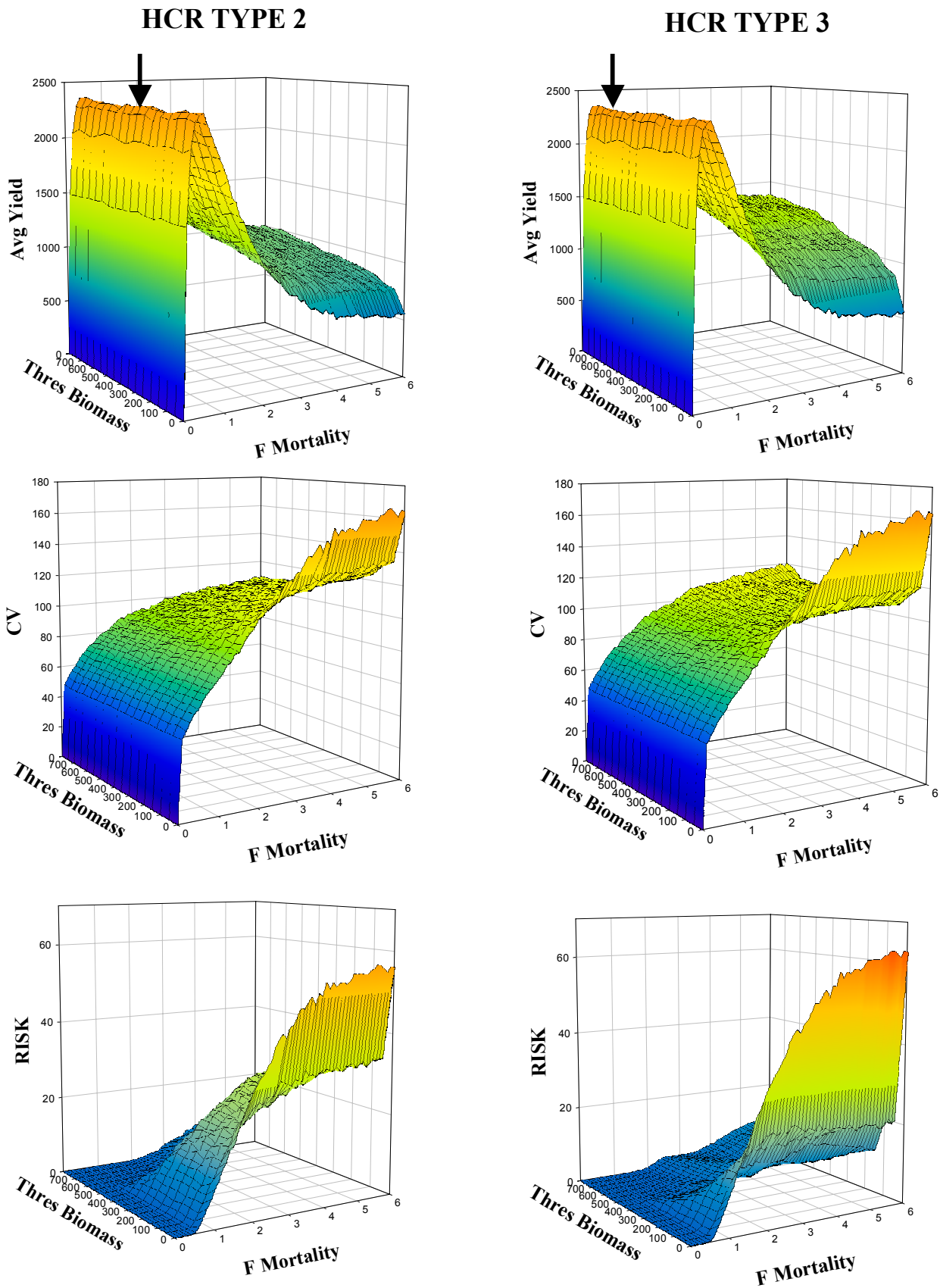


Figure 10 A summary of results (average annual yield, CV and risk) from the situation specific computer model simulation of HCR Type 2 and 3. The simulation was run for a time cycle of 50,000 years with set p and fishing variance (σ_F^2) values of 0.25 and 0.025, respectively. The arrows point to the maximum average yield.

Here, in this second situation specific simulation, there is no difference between the levels of fishing mortality at the maximum average yield for each HCR type. Type 1 has a maximum average yield (the maximum value of the average yield taken over 50,000 years) of 2348 units with a fishing mortality of 0.4 and CV and risk values of 59.3 and 0.01, respectively. For Type 2, the maximum average yield (2351 units) occurs at a fishing mortality of 0.4 and threshold biomass of 350 with corresponding CV=59.5 and risk=0. Type 3 gives the largest maximum average annual yield (2365 units) at a fishing mortality of 0.4 and threshold biomass of 750 (corresponding CV=59.1 and risk=0).

Figure 10 further suggests that for HCR Types 2 and 3, the average annual yield is very sensitive to the F parameter, but not to the B parameter. Also, clear tradeoffs are observed between average annual yield and the resulting CV and risk levels. Higher threshold biomass produces lower CV and risk for Types 2 and 3. Risk levels are notably lower for HCR Type 3 for increasing threshold biomass and fishing mortality values.

