Universidade do Algarve
Faculdade de Ciências e Tecnologia

Application of a control system based on fuzzy logic to the management of fisheries resources.

Aplicação de um sistema de controlo baseado em lógica difusa à gestão de recursos pesqueiros.

Marta Mosquera Quinteiro

Mestrado em Aquacultura e Pescas

Especialidade en Pescas

2011

Universidade do Algarve
Faculdade de Ciências e Tecnologia

Application of a control system based on fuzzy logic to the management of fisheries resources.

Aplicação de um sistema de controlo baseado em lógica difusa à gestão de recursos pesqueiros.

Dissertação orientada por Dr. Alberto Murta

Marta Mosquera Quinteiro

Mestrado em Aquacultura e Pescas
Especialidade en Pescas

2011

Resumo A sobreexploração e esgotamento dos estoques pesqueiros motivou o uso da avaliação das estratégias de gestão e os procedimentos de gestão, com a finalidade de os manter sobre um nível saudável enquanto se mantêm elevadas capturas. O procedimento de gestão consiste num modelo operativo e uma regra de controlo de captura (HCR). O seu desempenho está relacionado com os pontos de referência escolhidos, os procedimentos de avaliação do estoque e o regime de monitorização.

A teoria dos conjuntos difusos foi usada porque permite lidar de forma natural com as imprecisões na definição de um grupo, produzindo resultados equilibrados quando aplicada a HCRs.

O objectivo deste trabalho é comparar o desempenho de 2 HCR clássicas com as respectivas traducções a lógica difusa. Para o efeito, construiu-se uma população, bem como a respectiva pescaria e avaliação do estoque. Foram executadas projecções a 60 anos, com e sem variabilidade, resultando numa melhoria das condições do estoque e das méedias de producção, quando usados os modelos baseados em lógica difusa.

Palavras chave *Harvest Control Rules, HCR, Gestão de pescarias, Lógica difusa, Teoria dos conjuntos difusos, TAC, Total Allowable Catch.*

Abstract The overfishing and depletion of the fishing stocks motivated the use of management strategy evaluation and management procedures, in order to keep the fish stock above a healthy level while maintaining high catches. The management procedure consists of an operating model and a harvest control rule (HCR), and its performance is related to the chosen reference points, the stock assessment procedures and the monitoring regime.

Fuzzy set theory was used because it provides a natural way to deal with imprecision in the definition of a group, providing balanced results when applied to HCR.

The aim of this work is to compare the performance of 2 classic harvest control rules and their translation into fuzzy logic. To achieve this goal a fish stock was built as well as a fishery and stock assessment, and 60-year projections were performed, with and without variability, resulting in a general improvement in the stock health and in mean yields.

Keywords: *Harvest Control Rules, HCR, Fisheries management, Fuzzy logic, Fuzzy set theory, TAC, Total Allowable Catch.*

Aknowledgements: Foremost, I would like to thank my supervisor, Dr. Alberto Murta (IPIMAR), who shared with me a lot of his expertise and research insight, and to Dr. Karim Erzini for his support and helpfulness. I want to dedicate this work to William Silvert, who planted the seed for this work.

Contents

Glossary

ABC: Allowable biological catch.

B_{lim}: Minimum biomass below which recruitment is expected to be impaired or the stock dynamics unknown.

B_{MSY}: Biomass which can produce the maximum sustainable yield.

B_{pa}: Precautionary biomass level.

F_{lim}: Limit fishing effort.

F_{pa}: Precautionary fishing effort.

HCR: Harvest control rules.

MEY: Maximum economic yield.

MSR: Maximum surplus reproduction.

MSY: Maximum sustainable yield.

LRP: Limit reference point.

OM: Operating model is how stock and fisheries dynamics are represented.

SSB: Stock spawning biomass.

TAC: Total Allowable Catch.

TRP: Target reference point.

VABC: Variation of the allowable biological catch.

1 Introduction

1.1 Current procedures of fishery management.

According to FAO, most of the stocks of European Union are considered to be over-fished or depleted, and many are below safe biological limits (Froese et al., 2010; Cochrane et al., 1998), causing great losses of commercial fish species biomass in the coastal waters along with the degradation of the sea bottom, leading to a decreasing biodiversity in these areas (Pauly and Maclean, 2003). This whole picture caused concern among the general population (Cochrane et al., 1998).

This situation sparked the use of frameworks such as management procedures and management strategy evaluation (Rademeyer et al., 2007). Management procedures (MPs) are defined as sets of rules for calculating annual catch limits from available stock information. These rules have to be robust face to plausible changes in the assumptions underlying an operational model. To facilitate the definition of the rule sets, models of the dynamics of the stock are used (Cochrane et al., 1998).

Along with the fishing strategies, MPs are meant to satisfy multiple conflicting objectives, such as **maintain high annual catches, low risk of depletion and maximum industrial stability** besides social objectives (Rademeyer et al., 2007). MPs are closely related to the stock fished, the as-

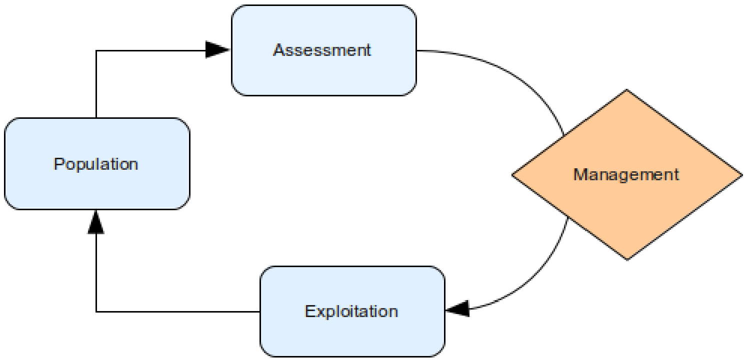

Figure 1.1: Management influence over a stock and its exploit.

sessment methods and the harvest control rules (HCR), affecting each other cyclically (fig.1.1).

These elements, or the methods applied to get them, are pre-specified to define the directions that make up the management action (Kell et al., 2006). The MP´s success depends on the interactions between the choice of reference points, the stock assessment procedures and the monitoring regime (Kell et al., 2005).

1.2 Reference points.

The main goal of the stock management is to achieve and maintain a healthy spawning stock biomass (*SSB*) level (Kell et al., 2006) and at the same time keeping the highest catches as possible. Target reference points (TRP) were fixed to define these levels within a single-stock fishery: at first it was proposed **MSY**, or maximum sustainable yield, defined as the largest yield or catch that can be taken from a species' stock when it is in equilibrium, over an indefinite period. The reference point (B_{MSY}) as the biomass which can produce the MSY, and F_{MSY} as the fishing effort that should be applied to get the MSY. Some other TRPs have been proposed and used, based in different parameters such as economy(MEY), recruitment (MSR), size of the fish caught or natural/total mortality (fig. 1.2) (Caddy and Mahon, 1998). But these points and the stock dynamics parameters such as current spawning stock biomass (*SSB*) or actual fishing mortality (F) can only be calculated with uncertainty.

In order to ensure that fisheries remain within safe limits this uncertainty had to be taken into account, the notion of precautionary approach was introduced. It consists of a dual system of conservation limits (limit reference points or LRPs): a reference point that the *SSB* should remain above, where recruitment remains undamaged (B_{lim}), and a buffer to account for uncertainty of the knowledge about the status relative to the conservation limit (B_{pa}). Also, both of these levels are expressed in terms of fishing mortality (F_{lim} and F_{pa}) (ICES, 2009).

Precautionary reference points (F_{pa} and B_{pa}) are set in order to avoid reaching B_{lim} with a high probability (Kell et al., 2005), so they are also employed to evaluate the fishery status (ICES, 2009) and to trigger management actions (Kell et al., 2006), although they should serve as a ceiling in the case of F, and as a minimum in the case of B when target levels are set by managers and stakeholders (Froese et al., 2010).

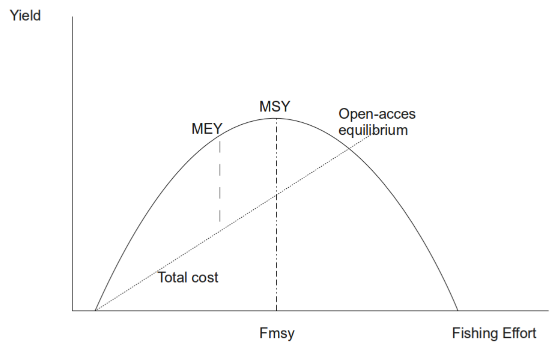

Figure 1.2: Example of reference points, representing Maximum Sustainable Yield and Maximum Economical Yield with the corresponding fishing effort. (Caddy and Mahon, 1998)

Recently, the concept of MSY was again made important by the European Commission, when the deadline of 2015 was defined as the date when all resources should be exploited at F_{MSY} level (com, 2011). This decision had the consequence of forcing all defined harvest control rules to be tested to see if they were compatible with MSY in the long-term.

1.3 Management strategies evaluation.

Management procedures (MPs) are tested applying long-term simulations under different sets of assumptions, and their are selected in order to achieve certain pre-agreed management objectives. Some of these objectives could be: minimize the risk of depletion of stock within the projection period, keep an average annual catch in the projected period and low inter-annual catch variability, among others that are involved with the ecological aspect, like improving recruitment scenarios and environmental stability. They are taken into account economic or operational facts as well (Cooke, 1999; Cochrane et al., 1998).

MPs specify a particular sampling regime and stock assessment technique, with appropriate HCRs and their implementation. The process starts by setting up groups of decision rules for a given fish stock, whose consequences have to be assessed for both the target resource and associated fisheries, in order to test their performance robustness to uncertainties about the stock dynamics (Rademeyer et al., 2007).

For that, a simulation framework is needed to reproduce the response of a fishery, both *true* (most plausible hypothetical system dynamics) and *observed* or assessed system dynamics to management, in order to select the more suitable set of rules (Kell et al., 2005).

The simulation framework is composed by one or a set of **operating models (OM)** which represent several scenarios for the resource stock dynamics, an **estimator** that provides information about the status of the stock and productivity, in a model-based MP, and a **harvest control rule (HCR)**, which outputs a management action (Rademeyer et al., 2007).

The stock dynamics are represented as an OM from which simulated data are gathered using an observation model, which simulates a sampling regime. The gathered data depict the commercial catch-at age matrix, and research vessel survey results are used to generate time-series of abundance estimates (Kell et al., 2005). The data used to build the historical component might be the best available parameter and state variable estimates, along with their ranges of uncertainty (Cochrane et al., 1998).

The OMs may include in addition to typical population parameters, such as growth and stock-recruitment relationship and their variability, discards, other species or even the ecosystem, but the assessment model will determine the nature of the data required.

These models are fitted and must be consistent with the available stock data (Rademeyer et al., 2007). Performance statistics are used to evaluate the behavior of the OM (Kell et al., 2005). The final choice of the reference OM must ensure that a sufficiently representative range of potential estimates is present. Once the OM is selected, both assessment model and OM are used to compute how the resource would respond to different levels of fishing pressure (Rademeyer et al., 2007). After the reference OM is selected, a range of robust-test scenarios has to be identified. They must reflect the true dynamics that may vary more widely and be less plausible or have less impact than those included in the reference set.

The aim of choosing a management model is to yield a harvest algorithm which performs well for management purposes, when combined with the estimation procedure and the control law (Cooke, 1999).

The estimator is the model-based framework within which the data from the fishery are analyzed and the current status and productivity are assessed. Related outputs are then fed into the HCR to provide a recommendation for the management action. The combination of the estimator and HCR provides the feedback mechanism within the MP. Hence, the MP is able to self-correct over time. It is defined as the statistical estimation process within an assessment; in a MP context, the component that provides information on resource status and productivity from past and generated future resource-monitoring data for input to the HCR. It is only used in a model-based MP.

Survey based stock assessments and fishery independent HCR arose because of the inaccuracy of commercial fishery data. They are also useful to provide alternative solutions to the management of exploited stocks or when either catch information does not exist or is not acceptable.

A **HCR**, or harvest algorithm, is the part of the MP of most concern because it provides a management recommendation in the form of TACs or allowable fishing effort, in relation with the outputs of the estimator (Rademeyer et al., 2007; Cooke, 1999).

There are three main types of HCR from which many modifications can be made (fig.1.3). Those are:

1. **Constant catch control rules:** removal of the same amount of biomass of fish each year, thereby allowing high F at low B levels.

2. **Constant fishing mortality or constant effort control rules:** same fishing mortality rate, so that regardless of B, harvest is proportional to B.

3. **Fixed escapement control rules** keep the B over some specified target level. Harvest would be intense above this threshold and zero otherwise.

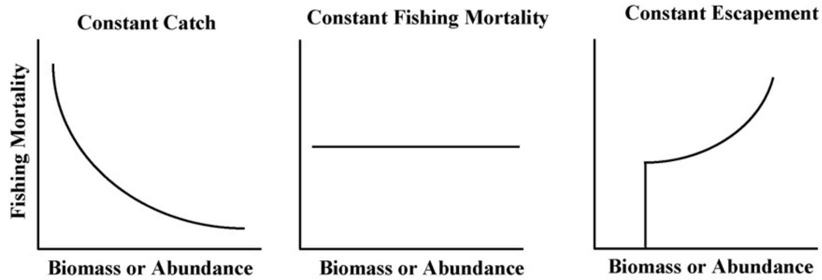

Figure 1.3: The three main types of HCR (Deroba and Bence, 2008)

To prevent drawbacks when implementing these HCR, conditions or thresholds may be added. Examples of these alternatives are **threshold control rules**, suggested as modifications to constant fishing rate rules that specify a biomass below which no fishing is permitted, but a constant F is used otherwise. **Adjustable rate rules** are control rules that scale F, usually adjusted proportionally to the stock size, downward when the population is below a threshold (Deroba and Bence, 2008).

A HCR is selected by comparison of its performance over a range of scenarios which include some random processes, such as sampling or recruitment to the fish stock variability. These simulations require a long time horizon to avoid the high influence of the starting conditions and to gain better understanding the properties of the assessed HCR (Cooke, 1999). The selected HCR would give the highest probability of achieving the MP objectives.

The main purpose of computing these performance criteria is to provide a means by which different algorithms or different tunings of the same algorithm can be compared. Once agreed upon, the management procedure should be implemented for a number of years, usually from 3 to 5. Then, it is reviewed and modified if necessary (Cochrane et al., 1998; Deroba and Bence, 2008) (fig. 1.1).

Four sources of errors can be found in this framework:

1. *Process variability*: attributable to natural variation in dynamic processes, such a recruitment variability or unestable natural mortality rate.

2. *Observation error*: generated during the data gathering or when modeling the dynamic process. For instance, an error in the assessment or in the initial premises.

3. *Model error*: due to the inexactitude of the models, which can never grasp the complexity of the *true* population.

4. *Implementation error*: arise from the imperfect implementation of management actions, such as setting higher TACs than recommended or the exceeding of catches by fishermen (Kell et al., 2005).

Since advice is based on precautionary reference points such as B_{lim} and F_{pa} as triggers of management actions (Apostolaki and Hillary, 2009) it may bring as a result high fluctuations in fishing effort (E_f).

One of the strategies used to achieve stability in the catches is the incorporation of TAC boundaries into the HCR. Though it is useful for some fisheries, for others this can result in a big delay in reaching the target biomass level (Kell et al., 2006).

1.4 Objectives of this work

The aim of this work is to compare stock and yield projections performed with classic HCR and fuzzy HCR, the latter ones obtained by translation of the classic HCR into fuzzy logic rules, and determine if the application of the fuzzy set theory to management procedures results in increased production while maintaining healthy biomass levels, reducing the variability of TACs from one year to another.

2
The Fuzzy Set Theory

The **Fuzzy Set Theory** was first published by Zadeh (1965) and Goguen (1967, 1969). The idea is to provide a natural way to deal with problems in which the source of imprecision or vagueness is the absence of sharply defined criteria of class membership rather than the presence of random variables.

In a classic logic, a set is characterized by the need of any given objects to belong or not to it, classifying its membership as "True" or "False". This dichotomy is hard to apply to the actual world, because some set's boundaries are not well defined. Examples of this kind of sets can be "old", "fast" or "small", because their definition is relative. The fuzzy sets theory allows to grade the membership of an object to one or more groups with a number between 0 and 1 (Zimmermann, 1992; Sangalli, 1998), using fuzzy functions that can be depicted as triangular, trapezoidal or bell-shaped graphs (fig. 2.1) (Sangalli, 1998).

A fuzzy set **A** is specified by a characteristic *membership function* which associates a real number in the interval [0, 1] to each point or element. The closer to the unit, the higher would be the membership to the point or element to **A**. For example, in classic logic, the membership function can only take values 1 and 0: if an object belonged to a set **B**, its membership degree would be 1. If it did not belong, its membership would be 0 (Zadeh, 1965).

The use of fuzzy sets involves several steps. The first of all implies constructing a linguistic model or putting instructions in ordinary language, in the form of operating rules. For example:

If a high resolution screen is large, then the price will be high .

The next step is encoding the relationships of the variables in terms of fuzzy sets, using labels for each fuzzy subset (the different levels a set has) and giving it a mathematical form, so that the latter rules become fuzzy inference rules. This mathematical form allows the construction of a new fuzzy subset, the "conclusion" (C) for the given premises (A and B). For example:

If a TV screen is large and has high resolution, then it will be expensive.
If a TV screen is small and has regular resolution, it will be cheaper.
If x is A and / or y is B, then z is C.

In most applications, the values of x and y are numbers and x_0 and y_0 are the result of measurements of numerical variables, meaning that x is A and y is B are interpreted as $x = x_0$ and $y = y_0$. The membership function of the fuzzy subset C' is defined by function (2.1), meaning that the grade of membership in C' of the number z is the smallest of the grades, in case of the AND operator, the biggest of the grades when using the OR operator *A*(x_0), *B*(y_0) *and C(z)* (Sangalli, 1998)

$$C'(z) = \{min\,(max)\;A(x_0),\, B(y_0),\, C(z)\} \tag{2.1}$$

The inferencing method outputs a membership function: for given input x_0 and y_0 values each rule will yield a fuzzy subset. The total of these new subset are combined into a final conclusion using the union of fuzzy sets operation. The result has to be then defuzzified to a crisp value. For that purpose there are several methods, but here the "centroid" method was used, which indicates the centre of mass of the output sets, favoring the rule with the output of greatest area.

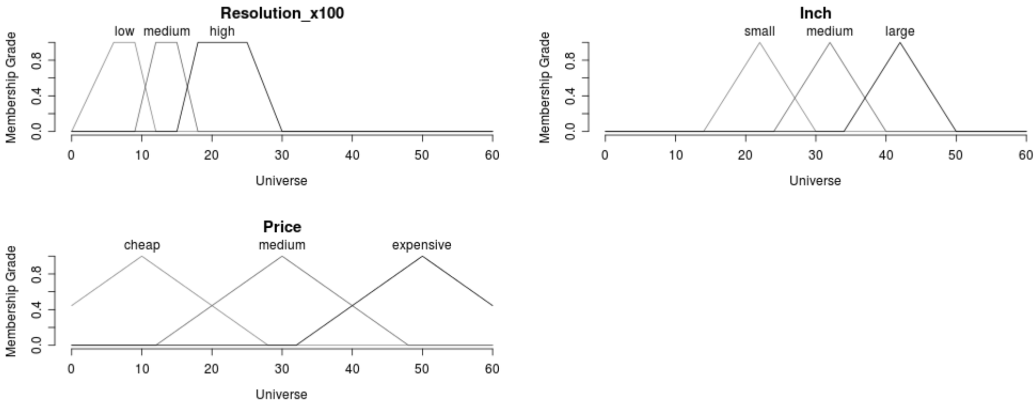

Figure 2.1: Example of a fuzzy system with triangular and trapezoidal membership functions (Sangalli, 1998)

This theory may also be used in management procedure, because vagueness or uncertainty exists in determining the status and modeling the dynamics of a fish population, and therefore in placing the reference points that trigger the management action.

3
Methods

In order to test the efficiency of the fuzzy logic methods, they are compared with two classic HCR, the one used by ICES (Kell et al., 2005), from now on referred to as *classic 1*, and the one proposed by Froese *et al.* (2010), from now on refered to as *classic 2*. The fuzzy HCR are obtained by translation of those classic HCR, and they were called *Fuzzy 1* and *Fuzzy 2* respectively.

The comparison takes place by building projections of the southern horse mackerel stock (ICES, 2011) within a sixty-year period applying the corresponding TACs, computed according to the SSB estimates on a yearly basis, for both the classic HCRs and the fuzzy HCRs. Each projection takes place under four scenarios:

1. Scenario 0: No noise or variation is applied.
2. Scenario 1: A normally distributed variation ($\mu = 1, \sigma^2 = 0.2$) of the recruitment is applied.
3. Scenario 2: A normally distributed error ($\mu = 1, \sigma^2 = 0.2$) of observation is applied in the assessment.
4. Scenario 3: Both variation and error are applied.

The results of the projections of both classic HCRs are compared with those of their fuzzy counterparts, remarking the development of the stock, TAC variations and yield .

For fuzzy logic HCRs the package "Sets" for R (Meyer and Hornik, 2009) was used .

The followed path is shown in fig.3.1. It starts with the initial data of the operating model. Yield, effort and the following assessment are estimated within the model.

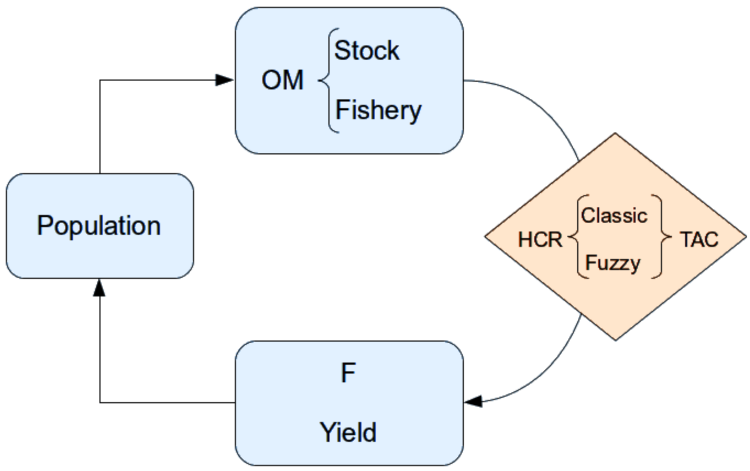

Figure 3.1: Flowchart showing the data needed the steps followed

3.0.1 The Fish Stock.

The initial data was gathered from the WGANSA report 2011 (table 3.0.1). Data from previous years (ICES, 2011) was used to find a stock-recruitment relationship that fitted. Then, to be able to apply HCR classic 2, it was needed to determine MSY and the reference points linked to it, F_{MSY} and SSB_{MSY}.

The following assumptions about the fishery biology have been applied to the stock:

1. The stock has a constant stock-recruitment relationship.

2. Recruitment takes place in September-October.

3. Fish have a constant growth rate (until age 11), and the parameters of the length-weight relationship are constant as well.

