FLBEIA: A toolbox to conduct Bio-Economic Impact Assessment of fisheries management strategies

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Abstract

FLBEIA is an R library which provides a flexible and generic tool to conduct Bio-Economic Impact Assessment of fisheries management strategies. It has been built under a Management Strategy Evaluation framework which consist in simulating the fisheries system together with the management process. The fisheries system is simulated in the so called Operating Model which describes the true dynamics of the system and the management process is simulated in the Management Procedure which generates an observed system from the reality. The management advice is generated based on the observed system, instead of on the real one.

The model is multistock, multifleet, seasonal and uncertainty is introduced by means of montecarlo simulation. In addition, it has a covariables component that allows introducing variables of interest not present in biological and fleets components. For example, it could be used to introduce relevant ecosystem components in a simple way. FLBEIA represents a middle way between complicated whole ecosystem models and simple bioeconomic fisheries models.

The fishery system and management process are divided in low level interlinked processes, providing the library one or several models to describe each of the process. The user chooses the models to be used in each specific model implementation and if the functions provided within FLBEIA do not fulfill the requirements for some of the components, the user can code the functions that adequately describe the dynamics of those processes and use the existing ones for the rest.

In this paper we present FLBEIA library describing how fishery system and management process are modeled, the low level process that build up the model and the available functions to model them, the necessary data and its form to condition the model and its principal advantages and limitations. Finally, we briefly present its application to 3 different case studies, Seabream artisanal fisheries in the Gulf of Cádiz, French deep-watter mixed-fisheries and Basque inshore sequential- fisheries.

1 Introduction

Fisheries systems are complex systems formed by fish populations and the fleets that exploit them. Apart from fishing fleets, there are other inland economic sectors dependent on fishing production. Fisheries need to be managed in order to assure a sustainable and efficient exploitation of marine resources. The system has three dimensions, the biological, the economical and the social one, which have to be taken into account when managing the system. Despite what are directly managed are the fisheries, historically, most of the attention has been paid to the biological dimension and the management advice has been based solely in the output of biological models. However in recent years, and driven by the Ecosystem Based Fisheries Management approach (Curtin and Prellezo, 2010), it has been recognized the need to incorporate the economic and social factors into the management process. Consequently, the management advice should be based not only on biological considerations but also on economical and social ones. Therefore, approaches that integrate the 3 disciplines are needed. But integrated approaches are scarce and usually very case specific. Additionally, scientists normally focus on one of the two, biology or economy, and tend to over-simplify the other. In the other hand, sociology is still quite undeveloped.

Multi-annual management plans (MMP) define *a priori* and for several years how much can be fished and how this catch must be taken (time, place, gear...). In addition, they can be established control and enforcement measures and data collection and assessment protocols. MMPs have a decision rule linked, which based on fishery system status and reference points, determines how much can be catch. Here we refer to these rules as Harvest Control Rules (HCRs). European Commission (EC) introduced multi-annual plans in the 2002 reform of the Common Fisheries Policy (CFP) as a tool to recover endangered stocks. Nowadays they are used routinely to recover stocks and to maintain them in sustainable and healthy levels with long term perspective (EC, 2008). FAO (Food and Agriculture Organization of the United Nations) define multi-annual plans as a key tool in the precautionary approach to fisheries management (FAO, 1996). MMPs provide a mechanism to automatically set Total Allowable Catches (TACs) annually and prevent discussions between stakeholders to agree on them. The associated HCRs are normally based on biological reference points and include mechanisms to avoid high annual variability in TACs for the stability of fishing sector. FAO in the precautionary approach framework states that MMPs should not be put in place before probing that they will not lead to undesirable results. This requirement inevitably involves some kind of simulation testing before the plan is stablished.

EC before approving a MMP runs an impact assessment (IA) where the outcome of the MMP in terms of biology, economy and sociology is predicted. A common problem in the IA is that the models used to predict biological and economical outcomes are not integrated and usually are even not congruents (Garcia et al., 2011; EC, 2010). Biological IA of MMPs are usually conducted under a Management Strategy Evaluation (MSE) framework (Butterworth, 2007; Butterworth and Punt, 1999; De la Mare, 1998; Punt and Donovan, 2007; Rademeyer et al., 2007). This approach evaluates the performance of management strategies by means of simulation and consists in simulating the fishery system together with the whole management process, from data collection to management advice. MSE implementations are generally biologically oriented, single stock, single fleet and case specific. The economic evaluation is run afterwards in an ad-hoc analysis.

Bioeconomic models can be classified in two categories, simulation (what if?) or optimization (what's best?). Optimization models are designed to find an optimal solution to an objective function under certain constraints. Simulation models strive to simulate a system by projecting a set of biological and economic variables. A wide range of operational models exists worldwide (see Prellezo et al. (2012) for an extensive review of them). `FLBEIA` is a simulation model but additionally to the existing ones it is framed under a MSE approach. In general operational models are built for analysing tactical management alternatives, with some exceptions in where strategical management of a national sector can be modeled. In this strategical management framework should be also located those ecosystem based fisheries models, such as EwE or Atlantis among others. These models focus their strength on implementing all the interactions throug the fish chain, from the roots of the primary production to the fleet catching fish. In same cases (for examples for the case of Atlantis) this is also made in a MSE framework.

Integrated bio-economical models which have enough detail in both biological and economical part to fulfill the requirements of IA are needed (EC, 2010). One of the problems to develop generic bioeconomic models are that fleet dynamics are very case specific, still poorly known and there are no popular standard models to describe them. In biology there are several standard population dynamics models endorsed by the scientist; production models, virtual population analysis or stock recruitment models (Quinn and Deriso, 1999). These approaches are great simplifications of reality, but despite of critics in specific cases, they are well assumed by the scientist and their use in management advice generation is generally approved. Furthermore there are methods to calculate biological reference points to base the management in. However, regarding fleet dynamics, there are no general models to describe their dynamics nor reference points on top of which a robust management framework can be built.

`FLBEIA` is a bio-economic simulation model oriented to facilitate the development of IA under MSE framework. The model can be used to evaluate the performance of a wide range of management strategies in a great variety of case studies. Under a rigid coding it would be almost impossible to obtain this, thus the model has been developed in an modular and extensible way. The fishery and management systems have been divided in processes and for each of the processes several alternative models have been coded. If the available models do not satisfy the needs, in an specific case, new models can be coded and used in the simulation. The library has been used in several case studies and its applicability in radically different cases has been proven. The biological and economic parts of the model are fully integrated, the biological component comprises both age and biomass structured populations and fleet or economic component includes effort allocation and price and capital dynamics. Further, there is room to introduce covariables not included in biological and fleet components.

In this article, first, we present the model in general terms, the philosophy behind it and its main features. Then, we describe the processes that build up the model, how they are interlinked and the already available functions to model them. Thirdly, we present the application of the model to three different case studies, Seabream and artisanal fisheries in the Gulf of Cadiz (Spain), French Deep Watter fisheries and Inshore sequential fisheries in Basque Country (Spain). Finally, we discuss the usefulness of the model for giving support to management agencies, to involve stakeholders in the management process and for research purposes. In the discussion we also identify some limitations of the model and how they can be overcome.

2 The Model

FLBEIA has been developed in R (R Development Core Team, 2012) using FLR libraries (Kell et al., 2007). The model follow a Management Strategy Evaluation Approach (Punt and Donovan, 2007; Rademeyer et al., 2007; De la Mare, 1998). This approach is widely used in fisheries modeling and management to evaluate the performance of management strategies taking into account the main sources of uncertainty present in the fishery system. It consist in simulating the real fishery system together with the management process. The simulation is divided in two big blocks, the Operating Model (dotted area in figures 1 and 2) and the Management Procedure (solid gray area in figures 1 and 2). The Operating Model (OM) represents the real fishery system formed by the stocks, the fleets and the covariables in FLBEIA. The Management Procedure Model (MPM) simulates the whole management process starting with data collection, followed by the assessment model and ending with the management advice. In this way, when a management strategy is tested, the management advice is not given based on the population simulated in the operating model (the real population as referred in MSE literature) but on the population estimated by the assessment model in the management procedure (the observed population as referred in MSE literature). Thus when the goodness of a management strategy is evaluated, not only the strategy itself is evaluated but also its performance in combination with the data collection and the assessment model.

The uncertainties in fishery systems were described and categorized in 6 groups by Francis in 1997. Three of them relate to the dynamics of the real fishery system process, implementation and institutional uncertainty and the other three to the accuracy in the management process, observation, model and estimation uncertainty. Except *institutional uncertainty*, which relates to objective misspecification by the managers, the effect of the other uncertainties in the performance of management strategies can be evaluated using FLBEIA:

- *Process uncertainty* relates to the natural variability in population dynamics. In FLBEIA all the data and parameters can be stochastic declaring a set of possible values for each of them.
- *Implementation uncertainty* represents the mismatch between the management advice and its execution in reality. In FLBEIA it is modeled in the short term dynamics of the fleets OM and depend on the model used.
- *Observation uncertainty* arises in the data collection and is due to sampling and measurement error. All the observable variables in the observation model have an associated error that is parameterized by the user
- *Model uncertainty* results from the mismatch between real population dynamics and dynamics modeled in the assessment model. It is introduced in FLBEIA using different dynamics in the OM and the assessment model within the MP.
- *Estimation uncertainty* relates to the error in parameter estimation, it arises naturally when an assessment model is used in the MP.

