EVALUATION OF MANAGEMENT PROCEDURES:
APPLICATION TO CHILEAN JACK MACKEREL FISHERY

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Abstract

This paper develops a theoretical framework to assess resources management procedures from a sustainability perspective, when resource dynamics is marked by uncertainty. Using stochastic viability, management procedures are ranked according to their probability to achieve economic and ecological constraints over time. This framework is applied to a fishery case-study, facing El *Niño* uncertainty. We study the viability of constant effort and constant quota strategies, when a minimal catch level and a minimal biomass are required. Conditions on the sustainability objectives are derived for the superiority of each of the two management methods.

Keywords: Sustainability, risk, fishery economics and management, viability, stochastic.

1   Introduction

The model of this paper has its origin in some actual management practices in Chilean fisheries. The Jack-Mackerel Chilean fishery faces *El Niño* uncertain cycles, which increase the uncertainty about this resource's availability [4], and thus makes the sustainability assessments more difficult. In some extreme cases, recruitment uncertainty and applied management decisions have led to the collapse of important pelagic stocks, as the Peruvian Anchovy in 1972-1973. Since the late 1990s, the Chilean Jack-Mackerel fishery has been managed under a yearly-defined Total Allowable Catches (TAC) regulation, complemented since year 2001 with the operation of an individual (company allocated) quota scheme [16]. The TAC scheme has had a particular concern about the stability of quota levels over time. Additionally, since the mid-2000s the Jack-Mackerel fishery has been one of the pioneering in Chile to include risk indicators in its management practice. Nevertheless, risk indicators are not yet implemented in a formally integrated decision-making framework, but rather like an additional ad-hoc objective aiming at capping biological (collapse) risk [17].

We are here interested in the definition of a framework to address *sustainable resource management issues*, accounting for both resource dynamics and risk.[1] Dynamic issues received a particular focus in the economic literature, especially in growth theory [18], providing the discounted utility criterion. The issue of decision under risk has also been widely addressed in the economic literature, back to the fundament of expected utility theory which has been axiomatized by [22]. Given these important contributions on dynamic issues on the one hand, and risk on the other hand, one should be surprised to notice that joint issues of risk and time have received less attention. Indeed, though discounted expected utility is the standard theoretical framework in economics, there seems to be few discussions on its axiomatic foundations. In his textbook, *The Economics of Risk and Time* [15], Gollier provides two arguments to justify the use of discounted expected utility with exponential discounting. First, it is time consistent, which is a good property. Second, it accounts for *pure preference for the present* (impatience) via discounting, which may have a sense in individual decision making but is criticized in the sustainability debate on long-run issues.[2]

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[1]In the paper, we will use "risk" and "uncertainty" equivalently, with the underlying economic meaning of *risk*, i.e., stochastic events with know probabilities. We do not address the economic *uncertainty* issue, i.e., unknown or uncomplete probabilities.

[2]Even if discounting implies a "dictatorship of the present," in the book *Sustainability: Dynamics and Uncertainty* by [8], risk and dynamics are addressed mainly in the discounted expected utility framework.

Optimality in fishery economics has been usually defined as the maximization of the total discounted revenue of the harvest, or its expected value under uncertainty [10, 20, 21]. This approach has the great advantage of defining optimal feedback decision rules, or making it possible to rank any alternative management procedure, with respect to a unique criterion and the associated value of discounted expected utility. However, from a sustainability point of view, discounted expected utility faces practical problems. First, there is controversy on the application of this framework for very long term (intergenerational) environmental issues, as it heavily discounts future generations utility [7]. Second, expected discounted utility is rarely used in the real practice of environmental goods management, when environmental and social issues have to be accounted for along with economic ones. Indeed, in practice, management strategies (often defined as simple "rule of thumb") are evaluated in so-called "multicriteria" frameworks with no clear axiomatic foundations [13, 14]. In particular, such methods do not offer an explicit ranking of alternative management procedure, as they provide no common value for conflicting objectives and risk.

This paper tackles the challenge of providing a method to define optimal management strategies or rank alternative management procedures, accounting for risk and conflicting sustainability issues. We address this issue with the so-called stochastic viability approach [11, 12]. Given a set of (multi-criteria) "outcome indicators" (for example, either referring to physical or economic variables) and its corresponding set of thresholds, the latter representing sustainability objectives (e.g., minimal biomass, minimal catch level), we aim at evaluating management procedures by maximizing the probability of achieving these objectives jointly and for all periods. We offer an illustration of the implications of using this approach in the field of fishery management under environmental uncertainty, using the case of the pelagic Jack-Mackerel Chilean fishery facing *El Niño* uncertainty.

The contribution of the paper is to build a bridge between the economic literature on optimal resource management under risk and the "practical oriented" literature on sustainable fisheries management. By providing a "common value" to a practical multi-criteria approach, we obtain an optimality framework which allows us to rank alternative management procedures according to their viability probability. Dealing with optimality, value, marginal analysis, and trade-offs, our approach appears to be closer to economics than the usual multicriteria Management Strategy Evaluation approaches.