4. There are no bio-metrical differences between the two sexes and there is no sex inversion.

5. There is no migration flux into or out of the population (i.e. a closed population).

6. The stock has a constant natural mortality rate within year classes.

7. The stock is uniformly distributed in the fishing area.

Table 3.1: Initial Data of the Stock (ICES, 2011)

Age	Initial population ('000)	Weight (kg.)	Maturity at age	Exploitation pattern	Natural mortality
0	2806204	0.02	0.00	0.0201	0.90
1	4812897	0.04	0.00	0.1073	0.60
2	596039	0.06	0.36	0.1373	0.40
3	347933	0.08	0.82	0.1225	0.30
4	126731	0.11	0.95	0.1007	0.20
5	62334	0.14	0.97	0.0763	0.15
6	107143	0.16	0.99	0.0775	0.15
7	147086	0.18	1.00	0.0831	0.15
8	109296	0.19	1.00	0.0831	0.15
9	43296	0.20	1.00	0.0831	0.15
10	62883	0.24	1.00	0.0831	0.15
11+	257507	0.38	1.00	0.0831	0.15

3.0.2 Fishery and Stock Assessment.

Some other characteristics associated to the fishing fleet and impact of fishing on the stock were also considered. Those are:

1. Fishing mortality is variable.

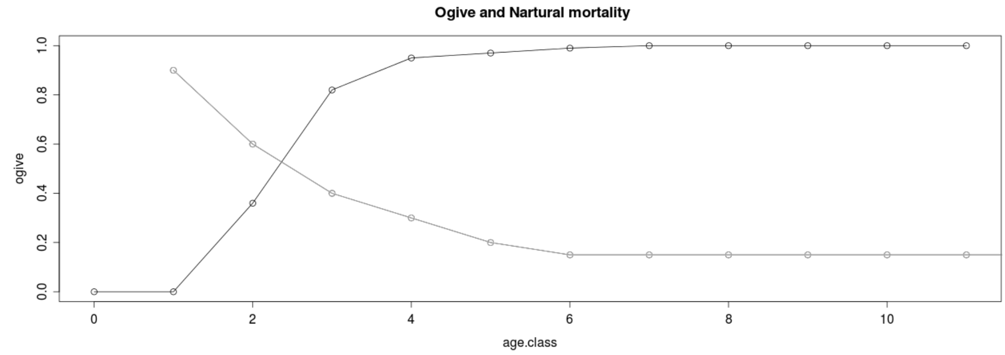

Figure 3.2: Ogive (black line) and natural mortality (gray line) of the stock.

2. Management rules are followed without bias.

3. TAC is always accomplished.

4. The fleet has a constant exploitation pattern or selectivity. Fig 3.3 is a plot depicting the exploitation pattern of this stock.

5. The percentage of new recruits affected by the fishing activity (25%) was taken into account.

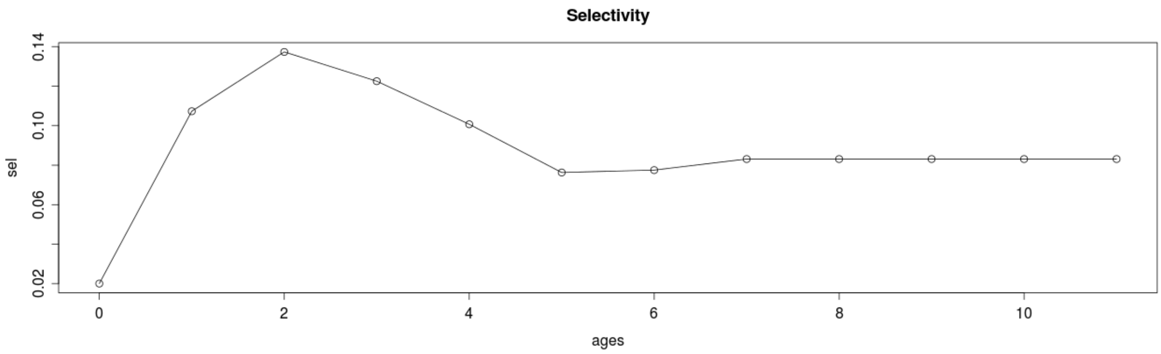

Figure 3.3: Selectivity of the stock.

To perform the projections, Deriso's stock-recruitment relationship (equation 3.1) was assumed, taking into account the spawning stock biomass and

Table 3.2: Previous years' stock-recruitment series.

Year	SSB (ton.)	Recruits ('000)	Landings (ton)
1992	274520	3749400	27858
1993	273680	2667100	31521
1994	271540	2633700	28450
1995	265840	3492900	25132
1996	270180	9075200	20360
1997	294400	3027600	29491
1998	300180	1941100	41661
1999	299860	2907900	27768
2000	299580	2641600	26160
2001	298260	3163500	24911
2002	294960	1750800	22506
2003	286480	3591500	18887
2004	281340	3921200	24485
2005	289240	2326400	22689
2006	297380	1097500	23895
2007	280220	1678400	22787
2008	259100	3043400	22993
2009	246420	3037400	25726
2010	241400	6057700	27217

recruitment series gathered the previous years 3.0.2 (ICES, 2011). Although it is not a reliable stock-recruitment relationship, because of the recruitment high variability and the lack of a range of SSB levels, they were used the following recruitment parameters: $a = 15$, $b = 1.5 \times 10^{-6}$, $g = 0.7$, so that the equation pass through the recruitment point cloud for the given levels of SSB. In order to apply some random variability, it was also added a fourth parameter, ν, which follows a normal distribution with mean $\mu = 1$ and variance $\sigma^2 = 0.2$.

$$R = a\,SSB\,(1 - b\,g\,SSB)^{\frac{1}{g}}(\nu) \tag{3.1}$$

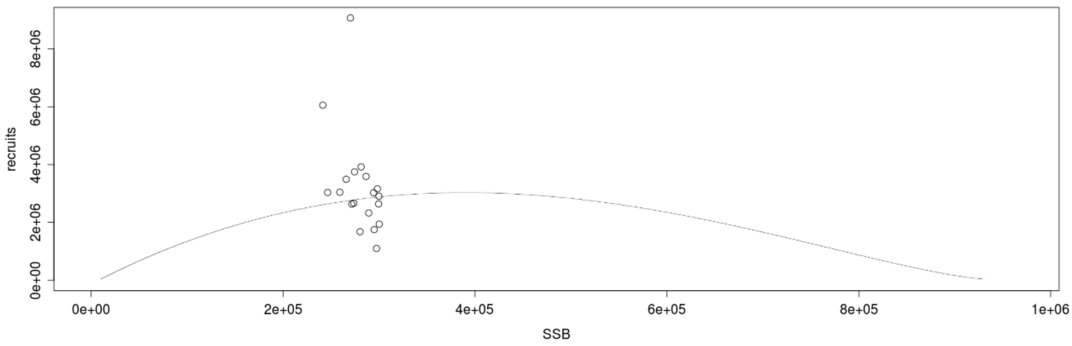

Figure 3.4: Fitted stock-recruitment curve.

The population in numbers by year class was calculated over a 60 year horizon using the equation

$$N_{i+1,j+1} = N_{i,j}\, e^{-(F\, s_{j-1} + M_{j-1})} \tag{3.2}$$

Where $N_{i,j}$ is the population in numbers per year and age class, F is the fishing mortality rate, s the exploitation pattern of the fishery per age class and M the natural mortality.

SSB was calculated using the equation:

$$SSB = \sum N\, W\, O \tag{3.3}$$

Where O means the maturity ogive, Yield per year was estimated using the Baranov catch equation:

$$Yield_{i,j} = W_{i,j} \left(\frac{F_i\, s_j}{F_i\, s_j + M} \right) N_{i,j} (1 - e^{-(M + F_j\, s_j)}) \tag{3.4}$$

Where W is the mean weight of the individuals of a cohort and the rest of symbols are the same as in equation 3.2.

Equation 3.4 was also used to determine F to apply the next year on the basis of the previously calculated TAC, optimizing the results into a range

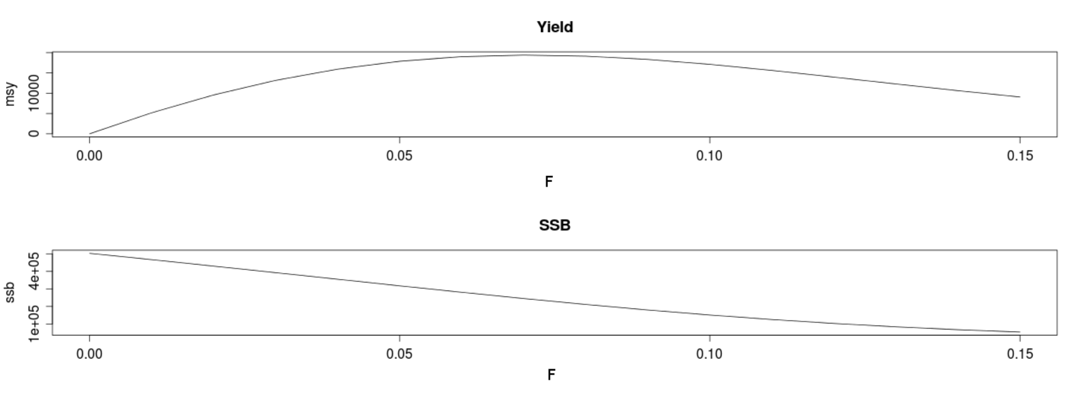

Figure 3.5: Yield and SSB obtained applying a range of fishing mortality values (0 to 0.15).

of 0 to 10.

In order to know how the population would evolve under no fishing effort, a first simulation over a horizon of 60 years was performed. It showed that this population grows quickly until the 12^{th} year, from less than 250000 to over 550000 tons. From that year on the population decreases slowly until it reaches a low of 499000 tons during the 26^{th} year. The population starts stabilizing and remains between 5×10^5 and 5.3×10^5 until the end of the simulation (fig. 3.6).

Recruitment during the first phase is around 2.6×10^6 and 2.8×10^6, but it decreases reaching 2.4×10^6 the 12^{th} year. It grows slowly until year 24^{th}, and since that it stays steady, with a recruitment level of 2.58×10^6 recruits until the end of the simulation.

To determine the MSY and the related reference points, the stock was projected over a 60 year horizon under a range of possible Fs, from 0 to 0.15 every 0.01. Only the last 30 years were taken into account, when the population is stabilized.

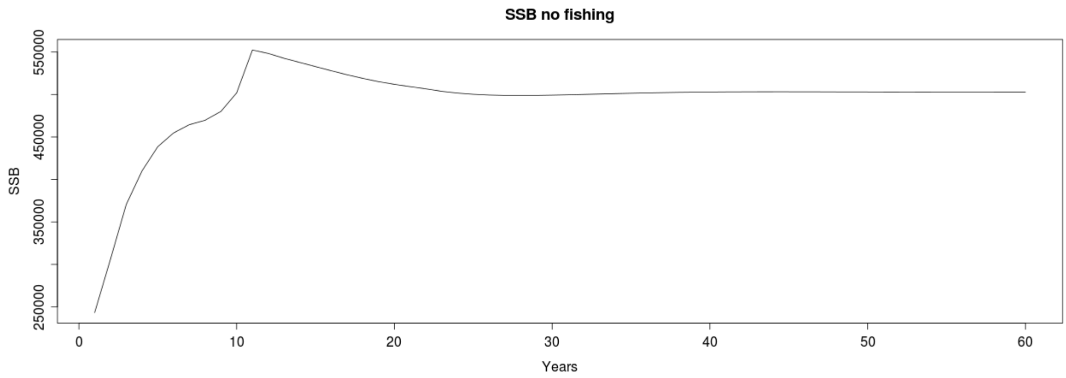

Figure 3.6: Evolution of the fish stock under no-fishing condition.

The resulting matrices and the plots suggest $MSY = 17912.3$ tons, $F_{MSY} = 0.05$ and $SSB_{MSY} = 317856$ tons. Imposing a constant F_{MSY}, it allows the population to grow rapidly until the 5^{th} year, reaching almost 3.7×10^5 tons. The biomass decreases until 3.4×10^5 tons, but it increases again, reaching a peak above 3.7×10^5 during the 10^{th} year. From that year on, it decreases logarithmically, becoming stabilized from the 32^{nd} year at around 3.1×10^5 tons. The amount of recruits is more or less constant (2.7×10^6), decreasing over time until 2.66×10^6 recruits the last year of the simulation. The 2^{nd} and 3^{rd} years are an exception in which recruitment is lower (2.4×10^6 and 2.5×10^6, respectively). Yield increases proportional to SSB until the 5^{th} year, from 1.3 to 2.5×10^4 tons. It decreases sharply the following two years until 1.9×10^4, recovering with the second peak in the SSB. It decreases until stabilized at around 1.7×10^4 until the end of the simulation (fig.3.7). This results are considered for starting the simulations with HCR classic 2.

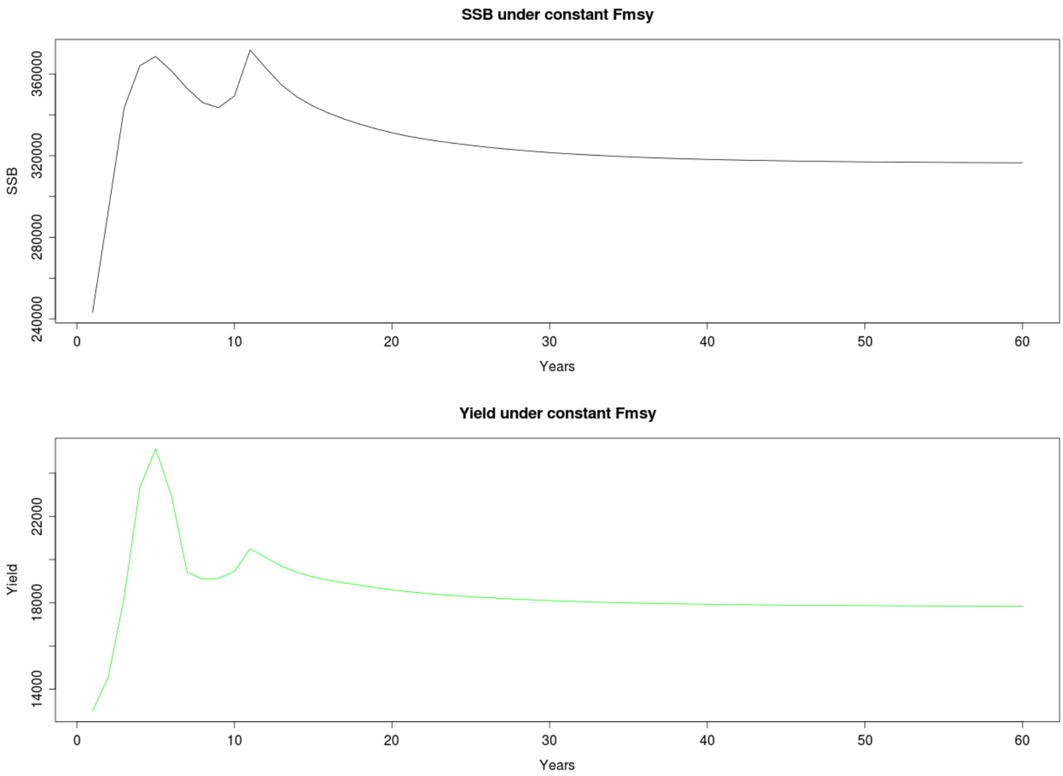

Figure 3.7: Evolution of the fish stock under constant fishing effort (F_{MSY}), equal to 0.05. The black line represents SSB, the green line, the yield.

3.0.3 Classic Harvest Control Rules.

Classic HCR 1 Considering that ABC, allowable biological catch, corresponds to the level of fishing mortality that will ensure that SSB remains above or recovers to the precautionary biomass level, the total allowable catch, TAC, are limits on fishing effort, and α the constraint on the annual change in TACs (Kell et al., 2006):

1. If $ABC_{t+1} \geqslant TAC_t(1+\alpha)$ then $TAC_{t+1} = TAC_t(1+\alpha)$

2. If $ABC_{t+1} \leqslant TAC_t(1-\alpha)$ then $TAC_{t+1} = TAC_t(1-\alpha)$

3. Otherwise $TAC_{t+1} = ABC_{t+1}$

Due to the requests made by fishermen and stakeholders, this HCR was modified in two ways, the first one taking off the imposed constraint:

1. $TAC_{t+1} = ABC_{t+1}$

and the second, keeping just the lower constraint:

1. If $ABC_{t+1} \leqslant TAC_t(1-\alpha)$ then $TAC_{t+1} = TAC_t(1-\alpha)$

2. Otherwise $TAC_{t+1} = ABC_{t+1}$

The latter two HCR are those which were translated into fuzzy HCRs.
The following definitions are applicable to both classic and fuzzy systems:

1. TAC is the same as the real TAC for the southern horse mackerel stock (25000 tons)

2. ABC was considered as a constant proportion of 10% of the total SSB, consitent with the current TAC and SSB and the catches from previous years (3.0.2).

3. The maximum constraint applied is 15%.

Classic HCR 2: proposed by Froese *et al.*(2010) Regarding the reference biomass B_{MSY}, the target biomass is set at: $1.3B_{MSY}$ and the limit biomass would be $B_{lim} = 0.5B_{MSY}$.

1. If B is on average $1.3B_{MSY}$ and always $\geqslant B_{MSY}$ then TAC will be set at its maximum level.

2. If $B < B_{MSY}$ then TAC is linearly reduced until B reaches $0.5B_{MSY}$

3. It $B \leq 0.5B_{MSY}$, then TAC is 0.

The average applied was that of the previous three years, and the maximum fishing level was defined by the fishing effort with which an amount close to MSY could be gathered (fig. 3.8).

The maximum level is set as F_{MSY} (F=0.05). For the first 3 years the first rule was avoided, and from the fourth year on the average taken into account was that of the 3 previous years.

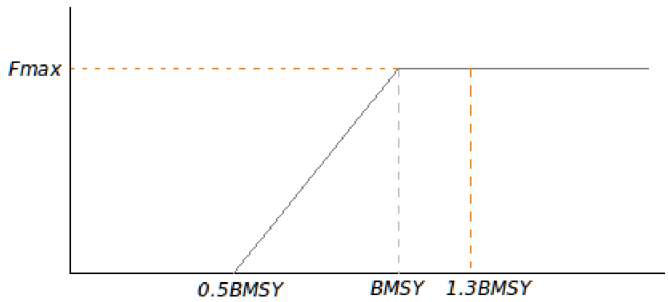

Figure 3.8: Classic HCR 2 shown graphically.

3.0.4 Fuzzy Harvest Control Rules.

Fuzzy HCR 1.

The Classic HCR 1 was translated into fuzzy logic, where the fuzzy element would be α. VABC, which is defined as the proportional increment of ABC from year$_t$ to year$_{t+1}$:

$$ABC_t \xrightarrow{VABC} ABC_{t+1}$$

was used.

To simplify, α is treated as a TAC increment. The constraint is realized by setting the minimum α as -15%. The fuzzy rules that were applied here can be read in tables 3.3 and 3.4.

The fuzzy system created with these rules and definitions is graphically shown in figs. 3.9.

α is defined as medium where no variation takes place, meaning $\alpha \simeq 0$, low or very low when α should be negative or high or very high when α is positive.

The α that applies is computed by doing inference (calculating the areas of the categories' sets regarding the rules and then superimpose them to

Table 3.3: Fuzzy rules for HCR1 without constraint.

If VABC	is	minimum	then α	is	minimum
If VABC	is	much lower	then α	is	very low
If VABC	is	low	then α	is	low
If VABC	is	medium	then α	is	medium
If VABC	is	high	then α	is	high
If VABC	is	much higher	then α	is	very high
If VABC	is	maximum	then α	is	maximum

Table 3.4: Fuzzy rules for HCR1 with a lower constraint.

If VABC	is	minimum	then α	is	minimum
If VABC	is	much lower	then α	is	minimum
If VABC	is	low	then α	is	minimum
If VABC	is	little	then α	is	minimum
If VABC	is	medium	then α	is	medium
If VABC	is	higher	then α	is	low
If VABC	is	high	then α	is	high
If VABC	is	much higher	then α	is	very high
If VABC	is	maximum	then α	is	maximum

form a new shape) of VABC within the fuzzy system and then defuzzifying to get the centroid of the inference. The resulting VABC were rounded to the nearest integer. If these values were not rounded, the package "Sets" would output an error. TAC is then calculated using the following function:

$$sTAC_{t+1} = TAC_t \times \left(1 + \frac{\alpha}{100}\right) \tag{3.5}$$

Fuzzy HCR 2.

The classic HCR 2 was translated into fuzzy logic resulting into a simpler fuzzy system than the previous one.

The fuzzy rules generated for HCR 2 can be found in table 3.5

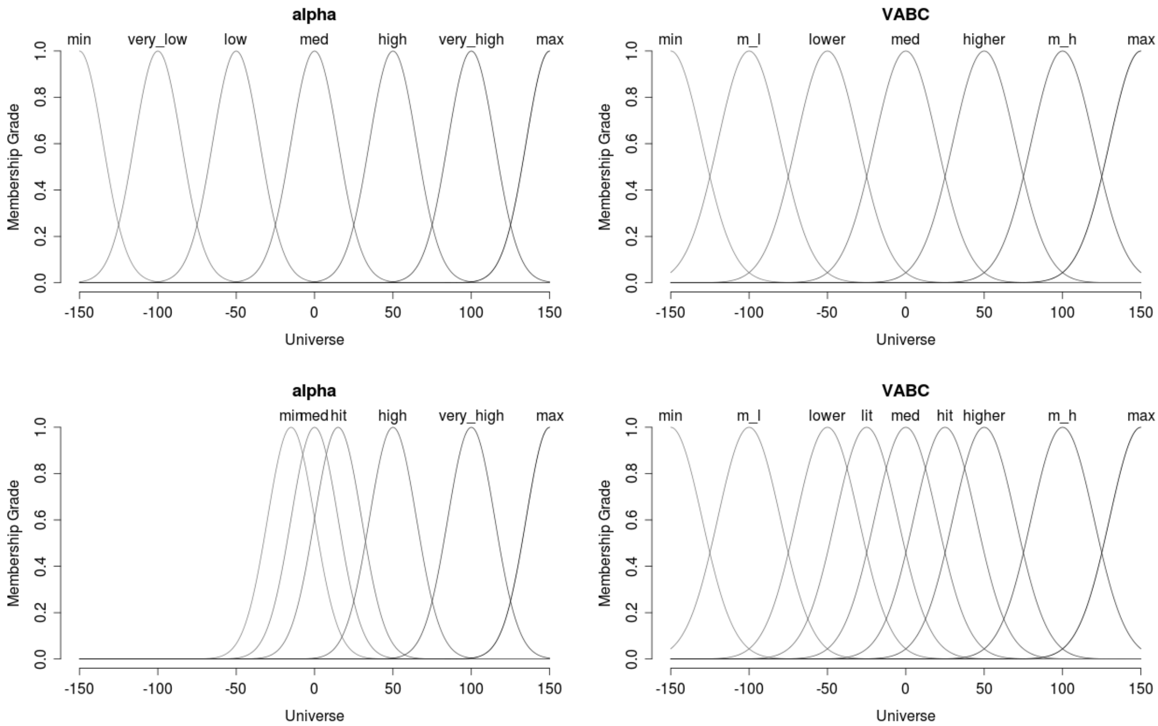

Figure 3.9: Fuzzy systems yielded according to the rules made up for HCR1. Upper: No constrain. Lower: 15% lower constraint.

The fuzzy system created is shown the following figure 3.10.

The relation between the projected biomass and (B) was rounded to the third decimal, the maximum allowed in the R package for this system. The resulting number was used as an input, i.e. how bigger or smaller than B_{MSY}, to do the inference into the fuzzy system. It was then defuzzified to get the centroid of the resulting inference. The resulting number was called "gd".

TAC was ascertained depending on the result of the process, as follows:

$$If\ gd \leq 0.5,\ TAC = 0$$
$$If\ gd \geq 1,\ then TAC = MSY$$
$$If\ 0.5 < gd < 1,\ TAC = MSY \times gd$$

Table 3.5: Fuzzy rules for HCR2

If	B	is very high	then TAC	is maximum.
If	B	is high	then TAC	is maximum.
If	B	is $\simeq B_{MSY}$	then TAC	is medium.
If	B	is low,	then TAC	is low.
If	B	is very low,	then TAC	is forbidden.