The algorithm has been developed in a modular way to ease checking and debugging but principally to allow its extension. It has been used a top-down approach as shown in Figure 1. The rectangles represent models and the ellipses particular blocks within a model component. The rectangles in grey indicate that the corresponding function is fixed

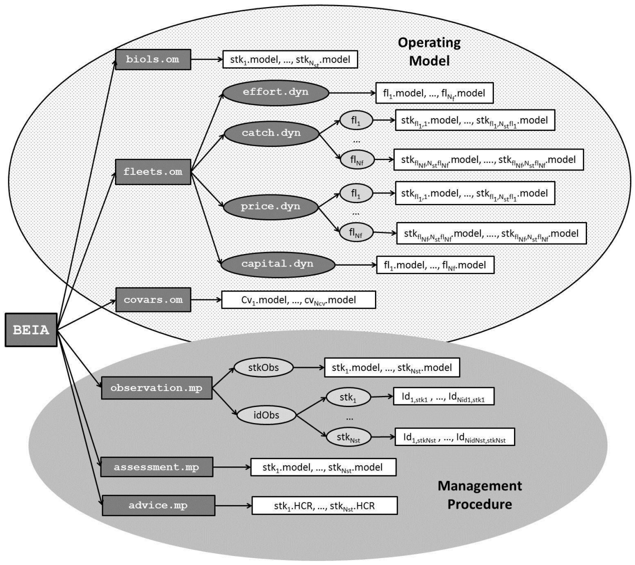

Figure 1: Scheme showing the top-down (left-right in the diagram) structure followed in the algorithm. Rectangles represent functions/models and elipses particular blocks within model components. Grey rectangles represent fixed models and white ones represent models that need to be specified by the user.

within the algorithm and the ones in white are chosen by the user. The user can choose among existing functions or develop new ones.

The algorithm is divided in 3 levels:

1. `BEIA`, the main function, is in the first (top) level,
2. `biols.om`, `fleets.om` and `covar.om`, in the OM, and `observation.mp`, `assessment.mp` and `advice.mp` functions in the MPM are in the second level. They are called by `BEIA` in the order shown in 1. The second level functions in the OM control how biological populations, fleets populations and covariables are projected every season into the future and those in the MPM control how observed data, estimated stock data and stock based advice is obtained every year.
3. In the third level there are the functions chosen by the user (white rectangles in figure 1) and they are called by the second level functions. Besides, depending on the way the third level functions are coded, at the same time, they could call functions at lower (fourth) level and so on. Several functions have been implemented for each process and new ones can be coded in R and used within `FLBEIA` if needed.

A flow chart which shows the scheme of the simulation algorithm is shown in figure 2. The chart shows what is done in each step of the simulation and how the simulation moves from one component to the other.

In the first step of the simulation the biological (fish) populations are projected forward one season, this is done stock by stock independently. After that fleets are projected independently and the projection is divided in four parts, effort allocation, catch production and price and capital dynamics. Effort allocation determines how much effort is

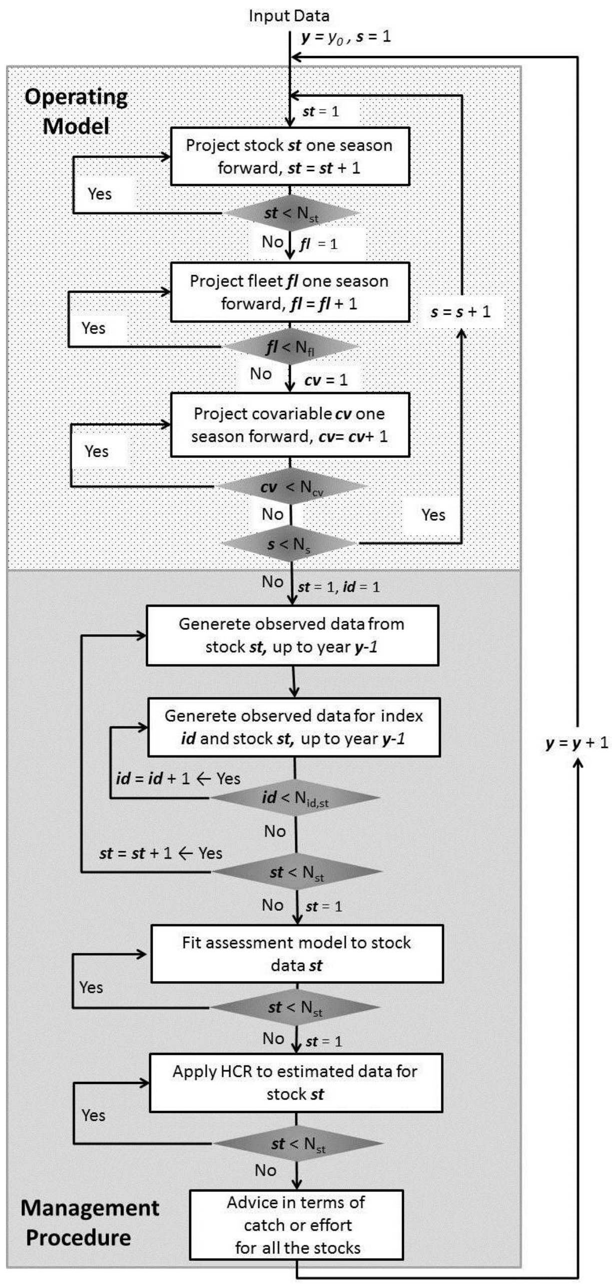

Figure 2: Flow chart of the algorithm.

exerted and how it is allocated among metiers[1] within a fleet and in the season depending on the state of the stocks, the management advice or others. Then prices are updated independently for each fleet and stock. Finally, and only in the last season, the variation in the capital of each fleet is forecasted. Capital dynamics represent the investment or disinvestment of the fishermen in new vessels or technological improvements. Finally within the OM the covariables are projected. As with stocks and fleets they are projected covariable by covariable independently. This part of the model is quite opened, the idea behind it, is to have room to incorporate into the model variables that are not included in biological and fleet OMs. The variables can be of any kind (environmental, ecosystem, social, economic...) and dynamic functions can be coded and used in the model to project them into the future. Coding them appropriately the covariables could interact with other components in the model.

The management procedure is run every year in the last season. The observed data is divided in two types, stock data and abundance indices [2]. Stock data corresponds with catch and biological data at stock level and is generated independently stock by stock. Abundance indices are also generated stock by stock and for each stock several indices can be simulated. After generating the data the stock assessment models are applied to the observed data independently stock by stock. The assessment models provide an estimate of the stock status, which in MSE terminology is known as the 'observed population'. Harvest control rules (HCR) are then applied to each observed population and a management advice is obtained for each stock. Finally this information is transmitted to the fleets in the OM and the loop starts again.

2.1 The Operating Model

The OM is the part of the model that simulates the true dynamics of the fishery system. Biological populations and fleets are its essential pieces and they interact through fishing effort and the catch. Covariables are not mandatory but can be useful to store or simulate information not present in stock and fleet data. They can interact with the stocks and the fleets.

2.1.1 Biological Operating Model

The model can incorporate as many stocks as desired and they can be age structured or aggregated in biomass. At the moment there are 3 models available to describe populations dynamics, `fixedPopulation`, `ASPG` (Age Structured Population Growth) and `BDPG` (Biomass Population Growth).

`fixedPopulation` returns the stock data unchanged. Implicitly it assumes that population growth is independent of the catch produced by the fleets, which is not sensible, but it can be useful. For example, when nothing is known about the dynamics of certain stock, but its incorporation into the model is justified due to its economic importance and its catch has been observed to be driven mainly by fleet's effort, as every stock must be present in biological component, population abundance high enough to support the future catches can be given as input data and use this function to simulate the population dynamics.