The maximum average annual yield results taken from Figures 9 and 10 are presented in schematic drawing of the simulation in Figure 11.

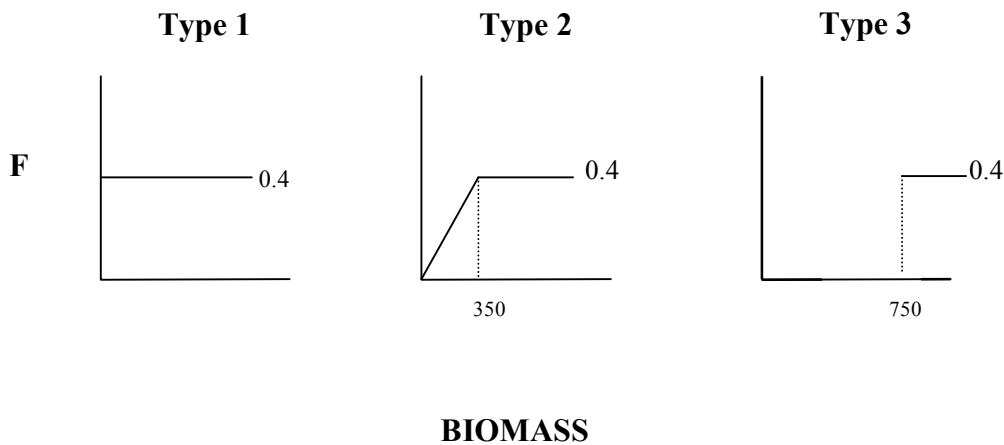


Figure 11 A diagram of the results of the simulation of 50,000 years with p (probability of a shift from an environmentally “good year” to a “bad year”) and σ_F^2 (fishing variance) set at 0.25 and 0.025, respectively. The threshold biomass reference point and fishing mortality (F) levels correspond to those in the simulation that produced the maximum average annual yield.

4. DISCUSSION & CONCLUSIONS

4.1 Discussion of Results

Hilborn and Walters (1992) note that a harvest strategy is made up of economic, biological, social and political components. Each of these components takes into consideration the tradeoffs between average yield, year-to-year variability and the costs of such variability to the stakeholders. My study consists of modeling a theoretical fish stock and evaluating resulting biological and economic components (in the terms of biomass and yield) after the application of an HCR. The social and other economic aspects (such as loss of jobs in fisheries due to overfishing) are not specifically included in the model, but are discussed in Section 4.3.

First, results of the sensitivity analysis calculated with the dynamical population equilibrium equation of the model's parameters and the corresponding figures confirm that the numerical levels chosen for the various parameters represent a viable fish population ($R_0 = 3.96$).

Results imply that harvest control rules can be similar in average yield, but very different in how these yields can be obtained due to the nature of the harvest regime. The simulations carried out during the span of the project and the simulation presented in this paper show that the best performing and most practical HCR is dependent on the levels of variance of the stochastic noise given to the model (results not shown).

For example, Figure 11 shows that to obtain quite similar yields, the optimal HCR Type 1 would allow the fishermen to fish at all levels of biomass at a fishing level of $F=0.4$. HCR Type 2 would allow the fishermen to harvest an increasing proportion of the biomass up to a biomass level of 350 where they would continue at a constant fishing level of $F=0.4$. Finally, HCR Type 3 would allow a fishing pressure of $F=0.4$ but only after the biomass had reached a level of 750. These results are given for only the maximum average yield at one level of environmental and fishing variances and meant to illustrate an example of the practicalities of each HCR in a specific situation. A prudent fisheries manager would use such a simulation to evaluate a potential harvest strategy with given environmental and fishing variability before implementation.

Overall, HCR Type 1 scores best in the simulations due to constant fishing which produced the highest average annual yield with lowest CV and risk values. Furthermore, in support of the success of HCR Type 1, Walters and Parma (1996) conclude that a fixed exploitation rate strategy performs quite robustly in the face of unpredictable environmental change. Hilborn and Walters (1992) also point out the benefits of a fixed harvest rate due to its strength when facing the dangers of over-

fishing. These conclusions are backed up by this study's results in which the fixed harvest rate HCR (Type 1) performed best.

Consequently, fisheries managers, fishermen and other stakeholders probably would value the HCR performance criteria differently. A utilitarian fisheries manager would perhaps value high average yield most, whereas fishermen would set heavy weight also on variability of the annual catches (CV). A conservationist could be concerned, above all, on having as small risk of biomass being below a minimum acceptable level as possible. Thus, the eventual choice among the three strategies would critically depend on the weighting of the various performance criteria. In particular, whether better performance is gained with a "complex" or a "simple" harvest control rule depends on the relative importance set on average yield versus year-to-year stability in yield. Profit-sharing schemes, combining reserves with threshold harvesting, insurance and a reduction in the fishing fleet capacity (see Section 5.3) are some ways to alleviate high CV of yield or possible year(s) of no fishing (Lande et al. 2003).