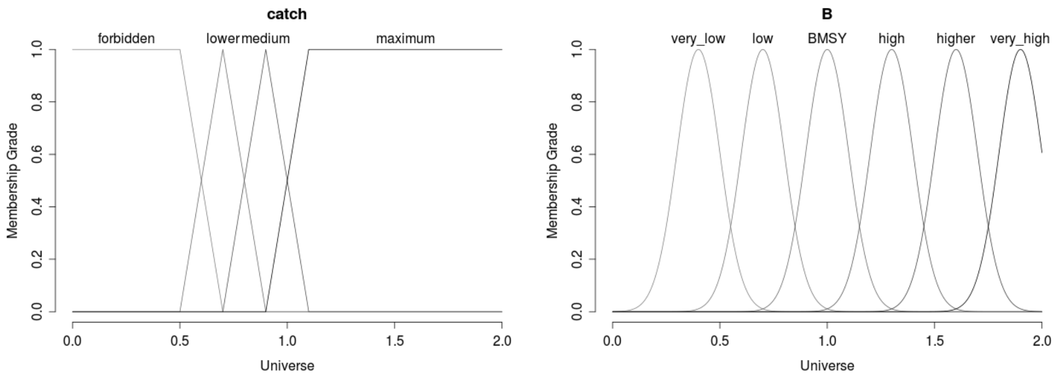

Figure 3.10: Fuzzy system produced following the rules made up for HCR2.

4

RESULTS.

4.1 Classic HCR 1 with no upper nor lower constraint α

To perform the following projections, the initial data that was taken into account covers the first TAC and effort, the first is the real TAC estimated for the population (25000 tons), and the latter is the corresponding F to yield that amount with the characteristics of the stock (f =0.1). The first ABC had to be calculated before running the simulations, as a 10% of the initial population SSB (assumed 25000 tons).

4.1.1 Classic HCR 1, Scenario 0.

Applying HCR classic 1 with no variation or error the population undergoes an increase of 44000 tons the first 3 years, reaching the maximum biomass in the simulation, 3.25×10^5 tons. From this point, the SSB decreases logarithmically until the end of the simulation, with the exception of a peak on the 10^{th} year, when the stock increases 10000 tons. By the end of the simulation, the declining rate is reduced, lowering 7000 tons in the latter 10 years, and maintaining the stock around 180 thousand tons for the last 15 years. TAC is always in conjunction with the SSB, equal to the estimated ABC, so it spreads the first 3 years from 28 thousand to 32.5 thousand tons. Since then, TAC is reduced in parallel with SSB, reaching its minimum the

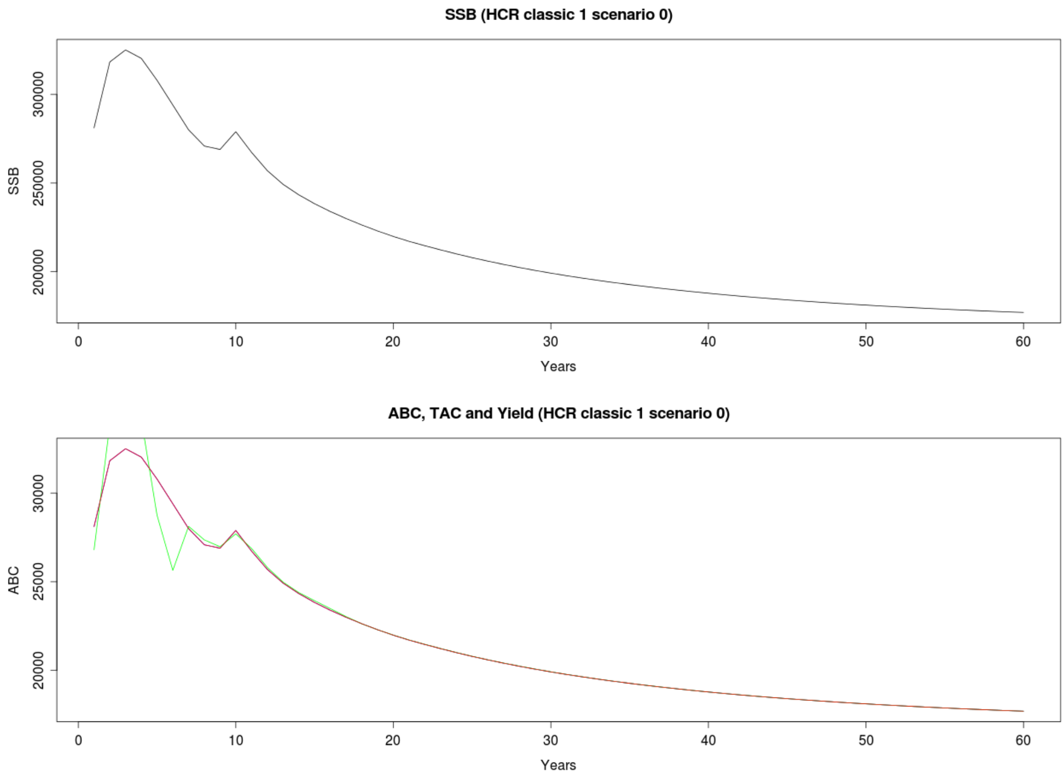

Figure 4.1: Projection of the stock when HCR classic 1 is applied without constraints nor variability or error. Black line = SSB, Blue line = ABC, red line = TAC, green line = yield. In this case the blue and the red lines are superimposed.

last year of the projection, with 17700 tons. The first period an amount bigger than the TAC recommendation would be yielded, achieving its maximum, 39.5 thousand tons, the 3^{rd} year. The following 3 years yield would drop until 25.6 thousand tons. TAC is well accomplished from the 7^{th} year, giving a yearly average of 21600 tons and a total of 1.3×10^6 tons for the 60-year period (fig. 4.1). Effort is maintained constant over the whole projection ($f \approx 0.09$), with the exception of the 3^{rd} and 4^{rd} year, when $f \approx 0.07$.

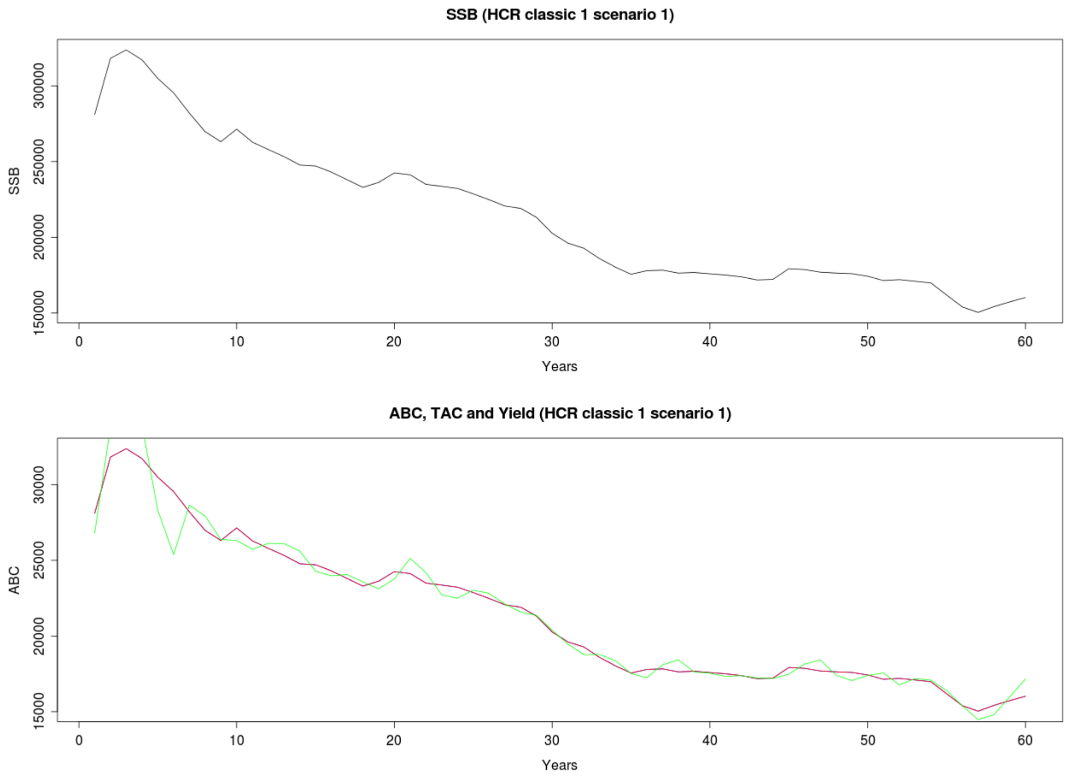

Figure 4.2: Projection of the stock when HCR classic 1 is applied without constraint and with an assumed variation on the recruitment of the 20%. Black line = SSB, blue line = ABC, red line= TAC, green line = yield. In this case the blue and the red lines are superimposed.

4.1.2 Classic HCR 1, Scenario 1.

SSB follows a similar trend as in the previous projection, but the decrease is less pronounced during the fist half of the simulation, keeping higher values than 2.3×10^5 tons until the 25^{th} year. Its maximum is a little bit lower, 3.23×10^5 tons reached the third year. The second half is characterized by being more or less stable with values ranging from 1.5×10^5 to 1.9×10^5 tons, but 1.7×10^5 as a mean. TAC follows the same trend, decreasing from a maximum of 3.23×10^4, and keeping high values during the first half of the projection. During the last part, it is estimated that TAC would be greater than 17000 tons until the 55^{th} year. For the first four years yield is estimated to be higher than TAC, exceeding it by more than 16000 tons in total, falling more than 8000 tons below TAC the next 2 years. During the forecast, yield more or less conforms the TAC. As the previous projection, f is estimated to be around 0.09 (fig 4.2).

4.1.3 Classic HCR 1, Scenario 2.

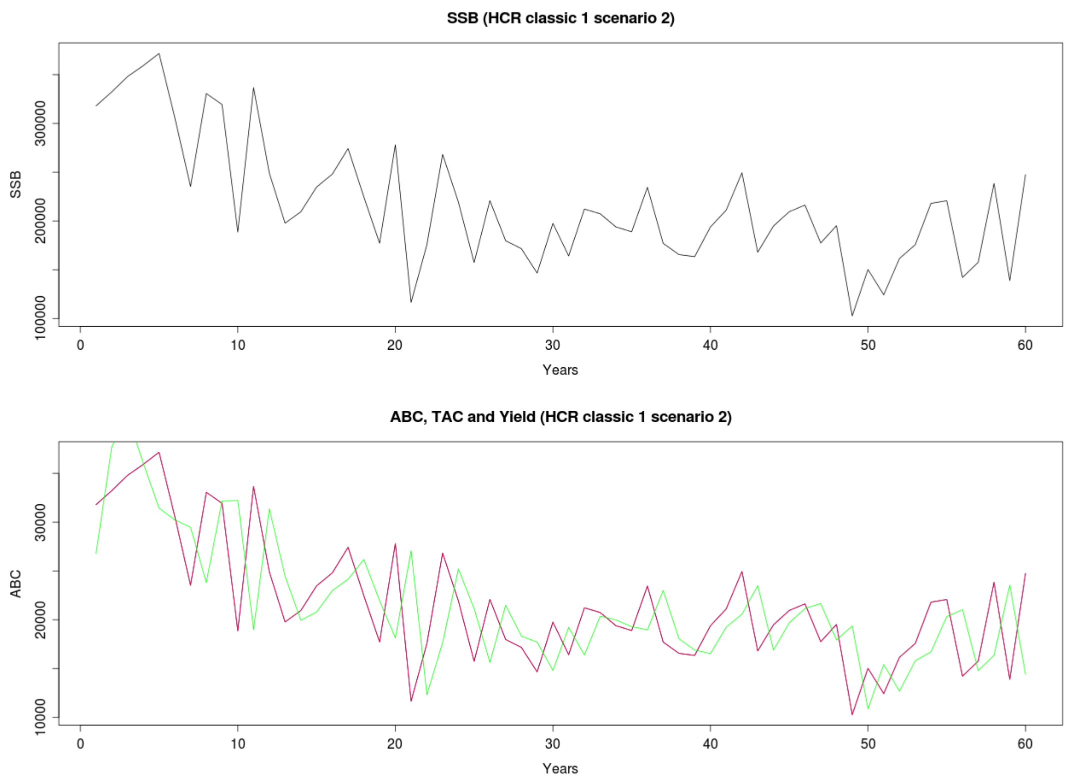

Figure 4.3: Projection of the stock when HCR classic 1 is applied without constraint and with an assumed error in the assessment of the 20%. Black line = SSB, blue line = ABC, red line= TAC, green line = yield. Note that SSB, ABC and TAC are estimated for the next year. In this case the blue and the red lines are superimposed.

In this projection a decreasing trend is observable but not as conspicuous as in the previous simulations. SSB varies from 370 to 100 thousand tons. The two first decades the lowering is characterized by very marked ups and downs that take place almost yearly. Two large variations take place during the periods from the 9^{th} to the 11^{th} and the 20^{th} to the 21^{st} year, when the biomass drops and jumps around 140000 tons from one year to another. From that point, along the forecast, it seems to have a tendency to stability with values ranging mostly from 1.6×10^5 to 2.1×10^5 tons, with scatter exceptions. Yield equates TAC as a 10% of the SSB along the simulation, with the exception of the first 4 years, in which it exceeds TAC in 17000 tons approximately. The mean yearly yield would be 21500 tons, with a top of 41000 and a bottom of 11000, summing a total of almost 1.3×10^6 (fig4.3). Effort ranges from 0.04 to 0.13.

4.1.4 Classic HCR 1, Scenario 3.

Along this projection, the SSB ups and downs are smoother, the largest takes place right at the beginning of the forecast (200 thousand tons) reaching 400 thousand tons, and the next is an increase of 126000 tons that occurs from the eleventh to the twelfth year. The lowest point reaches 88000 tons, but in general the SSB is maintained over 160000 tons and less than 210000. The first 4 years an amount of around 16000 tons more than the TACs applied would be yielded, reaching a maximum of 53700 tons the third year. After that period, there are no significant differences between TAC and yield, meaning that the yielded amount would range from 9200 to that maximum, but generally ranging between 15 and 21 thousand tons (fig 4.4). The average yield would reach 20500 tons, trespassing the 1.23×10^6 tons the total expected catch. The effort ranges among 0.07 and 0.1, with scattered exceptions that would reach 0.04 and 0.13.

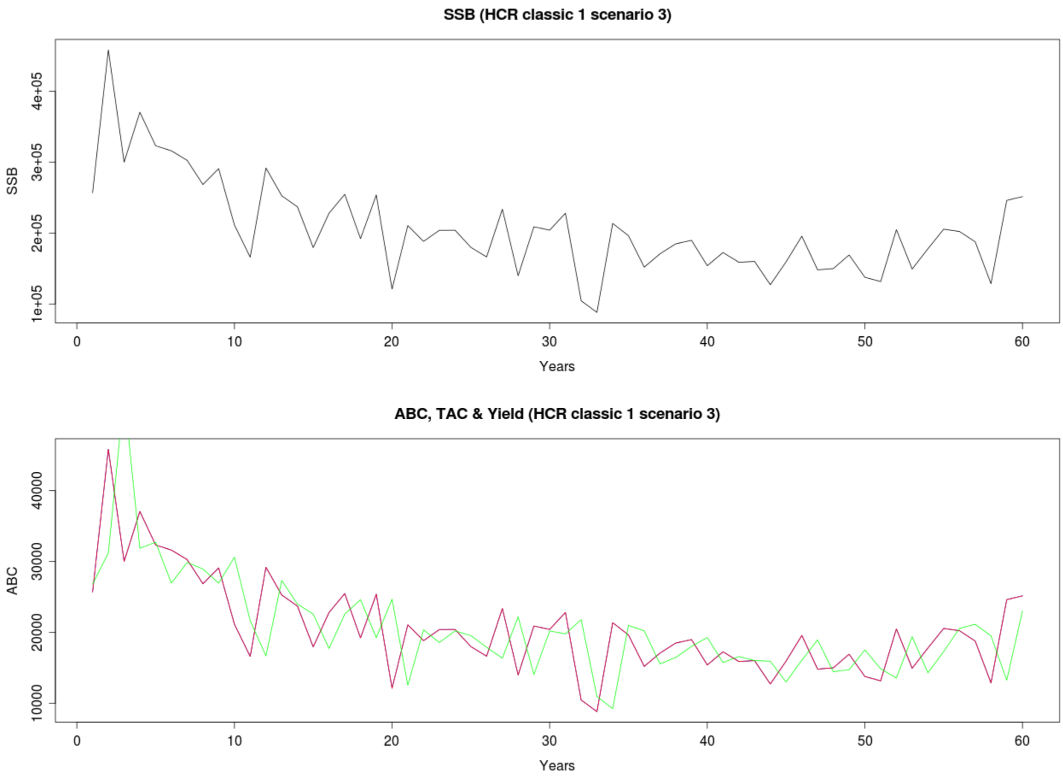

Figure 4.4: Projection of the stock when HCR classic 1 is applied without constraint and with an assumed error in the assessment and a variability in recruitment of the 20%. Black line = SSB, blue line = ABC, red line= TAC, green line = yield. Note that SSB, ABC and TAC are estimated for the next year. In this case the blue and the red lines are superimposed.

4.2 Classic HCR 1 with a lower TAC constraint α

The same initial data was used to simulate the following projections, but adding a lower TAC constraint of 15%.

4.2.1 Classic HCR 1, Scenario 0.

The result of this simulation is the same as in the previous scenario 0, since the variations from year to year do not go over 15% in ABC in any case (fig 4.1)

4.2.2 Classic HCR 1, Scenario 1.

The random variability applied to the scenario 1 is not enough to generate a difference big enough in SSB to implement the constraint in TAC. It stays the same as ABC, namely 10% of the SSB (fig 4.5).

4.2.3 Classic HCR 1, Scenario 2.

SSB shows a clear decreasing tendency, although there ups and downs that keep the biomass over 1.7×10^5 tons during the complete forecast, higher than the previous simulations. The maximum SSB is achieved by the third year, reaching 3.7×10^5 tons. There are some falls that exceeds 15%, the more remarkable ones occur from the 9^{th} to the 10^{th} year and from the 19^{th} to the 20^{th} year, dropping more than a 35%. The first would recover the next year with a growth of the 180 percent, while the second takes two years to reach the previous level. Other significant drops take place from the 34^{th} to the 35^{th} and 50^{th} to the 51^{st}. Is in this this kind of slackening when constraint on TAC works, maintaining it above 2×10^4 during the first 20 years, and 1.4×10^4 the rest of the forecast. The mean TAC for the last period of the simulation, when it seems to have a tendency to stability, is 1.88×10^4. Applying this TACs, the yield would range between 17500 and 24000 tons, with scarce exceptions, and achieving the highest values during

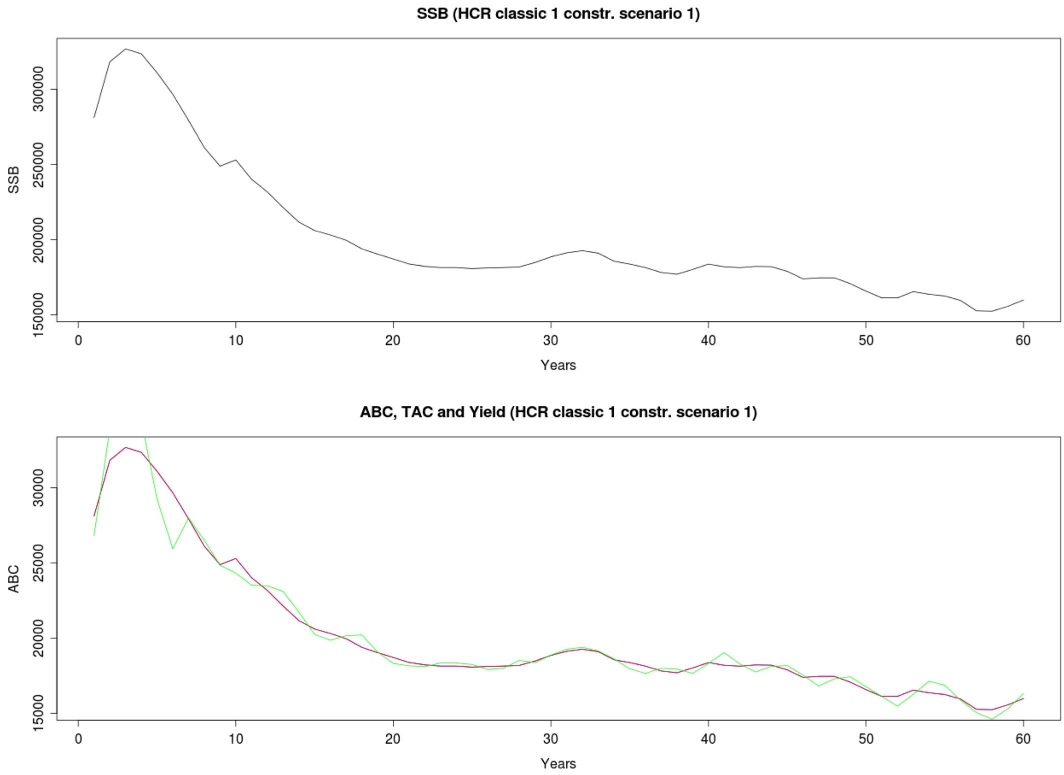

Figure 4.5: Projection of the stock when HCR classic 1 is applied with a lower constraint on TAC and variability in recruitment. Black line = SSB, Blue line = ABC, red line = TAC, green line = yield. The blue and the red lines are superimposed.

the first decade. The mean value is around 21700 tons, and the total catches sum more than 1.3×10^6 tons (fig.4.6) with f lying between 0.07 and 0.13.

4.2.4 Classic HCR 1, Scenario 3.

This projection shows that biomass evolves under a wide range, having a peak of 3.8×10^5 tons by the initial part of the simulation, and a trend to lower values that could reach 9×10^5 tons. The major oscillations occur during the first 25 years, when the SSB could drop a 50% in a 4-year period and grow more than a hundred percent in a year. During the last part of the simulation, SSB mostly ranges between 150 and 190 thousand tons.

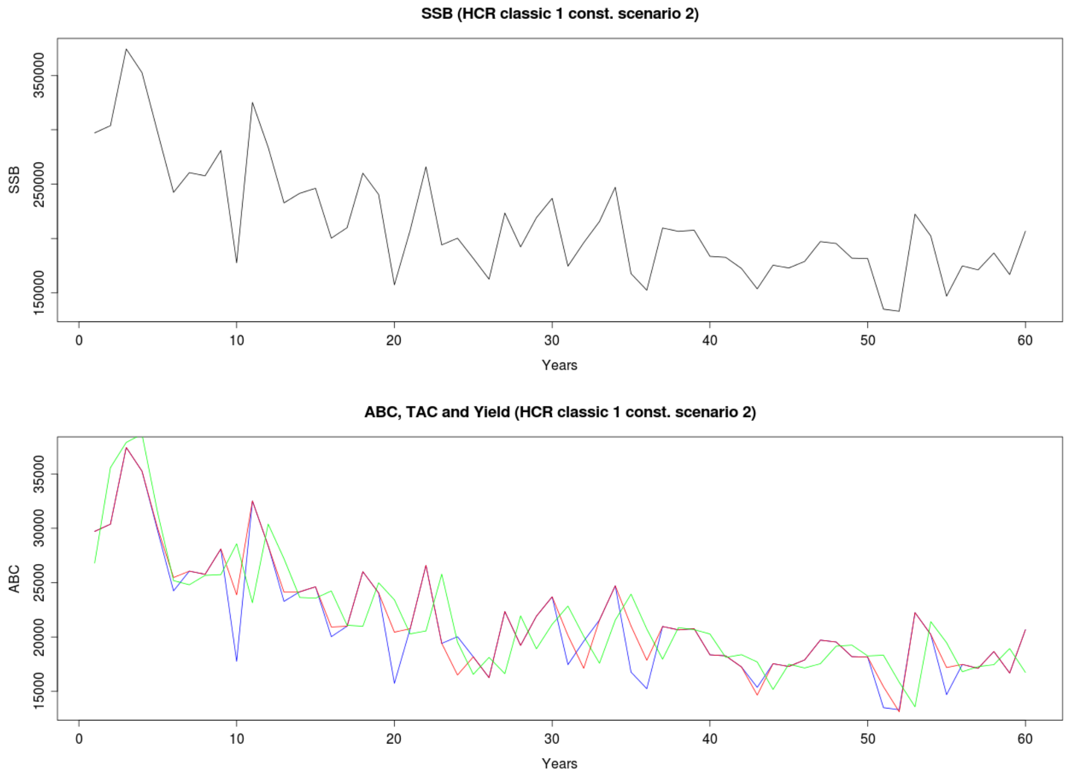

Figure 4.6: Projection of the stock when HCR classic 1 is applied with a lower constraint on TAC and variability in recruitment. Black line = SSB, Blue line = ABC, red line = TAC, green line = yield.