[1] In fisheries science metiers are defined as trips within a fleet that share the same characteristics in terms of gear used, fishing area and catch profiles (Marchal, 2008)

[2] Abundance indices are time series that are suppose to be related to the abundance of the stock, being the common relationship $I = q \cdot N^{\gamma}$, where I is the index, q the catchability, N the abundance and γ the hyperstability parameter

`ASPG` (Age Structured Population Growth) projects an age structured population one season forward using a stock-recruitment model for recruitment [3] [4] and exponential survival equation (Quinn and Deriso, 1999) for the existing age classes. The individuals are aggregated in cohorts that represent individuals born in the same year and season. And all the individuals move from one age class to the next in the first of January independently when they have born. The catch is assumed to take place instantaneously in the middle of the season. For the first season, $s = 1$, the model can be written mathematically as:

$$N_{i_a} = \begin{cases} \phi\left(RP_{y=y-a_0,s=s_{spwn,1}}\right) & a = a_0 \\ (N_{i_{a-1}} \cdot e^{-\frac{M_{i_{a-1}}}{2}} - C_{i_{a-1}}) \cdot e^{-\frac{M_{i_a}}{2}} & a_0 < a < A \\ (N_{i_{A-1}} \cdot e^{-\frac{M_{i_{A-1}}}{2}} - C_{i_{A-1}}) \cdot e^{-\frac{M_{i_{A-1}}}{2}} + & \\ (N_{i_A} \cdot e^{-\frac{M_{i_A}}{2}} - C_{i_A}) \cdot e^{-\frac{M_{i_A}}{2}} & a = A \end{cases} \tag{1}$$

where a, y, u, s are the subscripts for age, year, unit and season respectively, a_0 is the age at recruitment, $s_{spwn,1}$ the season when recruitment of the first season is spawn, A is the plusgroup [5] , $i_a = (a, y, u, 1)$, $i_a = (a-1, y-1, u, ns)$, $i_{A-1} = (A-1, y-1, u, ns)$ and $i_A = (A, y-1, u, ns)$ where ns is the number of seasons used in the model. N denotes number of individuals, M natural mortality, C catch in number of individuals, ϕ is the stock-recruitment model and RP denotes reproductive potential, the variable use as recruitment predictor.

For later seasons,

$$N_{a,y,u,s} = \begin{cases} \phi\left(RP_{y=y-a_0,s=s_{spwn,s}}\right) & a = a_0 \\ (N_{i_a} \cdot e^{-\frac{M_{i_a}}{2}} - C_{i_a}) \cdot e^{-\frac{M_{i_a}}{2}} & a_0 < a < A \end{cases} \tag{2}$$

where $i_a = (a, y, u, s-1)$ and $s_{spwn,s}$ is the season when recruitment of season s is spawn.

All the stock-recruitment models available in `FLCore` library of `FLR` can be used and new ones can be defined in `R` to be combined with `ASPG`.

`BDPG` (Biomass Population Growth) projects populations aggregated in biomass. The growth function available at the moment is Pella-Tomnlinson (Pella and Tomlinson, 1969) but new growth functions can be added in the same way done for recruitment. The catch is assumed to take place in the middle of the season. Mathematically:

$$B_{s,y} = \begin{cases} B_{s-1,y} + g(B_{s-1,y}) - C_{s-1,y} & s \neq 1, \\ B_{ns,y-1} + g(B_{ns,y-1}) - C_{ns,y-1} & s = 1. \end{cases} \tag{3}$$

Where B denotes total population biomass and g represents the seasonal population growth function. The following parameterization of Pella-Tomlinson growth model has been implemented:

[3]Recruitment in fisheries science is used to refer to the first year class available to the fishery thus it could be different to the first natural age class (age 0). Usually is the year class for which data is available. In this case it is used to refer to the first year class used in the OM but it could be lower that the first year class avaiable to the fishery.

[4]Stock-recruitment models are the cornerstone to model fish populations. They relate the stock's reproductive potential with the entry of new individuals. Different indicators are used as a proxy for stock's reproductive potential, total stock biomass, spawning stock biomass, egg production... Ricker and Beverton and Holt are the most popular models, information about these and other models can be find in (Quinn and Deriso, 1999)

[5]The plusgroup is an artificial age group where individuals of age A and older are merged.

$$g(B) = B \cdot \frac{r}{p} \cdot \left(1 - \left(\frac{B}{K}\right)^p\right) \tag{4}$$

where r represents the intrinsic growth rate, K is the carrying capacity [6] of the population and p is a parameters used to give flexibility to the model (for example p = 1 corresponds with logistic model).

The catch is assumed to take place in the middle of the season in `ASPG` and `BDPG` in accordance with the fleet dynamic functions defined in the fleets operating model (see section 2.1.2).

2.1.2 Fleets Operating Model

The model can incorporate as many fleets as desired and it is divided in four components, the catch, the effort, the price and the capital models. The activity of the fleets is divided in metiers and the projection is done independently fleet by fleet. Thus, the functions used to describe their dynamics can differ from fleet to fleet.

Catch model Catch model describes the catch produced by exerted effort and its allocation along metiers. Thus, the effort and the catch models are directly related, the catch is the product of the effort exerted by the fleet and the effort exerted by the fleet, depends on the catch it produces.

At the moment two functions have been implemented, Cobb Douglas production function at biomass level, `CobbDouglasBio`, and at age level, `CobbDouglasAge`. Cobb Douglas production function (Cobb and Douglas, 1928) is widely used by economists to describe production in industry in general and in fisheries in particular. The catch derived form Cobb Douglass production function at biomass leve is given by:

$$C_{st,f,m} = q_{st,f,m} \cdot (E_f \cdot \gamma_{f,m})^{\alpha_{st,f,m}} \cdot B_{st}^{\beta_{st,f,m}} \tag{5}$$

and at age level:

$$C_{st,f,m} = \sum_a q_{a,st,f,m} \cdot (E_f \cdot \gamma_{f,m})^{\alpha_{a,st,f,m}} \cdot B_{a,st}^{\beta_{a,st,f,m}} \tag{6}$$

where f and m are the fleet and metier subscripts respectively, q is the catchability [7] of the fleet for a certain metier, stock and age group (if relevant), E is the effort exerted by fleet f, $\gamma_{f,m}$ is the proportion of effort exerted by fleet, f, in metier, m ($0 \leq \gamma_{f,m} \leq 1$ and $\sum_m \gamma_{f,m} = 1$), α and β are the output elasticities for effort and biomass respectively (referred as labour and capital in economic literature).

One of `FLBEIA`'s objetive was to couple the models used in both disciplines, biology and economy. Exponential survival model and Cobb Douglas production model are among the most popular models in fisheries biology and economy respectively. But they can not be coupled in a natural way because the former models population growth and catch in a continuous way and the last one models catch production in a discrete and instantaneous way. To overcome this discrepancy in the functions implemented it has been assumed that the catch take place in the middle of the season. This approach, known as Pope's

[6] Carrying capacity is the maximum population size that the stock can support

[7] catchability it is a measure of fishing mortality generated on a stock by one unit of effort. Depending on the mathematical model used to relate catch, effort and stock abundance it has different meaning.

approximation (Pope, 1972) has been widely used in fisheries assessment models to overcome computational problems and has been probe to give similar results to the continuous version (Baranov catch equation) when natural and fishing mortalities are lower than 0.3 and 1.2 respectively (Quinn and Deriso, 1999).

Effort model The effort model describes the short term dynamics of the fleet. For each season it models how many effort is exerted and it is divided along metiers. In single-stock and single-metier fleet, assuming it executes the effort that produces exactly fleet's TAC share is a reasonable assumption but in multi-stock and multi-metier fleets the problem is not that simple. For these fleets two different groups can be distinguish, the fleets that catch at the same time a number of stocks and are unable to discriminate among them, the so called *mixed fisheries*, and two fleets that caught only one stock at each time and which metiers are single stock and associated to certain season, the so called *sequential fisheries*. The models already developed in `FLBEIA` try to describe the dynamics of these two kind of fisheries. In the most simple function, `fixedEffort`, all the parameters are given as input data. Thus the effort exerted is independent of the state of the stock or the management advice. Apart of this 3 more functions are available, `SMFB`, Simple Mixed Fisheries Behavior, `SSFB` Simple Sequential Fisheries Behavior and `MaxProf.StkConst`.

`SMFB` describes the dynamics of a fleet working in a mixed-fisheries context. In this case, the effort share along metiers is given as input parameter and only the total effort is calculated. First the effort corresponding to the quota-share of each stock is calculated, this returns one effort per stock caught by the fleet. Then different options are available to select the effort to be exerted by the fleet based on the efforts corresponding to the quota-shares (*min* the minimum, *max* the maximum, *mean* the mean, *previous* the most similar to the previous year effort and *stock-name* the effort corresponding to the stock specified). This approach is based on the Fcube method (Ulrich et al., 2011) used there to approximate mixed-fisheries dynamics in a fisheries management context.

`SSFB` relates to those fleets which fishing profile changes with the season of the year. In this case, the historical effort dynamics guides/dictates the present performance of the fleet. Seasonally, given a fleet, each metier has only one target species or stock, and thus the metier is uniquely defined by the stock it captures. The expected effort to be allocated to each metier follows the historical trend, but is restricted by total catch quota of the fleet. In case catch quota is exhausted for a stock, then the remaining effort is reallocated to metiers which target other stocks.

`MaxProf.StkCnst` calculates the total effort and the effort allocation among metiers that maximizes the profits. The total effort is constrained by the capacity of the fleet (capacity measured in the same units as effort) and by the catch of one of the stocks. Mathematically:

$$\max_{E,\gamma_1,\ldots,\gamma_{nmt}} \quad \sum_m \sum_{st} \sum_a \left(q_{m,st,a} \cdot B_{st,a}^{\beta_{m,st,a}} \cdot (E \cdot \gamma_m)^{\alpha_{m,st,a}} \right) \cdot P_{m,st,a} - E \cdot \gamma_m \cdot VC_m - FC \tag{7}$$

With the constraints:

$$0 \leq \gamma_m \leq 1 \text{ and } \sum_m \gamma_m = 1$$
$$E \leq \kappa,$$
$$C_{st} \leq QS_{st}.$$

Where pr is the price, VC the variable cost which depends on the metier and is given as cost per unit of effort, FC the fixed cost which is given at fleet level and in terms of cost per unit of fleet's capacity, κ is the capacity and QS is fleet's quota share (the part of the TAC that belongs to the fleet).