For fishermen, HCR Type 3 is impractical and a waste of time. In fact, HCR Type 3 has virtually no merits in comparison to the other two rules due to its very high escapement feature and subsequent low fishing pressure with little gain in yield and CV. Also, it is necessary to call attention to the high coefficient of variation (CV) values found in Table 2. For the year the produced the highest average yield, each of the corresponding CV values were 79.5, 80 and 82.9 respectively for HCRs Type 1, 2 and 3. These extremely high CV values in annual yield are way beyond what is acceptable for fishermen. In fact, a value of over 30% would likely be considered deplorable in the fishing community. As Figure 8 suggests, CV (and risk) values vary according to environmental conditions and fishing variance in this model. Moreover, Figures 9 and 10 illustrate the rise in CV and risk values with increasing fishing mortality (F). These graphs symbolize the tradeoffs in fisheries management between high yield and resulting high variation of yield and high risk of disturbing the population which could lead to commercial or biological extinction. One does notice, however, the sharp decrease in yield for each of the HCR types after a fishing mortality (F) value of approximately 1.0 (Figures 9 and 10). This suggests that higher fishing pressure only gives higher yield up to a point where fishing over this peak fishing pressure does not lead to more yield, only higher CV and risk.

Katsukawa (2004) used numerical models to find the optimal fishing three-parameter control rule for three different fish stocks. Different stock size and environmental uncertainty values were used in the simulation with results suggesting that the type of life history (e.g. natural mortality

rates) and stock size assessment error (uncertainty of the stock) should determine whether a simple or complex HCR should be implemented (Katsukawa 2004).

The life history of this study's stock was quite a robust one. The stock was seemingly able to bounce back after a year of bad recruitment (Figure 4). This most likely contributed to the success of the fixed exploitation rate HCR when applied to this model stock. The way stochasticity is implemented also increases the expected reproductive potential relative to the deterministic version (Figure 5).

In their chapter summary on sustainable harvesting, Lande et al. (2003) state that the optimal HCR is immediate harvesting of the biomass above the carrying capacity with no harvest below that amount (Lande et al. 2003, p. 137). Such an HCR would relate to this paper's HCR Type 3 but differs in the fact that Type 3 implies harvesting a fixed proportion above the threshold. In the event of uncertain population sizes, however, Lande et al. suggest a modified HCR Type 2 where only a proportion of the population after a threshold is harvested with no harvest below the threshold. This statement is backed up by results presented in Figure 10 where Type 2 fairs well in CV and risk for different levels of stochasticity with some exceptions.

Lande et al. (2003) further suggest that larger environmental stochasticity usually increases the optimal harvesting threshold for populations that persist for long time periods. Other simulations done with this model supported this statement. Environmental variation from a non-auto-correlated source (expressed as σ^2_s) gave increasing average annual yield for increasing environmental variation in the model (Housholder, Heino, and Fiksen 2003).

Also interesting is the way fishing can alter the behavior and evolution of fish species. For example, Heino (1998) found through age-structured models that selective harvesting of mature fish at the spawning grounds is able to cause evolutionary change. This change can increase sustainable yields whereas unselective harvesting at the feeding grounds can cause an unfavorable evolutionary change (i.e., earlier maturation) in the stock resulting in a reduction of sustainable yield. However, there are clear drawbacks to exclusive harvest at spawning grounds including limited fishing seasons and susceptibility to overexploitation (Heino 1998).

4.2 Limitations of the Model

Admittedly, the limitations of the population model used and presented in this thesis arise from its simplicity. This study assumes correct knowledge of the stock size and no measure of assessment uncertainty, besides that of fishing variance (F_y) is included in the model. Other dynamic

model studies (e.g. Walters and Parma 1996; Katsukawa 2004) include uncertainty of the stock, which is a very important parameter in working HCR models.

Again, this study focuses on a basic model and important factors absent in this study could be added in at a later time. Assumptions are made that the correct model parameters are known and the parameters are constant. To control the population as best possible, the fish stock modeled does not represent any “real” fish stock, nor is it modeled after any collected data. This was also done in order to focus the project on the performance of the HCRs and not on uncertainty of the population model.

The model’s resilience to collapse (the fish population never collapsed in any of the study’s simulations) is probably due to the fact that the age one year fish can always reproduce before they are exposed to fishing. Having fishing pressure occur before spawning would create a less resilient population. In addition, this model only has two age classes. A more detailed and complicated, but more realistic, model with several age classes with a maximum age leading to subsequent death would most likely make the population less resilient to increased fishing pressure and different levels of stochasticity. Another look at Figure 2 and how the environmental stochasticity affects the model may also show why the population is so durable. In a “good year” there is over a tripling in recruitment, while during a “bad year” recruitment is a little more than half of the original recruitment. The fact that recruitment is very good during a “good year” and not so bad during a “bad year” is due to the E_y levels that were probably too simply chosen (0.5 and 1.5) and because of the implementation of the E_y multiplier in the s_0 equation (Equation 4) which transforms the mean to asymptotic instead of geometric. Given more time, I would choose some different E_y levels (and/or bring the E_y multiplier out of the exponential parentheses) which would fit better around the original recruitment curve in Figure 2 and cause the population to react more realistically when faced with a “bad year”.