The constraint in TAC avoids to have large variations on catch, allowing a constant decrease that can take 4 or 5 years,, for example the first drop on the simulation and the one that occurs from the 25^{th} to the 29^{th} year. The mean TAC from the 25^{th} year would be around 17000 tons, with a minimum of 11200 and a maximum of 22800 tons. With the exception of the first decade, when the yield goes over TAC 6000 tons each year during the second and the third year and then drops with a difference with TAC of 3000 tons on the fifth and sixth year, the TAC is well accomplished. During the first 25-year period, the mean yield would be close to 25000 tons, ranging between 46 and 15.7 thousand tons. During the last period, the average yield would be above 17000 tons, ranging from 11600 to 26000 tons. The forecast average reaches

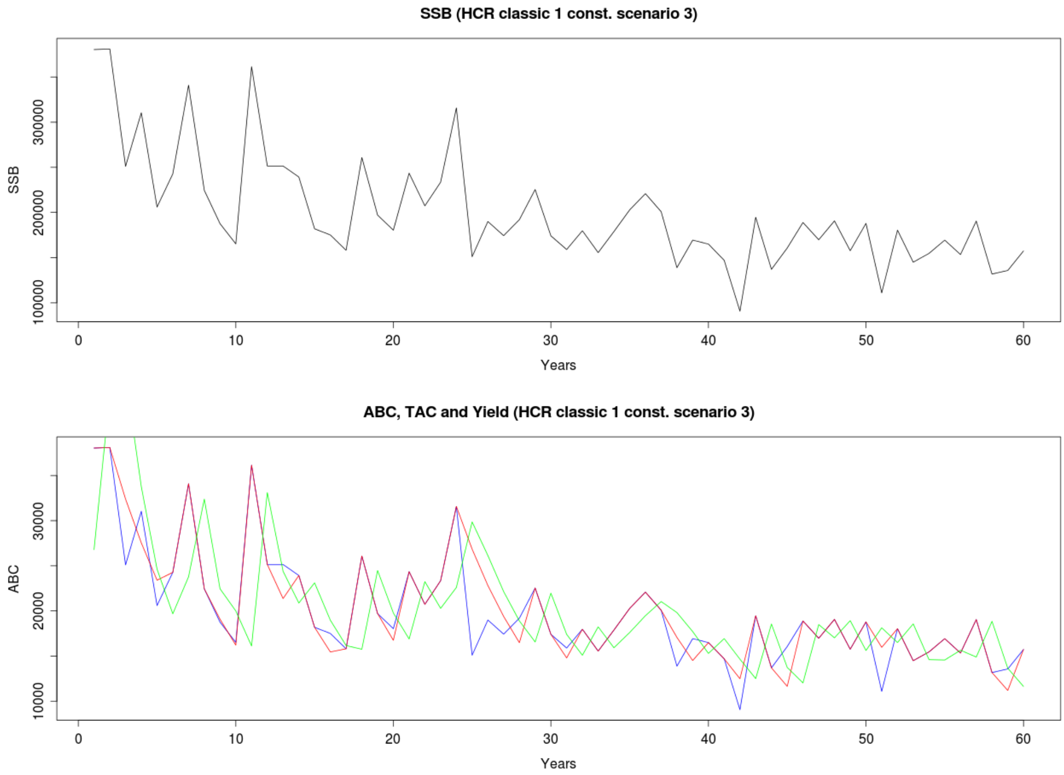

Figure 4.7: Projection of the stock when HCR classic 1 is applied with a lower constraint on TAC, variability in recruitment and an assumed error in the assessment. Black line = SSB, Blue line = ABC, red line = TAC, green line = yield.

20000 tons yearly, while it would sum 1.2×10^6 tons.

4.3 Fuzzy HCR 1 with no TAC constraint.

4.3.1 Fuzzy HCR 1, scenario 0.

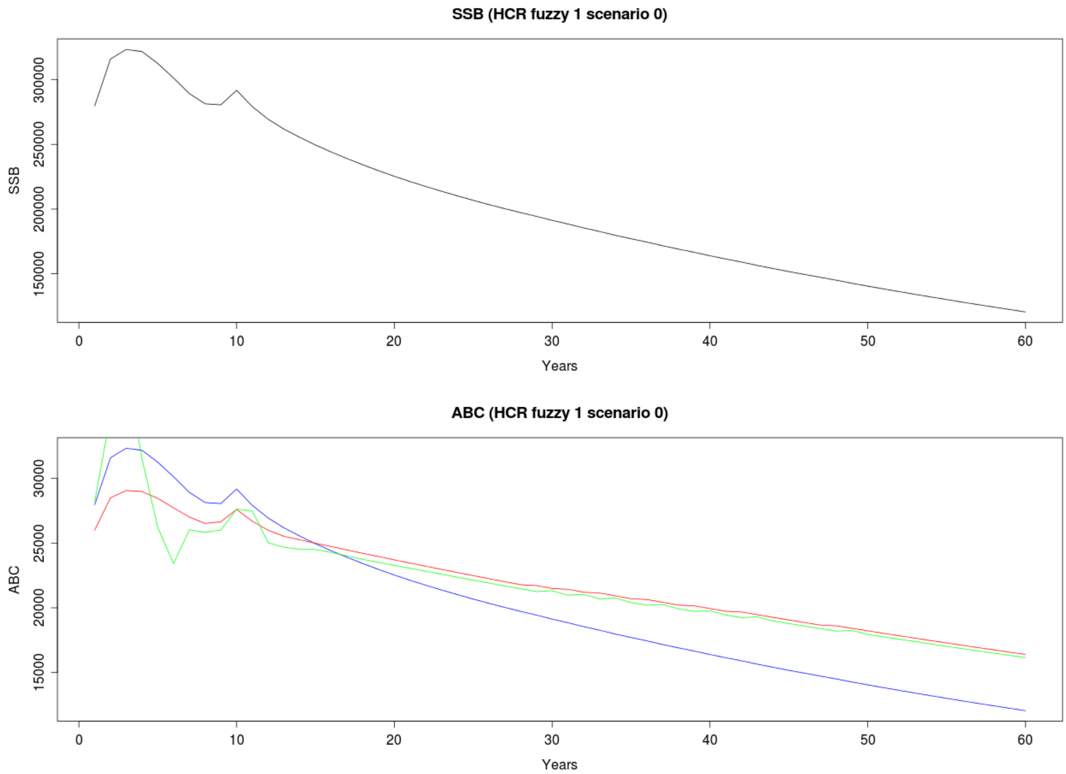

Figure 4.8: Projection of the stock when HCR fuzzy 1 is applied with no constraint, variability or error. Black line = SSB, red line = TAC, blue line = ABC, green line = yield.

The same pattern on SSB as the others forecasts is observed, although the decreasing rate is higher, bottoming at the end of the 60 year with 1.1×10^5 tons. This may be due to the higher TACs, which remain below ABC until the 14^{th} year, when they cross at the level of 25000 tons. From that point, TAC is reduced in a lower rate than ABC, reaching a difference of 4000 tons by the end of the simulation. The maximum yield would be reached by the third year, gathering 38800 tons, going down for the next two years until

23000 tons. It increases again towards 30000 tons until the 10^{th} year. From this point, it is expected to decrease linearly until it gets close to 16000 tons by the end of the forecast (fig.4.8). The applied effort would range between 0.07 and 0.12, in a continue growth.

4.3.2 Fuzzy HCR 1, scenario 1

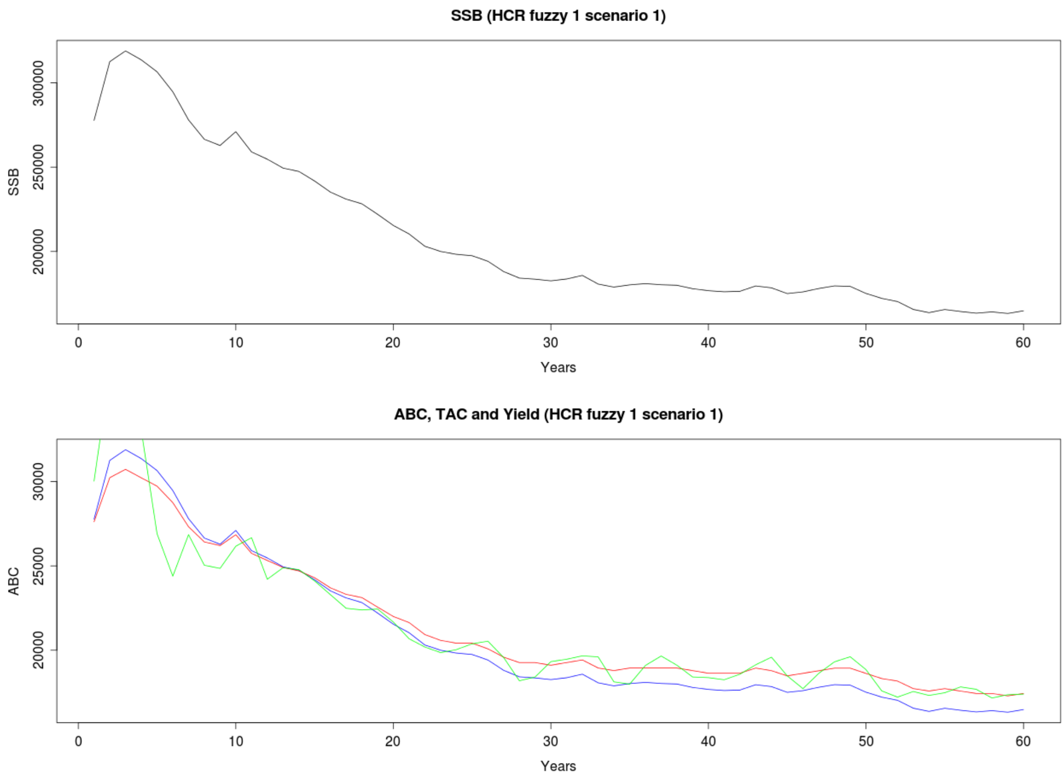

Figure 4.9: Projection of the stock when HCR fuzzy 1 is applied with no constraint nor error, but variability in recruitment. Black line = SSB, red line = TAC, blue line = ABC, green line = yield.

This simulation recovers the SSB levels of the previous HCR, reaching a maximum of 3.18×10^5 and a minimum of 1.63×10^5 tons. The TAC trend seen in the previous simulation is repeated, closer to ABC though. The maximum distance between them corresponds to 1000 tons, both at the beginning and at the end of the projection. TAC drecreases from its maximum (30 thousand tons) to 17 tons by the 60^{th} year. Yield bounces between TAC and ABC with the exception of the first decade, when the irregularities reproduce. In this period it reaches a maximum of 40 thousand tons. From this year its decreases until the last decade when it seems to stay stable at 17000 tons. The average amount yielded would be 21.3 thousand tons yearly, summing 1.28×10^6 tons for the total simulation (fig. 4.9). Effort ranges between 0.07 and 0.1.

4.3.3 Fuzzy HCR 1, scenario 2

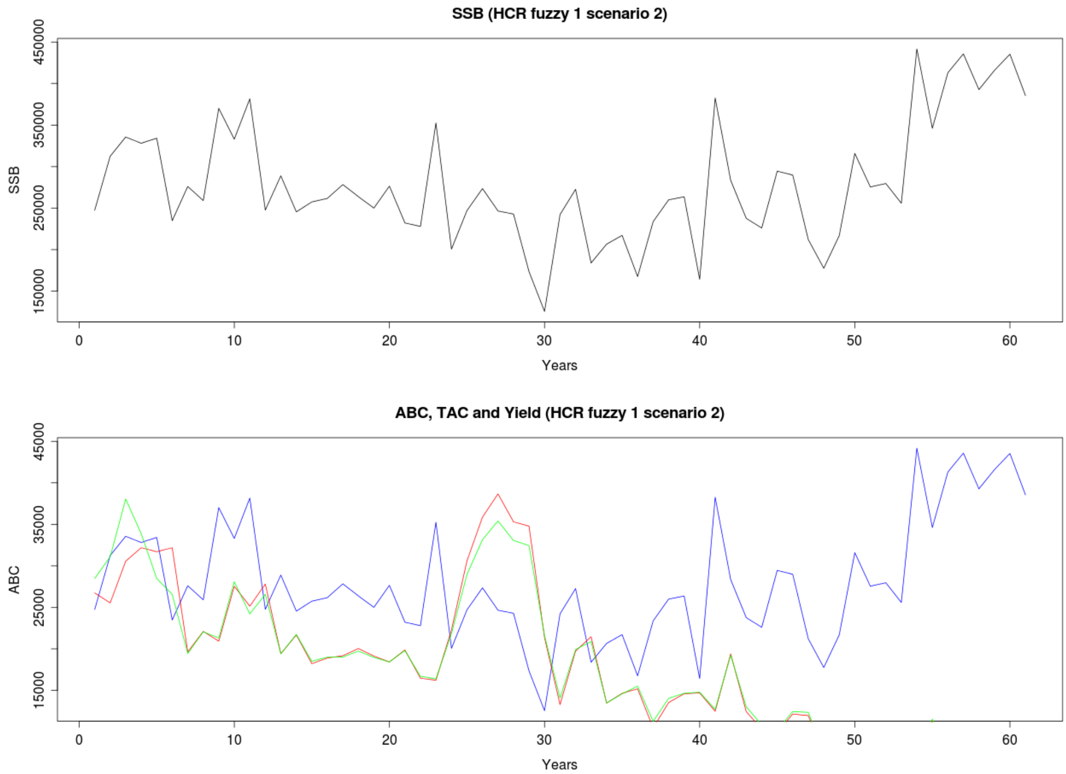

Figure 4.10: Projection of the stock where HCR fuzzy 1 is applied with no constraint nor recruitment variability, but assessment error. Black line = SSB, blue line = ABC, red line = TAC, green line = yield.

This forecast shows a reversal in the SSB trend, increasing in large amounts during the last years of the projection, although it varies under a wide range. It could be split in two phases: the first half, when it tends to decrease, and the last half, when it tends to grow exponentially. The inflexion point is the 30^{th} year, when the biomass downs to 125 thousand tons. The higher peak reaches4.41×10^5 tons and it takes place by the end of the simulation. TAC fails to follow these fluctuations and are placed below ABC most of the forecast, increasing the difference among them by the end of the simulation. It falls below 10000 tons from the 48^{th} year on, reaching a minimum on 6000 tons. In this simulation TAC is followed correctly, yielding amounts that range between 3.8×10^4 and 6×10^3 tons (fig. 4.10). The mean yield achieves 18300 tons and the sum of the whole projection would be 1.1×10^6 tons. The applicable f varies among 0.02 and 0.17.

4.3.4 Fuzzy HCR 1, scenario 3

The SSB fluctuates among a wide range (3.9×10^5 to 1.5×10^5 tons) keeping values above 1.8×10^5 most of the time. Even so it still shows a tendency to decrease until the 40^{th} year, when this trend changes towards stability. TAC follows the same pattern as in the previous projection, being below ABC most of the time and increasing the difference in time, with the dissimilarity that it only crosses the barrier of 10000 tons 3 scattered years and 3 peaks in which it exceeds 30 thousand tons. These TACs would achieve a mean yield of 20 thousand tons, ranging mostly between 1.4×10^4 and 2×10^5 tons (fig.4.11. The applicable f varies among 0.04 and 0.19.

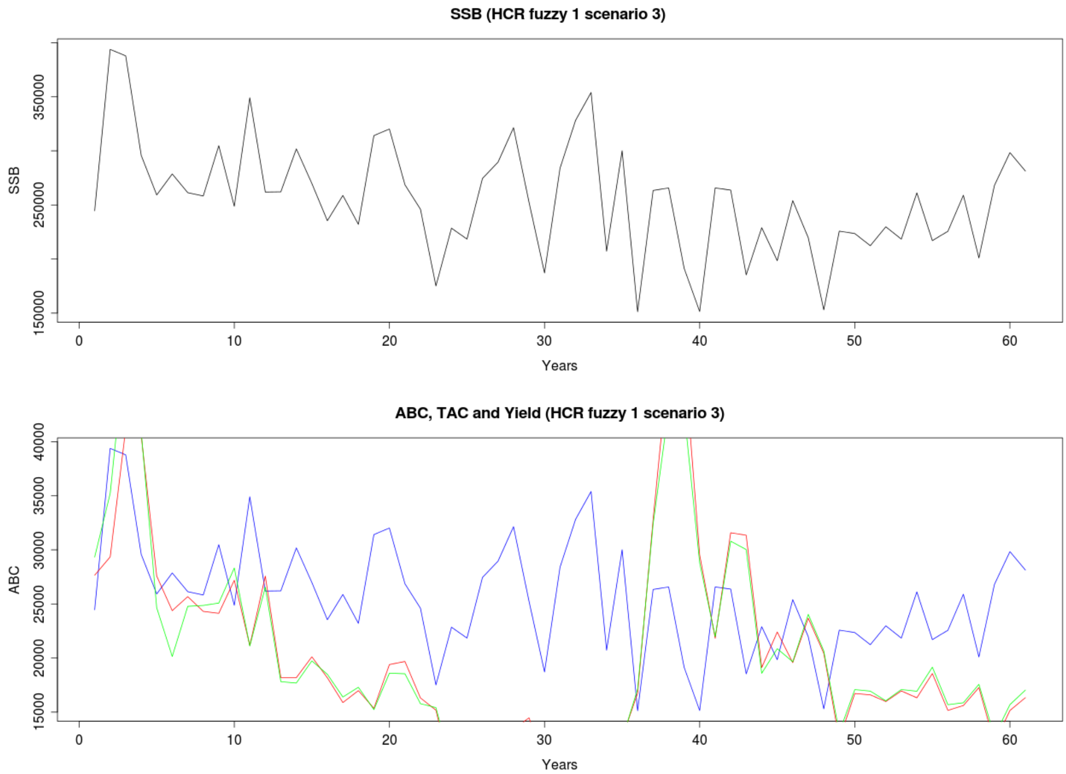

Figure 4.11: Projection of the stock where HCR fuzzy 1 is applied with no constraint but recruitment variability and assessment error. Black line = SSB, blue line = ABC, red line = TAC, green line = yield.

4.4 Fuzzy HCR 1 with a lower constraint (α)

4.4.1 Fuzzy HCR 1, scenario 0

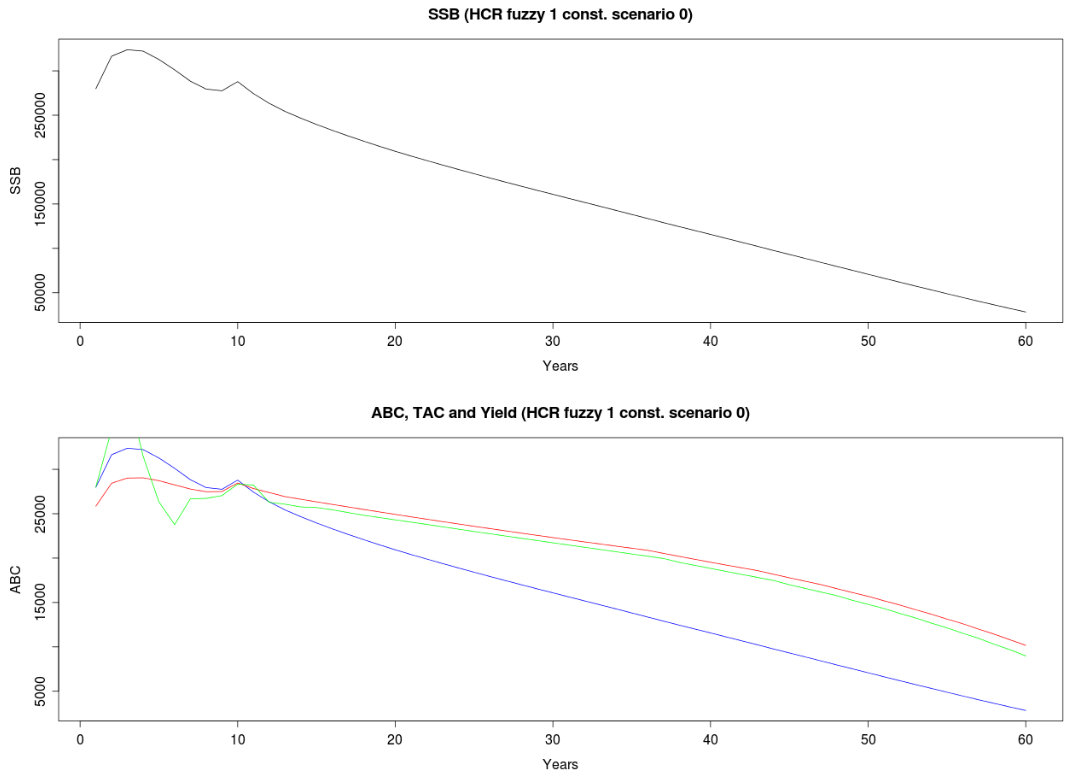

Figure 4.12: Projection of the stock where HCR fuzzy 1 is applied with a lower constraint on TAC, but no variability nor error. Black line = SSB, blue line = ABC, red line = TAC, green line = yield.

The application of this fuzzy system with such a little constraint causes the depletion of the stock, keeping high and stable estimated TACs. The stock declines 50% of its biomass in 30 years, while TAC reduces very slowly from 29 to 20 thousand tons in 37 years. Yield starts being high, reaching 38800 tons in the third year, then it starts falling accompanying TAC from the tenth year. The decrease takes place slowly, increasing its rate from the 40^{th} year. The mean yield is 21 thousand tons per year, summing 1.26×10^6

tons for the 60-year period (fig.4.12. The applicable f varies among 0.07 and 0.35.

4.4.2 Fuzzy HCR 1, scenario 1

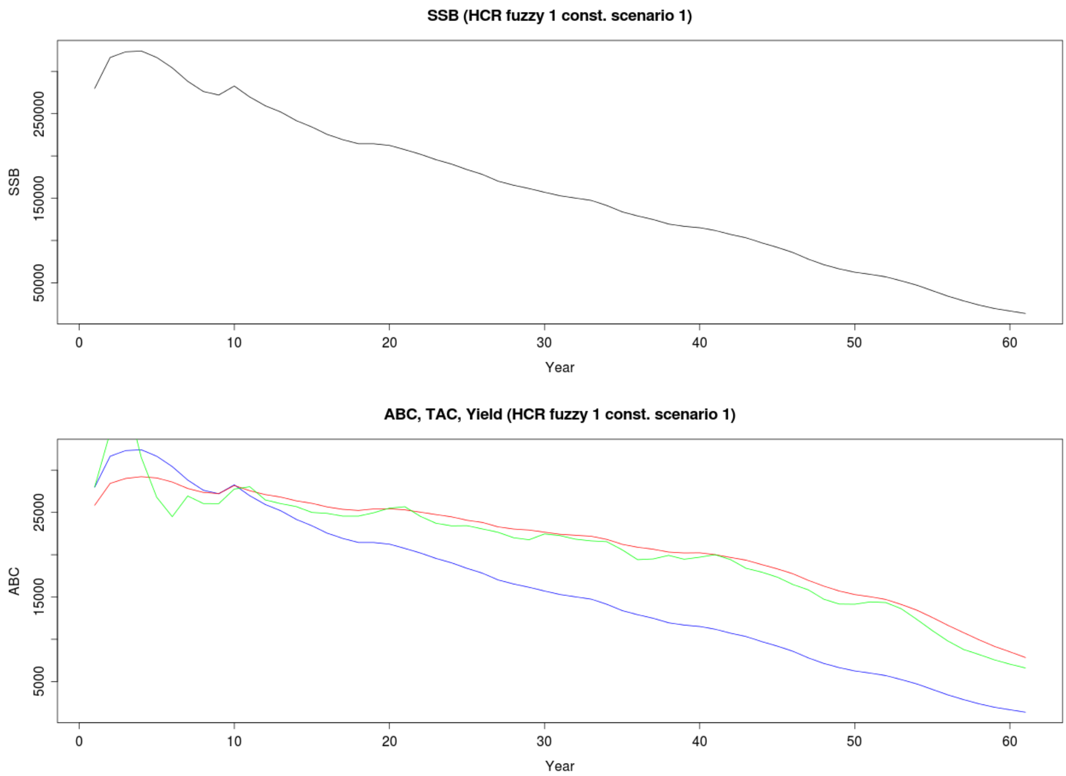

Figure 4.13: Projection of the stock where HCR fuzzy 1 is applied with a lower constraint on TAC and recruitment variability but with no assessment error. Black line = SSB, blue line = ABC, red line = TAC, green line = yield.

