



Decision analysis on the introduction of a new fishing fleet for skipjack tuna in the Southwest Atlantic

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Abstract. Usually fishery managers do not have complete information on the questions they are supposed to evaluate, hence they have to make decisions taking risks because of the underlying uncertainty. We used decision theory and a bayesian version of a biomass dynamic model to assess the problem of introducing a new purse-seine fleet in the skipjack tuna (*Katsuwonus pelamis*) fishery of the southwest Atlantic ocean (SWAO). Adaptive importance sampling (AIS) followed by the sampling importance resampling (SIR) were used to build and explore the posterior distributions. Because skipjack of the SWAO has been under-exploited increasing the catches by introducing purse-seine boats probably will not reduce too much the biomass. However the endorsement of purse-seine fishing days results in large economic risks for the traditional bait-boat fleet.

Key words: uncertainty, posterior probability, skipjack tuna, adaptive importance sampling, bayesian analysis.

Resumo. Análise de decisão sobre a introdução de uma nova frota pesqueira. Usualmente administradores pesqueiros não dispõem de todas as informações sobre as questões a serem avaliadas, e dessa forma eles têm que tomar decisões assumindo alguns riscos por conta das incertezas. Nós fizemos uso da teoria de decisão e de uma versão bayesiana de um modelo dinâmico de biomassa para avaliar o problema sobre a introdução de uma nova frota de cerco na pescaria do bonito-listrado (*Katsuwonus pelamis*) no sudoeste do oceano Atlântico (SWOA). Uma amostragem adaptativa ponderada (AAP) seguida de uma amostragem e reamostragem ponderada (ARP) foram utilizadas para a construção e exploração da distribuição posterior. O bonito do SWOA pode ser considerado sub-explorado no sentido de que aumentos das capturas com a introdução do cerco provavelmente não reduziriam muito a biomassa. Entretanto a permissão de pesca para barcos de cerco resultaria em grandes riscos econômicos para a frota de pesca tradicional de vara-e-isca-viva.

Palavras-chave: incerteza, probabilidade a posteriori, bonito-listrado, amostragem adaptativa ponderada, análise bayesiana.

Introduction

Fishery management deals with making decisions albeit the large uncertainties related to economic, social and ecological issues. Usually there are uncertainties on structure of fishery models, and on their parameters (e.g. growth rate, catchability). Observational and experimental statistical data provide information but do not eliminate all uncertainties. Hence, managers take risks in fisheries because all components of the problem are seldom known in advance.

Decision theory is a suitable approach for

fishery management because it is concerned with the problem of making decisions in the presence of uncertainty. The decision framework is flexible allowing the analyst to deal with multiple performance criteria (attributes) involving several objectives and tradeoffs. The formal decision analysis improves the management decisions because it helps to identify robust policies, and the information needed to reduce critical uncertainties.

Since 1980s decision analysis and the Bayesian statistical approach have been pointed out

as effective methods for stock assessment and for the evaluation of alternative strategies of exploitation (Clark 1985, Walters 1986, Hilborn *et al.* 1994, McAllister *et al.* 1994, Punt & Hilborn 1997, McAllister & Kirkwood 1998, Peterman *et al.* 1998). Statistical decision theory and Bayesian analysis are related because each of them embodies a description of one of the key elements of decision problems, and due to their flexibility of utilizing non-experimental sources of information (Berger 1985). Alternative actions and cost-revenue tradeoffs can be included in the decision analysis framework. It is straightforward and conceptually easy to deal with uncertainties within the Bayesian approach which also provides a formal and coherent procedure to show how they affect the outcome of alternative management actions. Hence it favours an effective presentation of the relevant results to decision makers, researchers and the public.

In Bayesian analysis the information acquired in the past – observational and/or experimental data – is summarized in a prior probability distribution, while the sampled data are modeled with a likelihood function. The properly rescaled product of prior and likelihood results in a posterior probability distribution for the quantities of interest (*e.g.* parameters of a model). Whenever conjugate families of distributions for the prior and the likelihood are available, the posterior can be obtained analytically. However, in most fishery problems the analytical calculation of the posterior is difficult or impossible, hence Monte Carlo approaches are the alternative (*e.g.* Markov Chain Monte Carlo – MCMC, sampling-importance-resampling – SIR, adaptive importance sampling – AIS, combinations of AIS and SIR – AIS/SIR) (Hastings 1970, Rubin 1988, Oh & Berger 1992, West 1993, McAllister *et al.* 1994, Kinias 1996).

The decision analysis described in this paper concerns a real fishery problem involving large uncertainties on economic quantities, stock biomass and fishing fleet dynamics. Nowadays the introduction of a new purse-seine fleet to catch tuna in the southwest Atlantic is an issue of concern in Brazil. Decision makers have been asking for analyses to what would happen with the future fishing yields (weight caught) and biomass of the skipjack population if the purse-seine boats were allowed to fish in the Brazilian Exclusive Economic Zone (SC/CPG/SEAP, 2003). In this paper we have used a Bayesian decision framework to show the expected outcomes of alternative feasible management actions (*e.g.* to allow for 100 purse-

seine fishing days each year). We not only provide specific results for the skipjack problem, but also have shown a method to deal with the general problem of introducing a new fishing fleet.

2 - Data and Analysis

2.1 - Outline for Decision Analysis

The approach we used lines up with those of Raiffa (1968), Lindley (1985) and Hammond *et al.* (1999). To those who are not familiar with decision analysis the following checklist provides general information on the involved steps:

i) To identify management *objectives*. Because the tuna fishery deals with social, economic, political, ecological and cultural issues, the objectives of different stakeholders can be conflictive. Some of them may want to raise the yields (*i.e.* tons caught), while stability of fishing mortality may be more important for others. However, those goals probably can not be accomplished concurrently.

ii) To identify management options or alternative management *actions* in order to achieve these objectives. In fisheries, primary alternative *actions* are typically related to rules about effort amount, total allowable catch (TAC), gear selectivity or closure of fishing seasons and areas. However other alternatives may be taken into account.

iii) To gather all useful information available about the problem. Besides experimental and observational data, all non-experimental relevant information gathered from experts should be taken into account as well.

iv) To select one or more models to use in the analyses of the dataset. Quantities of interest, usually called *states of nature* are estimated when fitting the models to the fishery database. Different structural models can be plausible and may be considered.

v) To check the fit of the model. The model may be satisfactory in some sense but fail in another. For example, a model that is adequate to explain the variance of the catch may prove to be unsatisfactory when used to predict time trends of the catch rate. Hence it is mandatory to check whether the model is useful to answer the primary questions of interest.

vi) To choose one (or more) predictive model to assess what are the expected outcome of the management action. Usually the predictive model is similar to that used in the analysis of the available database. Dynamic biomass models can be used to fit the observed catch rates as well as to predict catch rates in the future after the enforcement of some management rule.

vii) To choose criteria to verify how management *actions* accomplish the objective. Often there are more than one objective, hence more than one criterion is necessary. We denoted the measurable quantities used to assess how the actions reach the objectives as *attributes*. Sometimes the choice of one attribute comes up intuitively. For example, “cumulative catch landed” across a couple of years after enforcement of an action may be suitable to assess if the objective of raising the annual yields was reached. However, to figure out a measurable attribute standing for the “stock welfare” objective may be difficult. An ordinal instead of quantitative scale may help when choosing attributes.

viii) To obtain expected outcomes of alternative management actions by integrating the attributes over the uncertainties. Marginal expectations for each attribute are calculated over the Bayesian posterior probability distributions.

ix) To rank the different management actions. Tables and graphs must be used to show the trade-offs among actions and objectives. The choice of the decision makers depend on values they assign to each objective and on their attitude when they confront risks. For example, the decision maker may be unwilling to accept the increase of the mean yield in 30% if the chance of the biomass falling bellow some benchmark is 10%. Simple decision tables showing how actions accomplish each objective often contain most of the information the decision maker needs. Two or more attributes can also be weighted and summed up to obtain a single index on which ranking could be based. Here, we simply called this index “utility” although its meaning in standard texts on decision theory is more complex. Despite this difference, the best action is the one that maximizes the utility, which is in line with classical decision theory texts (Raiffa 1968, Lindley 1985).