In the 4 functions described above the catch is assumed to take place in the middle of the season.

Price model The price is updated in each step of the simulation and it is done at fleet and stock level. Two price models are available at the moment, `fixedPrice` and `elasticPrice`. In the first one the price is given as input parameter and in the second one the change in the price depends on the ratio between current landings and landings in a baseline year or period. Current landings may refer to the landings of the fleet itself or the total stock landings, because the price usually depends on the landings all the fleets. Furthermore the price can vary independently by age. The model is described in Kraak et al. (2004) and mathematically can be expressed as:

$$P_{aysf} = P_{0asf} \cdot \left(\frac{L_{0asf}}{L_{ays}}\right)^{e_{asf}} \tag{8}$$

where L are the fleet's or total stock landings, P_0 is a base price corresponding with base landings, L_0, and e is price's elasticity parameter.

Capital model Capital dynamics describe the long term dynamics of the fleets. They describe the investment or disinvestment of fishermen in new vessels or in improving fleet's technology. In `FLBEIA` the capital dynamics are modeled through changes in fleet's capacity or changes in fleet's catchability (technological improvements). Two models are available `fixedCapital` and `SCD` (Simple Capital Dynamics). In the first model, catchability and capacity, are given as input data.

In `SCD` only capacity is updated depending on some economic indicators and catchability is given as input data. The following variables and indicators are defined at fleet ant year level (fleet and year subscripts are omitted for simplicity):

FuC : Fuel Cost.

CrC : Crew Cost.

Vac : Variable Costs.

FxC : Fixed Costs (repair, maintenance and other).

CaC : Capital Costs (depreciation and interest payment).

Rev : Revenue:

$$Rev_f = \sum_m \sum_s \sum_a L_{msa} \cdot P_{as}$$

BER : Break Even Revenue, the revenue that make profit equal to 0.

$$BER = \frac{CrC + FxC + Cac}{1 - \frac{Fuc}{Rev} - \frac{VaC}{Rev}}$$

The maximum possible investment, $Inv_{\max}$, is determined by:

$$Inv_{\max} = \frac{Rev - BER}{Rev}$$

But not all the profits are dedicated to increase the fleet, thus:

$$Inv = \eta \frac{Rev - BER}{Rev}$$

where η is the proportion of the profits that is used to buy new vessels. Furthermore, investment in new vessels will only occur if the operational days of existing vessels is equal to maximum days. The investment/disinvestment decision, i.e the variation in capacity, Ω, follows the rule below:

$$\Omega_{y+1} = \begin{cases} Inv \cdot \kappa_y & \text{if } Inv < 0 \text{ and } -Inv < \omega_1, \\ -\omega_1 * \kappa_y & \text{if } Inv < 0 \text{ and } -Inv > \omega_1, \\ 0 & \text{if } Inv > 0 \text{ and } E_y < \kappa_y, \\ Inv \cdot \kappa_y & \text{if } Inv > 0 \text{ and } Inv < \omega_2, \\ \omega_2 * \kappa_{y-1} & \text{if } Inv > 0 \text{ and } Inv > \omega_2. \end{cases} \tag{9}$$

where ω_2 stands for the limit on the increase of the fleet relative to the previous year, and ω_1 for the limit on the decrease of the fleet relative to the previous year.

2.2 Covariables Operating Model

Covariables OM is thought to accommodate variables relevant to fishery system that are not included in biological and fleet data containers (see A for further details in data storage). It is expected for this variables to be dependent on specific problems and/or case studies. For example when `SCD` function is used the covariables OM is used to store the economic data not contained in fleets OM (FuC and CaC). In this case variables are maintained fixed within the simulation using `fixedCovar` function. A more elaborated example could bt to use covariables OM to simulate the abundance of a non-commercial species which abundance depends on the abundance of a commercial species present in the biological operating model.

At the moment the only function available to describe covariables dynamics is `fixedCovar`.

2.3 The Management Procedure

Management Procedure runs annually and it mimics the management process as it is done in reality. It has three components, the observation model, the assessment procedure and the management advice.

2.3.1 The Observation Model

The observation model simulates the data stock by stock and it simulates two kind of data, on the one hand it simulates catch and biological data and on the other hand abundance indices. All the simulated data is generated annually despite of OM's seasonal dimension an it is done stock by stock independently. In fisheries science observed data is subject to a significant error. As in every sampling, the data is subject to measurement and sampling error but in fisheries science there are systematic errors difficult eradicate, errors related to misreporting of catch, to low number of samples (for example in discards), to bias in measurement (for example in aging where bias is a common problem). The idea behind MSE is to identify and quantify these kind of errors and introduce them in the simulation of the observed data.

Stock data is formed by data related to fleets' production (landing and discard data), data related to biology of the stock (natural mortality, fecundity and individual weight) and data related to the status of the stock (number of individuals and harvest intensity). In real world, data related to stock status is not obtained in data collection but applying assessment models to observed data. However in simulation studies knowing this kind of data would be useful to evaluate the performance of management strategies assuming the stock status is known without error.

`PerfectObs` takes the data from biological populations and fleets without error. The only discrepancy with OM data could arise when temporal dimension is collapsed in OMs with time steps shorter than a year. In this function besides fleet and biology related data stock status data is also taken from the OM.

`age2ageDat` generates data related to stock biology and fleets' production for age structured stocks. Two kind of errors can be introduced in the data, error associated to aging problems and multiplicative errors associated to any other reason. Aging error is simulated using for each year and iteration a random square matrix, (Λ_{ij}), with dimension na (the number of age groups) in which the element λ_{ij} is the proportion of individuals of age i that are erroneously assigned age j. This matrix is matricially multiplied with the vector of real data at age to obtain the observed data. Multiplicative error is applied after applying aging error and for each year and iteration it consist in a vector of positive values and dimension na, ε_a .Mathematically:

$$\hat{x_a} = \left(\sum_{i=1}^{A} x_i \cdot \lambda_{ia}\right) \cdot \varepsilon_a$$

where x represents the real data in the population and $\hat{x}$ the observed data. x can be any observable variable, natural mortality, landings at age, maturity...

`bio2bioDat` generates data related to stock biology and fleets' production for stocks aggregated in biomass. Only multiplicative errors around the real data value are introduced. It is done in the same way as in age structured populations but without age dimension.

`age2BioDat` generates data related to stock biology and fleets' production at biomass level for age structured stocks. First the age dimension is collapsed applying the correct procedure for each data type (sum for catch in numbers, weighted mean for individual weight, ...) and then a multiplicative error is applied as in previous case.

`age2agePop`, `age2BioPop` and `bio2BioPop` complement the previous three functions providing observations of stock status and fishing mortality introducing aging and multiplicative errors if desired. In reality it is impossible to have this kind of information, but in practice they can be useful in cases where the interest is not on testing the goodness of the assessment model but the goodness of the management strategy itself.

An important source of information in fisheries management are the abundance indices. They are time series of stock abundance indicators that are supposed to be a linear or potential function of the true abundance, i.e:

$$I = q \cdot X^b \tag{10}$$

where I is the abundance index, q the catchability of the index, X the abundance (at age or biomass level and in weight or number of individuals) and b the exponent. Abundance indices are normally obtained from research surveys or from catch per unit of effort (CPUE) of commercial fleets. They are used within assessment models to tune the estimates or as input data in HCRs. Two different functions are provided to generate abundance indices `ageInd` to generate age structured indices and `bioInd` to generate indices aggregated in biomass. In the first function the abundance is measured in number of individuals and in the second one in total biomass. In both cases equation (10) is used, being q and b index and age dependent (if the index is age structured). Multiplicative and aging errors can be introduced in the observed indices in the same way it was done for stock data.

2.3.2 The Assessment Procedure

Assessment models are applied independently stock by stock in order to obtain estimates of abundance and/or exploitation level of the stock. These models returns estimates of the biological populations simulated in the OM ('*real populations*'), in MSE literature these estimates are known as '*perceived*' or '*observed*' populations. Any assessment model coded in *R* and which input data can be generated based on the data simulated in the OM can be used. `FLBEIA` does not include any assessment model.

2.3.3 The Management Advice

The management advice is generated by means of the harvest control rule (HCR). The advice in the HCR could be given in terms of catch or effort but at the moment only catch based HCRs are implemented. If effort based HCR were implemented they should be accompanied, in the OM, with effort models restricted by effort management advice. Two types of HCR are available, HCR based on abundance indices and HCR based on estimates of stock abundance and exploitation rate.