The paper is organized as follows. Section 2 presents our theoretical framework to assess risk and sustainability, and to compare resources management procedures when sustainability objectives are in conflict. We apply this framework to the Jack-Mackerel Chilean fishery case-study in section 3, and illustrate our results comparing constant effort and quota strategies. We conclude with some remarks on the relevance of our results for practical fisheries management in Section 4.

2   A risk metrics for sustainability objectives

In this section, we describe the theoretical framework which allows us to assess resource management procedures. We show how this framework can be used to define an optimal viable management rule under uncertainty, but also to compare the effectiveness of given (sub-optimal) management rules. We also present how our framework can be used to exhibit the necessary trade-offs between sustainability objectives represented by constraints to be satisfied over time.

2.1   Management strategy assessment by stochastic viability

Dynamic system   We start with a management resource mathematical model, which accounts for the dynamics, the uncertainties and the possible actions. For this, let us consider the following discrete-time control dynamical system

$$x(t+1) = G(t, x(t), u(t), \omega(t)), \quad t = t_0, \ldots, T-1, \quad x(t_0) = x_0, \tag{1}$$

where

- the *time* index t is discrete, belonging to $\{t_0, \ldots, T\} \subset \mathbb{N}$; in practice, the time period $[t, t+1[$ may be a year or a month for instance; T is the horizon, taken finite here;

- the *state* $x(t)$ is a vector belonging to $\mathbb{X} := \mathbb{R}^n$; $x(t) \in \mathbb{R}$ may represent the biomass of a single species, while a predator-prey system may be described by a couple $x(t) \in \mathbb{R}^2$; $x(t) \in \mathbb{R}^n$ may be a vector of abundances at ages for one or for several species, and it may also represent abundances at different spatial patches; the state $x(t)$ may also include capital (boats or infrastructures) or labor force.

- the *control* $u(t) \in \mathbb{U} := \mathbb{R}^p$ may represent catches or harvesting effort, or may be investment or consumption.

- $\omega(t) \in \mathbb{W} := \mathbb{R}^q$ denotes an *uncertainty* or *disturbance* which affects the dynamics at time t; this can include recruitment or mortality uncertainties in a population dynamic model, climate fluctuations or trends, unknown technical progress.

- $G : \mathbb{N} \times \mathbb{X} \times \mathbb{U} \times \mathbb{W} \to \mathbb{X}$ is the *dynamics* as, for instance, one of the numerous population dynamic models, such as logistic or age-class models; it may also include capital accumulation dynamics.

- $x_0 \in \mathbb{X}$ is the *initial state* for the *initial time* t_0, which is supposed to be deterministic and known.

Uncertainty and scenarios   For the time being, we make no assumptions that $\omega(t_0), \ldots, \omega(T-1)$ are random variables: they just form a sequence of vectors. We define

$$\Omega := \mathbb{W}^{T-t_0} \tag{2}$$

as the set of *scenarios*, the notation[3] for a scenario being

$$\omega(\cdot) := (\omega(t_0), \ldots, \omega(T-1)) \,. \tag{3}$$

Decision rules and management procedures   To design controls, we shall focus on state feedback policies based on the observation at time t of the state $x(t)$. Let us define a *(state) feedback* as a mapping $\widehat{u} : \mathbb{N} \times \mathbb{X} \to \mathbb{U}$. A feedback is a *decision rule* which assigns a control $u(t) = \widehat{u}(t, x) \in \mathbb{U}$ to any state x for any time t.[4] From now on, we shall use equivalently the vocables *state feedback*, *feedback* or *management strategy*.

Sustainability objectives described with indicators and thresholds

Consider K real-valued functions $\mathcal{I}_k : \mathbb{N} \times \mathbb{X} \times \mathbb{U} \to \mathbb{R}$, for $k = 1, \ldots, K$, that represent instantaneous *indicators*, having economic or biological meaning (spawning stock biomass, annual catches or profit, etc.). Attached to them are thresholds (reference points) $\iota_1 \in \mathbb{R}, \ldots, \iota_K \in \mathbb{R}$, measured in the same unit (tonnes, money, etc.).
Broadly speaking at this stage, we aim at finding paths along which the constraints[5] $\mathcal{I}_k(t, x(t), u(t)) \geq \iota_k$, are satisfied for all times $t = t_0, \ldots, T$ and for all $k = 1, \ldots, K$. This is the so-called *viability approach*.[6] A trajectory that does not satisfy one (or more) of the constraints at some time is not viable, whatever is the level of violation of the constraints. All the constraints must be satisfied at all times for sustainability. Within this "all or nothing" approach, there are trade-offs neither between time periods (as would be the case with discounted utility) nor between indicators. In a sense, the absence of trade-offs between time periods is related to intergenerational equity issues: there is no compensation from one generation to another, at least for the indicators considered.[7] In the same spirit, the absence of trade-offs between instantaneous indicators has to do with strong sustainability, considering that objectives are not substitutable, i.e., a bad realisation of an objective cannot be compensated for by a high realisation of another one. For example, some stocks may be required to be maintained, in particular natural resources.

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[3]In the sequel, the notation $u(\cdot)$ means a sequence $(u(t_0), \ldots, u(T-1))$, and $x(\cdot) = (x(t_0), \ldots, x(T))$. Indeed, by (1), there is a final state $x(T)$ produced by an ultimate control $u(T-1)$.