2.2 - The Skipjack Fishery Decision Problem - Data, Management Objectives and Actions

During the last decades the “International Commission for the Conservation of Atlantic Tunas” (ICCAT) has assumed that there are two stocks of skipjack in the Atlantic ocean (east and west coast) separated by the 30°W meridian (ICCAT, 2004). However, some researchers have argued that because skipjack populations show various fractions in the oceans with low mixing rates between, Economic Exclusive Zones may be suitable as management units (Hilborn & Sibert 1986). Controversial initially, the use of small management

units are considered reasonable nowadays by some experts (e.g. Fonteneau, 2003).

In fact, inside the limits of the traditional “west stock” of the Atlantic Ocean there are two large fishing grounds, separated by a huge distance. We denoted these two components as the northwest and the southwest Atlantic ocean fishing grounds (NWAO and SWAO). We are interested in the SWAO fishing ground which we consider a management unit motivated by ideas and results published by Hilborn & Sibert (1986), Fonteneau (2003), and Andrade & Kinas (2004).

The large scale industrial exploitation of surface tuna schools in the SWAO began in 1977 and skipjack tuna has been the main target (more than 90% of the total catch) of the Brazilian bait-boat fleet. The skipjack landings increased quickly in the beginning and then oscillated around 18000 tons until the mid 1990's and around 23000 tons until 2005 (Tab. I).

In the SWAO the skipjack has been caught along the Brazilian coast (Fig. 1) by a bait-boat fleet composed of close to 40 boats of up to 300 gross tonnages (GRT). Despite purse-seine fleets have been operating in all other tuna fisheries in the Atlantic Ocean, they are not present in Brazilian waters. Some discussions about the (in)convenience of purse-seine boats occurred among Brazilian conservationists, stakeholders and government in recent fishery meetings (Itajaí-SC meeting on skipjack fishery - July, 2004).

After introducing a new purse-seine fleet, how would the tuna catch increase (if so)? What would be the probability of confronting undesirable ecological scenarios (e.g. low biomass for a long time) in the future? Those are some typical questions that have been raised in these meetings. Based on them, we selected four major management objectives:

- i) Increase yield;
- ii) Avoid large variation of the annual yields;
- iii) Avoid “biological overexploitation”; and
- iv) Avoid overcapitalization also denoted “economic overexploitation”.

We considered several management actions based on effort enforcements to reach the above objectives. But the analysis could be done based on catch enforcements (e.g. Total Allowable Catch - TAC) as well. The actions we took into account can be pooled in four main branches:

- i) *status quo* - Maintain the bait-boat fleet effort (number of fishing days) and do not introduce purse-seine boats;
- ii) *increase the fleet* – Allow for fishing days

Table I: Catch (1000 tons) and standardized catch rate indexes (tons/fishing day) for the skipjack tuna (*Katsuwonus pelamis*) in the southwest Atlantic. String “NA” indicate there is not available record. Data source: Paiva (1997), ICCAT (2006), Andrade (2007).

Year	Catch	Catch Rate	Year	Catch	Catch Rate	Year	Catch	Catch Rate
1958	0.20	NA	1974	NA	NA	1990	20.13	5.64
1959	NA	NA	1975	NA	NA	1991	20.55	3.72
1960	NA	NA	1976	0.08	NA	1992	18.54	3.70
1961	0.30	NA	1977	0.19	NA	1993	17.77	3.77
1962	0.30	NA	1978	0.64	NA	1994	20.59	4.34
1963	0.30	NA	1979	2.07	NA	1995	16.56	3.69
1964	0.40	NA	1980	6.07	NA	1996	22.53	4.71
1965	0.50	NA	1981	13.91	NA	1997	26.56	5.81
1966	0.70	NA	1982	18.32	NA	1998	23.79	3.47
1967	1.50	NA	1983	15.95	3.58	1999	23.19	2.87
1968	0.80	NA	1984	13.57	3.12	2000	25.16	NA
1969	0.40	NA	1985	25.10	4.45	2001	24.15	4.06
1970	0.40	NA	1986	23.16	4.29	2002	18.34	3.99
1971	0.10	NA	1987	16.29	3.7	2003	20.42	3.85
1972	NA	NA	1988	17.32	3.76	2004	23.04	4.16
1973	NA	NA	1989	20.75	4.56	2005	26.39	NA

with purse-seine boats and/or increase the bait-boat fleet effort;

iii) diminish the fleet – Reduce the bait-boat fleet effort but do not introduce the purse-seine fleet and;

iv) replace the fleet - Replace some of the bait-boat fishing days by purse-seine fishing days.

Data available for the analysis are limited. There are landing reports and a few standardized catch rates as estimated by Andrade (2007) using commercial catch-per-unit-effort (CPUE) (Table I). Generalized linear models (GLM) were used to estimate standardized catch rates. Geographic position of the fishing sets, season of the year, and boat characteristics were included as factors in those linear models. Although the effect of these factors have been reduced and/or eliminated the catch rates estimated are still a limited index of abundance. See Andrade (2007) for more details about estimations and limitations of the available catch rates. Some could argue that no decision should be made until more informative data have been gathered. Nevertheless notice that the choice to wait is also an action (similar to the *status quo* option above). In fact decision makers often have to confront scenarios with sparse information and many uncertainties, particularly when dealing with tuna stocks management (ICCAT, 2004).

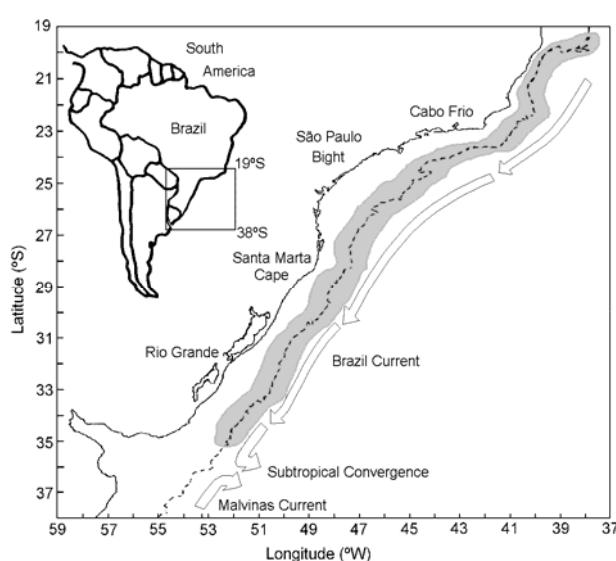


Figure 1: Skipjack (*Katsuwonus pelamis*) fishing ground (gray area) in the southwest Atlantic. Arrows stands for schematic representation of the surface current system and dashed line stands for the 200 meters isobath.

2.3 - The assessment model

A biomass dynamic model was used because only catch and catch rate times series were available. Despite simple models lack realism the result gathered with them are in many situations as useful

as those obtained with complex, more data demanding models (Ludwig & Walters 1985).

We used the following version of the Schaefer model.

$$(1) \quad B_t = [B_{t-1} - C_{t-1} + r \cdot B_{t-1} (1 - B_{t-1} / k)] \cdot e^u$$

where C and B are the catch and the biomass, and time is indexed by t . The parameter r is the population growth rate, k is the carrying capacity biomass, and u is normally distributed random process noise with variance W . The observation error in C_t is assumed to be negligible. The relationship between the biomass B_t and an observable index I_t of abundance is

$$(2) \quad I_t = q \cdot B_t \cdot e^v$$

where v is a normally distributed random variable with variance V accounting for observational noise, and q is the catchability coefficient.

We assumed q approximately constant relying on the “standardization” of the catch rates Andrade (2007) did using generalized linear models (GLM). Hence the effect of variations of q on the catch rate we used was reduced. For example, as far as fishing set geographic position and quarter were considered in the GLM, the effects of the variations of q due to area and seasons

on the catch rate were small. Such assumption can be made just because “area” and “season” factors were included in the standardization analysis. However, other components were not included in the GLM, hence they are still sources of variation of q in equation 2. For example, the catchability coefficient can still change across time due to biomass variations, which was not included in the standardization model of Andrade (2007). An attempt to deal with the possibility that q change according to biomass would be to consider more parameters and complex models to describe the relationship among I , q and B across the years. In order to gather estimates for such models the data would have to be very informative and/or auxiliary data such as age-structured catches would be necessary. However, our data set is rather limited. Hence we opted to use a simpler model. The results we gathered might be interpreted in the light of the hypothesis described in the equation 2, in which the variations of the abundance index I (standardized

catch rate as calculated by Andrade, 2007) are primarily caused by changes in the biomass.