Three HCR that use stock status estimates are available the HCR used in ICES MSY framework ICES (2011), `IcesHCR`, the HCR defined in Froese and Proelß (2010), `FroeseHCR` and a flexible HCR that allows setting absolute and relative targets and constraints in several stock indicators (biomass, SSB, fishing mortality, catch, landings and discards), `annualTAC`.

Two HCR use abundance indices, one is the HCR defined by the European Commission (EC) for data poor stocks for which the available information about the stock status are abundance indices (ICES, 2010) and a second one which corresponds with the HCR used in the management plan of Greenland Halibut (NAFO, 2010).

In all the HCR the TAC for year y is given based on observed population up to year $y-2$, as it happens in reality where in year $y-1$, when the TAC advice for year y is calculated, only data up to year $y-2$ is available.

`IcesHCR` is shown in figure 3. The objective of the HCR is to maintain the fishing mortality at F_{msy} level, so the TAC advice is the catch corresponding to this fishing mortality. When spawning stock biomass (SSB) is below $B_{trigger}$ and above $B_{???}$ the

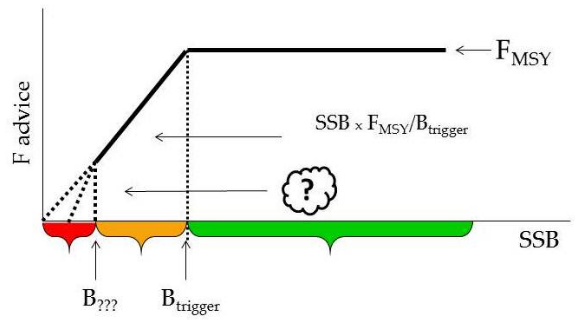

Figure 3: Graphical representation of IC ES MSY framework HCR

fishing mortality is reduced proportionally. When SSB is below $B_{???}$ ICES has not fixed a common rule, in this case when this occurs zero TAC advice is given. The reference points F_{msy}, $B_{trigger}$ and $B_{???}$ are defined by the user.

`FroeseHCR` is a biomass based HCR and its objective is to maintain the SSB above B_{msy} reference point. Above this point the management advice is a percentage of the catch at MSY where this percentage is defined by the user. Below B_{msy} the catch advice is reduced proportionally up to a percentage of B_{msy} below which TAC advice is zero catch.

`AnnualTAC` is a quite open HCR which main feature is that it produces annual TAC advice. It uses the `FLash FLR` library (http://www.flr-project.org/) which allows setting absolute and relative targets and constraints in several stock indicators, `annualTAC` (biomass, SSB, fishing mortality, catch, landings and discards). This HCR allows for example to implement the typical HCR used in recovery plans in Europe ((COM, 2003, 2004)).

`AnnexIVHCR` compares the mean abundance index in years $y-2$ and $y-3$ with the mean in years $y-4$, $y-5$ and $y-6$. If the difference, in percentage, is greater than a certain proportion, δ, the TAC is increased in a ϖ percent and if the contrary occursm, i.e. if it is lower than a certain proportion, δ, the TAC is decreased in a ϖ percent. When the variation is between plus or minus δ percent there are two options, one is to maintain the TAC unchanged and the second one to vary it linearly making the extremes to coincide with $1-\varpi$ and $1+\varpi$ variation.

`ghlHCR` first calculates the slopes of a set of abundances indices in the last 5 years and then it calculates the mean of the slopes, *slp*. The TAC for year $y+1$ is given by:

$$TAC_{y+1} = TAC_y \cdot (1 + \lambda \cdot slp)$$

where λ depends on the value of *slp*, if *slp* is positive then $\lambda = 1$ and if it is negative $\lambda > 1$. Furthermore the annual variation in TAC is restricted by a percentage selected by the user.

2.4 Model Initialization

Initial data (or historical population) can comprise just one year or an historical period. It depends mainly on the management procedure. If the assessment model or the HCR depend on the historic period, the initial population should included this data, if not, just one year to start the simulation would be enough.

To start the simulation it is necessary to fill some special data containers (see A) associated to the OM components and a set of control objects. One control object associated to the main function `BEIA` and one associated to each of the second level processes in the OM and the MP.

The control objects are lists and they have, at least, one element per stock and/or fleet with the name of the function to be used in the third level processes. The rest of the elements of the control objects depend on the model selected to describe the third level process. (see the manual inside `FLBEIA` for a detailed description of these objects)

The model is designed to introduce uncertainty by means of Montecarlo simulation. The model is run in parallel the number of iterations specified by the user. In each run different set of data and parameters are used. The data containers have special room to store random values for the data and almost all of them can have a set of possible values. As the user need to specify each of these possible values the approach is very flexible and the values can come from a probability distribution, a bootstrap or from wherever.

3 Model Application

The model has been applied to different case studies with very different characteristics, in present work we present briefly the application to two case studies, Seabream of gulf of Cadiz (Spain) and French deep-watter mixed fisheries.

3.1 Seabream of gulf of Cadiz

Seabream of gulf of Cadiz is a deep-watter stock exploited by an artisanal fleet. The fleet is formed by longliners which targets Seabream in a 65% percent of the trips and in these trips they only catch Seabream. The vessels involved in the fishery form an homogeneous group in terms of technical characteristics. Thus the model was conditioned as single stock and single fleet. The catch data is known through sales data but for effort the only information is the number of days in which vessels sell fish. XSA (Shepherd, 1999) is routinely applied in the assessment working group, however due to the uncertainty in the abundance index and low stability of the fit, the assessment is not approved and used to inform management agencies.

To generate the initial random population 3 important sources of uncertainty were identified:

1. Abundance index used to tune the XSA. As the time series was short and alternative information scarce to quantify the real uncertainty present in the index, it was assumed that its variability followed a lognormal distribution with mean equal to one and a coefficient of variation (CV) of a 30%. Random numbers drawn from these distribution were multiplied to the original index and a random abundance index with 500 iteration was obtained.

2. Individual growth in length. Age length data available to obtain the growth in length model for the stock is poor so the age length keys used to derive 'at age' data are subject to as great uncertainty. A bayesian Von Bertalanffy growth model was fit to the available data and from the join probability distribution obtained for the parameters a set of random age-length keys was obtained. Random age-length

keys were applied to length distributions of catch, weight and abundance indices to obtain random matrices of catch-, weight- and abundance indices-at-age.

3. Effort executed by the fleet. The exact effort measured in number of hooks used per day at sea and total number of days at sea for a number of years was known for a couple of vessels. Using this sample a random relationship between effort, measured in numbers of hooks, and sales days was obtained. The relationship was applied to the available data on annual sales days and a random distribution for the total annual effort exerted by the fleet was obtained.

XSA was applied to the random abundance indices, catch at age and weight at age matrices described above and random matrices of numbers at age and fishing mortality at age were obtained. Using this random matrices and the random effort described above a historical random biological population and a historical random fleet with 500 iterations were constructed.

The stock dynamics in the projection were simulated using `ASPG` combined with a segmented regression stock-recruitment relationship. To account for the uncertainty in the recruitment process, the parameters of the stock-recruitment relationship were iteration dependent and besides a lognormal random error was multiplied to the point estimate in each year and iteration.

Fleet short term dynamics were simulated using `SMFB` function, as it is a single-stock single-metier case, the function returned the exact effort neccesary to catch the TAC or the amount of catch passed to the function. It is known that this fishery overshoots the TAC systematically, thus scenarios were run assuming that the fleet overshot the TAC. The overshooting was parameterized stochastically using a triangular distribution (Weisstein), the minimum, maximum and mode of the distribution corresponded with the observed values of this indicators. Price was modeled using `elasticPrice` function and the elasticity parameter was estimated using the historic data.

In this work we present 7 scenarios to illustrate the performance of three HCRs, the currect management that corresponds with a fixed and constant TAC (TAC = 270 t), `IcesHCR` and `annexIVHCR`. Each of the HCR was used in 2 scenarios, in a first scenario the TAC was fulfilled by the fleet and in a second scenario the overshooting was modeling using a triangular distribution. In the 6 scenarios `perfectObs` was used to generate observations, so no assessment model was necessary to generate the advice. An additional scenario is presented were XSA is used within the MP to estimate an *observed population* on top of which `IcesHCR` was applied. TAC overshooting was introduce in the implementation of the advice. In the observation model an aging error was introduced and the overshooting was observed as it happens in reality.

Figure 4 shows recruitment, SSB, catch and fishing mortality indicators, in median, for the scenarios where the HCR was applied directly to the real population, i.e. there were no errors due to errors in observed of data or assessment model. The only difference between real population and the population used to calculate the TAC arose in the time lag between management and advice. If the advice was to be given for year y, the real population was observed up to year $y-2$ and it was projected under certain assumptions about recruitment, fishing mortality and biological parameters up to year y to obtain the TAC.

The recruitment was the same for all the scenarios which means that SSB did not fall below the breakpoint in the stock-recruitment relationship for any of the scenarios. The scenarios where there was implementation error and the advice was constant (TAC = 270 t) or was produced using `annexIVHCR` gave the same results for all the scenarios.