Various biological interactions such as predation, cannibalism, and interspecies competition are not purposely represented in the model, but are lumped together in the natural mortality parameter, M . The density dependence on recruitment in the model qualifies as a biological interaction according to Magnússon (1999), which implies some interaction between the resources or predators of the focal population. Evolution, for example, is not taken into consideration although the model was run for 50,000 years in the second simulation.

There is no guarantee that the obtained results would hold in more complex models. However, a good model should have some structural stability, i.e., results are not essentially changed if model structure is slightly changed. So far there has been no indication that this would not hold for the model. Of course, theoretical models are based on parameter choice and “optimal strategies” will always shift (Mangel, Fiksen, Giske 2001). Furthermore, a theoretical model is totally dependent

upon the parameters and their values chosen to describe the model. This is important to remember and is the main difference between empirical and theoretical models.

4.3 Brief on Social, Cultural, Economic, and Biological components of Fishing

Theoretical models have their place in fisheries biology, but one must remember that fisheries biology and management is a branch of science that is very economically, and thus, politically motivated. Hence, awareness of real-life problems, such as harvest rule acceptance by fishermen and politicians and the implementation of fishing laws, is of utmost importance in order to make the transition from theory to reality. But also, a clear look at the reality of the state of fisheries today must be understood and accepted by all stakeholders and dealt with accordingly.

In a letter to *Nature*, Myers and Worm (2003) write that 90% of the world's large fish (i.e. Atlantic cod, tuna, swordfish marlin, halibut, shark and flounder) have succumbed to commercial fishing. According to the *Wall Street Journal* (November 9, 2003), overfishing affects approximately 33% of assessed stocks in the United States. Most recently, Baum and Myers (2004) report a 99% decline of the oceanic whitetip shark since the 1950s due to overfishing in the Gulf of Mexico. The fact that the absence of the whitetip shark, once one of the world's most common sharks in the tropics, in the Gulf of Mexico goes unnoticed today represents a clear example of shifting baselines (Baum and Myers 2004).

But what are the consequences of overfishing? A good example is the short history of Atlantic cod.

The long cultural and economic importance of Atlantic cod (*Gadus morhua*), or codfish, began with the tenth century European Basques and continued through the centuries with almost all the countries that border the North Atlantic Ocean: Portugal, Spain, France, Britain, Norway, Iceland and the United States (Ellis 2003). Because the absolute abundance of cod and the positive religious connotations associated with cod consumption, the Puritans in the fifteenth and sixteenth century America included codfish on their dinner plates (Ellis 2003) as well as in the portraits and paintings of the city halls and churches. Some experts even agree that the Puritans came to America to fish cod as much as they came to flee religious intolerance.

Four centuries later, due to overfishing, the tragic fate of one of the most prolific species in the Animal Kingdom becomes that of commercial extinction. The east coast of the United States and Canada, consequently, has been subject to a loss of thousands of fisheries jobs, not to mention loss of a cultural institution, due to the collapse of the cod stocks.

There are also substantial financial costs of inadequate fisheries management. A multi-million dollar government buy-out is in store for many of the remaining fishermen in the troubled regions along the American west coast in order to control the fleet and sustain the overfished stocks. The idea of reducing fishing fleets in attempts to control fishing mortality is, in my opinion, a good one. Smaller fleets would be easier for fisheries scientists to observe and manage and improved technology (global positioning systems, water temperature readings and other satellite data) will add to the proficiency of fishermen to avoid bycatch. Government buy-outs on fishermen could be a costly answer, but an investment at the same time, needed to be made today in order to preserve and rebuild ailing stocks.

The economics of fishing is very important to understand when creating an appropriate HCR. Hartwick and Olewiler (1986) and Clark (1990) give good introductions to the economics of a fishery and present economic strategies for such an open-access resource. They point out that a desired steady-state bio-economic equilibrium occurs when the rate of harvest is equal to the net growth rate of the fish stock. Hartwick and Olewiler (1986) also offer economic models of the fishery, with biological mechanics and environmental factors included. Admittedly, the more variables and parameters added to a model, the more difficult the model becomes. Hilborn and Walters (1992) specifically warn against complexity in dynamic fisheries models. They note that that the system should be able to be described using one or two variables to determine an optimal harvest policy in regards to a single criterion, such as biomass. Parameter complexity, however, is necessary to describe a complex system such as a marine fishery and for determining an optimal feedback regime for the fishery (Hilborn and Walters 1992).

Hardin (1968) coined the term “tragedy of the commons” to describe the dilemma of population growth, nuclear war and ecological concerns. Hardin argues “freedom is the recognition of necessity” to bring about awareness of the problems of sharing one world (or one resource). On the subject of nuclear war Hardin quotes J. B. Wiesner and H. F. York: “If the great powers continue to look for solutions in the area of science and technology only, the result will be to worsen the situation.” (Hardin 1968) The conclusion that there is no technical solution to such dilemmas is applicable to fisheries management today.