In the state-space model as described in equations 2 and 1, besides the nuisance parameters W and V , there are three parameters of interest, r , k and q . Because it is mathematically more convenient to deal with parameters defined over the real line, we define $\theta = \{\log r, \log k, \log q\}$ as the three dimensional parameter vector of interest in the Bayesian approach.

2.4 - Bayesian approach to the assessment model

Bayesian inference of θ is obtained using prior probability density distribution $\pi(\theta)$ and likelihood $L(\theta) = p(\text{data} | \theta)$ after the data have been sampled. The posterior density distribution for θ is

$$(3) \quad p(\theta | \text{data}) = \frac{\pi(\theta) \cdot L(\theta)}{\int \pi(\theta) \cdot L(\theta)}$$

We first describe the likelihood function, then we explain how we built the prior and posterior probability distributions.

Likelihood

In order to estimate θ only the observational error was considered. The solution developed by Kinias (1993 and 1996) is summarized below. After taking the logarithm of equation 2 and for notational convenience, we define $Y_t = \log I_t$ and $\mu_t(\theta) = \log(q \cdot B_t)$. The probability model for data point Y_t is

$$(4) \quad p(Y_t | \theta, V) \sim N(\mu_t(\theta), V)$$

where $N(\mu_t(\theta), V)$ is an one-dimensional normal distribution with mean $\mu_t(\theta)$ and variance V . Let the complete data set be $Y(\tau) = \{Y_1, \dots, Y_\tau\}$, hence the joint likelihood is $L(\theta, V) = p(Y(\tau) | \theta, V)$. If independent prior distributions are assumed for θ and for V , say $\pi(\theta, V) = \pi(\theta) \cdot \pi(V)$, then the likelihood $L(\theta)$ is obtained by marginalization with respect to V

$$(5) \quad L(\theta) = \int p(Y(\tau) | \theta, V) \pi(V) dV$$

If the prior for V is an inverse-gamma density distribution, say $\pi(V) \sim IG(\alpha, \beta)$, the solution is

$$(6) \quad L(\theta) \propto \left\{ 2\beta / \left[2 + \beta \sum_{t=1}^{\tau} (Y_t - \mu_t(\theta))^2 \right] \right\}^{\alpha + \tau/2}$$

$$(7) \quad E[V | Y(\tau)] = \frac{1}{\alpha + \tau/2 - 1} E^{p(\theta|Y(\tau))} \left\{ \left[2 + \beta \sum_{t=1}^{\tau} (Y_t - \mu_t(\theta))^2 \right] / 2\beta \right\}$$

and

$$(8) \quad E[V^2 | Y(\tau)] = \frac{1}{(\alpha + \tau/2 - 1) \cdot (\alpha + \tau/2 - 2)} E^{p(\theta|Y(\tau))} \left\{ \left[\frac{2 + \beta \sum_{t=1}^{\tau} (Y_t - \mu_t(\theta))^2}{2\beta} \right]^2 \right\}$$

where $E[\cdot]$ and $E^{p(\theta|Y(\tau))}[\cdot]$ represent the expectation and the expectation over the posterior.

In order to calculate the likelihood (eq. 6), biomasses are estimated recursively using equation 1. Hence an initial value, the biomass for the first year, needs to be defined in advance. We assumed the initial biomass equal to the carrying capacity (k) because large commercial fishery had not begun previously to the time series of available data (Table I). Furthermore, under this assumption, the bias when estimating effort at the MSY is not large whenever the observational error is used to fit the model (Punt 1990).

Prior

The prior may strongly affect the posterior distribution when database is non-informative. Therefore, it is very important to show how the priors have been built. We shall use a three dimensional non-central student distribution for $\theta = \{\log r, \log k, \log q\}$, so that $\pi(\theta) \sim T_3(df, m, c)$, where df is the degree of freedom, m is the mean vector and c is the main diagonal of the (3x3) covariance matrix of the three dimensional student density function $T_3(\cdot)$. We assumed independence among the parameters so that all off-diagonal terms of the covariance matrix are zero. The impact on the posterior was evaluated by using two different prior distributions. In the “informative” prior we summarized all available knowledge on the

That choice is convenient because the inverse-gamma is conjugated with the normal probability in equation (5). The resulting likelihood equation is simple in the sense that it only depends on the residuals with respect to $\mu(\theta)$ and on the prior parameters for V . The first and the second central moments for the posterior inverse-gamma distribution of V are

parameters to the best of our knowledge. In the “diffusive” prior we exaggerated our ignorance by inflating variances. In order to define these prior distributions we first build suitable independent normal distributions for each component of the vector, then we used the means and the variances of these three distributions to build vector m and the main diagonal of the covariance matrix c in the three dimensional student prior. All the components of the priors were based on information published in scientific journals.

We did not find estimates of r for skipjack, hence we have build the informative prior based on estimates for other tuna stocks (south Atlantic albacore and yellowfin tuna) published elsewhere (e.g. Polacheck *et al.* 1993, Su & Liu 1998, Anonymous, 2004). The estimates of r for yellowfin ranged from 0.3 to 0.9, but we opted for a more conservative prior (*i.e.* a coefficient corresponding to a less productive stock) for skipjack.

Jablonski & Matsuura (1985) and Vilela & Castello (1993) have estimated the standing biomass in mid 1980's using traditional “cohort analysis” ($\sim 70,000$ tons) and “virtual population analysis” ($\sim 100,000$ tons) respectively. In order to estimate biomass Jablonsky & Matsuura (1985) converted catch-at-length in catch-at-age using estimations of growth parameters, while Vilela & Castello (1993) have used an age-length key. We used the lower of the above estimates ($\sim 70,000$ tons) to approximate the median for the prior on the

carrying capacity biomass. That was a conservative choice because the biomass before the beginning of the fishery was probably larger than in mid 1980's.

To build the prior on the catchability coefficient we considered that the standing stock biomass of the mid 1980's, as estimated by Jablonsky & Matsuura (1985) and Vilela & Castello (1993) had fallen to close to 40000 by the end of 1990's due to the increasing annual catches. We then used the catch rate of the end of 1990's and equation (2) without the error term to get the estimate $q = I / B = 5 / 40000 = 1.25E - 4$, which we took as the median of the informative prior for catchability.

The informative mean and covariance diagonal are $m = \{-1.3, 11, -9.3\}$ and $c = \{0.16, 0.16, 0.16\}$, while the diffuse mean and covariance are $m = \{-1.9, 10.7, -9.4\}$ and $c = \{1.00, 1.21, 0.81\}$. The df was 9 for both, diffuse

and informative prior distributions, hence the priors have heavy-tails with respect to the normal curve. In the inverse-gamma prior distribution for V we used $\alpha = 7$ and $\beta = 14$. A plot of the prior distributions for the parameters of primary interest r , k and q in the original scales is in Figure 2.

It is important to mention that we used all the available evidence to build the prior distributions. Probably other researchers would build priors similar to ours if the information we had were also all the information made available to them. Furthermore, the diffuse prior largely exaggerates the uncertainty on the knowledge about the parameters, so that the influence of our subjective "guesses" on the results could be evaluated by comparing the posterior distributions as estimated using informative and diffuse prior distributions.

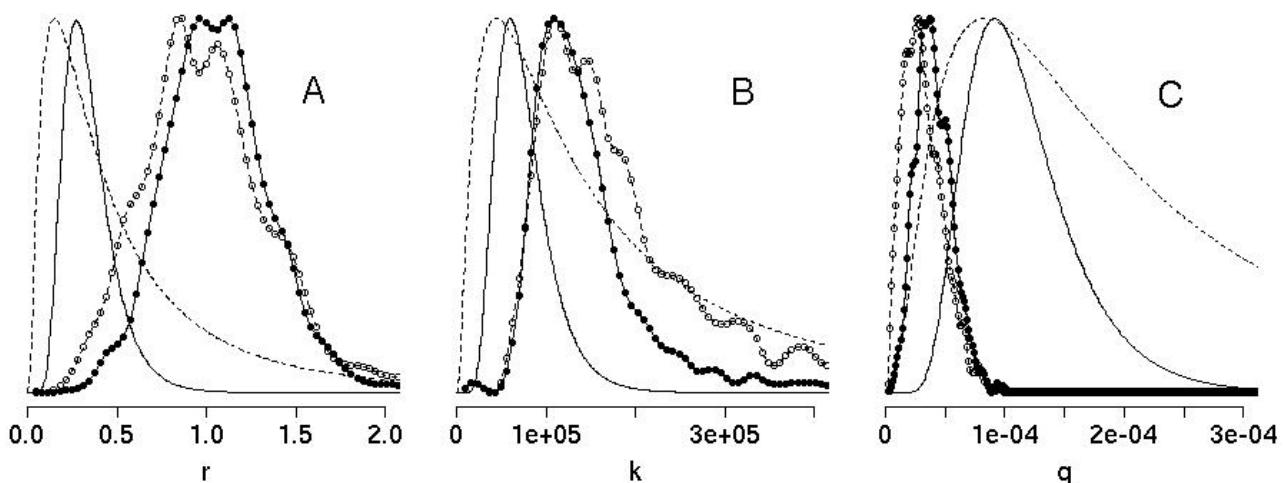


Figure 2: Informative and diffuse prior and posterior distributions for parameters of the dynamic biomass model: (r) population intrinsic growth rate, (k) biomass at carrying capacity, and (q) catchability coefficient. Solid lines stand for informative prior, while dashed lines stand for diffuse prior. Empirical informative posterior distributions are indicated by filled circles, but lines with opened circles represent diffuse posterior distributions.