There are no significant differences in the behavior of SSB and TAC from the previous forecast. The line that yield follows reflects the waves that are produced in SSB. The average catch rounds 21000 tons, while sums 1.26×10^6 tons (fig.4.13).

4.4.3 Fuzzy HCR 1, scenario 2.

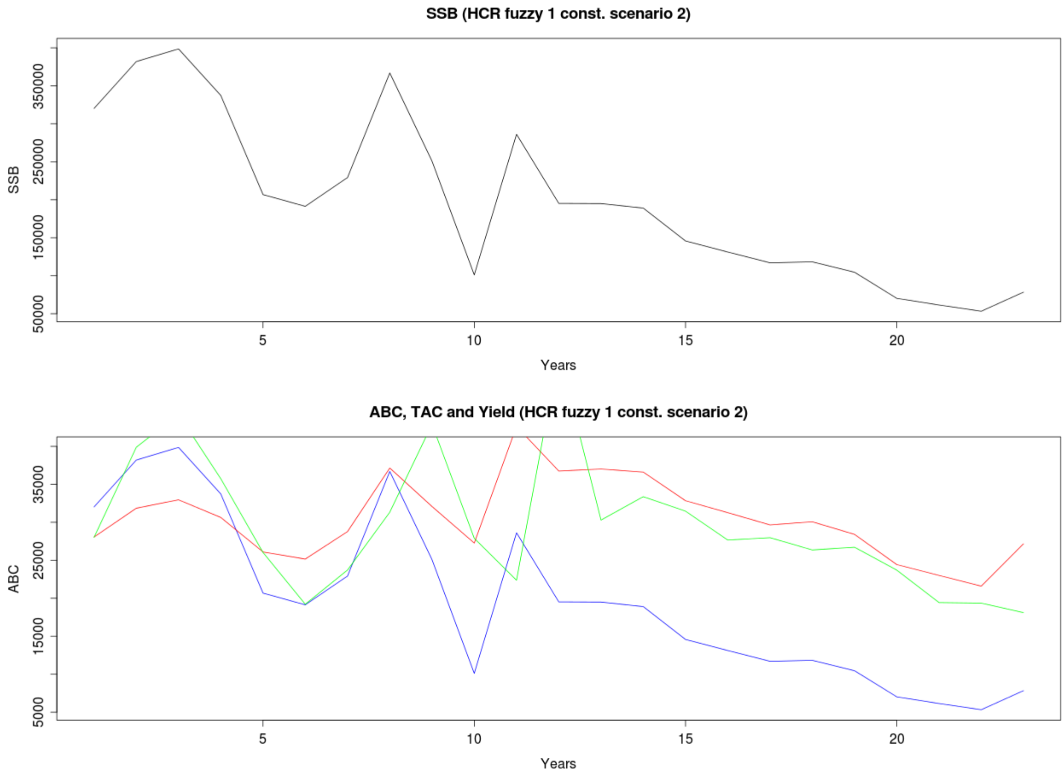

Figure 4.14: Projection of the stock where HCR fuzzy 1 is applied with a lower constraint on TAC and assessment error but no recruitment variability. Black line = SSB, blue line = ABC, red line = TAC, green line = yield.

Several simulations under this characteristics and this fuzzy system, but all of them the depletion of the stock occurs before 30 years. TAC cannot follow the continuous reductions in the stock, maintaining high values during the whole projection which could enhance the decrease in biomass, while f reaches values higher than 0.35.

4.4.4 Fuzzy HCR 1, scenario 3.

Despite a slower reduction in SSB, projections made within this framework end in depletion. TAC evolves correctly during the first decade, but it starts

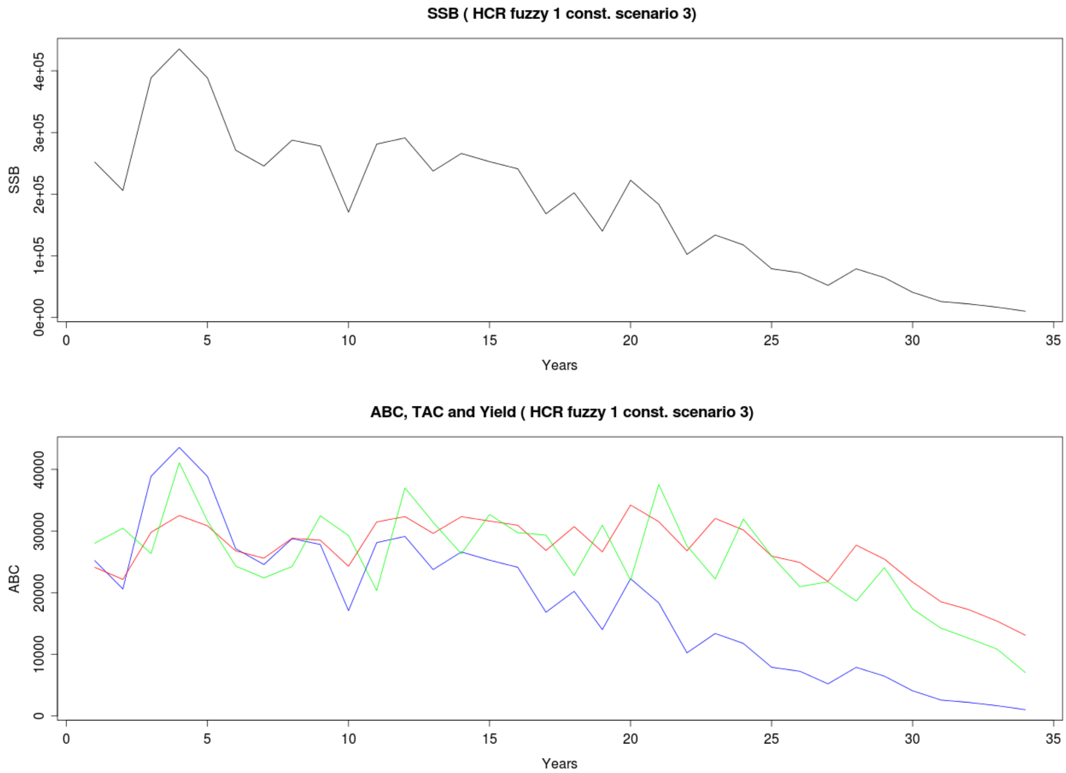

Figure 4.15: Projection of the stock where HCR fuzzy 1 is applied with a lower constraint on TAC and assessment error and recruitment variability. Black line = SSB, blue line = ABC, red line = TAC, green line = yield.

growing over the ABC from the tenth year maintaining values around 30000 tons.

4.5 Classic HCR 2

4.5.1 Classic HCR 2, scenario 0.

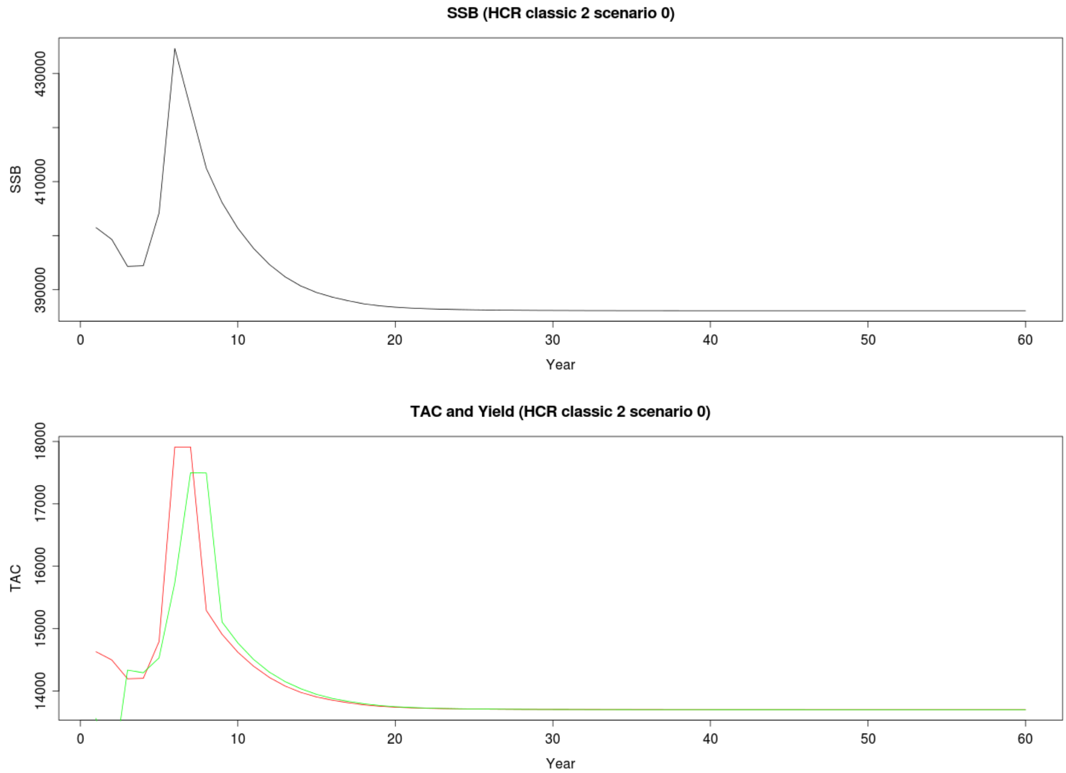

Figure 4.16: Projection of the stock when HCR classic 2 is applied without noise. Black line= SSB, red line= TAC, green line = yield. Note that TAC is calculated for the next year.

This second classic HCR adjusts quite well to the stock development, that has two different phases. The first one suffers a very steep up and down, then it stabilizes from the 25^{th} year on with a SSB of 3.86×10^5 (fig 4.16). During this first phase, the population biomass ranges between 3.87×10^5 and 4.35×10^5 tons.

In the first phase, TACs range between 13700 and 17900 tons. The major increase in TAC takes place from the 5^{th} to the 6^{th}year, 3000 tons. The maximum decrease takes place between 7^{th} and 8^{th}, 2600 tons. Implementing those TACs, the yield would range between 12500 and 17500 tons, and it would be constant from the 18^{th} year, with 1.37×10^4 The total yield for the 60-year period reaches 838000 tons (Fig 4.16). F is constants and equals 0.03.

4.5.2 Classic HCR 2, scenario 1.

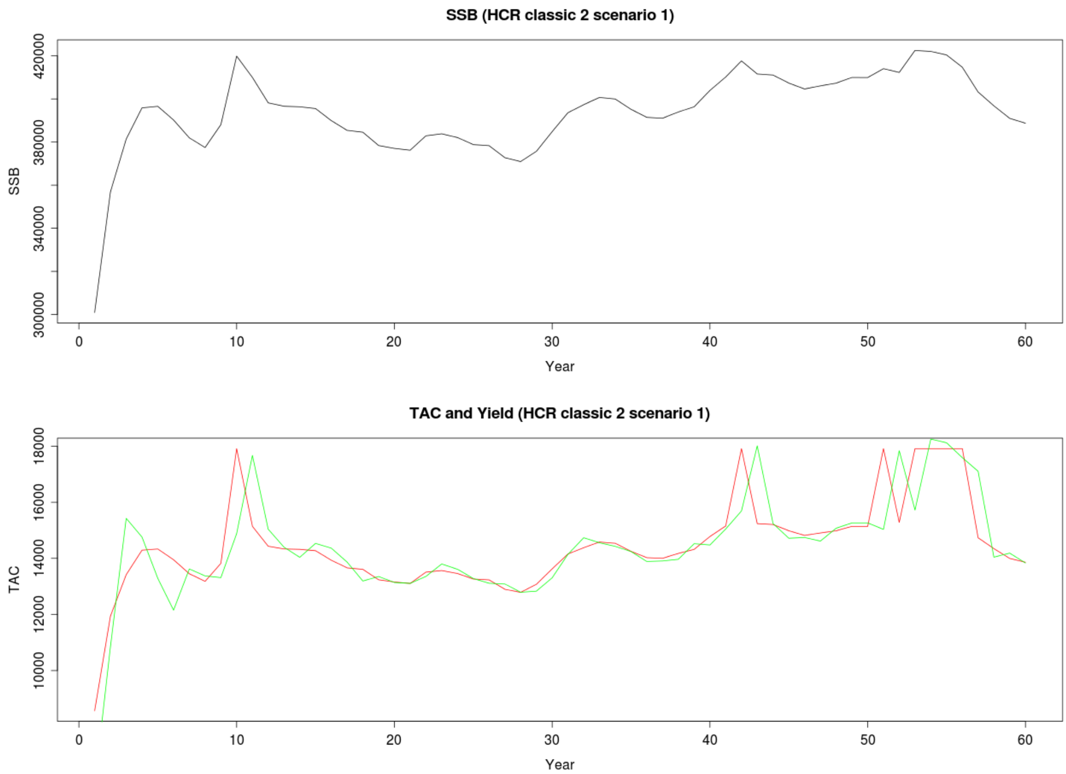

Figure 4.17: Projection of the stock when HCR classic 2 is applied assuming a normally distributed 20% recruitment variablity. Black line= SSB, red line= TAC, green line = yield. Note that TAC is calculated for the next year.

To perform this projection a random normally distributed variation (ν)

of recruitment was applied. The result is a variable population which suffers smooth ups and downs all along the 60-year horizon. The first two peaks that appear during the first decade coincide in time with those of the constant F_MSY projection, but the highest peak reaches 4.2×10^5 tons during the 10^{th} year. From that ceiling, the stock stays between 3.8×10^5 and 4.1×10^5, with the exception of two peaks of 4.2×10^5 tons during the 44^{th} year and between the 53^{rd} and 56^{th} year, making a yearly mean above 390000 tons. During those periods of very high SSB, TAC was set as the maximum, 17900 tons. Along the rest of the simulation, TAC proportionally follows the SSB, ranging from around 13000 (with the exception of the first year) and 15000 tons. Yield follows TAC during all the 60-year period, it only shows a significant discrepancy in the 4^{rd} and 6^{th} year: Yield is 3000 tons bigger than the TAC calculated on the 3^{rd} year, and the 6^{th} is 2000 tons lower. The mean yield is 14300 tons and the total achieves 881500 tons (Fig 4.17). Effort varies among 0.02 and 0.04.

4.5.3 Classic HCR 2, scenario 2.

The second scenario is characterized by an assumed error in the assessment. It was applied a maximum of 20% of normally distributed error (ν), resulting a high variability in the stock biomass. It suffers uneven and sharp ups and downs all along the 60-year horizon, for example, the population jumps from 185000 tons to 456500 in a year. It reaches its maximum of 5.9×10^5, but most of the years the SSB ranges between 3×10^5 and 4.5×10^5, giving a mean SSB of 3.8×10^5. The maximum TAC is allowed in 18 years out of the 60-year period, but only in 25 the TAC gets over 14000. TAC is less than 13000 tons in 29 years. Yield is also variable, ranging from 1600 to 19500 tons, but it mostly ranges from 11000 to 17500 tons, making an average of 12800 tons. The total yield of the whole projection reaches 772000 tons (Fig 4.18). Effort varies among 0.02 and 0.04.

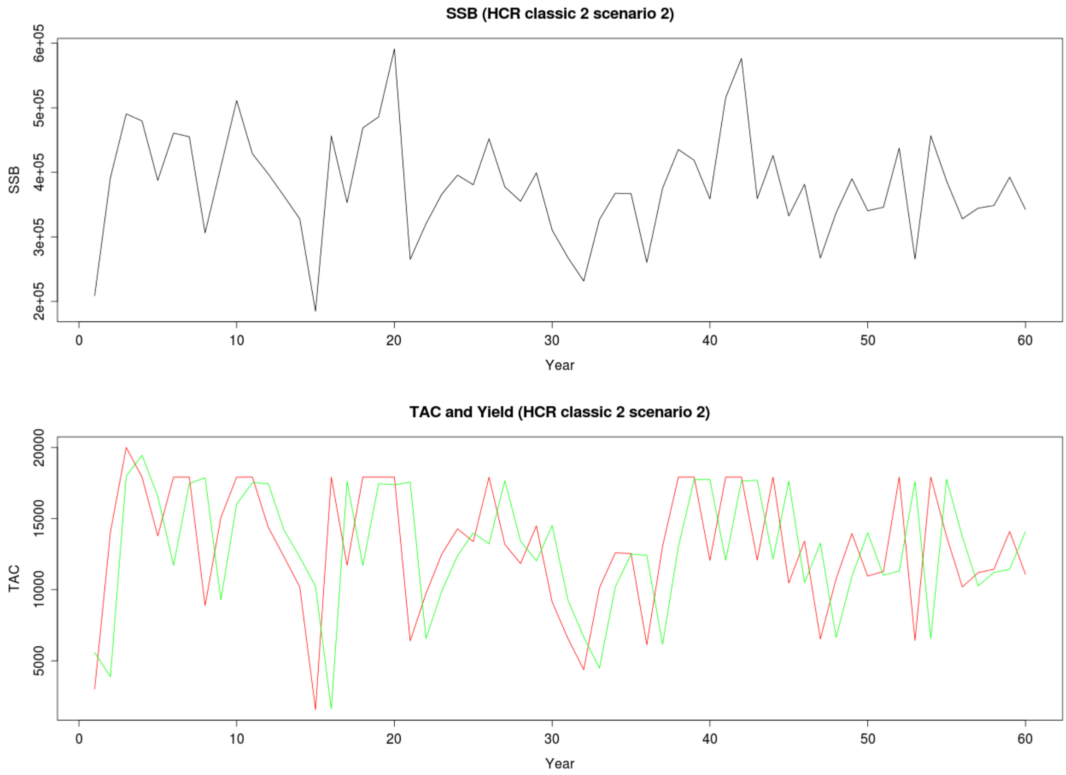

Figure 4.18: Projection of the stock when HCR classic 2 is applied assuming a normally distributed 20% assessment error. Black line= SSB, red line= TAC, green line = yield. Note that TAC is calculated for the next year.

4.5.4 Classic HCR 2, scenario 3.

This scenario takes into account the variation in recruitment and the error in the assessment. The stock biomass behaves as in the previous scenario, brisk ups and downs ranging from 200000 to 590000 tons, but the average SSB is higher, achieving 4×10^5. Most of the years, the SSB lies between 350000 and 450000 tons. This general increase in SSB allows 23 years of maximum TAC and 29 years of TAC bigger than 14000 but 24 years with smaller than 13000 tons TACs. The amounts yielded would be very similar to those recommended by TACs, with the exception of the second and third years, which would have yielded 3500 and 4000 tons more than recommended respectively. The mean yield is close to 14000 tons yearly, gathering more

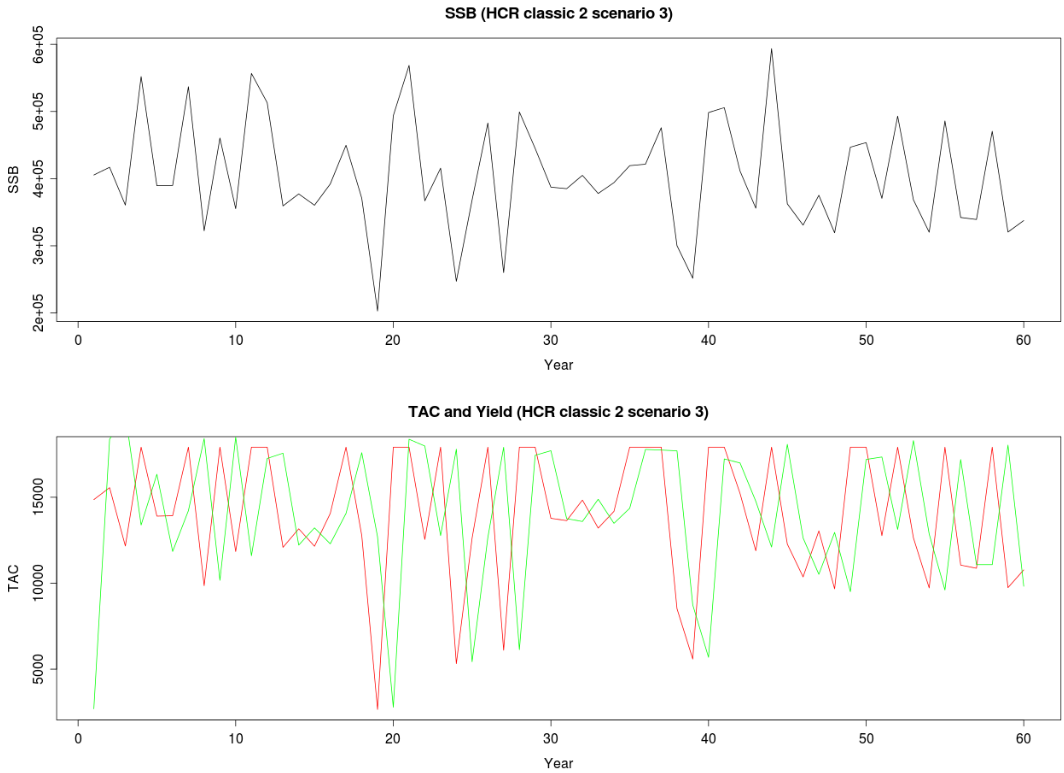

Figure 4.19: Projection of the stock when HCR classic 2 is applied assuming a normally distributed 20% assessment error and variation in recruitment. Black line= SSB, red line= TAC, green line = yield. Note that TAC is calculated for the next year.

than this amount in 30 out of 60 years of the simulation. During the whole projection, the total yield reaches 8.37×10^5 tons (Fig 4.19). Effort varies among 0.01 and 0.04.

4.6 Fuzzy HCR 2

4.6.1 Fuzzy HCR 2, scenario 0.

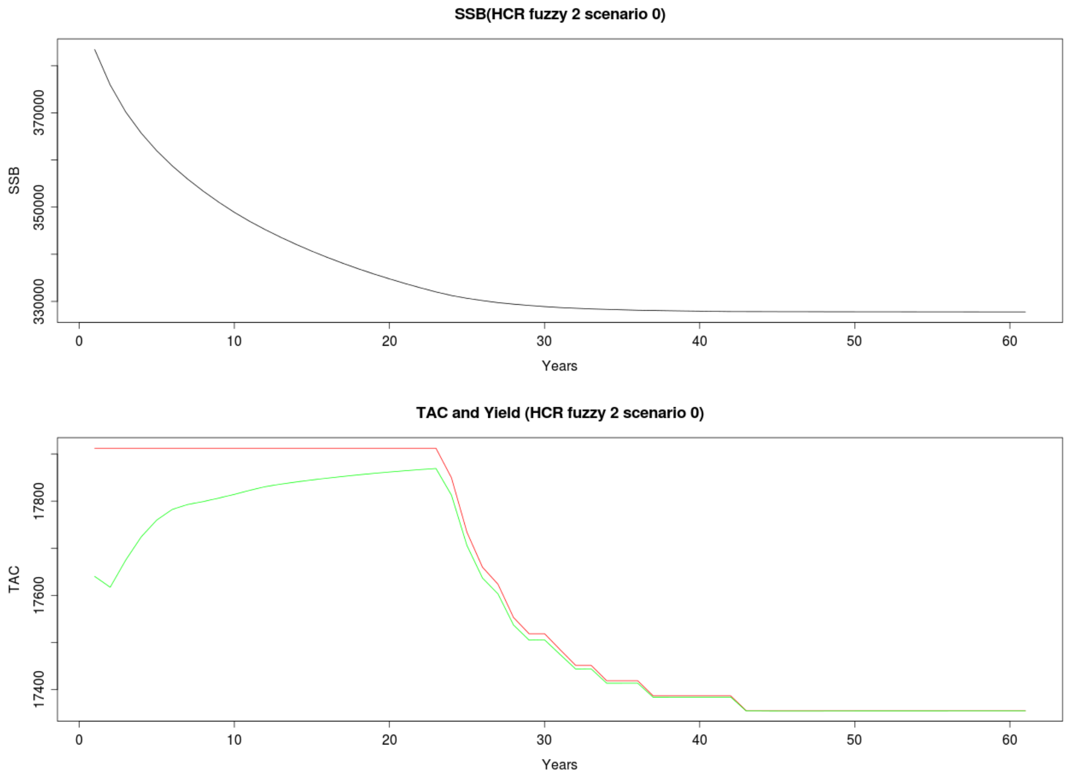

Figure 4.20: Projection of the stock when HCR fuzzy 2 is applied without variability or error. Black line= SSB, red line= TAC, green line = yield. Note that TAC is calculated for the next year.