Economists can explain overfishing by this term “tragedy of the commons” which describes the fishing phenomenon of lack of ownership to the fish stocks causing no incentive to protect fish stocks for future generations (*Wall Street Journal*, November 9, 2003).

But now, some economically-minded environmentalists have come up with a way that could save fisheries around the world by incorporating an important free-market strategy: ownership of the

fish in the form of an ‘individual fishing quota’ (IFQ). The total allowable catch (TAC) is found by fisheries managers for a fish stock, and then each fisherman receives his own fishing quota allocated from the TAC. The fishermen suddenly have their own quotas, which then become their ‘property right’ to the fish stock. IFQs can also be bought and sold between fishermen. “And because fishermen have access to the guaranteed share of the catch, they don’t race to compete, fishing seasons lengthen, prices rise and fish stocks grow.” (*Wall Street Journal*, November 9, 2003 “A Fish Story” p. A10)

Hilborn and Walters (1992) discuss individual transferable quotas (ITQ) and express concerns arising from falling prices or allowable catches which in turn could drive investors bankrupt. Also, they note the increase incentive of selling fish illegally in an ITQ system along with the incentive of discarding low-grade fish.

New Zealand began first with IFQs in 1986 and has seen success in a reduction of the fishing fleet, recovery and growth in fish stocks and a doubling of the market value of IFQ fisheries from 1990-2000. Similar successes have been experienced by Iceland, Greenland, the Netherlands and Australia. IFQs represent a successful transition from over-investment in equipment to investing in transferable quotas (Hilborn and Walters 1992). The United States is looking to implement IFQ programs now in efforts to save the remaining fisheries and to try to bolster the economy in an environmentally friendly way. Indeed, ownership is a key policy in successful economics and should be incorporated in bioeconomics as well.

4.4 Conclusions

In short, this study’s simulation results show that the simplest HCR tested was better than the more complex HCRs. The constant fishing mortality regime, HCR Type 1, performed best regarding CV and risk in most levels of fishing variance and environmental variability tested. The winning quality of Type 1 is that the fisherman is able to consistently exploit the resource at all levels of biomass without risking significant loss of yield or jeopardizing the fish population. There is a remarkable observed resilience in the artificial population used for HCR simulation which most likely helped Type 1 perform better than expected in the risk criterion. This resistance may not persist in more realistic population models.

Type 2 is a good compromise between utilitarian and conservationist managers because both exploitation and zero risk of the biomass dropping to -10% of the virgin biomass are happening simultaneously. It could, however, become unprofitable for fishermen to fish at low stock sizes.

Finally, Type 3 has the merit of low risk values for increasing threshold biomass and fishing mortality (Figure 10), but it's high escapement feature and high CV levels offer little to fishermen.

Since each HCR gives different 'optimal' results according to the specific stochastic levels of survival and fishing suggests that environmental and/or biological variation of an ecosystem or fish population needs to be studied before the appropriate application of a one- or multi-parameter harvest control rule (Hartwick and Olewiler 1986; Katsukawa 2004). Moreover, data from the fishing fleet is important to determine bycatch and fishing variance to include in the criteria to construct an optimal HCR. If these factors are unknown or hard to predict for a certain fish stock, the Type 2 strategy would be recommended by the results of this study since CV and risk are lowest at most levels of variance tested.

Not to be ignored, the biology (i.e., life history, place in ecosystem) and ecology of the exploited population must be known and well-studied in order to carry out a successful management program (Pitcher and Hart 1982; Heino 1998). Habitat, migration, as well as spawning and feeding grounds are all important aspects of the life history of fish in an exploited population.

Once a proper HCR has been proposed and evaluated, the next step in proper implementation of the management strategy. Walters and Parma (1996) implied that more research into effective regulation of fishing is needed at the expense of trying to explain and predict climatic effects. Truly, what good is an HCR if it is not implemented properly? The practicalities of realizing an HCR in the real world should be an important part of choosing an appropriate management strategy.

Now is the time for well-run fisheries management. "If we could step back in with strong management decisions we could restore the ecosystem (including populations of large fish species), but that's a matter of political will and funding and a lot of other influences that are difficult to predict," says Karen Bjorndal, zoology professor at the University of Florida. Bjorndal was one of the authors of a paper that argued that overfishing disturbs the ecological balance of the marine ecosystem (Pandolfi et al. 2003).

To sum up, fisheries management is a complex field that includes not only biology and economics, but social and political elements as well as stocks are analyzed and laws are passed. Advanced tools for fisheries managers exist in the form of computer modeling to describe and predict different management scenarios. Obviously, the issue of increasing complexity in fisheries models is of concern and the transition from theory to realization in fisheries management is easier said than done (Thompson 1999). Through the understanding of basic models, however, complexity can be built up to create a model, which is then able to describe the subject in sight. If problems in the

model due to complexity occur, the modeler can then work backwards to remove layers of complexity in order to find the problem and correct the mistake.