Posterior

In order to draw a sample from the posterior distributions using the Monte Carlo methods the initial step is the choice of a suitable importance function. A good importance function must be easy to sample from and should be similar to the true posterior density distribution function. The standard importance function is a multivariate normal or student distribution centered at the maximum likelihood estimates and with covariance matrix proportional to the Hessian matrix (Gelman *et al.* 1995). Some improvement in the method of choosing importance function when using the sampling importance resampling (SIR) algorithm has been developed by McAllister & Ianelli(1997).

The mixture of student distributions is another alternative to improve the first importance function (West 1992, 1993). This procedure called adaptive importance sampling (AIS) can be followed by a SIR when drawing the final sample, and was the method we chose. Relative entropy (RE) as suggested by West (1993) was the diagnostic measurement we used in the AIS/SIR procedure to assess the convergence. RE approximates 1 as $g(\theta)$ approaches $p(\theta | data)$. The adaptive updating procedure of $g(\theta)$ is performed recursively until a target minimum relative entropy has been reached. Further details on AIS algorithm and it's technical issues are in Kinas (1993) and Andrade (2004).

2.5 - Checking the fit of the model

Model checking can be done by comparing the posterior predictive distribution of observations with the actual data (Gelman *et al.* 1995). The procedural steps are: *i*) to draw simulated values from the posterior distribution; *ii*) to use these values to predict a replicated data set; and finally *iii*) to compare these predicted samples to the actual observed data using some measurement of discrepancy.

We shall use $T(y, \theta)$, in which y is the response variable and θ is the estimand, to denote the measure used as standard to compare the data to the predictive simulations. Since in this work we are primarily interested in the time trend of the biomass, $T(y, \theta)$ is the slope of a simple linear model fitted to the catch rate data points as calculated for the most recent ten years to show up in the time series.

A Bayes p -value is defined as the posterior probability that the test quantity $T(\cdot)$ for the replicated data (y^{rep}) be more extreme than for the observed data (y):

$$(16) \quad p = \Pr(T(y^{rep}, \theta) \geq T(y, \theta) | y)$$

To calculate this probability, s vectors of θ are drawn from the posterior, one y^{rep} is simulated for each of the s vectors and $T(y^{rep}, \theta)$ is calculated. The p -value is the proportion of the s simulations of equal or larger than the observed value $T(y, \theta)$. A small value of p indicates a poor fit of the model.

2.6 - Expected catch and stock biomass

A predictive model shall be used to project biomass and catch into the future under different exploitation regimes (*i.e.* management actions). Future fishery scenarios can be simulated in different ways. One of them is to assume enforcements on total allowable catch (TAC). However, two reasons motivated us to deal with fishing effort and catchability instead: *i*) We were interested in estimating how many purse-seine fishing days would be necessary to achieve a target catch – if we had simulated the catch directly, this number of fishing days would remain unknown; and *ii*) Apparently, it is easier to restrict the effort (*i.e.* fishing days) instead of implementing catch control programs in this fishery.

We rely on basic fishery theory (*e.g.* Clark 1985, Gulland 1983) and assumed that the catch at

time t is

$$(17) \quad C_t = F_t \cdot B_t$$

where F_t is the fishing mortality at time t caused by all the fleets. Fishing mortality at time t is the sum of fishing mortalities caused by b fishing fleets

$$(18) \quad F_t = \sum_b F_{t,b}$$

Finally, we assumed that fishing mortality caused by each fleet could be unfolded as

$$(19) \quad F_{t,b} = f_{t,b} \cdot q_b$$

where $f_{t,b}$ is the effort of the b^{th} fishing fleet at time t and q_b is the coefficient of catchability for this b^{th} fleet. Therefore, if $f_{t,b}$ is enforced by some management action and estimates of r , k and q_b ($q_{bb} = q_{b=bait boat}$, and $q_{ps} = q_{b=purse seine}$) are available, future catches and biomasses can be simulated using the set of equations 19, 18 and 17 and the biomass dynamic model (eq. 1).

The posterior distribution for θ provides sets of r , k and q_{bb} . Results published by Almeida & Andrade (2002) and Andrade (2007) suggest that the ratio $q_{ps/bb} = q_{ps} / q_{bb}$ is probably between 1 and 4. Therefore we used the following continuous uniform distribution to simulate uncertainties in $q_{ps/bb}$:

$$(20) \quad P(q_{ps/bb}) \sim U(1,4)$$

If $q_{ps/bb}$ and q_{bb} are available, q_{ps} can be calculated. Some comments are warranted. In order to get estimations of the ratio $q_{ps/bb}$ Almeida & Andrade (2002) calculated the ratio between commercial catch-per-unit-efforts of purse-seine and bait-boats that fished at the same place and time. Theoretically the difference between the two CPUE would be due to the differences between the vulnerability of skipjack to the two types of boats. Andrade (2007) used another approach. Estimations of $q_{ps/bb}$ were based on coefficients as calculated using generalized linear models in which “type of fleet” was included as explanatory factor, and CPUE was the response variable.

In order to project the catches and the biomass, we needed to simulate future efforts across T years into the future. Firstly we calculated the

effort vector for the most recent years (≥ 1995) as the ratio between catch and catch rate indexes. Secondly we calculated the average (“base effort value” - f_{base}) of that vector. Finally, the future effort vector under the four different alternative management actions were defined as follows:

i) Status quo actions – Base effort (f_{base}) was used as the expectation of the bait-boat effort in each one of the next T years. Purse-seine fishing days are not allowed.

ii) Increase the fishing fleet

ii.1) Base effort was used as the expectation of the bait-boat effort in each of the next T years. The amount of purse-seine fishing days allowed is constant over the next T years.. We simulated several scenarios using a different constant value between 300 up to 3000 fishing days.

ii.2) Purse-seine fishing days are not allowed, but the bait-boat effort in each of the next T years is constant and larger than f_{base} . We simulated that effort raised from five to twenty percent with respect to base effort. For example the constant $1.05 \cdot f_{base}$ was used to emulate an increase of 5% of the bait-boat effort.

ii.3) Purse-seine fishing effort was simulated like in *ii.1*, and bait-boat fishing effort was simulated like in *ii.2*.

iii) Diminish the fishing fleet – Purse-seine fishing days are not allowed. Expectation of bait-boat effort in each of the next T years is constant but smaller than f_{base} . We simulated that effort decreased five to twenty percent with respect to base effort. For example the constant $0.80 \cdot f_{base}$ was used to emulate an effort decrease of 20 %.

iv) Replace the fishing fleet – Purse-seine fishing effort was simulated like in *ii.1*, and bait-boat fishing effort was simulated like in *iii*.

We gathered close to 11,000 vectors using AIS and extracted final SIR samples with 1,650 values from both, diffuse and informative posterior distributions. Therefore all fishery management scenarios cited above were simulated 1,650 times. In all simulations we used $T = 5$ years.

Process error was not considered in the estimation, but optimal effort is overestimated if that error is not used in the projection of future outcomes (see Ludwig & Walters 1989). Hence we used half of the expectation of the variance of the estimation model (eq. 7) as process error variance (W), and half was used as observation error (V) in the Monte Carlo simulations of future outcomes. Similar solutions

had been adopted elsewhere (e.g. Ludwig & Walters 1985, Kinas 1996).