The implementation of the fuzzy HCR 2 results in a slow logarithmic decrease of 50000 tons in the SSB form a starting amount of 3.84×10^5 tons. This new quantity (3.28×10^5) remains steady from 30^{th} year. The maximum TAC is allowed (17900 tons) from the start of the forecast to the 23^{rd} year, when the SSB falls below 3.32×10^5. It decreases until it stabilizes at a 12400 tons. From the start of the simulation, every year yield increases from 17600 to over 17800 tons, reaching this maximum by the 23^{rd} year.

From that year on TAC is well accomplished. The mean yield of the first period, when the SSB is high, would be 1.78×10^4 and the following part would have a yearly average of 1.74×10^4, making a total mean of 1.75×10^4 tons (Fig. 4.20). Effort grows from 0.04 to 0.05.

4.6.2 Fuzzy HCR 2, scenario 1.

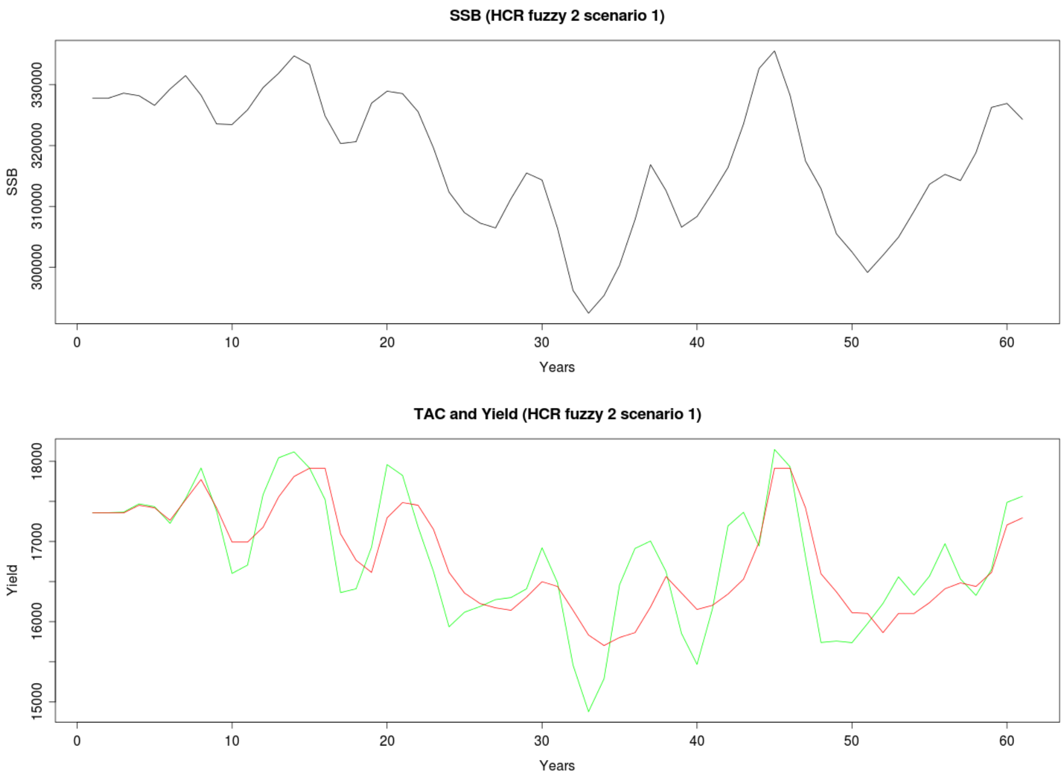

Figure 4.21: Projection of the stock when HCR fuzzy 2 is applied assuming a 20% of variability on recruitment. Black line= SSB, red line= TAC, green line = yield.

This simulation shows that the SSB bounces irregularly from 2.92×10^5 to 3.35×10^4. The main drop occurs during the period between the 45^{th} to the 51^{st} year, in which it falls from 3.35×10^5 to 2.99×10^5 tons. The mean SSB for the 60-year period is 3.18×10^4. TAC evolves as SSB, keeping their proportionality, ranging between 16000 and the maximum TAC, 17900 tons. The yield is more variable in relation with TAC than the previous projections, trespassing or staying below the given TAC. It ranges from 14900 (33^{th} year) to 18100 tons by the 45^{th} year, and 50 out of 60 years more than 16000 tons would be yielded. The average yield would be 16800 tons, and the total would sum over a million tons. (Fig. 4.21). Effort grows from 0.04 to 0.05.

4.6.3 Fuzzy HCR 2, scenario 2.

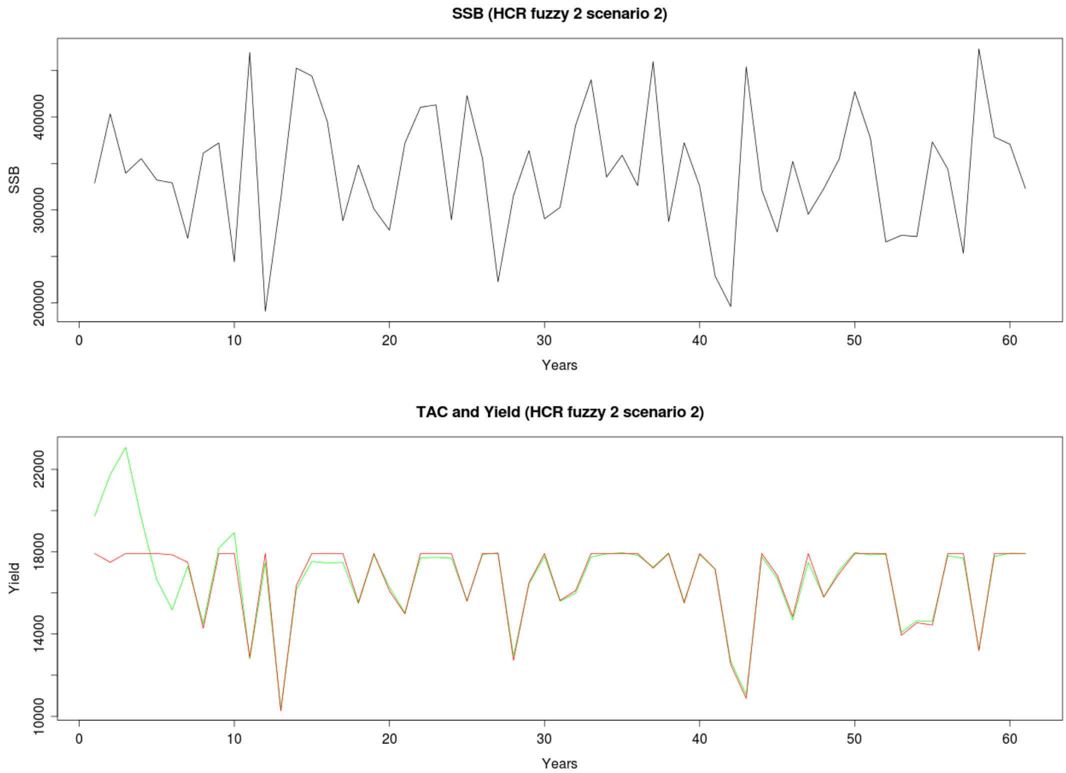

Figure 4.22: Projection of the stock when HCR fuzzy 2 is applied with a random normal error on 20% in the assessment. Black line= SSB, red line= TAC, green line = yield. Note that TAC is calculated for the next year.

In this projection SSB varies over a wide range, from 1.9×10^5 to 4.7×10^5 tons, the biggest slopes occurring during the period between the 9^{th} and the

11^{th} years, with differences of 1.28×10^5 and 2.25×10^5, and during the 42^{nd} and 43^{rd}, when an increase of 2.58×10^5 tons occurs. The average SSB is around 3.4×10^5, lying between 300000 and 400000 tons most of the simulation. Most of the time (36 years) maximum TAC or a very close value is allowed. During the first big down of the SSB, TAC goes from the maximum TAC to a TAC of 12800 tons, moving back to the maximum next year. In the second slope, it raises from a TAC over 10000 tons to the maximum TAC. The TAC is well accomplished with the exception of the first decade, in which the yield differ from TAC in a range of 1700 to 5500 tons. As an average, 16700 tons would be yielded yearly, making a total for 60 years of over a million tons (Fig. 4.22). Effort ranges from 0.02 to 0.06.

4.6.4 Fuzzy HCR 2, scenario 3.

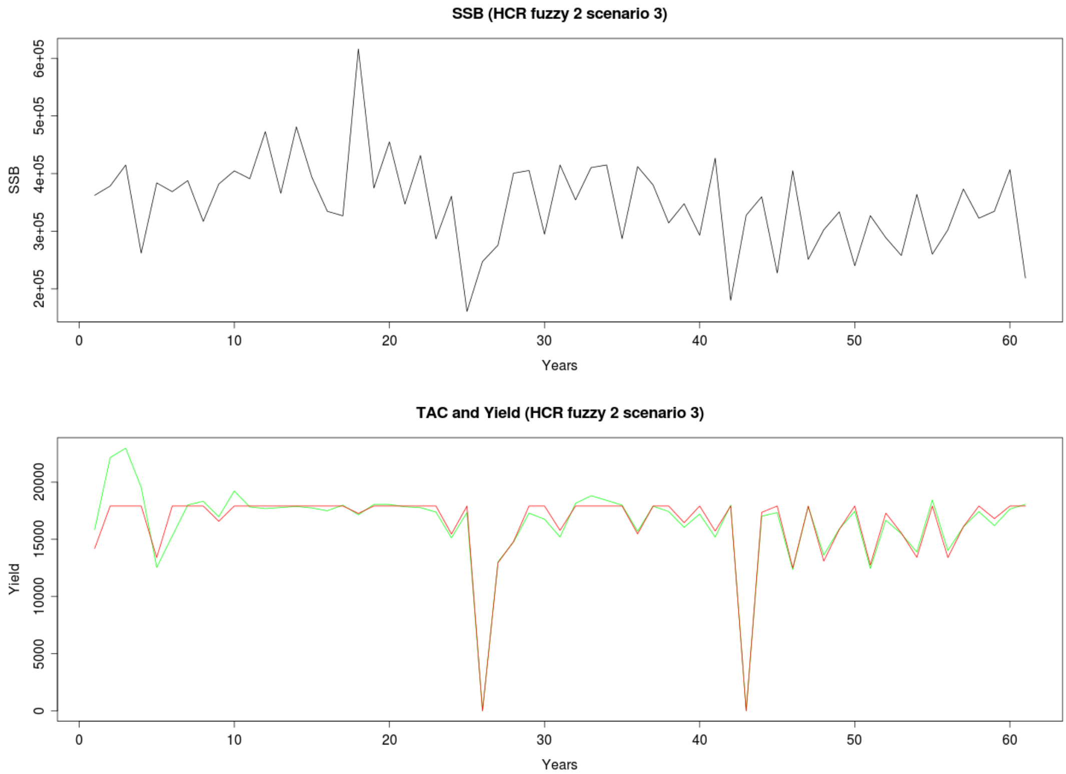

Figure 4.23: Projection of the stock when HCR fuzzy 2 is applied assuming a 20% error in the assessment and a 20% of variability in recruitment. Black line= SSB, red line= TAC, green line = yield. Note that TAC is calculated for the next year.

In this scenario, SSB suffers steep ups and downs, ranging from 1.6×10^5 to $6.1\, times\, 10^5$ tons. It is clear from fig. 4.23 that during the first half of the projection SSB ranges from 300 to 400 thousand tons, while in the second half the lower limit decreases to 250 thousand tons and the upper barely reaches the previous one. This high biomass allows during this first phase the implementation of the maximum TAC 20 years out of 25. The SSB estimated for the 25^{th} is close to the limit reference point, $0.5B_{MSY}$. With this algorithm the fishery for the next year should be closed. The same pattern is repeated but in a shorter time period, 16 years of high SSB, until it falls to a level close to $0.5B_{MSY}$. The next years SSB is always bigger than 2.6×10^5 so the TAC varies between 12500 and 17900 tons. During the first two years, more than 6000 tons would be yielded out of TAC. Until the first drop of SSB, high amounts of fish would be yielded, 17760 tons per year as a mean, and from the first to the second drop, this mean decreases until 16700 tons. In the last phase it would decrease to 15800 tons, making an average for the total projection of 16300 tons, and a total of 9.8×10^5 tons (fig.4.23). Effort grows from 0.0 to 0.05.

4.7 Summary and contrast of results

Fourteen of the twenty-four simulations show a tendency to stability or even to increase in SSB, half of them occurs under the fuzzy-logic harvest control rules. The yield average under HCR 1, both fuzzy and classic, rounds 20 thousand tons, while allowing hiher TACs than the estimated MSY, gathering totals around 1.3 million tons in 60 years. The results of both projections of HCR 1 without constraint are similar, but showing an improvement in the growth trend of the population and smoothing the variability on TACs. The decreasing pattern of biomass is most remarkable in those simulations in which a lower TAC constraint of 15% was applied, leading to a quick depletion under the fuzzy logic HCR.

HCR 2 shows interesting results, keeping the biomass stable in average under all scenarios. In average, during the last 30 years of all of the forecasts, SSB is bigger than 317856 tons, the previously estimated B_{MSY}. The closer value to this amount was given by the HCR fuzzy 2 scenario 1 (variability in recruitment), reaching 328000 tons. The target defined in classic HCR 1, $1.3B_{MSY}$ was only accomplished in HCR classic 1 scenarios 2 and 3, characterized by having the highest variability in SSB. The amount yielded per year under the fuzzy logic models raises from 2500 to 4000 tons, depending on the scenario. This also means an enlargement on the global forecast production, increasing over 150 thousand tons and reaching the million. The four different scenarios repeated this situation.

Table 4.1: Summary.

HCR	**scenario**	**SSB trend**	**minimum SSB** ($\times 10^4$ tons)	**TAC ranges** ($\times 10^4$ tons)	**Yield ranges** ($\times 10^4$ tons)	**mean Yield** ($\times 10^4$ tons)	**total Yield** (million tons)
Classic 1 no α	0	decrease	17.7	1.77-3.25	1.77-3.95	2.16	1.30
Classic 1 no α	1	decrease to stability	15.0	1.55-3.23	1.55-3.50	2.15	1.28
Classic 1 no α	2	decrease to stability	10.0	1.00-3.70	1.10-4.10	2.15	1.30
Classic 1 no α	3	decrease to stability	8.8	0.80-4.00	0.92-5.37	2.05	1.23
Classic 1 α	0	decrease	17.7	1.77-3.25	1.77-3.95	2.16	1.30
Classic 1 α	1	decrease	15.2	1.52-3.27	1.46-3.95	2.08	1.20
Classic 1 α	2	decrease	13.3	1.31-3.74	1.35-3.86	2.17	1.30
Classic 1 α	3	decrease	9.0	1.10-3.81	1.16-4.60	2.03	1.22
Fuzzy 1 no α	0	decrease	12.0	0.64-2.90	0.61-3.88	2.19	1.31
Fuzzy 1 no α	1	decrease to stability	16.3	1.73-3.07	1.71-4.09	2.13	1.28
Fuzzy 1 no α	2	decrease- increase	12.5	0.62-3.87	0.64-3.80	1.83	1.10
Fuzzy 1 no α	3	decrease to stability	15.1	0.71-4.78	0.71-4.90	2.03	1.24
Fuzzy 1 α	0	decrease to depletion	2.8	1.01-2.90	0.90-3.89	2.10	1.26
Fuzzy 1 α	1	decrease to depletion	1.4	0.78-2.92	0.66-3.98	2.07	1.27
Fuzzy 1 α	2	depletion	-	-	-	-	-
Fuzzy 1 α	3	depletion	-	-	-	-	-
Classic 2	0	stable	38.6	1.37-1.79	1.25-1.75	1.38	0.84
Classic 2	1	increase	30.0	0.85-1.17	0.58-1.82	1.43	0.88
Classic 2	2	stable	20.9	0.30-1.79	1.50-1.95	1.28	0.77
Classic 2	3	stable	20.3	1.04-1.79	1.02-1.98	1.40	0.84
Fuzzy 2	0	decrease to stability	32.8	1.73-1.79	1.73-1.78	1.7500	1.05
Fuzzy 2	1	decrease to stability	29.2	1.57-1.79	1.49-1.81	1.6800	1.00
Fuzzy 2	2	stable	19.1	1.03-1.79	1.03-2.30	1.6700	1.00
Fuzzy 2	3	decrease to stability	16.0	0.00-1.79	0.00-2.30	1.6400	0.98

5

Discussion.

The goals of this work were to compare the performance of fuzzy vs. classic HCR. Two different HCR were chosen, one based on a proportion of the stock, the biological allowable catch, and the other based on MSY reference points. Once they were translated into fuzzy logic systems, both classic and fuzzy HCRs were put into practice under 4 different scenarios that took into account variability in recruitment and observation error in the assessment.

The first HCR was tested under two frameworks: the first, TAC would be equal to ABC; the second, TAC would be equal to ABC but the maximum TAC drop allowed would be 15%. Scenario 0 gives an immediate idea that the percentage set as ABC (10% of the total SSB) is too high for this population since it decreases logarithmically and does not reach a steady phase until the end of the simulations. Nevertheless, the fuzzy HCR where no TAC constraint is applied, maintains in general the stock in a better shape than the classic HCR while keeping similar yield levels. When speaking of HCR with a constraint, the added factor α (15%) may be too narrow, and would be the major cause of the decrease enhance of the stock biomass when added to the HCR. The depletion of the stock that occurs when the lower constraint is applied gives a picture that α is the main cause of the shrinking, keeping TAC values higher than the population could afford.

The performance of the second HCR suggest that it would be a better choice to the exploitation of this stock, than either the classic or the fuzzy system. They are both capable of keeping a healthy level of SSB while providing an efficient recovery method in case the stock suffered a serious fall. Nevertheless, it is remarkable that using the fuzzy control system the captures improve and TAC fluctuations are less aggressive to fishermen and industry related, desirable characteristics in a fishery control system (Caddy, 2002). This may be due to the feature of the fuzzy control rule that automatically raises the limit reference point from $0.5B_{MSY}$ to almost $0.6B_{MSY}$ (fig. 4.23), fact that may improve the resilience of the stock and prevents the limit level to be reached.

The fuzzy logic HCR used are characterized by their plasticity. The effects of previous decisions can be taken into account to tune the predefined rules adding adaptivity to management. The fuzzy logic system is easy to use in R, but the packages that provide this kind of calculations are still developing. Nevertheless, the used package (Meyer and Hornik, 2009) allows to add categories to the system, combining them into the fuzzy rules with the operators AND, NOT and OR, and use a wide range of set types.

The information sharing among fishery managers, stakeholders and decision-makers has been difficult, because of the different terms and units used. The final decisions may not be understood by fishermen and fishery industry, sparkling irritations amongst the different groups that take part in the final decision. The need of easily explicable models challenged fishery scientists, who are trying to find more fitted models as well. Fuzzy logic HCRs can be a helpful tool, using simple linguistic levels such as "high - low" or "much - less" in stead of sharp numeric levels of scientific measures. Besides, the historical data availability and the simplicity of the fuzzy system to map linguistic expressions onto numerical variables, makes easy to pass on and include the opinions and settings of stakeholders into the HCRs. This settings may include different biomass measuring units easier for them to understand such as catch per unit effort (CPUE) and space and/or weather references (Verweij et al., 2010; Mackinson, 2001). It could be also considered the variation of the fishermen's knowledge. Adding this kind of information, it would be expected that models and HCR improve. But the more categories added to the system, the more difficult it is to tune, since different outputs are expected from using different types or width of the categories' sets, which have to be consistent with the historical data.

An example of fuzzy logic applied to fisheries was carried on by Mackinson (2000) who created a heuristic-rule based system integrating fishers and other stakeholders with scientific knowledge in order to create a highly predictive and flexible system, where the shape, spread, deep and distribution of shoals,a mong other parameters, are forecast according to the inputs, such as weather, wind direction, night or daytime. Accuracy of results rely on the realism of the inputs. The forecast of fish behavior improved when the local knowledge was added. The aim of his work was to represent and bring this new expertise to the system users, but it does not take a part in the harvest control system.

Another approach to fuzzy logic in fisheries management was in the traffic light system (Caddy, 1998). It was designed to be used by fishery managers who were unlikely to have access to to time series of data on stock and recruitment. It was used to present indices related to fisheries biology and take management decisions taking into account the overall output: the more number of "red" indices, the more severe management restriction (Caddy, 2002). It was modified over the past years with fuzzy logic to be used to present large volume of data, using the indicators as fuzzy sets. They could be used two ways to present the results to an assessment by merging colors or and dividing the area of the traffic-light spot depending on the values of the indicators (fig. 5.1). That way information can be weighted, resolution increased and uncertainty reduced. Plus, it is easy to realize the state of the fishery taking a look on the color changes of the different indicators over time (Halliday et al., 2001). It provides an estimation of how the stock is evolving under the current and the previous years levels of exploitation, but it does not provide the specific level of harvest that the stock could afford or when to stop fishing to rebuild it.

Fuzzy logic was used before in other approaches in fisheries, such as the ecosystem approach, using different softwares like NetWeaver or MATLAB. Their performance was compared to a Boolean system's to predict recruitment, taking into account female spawning population and spawning, transport and recruitment areas for eggs and larvae, outputting similar results (Jarre et al., 2008). It is also remarkable that neural networks are increasingly being used in fisheries and environmental management, for example, the Fuzzy Adaptive Resonance Theory (FuzART), is used in fisheries biology and physiology (Suryanarayana et al., 2008) or to estimate vulnerabilities (Cheung et al., 2005) to integrate multi-factor analysis.

All of this successful examples bring to mind that fuzzy logic is a powerful tool to use in fisheries and environmental sciences, but there is a lack of this kind of models to fisheries management. The application of fuzzy logic to HCRs may provide an improvement in stock rebuild and conservation, as well as more stable yield rates, affecting positively the fishery sector's economy. It would be needed a deeper research, comparing the currently used HCRs and well-known stocks to the fuzzy logic system. Plus, the extended use of R is driving to a high development of this kind of packages, where other kinds of defuzzification could be used, or use, as W. Silvert proposed, no defuzzification of the inference results to continue a forecast.