[4]With such a definition, we implicitly assume that the state is (at least partially) measured. As a consequence, we shall not consider the case where only a corrupted observation of the state is available to the decision-maker (as it is the case in practical situations).

[5]The indicator $\mathcal{I}_k$ is above the threshold ι_k. However, for an indicator – like CO_2 concentration – to be below a threshold, we just change the sign.

[6]The constraint functions formalism is quite general, as it can include absence of constraints (take $\mathcal{I}_k$ having constant value $> \iota_k$), or final target constraint (take $\mathcal{I}_k(t, x, u) > \iota_k$ for all $t = t_0, \ldots, T-1$ but not for $\mathcal{I}_k(T, x)$).

[7]Note that from a general point of view, saying that time periods are treated separately does not mean that they also are identically. Indicators may vary with time, and thresholds could also vary from period to period.

However, trade-offs cannot be escaped, due to limited resources, and we shall promptly "soften" this approach, first by accepting constraints violations with low probability, second by treating the thresholds level as parameters and providing a common value to evaluate trade-offs between these levels.

Viability probability of a management strategy

In an uncertain framework, it is generally impossible that constraints are satisfied for all scenarios. Following [11] and [12], we adapt the viability approach to the stochastic case.

As said above, in contrast to the deterministic case, paths can no longer be evaluated and compared, but decision rules can. For any management strategy $\widehat{u}$, initial state x_0, and initial time t_0, let us define the set of *viable scenarios* by:

$$\Omega_{\widehat{u},t_0,x_0} := \left\{ \omega(\cdot) \in \Omega \; \middle| \; \begin{array}{l} x(t_0) = x_0 \\ x(t+1) = G(t,x(t),u(t),\omega(t)) \\ u(t) = \widehat{u}(t,x(t)) \\ \mathcal{I}_k(t,x(t),u(t)) \geq \iota_k \\ k = 1,\ldots,K \\ t = t_0,\ldots,T \end{array} \right\}. \tag{4}$$

Any viable scenario $\omega(\cdot)$ in $\Omega_{\widehat{u},t_0,x_0}$ is such that the state and control trajectory driven by the feedback $\widehat{u}$ satisfies the constraints.

In a sense, a management strategy $\widehat{u}$ is better than another if the corresponding set of viable scenarios is "larger". To give precise meaning to this, we shall from now on assume that the set Ω is equipped with a *distribution probability* $\mathbb{P}$.[8] The notation $\omega(\cdot) = (\omega(t_0),\ldots,\omega(T))$ still denotes a generic point in Ω; however, it may also be interpreted as a sequence of random variables when $\omega(\cdot)$ is identified with the identity mapping from Ω to Ω. In practice, one assumes that the random variables $(\omega(t_0),\ldots,\omega(T-1))$ are independent and identically distributed, which defines the probability $\mathbb{P}$, or that they form a Markov chain.

We say that $\mathbb{P}\left[\Omega_{\widehat{u},t_0,x_0}\right]$ is the *viability probability* associated with the initial time t_0, the initial state x_0 and the management strategy $\widehat{u}$.

So, in the stochastic viability framework described above, it is possible to rank management procedures with respect to their viability probability, for any given set of sustainability objectives thresholds $\iota_1,\ldots,\iota_K$.

To stress the dependency upon thresholds, let us introduce the notation

$$\Pi(\widehat{u},\iota_1,\ldots,\iota_K) := \mathbb{P}\left[\Omega_{\widehat{u},t_0,x_0}\right]. \tag{5}$$

In our approach, a management rule is preferred if it results in a high viability probability. It is thus of interest to determine the optimal management rule, i.e., the management rule that maximizes the viability probability. Given sustainability objectives $\iota_1,\ldots,\iota_K$, an *optimal strategy* $\widehat{u}^\star$ is one which maximizes $\Pi(\widehat{u},\iota_1,\ldots,\iota_K)$. The *maximal viability probability* $\max_{\widehat{u}} \Pi(\widehat{u},\iota_1,\ldots,\iota_K)$ is an upper bound for any strategy. Notice that optimal strategies depend on the objective levels.

From a general point of view, determining optimal feedback rules in dynamic optimization problems under uncertainty is not easy, either for optimal control or stochastic viability problems. Such feedback rules will depend on the characteristics of dynamics of the system, and other assumptions or restrictions to the model. However, in some cases as studied in [12], some optimal strategies can be identified and explicitly described. When this is possible, one can draw the envelope of maximal probabilities of achieving sustainability objectives as a function of these latter. This defines a probability frontier within which lie all strategies.

When it is not possible to define an optimal policy, it is of interest to compare given policies. While we recognize the pitfalls of making such comparisons with an *ad hoc* reduce number of management strategies, our present aim is simply to compare the properties of various in-use policies and define to which range of objectives they are dominant sub-optimal solutions of the stochastic viability problem. Moreover, letting sustainability objectives vary, we obtain regions where one strategy dominates the other one.

We illustrate such an analysis in the next section, in the Chilean Jack-Mackerel fishery case.