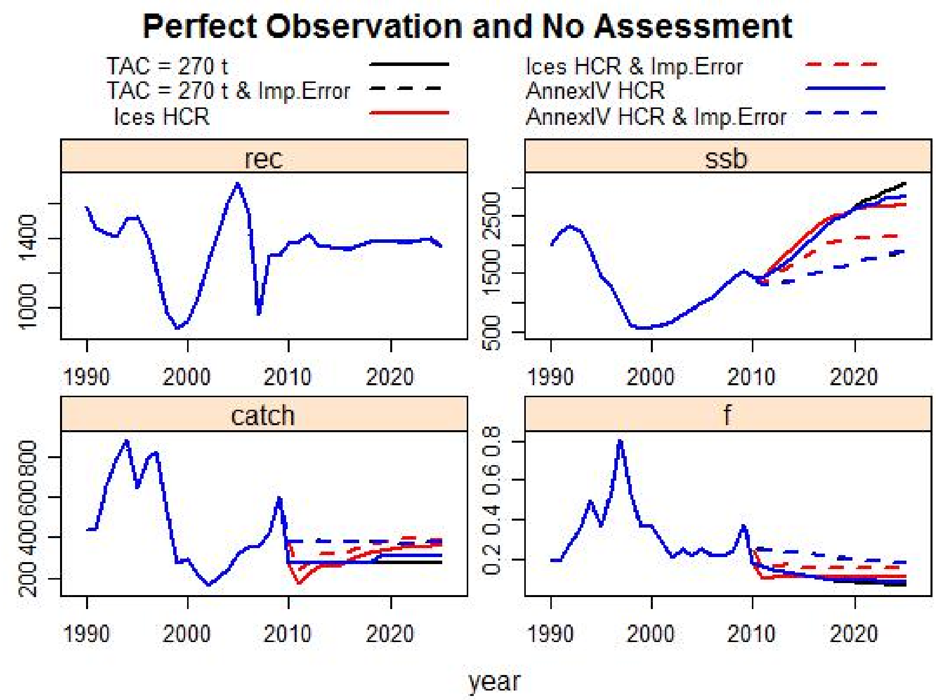

Figure 4: Recruitment, SSB, catch and fishing mortality indicators, in median, for the scenarios where the HCR is applied directly to the real population, i.e, the observation of the population is perfect and it is not necessary to apply any assessment model.

This is not a strange result because `annexIVHCR` maintains the TAC constant provided that the change in biomass is not enough high. Thus this means that the change in biomass was not enough high to change the TAC using `annexIVHCR` in the scenario with implementation error. In fact SSB time series for this scenario showed an increasing trend but very smooth. In the analogous scenario but with perfect implementation differences arose in the long term. The TAC in `annexIVHCR` scenario was maintained constant up to year 2018. The increase in SSB in these scenarios was significantly shaper. In terms of SSB and fishing mortality the scenarios with perfect implementation of the advice gave very similar results, in the catch the differences were more significant. In the short term the catch in `IcesHCR` scenario decreased below 200 t but soon it started increasing and in the long term the catch almost matched the catch in the scenarios with implementation error. The indicators in the `icesHCR` scenario with implementation error were in the middle of the scenarios without implementation error and `annexIVHCR` and constant TAC scenarios with implementation error. Fishing mortality in the scenarios with implementation error was around 0.2 ($F_{MSY} = 0.11$) and in the scenarios with `annexIVHCR` and constant TAC with perfect implementation, in the long term, the fishing mortality was below F_{MSY}. In `icesHCR` scenario with perfect implementation the fishing mortality was equal to F_{MSY}.

Figure 5 shows recruitment, SSB, catch and fishing mortality indicators in the scenario where XSA was used to obtain the observed population. Median fishing mortality had a decreasing trend in the projection and after 2018 it fell below the target. In many of the iterations fishing mortality after 2018 was equal to zero being the SSB above $B_{trigger}$

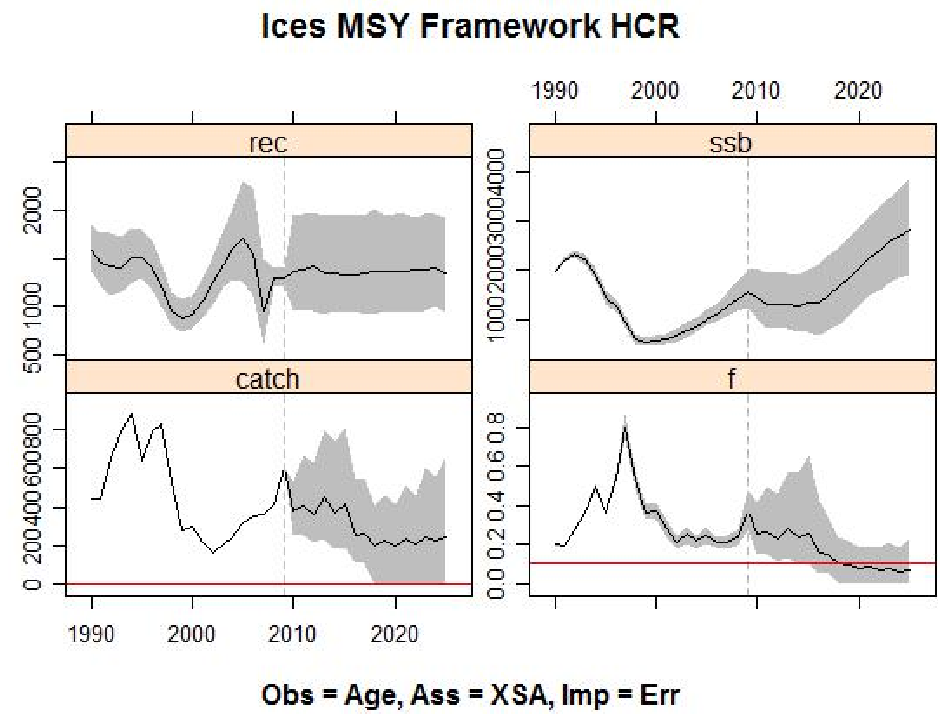

Figure 5: Recruitment, SSB, catch and fishing mortality indicators for icesHCR, with aging error in the observation, XSA and implementation error scenario. Black line corresponds with the median and the shadow indicates the 5% to 95% confidence interval. Red horizontal line corresponds with target fishing mortality $F_{0.1} = 0.11$

and $B_{???}$. This failure in the management procedure was a consequence of a failure in the XSA. In many iterations XSA started overestimating fishing mortality and underestimating biomass which produced a decrease in TAC. The decrease in the catch produced by the decrease in the TAC in turn produced a higher overestimation of fishing mortality and underestimation of SSB in following years, thus it arose feedback loop which at the end produced zero TAC advice. In somewhat less than 50% of the iterations the management procedure worked well, due to implementation error the fishing mortality maintained above the target but the SSB increased and maintained in healthy levels.

3.2 French deep-watter mixed fisheries

French deep-water mixed fisheries case study is formed by 5 stocks and 7 fleets. Most deep-water stocks are characterized by being deep watter and long lived species. Long lived species are usually slow growing species with late age of maturity. Thus,these stocks have a hard time recovering from overexploitation and it is crucial to manage them properly to avoid overexploitation. he stocks considered are caught by mixed fisheries fleets, with catch the 5 stocks at the same time. They are caught by fleets of different nationalities but in these study only French fleets are considered explicitly.

The stocks

Black Scabbarfish (*Aphanopus carbo*, BSF) : It was simulated as a population aggregated in biomass. The historic population was obtained using a deterministic Schaefer production model. In the projection the same model was used to simulate the population through `BDPG`. There is no agreed HCR to set the TAC and ICES advice is based on the trends of two abundance indices.

Blueling (*Molva dypterygia*, BLI) : It was simulated as an age structured population. The historic population was obtained using XSA and randomness was introduced doing a bootstrap of the catchability residuals. In the projection `ASPG` was used to simulate the population and segmented regression model was used to simulate recruitment. There is no agreed HCR to set the TAC and ICES advice is based on the output of two, non approved, assessment models.

Roundnose Grenadier (*Coryphaenoides rupestris*, RNG) : It was simulated as a population aggregated in biomass. The historic population was obtained using a Bayesian Schaefer production model. In the projection the same model was used to simulate the population through `BDPG` function. In this case for each of the iterations a different set of parameters, which came from the Bayesian fit, was used in the production model. There is no agreed HCR to set the TAC but last ICES management advice was based on MSY indicators.

Saithe (*Pollachius virens*, POK) : It was simulated as an age structured population. The historic population was obtained using XSA and randomness was introducing doing a bootstrap of the catchability residuals. In the projection `ASPG` was used to simulate the population and segmented regression model was used to simulate recruitment. At the moment Saithe is subject to a management plan.

Sikis (SKH) : It was simulated as a population aggregated in biomass. The historic population was obtained using a deterministic Schaefer production model. In the projection the same model was used to simulate the population through `BDPG` function. At the moment landings are forbidden for Sikis but discards are not banned, i.e TAL = 0.