2.7 - Criteria to assess the performance of alternative management actions

Four attributes were defined to evaluate alternative management actions. :

i) Present value of the accumulated catch over the next T years (AC_T);

ii) Coefficient of variation of the annual catches (CV_c);

iii) Probability that expectation of catch rate of bait-boats decrease and remain bellow 4 tons/fishing day during three subsequent years (“*catch rate failure*” risk - CRF);

iv) Probability that biomass falls and remains bellow B_{MSY} during three subsequent years (“*biomass failure*” - BF).

The first attribute stands for the objective of increasing yield, which is one of the main goals of the fishery industry and government. To calculate the present value of the accumulated catch (AC_T) we used an exponential discounting factor (see Clark 1985):

$$(21) \quad AC_T = \sum_{t=1}^T \left(\sum_{b=\text{bait-boat; purse-seine}} C_{t;b} \cdot ev_b \right) \cdot e^{-\delta \cdot t}$$

where $C_{t;b}$ is the catch of the b^{th} fishing fleet in year t , δ is the annual *discount rate*, and ev_b is the relative economic value of the catch of the b^{th} fleet. We used $\delta = 0.05$ just as an example, but other value could be used as well. The influence of the discount rate is predictable, the larger the δ the less conservative would be the decision.

There is some consensual bat vague opinion that purse-seine is probably more efficient in the economic sense, hence we used $ev_{b=\text{bait-boat}} = 1.0$ and $ev_{b=\text{purse-seine}} = \{0.9, 1.0, \dots, 1.4\}$ to express the economists uncertainty exposed in the Itajaí-SC meeting on skipjack fishery, July, 2004.

The second attribute (CV_c) is associated with the objective of avoiding large variations of yields across the years, while the third attribute (CRF) is associated to the economic risk for the bait-boat fleet. We used CRF as an indicator for the “economic overexploitation” objective. We calculated CRF as the proportion of vectors (length T) of future catch rates of bait-boat in which occurred three subsequent values smaller than 4

tons/fishing day. In fact an estimation of the minimum catch rate required to pay the costs of a fishing day is not available. This threshold was an arbitrary choice among several values suggested by stakeholders during the Itajaí-SC, 1994 public meeting.

The fourth attribute (BF) is associated with the objective of maintaining the stock at sustainable levels. We calculated BF as the proportion of simulated future biomass vectors (length T) in which at least three subsequent values of biomass were smaller than B_{MSY} . The MSY threshold is reasonable for populations of tropical small tunas like skipjack, because they are very productive (see comments in Hilborn & Walters 1992 and Longhurst 1998).

In order to combine all attributes in a single measurement, we standardized them to make them comparable. Given the attribute A_i with $i = \{1, 2, 3, 4\}$ indexing posterior expected values of AC_T , CV_c , BF and CRF , we defined

$$(22) \quad U_i = \frac{A_i - \min(A_i)}{\max(A_i) - \min(A_i)}$$

where $\min(A_i)$ and $\max(A_i)$ denote smallest and largest values of A_i over all management actions under consideration.

Notice that $0 \leq U_i \leq 1$ and that the best performance is indicated by $U = 1$ for AC_T ($i = 1$) while it is indicated by $U = 0$ for all other attributes ($i = 2, 3, 4$). Because we would like to maximize AC_T and minimize CV_c , BF and CRF .

A simple overall measure is

$$(23) \quad U_T = \frac{\sum_{i=1}^4 wu_i \cdot U_i}{\max\left(\sum_{i=1}^4 wu_i \cdot U_i\right)}$$

where wu_i is the weight of the i^{th} attribute U_i . Only wu_1 (the weight of the $U_1 = AC_T$) is positive, and all other weights are negative because other attributes denote non-desirable qualities (i.e. $U_4 \approx BF$ that is the biomass risk failure). The order of preference among management actions is related to increasing values of U_T . The

denominator of equation 23 assures that $\max(U_T) = 1$. Best option among contenders, is the one that maximizes U_T . We used equal absolute weights for all attributes as baseline, but we also calculated U_T using variations of this standard case in which some of the attributes are considered more important than others.

3 - Results

3.1 - Model fitting and posterior estimation

Relative entropy (RE) reached 0.98 in just four adaptive adjustments of the importance function. As far as RE was close to 1, the convergence was assumed satisfactory. First and second central moments for the posterior distribution of the variance of the observational error (V) were 2.2E-2 and 5.1E-4 for both, the informative and the diffuse prior distributions. Summaries of the marginal posterior distributions of r , k and q are in Figure 2 and in Table II. Posterior distributions were not strongly affected by priors (Fig. 2). Central trends of prior and posterior distributions are very different (Fig. 2). Posterior estimates for r are much larger, while the posterior estimates for q are much smaller than those of the prior distributions. The posterior for r is especially of concern because it includes values (i.e. > 1.5) that are suspicious from the biological point of view.

Usually posteriors calculated from diffuse priors include a wider range of values than those calculated using informative priors. However, note that only for the carrying capacity parameter (k) the diffuse posterior indeed has a heavier right tail than the informative posterior (Fig. 2).

Because of the overall similarities between the posterior distributions obtained from diffuse and informative priors, we proceed showing only the latter results. Large uncertainties on the parameter estimates are evident from the contour plots for the joint posterior distributions (Fig. 3). The three parameters are strongly correlated, which is typical in results gathered with dynamic biomass models (Hilborn & Walters 1992). Also notice the “banana shape” of the joint posterior for k and q (Fig. 3 c) indicating a non-linear correlation between the parameters. The correlations involving k are strong and negative, while the correlation between q and r is positive.

Catch rate data and model fits as described by samples of θ from the

Table II: Summary of the posterior distributions for the parameters of the biomass dynamic models as estimated using informative and diffuse prior distributions.

Estimate	Informative				
	5%	25%	median	75%	95%
R	0.579	0.812	1.022	1.250	1.614
k	75422	103451	132375	180010	385192
q	1.168E-5	2.650E-5	3.756E-5	4.959E-5	7.084E-5

Estimate	Diffuse				
	5%	25%	median	75%	95%
r	0.479	0.752	0.976	1.229	1.653
k	80654	117394	161816	239692	489258
q	8.729E-6	1.910E-5	2.962E-5	4.259E-5	6.551E-5

posterior are shown in Figure 4. To further check the fit of the model to data, we used the slope of the regression of catch rates over the latter ten years in the time series as our discrepancy measure $T(y, \theta)$ (see item “Checking the Fit of the Model” above). Predictive probability of the slope estimated from the posterior being larger than the slope estimated from the real data was $p = 0.64$. Because that value is not extreme, we assumed the model is acceptable. In addition estimations indicate the central trend of slopes is close to zero (≈ -0.05), though with large variance.

3.2 - Biomass and exploitation rate estimations

Because we assumed the relationship between catch rate (*i.e.* index of abundance) and biomass is log-linear (see eq. 2), time trend variations of these quantities are similar. Therefore slight decreasing trends of the catch rates mean that there is not evidence of strong variations of biomass across the last years. Although uncertainties are high (large variance), the results

suggest that there was not a strong decreasing trend since the industrial fishery began in early 1980’s (Fig. 5).

Biomass point estimates were also gathered by Jablonski & Matsuura (1985) and Vilela & Castello (1993) using virtual population and length cohort analyses without auxiliary information (Gulland 1965, Pope 1972, Jones 1984). Estimation published in Vilela & Castello (1993) are consistently lower (~ 70,000) than those we have calculated, while the Jablonski & Matsuura (1985) estimates using natural mortality (M) equal to 0.8 year⁻¹ (~ 100,000) are in line with the median of our posterior.