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[8]The set Ω, product of copies of $\mathbb{R}$, is equipped with its Borel σ-field. The mappings G, $\mathcal{I}_1$, $\ldots$, $\mathcal{I}_K$, and all management strategies $\widehat{u}$ are supposed to be measurable.

3   Modeling the Chilean Jack-Mackerel fishery

In [23], the Chilean Jack-Mackerel fishery has been studied, using *Instituto de Fomento Pesquero* (IFOP)'s official data [1, 2] and its age-structured model for this fishery, by adding to the model more structure into the stock-recruitment function. Indeed, a Ricker recruitment function is estimated by using linear time-series analysis[9]. Additionally, a generating (sinusoidal) function for *El Niño* uncertain cycles is estimated by using a non-linear iterative technique [23, p. 64]. Then, and following the line of [5] and [6], [23] performs a Management Strategy Evaluation. The analysis at our paper will thus be based on the estimation results provided by [23].

3.1   A bioeconomic model for the Chilean Jack-Mackerel fishery

Economics.   We make the following economic assumptions, which are standard ([9, 20, 10]).

- Demand is infinitely elastic. Indeed, harvest from this fishery is mainly processed as fish meal, a commodity which faces high demand substitution. Thus, the fishing industry is essentially a price-taking industry, and we assume that any unit harvested is sold for a fixed price, invariant in time.

- Per unit harvesting costs (either in numeraire or in effort unit) are not dependent of harvest size, but vary with population abundance. These costs increase as the size of the population decreases. To represent this assumption, we will define effort as a fishing mortality multiplier within a Baranov-type catch function (cf. (10); see also [19]). This assumption is equivalent to assume that fishing effort (defined in time unit, for example) has a constant unit cost, and that Catches Per Unit of Effort (CPUE) decrease when the stock decreases.

To simplify the analysis, we eliminate price and fishing costs from the profit expression, since quotas are defined in quantity terms, and price and costs do not have a qualitative effect on our results. We thus concentrate on harvest quantity and fishing effort as proxy of revenue and fishing costs. This assumption is the same as in [20], [10] and [21], in which the expected discounted sum of harvest is maximized in place of that of profit.

Under these assumptions, as the CPUE decreases when the stock size falls, there is a minimal stock size under which the marginal cost of fishing effort (which is constant) is higher than the marginal revenue of fishing effort. The marginal profit, defined as the difference between marginal revenue and marginal fishing cost, is then negative. We assume that no extra fishing effort is done once the marginal profit is nil. It implies that there are an upper value for the fishing effort (λ^{sup} hereafter).

Biology.   Let us describe the dynamics of the Chilean Jack-Mackerel stock by an age-class model (see for instance [19]). Time is measured in years, and the time index $t \in \mathbb{N}$ represents the beginning of year t. Let A = 12 denote the maximum age group, and $a \in \{1,\ldots,A\}$ an age class index, all expressed in years. The vector $N = (N_a)_{a=1,\ldots,A} \in \mathbb{R}_+^A$ is made of *abundances* at age: for $a = 1,\ldots,A-1$, $N_a(t)$ is the number of individuals of age between $a-1$ and a at the beginning of year t; $N_A(t)$ is the number of individuals of age greater than $A-1$. The fishing activity is represented by a *fishing effort multiplier* $\lambda(t)$, supposed to be applied in the middle of period t.

For all classes, except for the recruits, we have:

$$N_{a+1}(t+1) = e^{-(M_a+\lambda(t)F_a)}N_a(t) , \quad a = 2,\ldots,A-1 , \tag{6}$$

where M_a is the *natural mortality rate* of individuals of age a, F_a is the mortality rate of individuals of age a due to harvesting between t and $t+1$, supposed to remain constant during period t (the vector $(F_a)_{a=1,\ldots,A}$ is termed the *exploitation pattern*). The values for parameters M_a and F_a are taken from IFOP's official model for this fishery, so that M_a is equal to 0.23 for all a and F_a will be equal to the vector of averages values of F_a during 2001-2002 (cf. [3]). For the recruits, we rely upon a statistical study in [23] which relates them to the *spawning stock biomass*

$$SSB(N) := \sum_{a=1}^{A} \gamma_a \varpi_a N_a , \tag{7}$$

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[9]The Ricker model is normally used for species with highly fluctuating recruitment, involving high fecundity as well as high natural mortality rates. These two features are indeed present in the case of small pelagic species, such as jack mackerel. (Begon and Mortimer 1986; Haddon 2001).

where $(\gamma_a)_{a=1,\dots,A}$ are the *proportions of mature individuals* (some may be zero) and $(\varpi_a)_{a=1,\dots,A}$ are the *weights* (all positive). The following two-years delay dynamic relationship obtained is

$$N_1(t+1) = \alpha SSB(N(t-1))\exp\left(\beta SSB(N(t-1)) + w(t)\right), \tag{8}$$

where parameters are set $\alpha = e^{2.39}$ and $\beta = 2.2 \cdot 10^{-7}$, and $\{w(t)\}$ is a random process reflecting the impact of climatic factors in the stock recruitment relationship. Notice that the recruitment relationship is given by a Ricker type function applied to the spawning stock biomass of two previous periods.