The Fleets

FL01 : It is formed by large scale mixed fisheries trawlers. Its activity is divided in 10 metiers differenced by the stocks caught and their catchability. The price and weight of the stocks and the variable costs were common to all the metiers. This fleet accounted for most of the French catch, $\approx$ 80% and a significant part of the stocks considered, 42% of BLI catch, 29% of BSF catch, 16% of POK catch, 44% of RNG catch and 12% of SKH catch.

FL02 : It is formed by large scale mixed fisheries trawlers. Its activity is divided in 10 metiers differenced by the stocks caught and their catchability. No economic data was available for this fleet. This fleet only represented the 20% of total French catch and its contribution to the total international catch was 15% for BLI, 20% for BSF, 2% for POK, 22% for RNG and 9% for SKH. No economic data was available for this fleet.

FLBLI, FLBSF, FLRNG, FLPOK, FLSKH : These fleets represented 'artificial' fleets constructed to account for non-French international catch. Each of them accounted for the catch of one stock and they were single stock and single metier. They represent a significant part of total catch of the stocks, 43% for BLI, 50% for BSF, 81% for POK, 35% for RNG and 79% for SKH. As artificial fleets economic data was not available

The Scenarios Six scenarios were run which differed on the function used to simulate the effort dynamics of the fleets (total annual effort exerted and its allocation along metiers). The biogical OM was common to all the scenarios. Except in the first scenario, where MP was inexistent, `PerfectObs` in the observation model was combined with `IcesHCR` for BLI, BSF and RNG and for POK `PerfectObs` was combined with its management plan.

Status quo, sc0 : In the projection total effort and its distributions along metiers was equal to the average of the last 3 historical years. As the effort was not restricted by the management at all, MP was not applied for any of the stocks.

`SMFB` **with BLI restriction, *sc2*** : `SMFB` model with BLI restriction was used to simulate effort dynamics in the fleets that caught BLI (i.e, FL01, FL02 and FLBLI) in the rest `SMFB` was used being the restraining stock the only stock they catch.

Maximum profit with BLI restriction, *sc3* : In FL01 total effort and its allocation among metiers were those that maximized the benefits and in turn the catch quota for BLI was respected. For the rest the same function used it *s2* was used.

`SMFB` **with SKH restriction (TAL = 500 t), *sc4*** : `SMFB` model with SKH restriction was used to simulate effort dynamics in the fleets that caught SKH (i.e, FL01, FL02 and FLSKH) in the rest `SMFB` was used being the restraining stock the only stock they catch. Furthermore TAL = 500t for SKH.

Maximum profit with SKH restriction (TAL = 500 t), *sc5* : In FL01 total effort and its allocation among metiers were those that maximized the benefits and in turn the catch quota for SKH was respected. For the rest the same function used it *s4* was used. Furthermore TAL = 500t for SKH.

Maximum profit with SKH restriction (TAL = 2500 t), *sc6* : The same as *sc5* but TAL for SKH increased to 2500 t.

Figure 6 shows the time series of biomass, in median, resulted in the 6 scenarios for all the stocks. The lowest values were obtained in *status quo* scenario, which mean that the highest effort was exerted in this scenarios. BLI's biomass experimented a high and maintained decrease in the projection, SKH's increased very slightly and RNG's maintained almost constant. POK's biomass increased and reached historical level in the long term, BSF's biomass also increased but maintained well below historical levels. In the other scenarios biomasses increased for all the stocks and the highest increases were obtained in the scenarios restricted by SKH, specially in the scenario where profits were maximized and TAL = 500 t (*sc5*). For POK and SKH the biomasses in scenarios *sc2,...,sc6* where very similar, but for the rest there were high differences. The biomasses in `sc2` were in the middle of biomasses in `sc1` scenarios and the rest of the scenarios being a clear difference between groups for BLI, RNG and BSF.

The economic indicators, effort, costs and profits, for FL01, in median, for all the scenarios are shown in Figure 7. In the projection the costs were computed as fixed cost (constant along time) plus variable cost per unit of effort (constant along time) times effort,

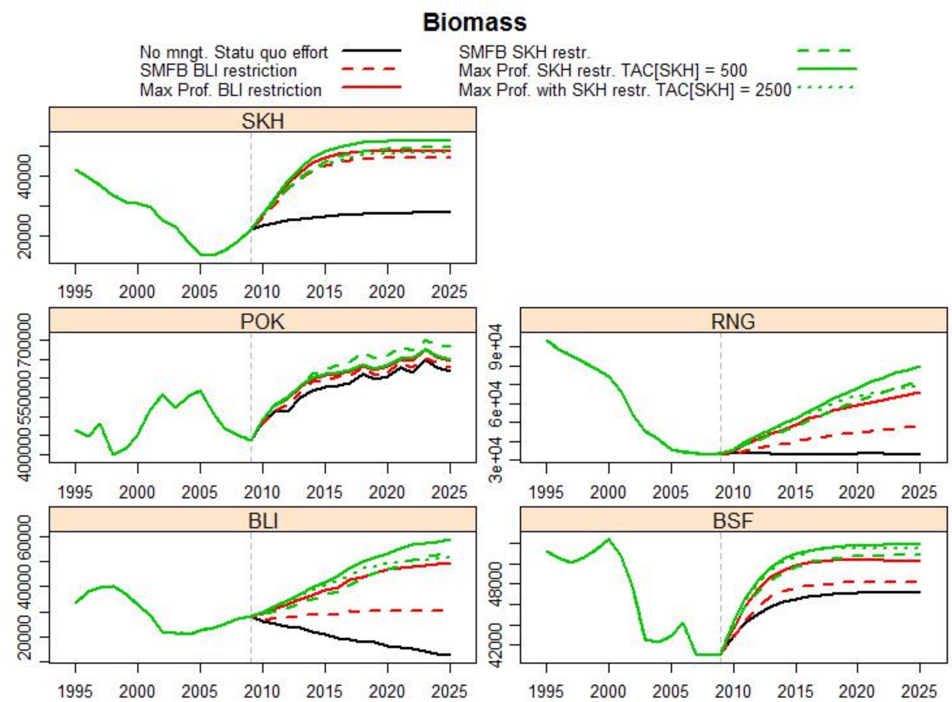

Figure 6: Biomass time series in median for all the stocks and all the scenarios.

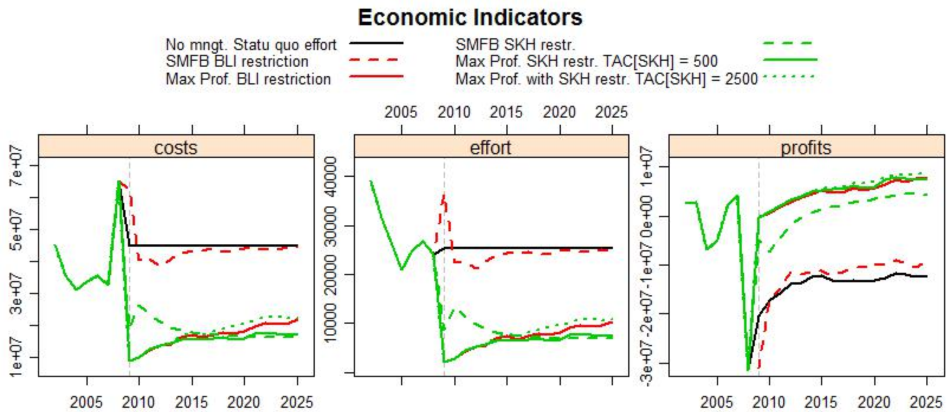

Figure 7: Effort, costs and profits time series in median for FL01 in all the scenarios.

thus effort and costs time series showed exactly the same trends. The profits in *status quo* scenario had increasing trend up to year 2015 and then they showed quite stable trend. In *sc1* scenario, the effort increased sharply in the first projection year and then it decreased below *status quo* level but maintained close to it in the whole projection. The profits in this scenario were lower that in *status quo* scenario in the first year and in the rest of the projection they were slightly higher. The scenarios where the profits were maximized, *sc3, sc5* and *sc6* were equal up to year 2014. Up to this year none of the quotas were restraining the effort and maximum benefit in FL01 was obtained with very low effort without reaching the quota shares. After this year there were small differences between the three scenarios, the differences were higher in effort and cost than in profits. The highest effort and profit, excluding *sc1* and *sc2*, was obtained in the scenario where profits were maximized and the constraint was SKH's TAC = 2500 t. The profits in scenario *sc3*, SMFB with SKH restriction were somewhat below profits in maximization scenarios, regarding effort in the first years it was significantly higher that in maximization scenarios and then it the effort was very similar to *sc4* scenario.