Summary of relevant quantities for management as estimated from the posterior are in Table III. There is a low probability that skipjack had been biologically overexploited in the last years. Median point estimates provide an optimistic scenario if the reference MSY is the management objective. Exploitation rates and catches have been smaller than those corresponding to the MSY. On the other hand, the biomass in 2005 - the most recent

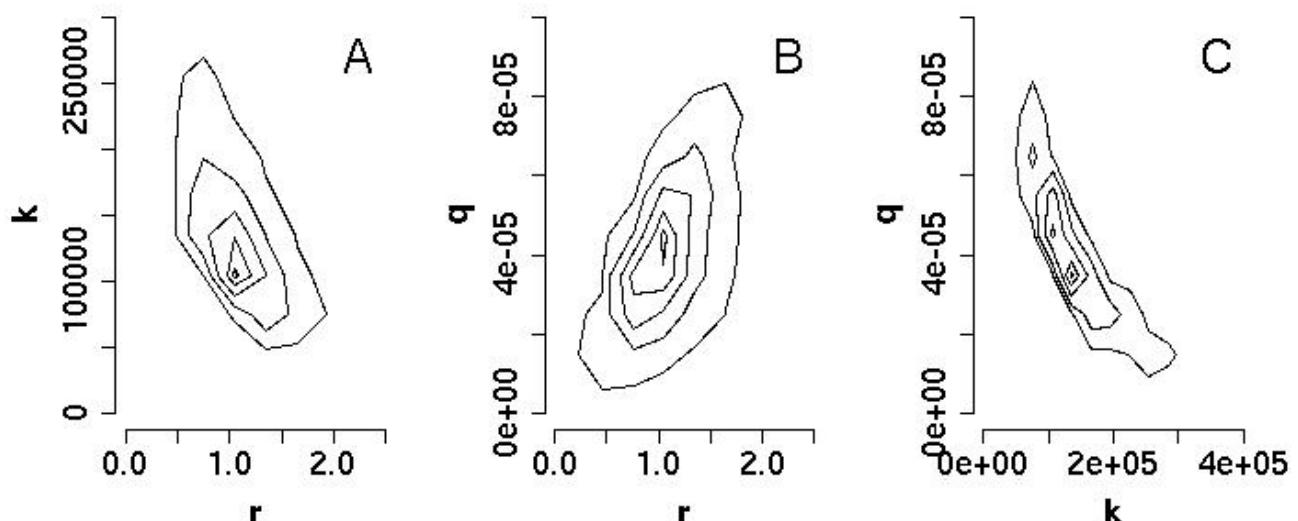


Figure 3: Joint posterior distributions for the dynamic biomass model parameters (r , k and q). The lines are at the 0.05, 0.25, 0.50, 0.75 and 0.95 of the largest density.

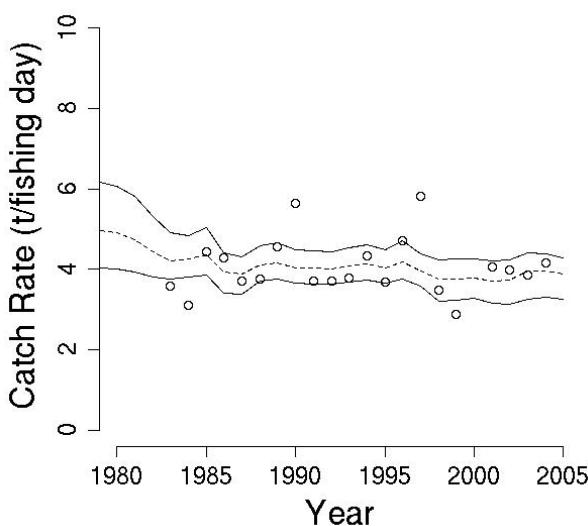


Figure 4: Catch rate and the fitting of de models as described by the samples of θ draw from the posterior. Solid lines stands for the minimum and maximum catch rates as predicted with all sampled θ vectors. Dashed line is the median.

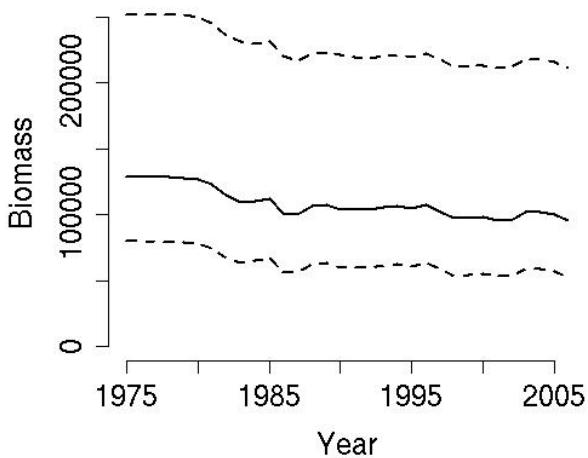


Figure 5: Projection of the biomass as predicted using posterior empirical distribution as estimated using informative prior distribution. Solid line stands for the median, while dashed lines stand for the quantiles of 0.05 and 0.95.

year in the data time series - was probably 50% larger than the B_{MSY} , though uncertainties are large as can be verified from the inter-quartile range.

3.3 - Management actions and objectives

Expectations as calculated using posterior distributions are in Table IV. If effort levels remain like they are nowadays (*status quo* – BB = 0 and PS = 0 in Table IV) expectations of annual catches is close to 21,500 tons over the next $T = 5$ years. Similar yields could be obtained by replacing 20% of the current bait-boat effort by 600 fishing days of purse-seine boats. The proportion of skipjack

catches by bait-boats decreases sharply concurrent with the authorization of fishing days for purse-seine boats. Expectations of the coefficient of variation (CV) are between 0.1 and 0.2 no matter the management action adopted.

If 1200 purse seine fishing days were allowed together with current bait-boat effort (BB = 0) the annual landings would increase to 29,000 tons, but the risk of economic struggles for bait-boats (CRF) would be large (> 0.25). In fact, the risks for catch rates of bait-boats seem to be of more concern than risks about the skipjack biomass (BF), which were all quite low.

Relationships among the four measurement criteria for all alternative actions are in Figure 6. All the correlations are positive, but non-linear. If the accumulated yield (AC_T) increases, the coefficient of variation (CV) and the risk measurements (BF and CRF) increase as well. The point is how decision makers deal with compensations between risks and earnings. The shape of the curves representing the relationship between AC_T and CRF and between AC_T and BF are similar, but the catch rate failure risk (CRF), that stands for the economic struggles of the bait-boat fleet, increases faster and is comparatively larger than the biomass failure risk (BF). For example, if the current bait boat effort is maintained and 1200 purse-seine fishing days are allowed, than the catch rate risk will be much larger ($> 25\%$) and the biomass risk will remain low (Table IV). Most of the aggressive management actions, like allowing for 2100 or more purse-seine fishing days, result in large catch rate failure risk (CRF) but also in large accumulated catches (AC_T) (Fig. 6).

The five top management actions as ranked using the overall performance measure U_T are in Figure 7. In the base case (equal weights for all attributes) just a slight increase of bait-boat fleet (5%) is the best choice, because it maximizes U_T (Fig. 7 A). Status quo and even some replacement of bait-boats by purse-seine boats are also in the top five actions. When the weight of the risk for biomass (BF) is large, the results are similar to those of the base case (Figs. 7 A and B). However, sharp management strategy changes are requested if the weight of accumulated yield (AC_T) is large, because aggressive replacement of bait-boats by purse-seiners are the solution (Fig. 7 C). Finally, if the weight for the risk of economic struggle for bait-boat fleet (CRF) is large, we should expect that reductions of the fleet to be the action that maximizes U_T .

Table III: Summary of the estimates as calculated using the joint informative posterior distribution. C, B and ER are catch, biomass and exploitation rate respectively. The term MSY indicates the estimated values at the traditional “Maximum Sustainable Yield” and LAST stands for the estimates in the last year analyzed.

	5%	25%	median	75%	95%
C_{MSY}	25271.85	28539.74	31930.60	38217.33	55373.80
B_{MSY}	39784.97	51338.92	64341.63	80869.19	126019.10
B_{LAST}	56620.09	77098.74	100201.62	129862.90	215462.64
ER_{MSY}	0.31	0.43	0.52	0.62	0.78
B_{LAST}/B_{MSY}	1.36	1.48	1.55	1.64	1.77
C_{LAST}/C_{MSY}	0.48	0.69	0.83	0.92	1.04
C_{LAST}/B_{LAST}	0.12	0.20	0.26	0.34	0.47
ER_{LAST}/ER_{MSY}	0.27	0.42	0.53	0.63	0.77