El Niño **cycles model.** The residual term $w(t)$ in the estimated equation (8) has a periodic part and an error term and is supposed to capture the effects of the *El Niño* phenomenon (a cycle with random shocks). Indeed, the statistical analysis at [23] implies the following structure for the residual $w(t)$:

$$w(t) = -0.12 \times \text{niño}(t) + \epsilon(t), \tag{9}$$

where

- $\{\epsilon(t)\}$ is a sequence of i.i.d. random variables with Normal distribution $\mathcal{N}(0; 0.18)$

- $\text{niño}(t) = \mathbf{1}_{\{-1.2\sin(18.19+2\pi(t-1959)/3.17)>0.5\}}$ is a *dummy (0 or 1) variable* reflecting the presence of *El Niño* phenomena.

El Niño phenomenon is the result of a wide and complex system of climatic fluctuations between the ocean and the atmosphere, and nowadays it is considered to be an important signal of the global weather. However, there is no consensus about its future behavior, as literature comprises contradictories versions about its future frequency and intensity.

Based on Chilean marine biologists advice, the authors calculated the occurrence of *El Niño* phenomenon from the *National Oceanic and Atmospheric Administration (NOAA)* data on sea surface temperatures measured at *region Niño 3.4* (120W-170W, 5N-5S). NOAA computes the *Oceanic El Niño Index (ONI)* as a difference of the sea surface temperature with respect to the historical average of temperatures obtained from the period 1971-2000. Then a time average is computed, and it is said that *El Niño* occurs when this average is greater than 0.5 °C (see the expression of niño(t)). The ONI is modeled via a sinusoidal function whose parameters are obtained via statistical methods. This sinusoidal estimation allows to represent the different cycles as can be seen in Figure 1. Indeed, one can identify cycles of around six years for time period 1951-1964; between three and four years for time period 1965-1990; and near to three years for time period 1991-2002. Each one of these three periods of time were treated differently from a statistical point of view. In this paper, we shall only focus on the last period 1991-2002.

3.2 Viability assessment of constant quota and constant effort management procedures for the Chilean Jack-Mackerel fishery

In this section we used the stochastic viability approach to compare management procedures for the Chilean Jack-Mackerel fishery. We focus on two different types of MPs: constant constant quota and constant fishing effort, both stationary over a fixed period of time ($T = 10$ years). For these classes of MPs, we compute their viability probability associated to two constraints, biological and economical.

Economic and biological constraints We shall consider, on the one hand, the following *economic constraint*. Firstly, the total annual catch Y, measured in biomass (millions of tons), is given by the *Baranov catch equation*[10] [19, p. 255-256]:

$$Y(N,\lambda) = \sum_{a=1}^{A} \varpi_a \frac{\lambda F_a}{\lambda F_a + M_a}\left(1 - e^{-(M_a + \lambda F_a)}\right)N_a. \tag{10}$$

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[10]Y measures the aggregated catch in period t which adds up catches from the Chilean and foreign fleets. During the 2000s the chilean fleet's annual catches have ranged between 1.1-1.4 million tons (though at year 2009 this figure fell to 700 thousand tons), while foreign fleet's annual catches have varied between 200-400 thousand tons.
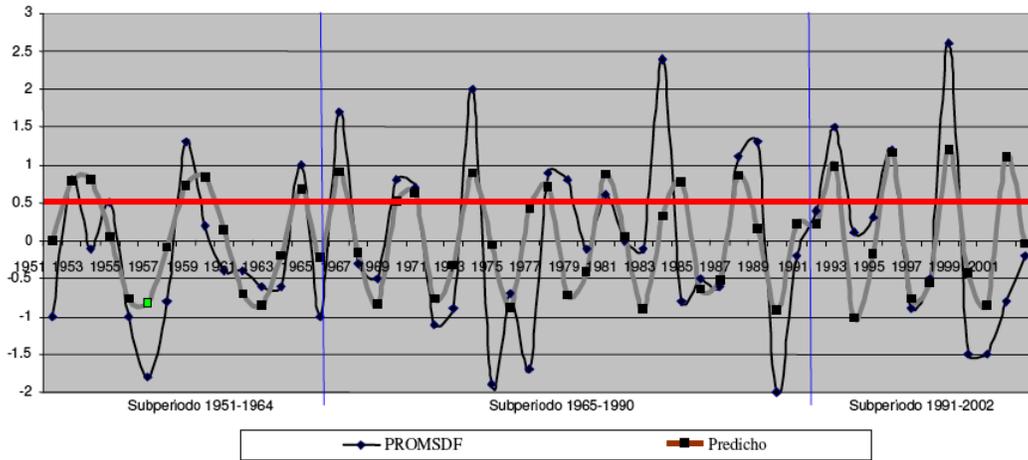
Figure 1: Construction of *niño*(t) dummy variable

With this definition, consider the economic constraint

$$Y(N(t), \lambda(t)) \geq y_{\min}, \quad \forall t = t_0, t_0 + 1, ..., T, \tag{11}$$

where the parameter $y_{\min}$ is the minimum level of landing (or annual total catches) that we expect to harvest each period of time. This parameter takes values from 1 to 1.5 millions of tons, which means that the yield should be above landings of 1 to 1.5 millions of tons, respectively. Using the notation of Section 2.1, the constraint (11) corresponds to the following indicator and threshold: $I_2(t, x(t), u(t)) := Y(N(t), \lambda(t))$ and $\iota_2 := y_{\min}$.