On the other hand, fisheries managers must remember that no mathematical model is able to precisely describe a biological process and thus should incorporate robust harvest regimes to take various uncertainties into account (Hilborn and Walters 1992; Mangel, Fiksen, Giske 2001; Schnute and Richards 2001). Finally, care should also be taken when trying to describe an “optimal” HCR, as optimality tends to shift according to different levels of stochastic variance as well as the life history of the fish stock at hand (Hartwick and Olewiler 1986; Housholder, Heino, Fiksen 2003; Katsukawa 2004).

Management policies in the form of HCRs can be described and predicted explicitly and fairly. The effects of HCRs should be modeled before implemented to help evaluate aspects of a proposed management policy. This is in the interest of all stakeholders of the world’s fish resources.

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7. APPENDICES

7.1 Fortran model code

```

program simulation
implicit none
integer, parameter ::nyears = 5000, st_year = 100      !number of years to simulate program
integer age, year, FM, FM1, FM2
integer(4) iseed
integer ihr, imin, isec, i100th
integer hcr_type
real k1(0:nyears), survival0, prob
real N0(0:nyears), N1(0:nyears), N2(0:nyears), R0, criticalR0
real yield(0:nyears), catch(0:nyears),stock_biom(0:nyears)
real B1, B2, B12, s0, s1, s2, fec1, M0, M1, M2, fecundity1, fecundity2, fec2, SLOPE
real w1,w2,f0,f1,f2, k, alfa, Z, risk, CV, V, sd, k_param
real MPS0, MPS1, MPS2, MPS12,avg_yield,avg_stock_biom, Sb, Sg, p, R
real N_dev, U1, U2, md, ave, var, F_var, Mort0(0:nyears), Mort1(0:nyears), Mort2(0:nyears)
real variance, F_variance, F_vari
real B,F_parm1, F_parm2, B_parm, F, below_biom_percent
real critical(0:nyears), criticallevel, relativelevel, below_biom(0:nyears), virgin_biom
real, parameter ::pi = 3.141592
real maxrisk,maxCV,max_risk,max_CV,maxyield,max_F_parm1,max_F_parm2,max_B_parm,max_biom

```

```

real max_risk_unconstr,max_CV_unconstr,maxyield_unconstr,max_F_parm1_unconstr,max_F_parm2_unconstr
real max_B_parm_unconstr,max_biom_unconstr
real mu, sigma, lognormal, F_multiplier, s0_multiplier
integer n
include 'simulationparam.txt'
CALL GETTIM (ihr, imin, isec, i100th)

open(42, file = 'hcr3_3D_p&f.txt')
open(43, file = 'hcr2_3D_p&f.txt')
open(44, file = 'hcr1_3D_p&f.txt')

open(45, file = 'hcr1_3D_single.txt')
open(46, file = 'hcr2_3D_single.txt')
open(47, file = 'hcr3_3D_single.txt')

do hcr_type= 1,3

    do F_variance = 0, 100, 25
        F_vari= F_variance*0.001

            do prob= 10, 50, 10
                p= prob*0.01

                    !initialize the search routine
                    maxyield=0
                    maxyield_unconstr=0
                    max_F_parm1=-1
                    max_F_parm2=-1
                    max_B_parm=-1
                    CALL GETTIM (ihr, imin, isec, i100th)
!*****

                    do FM = 0, 800, 50          !This is the loop for F1 parameter values
                        F_parm1=FM*0.01
                            do FM1 = 0, 800, 50          !This is the loop for F2 parameter values
                                F_parm2=FM1*0.01
                                    do FM2 = 0, 18000, 50          !Loop for B parameter values
                                        B_parm=FM2*1.
!*****

                                do year = 0, nyears-1
!-----
                                    rnd = ran(iseed)

                                    !implementing good year/bad year stochasticity

                                    if (rnd<p) then
                                        if (s0_multiplier==Sg) then
                                            s0_multiplier=Sb
                                        else
                                            s0_multiplier=Sg
                                        endif
                                    endif

!-----
                                    R0= exp(-M0) * (fec1 + (exp(-M1)*fec2)/1-exp(-M2))