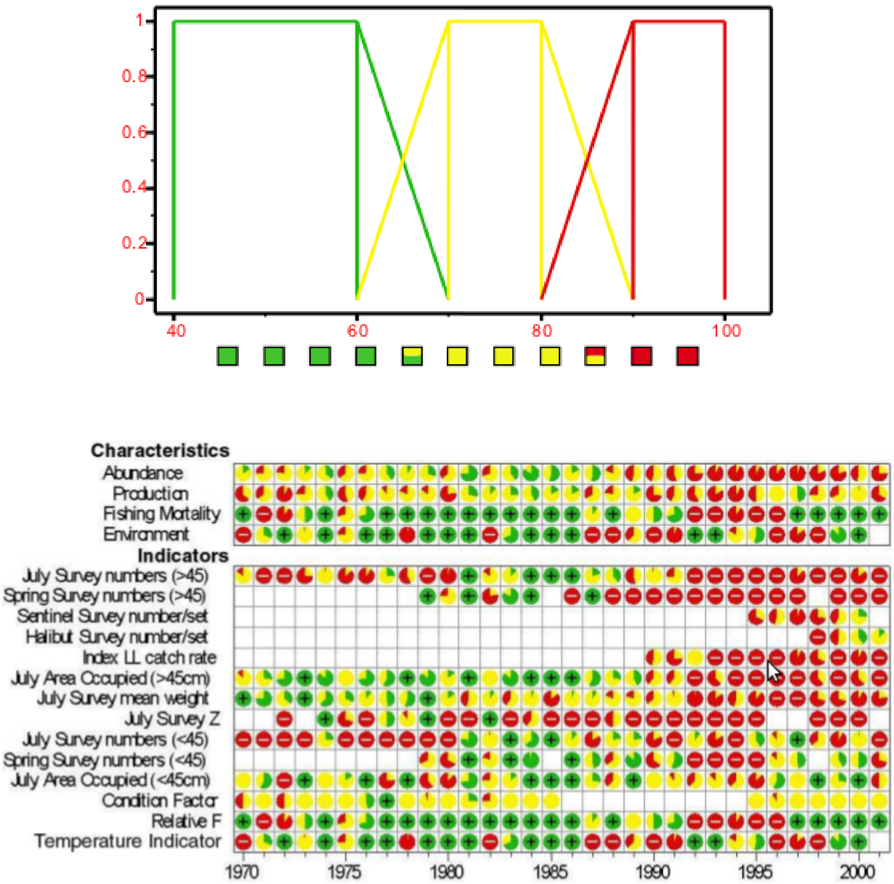

Figure 5.1: Upper: Schematic for Fuzzy Traffic Lights. Light assignments for arbitrarily selected values are shown below. Lower: Fuzzy traffic lights for white hake (Halliday et al., 2001)wi.

Bibliography

(2011). Comunicación de la comisión relativa a una consulta sobre las posibilidades de pesca (com (25/5/2011)298).

Apostolaki, P. and Hillary, R. (2009). Harvest control rules in the context of fishery-independent management of fish stocks. *Aquatic Living Resources.*, 22:217–224.

Caddy, J. (2002). Limit reference points, traffic lights, and holistic approaches to fisheries management with minimal stock assessment input. *Fisheries Research*, 56(2):133 – 137.

Caddy, J. and Mahon, R. (1998). Reference points for fisheries management. 347:83.

Caddy, J. F. (1998). *A short review of precautionary reference points and some proposals for their use in data poor situations.*, volume T379 of *FAO Fisheries Technical Paper.*

Cheung, W. W. L., Pitcher, T. J., and Pauly, D. (2005). A fuzzy logic expert system to estimate intrinsic extinction vulnerabilities of marine fishes to fishing. *Biological Conservation.*, 124:97–111.

Cochrane, K. L., Butterworth, D. S., de Oliveira, J. A. A., and Roel, B. A. (1998). Management procedures in a fishery based on highly variable stocks and with conflicting objectives: experiences in the south african pelagic fishery. *Reviews in Fish Biology and Fisheries*, 8:177–214.

Cooke, J. (1999). Improvement of fishery-management advice through simulation testing of harvest algorithms. *ICES Journal of Marine Science.*, 56:797–810.

Deroba, J. and Bence, J. (2008). A review of harvest policies: Understanding relative performance of control rules. *Fisheries Research*, 94:210–223.

Froese, R., Branch, T., Poelss, A., Quass, M., Sainsbury, K., and Zimmermann, C. (2010). Generic harvest control rules for european fihseries. *Fish and Fisheries.*, 12(3):340–351.

Halliday, R. G., Fanning, L. P., and Mohn, R. K. (2001). Use of the traffic light method in fishery management planning. Research Document 2001/108 Bedford Institute of Oceanography, Dartmouth, NS, B2Y 4A2.

ICES (2009). Report of the ices advisory comittee. ICES Books 1-11. 1,420 pp.

ICES (2011). Report of the Working Group on Anchovy and Sardine (WGANSA). ICES CM 2011/ACOM:16 . 8 pp.

Jarre, A., Paterson, B., Moloney, C., Miller, D., Field, J. G., and Starfield, A. (2008). Knowledge-based systems as decision support tools in an ecosystem approach to fisheries: Comparing a fuzzy-logic and a rule-based approach. *Progress In Oceanography*, 79(2-4):390 – 400.

Kell, L. T., Pilling, G. M., Kirkwood, G. P., M. Pastoors, B. Mesnil, K. K., Abaunza, P., Aps, R., Biseau, A., Kunzlik, P., Needle, C., Roel, B. A., and Ulrich-Rescan, C. (2005). An evaluation of the implicit management procedure used for some ices roundfish stocks. *ICES Journal of Marine Science*, 62:750–759.

Kell, L. T., Pilling, G. M., Kirkwood, G. P., M. Pastoors, B. Mesnil, K. K., Abaunza, P., Aps, R., Biseau, A., Kunzlik, P., Needle, C., Roel, B. A., and Ulrich-Rescan, C. (2006). An evaluation of multi-annual management strategies for ices roundfish stocks. *ICES Journal of Marine Science*, 63:12–24.

Mackinson, S. (2000). An adaptive fuzzy expert system for predicting structure, dynamics and distribution of herring shoals. *Ecological Modelling.*, 126:155–178.

Mackinson, S. (2001). Integrating local and scientific knowledge: An example in fisheries science. *Environmental Management.*, 27(4):533–545.

Meyer, D. and Hornik, K. (2009). Generalized and customizable sets in "R". *Journal of Statistical Software.*, 31(2):1–27.

Pauly, D. and Maclean, J. (2003). *In a perfect ocean.The state of fisheries and ecosystems in the North Atlantic Ocean.* Island Press.

Rademeyer, R. A., Plagànyi, E., and S.Butterworth, D. (2007). Tips and tricks in designing management procedures. *ICES Journal of Marine Science*, 64(4):618–625.

Sangalli, A. (1998). *The importance of being fuzzy and other insights from the border between math and computers.* Princetown University Pressnull.

Suryanarayana, I., Braibanti, A., Rao, R., Ramam, V., Sudarsan, D., and Rao, G. (2008). Neural networks in fisheries research. *Fisheries Research*, 92(2-3):115 – 139.

Verweij, M., van Densen, W., and Mol, A. (2010). The tower of babel: Different perceptions and controversies on change and status of north sea fish stocks in multi-stakeholder settings. *Marine Policy*, 34(3):522 – 533.

Zadeh, L. (1965). Fuzzy sets. *Information and Control*, 3:338–353.

Zimmermann, H.-J. (1992). *Fuzzy Set Theory and Its Applications.* Kluwer Academic Publishers.

A

R scripts.

Stock-recruitment relation.

```
## Define functions needed to simulate the evolution of the
## population under ifferent harvest control rules:
## Function to calculate the recruitment (in million of fish)
##  as a function of spawning stock biomass,
## using Deriso's generalized stock-recruitment model
SRrelation <- function(params, ssb){
  param.a <- params[1]
  param.b <- params[2]
  param.g <- params[3]
  recruitment <- param.a *ssb *(1 - param.b * param.g * ssb)^
  (1/param.g)
  return(recruitment)
}
## Functions to calculate which effort corresponds to a
## given TAC.
## The function "tac2f" makes a non-linear optimization of
## function "calcF" to estimate the value of effort.
tac2f <- function(pop, fleet){
  result.optim <- optimize(f = calcF, interval = c(0:10),
 pop=pop,  fleet=fleet)
  return(result.optim$minimum)
```

```
}

calcF <- function(fpar, pop, fleet) {## sum of squares of
## difference between TAC and expected catch.
  sel<- fleet$sel
  sel[1]<- fleet$sel[1]*pop$prop.rec
  return((fleet$TAC -  sum(pop$wage * (fpar * fleet$sel/
  (fpar * fleet$sel + pop$natmort)) * pop$nage *
  (1 - exp(-fpar * fleet$sel - pop$natmort))))^2)
}
##
## Function to calculate the spawning stock biomass of the
##  current population.
calcSSB <- function(pop){
  return(sum(pop$nage * pop$wage * pop$ogive))
}

## Simulated population with the following attributes:
##  "nage" - number of fish at each age class (in millions)
##  "wage" - mean weigth of the fish in each age (in grams)
##  "ogive" - proportion of fish mature at age
##  "natmort" - natural mortality rate at age
##  "rec.pars" - parameters for the Deriso's generalized stock-
## recruitment model
##  "spbiom" - spawning stock biomass
##  "prop.rec" - proportion of fishing mortality that acts on
## recruits
## (0.25 corresponds to recruitment in October)
fish.stock <- list(
  nage = c(2806204, 4812897, 596039, 347933, 126731, 62334,
   107143, 147086, 109296, 43296, 62883, 257507),
  wage = c(0.020, 0.040, 0.060, 0.080, 0.110, 0.140, 0.160,
   0.180, 0.190, 0.200, 0.240, 0.380),
```

```
  ogive = c(0, 0, 0.36, 0.82, 0.95, 0.97, 0.99, 1, 1, 1, 1, 1),
  natmort = c(0.9, 0.6, 0.4, 0.3, 0.2, 0.15, 0.15, 0.15, 0.15,
  0.15, 0.15, 0.15),
  rec.pars = c(15, 1.5e-6, 0.7),
  spbiom = NA,
  prop.rec = 0.25
          )
fish.stock$spbiom <- calcSSB(fish.stock)

## Define a simulated fishing fleet with the following
## attributes:
## "sel" - vector of selectivity at age
## "effort"-fishing effort at the current year, "sel"*"effort"
## gives the fishing mortality for each age class in that year
##  "TAC" - the Total Allowed Catch (in tons) for that year.

fish.fleet <- list(
sel = c(0.0201, 0.1073, 0.1373, 0.1225, 0.1007, 0.0763, 0.0775,
0.0831, 0.0831, 0.0831, 0.0831, 0.0831),
  effort = 0.05,
  TAC =0
          )
## Function to project the population in future for a given
## number of years (ny). Returns the spawning stock biomass
## and the number of invdividuals at age in each year.
## This function and returns the yield (total catch in tons)
## obtained from that population in each year.
project <- function(pop=fish.stock, fleet=fish.fleet, ny=60){
  na <- length(pop$nage)
  N <- matrix(0, na, ny)
  ssb <- numeric(ny)
  N[,1] <- pop$nage
ssb[1] <- pop$spbiom
```

```
  for(i in 2:ny){
    N[1,i] <- SRrelation(pop$rec.pars, ssb[i-1]) ## assume that
 ## a year's SSB influences the recruitment of the following year.
    print(paste(ssb[i-1], N[1,i], sep=" "))
    N[2,i] <- N[1, i-1] * exp(-fleet$effort * fleet$sel[1] *
    pop$prop.rec - pop$natmort[1])
    for(j in 3:(na-1)){
      N[j,i] <- N[j-1,i-1] * exp(-fleet$effort * fleet$sel[j-1]-
      pop$natmort[j-1])
      ## calculates number-at-age
    }
    N[na,i] <- N[na-1, i-1] *exp(-fleet$effort * fleet$sel[na-1]-
    pop$natmort[na-1]) +
    N[na, i-1] * exp(-fleet$effort * fleet$sel[na] -
     pop$natmort[na])
     ## number-at -age for the plus-group
    pop$nage <- N[,i]
    pop$spbiom <- calcSSB(pop) ## calculates SSB
    ssb[i] <- pop$spbiom
  }
  yield <- c()
  for( i in 1:ny){
    yield <- c(yield, sum(pop$wage * (fleet$effort * fleet$sel/
    (fleet$effort * fleet$sel + pop$natmort)) *
   N[,i] * (1 - exp(-fleet$effort * fleet$sel - pop$natmort))))
   ##calculates catches
  }
  return(list(SSB=ssb, Nage=N, Yield=yield))
}

biom <- seq(0,1e6,1e4)
plot(biom, SRrelation(c(15, 1.5e-6, 0.7), biom), type="l")
SSBlist <- project(ny=40)$Nage
```

R script. Reference points

```
## The previous functions are used to calculate the maximum
## sustainable yield and related reference points, taking
## into account the last 30 years of a 60-year projection,
## under a sequence of Fs
fish.stock <- list(
  nage = c(2806204, 4812897, 596039, 347933, 126731, 62334,
  107143, 147086, 109296, 43296, 62883, 257507),
  wage = c(0.020, 0.040, 0.060, 0.080, 0.110, 0.140, 0.160,
   0.180, 0.190, 0.200, 0.240, 0.380),
  ogive = c(0, 0, 0.36, 0.82, 0.95, 0.97, 0.99, 1, 1, 1, 1, 1),
  natmort = c(0.9, 0.6, 0.4, 0.3, 0.2, 0.15, 0.15, 0.15, 0.15,
  0.15, 0.15, 0.15),
  rec.pars = c(15, 1.5e-6, 0.7),
  spbiom = NA,
  prop.rec = 0.25
          )
fish.stock$spbiom <- calcSSB(fish.stock)

fish.fleet <- list(
  sel = c(0.0201, 0.1073, 0.1373, 0.1225, 0.1007, 0.0763, 0.0775,
  0.0831, 0.0831, 0.0831, 0.0831, 0.0831),
  effort = 0.05,
  TAC =0
          )

SRrelation <- function(params = rec.pars, ssb){
  param.a <- params[1]
  param.b <- params[2]
  param.g <- params[3]
  recruitment <- param.a * ssb * (1 - param.b * param.g * ssb)
  ^ (1/param.g)
  return(recruitment)
```

```
}

tac2f <- function(pop, fleet){

result.optim <- optimize(f = calcF, interval = c(0:10),
pop=pop, fleet=fleet)
  return(result.optim$minimum)
}
calcF <- function(fpar, pop, fleet) {
  sel<- fleet$sel
  sel[1]<- fleet$sel[1]*pop$prop.rec
  return((fleet$TAC -  sum(pop$wage * (fpar * fleet$sel/
  (fpar * fleet$sel + pop$natmort)) * pop$nage * (1 -
  exp(-fpar * fleet$sel - pop$natmort))))^2)
}

calcSSB <- function(pop){
  return(sum(pop$nage * pop$wage * pop$ogive))
}

project <- function(pop=fish.stock, fleet=fish.fleet, ny=60){
  na <- length(pop$nage)
  N <- matrix(0, na, ny)
  ssb <- numeric(ny)
  N[,1] <- pop$nage
ssb[1] <- pop$spbiom
  for(i in 2:ny){
    N[1,i] <- SRrelation(pop$rec.pars, ssb[i-1])
    print(paste(ssb[i-1], N[1,i], sep=" "))
    N[2,i] <- N[1, i-1] * exp(-fleet$effort * fleet$sel[1] *
    pop$prop.rec - pop$natmort[1])
    for(j in 3:(na-1)){
      N[j,i] <- N[j-1,i-1] * exp(-fleet$effort * fleet$sel[j-1]
```

```
        - pop$natmort[j-1])
      ## calculates number-at-age
    }
    N[na,i] <- N[na-1, i-1] * exp(-fleet$effort * fleet$sel[na-1]-
    pop$natmort[na-1]) +
    N[na, i-1 *exp(-fleet$effort * fleet$sel[na] -pop$natmort[na])
    pop$nage <- N[,i]
    pop$spbiom <- calcSSB(pop)
    ssb[i] <- pop$spbiom
  }
  yield <- c()
  for( i in 1:ny){
    yield <- c(yield, sum(pop$wage * (fleet$effort * fleet$sel/
    (fleet$effort * fleet$sel + pop$natmort)) *
   N[,i] * (1 - exp(-fleet$effort * fleet$sel - pop$natmort))))
  }
  return(list(SSB=ssb, Nage=N, Yield=yield))
}
  return(list(SSB=ssb, Nage=N, Yield=yield))
}

## With those functions, calculate the maximum sustainable yield
## and related reference points for that population (MSY,
## Fmsy, Bmsy):
catches <- matrix(0,30,1) ## creates empty matrix of catches
spbiom <- matrix(0,30,1) ## creates empty matrix of SSB
for(f in seq(0, 0.15, 0.01)){
  fish.fleet$effort <- f
  proj.exper <- project()
  catches <- cbind(catches, proj.exper$Yield[31:60])
  ## just keeps the 30 last years of projection
  spbiom <- cbind(spbiom, proj.exper$SSB[31:60])
  ## just keeps the 30 last years of projection
```

```
}
catches <- catches[,-1] ## removes initial column of zeros
spbiom <- spbiom[,-1] ## removes initial column of zeros
par(mfrow=c(2,1))
msy <- apply(catches, 2, median)
ssb <- apply(spbiom, 2, median)
plot(seq(0,.15,0.01), msy, main = "Yield", type ="l")
plot(seq(0,.15,0.01), ssb, main = "SSB", type = "l")
```

HCR Classic 1

```
## HCR classic 1, TAC = ABC,
## recruitment variation and assessment error are simulated by
## adding a random normally distributed factor
SRrelation <- function(params, ssb){
  param.a <- params[1]
  param.b <- params[2]
  param.g <- params[3]
  recruitment <- (param.a * ssb * (1 - param.b * param.g * ssb)
   ^ (1/param.g))# *rnorm(1,1,0.2) ## switch on to add variability
  return(recruitment)
}

tac2f <- function(pop, fleet){
  result.optim <- optimize(f = calcF, interval = c(0:10), pop=pop,
   fleet=fleet)
  return(result.optim$minimum)
}

calcF <- function(fpar, pop, fleet) {
  sel[1]<- fleet$sel[1]*pop$prop.rec
  return((fleet$TAC -  sum(pop$wage * (fpar * fleet$sel/(fpar *
  fleet$sel + pop$natmort)) * pop$nage * (1 - exp(-fpar * fleet$sel
  - pop$natmort))))^2)
}
calcSSB <- function(pop){
  return((sum(pop$nage * pop$wage * pop$ogive))#*rnorm(1,1,0.2))
  ## switch on to add noise
}
##wage in kg, nage in thousands
fish.stock <- list(
  nage = c(2806204, 4812897, 596039, 347933, 126731, 62334,
   107143, 147086, 109296, 43296, 62883, 257507),
```

```
  wage = c(0.020, 0.040, 0.060, 0.080, 0.110, 0.140, 0.160, 0.180,
   0.190, 0.200, 0.240, 0.380),
  ogive = c(0, 0, 0.36, 0.82, 0.95, 0.97, 0.99, 1, 1, 1, 1, 1),
  natmort = c(0.9, 0.6, 0.4, 0.3, 0.2, 0.15, 0.15, 0.15, 0.15,
   0.15, 0.15, 0.15),
  rec.pars = c(15, 1.5e-6, 0.7),
  spbiom = NA
  prop.rec = 0.25
                  )
fish.stock$spbiom <- calcSSB(fish.stock)

fish.fleet <- list(
  sel = c(0.0201, 0.1073, 0.1373, 0.1225, 0.1007, 0.0763, 0.0775,
   0.0831, 0.0831, 0.0831, 0.0831, 0.0831),   effort = 0.1,
   ## effort that yields more or less 25000
   TAC =25000 ## 10% of the initial SSB
                  )

project <- function(pop=fish.stock, fleet=fish.fleet, ny=60){
  na <- length(pop$nage)
  N <- matrix(0, na, ny)
  ssb <- numeric(ny)
  N[,1] <- pop$nage
ssb[1] <- pop$spbiom
  for(i in 2:ny){
    N[1,i] <- SRrelation(pop$rec.pars, ssb[i-1])
    print(paste(ssb[i-1], N[1,i], sep=" "))
    N[2,i] <- N[1, i-1] * exp(-fleet$effort * fleet$sel[1] *
    pop$prop.rec - pop$natmort[1])
    for(j in 3:(na-1)){
      N[j,i] <- N[j-1,i-1] * exp(-fleet$effort * fleet$sel[j-1] -
      pop$natmort[j-1])
    }
```

```
    N[na,i] <- N[na-1, i-1] * exp(-fleet$effort * fleet$sel[na-1] -
     pop$natmort[na-1]) +
      N[na, i-1] * exp(-fleet$effort * fleet$sel[na] -
       pop$natmort[na])
    pop$nage <- N[,i]
    pop$spbiom <- calcSSB(pop)
    ssb[i] <- pop$spbiom
  }
  yield <- c()
  for( i in 1:ny){
    yield <- c(yield, sum(pop$wage * (fleet$effort * fleet$sel/
    (fleet$effort * fleet$sel + pop$natmort)) *
    N[,i] * (1 - exp(-fleet$effort * fleet$sel - pop$natmort))))
  }
  return(list(SSB=ssb, Nage=N, Yield=yield))
}

calcABC<-function (SSB=proj.result$SSB[2]){
  ABC<- SSB*0.10
  return (ABC)
  }

## HCR-> switch on and off the following functions to select among
## no alpha or with alpha.

##no alpha
HCRclassic1<- function (ABC, TAC){
    TAC = ABC.vec[length(ABC.vec)]
    return (TAC)
 }
## inf alpha
##HCRclassic1<- function (ABC, TAC){
# alpha=.15
```

```
#if (ABC.vec[length(ABC.vec)] < TAC.vec [length(TAC.vec)-1]*
(1- alpha) ) {
#     TAC <- TAC.vec [length(TAC.vec)] *(1-alpha)}
#else (TAC = ABC.vec[length(ABC.vec)])
#    return (TAC)
#}

proj.result<- project(fish.stock, fish.fleet, ny=2)
ABC<- calcABC(SSB=proj.result$SSB[2])
num.years <- 1
ssb.vec <- c()
yield.vec <- c()
recruit.vec <- c()
TAC.vec<- c()
effort.vec <-c()
TAC.vec[1]<-25000
effort.vec [1] <- 0.1
ABC.vec<-c()
ABC.vec[1]<- 25000

for(i in 1:num.years){
fish.fleet$TAC <- HCRclassic1(ABC, TAC=fish.fleet$TAC)
fish.fleet$effort <- tac2f(pop=fish.stock, fleet=fish.fleet)
proj.result <- project(ny=2)
fish.stock$nage <- proj.result$Nage[,2]
fish.stock$spbiom <- proj.result$SSB[2]
ssb.vec <- c(ssb.vec, proj.result$SSB[2])
yield.vec <- c(yield.vec, proj.result$Yield[2])
recruit.vec <- c( recruit.vec, proj.result$Nage[1,2])
TAC.vec <- c( TAC.vec, HCRclassic1(ABC,TAC))
effort.ve <-c(effort.vec, tac2f(pop=fish.stock, fleet=fish.fleet))
 ABC.vec<- c(ABC.vec, calcABC(SSB=proj.result$SSB[2])) }
```