On the other hand, we consider the *biological constraint*

$$SSB(N(t)) \geq pSSB_{\text{virg}}, \quad \forall t = t_0, t_0 + 1, ..., T, \tag{12}$$

where SSB is the spawning stock biomass defined in (7), $SSB_{\text{virg}} = 6.44$ millions tons is the *virginal spawning stock biomass* of the fishery, and the parameter p denotes the desired percentage of SSB_{virg} expected to be preserved along the exploitation time. In all our computations, parameter p takes values from 0 to 0.4, which means that $SSB(N(t))$ should be above the values of 0% to 40 % of the virginal spawning stock biomass, respectively. Using the notation of Section 2.1, the constraint (12) corresponds to the following indicator and threshold: $I_1(t, x(t), u(t)) := SSB(N(t))$ and $\iota_1 := pSSB_{\text{virg}}$.

Viability assessment of constant quota and constant effort strategies   Considering the *state vector* ($A + 1$-dimensional)

$$x(t) = (N_1(t), \ldots, N_A(t), SSB(N(t-1))),$$

and a *control variable*

$$u(t) = \lambda(t).$$

From (6)–(7)–(8), we obtain a control dynamical system in state form:

$$x(t+1) = G(x(t), u(t), w(t)), \quad t = t_0, t_0 + 1, \ldots, T, \qquad x(t_0) \text{ given.}$$

In what follows, we shall take the initial year $t_0 = 2002$. With this state model, we are in the framework of Section 2.1.

Definition of strategies

A *constant effort strategy* (CES) is a constant strategy defined by $\widehat{\lambda}(t,N) = \overline{\lambda}$, yielding the constant effort[11] $\lambda(t) = \overline{\lambda}$. A *constant quota strategy* (CQS) is a strategy $\widehat{\lambda}(t,N) = \lambda$ implicitly defined by $Y(N,\lambda) = \overline{Y}$, when possible (else $\widehat{\lambda}(t,N) = 0$).

Viability assessment of one constant effort and of one constant quota strategies

Our first application consists in computing the viability probability of two specific management procedures: a CES $\overline{\lambda} = 0.2$ and a CQS at level $\overline{Y} = 1.2$ millions of tons, just about the current quota level in this fishery. Following the framework of Sect. 2.1, these probabilities are computed for each couple $(p, y_{\min}) \in [0, 0.4] \times [1, 1.5]$ of biological and economic thresholds. We thus obtain 3D graphics in Figure 2 (left: CQS; right:CES).
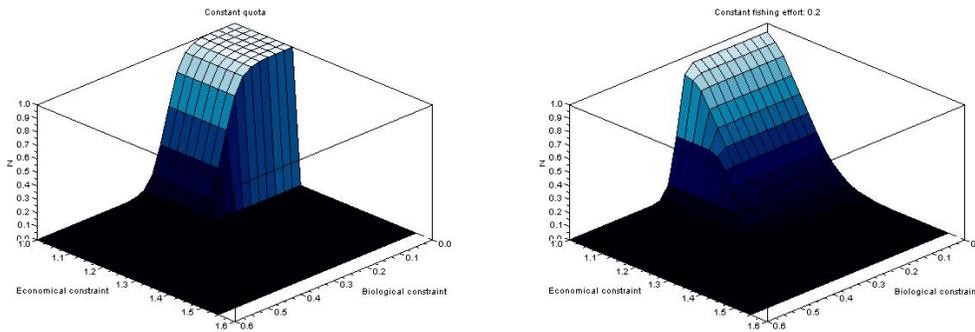

Figure 2: Viability probabilities: left: CQS $\overline{Y} = 1.2$ millions of tons; right: CES $\overline{\lambda} = 0.2$

Let us illustrate how these graphics make different types of comparisons possible. A preliminary visual comparison shows that, for moderate economic thresholds between 1.1 and 1.2 millions of tons and low biological thresholds, the CQS provides a higher viability probability than the CES.

Which constant quota and constant effort performs better within each management strategy family?

Our second application consists of identifying the best strategy within each family of policy types, namely, either CES or CQS. We will define the best strategy as the one which gives the highest viability probability within each policy type. For each couple $(p, y_{\min}) \in [0, 0.4] \times [1, 1.5]$ of biological and economic thresholds, we compute the highest viability probability for a given kind of policy. For computational purposes, for the CES case we consider values of λ within the range $[0, 0.4]$, and for the CQS case, we consider TAC levels within the range $[1, 1.4]$ million of tons. Then, we obtain two 3D graphics (one for each type of strategies) as can be seen in Figure 3.

By introducing flexibility within each policy family, that is that we can change the level of the constant policy, we observe that a larger range of combinations of biological and economic thresholds become "viable", with a strictly positive probability (compare Figure 2 and Figure 3)

Constant quota or fishing effort strategies? Which management family performs better?