```



```
call HCR(hcr_type,B1+B2,F_parm1,F_parm2,B_parm,F1)
```

```
F_multiplier = max(0.,1+N_dev(iseed)*sqrt(F_vari)) !random variable with mean 1 multiplied by SD  
F1=F1*F_multiplier
```

```
! FIRST, the fish spawn and the eggs survive to to become the new recruits
```

```
N0(year) = fec1*N1(year) + fec2* N2(year)
```

```
! SECOND, the fish survive
```

```
s0 = exp(-M0* s0_multiplier)/(1+k*N0(year))
```

```
!Beverton & Holt density dependency which never produces chaos WITH
```

```
s1 = exp(-(M1 + F1))
```

```
s2 = exp(-(M2 + F1))
```

```
N0(year+1) = (fec1 * s1* N1(year)) + (fec2 * s2 * N2(year)) !New recruits
```

```
N1(year+1) = s0 * N0(year)
```

```
!Survival of 0-group = numbers in age 1
```

```
N2(year+1) = s1 * N1(year) + s2 * N2(year)
```

```
!Numbers in age 2+
```

```
B1 = w1 * N1(year)
```

```
B2 = w2 * N2(year)
```

```
!Biomass equations
```

```
stock_biom(year) = B1+B2
```

```
yield(year) = (1-exp(-F1))*(N1(year)*w1) + (1-exp(-F1))*(N2(year)*w2)
```

```
!
```

```
if (stock_biom(year)<B_parm) then
```

```
below_biom(year) = 1
```

```
else
```

```
below_biom(year) = 0
```

```
endif
```

```
criticallevel=relativelevel*avg_stock_biom
```

```
virgin_biom = criticallevel/relativelevel
```

```
if(B1+B2<criticallevel) then
```

```
!Defining the 'flags' for critical years when biomass is less than
```

```
critical level
```

```
critical(year) = 1
```

```
else
```

```
critical(year) = 0
```

```
endif
```

```
end do
```

```
!end time cycle
```

```
!*****
```

```
N0(nyears) = (fec1 * N1(nyears)) + (fec2 * N2(nyears)) !New recruits
```

```
MPS1 = sum(N1(st_year:nyears))/(nyears-st_year+1) !These are the mean pop. sizes for the time cycle for each cohort
```

```
MPS2 = sum(N2(st_year:nyears))/(nyears-st_year+1) !These are the mean pop. sizes for the time cycle for each cohort
```

```
MPS12 = MPS1 + MPS2
```

```
!Total exploitable (N1&N2) mean pop. sizes for the time cycle
```

```
B12 = MPS1*w1 + MPS2*w2
```

```
risk = sum(critical(st_year:nyears))/(nyears-st_year+1)*100
```

```
below_biom_percent = sum(below_biom(st_year:nyears))/(nyears-st_year+1)*100
```

```
!*****
```

```
avg_yield = sum(yield(st_year:nyears))/(nyears-st_year+1)
```

```
avg_stock_biom = sum(stock_biom(st_year:nyears))/(nyears-st_year+1)
```

```

sd = sum((yield(st_year:nyears)- avg_yield)**2.)    !This is the stand. dev. for the mean pop. size of N1 in the
time cycle
sd = sd/(nyears-st_year)
sd = sqrt(sd)
V= sd**2
CV = (sd/(avg_yield+1E-10)) * 100                !coefficient of variation of mean yield as a percent

```

```

!*****

```

```

    if(avg_yield>=maxyield.and.CV<=maxCV.and.risk<=maxrisk) then
maxyield=avg_yield
max_F_parm1=F_parm1 !Defining a HCR that has acceptable yield and levels of CV and risk
max_F_parm2=F_parm2
max_B_parm=B_parm
max_biom=avg_stock_biom
max_CV=CV
max_risk=risk
endif

```

```

    if(avg_yield>=maxyield_unconstr) then
maxyield_unconstr=avg_yield
max_F_parm1_unconstr=F_parm1 !Defining levels of CV and risk for an HCR(unconstrained)
max_F_parm2_unconstr=F_parm2
max_B_parm_unconstr=B_parm
max_biom_unconstr=avg_stock_biom
max_CV_unconstr=CV
max_risk_unconstr=risk
endif

```

```

    if(hcr_type==1)then
write(48,'(I3, 2000F100.6)', hcr_type, k, avg_yield,F_parm1, CV, risk
endif

```

```

    if(hcr_type==2)then
write(49,'(I3, 2000F100.6)', hcr_type, avg_yield,F_parm1, B_parm, CV, risk
endif

```

```

    if(hcr_type==3)then
write(50,'(I3, 2000F100.6)', hcr_type, avg_yield,F_parm2, B_parm, CV, risk
endif

```

```

    if(hcr_type==1)then
write(44,'(I3, 2000F100.2)', hcr_type, p, F_vari, maxyield, CV, risk, maxyield_unconstr, max_CV_unconstr,
max_risk_unconstr
elseif(hcr_type==2)then
write(43,'(I3, 2000F100.2)', hcr_type, p, F_vari, maxyield, CV, risk, maxyield_unconstr, max_CV_unconstr,
max_risk_unconstr
elseif(hcr_type==3)then
write(42,'(I3, 2000F100.2)', hcr_type, p, F_vari, maxyield, CV, risk, maxyield_unconstr, max_CV_unconstr,
max_risk_unconstr
endif

```

```

print*, '(I3,2000F10.4)', hcr_type, avg_yield, F_parm2, B_parm, CV, risk

```

```

                                end do                !end of FM2 B_parm
                        end do                !end of FM1 F_parm2
                end do                !end of FM F_parm1
        end do                !end of p loop