The effort share of FL01 along metiers for its main metiers is shown in Figure 8. The effort share in *status quo* scenario and SMFB scenarios (*sc1, sc2* and *sc4*) is the same and equal to the average of the last 3 historical years in the whole projection. Effort share in metiers 'OTHER6', 'REF5', 'EDGE6' and 'NEW5' was significant in the historical period but when the profits were maximized it decreased up to almost zero. In the short and medium term the effort share in those metiers transfered mainly to 'DEM4' metier where the effort share increased from 35% to 90%. In short and medium term the effort share was almost the same in all maximization scenarios. In the medium term the effort share in 'DEM4' started decreasing and it transfered to 'NEW6' metier. The decrease in 'DEM4', and hence the increase in 'NEW6', was dependent on maximization scenario. The variation was similar in BLI maximization scenario and SKH maximization scenario with TAC = 500 t. In these to scenario the variation was not very sharp, around a 10%. The variation in the scenario where SKH's TAC = 2500 t the variation reached a 30%.

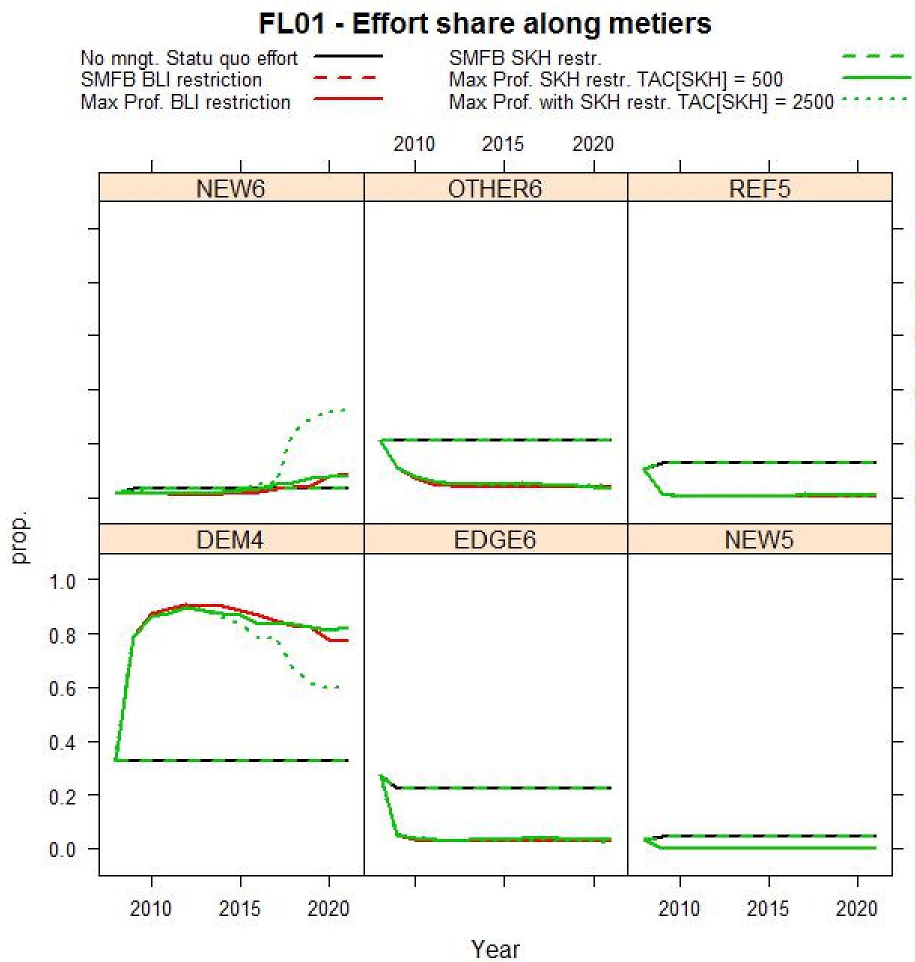

Figure 8: Effort share time series, in median, along FL01's metiers in all the scenarios. The time series for metiers with almost zero efffort are not shown.

4 Discussion and Conclusions

Regarding Seabream simulations, current management (TAC = 270 t) was found to be sustainable even when implementation error was introduced in the simulation. When the advice was implemented correctly the SSB reached historical levels, however when implementation error was introduced historical levels were not reached.

Ices MSY framework HCR, under perfect knowledge of the biological population, gave satisfactory results. Under perfect implementation the results were similar to current management and with implementation error the results were something better. In the long term the HCR without implementation error produced similar catches to the case with implementation error, however in the short term the catch under perfect implementation was significantly lower. Thus, a sacrifice in the short term would produce similar level of catch in the long term under a significantly better status of the stock.

In reality, to apply Ices MSY framework HCR it is necessary to have an assessment model which gives estimates of exploitation level and biomass. XSA was tested and it did not work properly. In many of the iterations it estimated high exploitation and low biomass levels and the TAC advice decreased gradually to zero catch. Thus, in the absence of a robust assessment model for the stock, this HCR is not a possible management tool for it.

AnnexIV HCR and current management gave similar results. This HCR depends on the existence of a reliable abundance index, at the moment there is an index for the stock but in the future it may not be available.

Current management, TAC = 270 t, demonstrated to be almost as good as alternative management based on HCRs which depend on stock status or abundance index. However in reality if this management continued it would be necessary to have an alternative system to monitor stock status to realize about possible alarms.

Regarding Mixed-fisheries case study the performance of the management strategy was driven by the fleet dynamics used in the fleets OM. Best results, both biological and economic, were obtained when the effort allocation used maximized FL01's profits. This dynamic was tested using BLI and SKH as restraining stocks. In the first year of the simulation the effort decreased sharply and FL01 did not reach the quota share of this stocks, thus in the short term the management used was somewhat irrelevant.

Status quo situation (in terms of effort) was not sustainable for BLI and RNG and in economic terms it was not profitable for FL01.

If the fleets followed profit maximization behaviour both biological and economic performance would improve. In this case only 5 stocks were taken into account and price was considered fixed. If there were more stocks economically relevant for FL01 fleet they should be taken into account. The inclusion of more stocks would change the economic performance of the fleet and optimum effort allocation would be different. Price normally depends on the landings thus using a dynamic model to model it should be desirable. A big part of the fishery has been considered in an artificial way, it should be desirable to use a realistic segmentation of the whole fishery. Applying profit maximization to the whole fishery would have a great impact in the bio-economic results.

`FLBEIA` provides a tool to conduct impact assessment of HCR in a wide range of case studies. From the biological point of view it considers the two structures most used in population dynamics modeling, age structure and total biomass, age structured stocks having, if appropriate, seasonal cohorts. From economic point of view it provides several fleet-base short term behavior models and allows incorporating new ones. Although not tested here it also provides a model to simulate fleets' long term dynamics. The biological and economic parts are fully congruent and coupled. The MP describes the management process followed by most European fish stocks and the typical HCR proposed in the management plans can be simulated. Thus, `FLBEIA` represents an appropriate option to be used in the bio-economic impact assessment of long term management plans.

MSE has been historically focused on single stock approaches and biological performance of management strategies. `FLBEIA` has proven to be a valid model to evaluate management strategies, in a mixed fisheries context, under MSE approach, taken into account the biological and economic dimensions of the problem. Furthermore social and ecological variables would be included in the model if needed. Thus it represents a step forward from single stock MSEs to full Ecosystem models.

In order to make realistic evaluation of management strategies in a mixed fisheries context it is crucial to advance in the understanding of fleet dynamics. Thus further investigation is needed in this part of fisheries modeling. As shown here depending on the fleets' behavior the management of the stocks can be irrelevant. No matter how good is a management strategy if the fishermen do not comply with it.

At this time `FLBEIA` does not provide any population dynamic model which considers trophic interactions. However, its structure allows incorporating this kind of models. Including them in the library would signify a great step forward and it would be very useful to allow evaluating management strategies from multispecies point of view. Nevertheless in most cases the main gap in multispecies modeling is the lack of data about species interactions.

One of the problems in applicability of bioeconomic models is their specificity, principally from fleet dynamics point of view. In this sense `FLBEIA` has been constructed in such a way that the models are stock, fleet or covariable specific and new models can be added by the users for almost any model component. Adding new models requires a background in `R/FLR` programming.

5 Acknowledgments

This work was carried out with financial support from Basque Country Government (Agriculture and Fisheries Department) and the Commission of the European Communities under the DEEPFISHMAN project (Grant agreement no. 227390).

A Data Containers

The data are introduced into the model using special `R S4` objects defined in `FLCore` package (the core package of FLR, (Kell et al., 2007)) and `FLBEIA` itself. There are 4 main objects,

`FLBiol`: it is used to store data related to the biology of the stock, number of individuals, natural mortality, individual weight and fecundity. Per stock, one object of this class is needed.

`FLFleetExt`: an extension of the original `FLFleet` object, including Cobb-Douglass production function parameters. This object has data at fleet level (capacity, crew-share, effort and fixed cost), metier level (effort share and variable costs) and stock level (discards, landings, price, individual weight and Cobb Douglas parameters).

`FLSRsim`: This object is used to simulate the recruitment using a stock-recruitment model. It stores the stock-recruitment parameters, biomass and recruitment, some additional data to add uncertainty and control parameters to tune the simulation. This object is only used in age structured populations.

`FLBDsim`: This object is used to simulate the population growth in biomass dynamic populations. It stores growth function parameters, biomass, catch and growth, some additional data to add uncertainty and control parameters to tune the simulation. This object is only used in biomass dynamic populations.

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