Our third application consists of, after identifying the best strategy within each CES or CQS family, comparing these optima between families.

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[11]In our model, fishing mortality is proportional to fishing effort when the fishing pattern, *i.e.* the technology, is constant. The constant effort strategy is thus identical to the constant fishing mortality strategy depicted here.
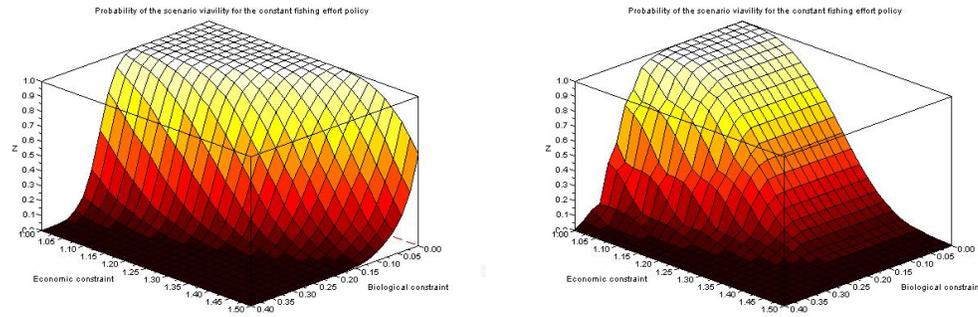
Figure 3: Maximal viability probability within CQS (left) and SFRS (right)

The results produced in the preceding sections are useful to identify circumstances under which each strategy is likely to be preferable. Indeed, this comparison can be obtained from Figure 3: the 2D graphic of Figure 4 exhibits, for each couple $(p, y_{\min}) \in [0, 0.4] \times [1, 1.5]$ of biological and economic thresholds, for which family is the maximum of the two surfaces is achieved. However, due to confidence interval, we in fact represent the domain where one strategy strictly dominates the other, that is one for which the resulting probability interval lies strictly above the other one. The best policy type is identified by a specific given color: the dark (blue) area identifies the biological and economic thresholds $(p, y_{\min})$ where the best constant quota strategy has higher probability than the best constant effort strategy, the light (yellow) area has exactly the opposite meaning, and the intermediary area identifies the thresholds for which both policy types have equal probability (that is, the confidence intervals cross).

We have also plotted two lines denoting the iso-probabilities at a level of 90% and 10%. So, for the thresholds $(p, y_{\min})$ below the 0.9-line, we have a viability probability equal or greater than 90%, and for the thresholds $(p, y_{\min})$ above the 0.1-line we have a viability probability equal or lower than 10%.

From this output we can show that CQS seem to perform better than CES for small values of biological threshold p. On the other hand, for larger values of this parameter (p above 0.18), CES perform better than CQS.

4   Conclusions

Many natural resources management problems are marked by dynamics and uncertainty. This is for example the case of fishery management where conflicting economic, ecological and social objectives require evaluation methods to rank the potential management procedures, taking into account uncertainty. This is the purpose of the Management Strategy Evaluation approach, which describes trade-offs in management objectives, and characterizes potential management procedures with a set of performance statistics. However, due to the absence of a "common currency" for conflicting performance measures which should be approved by all parties, the decision-makers are left with clearer perspectives but without tools to rank the various management procedures.

To contribute to decision making in natural resource management problems, we have developed a viability analysis based on the definition of a set of constraints that represents the various sustainability objectives. We propose to rank management strategies by the probability that the resulting intertemporal trajectory satisfies all of the objectives over the planning horizon. An optimal management rule is one that results in the highest viability probability. The "common currency" to rank the various management decisions is thus the viability probability.

This stochastic viability framework allows us to exhibit the trade-offs between sustainability objectives (thresholds) and viability probability. It also describes the set of sustainability objectives that can be achieved given an assumed risk level, helping the decision maker in the definition of thresholds.

The results we present are based on a case-study, with estimated parameters. While these results are derived using
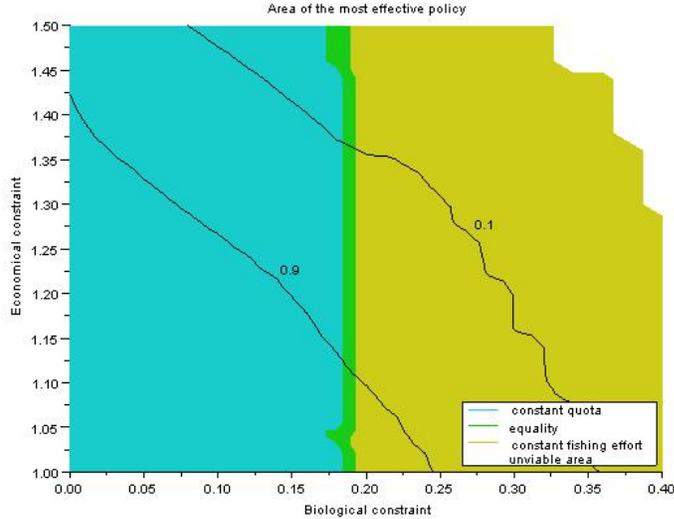
Figure 4: Comparison of the CES and CQS policy families

numerical techniques, the proposed stochastic viability methodology is general and can be applied to a wide range of problems.Our approach is a step toward defining consistent sustainable fishery management analysis, in a multicriteria framework. We provide a first application of stochastic viability to the assessment of resources management procedures. We examine the efficiency of two kind of fishery management policies, namely constant quotas and fishing effort, to achieve sustainability objectives defined as intertemporal constraints on biological and economic indicators. Monte Carlo simulations with markovian uncertainty are run to obtain viability probability of each policy, with respect to the objectives. The method can thus be used to bridge the gap between optimality literature and practical decision-making.