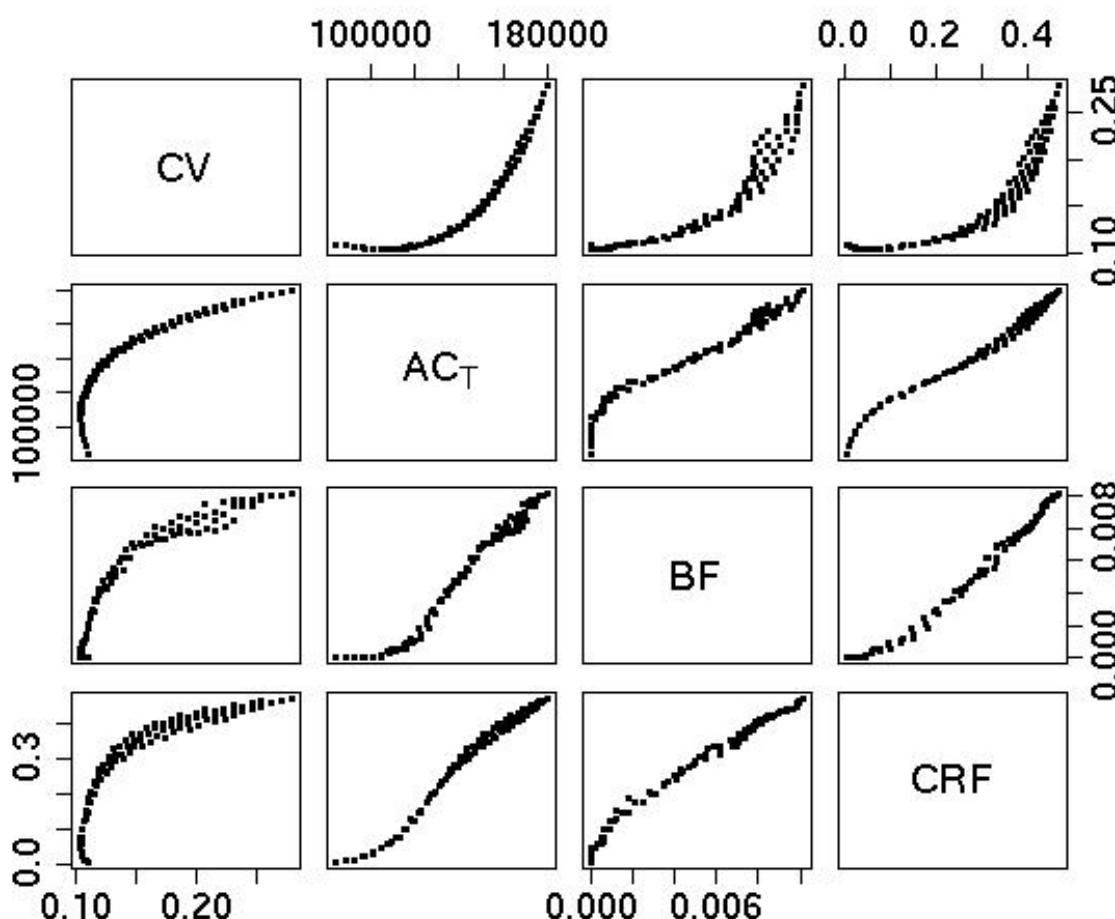


Figure 6: Trade-off between attributes: CV - coefficient of variation of the catches, AC_T - Present value of the accumulated catch, BF - biomass failure risk and CRF - catch rate failure risk. Different management actions are represented by dots.

Results we gathered could be also used to grossly generalize catch instead of “fishing days” enforcement.

Expected annual total landings given in Table IV could be used as TAC. For example, if decision makers choose to replace 20% of bait-boat

fleet by 600 purse-seine fishing days, they could allow for an annual TAC equal to 22,566 tons. The total TAC could be shared by fleets according to the PB proportion which is also shown in Table IV. Close to 17,150 tons ($\approx 76\%$ of the total TAC) should be caught by bait-boat fleet.

Table IV: Expectation of quantities of interest after enforcement of 36 different management actions. Numbers in the column “BB” are the alteration (%) of bait-boat effort, while in the column “PS” they are the number of fishing days allowed for purse-seine fleet. “C” stands for expected means of annual catches over 5 years, while “PB” stands for the proportion of total yields that is caught by bait-boat fleet. Attributes evaluated are: AC_T - Present value of the accumulated catch, CV - coefficient of variation of the catches, CRF - catch rate failure risk, and BF - biomass failure risk.

BB	PS	C	PB	CV	AC_T	BF	CRF	BB	PS	C	PB	CV	AC_T	BF	CRF
-20	0	17876	1.00	0.11	84069	0 ⁺	0.01	0	1200	29202	0.67	0.13	140117	0 ⁺	0.29
-20	600	22566	0.76	0.10	107560	0 ⁺	0.06	0	2100	33160	0.54	0.18	160464	0.01	0.39
-20	1200	26519	0.62	0.11	127465	0 ⁺	0.20	5	0	22313	1.00	0.10	105027	0 ⁺	0.05
-20	2100	31116	0.49	0.16	150843	0.01	0.33	5	600	26429	0.80	0.11	125795	0 ⁺	0.18
-15	0	18806	1.00	0.11	88460	0 ⁺	0.01	5	1200	29821	0.68	0.13	143042	0.01	0.31
-15	600	23381	0.77	0.10	111403	0 ⁺	0.08	5	2100	33623	0.55	0.19	162647	0.01	0.40
-15	1200	27221	0.63	0.12	130772	0 ⁺	0.22	10	0	23136	1.00	0.10	108921	0 ⁺	0.07
-15	2100	31656	0.50	0.16	153384	0.01	0.35	10	600	27138	0.81	0.11	129149	0 ⁺	0.21
-10	0	19715	1.00	0.11	92751	0 ⁺	0.02	10	1200	30419	0.69	0.14	145871	0.01	0.33
-10	600	24175	0.78	0.11	115148	0 ⁺	0.10	10	2100	34067	0.56	0.19	164743	0.01	0.42
-10	1200	27902	0.64	0.12	133983	0 ⁺	0.24	15	0	23937	1.00	0.10	112715	0 ⁺	0.08
-10	2100	32177	0.52	0.17	155833	0.01	0.36	15	600	27826	0.82	0.11	132406	0 ⁺	0.24
-5	0	20603	1.00	0.10	96943	0 ⁺	0.02	15	1200	30998	0.70	0.14	148606	0.01	0.35
-5	600	24947	0.79	0.11	118795	0 ⁺	0.12	15	2100	34493	0.57	0.20	166753	0.01	0.43
-5	1200	28562	0.66	0.12	137098	0 ⁺	0.26	20	0	24717	1.00	0.10	116412	0 ⁺	0.10
-5	2100	32678	0.53	0.17	158193	0.01	0.38	20	600	28493	0.82	0.12	135567	0 ⁺	0.27
0	0	21468	1.00	0.10	101035	0 ⁺	0.03	20	1200	31556	0.70	0.15	151248	0.01	0.37
0	600	25699	0.8	0.11	122343	0 ⁺	0.15	20	2100	34901	0.58	0.21	168680	0.01	0.44

4 - Discussion

If there is no contrast in the fishing effort time series – periods of low effort alternating with periods of high effort - then the estimations of biomass dynamic model parameters are unreliable (Hilborn & Walters 1992). However the data set we analyzed is reasonably informative because prior distributions were clearly updated for r and q parameters.

Posterior estimation of r was too large and has no biological meaning. Maybe we should look at this estimate just as mathematical coefficient suitable to fit the data. In fact Laloë (1995) argues that parameters of biomass dynamics models should not be interpreted as biological attributes. Whatever, large estimates of r are not uncommon for tunas. For example in a recent stock assessment of South Atlantic yellowfin tuna, a log-normal prior, $N(\mu = 0.8; \sigma = 0.05)$, together with

bounds for r at 0.65 and 0.9 resulted in a final point estimation close to 0.8 (Anonymous, 2004). Hence, the estimate we gathered for the skipjack in the Southwest Atlantic might indicate that the populations of the small skipjack tuna is probably more productive than the yellowfin tuna population. Skipjack ranked fourth in the world landings (FAO, 2002).