```

```

        end do
end do
!
print*, 'HCR Type:', hcr_type
print*, 'Fishing variance level:', F_vari
print*, 'Virgin biomass:', virgin_biom
print*, 'max_F_parm2:', max_F_parm2
print*, 'Unconstrained max_F_parm2:', max_F_parm2_unconstr
print*, 'max_B_parm:', max_B_parm
print*, 'Unconstrained max_B_parm:', max_B_parm_unconstr
print*, 'max_F_parm1:', max_F_parm1
print*, 'Unconstrained max_F_parm1:', max_F_parm1_unconstr
print*, 'Maximum average yield:', maxyield
print*, 'Unconstrained Maximum average yield:', maxyield_unconstr
print*, 'CV:', max_CV
print*, 'Unconstrained CV:', max_CV_unconstr
print*, 'RISK:', max_risk
print*, 'Unconstrained RISK:', max_risk_unconstr
print*, 'Percent of years of stock biomass below B_parm:', below_biom_percent
!*****
        end program simulation

function N_dev(iseed)
implicit none
integer(4) iseed
real, parameter ::pi = 3.141592
real N_dev, U1, U2
U1 = max(0.00001,ran(iseed))
U2 = ran(iseed)
N_dev = sqrt(-2.*alog(U1))*cos(2*pi*U2)
end function N_dev

SUBROUTINE HCR(hcr_type,B,F_parm1,F_parm2,B_parm,F1)
implicit none
!Calculates the harvest control rule
integer hcr_type
real B,F_parm1,F_parm2,B_parm,F1

if (hcr_type==0) then
F1=0.
!No F

elseif (hcr_type==1)then
F1=F_parm1
!constant F (1 parameter HCR)

elseif (hcr_type==2) then
!Slope F to a limit B_parm(2 parameter HCR)
if(B<B_parm)then
F1 = F_parm1*B/B_parm
else
F1 = F_parm1
endif

elseif (hcr_type==3) then
!Step F at B_parm (2 parameter escapement HCR)
if(B<B_parm)then
F1=0
else
F1=F_parm2
endif
endif
endif

```

```

end subroutine hcr

SUBROUTINE avevar(k,n,ave,var)
IMPLICIT NONE
REAL , INTENT(OUT) :: ave,var
INTEGER , INTENT(IN) :: n
REAL , INTENT(IN) :: k(0:n)
REAL , DIMENSION(size(k)) :: s
ave=sum(k(:))/n
s(:)=k(:)-ave
var=dot_product(s,s)
var=(var-sum(s)**2/n)/(n-1)
END SUBROUTINE avevar

```

7.2 Dynamical Population Equilibrium Equation (in FORTRAN code)

```

program population_equil
implicit none
integer(4) iseed
integer ihr, imin, isec, i100th
real N0, N1, N2
real B1, B2, B12, s0, s1, s2, fec1, M0, M1, M2, fecundity1, fecundity2, fec2
real f0,f1,f2, k
real Mort0, MortF1, MortF2
real MF1, MF2

real, parameter ::pi = 3.141592

open(20, file = 'pop_equil_N0.txt')
open(21, file = 'pop_equil_N1.txt')
open(22, file = 'pop_equil_N2.txt')

open(23, file = 'pop_equil_fec1.txt')
open(24, file = 'pop_equil_fec2.txt')
!-----

! Parameters

do Mort0 = 0, 50, 1
M0= Mort0*0.1      !natural mortality at time 0

      do MortF1 = 0, 50, 1
MF1= MortF1*0.1    !natural mortality at time 1

            do MortF2 = 0, 50, 1
MF2 = MortF2*0.1    !natural mortality at time 2

                    do fecundity1= 0, 2000, 50
fec1=fecundity1     !fecundity at time 1 proportional to the weight of N1

                            do fecundity2= 0, 5000, 50
fec2=fecundity2

                                    k= 0.0001      !constant in BH
!-----
N0= (1-exp(MF2) + (exp(-M0) *(-1+exp(MF2))* fec1) + (exp(-M0-MF1+MF2)*fec2))

```

```

N0 = N0/((-1+exp(MF2))*k)
!-----
N1= (exp(-M0) * (exp(M0+MF1) * (-1+exp(MF2))) - (exp(MF1) * (-1+exp(MF2) * fec1) - (exp(MF2) * fec2)))
N1= N1/(((exp(MF1) * (-1+exp(MF2)) * fec1) + (exp(MF2) * fec2)) * k)
!-----
N2= -(exp(-M0-MF1+MF2) * (exp(M0+MF1) * (-1+ exp(MF2)) - (exp(MF1) * (-1 + exp(MF2)) * fec1) - (exp(MF2) * fec2)))
N2= N2 / (((exp(MF1) * (-1+exp(MF2) * fec1) + exp(MF2) * fec2)) * k)
!-----
print *, 'N0', N0, 'N1', N1, 'N2', N2

write(20,'(2000F100.2)'), M0, N0, N1, N2
write(21,'(2000F100.2)'), MF1, N0, N1, N2
write(22,'(2000F100.2)'), MF2, N0, N1, N2

write(23,'(2000F100.2)'), fec1, N0, N1, N2
write(24,'(2000F100.2)'), fec2, N0, N1, N2

                                end do !fec2
                            end do !fec1
                        end do !MF2
                    end do !MF1
                end do ! M0

                end program population_equil

```