References

[1] Cuota global de captura para la pesquería del recurso jurel, año 2001. Technical report, Subsecretaria de Pesca, SUBPESCA, Valparaíso, 2000. Documento de trabajo.

[2] Informe complementario investigación ctp jurel, 2003: Indicadores de reclutamiento. Technical report, Instituto de Fomento Pesquero (IFOP), Valparaíso, 2003. Documento de trabajo.

[3] Pre informe final. investigación evaluation y ctp jurel, 2006. Technical report, Subsecretaria de Pesca, SUBPESCA, Valparaíso, Marzo 2006. BIP 30033881-0.

[4] R.T. Barber and F.P. Chavez. Biological consequences of El Niño. *Science*, 222(4629):1203–1210, 1983.

[5] D.S. Butterworth and M.O. Bergh. The development of a management procedure for the south african anchovy resource. In J.J. Hunt S.J. Smith and D. Rivard, editors, *Risk Evaluation and Biological Reference Points for Fisheries Management*, pages 83–99. Canadian Special Publication of Fisheries and Aquatic Science 120, National Research Council and Department of Fisheries and Oceans, Ottawa, 1997.

[6] D.S. Butterworth, K.L. Cochrane, and J.A.A. De Oliveira. Management procedures: a better way to manage fisheries? The South African experience. In D. D. Huppert E. K. Pikitch and M. P. Sissenwine, editors, *Global Trends: Fisheries Management*, pages 83–90. American Fisheries Society Symposium 20, 1997.

[7] G. Chichilnisky. An axiomatic approach to sustainable development. *Social Choice and Welfare*, 13(2):219–248, 1996.

[8] G. Chichilnisky, G. Heal, and A. Beltratti. *Sustainability: Dynamics and Uncertainty*. Kluwer Academic Publishers, Dordrecht, 1998.

[9] C. W. Clark. *Mathematical Bioeconomics*. Wiley, New York, second edition, 1990.

[10] C.W. Clark and G.P. Kirkwood. On uncertainty renewable resource stocks: Optimal harvest policy and the value of stock surveys. *Journal of Environmental Economics and Management*, 13:235–244, 1986.

[11] M. De Lara and L. Doyen. *Sustainable Management of Natural Resources. Mathematical Models and Methods*. Springer-Verlag, Berlin, 2008.

[12] M. De Lara and V. Martinet. Multi-criteria dynamic decision under uncertainty: A stochastic viability analysis and an application to sustainable fishery management. *Mathematical Biosciences*, 217(2):118–124, February 2009.

[13] J. A. A. De Oliveira and D. S. Butterworth. Developing and refining a joint management proceduree for the multispecies South African pelagic fisheries. *ICES Journal of Marine Science*, 61:1432–1442, 2004.

[14] H. F. Geromont, J. A. A. De Oliveira, S. J. Johnston, and C. L. Cunningham. Development and application of management procedures for fisheries in Southern Africa. *ICES Jounal of Marine Science*, 56:952–966, 1999.

[15] C. Gollier. *The Economics of Risk and Time*. MIT Press, Cambridge, 2001.

[16] A. Gomez-Lobo, J. Pe na Torres, and P. Barria. Itqs in chile: Measuring the economic benefits of reform. Working Papers Series I-179, Faculty of Economics & Business, Universidad Alberto Hurtado, March (http://economia.uahurtado.cl/pdf/publicaciones/inv179.pdf), 2007.

[17] IFOP. Investigación evaluación de stock y ctp jurel 2006. Technical report, Valparaiso, Chile, March 2006. Informe Final Proyecto BIP 30033881-0.

[18] T. C. Koopmans. On the concept of optimal economic growth. *Academia Scientiarium Scripta Varia*, 28:225–300, 1965.

[19] T. J. Quinn and R. B. Deriso. *Quantitative Fish Dynamics*. Biological Resource Management Series. Oxford University Press, New York, 1999. 542 pp.

[20] W. Reed. Optimal escapement levels in stochastic and deterministic harvesting models. *Journal of Environmental Economics and Management*, 6:350–363, 1979.

[21] G. Sethi, C. Costello, A. Fisher, M. Hanemann, and L. Karp. Fishery management under multiple uncertainty. *Journal of Environmental Economics and Management*, 50:300–318, 2005.

[22] J. von Neuman and O. Morgenstern. *Theory of games and economic behaviour*. Princeton University Press, Princeton, 1947. 2nd edition.

[23] M. Yepes. Dinámica poblacional del jurel: Reclutamiento asociado a factores ambientales y sus efectos sobre la captura, 2004. Master Thesis in Economics.