If we compare k and the biomass estimated for the last simulated year (*i.e.* 2006) it becomes apparent that the biomass has decreased 25% across the last decades if compared with original unfished level, probably due to the fishery mortality mainly. That reduction in the stock biomass is similar to that observed for the Western and Central Pacific oceans (WPO), where current catch levels are considered sustainable for current stock productive conditions (Langley *et al.* 2004). In the eastern Pacific ocean (EPO) the current catches are considered below the MSY (Maunder, 2003) and the stock biomass has

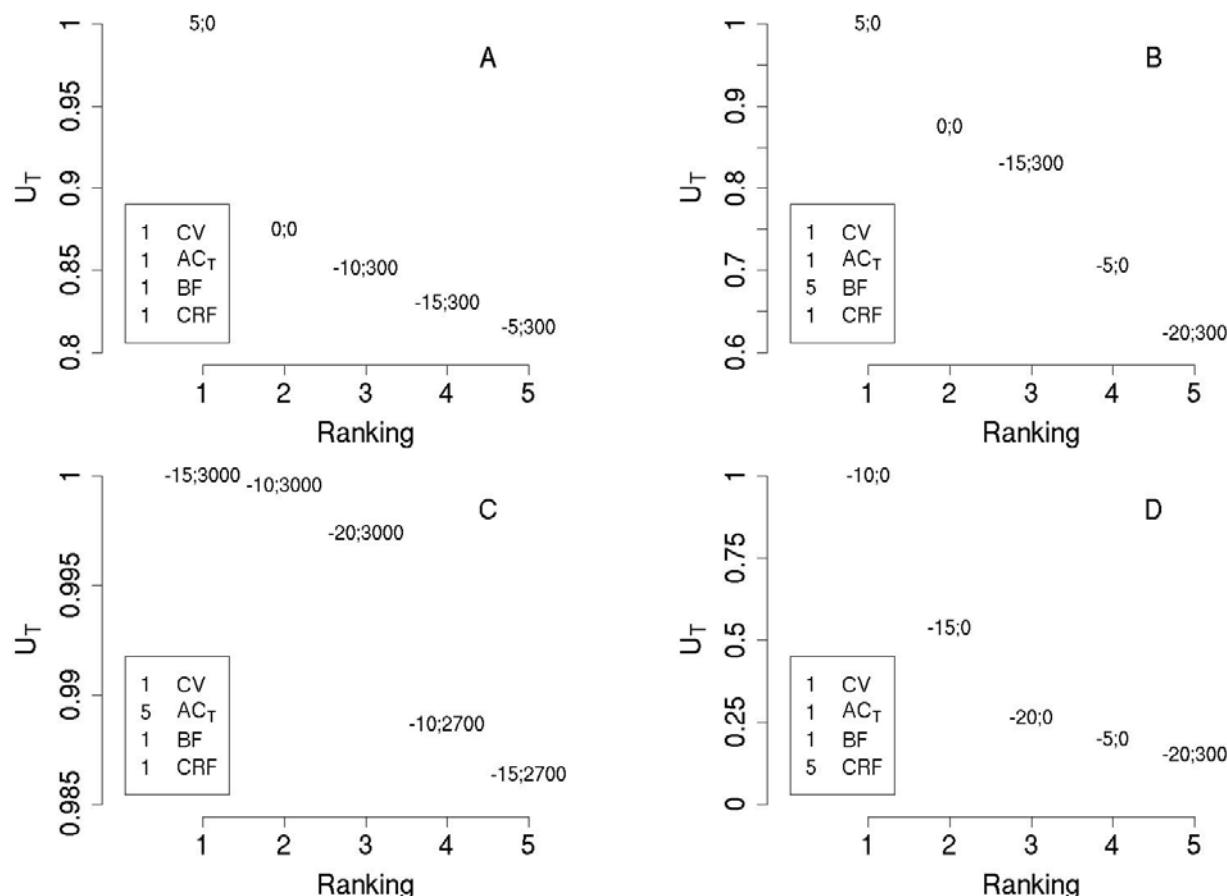


Figure 7: Performance as measured using U_T of ten of the better actions in three simulations. Coefficient of variation (CV) of catches, cumulated catch over T years (AC_T), risk for stock biomass (BF) and economic risk for the traditional bait-boat fleet (CRF) are the measurements used to calculate U_T . The weights of the attributes are the numbers in the boxes inside the panels. The paired numbers in the main area of the panel stands for the management actions. The number at left stands for modifications (%) of the bait-boat effort while the number at right stands for modifications (fishing days) of the purse-seine effort.

not changed too much in the EPO (IATTC, 2003). The results we gathered for the Southwest Atlantic (SWAO) are similar to those of the Western, Central and Eastern Pacific (WPO and EPO). In contrast, for the East Atlantic (EAO) fishing ground, the scenario is not so optimistic. Although no formal assessment analysis has been done, Fonteneau (2003) suggests that the decreasing trends in the catch per unit of effort and in the average length and weight of fish landed, is an indication that skipjack is fully exploited in the EAO.

Probably the main restrictions to our results are related to the assumption of a constant catchability coefficient (q). The validity of such assumptions depends on the believes that standardization analysis of the catch rate (Andrade, 2007) was enough to produce reliable abundance indexes. Here we just assume that the available indexes are reasonable. Another issue related to q is that we assumed it would remain constant for bait-boat and purse-seine when calculating the predictive outcomes of alternative management actions into

the next five years. Although this is speculative, any attempt to estimate the future modifications of q would be probably a speculation as well. Hence, our choice was to adopt the simplest approach.

In order to use more complex and realistic models, and to relax restrictive assumptions on relevant parameters like q , more information would be necessary. An alternative would be to integrate into a model the catch rates as available in the paper of Andrade (2007), and the catch-at-length (or catch-at-age) data as published in Jablonski & Matsuura (1985) and Vilela & Castello (1993). Those extended models should be evaluated in future studies but are not available to decision makers today.

Although there are international institutions in charge of the tuna stocks management worldwide, there are no management recommendations for the skipjack fishery. The lack of fishery assessment analysis results in inexistence of formal management actions in the Atlantic. Hence skipjack fishing activities have been working similarly to an open-access fishery system. Most of

those types of fishery systems tend to biological overexploitation scenarios, for which skipjack provide one of the few exceptions (Clark 1985, Hilborn & Walters 1992). When the prices are low and/or markets saturate, there is no advantage in increasing catches. This seems to be very true for skipjack fisheries. The inclusion of market prices into the analysis framework seems to be mandatory in order to model the behavior of fishery systems. Examples of such economic analyses can be found in Clark (1985).

Economic factors probably prevent biological overexploitation in the skipjack fishery. Biomass has been larger than MSY in the SWAO in spite of more than 20 years of unregulated industrial fishery. Indeed the economic risks of expanding the Brazilian fishing operations are much larger than risks for the skipjack stock. Expansion of industrial fisheries depends primarily on the possibilities of increasing the economic efficiency of the systems. The introduction of a purse-seine fleet could enhance the overall fishing fleet efficiency, but it would increase the risks of economical problems for the traditional bait-boat fleet. In fact "replacement" actions are apparently the better management alternatives if the objective is to increase the accumulated economic gains across the coming years. The "aggressiveness" of the implementation depends on the profile of the decision makers. Risk prone decision makers will favour a large number of purse-seine fishing days and the elimination of some bait boats, while risk averse decision makers will tend to replace a moderate number of bait-boats by a small (maybe moderate) number of purse-seine fishing days.

Finally, it is important to highlight that, as new data become available, follow-up studies about the Brazilian skipjack tuna should include other criteria to measure how suitable the exchange between purse-seine and bait-boats is. Changes in the number of jobs should be one of the criteria among the "social" ones. Among the ecological issues the risk of catching undesirable juveniles and/or adults of other marine species, is also of primary interest.

5 - Conclusion

To this day, the main argument against introducing purse-seine is the economic difficulties it would cause to the traditional bait-boat fleet. Although we only did a partial evaluation of effects from introducing a new tuna purse-seine fleet, we would like to highlight some things we have learned about skipjack tuna management in the SWAO from this exercise.

In any business, including those related to exploration of natural resources, the reduction of uncertainty usually helps when choosing options assuming less risks and increased benefits (Raiffa 1968, Walters 1986, Frederick & Peterman 1995). In special, we highlight that the smaller the uncertainty on the relative efficiency of purse-seiners (e.g. $q_{ps/bb}$), the more accurate are estimates and predictions about the suitable actions from an economic point of view. Any effort to estimate more reliable indexes of abundance, and to build an up to date catch-at-length (or catch-at-age) database should be encouraged. Those are the critical information to reduce uncertainty on the estimates which are necessary to take management decisions.

It is hard to guess what would happen with the fishery system, before effectively implementing some action one is interested in. To a certain extend optimal levels of exploitation must be determined by trial and error. In this sense, endorsement of few fishing days for purse-seiners seems to be positive in promoting acquisition of knowledge with small risks for biomass. Informative but reversible experiments seem always the best alternative (Ludwig *et al.* 1993). In this sense, we believe that experiments with chartered purse-seine vessels on temporary contracts are a sensible first step before taking chances with a long-term, maybe irreversible, decision.

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