HCR Fuzzy 1 no constraint

```
## TAC is calculated using fuzzy functions using package "sets".
## functions and standard deviations have to be tunned for best
## results



library("sets")
SRrelation <- function(params, ssb){
  param.a <- params[1]
  param.b <- params[2]
  param.g <- params[3]
  recruitment <- (param.a * ssb * (1 - param.b * param.g * ssb)^
  (1/param.g))#*rnorm(1,1,0.2)  ##switch on to add variability
  return(recruitment)
}

tac2f <- function(pop, fleet){
  result.optim <- optimize(f = calcF, interval = c(0:10), pop=pop,
  fleet=fleet)
  return(result.optim$minimum)
}

calcF <- function(fpar, pop, fleet) {
  sel<- fleet$sel
  sel[1]<- fleet$sel[1]*pop$prop.rec
  return((fleet$TAC -  sum(pop$wage * (fpar * fleet$sel/(fpar *
  fleet$sel + pop$natmort)) * pop$nage * (1 - exp(-fpar * fleet$sel
   - pop$natmort))))^2)
}
calcSSB <- function(pop){
  return((sum(pop$nage * pop$wage * pop$ogive))#*rnorm(1,1,0.2))
  ##switch on to add error.
}
```

```
##wage in kg, nage in thousands
fish.stock <- list(
  nage = c(2806204, 4812897, 596039, 347933, 126731, 62334, 107143,
  147086, 109296, 43296, 62883, 257507),
  wage = c(0.020, 0.040, 0.060, 0.080, 0.110, 0.140, 0.160, 0.180,
   0.190, 0.200, 0.240, 0.380),
  ogive = c(0, 0, 0.36, 0.82, 0.95, 0.97, 0.99, 1, 1, 1, 1, 1),
  natmort = c(0.9, 0.6, 0.4, 0.3, 0.2, 0.15, 0.15, 0.15, 0.15, 0.15,
   0.15, 0.15),
  rec.pars = c(15, 1.5e-6, 0.7),
  spbiom = NA,
  prop.rec = 0.25
               )
fish.stock$spbiom <- calcSSB(fish.stock)



fish.fleet <- list(
  sel = c(0.0201, 0.1073, 0.1373, 0.1225, 0.1007, 0.0763, 0.0775,
   0.0831, 0.0831, 0.0831, 0.0831, 0.0831),
  effort = 0.1,
  TAC =25000 ## 10% of the initial SSB
                   )

project <- function(pop=fish.stock, fleet=fish.fleet, ny=60){
  na <- length(pop$nage)
  N <- matrix(0, na, ny)
  ssb <- numeric(ny)
  N[,1] <- pop$nage
ssb[1] <- pop$spbiom
  for(i in 2:ny){
    N[1,i] <- SRrelation(pop$rec.pars, ssb[i-1])
    print(paste(ssb[i-1], N[1,i], sep=" "))
```

```
    N[2,i] <- N[1, i-1] * exp(-fleet$effort * fleet$sel[1] *
    pop$prop.rec - pop$natmort[1])
    for(j in 3:(na-1)){
      N[j,i] <- N[j-1,i-1] * exp(-fleet$effort * fleet$sel[j-1] -
      pop$natmort[j-1])
    }
    N[na,i] <- N[na-1, i-1] * exp(-fleet$effort * fleet$sel[na-1]-
     pop$natmort[na-1]) +
      N[na, i-1] * exp(-fleet$effort * fleet$sel[na] -
      pop$natmort[na])
    pop$nage <- N[,i]
    pop$spbiom <- calcSSB(pop)
    ssb[i] <- pop$spbiom
  }
  yield <- c()
  for( i in 1:ny){
    yield <- c(yield, sum(pop$wage * (fleet$effort * fleet$sel/
    (fleet$effort * fleet$sel + pop$natmort)) *
   N[,i] * (1 - exp(-fleet$effort * fleet$sel - pop$natmort))))
  }
  return(list(SSB=ssb, Nage=N, Yield=yield))
}

calcABC<-function (SSB=proj.result$SSB[2]){
  ABC<- SSB*0.10
  return (ABC)
  }

HCRfuzzy1<- function (TAC){

sets_options("universe", seq(-150, 150, 1))
variables<- set(
 VABC= fuzzy_partition (varnames = c(min = -150, m_l = -100,
```

```
 lower= -50, med = 0, higher = 50, m_h = 100, max = 150),
             FUN= fuzzy_normal, sd=20),

 alpha = fuzzy_variable (varnames = c(min = -150, very_low = -100,
 low = -50, med = 0, high = 50, very_high = 100, max = 150),
             FUN= fuzzy_normal, sd= 15))

rules <- set(
  fuzzy_rule (VABC %is% min, alpha %is% min),
  fuzzy_rule (VABC %is% m_l, alpha %is% very_low),
  fuzzy_rule (VABC %is% lower, alpha %is% low),
  fuzzy_rule (VABC %is% med, alpha %is% med),
  fuzzy_rule (VABC %is% higher, alpha %is% high),
  fuzzy_rule (VABC %is% m_h, alpha %is% very_high),
  fuzzy_rule (VABC %is% max, alpha %is% max))

system<- (fuzzy_system (variables, rules))
print (system)
plot (system)

  inference<- fuzzy_inference (system, list(VABC=NABC))
plot(inference)
gd <- gset_defuzzify (inference, "centroid")
gd

TAC<-TAC.vec[length(TAC.vec)]*(1+gd/100)

return (TAC)}

proj.result<- project(fish.stock, fish.fleet, ny=2)
num.years <- 1
SSB.vec <- c()
yield.vec <- c()
```

```
recruit.vec <- c()
TAC.vec<- c()
effort.vec <-c()
TAC.vec[1]<-25000
effort.vec [1] <- 0.1
ABC.vec<-c()
ABC.vec[1]<- c(25000)
NABC<-15

for(i in 1:num.years){
fish.fleet$TAC <- HCRfuzzy1(TAC=fish.fleet$TAC)
fish.fleet$effort <- tac2f(pop=fish.stock, fleet=fish.fleet)
proj.result <- project(ny=2)
fish.stock$nage <- proj.result$Nage[,2]
fish.stock$spbiom <- proj.result$SSB[2]
SSB.vec <- c(SSB.vec, proj.result$SSB[2])
ABC.vec<- c( ABC.vec, calcABC(SSB=proj.result$SSB[2]))
NABC <-round(100-ABC.vec[length(ABC.vec)-1]/ABC.vec[length
(ABC.vec)]*100)
yield.vec <- c(yield.vec, proj.result$Yield[2])
recruit.vec <- c(recruit.vec, proj.result$Nage[1,2])
TAC.vec <- c(TAC.vec, HCRfuzzy1(TAC))
effort.vec <- c(effort.vec, tac2f(pop=fish.stock,
 fleet=fish.fleet))   }
```

HCR Fuzzy 1 with constraint.

```
## TAC is calculated using fuzzy functions using package "sets".
## functions and standard deviations have to be tunned for best
## results
library("sets")
SRrelation <- function(params, ssb){
```

```
  param.a <- params[1]
  param.b <- params[2]
  param.g <- params[3]
  recruitment <- (param.a * ssb * (1 - param.b * param.g * ssb) ^
  (1/param.g))#*rnorm(1,1,0.2)
  return(recruitment)
}

tac2f <- function(pop, fleet){
  result.optim <- optimize(f = calcF, interval = c(0:10), pop=pop,
  fleet=fleet)
  return(result.optim$minimum)
}

calcF <- function(fpar, pop, fleet) {
  sel<- fleet$sel
  sel[1]<- fleet$sel[1]*pop$prop.rec
  return((fleet$TAC -  sum(pop$wage * (fpar * fleet$sel/(fpar *
  fleet$sel + pop$natmort)) * pop$nage * (1-exp(-fpar * fleet$sel
  - pop$natmort))))^2)
}

calcSSB <- function(pop){
  return(sum(pop$nage * pop$wage * pop$ogive))#*rnorm(1,1,0.2))
}
##wage in kg, nage in thousands
fish.stock <- list(
 nage = c(2806204, 4812897, 596039, 347933, 126731, 62334, 107143,
 147086, 109296, 43296, 62883, 257507),
 wage = c(0.020, 0.040, 0.060, 0.080, 0.110, 0.140, 0.160, 0.180,
 0.190, 0.200, 0.240, 0.380),
 ogive = c(0, 0, 0.36, 0.82, 0.95, 0.97, 0.99, 1, 1, 1, 1, 1),
 natmort = c(0.9, 0.6, 0.4, 0.3, 0.2, 0.15, 0.15, 0.15, 0.15,
```

```
 0.15, 0.15, 0.15),
 rec.pars = c(15, 1.5e-6, 0.7),
 spbiom = NA,
 prop.rec = 0.25
           )
fish.stock$spbiom <- calcSSB(fish.stock)

fish.fleet <- list(
 sel = c(0.0201, 0.1073, 0.1373, 0.1225, 0.1007, 0.0763, 0.0775,
 0.0831, 0.0831, 0.0831, 0.0831, 0.0831),
  effort = 0.1,
 TAC =25000 ## 10% of the initial SSB
                   )

project <- function(pop=fish.stock, fleet=fish.fleet, ny=60){
  na <- length(pop$nage)
  N <- matrix(0, na, ny)
  ssb <- numeric(ny)
  N[,1] <- pop$nage
ssb[1] <- pop$spbiom
  for(i in 2:ny){
    N[1,i] <- SRrelation(pop$rec.pars, ssb[i-1])
    print(paste(ssb[i-1], N[1,i], sep=" "))
    N[2,i] <- N[1, i-1] * exp(-fleet$effort * fleet$sel[1] *
    pop$prop.rec - pop$natmort[1])
    for(j in 3:(na-1)){
      N[j,i] <- N[j-1,i-1] * exp(-fleet$effort * fleet$sel[j-1] -
      pop$natmort[j-1])
    }
    N[na,i] <- N[na-1, i-1] * exp(-fleet$effort * fleet$sel[na-1] -
     pop$natmort[na-1]) +
      N[na, i-1] * exp(-fleet$effort * fleet$sel[na] -
      pop$natmort[na])
```

```
    pop$nage <- N[,i]
    pop$spbiom <- calcSSB(pop)
    ssb[i] <- pop$spbiom
  }
  yield <- c()
  for( i in 1:ny){
    yield <- c(yield, sum(pop$wage * (fleet$effort * fleet$sel/
    (fleet$effort  * fleet$sel + pop$natmort)) *
   N[,i] * (1 - exp(-fleet$effort * fleet$sel - pop$natmort))))
  }
  return(list(SSB=ssb, Nage=N, Yield=yield))
}

calcABC<-function (SSB=proj.result$SSB[2]){
  ABC<- SSB*0.10
  return (ABC)
  }

HCRfuzzy1<- function (TAC){
sets_options("universe", seq (-150, 150, 1))

variables<- set(
   VABC= fuzzy_partition(varnames = c(min = -150, m_l = -100,
   lower = -50, lit= - 25, med = 0, hit = 25, higher = 50,
    m_h = 100, max = 150),
        FUN= fuzzy_normal, sd=20),

   alpha = fuzzy_variable(varnames = c(min = -15, med = 0,
    hit = 15,  high = 50, very_high = 100, max = 150),
        FUN= fuzzy_normal, sd= 15))

rules <- set(
    fuzzy_rule (VABC %is% min , alpha %is% min),
```

```
    fuzzy_rule (VABC %is% m_l , alpha %is% min),
    fuzzy_rule (VABC %is% lower, alpha %is% min),
    fuzzy_rule(VABC%is% lit, alpha %is% min),
    fuzzy_rule (VABC %is% med , alpha %is% med),
    fuzzy_rule (VABC %is% hit , alpha %is% hit),
    fuzzy_rule (VABC %is% higher , alpha %is% high),
    fuzzy_rule (VABC %is% m_h , alpha %is% very_high),
    fuzzy_rule (VABC %is% max , alpha %is%  max)
         )

  system1 <- fuzzy_system (variables, rules)
  print(system1)
  plot(system1)

inference <- fuzzy_inference (system1, list(VABC =NABC))
plot(inference)
applyalpha <- gset_defuzzify (inference, "centroid")
applyalpha

    TAC<-TAC.vec[length(TAC.vec)]*(1+applyalpha/100)

return (TAC)}

proj.result<- project (fish.stock, fish.fleet, ny=2)

num.years <- 1
SSB.vec <- c()
yield.vec <- c()
recruit.vec <- c()
TAC.vec<- c()
effort.vec <-c()
TAC.vec[1]<-25000
ABC.vec<-c()
```

```
ABC.vec[1]<-25000
NABC<- 15

for(i in 1:num.years){
fish.fleet$TAC <- HCRfuzzy1(TAC=fish.fleet$TAC)
fish.fleet$effort <- tac2f(pop=fish.stock, fleet=fish.fleet)
proj.result <- project(ny=2)
fish.stock$nage <- proj.result$Nage[,2]
fish.stock$spbiom <- proj.result$SSB[2]
SSB.vec <- c(SSB.vec, proj.result$SSB[2])
ABC.vec<- c( ABC.vec, calcABC(SSB=proj.result$SSB[2]))
NABC <-round(100-ABC.vec[length(ABC.vec)-1]/ABC.vec
 [length(ABC.vec)]*100)
yield.vec <- c(yield.vec, proj.result$Yield[2])
recruit.vec <- c(recruit.vec, proj.result$Nage[1,2])
TAC.vec <- c(TAC.vec, HCRfuzzy1(TAC))
effort.vec <- c(effort.vec, tac2f(pop=fish.stock,fleet=fish.fleet))
 }
```

HCR Classic 2

```
## HCR classic 2
## TAC is proportional to biomass, unless it reaches a limit point,
## Maximum TAC = MSY

SRrelation <- function(params, ssb){
  param.a <- params[1]
  param.b <- params[2]
  param.g <- params[3]
  recruitment <- (param.a * ssb * (1 - param.b * param.g * ssb) ^
   (1/param.g))#*rnorm (1,1,0.2)
  return(recruitment)
}

tac2f <- function(pop, fleet){
  result.optim <- optimize(f = calcF, interval = c(0:10), pop=pop,
  fleet=fleet)
  return(result.optim$minimum)
}

calcF <- function(fpar, pop, fleet) {
  sel<- fleet$sel
  sel[1]<- fleet$sel[1]*pop$prop.rec
  return((fleet$TAC -  sum(pop$wage * (fpar * fleet$sel/(fpar *
  fleet$sel + pop$natmort)) * pop$nage * (1-exp(-fpar * fleet$sel
   - pop$natmort))))^2)
}
calcSSB <- function(pop){
  return((sum(pop$nage * pop$wage * pop$ogive))#*rnorm (1,1,0.200))
}
##wage in kg, nage in thousands
fish.stock <- list(
```

```
  nage = c(2806204, 4812897, 596039, 347933, 126731, 62334, 107143,
  147086, 109296, 43296, 62883, 257507),
  wage = c(0.020, 0.040, 0.060, 0.080, 0.110, 0.140, 0.160, 0.180,
  0.190, 0.200, 0.240, 0.380),
  ogive = c(0, 0, 0.36, 0.82, 0.95, 0.97, 0.99, 1, 1, 1, 1, 1),
  natmort = c(0.9, 0.6, 0.4, 0.3, 0.2, 0.15, 0.15, 0.15, 0.15, 0.15,
   0.15, 0.15),
  rec.pars = c(15, 1.5e-6, 0.7),
  spbiom = NA,
  prop.rec = 0.25
                 )
fish.stock$spbiom <- calcSSB(fish.stock)

Bmsy<- 317856
MSY<-17912.3
fish.fleet <- list(
 sel = c(0.0201, 0.1073, 0.1373, 0.1225, 0.1007, 0.0763, 0.0775,
  0.0831, 0.0831, 0.0831, 0.0831, 0.0831),
   effort = 0.05,
 TAC =NULL
                   )

project <- function(pop=fish.stock, fleet=fish.fleet, ny=60){
  na <- length(pop$nage)
  N <- matrix(0, na, ny)
  ssb <- numeric(ny)
  N[,1] <- pop$nage
ssb[1] <- pop$spbiom
  for(i in 2:ny){
    N[1,i] <- SRrelation(pop$rec.pars, ssb[i-1])
    print(paste(ssb[i-1], N[1,i], sep=" "))
    N[2,i] <- N[1, i-1] * exp(-fleet$effort * fleet$sel[1] *
    pop$prop.rec - pop$natmort[1])
```

```
    for(j in 3:(na-1)){
      N[j,i] <- N[j-1,i-1] * exp(-fleet$effort * fleet$sel[j-1] -
      pop$natmort[j-1])
    }
    N[na,i] <- N[na-1, i-1] * exp(-fleet$effort * fleet$sel[na-1] -
     pop$natmort[na-1]) +
      N[na, i-1] * exp(-fleet$effort * fleet$sel[na] -
       pop$natmort[na])
    pop$nage <- N[,i]
    pop$spbiom <- calcSSB(pop)
    ssb[i] <- pop$spbiom
  }
  yield <- c()
  for( i in 1:ny){
    yield <- c(yield, sum(pop$wage * (fleet$effort * fleet$sel/
    (fleet$effort * fleet$sel + pop$natmort)) *
    N[,i] * (1 - exp(-fleet$effort * fleet$sel - pop$natmort))))
  }
  return(list(SSB=ssb, Nage=N, Yield=yield))
}

##Bmsy<- 317856. 05*Bmsy<-158928

HCRclassic2 <- function(ssb, Bmsy, MSY){
  TAC<- 0.0603*ssb- 9580.97## calculated linear equation having
  ## identified limit reference point and target reference point
 if (mean(SSB.vec[length(SSB.vec)],SSB.vec[length(SSB.vec)-1],
 SSB.vec[length(SSB.vec)-2])>1.3*Bmsy & ssb> Bmsy){TAC <- MSY}
  if(ssb <=0.5*Bmsy) {
    TAC <- 0
  }
  return(TAC)
}
```

```
proj.result<- project(fish.stock, fish.fleet, ny =2)

num.years <-1
SSB.vec <- c()
yield.vec <- c()
recruit.vec <- c()
TAC.vec <- c()
effort.vec <- c()

for(i in 1:num.years){
fish.fleet$TAC <- HCRclassic2(ssb=fish.stock$spbiom, Bmsy, MSY)
fish.fleet$effort <- tac2f(pop=fish.stock, fleet=fish.fleet)
proj.result <- project(ny=2)
fish.stock$nage <- proj.result$Nage[,2]
fish.stock$spbiom <- proj.result$SSB[2]
SSB.vec <- c(SSB.vec, proj.result$SSB[2])
yield.vec <- c(yield.vec, proj.result$Yield[2])
recruit.vec <- c( recruit.vec, proj.result$Nage[1,2])
TAC.vec <- c(TAC.vec, HCRclassic2(ssb=fish.stock$spbiom, Bmsy, MSY))
effort.vec <- c(effort.vec, tac2f(pop=fish.stock, fleet=fish.fleet))
}
```

HCR Fuzzy 2.

```
## HCR fuzzy 2.
## TAC is calculated using fuzzy functions using package "sets".
## functions and standard deviations have to be tunned for best
## results.

library("sets")
SRrelation <- function(params, ssb){
```

```
  param.a <- params[1]
  param.b <- params[2]
  param.g <- params[3]
  recruitment <- (param.a * ssb * (1 - param.b * param.g * ssb)
   ^ (1/param.g))#*rnorm(1,1,0.2)
  return(recruitment)
}

tac2f <- function(pop, fleet){
  result.optim <- optimize(f = calcF, interval = c(0:10), pop=pop,
  fleet=fleet)
  return(result.optim$minimum)
}

calcF <- function(fpar, pop, fleet) {
  sel<- fleet$sel
  sel[1]<- fleet$sel[1]*pop$prop.rec
  return((fleet$TAC -  sum(pop$wage * (fpar * fleet$sel/(fpar *
  fleet$sel + pop$natmort)) * pop$nage * (1 - exp(-fpar *
   fleet$sel - pop$natmort))))^2)
}
calcSSB <- function(pop){
  return((sum(pop$nage * pop$wage * pop$ogive))#*rnorm(1,1,0.2))
}
##wage in kg, nage in thousands
fish.stock <- list(
  nage = c(2806204, 4812897, 596039, 347933, 126731, 62334,
  107143, 147086, 109296, 43296, 62883, 257507),
  wage = c(0.020, 0.040, 0.060, 0.080, 0.110, 0.140, 0.160,
   0.180, 0.190, 0.200, 0.240, 0.380),
  ogive = c(0, 0, 0.36, 0.82, 0.95, 0.97, 0.99, 1, 1, 1, 1, 1),
  natmort = c(0.9, 0.6, 0.4, 0.3, 0.2, 0.15, 0.15, 0.15, 0.15,
   0.15, 0.15, 0.15),
```

```
  rec.pars = c(15, 1.5e-6, 0.7),
  spbiom = NA,
  prop.rec = 0.25
                  )
fish.stock$spbiom <- calcSSB(fish.stock)

fish.fleet <- list(
 sel = c(0.0201, 0.1073, 0.1373, 0.1225, 0.1007, 0.0763, 0.0775,
  0.0831, 0.0831, 0.0831, 0.0831, 0.0831),
  effort = 0.05,
  TAC = NULL
   )

project <- function(pop=fish.stock, fleet=fish.fleet, ny=60){
  na <- length(pop$nage)
  N <- matrix(0, na, ny)
  ssb <- numeric(ny)
  N[,1] <- pop$nage
ssb[1] <- pop$spbiom
  for(i in 2:ny){
    N[1,i] <- SRrelation(pop$rec.pars, ssb[i-1])
    print(paste(ssb[i-1], N[1,i], sep=" "))
    N[2,i] <- N[1, i-1] * exp(-fleet$effort * fleet$sel[1] *
     pop$prop.rec - pop$natmort[1])
    for(j in 3:(na-1)){
      N[j,i] <- N[j-1,i-1] * exp(-fleet$effort * fleet$sel[j-1] -
      pop$natmort[j-1])
    }
    N[na,i] <- N[na-1, i-1] * exp(-fleet$effort * fleet$sel[na-1]-
     pop$natmort[na-1]) +
      N[na, i-1] * exp(-fleet$effort * fleet$sel[na] -
       pop$natmort[na])
    pop$nage <- N[,i]
```

```
    pop$spbiom <- calcSSB(pop)
    ssb[i] <- pop$spbiom
  }
  yield <- c()
  for( i in 1:ny){
    yield <- c(yield, sum(pop$wage * (fleet$effort * fleet$sel/
    (fleet$effort * fleet$sel + pop$natmort)) *
    N[,i] * (1 - exp(-fleet$effort * fleet$sel - pop$natmort))))
  }
  return(list(SSB=ssb, Nage=N, Yield=yield))
}

HCRfuzzy2 <- function (ssb, Bmsy, MSY, X){
sets_options("universe", seq (from = 0, to = 2, by = 0.001))
variables<-
 set(B = fuzzy_partition (varnames = c(very_low = 0.4, low = 0.7,
    BMSY = 1, high = 1.3,   higher= 1.6,
    very_high = 1.9),
                          FUN = fuzzy_normal, sd = 0.1),
catch = fuzzy_variable (
forbidden = fuzzy_trapezoid (corners = c(-2, 0, 0.5,
 0.7)),
            lower = fuzzy_triangular (corners = c(0.5, 0.7, .9)),
            medium = fuzzy_triangular (corners = c(0.70, 0.9,
            1.1)),
            maximum = fuzzy_trapezoid (corners = c (.9, 1.1, 2,
            2.3 ))))

rules <- (set
 (fuzzy_rule (B %is% very_low, catch %is% forbidden),
      fuzzy_rule (B %is% low, catch %is%lower),
      fuzzy_rule (B %is% BMSY, catch %is% medium),
      fuzzy_rule (B %is% high, catch %is% maximum),
```

```
      fuzzy_rule (B %is% higher, catch %is% maximum)
))

  system2<-fuzzy_system (variables, rules)
  print(system2)
  plot(system2)

inference2 <- fuzzy_inference (system2, list (VABC=X))

plot(inference2)

gd<-gset_defuzzify(inference2, "centroid")
gd


if (gd <=0.5) {TAC = 0}

else if (gd >= 1) {TAC = MSY}

else { TAC <- MSY * gd}
return (TAC)
  }

proj.result<- project(fish.stock, fish.fleet, ny=2)
num.years <-1
ssb.vec <- c()
yield.vec <- c()
recruit.vec <- c()
TAC.vec <- c()
effort.vec <- c()
X<- 2
```

```
for(i in 1:num.years){
fish.fleet$TAC <- HCRfuzzy2(ssb=fish.stock$spbiom, Bmsy, MSY,
 X)
fish.fleet$effort <- tac2f(pop=fish.stock, fleet=fish.fleet)
proj.result <- project(ny=2) ## project 1 year
fish.stock$nage <- proj.result$Nage[,2]
fish.stock$spbiom <- proj.result$SSB[2]
ssb.vec <- c(ssb.vec, proj.result$SSB[2])
yield.vec <- c(yield.vec, proj.result$Yield[2])
recruit.vec <- c( recruit.vec, proj.result$Nage[1,2])
TAC.vec <- c(TAC.vec, HCRfuzzy2(ssb=fish.stock$spbiom, Bmsy,
MSY, X))
effort.vec <- c(effort.vec, tac2f(pop=fish.stock,
fleet=fish.fleet))
 X <- round (proj.result$SSB[2]/Bmsy, 3)
}
```